Journal of Applied Data Sciences
Vol. 6, No. 2, May 2025, pp. 1426-1436

Price Prediction of Aglaonema Ornamental Plants Using the Long Short-Term Memory (LSTM) Algorithm

Yuni Sugiarti[1,], Arif Imam Suroso[2,*,], Irman Hermadi[3,], Euis Sunarti[4,], Fadhilah Bt Mat Yamin[5]

[1] *School of Data Science, Mathematics, and Informatics IPB University Bogor, Indonesia*

[1]*Information Systems Study Program Faculty of Science Technology, UIN Syarif Hidayatullah Jakarta, Indonesia*

[2]*School of Business, IPB University Bogor, Indonesia*

[3]*School of Data Science, Mathematics, and Informatics, IPB University Bogor, Indonesia*

[4]*Department of Family and Consumer Sciences, Faculty of Human Ecology, IPB University Bogor, Indonesia*

[5]*School of Technology Management and Logistics, UUM COB, Universiti Utara Malaysia, Sintok, Kedah, Malaysia*

(Received: January 26, 2025; Revised: February 28, 2025; Accepted: April 8, 2025; Available online: May 14, 2025)

Abstract

The Aglaonema ornamental plant is a horticultural commodity with high economic value and promising prospects. It is well known for its attractive leaf variations, earning it the nickname "Queen of Leaves." However, unpredictable price fluctuations make investing in Aglaonema speculative and high-risk. This research aims to predict the price of Aglaonema over the next five years using the Long Short-Term Memory (LSTM) algorithm. LSTM is considered superior to other algorithms in handling time series data. The model's performance was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) on a weekly Aglaonema price dataset covering the period from January 2012 to December 2023. The results demonstrate that the LSTM algorithm can predict Aglaonema prices with high accuracy, as indicated by the following metrics: MSE: 0.005 – Represents the average squared difference between predicted and actual prices. A lower MSE indicates higher model accuracy. RMSE: 0.07-RMSE provides a more interpretable error measurement as it retains the same units as the original data. A low RMSE signifies that the model's predictions closely align with actual values. MAE: 0.04 – Measures the absolute average difference between predicted and actual prices. A lower MAE value reflects a smaller prediction error. Thus, this research makes a significant contribution to the development of a machine learning-based price prediction system for the ornamental plant industry.

Keywords: Price prediction Aglaonema, LSTM, MSE, RMSE, MAE

1. Introduction

Ornamental plants are not just a hobby, but have become one of the horticultural commodities that are prospective and have high economic value. One type of ornamental plant that is in great demand by consumers is Aglaonema. The strength of Aglaonema lies in the variety of attractive leaf variants, ranging from: motifs, colors, shapes, and sizes, so it is nicknamed "The Queen of Leaves". The demand for this type of ornamental plant tends to increase along with the increasing welfare of the community. During the pandemic, aglaonema production has decreased even though its presence in the market is limited. On the other hand, the welfare of aglaonema farmers is still far from prosperous.

Aglaonema ornamental plants have become one of the commodities in demand by the public, especially in recent years. Its popularity is not only due to the beauty of its diverse leaves, but also because of its increasing economic value. Since 2012 to 2023, the price of Aglaonema ornamental plants has fluctuated significantly, influenced by various factors such as market trends, consumer demand, and stock availability. In this context, price predictions are very important for business actors, both sellers and buyers, to make the right decisions. One of the challenges in predicting prices is the complexity of data patterns that are non-linear and influenced by many variables. To overcome this, a method is needed that is able to handle time series data well. The Long Short-Term Memory (LSTM) algorithm is one

***Corresponding author: Arif Imam Suroso(arifimamsuroso@apps.ipb.ac.id)**
DOI: https://doi.org/10.47738/jads.v6i2.640

of the deep learning methods that has been proven effective in modeling time series data because of its ability to remember long-term information. By using LSTM, it is expected to produce more accurate Aglaonema price predictions. The variance regression score for Bitcoin predictions was reported at 0.95, indicating strong predictive performance [1].

One of the studies that has been widely used by experts to build predictive models is data mining [2]. Deep learning algorithms have been successfully applied in a variety of fields, including natural language processing, medical diagnostics, and remote sensing, demonstrating their adaptability and effectiveness [3]. One of the deep learning algorithms that has been proven successful in predicting time series data is the LSTM algorithm which is a derivative of the Recurrent Neural Network (RNN) [4].

Several studies on LSTM have been conducted previously. LSTM RNN is considered effective [5]. LSTM has been used to predict Bursa Malaysia closing price data from 2/1/2020 to 19/1/2021 will be evaluated using the root mean square error (RMSE) and the mean absolute percentage error (MAPE). Research shows that LSTM models achieved over 90% accuracy in predicting stock prices during the pandemic, outperforming traditional models such as ARIMA. [4]. Long Short-Term Memory LSTM [6] is a development of one of the deep learning algorithms, namely the RNN. GRUs are a simplified version of LSTMs, combining the forget and input gates into a single update gate. They also address the vanishing gradient problem and are computationally more efficient than LSTMs, making them suitable for similar applications [7].

