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Red Onion Price Prediction in Bandar Lampung Using Long Short-Term Memory

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ABSTRACT

Shallots are a food commodity with fluctuating prices and influence people's needs. Unpredictable price changes can make it difficult for consumers, traders, and related parties to make decisions. This study aims to predict shallot prices in Bandar Lampung using the Long Short-Term Memory (LSTM) method. The data used are historical shallot price data from 2020 to 2025. The research stages include data preprocessing, normalization using Min-Max Scaler, dividing training data and test data with a 70:30 ratio, generating sequence data using a sliding window, parameter tuning experiments, LSTM model training, and model evaluation. Based on the experimental results, the best parameters were obtained at a lookback of 14, the number of neurons 50, the tanh activation function, a batch size of 48, a learning rate of 0.001, a maximum epoch of 150, and a patience of 15. The model produced a Mean Absolute Percentage Error (MAPE) value of 2.8035% with an accuracy of 97.1965% on the test data. These results indicate that the LSTM method is capable of predicting shallot prices in Bandar Lampung effectively and can follow price change patterns based on historical data. Furthermore, a comparison was conducted with the Gated Recurrent Unit (GRU) method using the same dataset and training parameters to evaluate the performance of the proposed model. The test results showed that the LSTM model performed better than the GRU.

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1. Introduction

Shallots are one of the most important and highly sought-after food commodities, particularly in countries where they serve as an essential ingredient in daily cooking. Their widespread use in households, restaurants, and food-processing industries makes them a strategic agricultural product with significant economic value. Because shallots are consumed regularly by a large portion of the population, maintaining their availability and affordability is crucial for ensuring food security and supporting household welfare. Consequently, fluctuations in shallot prices attract considerable attention from consumers, traders, policymakers, and other stakeholders involved in the agricultural supply chain.

Unstable shallot prices can have far-reaching consequences for various groups. For consumers, rising prices can increase household expenditures and reduce purchasing power, especially among low-income families. For traders and distributors, unpredictable price movements may create uncertainty in business planning and inventory management. From the government's perspective, significant price volatility can complicate efforts to maintain food price stability and control inflation. Therefore, understanding the factors that contribute to price changes is essential for developing effective policies and market interventions.

Price fluctuations in food commodities are a common phenomenon because commodity prices are dynamic and influenced by numerous interconnected factors. These factors include changes in supply and demand, seasonal harvest cycles, weather conditions, transportation costs, production inputs, market competition, and broader economic circumstances. Disruptions in any part of the supply chain can trigger substantial price changes within a relatively short period.

Previous studies on national staple food prices have shown that unstable food prices can become a significant economic challenge that requires careful monitoring and analysis. As a result, continuous observation and accurate future price prediction are increasingly important. Reliable forecasting can help stakeholders anticipate market changes, make informed decisions, minimize risks, and support the development of strategies aimed at maintaining price stability and ensuring sustainable food availability.[1].

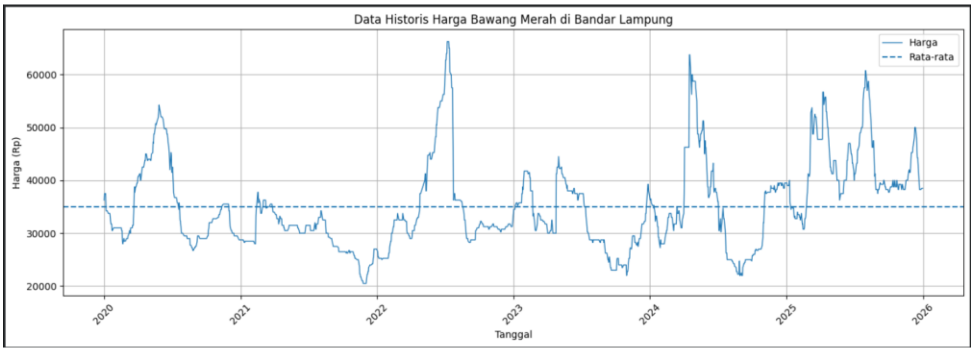

Figure 1. Shallot Price Graph in Bandar Lampung

Food price prediction is one approach that can be used to assist decision-making. With price prediction, relevant parties can estimate potential price changes, allowing for early anticipatory measures. Several previous studies have applied prediction methods to food commodities such as chilies, rice, cooking oil, and other agricultural commodities. Research on predicting the price of curly red chilies in Yogyakarta using LSTM showed that this method was able to produce a MAPE value of 3.6995% with an accuracy of 96.3005% at a data ratio of 70:30 [2]. Another study on chili prices in Malang City also used LSTM and obtained the best results with a data ratio of 70:30, 21 sequences, 128 hidden units, and 150 epochs [3].

