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Stock Price Forecasting on Time Series Data Using the Long Short-Term Memory (LSTM) Model

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ABSTRACT: Stock price forecasting on time series data is a complex task due to the dynamic and uncertain nature of financial markets. This research aims to forecast stock prices by applying an advanced machine learning model, namely Long Short-Term Memory (LSTM), a deep learning architecture that excels in capturing long-term dependencies in time series data. The dataset used in this study consists of 1221 daily ANTM.JK stock price data over the period April 30, 2019 to April 30, 2024. The model was trained and evaluated using performance metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) in measuring the level of forecasting accuracy. The results show that the LSTM model can accurately predict stock prices on time series data, as evidenced by the MAPE accuracy evaluation value of 2.52% and RMSE of 54.64. These findings indicate that the LSTM model is effective in predicting stock prices on time series data and can be used as a supporting tool in making the right investment decisions.

KEYWORDS: Accuracy, Forecasting, LSTM, Stock Price, Time Series.

INTRODUCTION

Time series forecasting is a method of estimating future events using past data (Hewamalage et al., 2021). Forecasting is one way to maintain or increase personal and business profits (Lubis & Azhar, 2022). Forecasting can provide useful information in making a decision, especially in a stock investment (Anshory et al., 2020). Stock investment is the activity of buying shares of a company with the aim of benefiting from an increase in stock prices or the distribution of company profits in the form of dividends. Stocks are highly volatile markets and are characteristic of a company whose movements are influenced by market-related factors (Li & Bastos, 2020). The stock market or equity market has a very strong impact in today's economy. The average interest of investors and business people in recent times has grown exponentially in stock prices. This is due to the many billions worth of assets that are traded on the stock exchange every day in order to profit from the investments that investors have made (Saluza et al., 2023.). Given the variety of investments available, it is imperative for every investor to be aware of current and potential future dangers. The rise or fall of stock prices plays an important role in determining investment returns (Jange et al., 2021).

Predicting stock prices is one of the most difficult problems in time series data analysis. High stock price fluctuations are a major challenge for investors in making investment decisions. The main challenge lies in the ability of the model to capture complex patterns and non-linear relationships in time series data. Therefore, the ability to accurately predict stock price movements on time series data is a major requirement for investors. One of the efforts to overcome this problem is with a precise and accurate forecasting model approach, and being able to read patterns in time series data such as a non-parametric approach, namely machine learning (Rahaman et al., 2024).

The machine learning approach is an approach that allows users to find and describe structural patterns in data, so that by using the structural patterns in the data, machine learning can perform forecasting in the future (Sarker, 2021). Machine learning algorithms that are currently popular in modeling time series predictions are deep learning-based algorithms (Rahimzad et al., 2021). One of the time series forecasting methods from the deep learning group is Long Short-Term Memory (LSTM) based on Recurrent Neural Network (RNN) (He et al., 2022).

LSTM is an extension of RNN designed to capture long-term data patterns and non-linear relationships often found in stock price data. LSTM has the advantage of handling data with complex fluctuations and long-term data dependencies, so it can produce more accurate predictions, compared to traditional methods such as MA, ES, and ARIMA. Several studies have proven the superiority of the LSTM method in forecasting time series data, one example, research conducted by (Meng et al., 2021), proposed the Prophet and LSTM methods in testing prediction performance using a 3-year drug sales time series dataset. The results showed that the LSTM model showed better performance than the Prophet method, with the comparison of RMSE error accuracy for the two methods being 0.047 (LSTM) and 0.050 (Prophet). Another study conducted by (Primawati et al., 2023.), by comparing the LSTM and Prophet methods on daily cow's milk production time series data, resulted in an evaluation of the performance of the LSTM method with MSE of 39.293, RMSE of 6.268, MAPE of 9.98%, and R2 of 0.3789. While the Prophet method with an MSE value of 41.128, RMSE of 6.413, MAPE of 9.99%, and R2 of 0.3496. Then research conducted by (Sirisha et al., 2022), by building time series models (ARIMA, SARIMA, and LSTM) in predicting stock profits and comparing the performance of the resulting model from the evaluation values of RMSE, ME, MPE, MAE, MAPE, Corr, and MinMax Error, resulting in the LSTM method with better performance, which is 3.917264522 (RMSE), 0.470382847 (ME), 0.004556761 (MPE), 3.257199791 (MAE), 0.029891568 (MAPE), 0.840131571 Corr), and 0.178130191 (MinMax Error). Based on this evaluation, the average accuracy of the LSTM method with MAPA is 97.01%, while the ARIMA method with MAPA averages an accuracy of 93.84% and SARIMA 94.38%.

Based on this background, this research aims to apply the LSTM model to stock price data as a solution to the need for more accurate forecasting. In addition, the model that has been built is then evaluated using the MAPE and RMSE methods to test the accuracy of the model in producing stock price predictions. With the ability of LSTM to capture long-term patterns and complex fluctuations, this research is expected to provide predictive results that are relevant and useful in making investment decisions.