XGBoost This model has demonstrated superior performance, achieving over 92% accuracy in predicting Bitcoin prices by effectively handling high-dimensional data and nonlinear relationships [8], stock price prediction [9], cryptocurrency price prediction [10], [11]. Predicting future customer behavior is an important task to offer the best experience and increase their satisfaction [12]. LSTM for stock price prediction performance is better [13]. This approach combines convolutional neural networks with LSTMs, demonstrating improved predictive capabilities for applications such as aircraft trajectory forecasting [14]. To be able to make such predictions, historical data is needed that can show patterns of past events [15].

According to [16] conducted a study using 4 different methods to build stock price prediction modeling including Moving Average (MA), Exponential Moving Average (EMA), Support Vector Machine (SVM) and LSTM. The test results showed that LSTM has the highest accuracy compared to other methods. Apart from according to [17] has proven in his research that he created a predictive model using LSTM to predict stock prices in the banking sector. The results of his research show that the LSTM algorithm has a high accuracy value based on the RMSE value and the data model obtained in the Epoch value variation.

To see the accuracy of the model built in this study, calculations were used with scaling parameters on the prepared dataset to minimize errors when testing the prediction model. Combining LSTM with optimization methods such as Genetic Algorithms has been shown to improve prediction accuracy, with a reduction in Mean Absolute Error (MAE) from 0.11 to 0.01[18]. It is important to consider the error distribution when choosing RMSE or MAE for model evaluation [19]. Based on the data described above, the purpose of this study is to predict the price of Aglaonema ornamental plants using the LSTM algorithm based on time series data from 2012 to 2023.

2. Literature Review

Based on the literature study on the RNN-LSTM algorithm, it is concluded that the RNN-LSTM algorithm is identified as the best model for prediction in predicting prices [20] and several studies related to price prediction in the research table on RNN-LSTM. And the proposed RNN-LSTM model has been found to be 90% more accurate than KNN (74%) and SVM (87%) for predicting priority level assignment (high or low) for each bug report [21]. Therefore, the algorithm for predicting prices using RNN-LSTM is very suitable for predicting future price trends for Aglaonema ornamental plants. Because with the RNN-LSTM algorithm, price predictions can be obtained with very high accuracy. According to [14] conducted a study using 4 different methods to build stock price prediction modeling including Moving Average (MA), Exponential Moving Average (EMA), SVM and LSTM. The test results showed that LSTM has the highest accuracy compared to other methods.

ISSN 2723-6471

In addition, according to [22] it has been proven in his research to create predictive modeling using LSTM to predict stock prices in the banking sector. The results of his research show that the LSTM algorithm has a high accuracy value based on the RMSE value and the data model that can be used in the Epoch value variation. To see the accuracy of the model built in this study, calculations were used with scaling parameters on the prepared dataset to minimize errors when testing the prediction model. Root Mean Square Error (RMSE). RMSE is a common method commonly used to calculate the error rate of a quantitative data prediction model. The RMSE value is obtained from the average of the squares of the number of errors in the prediction model.

3. Methodology

The stages in this study are divided into eight research stages, namely data collection, preprocessing, LSTM model design, training, model evaluation with MAE, and analysis of research results. The flow of research stages can be seen in figure 1.

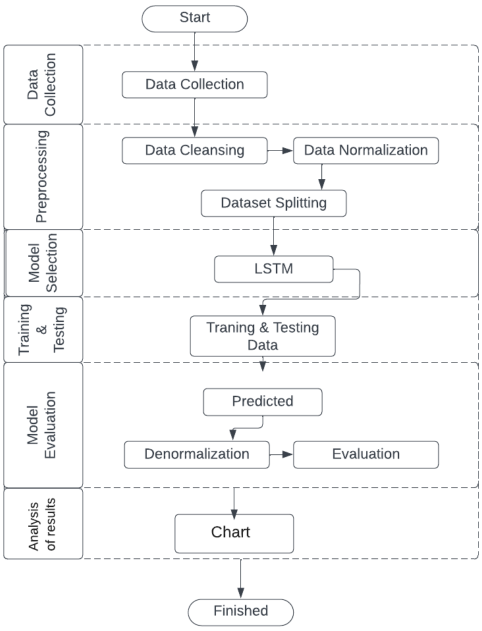

Figure 1. Research Stages

3.1. Data Collection

The types of Aglaonema that will be used are local types and imported aglaonema from Thailand which have been cultivated by farmers in Depok and Sawangan (as aglaonema centers). The data set used is Aglaonema data from the past 12 years, namely 2012 to 2023. For the aglaonema data used, 181 types were obtained from farmers when conducting a preliminary study. This research was applied to Aglaonema farmers who were involved in the KTNA (Indonesian Farmer and Fisherman Contact) organization which is spread throughout Indonesia under the auspices of the Indonesian Ministry of Agriculture. The data collected includes daily, weekly or monthly prices of Aglaonema ornamental plants, as well as other factors that influence prices, such as season, market trends or stock availability.