Food price data is considered time series data because it is ordered based on time. Time series data prediction is performed by studying historical patterns to estimate future values. Several methods can be used for time series prediction, but deep learning methods such as Long Short-Term Memory (LSTM) are widely used because they are able to learn long-term patterns in sequential data. Research on national staple food prices explains that staple food prices are non-linear and time-series based. Therefore, the LSTM method is used because it can overcome the weaknesses of Recurrent Neural Networks (RNNs), particularly the vanishing gradient problem [1]. Furthermore, LSTM has also been used to predict wholesale rice prices in Indonesia and has demonstrated that this method can be used to predict food prices quite well [4].

LSTM has been widely applied to food commodities and has shown mixed results. Predicting medium-sized rice prices in East Java using Stacked LSTM was done to anticipate rice price increases that could impact inflation [5]. Predicting bulk and packaged cooking oil prices using LSTM also demonstrated that the model is capable of recognizing cooking oil price patterns based on time-series data [6]. Furthermore, research on red chili price prediction in East Java compared LSTM and GRU, finding that LSTM performed better in a scenario with 80% training data [7]. This indicates that LSTM has been widely used for food commodity price prediction and is capable of performing well on data with fluctuating patterns.

In addition to food prices, LSTM has also been applied to various other types of time series data, such as the rubber producer price index, gold prices, stock prices, and weather parameters. Research on the rubber producer price index showed that the best parameter combination produced a MAPE of 1.09% for the test data [8]. In gold price prediction, LSTM was compared with GRU using MAE, RMSE, and MAPE metrics [9]. Research on Islamic stock prices also showed that LSTM was capable of producing low MAPE values for several issuers [10]. Several other stock studies have shown that LSTM is capable of capturing temporal dependencies and non-linear patterns in historical data [11], [12], [13]. In the weather sector, LSTM is also used to predict time series data such as temperature, humidity, rainfall, and other weather parameters [14], [15].

Based on previous studies, LSTM has proven capable of predicting time series data, particularly price data with fluctuating patterns. However, research on predicting shallot prices in Bandar Lampung is still needed because each commodity and region has different price characteristics. Therefore, this study aims to predict shallot prices in Bandar Lampung using the LSTM method. This study uses historical shallot price data from 2020 to 2025, conducts data preprocessing, Min-Max normalization, sequence data generation using a sliding window, and parameter tuning experiments to obtain the best model. The research results are expected to provide an overview of shallot price predictions and serve as a reference in decision-making related to food price stability.

2. Research methods

This study uses a quantitative approach with the Long Short-Term Memory (LSTM) method to predict shallot prices in Bandar Lampung. LSTM was chosen because it is able to learn sequential or time series data patterns and handle long-term dependencies on historical data. Several previous studies have shown that LSTM is effective for predicting prices of staple foods, chilies, rice, cooking oil, stocks, and other time series data [1], [6].