3.2. Data Preprocessing

The main steps of preprocessing include: Data Collection, Data Cleaning, data normalization, and data sharing. With good preprocessing, the LSTM model will be more accurate in predicting Aglaonema prices and avoid errors due to data that is not well structured. Consists of data cleaning stages, namely handling missing values, outliers (inconsistent data is not valid). Normalizing data using the Min-Max Scaling technique to change the data scale to a range suitable for LSTM modeling. Dividing the dataset into training data and testing data with a ratio of 80:20 with considerations based on the results of the trial and the author's considerations after several experiments on various comparisons of the number of training and testing data. And finally converting the data into a time series format suitable for LSTM model input, by determining the time step (for example, 30 days ago to predict the next day's price).

3.3. Data Modeling

Building an LSTM model with several layers, namely the input layer that receives time series data. LSTM layer to capture temporal patterns in data. Fully connected layer (Dense layer) to produce prediction output. Output layer with one neuron for price prediction. Determining the hyperparameters of the number of LSTM units, the number of epochs, batch size, and learning rate through experiments or tuning. Using activation functions such as ReLU or Tanh in the LSTM layer and linear functions in the output layer.

3.4. Training

Train the LSTM model using the training data by minimizing the loss function (Mean Squared Error) using Adam or RMSprop optimizer. Model Validation: Using validation techniques such as k-fold cross-validation or validation data splitting to ensure the model is not overfitting. Early Stopping: Applying early stopping to stop training if the model performance on the validation data does not improve after several epochs. Activation Function (tanh) is more often used in LSTM because it can handle data with negative and positive values effectively. The Optimization Algorithm (Adam) is often used because its convergence is faster and more stable than SGD. Selection of Other Parameters (number of neurons, batch size) i.e. explaining how these values were determined (e.g. via Grid Search or experiment) provides a stronger justification.

3.5. Model Evaluation Using RMSE

Evaluation Metrics: Evaluate model performance using metrics: MSE: Measures the average of the squared differences between predicted and actual values. The formula is MSE:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2 \tag{1}$$

RMSE: The square root of MSE, providing easier interpretation in the same units as the data. The formula is RMSE:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \tag{2}$$

MAE: Measures the absolute average of the differences between predicted and actual values. The formula is MAE:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

3.6. Results Analysis

Create a comparison chart between actual and predicted prices to see how well the model follows the data pattern. Analyze MSE, RMSE, and MAE values to determine model accuracy. Identify price patterns or trends that the LSTM model successfully captures.

4. Result and Discussion

In this study, the LSTM algorithm is used to predict the price of Aglaonema ornamental plants based on datasets from 2012 to 2023. The results and discussions are divided into several parts, namely data pre-processing results, LSTM model performance, metric evaluation, and price prediction analysis. Here is a detailed explanation:

4.1. Data Pre-Processing Results

In time series methods such as LSTM, data preprocessing plays an important role in preparing the data for analysis and forecasting. The first step in data preprocessing is to check the data type of the 'Date' column to ensure that the time column is set as an index and has a 'datetime' data type. Once the data is collected into a dataset, the next step is to clean the data. This involves checking for null values (NA) and ensuring that there are no gaps in the time period. Since the dataset that has been obtained is free from null values and is fulfilled in terms of time series, the data cleaning step can be ignored. After the dataset is cleaned, the next step is data normalization. For example, for the 'Suksom Jaipong' plant type, where the price range varies from 150,000 to 570,000, the difference in this range can produce significant errors in the model built. To overcome this, normalization needs to be done to convert the actual price into a value with an interval range of 0-1. One of the common normalization techniques used is min-max normalization using the calculation below.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (4)$$

x' is the scale of the data in the new range, X is the value of the data to be normalized, Xmax is the maximum value of the variable, Xmin is the minimum value of the variable. After normalizing the dataset, the dataset is divided into three types, namely training data, test data, and validation data. Training Data is to teach model patterns in data. Data Validation is to tune hyperparameters and prevent overfitting. Testing Data is to measure the final performance of the model on data that has never been seen before. The division is done with a ratio of 80:20, where 80% of the total dataset will be used as training data, 20% is used as test data, and 20% of the test data is used as validation data. This ratio helps avoid overfitting and underfitting and produces a more accurate and generalizable model. The selection of this combination is based on the results of the trial and the author's considerations after several experiments on various comparisons of the amount of training and testing data. As a result, there are 502 rows of data representing the first 502 weeks as training data, 125 rows of data representing the last 125 weeks as test data, and the last 25 rows of data from the test data are used as validation data in the learning process of the LSTM model built. With this approach, it is expected that the model can learn patterns well from training data, be tested with test data for performance evaluation, and be verified using validation data to prevent overfitting and ensure optimal model generalization. The following is the composition of the data used.