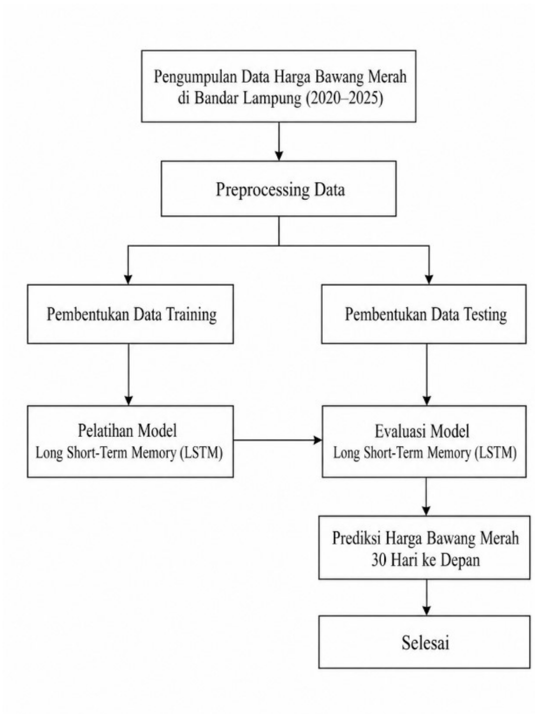

Figure 2. Research Flow

2.1. Red Onion Price Dataset in Bandar Lampung

The dataset used in this study is historical shallot prices in Bandar Lampung for the period 2020 to 2025. The initial data consisted of 1,566 rows with the main attributes being date and price. After data cleaning, the number of valid data points was reduced to 1,517. The data used is time series data because each price value is ordered by date.

The use of historical data as a basis for predictions is also applied in various time series-based studies, such as Bitcoin price prediction and sales forecasting, because LSTM is able to learn patterns from past data to estimate future values [16], [17].

The dataset was collected by copying data directly from the National PIHPS website at https://www.bi.go.id/hargapangan/RataHarga/PasarTradisionalDaerah. Table 1 contains some of the data that will be used.

Table 1. Some Shallot Prices in Bandar Lampung

Commodity	Date	Price
Red onion	02/ 01/ 2020	36250
Red onion	03/ 01/ 2020	37500
Red onion	06/ 01/ 2020	37500
Red onion	07/ 01/ 2020	34250

Red onion	08/ 01/ 2020	34250
Red onion	09/ 01/ 2020	34250
Red onion	10/ 01/ 2020	34250
Red onion	13/ 01/ 2020	33750
Red onion	14/ 01/ 2020	33750
Red onion	15/ 01/ 2020	33750

2.1. Data Preprocessing

The preprocessing stage is performed to prepare the data before use in the model. This process includes attribute selection, date conversion, price conversion to numeric values, removal of blank data, removal of duplicates, and sorting the data by date. After the data is cleaned, normalization is performed using a Min-Max Scaler to ensure the price values are within the range of 0 to 1.

Preprocessing is a crucial stage in LSTM-based prediction because unclean data can affect model training results. In stock prediction research using RNN-LSTM, preprocessing such as handling missing values and normalization is used to help the model process complex historical data [11]. The Min-Max normalization formula is shown in equation (1).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Information: X' is the normalized value, $X$is the original data value, X_{min} is the minimum value of the data, and X_{max} is the maximum value of the data.

2.1. Formation of Training and Testing Data

The normalized dataset was divided into training and testing data in a 70:30 ratio. The training data was used to train the model, while the testing data was used to test the prediction results. The data was divided sequentially by time to maintain the time series pattern.

Next, the data was formed into a sequence using a sliding window technique, where a number of previous price data points were used as input to predict the next price. This use of sequential historical data aligns with the characteristics of LSTMs, which are designed to learn temporal relationships in time series data [18].

Table 2. Data Table from Train Dataset

X-10	X-9	X-8	X-7	X-6	X-5	X-4	X-3	X-2	X-1	X
0.34426	0.37159	0.37159	0.30055	0.30055	0.30055	0.30055	0.28962	0.28962	0.28962	0.28962
0.37159	0.37159	0.30055	0.30055	0.30055	0.30055	0.28962	0.28962	0.28962	0.28962	0.28962
0.37159	0.30055	0.30055	0.30055	0.30055	0.28962	0.28962	0.28962	0.28962	0.28962	0.2459
0.30055	0.30055	0.30055	0.30055	0.28962	0.28962	0.28962	0.28962	0.28962	0.2459	0.2459
0.30055	0.30055	0.30055	0.28962	0.28962	0.28962	0.28962	0.28962	0.2459	0.2459	0.2459
0.30055	0.30055	0.28962	0.28962	0.28962	0.28962	0.28962	0.2459	0.2459	0.2459	0.21858
0.30055	0.28962	0.28962	0.28962	0.28962	0.28962	0.2459	0.2459	0.2459	0.21858	0.21858
0.28962	0.28962	0.28962	0.28962	0.28962	0.2459	0.2459	0.2459	0.21858	0.21858	0.22951
0.28962	0.28962	0.28962	0.28962	0.2459	0.2459	0.2459	0.21858	0.21858	0.22951	0.22951
0.28962	0.28962	0.28962	0.2459	0.2459	0.2459	0.21858	0.21858	0.22951	0.22951	0.22951