4.2. Data Modeling Results

In figure 2 LSTM is a type of artificial neural network that is a modification of the recurrent neural network (RNN). Unlike RNN which is susceptible to gradient dropout problems, LSTM is designed with a structure that allows it to retain long-term information over a wider time span.

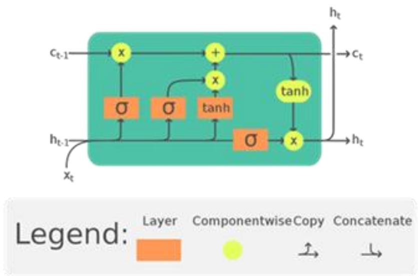

Figure 2. LSTM modeling

In this study, after the dataset goes through the data preprocessing and dataset splitting stages, the next step is to adjust the data dimensions for use in the LSTM model. This includes the amount of data, time steps, and the number of prediction columns in each data subset, namely training data, test data, and validation data. In this process, the time step set is 4 data inputs to predict the target in the next data. For example, if initially the dataset consists of rows x1 to x5, then for each time step, the input will shift one column forward so that at the first time step the input is x1 to x4 and the target is x5. This process continues by shifting the time step forward so that at the second time step the input becomes x2 to x5 and the target is x6, and so on. By using LSTM, the model is trained at each time step of the input sequence to predict the next value. This allows the model to understand patterns and relationships between data temporally, which is important in time series data.

4.3. Training Results

The training process of the LSTM model with training data is carried out through the model layers that have been created. The LSTM model training process begins by inputting the training data into the designed model. Each input then undergoes a series of computations within the LSTM architecture, starting with the forget gate, which filters out irrelevant information. Next, the input gate determines the new information to be added to the memory cell, while the cell gate updates the cell state based on this new information. Finally, the output gate determines the value that will be passed to the next layer. In this study, the epoch or iteration used was 100 iterations with the results of loss and RMSE values as shown in figure 3. In figure 4, it can be seen that in both performance matrices of the model on training data and validation data, the loss and RMSE values tend to decrease with the last validation loss value of 0.0175 and the last validation RMSE of 0.1323. This indicates that the model learns quite well from training data and has good generalization on data that has never been seen before, namely validation data.

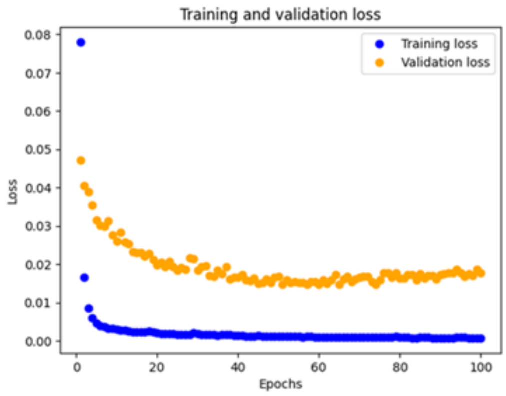

Figure 3. Model performance using training loss and validation loss

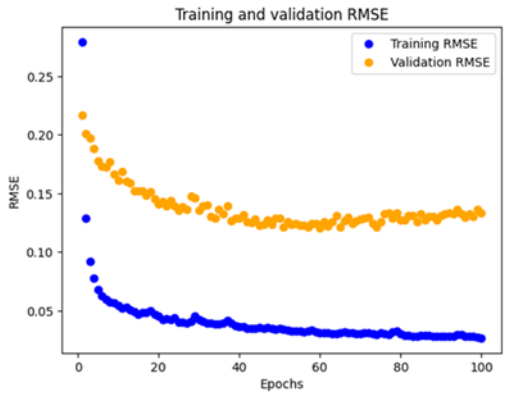

Figure 4. Model performance using RMSE values on training data

4.4. Testing Data

After the LSTM model has been trained, the next stage is testing using the previously prepared test data. The testing process begins by inputting the test data into the model, where fixed time steps are maintained at the same number as in the training stage to ensure consistency in data processing. The trained LSTM model is then used to predict values based on previously learned patterns. The predicted results, which are still in a normalized form, are then converted back to their original scale through a denormalization process. This step ensures that the predictions can be directly compared with the actual prices of each type of Aglaonema plant. Finally, the model's performance is evaluated using RMSE and MAPE. These two metrics indicate how far the model's predictions deviate from actual values, with lower values representing higher accuracy.

4.5. Model Evaluation Results

The LSTM model that has gone through the training and testing stages in the previous stage will be used to predict plant type price data for the next 5 years with a total of 313 weeks with a range of 2024 to 2029. After the prediction data is obtained using the existing LSTM model, a Denormalization process is needed to return the previously normalized prediction values, namely in the form of a range of values 0 to 1 to the actual value according to the price of each type of plant. Continued with the model evaluation stage to determine the accuracy of the model that has been created. In this study, the model evaluation uses the MAPE. MAPE can be calculated by finding the average of the absolute difference between the actual price and the predicted price divided by the actual price. The MAPE formula can be seen in the equation. The resulting MAPE values need to be grouped into several categories based on the range of values to determine the quality of the model used in predicting sharia stock prices. So that it can be easy to draw conclusions whether the prediction is in the accurate category or not. The grouping of MAPE values can be seen in table 1.

Table 1. Grouping of MAPE

No.	MAPE	Category
1	< 10	Accurate prediction model performance
2	10 - 20	Good prediction model performance
3	20 – 50	Performance of the prediction model is reasonable
4	21 > 50	Prediction model performance is not accurate

The MAPE value on the test data was 7.9, this means that the LSTM model created is included in the category of models with accurate prediction performance because it is less than 10 for its magnitude. The following is one type of plant from the prediction results that have been carried out.

4.6. Analysis results

In figure 5, it is shown with a two-color chart. The blue color shows the actual price data while the orange color shows the predicted price data. The image shown is the image with the best MAE value on the tested aglaonema.

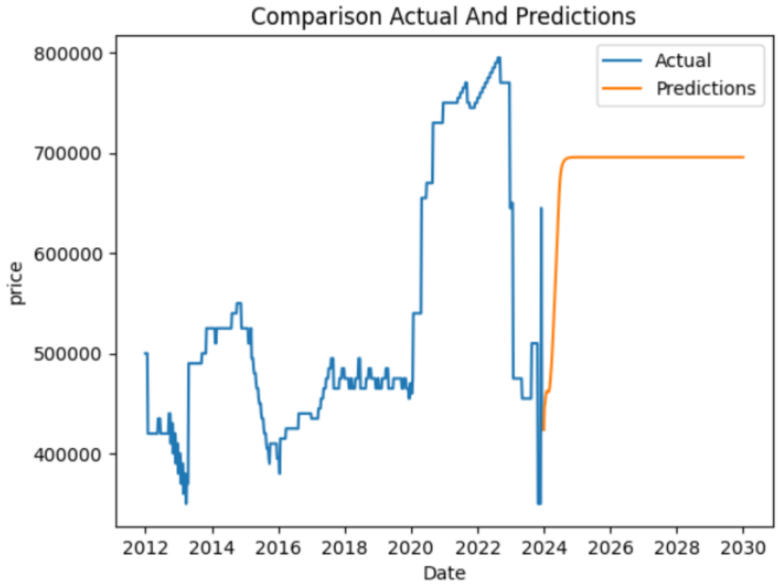

Figure 5. Graph of Suksom Jaipong prediction results with epoch 100

Figure 6 shows the price of aglaonema. First, the last 60 days of data are taken from the data set and normalized using the previously created scaler object. Furthermore, the normalized data is inserted into the X_pred array and reshaped into (1,60,1) to be predicted by the model. The prediction results are then normalized again using the scaler and stored in the pred_price variable. Furthermore, the code will display the price prediction results for the next 10 years. In the for loop, the asset price will be calculated in the i-th year using the investment formula which is assumed to grow 5% annually. The results will then be displayed in rupiah format using the format function.

Date	Suksom Jaipong	Suksom Merapi
2012-01-01	200000	500000
2012-01-08	210000	500000
2012-01-15	200000	500000
2012-01-22	205000	500000
2012-01-29	190000	420000
2012-02-05	195000	420000
2012-02-12	200000	420000
2012-02-19	190000	420000
2012-02-26	200000	420000
2012-03-04	205000	420000
2012-03-11	210000	420000
2012-03-18	205000	420000
2012-03-25	215000	420000
2012-04-01	220000	420000

Date	Suksom Jaipong	Suksom Merapi
2024-01-07	267816	447783
2024-01-14	273318	470473
2024-01-21	269351	484619
2024-01-28	265222	492686
2024-02-04	262217	497832
2024-02-11	262211	500858
2024-02-18	263550	503121
2024-02-25	265472	504952
2024-03-03	267176	506908
2024-03-10	268774	508758
2024-03-17	270251	510307
2024-03-24	271475	511316
2024-03-31	272474	511585
2024-04-07	273082	510758

Figure 6. Shows the price of the Jaipong Suksom type in 2012 and 2024

In figure 7, shows the MAE value of 0.06042931 in testing using 100 epochs. 100 epochs were chosen because it was enough to study the Aglaonema price pattern without requiring too long training time. And the consideration is to balance between underfitting and overfitting. Can be adjusted based on the results of the model evaluation. It is better to use early stopped to optimize the number of epochs automatically. The purpose of separating the dataset into training data, test data and validation data is to ensure that the machine learning model to be built is not only able to produce good performance on training data, but also able to generalize and provide good results on data that has never been