Table 3. Data Table from Train Dataset

X-10	X-9	X-8	X-7	X-6	X-5	X-4	X-3	X-2	X-1	X
0.30055	0.28962	0.2623	0.25683	0.22951	0.22951	0.22951	0.2623	0.28962	0.37159	0.56284
0.28962	0.2623	0.25683	0.22951	0.22951	0.22951	0.2623	0.28962	0.37159	0.56284	0.56284
0.2623	0.25683	0.22951	0.22951	0.22951	0.2623	0.28962	0.37159	0.56284	0.56284	0.56284
0.25683	0.22951	0.22951	0.22951	0.2623	0.28962	0.37159	0.56284	0.56284	0.56284	0.56284
0.22951	0.22951	0.22951	0.2623	0.28962	0.37159	0.56284	0.56284	0.56284	0.56284	0.56284
0.22951	0.22951	0.2623	0.28962	0.37159	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284
0.22951	0.2623	0.28962	0.37159	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284
0.2623	0.28962	0.37159	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284
0.28962	0.37159	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284
0.37159	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.56284	0.94536

2.1. Model Long Short-Term Memory

The model used in this study is Long Short-Term Memory (LSTM). LSTM is a development of Recurrent Neural Network (RNN) that is able to learn sequential data patterns and handle long-term dependencies. LSTM is widely used to predict time series data because it is able to capture historical patterns and non-linear relationships in the data [19].

2.2. Model Gated Recurrent Unit (GRU)

As a comparison model, this study also applied the Gated Recurrent Unit (GRU) method. GRU is a development of the Recurrent Neural Network (RNN) designed to process sequence and time series data. GRU uses update gate and reset gate mechanisms to control the flow of information during the training process, thus handling temporal dependencies in historical data.

In this study, the GRU model used the same parameters as the LSTM model: a lookback of 14, a number of neurons of 50, a tanh activation function, a batch size of 48, a learning rate of 0.001, a maximum epoch of 150, and a patience value of 15. The use of identical parameters aimed to ensure a fair comparison between the two methods.

2.3. Evaluasi Model

Model evaluation was conducted to determine the level of prediction error against actual data. The evaluation metrics used were Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and accuracy. The use of evaluation metrics such as MAE, RMSE, and MAPE was also applied to sales transaction prediction research using LSTM Regression to measure the level of model error [20].

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i-\widehat{Y}_i}{Y_i}\right| \times 100\% \tag{2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \widehat{Y}_i\right| \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2} \tag{4}$$

Information: Y_i is the actual value, $\widehat{Y}_i$ is the predicted value, and n is the number of test data.

3. Results and Discussion

3.1. Data Preprocessing Results

The initial dataset consisted of 1,566 data points with the attributes Commodity, Date, and Price. In the preprocessing stage, only Date and Price were used because the research focused on predicting shallot prices based on historical data.

The inspection revealed 49 blank data points in the price column, marked with a "-" symbol, and therefore, these data points were removed. Furthermore, the date format was converted to datetime, the price was converted to numeric, the data was sorted by date, and duplicates were removed.

After the cleaning process, the number of valid data points was 1,517, spanning the dates January 2, 2020, to December 31, 2025. The minimum price was Rp20,500, the maximum price was Rp66,250, and the average price was Rp35,057.45.

	Tanggal	Harga
count	1517	1517.000000
mean	2023-01-17 08:33:32.392880896	35057.448912
min	2020-01-02 00:00:00	20500.000000
25%	2021-07-23 00:00:00	29000.000000
50%	2023-01-30 00:00:00	32750.000000
75%	2024-07-18 00:00:00	39000.000000
max	2025-12-31 00:00:00	66250.000000
std	NaN	8467.327819

Figure 3. Data Preprocessing Results

3.2. Results of Training and Testing Data Formation

After preprocessing, the data was divided into training and testing data in a 70:30 ratio. The training data was used to train the LSTM model, while the testing data was used to evaluate the model's predictive ability. The data was divided sequentially by time to maintain the time series pattern.