ISSN 2723-6471

seen before, namely testing data and validation data. This data set separation can also help identify whether the LSTM model built is overfitting or not.

```
MAE Value: 0.05668433645901926
MSE Value: 0.009770063276174615
RMSE Value: 0.0988436304279371
```

Figure 7. Shows the MAE, MSE, and RMSE values of the whole

Figure 7 shows the MAE, MSE, and RMSE values for the total of all types of Aglaonema. The model is evaluated using three metrics, namely MSE, RMSE, and MAE. The reason is that MSE provides information on how the model handles large errors. RMSE makes the results easier to interpret in the context of price. MAE shows the average error without magnifying the effects of outliers. By using these three metrics, we get a more complete picture of how well the model predicts the price of Aglaonema and how the model handles large and small errors. In Figure 8, the results of the model evaluation on the test data: MSE (Mean Squared Error): The resulting MSE value is 0.011. This value shows the average squared difference between the predicted price and the actual price. A low MSE indicates that the model has good accuracy. RMSE (Root Mean Squared Error): The RMSE value is 0.10. RMSE provides easier interpretation because it is in the same units as the original data. A low RMSE value indicates that the model prediction is close to the actual price. MAE (Mean Absolute Error): The MAE value is 0.06. MAE measures the absolute average of the difference between the predicted price and the actual price. A low MAE value indicates that the model's prediction error is relatively small.

4.7. Discussion

The results above show that the low MSE, RMSE, and MAE values indicate that the LSTM model is able to predict the price of Aglaonema with high accuracy. The relatively small RMSE and MAE (0.005 and 0.004) indicate that the model prediction is very close to the actual price. For example, in predicting peanut prices, LSTM achieved lower RMSE, MAE, and MAPE values compared to ARIMA, indicating superior accuracy. In the context of rice price prediction, LSTM models showed higher forecast errors compared to ARIMA, indicating that although LSTM is robust, its performance may vary based on commodity characteristics and specific datasets [23], [24]. RMSE is a common metric for evaluating forecasting accuracy, especially in studies comparing traditional and deep learning models. A new framework combining LSTMs with improved optimization techniques has shown significant performance improvements, achieving up to 52% reduction in MAE for certain datasets [25].

LSTM has been applied to dynamical system identification, showing superior performance compared to conventional RNNs and single LSTM networks [26]. LSTM models are particularly effective in handling sequence data with long-term dependencies, making them suitable for predicting the price of ornamental plants such as oriental lilies. LSTM networks utilize memory cells that retain information over long periods, effectively addressing the vanishing gradient problem common in traditional RNNs [27]. LSTM's ability to capture long-term temporal patterns (long-term dependencies) makes it suitable for predicting the price of Aglaonema which has complex fluctuations. This model is also able to overcome the vanishing gradient problem that often occurs in conventional RNNs.

Low RMSE is a strong indicator of the superiority of a Long Short-Term Memory (LSTM) model, as it reflects the model's ability to accurately predict outcomes across a wide range of domains. LSTM networks are particularly adept at handling time series data due to their capacity to capture long-term dependencies, which is critical for accurate forecasting. This capability has been consistently demonstrated across a wide range of applications, as evidenced by the low RMSE scores reported in several studies. In stock market predictions, The LSTM framework has demonstrated competitive performance against traditional models, with experimental results highlighting their adaptability under varying market conditions [28]. For oil price forecasting, LSTM networks outperform traditional time series models such as ARIMA, with much lower RMSE values, indicating their adaptability to volatile market conditions [29], [30]. While low RMSE values underscore the superiority of LSTM models, it is important to consider that these models may require significant computational resources and careful hyperparameter tuning to achieve optimal performance. In addition, the integration of multivariate analysis and hybrid models can further improve the predictive capabilities of LSTM networks, suggesting avenues for future research and development [31].

5. Conclusion

Based on the results and discussion above, it can be concluded that the LSTM algorithm is able to predict the price of Aglaonema ornamental plants with high accuracy, as evidenced by the low MSE, RMSE, and MAE values, namely the suksom jaipong type 0.0461235269904137. This model also successfully captures trends and seasonal patterns in Aglaonema price data. Thus, this study makes a significant contribution to the development of a machine learning-based price prediction system for the ornamental plant industry.