Of the 1,517 data sets, 1,061 training data sets and 456 testing data sets were obtained. The data was then formed into sequences using a sliding window technique. In the initial stage, a lookback value of 10 was used, i.e., the 10 previous price data sets were used as input to predict the next price.

The resulting sequence formation produced training and testing data in three-dimensional input formats that meet the needs of the LSTM model, including samples, timesteps, and features.

Table 4. Training and Testing Data Distribution

Data Types	**Amount of Data**	**Date Range**
Training	1061	2020-01-02 sampai 2024-04-02
Testing	456	2024-04-03 sampai 2025-12-31

Table 5. Data Form After Windowing

Data	**Data Form**
X_train	(1051, 10, 1)
y_train	(1051,)
X_test	(456, 10, 1)
y_test	(456,)

3.3. Parameter Tuning Experiment Results

Parameter tuning experiments were conducted to obtain the best LSTM model configuration. The parameters tested included the lookback value, number of neurons, activation function, batch size, learning rate, number of epochs, and patience value for Early Stopping. The best parameters were selected based on the smallest MAPE value.

Based on the experimental results, the best configuration was obtained with a combination of 14 lookback values, 50 neurons, tanh activation function, batch size 48, learning rate 0.001, maximum epochs 150, and patience 15. This configuration produced a MAPE of 2.8055%, an accuracy of 97.1944%, an MAE of 1143.745, and an RMSE of 1922.593.

Table 6. Parameter Tuning Experiment Results Table

lookback	**neurons**	**activation**	**batch_size**	**epochs_max**	**learning_rate**	**epoch_ran**	**mape**	**accuracy**	**mae**	**rmse**
14	50	tanh	48	150	0.001	150	2.805543	97.19446	1143.745	1922.593
21	50	tanh	48	150	0.001	150	2.809617	97.19038	1155.859	1959.866
10	30	tanh	48	150	0.001	150	2.923246	97.07675	1194.684	1989.603
10	50	tanh	48	150	0.001	150	2.97733	97.02267	1216.755	2040.766
14	30	tanh	48	150	0.001	150	3.092989	96.90701	1269.039	2110.383
14	30	relu	48	150	0.001	123	3.204959	96.79504	1323.657	2115.177
21	30	tanh	48	150	0.001	150	3.220721	96.77928	1319.178	2159.349
21	30	relu	48	150	0.001	150	3.25219	96.74781	1302.754	2068.039
10	50	relu	48	150	0.001	92	3.440355	96.55964	1418.902	2263.155
21	50	relu	48	150	0.001	104	3.648237	96.35176	1480.963	2244.299
10	30	relu	48	150	0.001	56	3.779595	96.22041	1562.233	2438.543

14	50	relu	48	150	0.001	51	4.034 223	95.96 578	1659. 524	2509. 054

These results indicate that using a lookback of 14 provides sufficient historical information for the model to learn price change patterns. Furthermore, using 50 neurons and a tanh activation function yielded the best performance compared to other parameter combinations. Therefore, this configuration was used as the final model parameters in the next stage.

3.4. Sub section 3

The final LSTM model was built using the best parameters from the tuning experiments: a lookback of 14, 50 neurons, a tanh activation function, a batch size of 48, a learning rate of 0.001, and a maximum epoch of 150. Early stopping with a patience value of 15 was also used during the training process to stop training if the validation loss value did not improve.

Based on the training process, the model was successfully trained to achieve optimal performance on the validation data. The training loss and validation loss values were used to assess the stability of the training process. If both loss values decreased and did not differ significantly, the model was considered to be learning well without any significant indication of overfitting.

Figure 4. Training Loss and Validation Loss Graphs

In general, the training results indicate that the LSTM model can learn the patterns in the shallot price data well. The final trained model was then used to make predictions on the test data.

3.5. Evaluasi Model

Model evaluation was conducted using testing data to determine the level of prediction accuracy generated by the LSTM model. The evaluation metrics used were Mean Absolute Percentage Error (MAPE), accuracy, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

Based on the evaluation results, the model achieved a MAPE of 2.8035%, an accuracy of 97.1965%, an MAE of 1145.4057, and an RMSE of 1931.7090. A low MAPE value indicates that the model has a low level of prediction error relative to the actual data.

Table 7. Model Evaluation Results

Metrik	**Nilai**
MAPE	2,8035%
Akurasi	97,1965%
MAE	1145,4057
RMSE	1931,7090

These results indicate that the LSTM model performs very well in predicting shallot prices in Bandar Lampung. An accuracy value of 97.1965% indicates that the model is able to produce predictions that are close to the actual data.

3.6. Comparison of Actual and Predicted Data

After the model was evaluated, the prediction results were compared with actual data to determine whether the predicted pattern matched the actual price. The comparison was conducted using test data, displaying the Actual Price, Predicted Price, Absolute Error, and Percentage Error.

Based on the comparison results, the model generally followed the pattern of shallot price changes well. Although there were some discrepancies at certain points, the predicted values were still close to the actual values. This is consistent with the low MAPE value in the model evaluation results.

Table 8. Actual vs. Predicted Table

Tanggal	Harga_Aktual	Harga_Prediksi	Error_Absolut	Error_Persen
4/3/2024	46250	36073	10177	22
4/4/2024	46250	42984	3266	7.06
4/5/2024	46250	47227	977	2.11
4/8/2024	46250	48802	2552	5.52
4/9/2024	46250	48695	2445	5.29
4/10/2024	46250	47959	1709	3.7
4/11/2024	46250	47242	992	2.14
4/12/2024	46250	46775	525	1.14
4/15/2024	46250	46549	299	0.65
4/16/2024	63750	46478	17272	27.09
4/17/2024	63750	58210	5540	8.69
4/18/2024	62500	66090	3590	5.74
4/19/2024	61250	67947	6697	10.93
4/22/2024	56250	65890	9640	17.14

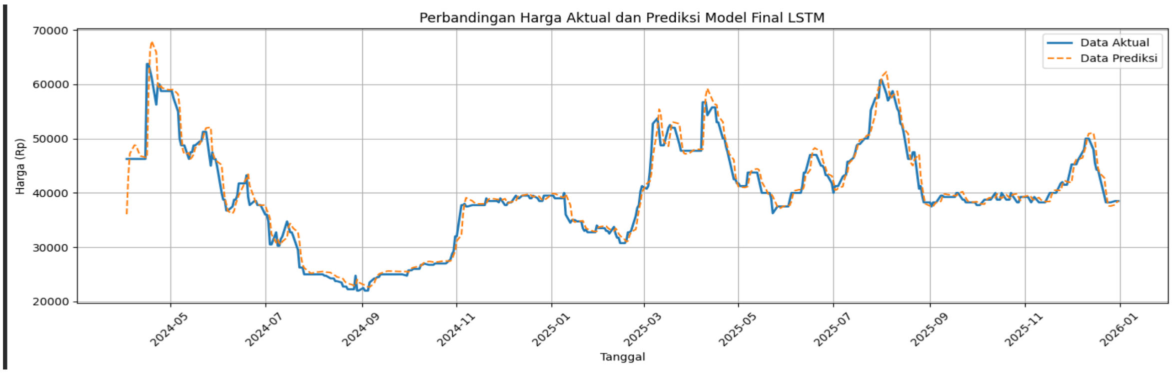

Figure 5. Actual vs. Predicted Graph

The comparison graph between the actual and predicted data shows that the predicted line tends to follow the actual data pattern. Thus, the LSTM model developed is able to recognize historical shallot price patterns and produce fairly accurate predictions.

3.7. Comparison of LSTM and GRU Models

Table 9. Comparison of LSTM and GRU Model Performance

Metode	**MAPE (%)**	**Akurasi (%)**	**MAE**	**RMSE**
LSTM	2,8035	97,1965	1145,4057	1931,7090
GRU	3,2845	96,7155	1352,6429	2209,7805

To demonstrate the superiority of the proposed model, a comparison was conducted between the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) methods using the same dataset, preprocessing, data splitting, and training parameters. The test results showed that the LSTM model produced a MAPE value of 2.8035%, while the GRU model produced a MAPE value of 3.2845%.

Furthermore, the LSTM model obtained an MAE value of 1145.4057 and an RMSE of 1931.7090, lower than the GRU model, which obtained an MAE value of 1352.6429 and an RMSE of 2209.7805. The LSTM model's accuracy value of 97.1965% was also higher than the GRU model's accuracy of 96.7155%.