6. Declarations

6.1. Author Contributions

Conceptualization: Y.S., A.I.S., I.H., E.S., and F.B.M.Y.; Methodology: A.I.S.; Software: Y.S.; Validation: Y.S., I.H, and F.B.M.Y.; Formal Analysis: Y.S., A.I.S, and I.H.; Investigation: Y.S.; Resources: E.S.; Data Curation: Y.S.; Writing Original Draft Preparation: Y.S., E.S., and F.B.M.Y.; Writing Review and Editing: E.S., Y.S., and A.I.S.; Visualization: Y.S. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Y. Sugiarti, A. T. N., U. Maman, F. Mintarsih, E. O. M. Anwas and E. Syarifah, "Design and Build Mango E-Commerce Information System," *2019 7th International Conference on Cyber and IT Service Management (CITSM), Jakarta, Indonesia,* vol. 2019, no. Nov., pp. 1-4, 2019. doi: 10.1109/CITSM47753.2019.8965402.

[2] S. Deo, G. Kumar, S. Soni and G. Singh, "Cryptocurrency PricePrediction using LSTM," *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT),* Delhi, India, vol. 2023, no. 1, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10306885.

[3] K. T. Baghaei, A. T. Payandeh, P. Fayyazsanavi, S. Rahimi, Z. Chen, and S. B. Ramezani, "Deep representation learning: Fundamentals, perspectives, applications, and open challenges," *arXiv preprint,* arXiv:2211.14732, vol. 2022, no. 1, pp. 1-12, 2022, doi: 10.48550/arXiv.2211.14732.

[4] M. K. Ho, "Stock price prediction using ARIMA, neural network and LSTM models," *J. Phys.: Conf. Ser.,* vol. 1988, no. 1, pp. 1-21, 2021, doi: 10.1088/1742-6596/1988/1/012041.

[5] A. Akers, "Synopsis of guidelines for the clinical management of cerebral cavernous malformations: Consensus recommendations based on systematic literature review by the Angioma Alliance Scientific Advisory Board Clinical Experts Panel," *Clin. Neurosurg.,* vol. 80, no. 5, pp. 665–680, 2017, doi: 10.1093/neuros/nyx091.

[6] A. Ferdiansyah, "A LSTM-Method for Bitcoin Price Prediction: A Case Study Yahoo Finance Stock Market," *in International Conference on Electrical Engineering and Computer Science (ICECOS),* vol. 2019, no. 1, pp. 1-7, 2019.

[7] A. Tsantekidis, N. Passalis, and A. Tefas, "Chapter 5 - Recurrent neural networks," *in Deep Learning for Robot Perception and Cognition,* A. Iosifidis and A. Tefas, Eds., 1st ed. Academic Press, 2022, pp. 101–115. doi: 10.1016/B978-0-32-385787-1.00010-5.

[8] S. Terence, J. Immaculate, D. B. Naik, and S. Selvarathi, "Machine learning based Bitcoin price prediction," *in Proc. 2024 Int. Conf. Data Intelligence and Computing Innovations (ICDICI)*, vol. 2024, no. 1, pp. 1070–1074, 2024. doi: 10.1109/icdici62993.2024.10810810.

[9] Z. Wang, "Stock price prediction using LSTM neural networks: Techniques and applications," *Applied and Computational Engineering*, vol. 86, no. 1, pp. 294–300, 2024, doi: 10.54254/2755-2721/86/20241605.

[10] C. L. Santolaya, "Prospective evaluation of a model of prediction of invasive bacterial infection risk among children with cancer, fever, and neutropenia," *Clin. Infect. Dis.*, vol. 35, no. 6, pp. 678–683, 2002, doi: 10.1086/342064.

[11] A. S. Saud and S. Shakya, "Analysis of look-back period for stock price prediction with RNN variants: A case study on banking sector of NEPSE," *Procedia Computer Science*, vol. 167, no. 2, pp. 788–798, 2020, doi: 10.1016/j.procs.2020.03.419.

[12] Anubha, "Onion price prediction for the market of Kayamkulam," *in Data Analytics and Management, Lecture Notes on Data Engineering and Communications Technologies*, vol. 2021, no. 1, pp. 77–85, 2021. doi: 10.1007/978-981-15-8335-3_8.

[13] T. Bi, J.-W. Lyu, and T. He, "Based on the improved LSTM model aircraft long track prediction research," *in Proc. 2023 Int. Conf. on Software Engineering and Artificial Intelligence (SEAI)*, vol. 2023, no. 1, pp. 1-12, 2023. doi: 10.1109/seai59139.2023.10217708.

[14] T. Gao, Y. Chai, and Y. Liu, "Applying long short-term memory neural networks for predicting stock closing prices," *in Proc. IEEE Int. Conf. Softw. Eng. Serv. Sci. (ICSESS)*, vol. 2018, no. 1, pp. 575–578, 2018. doi: 10.1109/ICSESS.2017.8342981.

[15] P. A. Riyantoko and T. M. Fahruddin, "Analysis of stock price prediction in the banking sector using the long short-term memory (LSTM) algorithm," *in Semin. Nas.*, vol. 2020, no. 1, pp. 427–435, 2020.