These results indicate that the LSTM model is better able to learn historical patterns of shallot prices in Bandar Lampung than the GRU model. LSTM's ability to retain long-term information through a memory cell mechanism enables the model to better recognize temporal patterns and price fluctuations, resulting in lower prediction error rates.

3.8. 30 Days Forecast

After the final LSTM model was trained and evaluated, it was used to predict shallot prices for the next 30 days. The predictions were made using recent historical data as initial input, and then the prediction results were reused as input to predict the following day.

Based on the prediction results, shallot prices in Bandar Lampung are expected to move within a certain range, consistent with the historical patterns learned by the model. These prediction results can be used as a preliminary indication of possible short-term price changes.

Table 10. 30-Day Price Prediction

Tanggal	Prediksi_Harga
1/1/2026	38715
1/2/2026	38906
1/3/2026	39108
1/4/2026	39320
1/5/2026	39542
1/6/2026	39772
1/7/2026	40008
1/8/2026	40251
1/9/2026	40499
1/10/2026	40751
1/11/2026	41006
1/12/2026	41265
1/13/2026	41528
1/14/2026	41794
1/15/2026	42064
1/16/2026	42337
1/17/2026	42614
1/18/2026	42894
1/19/2026	43179
1/20/2026	43467
1/21/2026	43760
1/22/2026	44057
1/23/2026	44359
1/24/2026	44666
1/25/2026	44979
1/26/2026	45296
1/27/2026	45620
1/28/2026	45949
1/29/2026	46286

Figure 6. 30-Day Price Prediction Graph

In general, the 30-day forecast results indicate that the LSTM model is capable of generating price estimates based on historical data patterns. However, these predictions remain model estimates and are subject to change due to external factors such as changes in supply, market demand, weather, or pricing policies.

Conclusion

This study successfully applied the Long Short-Term Memory (LSTM) method to predict shallot prices in Bandar Lampung using historical data from 2020 to 2025. The LSTM method was relevant for this study because it is a development of the Recurrent Neural Network (RNN) designed to address the vanishing gradient problem and is capable of learning long-term data dependencies [21]. Furthermore, LSTM has also been widely applied to time series data due to its ability to retain long-term information during the prediction process [21]. After preprocessing, 1,517 valid data sets were obtained for use in the modeling. The preprocessing and data normalization stages are crucial because previous research also implemented missing value checking and min-max normalization before training the LSTM model [22].

Based on the results of the parameter tuning experiment, the best configuration was obtained with a lookback of 14, 50 neurons, a tanh activation function, a batch size of 48, a learning rate of 0.001, a maximum epoch of 150, and a patience of 15. Parameter selection such as timestep, batch size, epoch, and number of neurons were also used in stock price prediction research with LSTM to obtain the best model [22]. The model produced a MAPE value of 2.8035%, an accuracy of 97.1965%, an MAE of 1145.4057, and an RMSE of 1931.7090. The low MAPE value indicates that the model has a low prediction error rate, in line with the GOTO stock price prediction study which obtained a MAPE of 2.28% and concluded that LSTM is capable of producing predictions with a low error rate [22]. Thus, it can be concluded that LSTM is capable of predicting shallot prices with a low error rate and high accuracy.

Furthermore, the model was also used to predict prices over the next 30 days as an initial overview of short-term price movements. The application of next-period predictions was also carried out in Dogecoin price prediction research using LSTM, which utilizes historical data to generate price predictions for the next period [23]. However, this research was still limited to historical price data, so future research is recommended to add external variables such as weather, harvest season, supply, market demand, and pricing policy to improve prediction accuracy. The addition of these external variables is relevant because research on rainfall prediction shows that meteorological data can be used in deep learning-based modeling to support the prediction process [24]. Furthermore, research on air quality prediction also shows that using multiple input attributes can help the model predict target values more informatively [25].

Comparison results with the GRU method indicate that the LSTM model performs better. The LSTM model produced a MAPE value of 2.8035%, while the GRU model produced a MAPE value of 3.2845%. Furthermore, the MAE and RMSE values obtained by the LSTM model were also lower than those of the GRU model. Thus, the LSTM method is considered more suitable for use in predicting shallot prices in Bandar Lampung in this research dataset.

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