[16] F. Faturohman, B. Irawan, and C. Setianingsih, "Sentiment analysis on BPJS Health using recurrent neural network," *E-Proceeding Eng.*, vol. 7, no. 2, pp. 4545–4552, 2020.

[17] B. N. Haqiqi and R. Kurniawan, "Comparative analysis of Fuzzy C-Means and Subtractive Fuzzy C-Means methods," *Media Statistics*, vol. 8, no. 2, pp. 59–67, 2015, doi: 10.14710/medstat.8.2.59-67.

[18] X. Sha, "Time series stock price forecasting based on genetic algorithm (GA)-long short-term memory network (LSTM) optimization," *Advances in Economics, Management and Political Sciences*, vol. 91, no. 1, pp. 142–149, 2024, doi: 10.54254/2754-1169/91/20241031.

[19] T. Chai and R. R. Draxler, "Root mean square error (RMSE) or mean absolute error (MAE)," *Geoscientific Model Development Discussions*, vol. 7, no. 1, pp. 1525–1534, 2014, doi: 10.5194/GMDD-7-1525-2014.

[20] S. Selvin, R. Vinayakumar, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman, "Stock price prediction using LSTM, RNN and CNN-sliding window model," *in Proc. 2017 Int. Conf. Adv. Comput. Commun. Informatics (ICACCI)*, Udupi, India, vol. 2017, no. 1, pp. 1643–1647, 2017. doi: 10.1109/ICACCI.2017.8126078.

[21] H. Bani-Salameh, M. Sallam, and B. Al Shboul, "A deep-learning-based bug priority prediction using RNN-LSTM neural networks," *E-Informatica Software Engineering Journal*, vol. 15, no. 1, pp. 29–45, 2021, doi: 10.37190/E-INF210102.

[22] H. Wang, "Enhancing stock price forecasting accuracy using LSTM and Bi-LSTM models," *ITM Web of Conferences*, vol. 70, no. 1, pp. 1-8, 2025, doi: 10.1051/itmconf/20257004008.

[23] U. Maman, H. T. Nindyantoro, Sukmana, E. O. M. Anwas, and T. T. Margono, "From single to dual system: initiating the model of wet rice field management to optimize staple food availability," *Journal of Engineering and Applied Sciences*, vol. 13, no. 1, pp. 9259–9268, 2018, doi: 10.36478/jeasci.2018.9259.9268.

[24] M. Yusup, S. Y. J. Prasetyo, and T. Wellem, "Evaluation of prediction accuracy in ARIMA and LSTM algorithms for agricultural commodity prices," *in 2024 IEEE ICCIT*, vol. 2024, no. 1, pp. 1–7, 2024, doi: 10.1109/iccit62134.2024.10701123.

[25] R. P. Varshney and D. K. Sharma, "Optimizing time-series forecasting using stacked deep learning framework with enhanced adaptive moment estimation and error correction," *Expert Systems with Applications*, vol. 249, no. 1, pp. 1-17, 2024, doi: 10.1016/j.eswa.2024.123487.

[26] Z. Wang, "Deep learning-based stock price prediction using LSTM model," *Proc. Bus. Econ. Stud.*, vol. 7, no. 5, pp. 1-12, 2024, doi: 10.26689/pbes.v7i5.8611.

[27] R. Sahu, S. Srivastava, and R. Kumar, "Modelling of a non-linear dynamic system using long short-term memory," *in Proc. 2023 IEEE ICCCIS*, vol. 2023, no. 1, pp. 1016–1021, 2023, doi: 10.1109/icccis60361.2023.10425027.

ISSN 2723-6471

[28] A. Gaurav, V. Arya, K. T. Chui, B. B. Gupta, C. Choi, and O.-J. Lee, "Long Short-Term Memory Network (LSTM) based Stock Price Prediction," *Proceedings of the ACM International Conference*, New York, NY, USA, vol. 2023, no. 1, pp. 1-7, 2023. doi: 10.1145/3599957.3606240.

[29] M. S. Brown, "Comparative analysis of LSTM and traditional time series models on oil price data," Preprints, 2024, doi: 10.20944/preprints202410.2355.v1.

[30] Y. Sugiarti, Sumanto, A. Supriyatna, I. Carolina, R. Amin, and A. Yani, "Model naïve Bayes classifiers for detection apple diseases," *in Proc. 2021 9th Int. Conf. Cyber IT Serv. Manag. (CITSM)*, vol. 2021, no. 1, pp. 1-7, 2021. doi: 10.1109/CITSM52892.2021.9588801.

[31] L. Zeng, "LSTM-based gasoline price prediction - an example of Gasoline 95# in Beijing," *Highlights Sci. Eng. Technol.*, vol. 111, no. 1, pp. 264–271, 2024, doi: 10.54097/gg6zvt07.