RESEACH METHODS

This research is carried out with several steps, such as data collection, data preprocessing, data split (80% training data, and 20% testing, and 20% training data is taken for validation data), then the LSTM model is trained, and stored. After the model is trained, the model is then tested using validation data, and evaluates the accuracy of the model to ensure the model has produced the best method. After the testing stage is complete, the LSTM model is then predicted using testing data, and denormalization is carried out, as well as evaluating the accuracy performance of the resulting model.

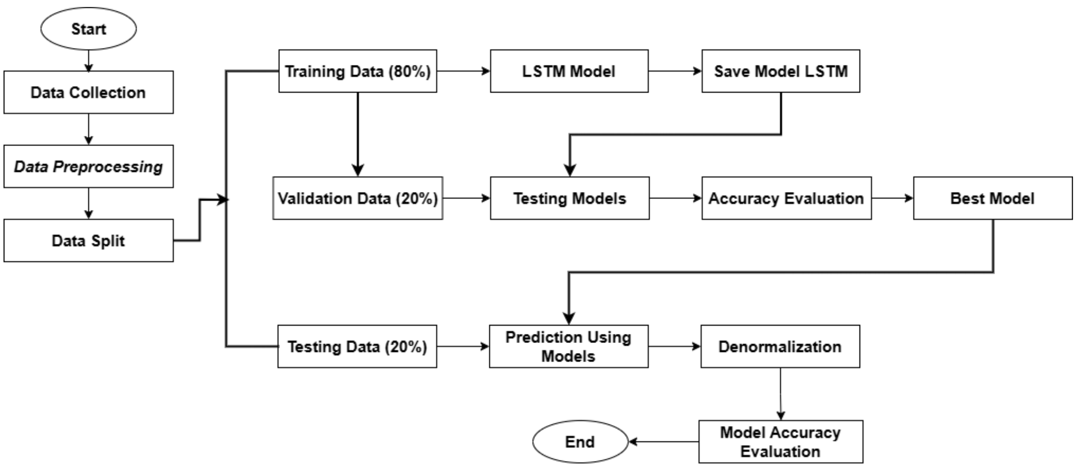

Figure 1. Research procedure

Figure 1 is the stages of the research procedure. These stages are carried out so that the research process can run regularly. The following is an explanation or review of the process of each stage of the research procedure carried out:

A. Data Collection

This stage aims to collect data that will be used in research from reliable sources and in accordance with research needs, namely historical stock price data.

B. Data Preprocessing

The preprocessing stage is carried out by data cleaning, data transformation, and normalization. Data cleaning is done by deleting data that is not used in forecasting such as deleting open, high, low, adj close, and volume features. Data formatting is done by

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changing the date data feature to Indexes. Meanwhile, the normalization stage is carried out by equalizing the value of all data with a uniform scale between 0.0 and 1.0. The normalization process is carried out using the Min-Max Scaling method, as in equation 1 (Kurniawati et al., 2023).

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where, x' is the denormalized data value, x is the actual value, ***min(x)*** is the smallest data value, and ***max(x)*** is the largest data value.

C. Data Split

Data division is done by dividing the data into two, namely training data and testing data, using the holdout method, namely with a ratio of 80:20 or 80% training and 20% testing (Setiawan & Kartikasari, 2022). The division of training and testing data is carried out using modified equations as in equations 2 and 3 (Darmawan & Amini, 2022).

$$Total\ Training\ Data = \lceil Training\ Data\ Proportion * N \rceil \tag{2}$$

$$Total\ Testing\ Data = N - Total\ Training\ Data \tag{3}$$

Where, the proportion training data is the sum of the ratio of training data, and N is the total amount of data, and **⌈ ⌉** is a rounding function. After the data is divided, the result of the training data is 80%, 20% of the data is taken again to be used as validation data. Training data is data used for the model training process. Validation data is data used to evaluate the performance of the model during training and helps in the hyperparameter tuning process, and helps prevent overfitting. While testing data is data used to measure the final performance of the model on new data that has not been seen during training and validation, with the aim of ensuring the generalization ability of the model.

D. LSTM Model

This stage involves building and training a Long Short-Term Memory (LSTM) model to predict stock prices on time series data. This process uses the training data that has been divided previously. The LSTM model training process utilizes several key components of LSTM to manage the information received at each timestep.

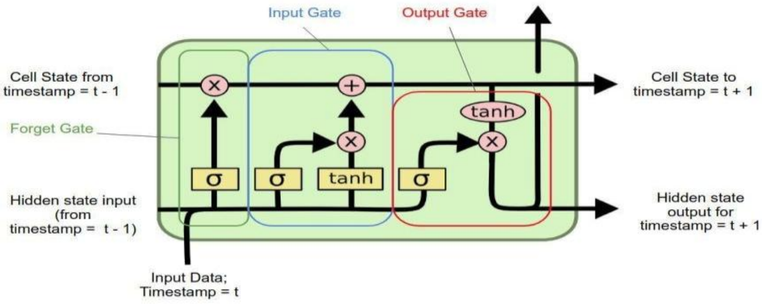

Figure 2. Architecture of the LSTM model

Figure 2 shows the architecture of the LSTM model, this architecture includes the forget gate (ft), input gate (it), and output gate (ot), which work simultaneously to regulate the flow of information in the memory cell at each timestep. Mathematically, the flow of the LSTM model can be done using equation 4-9 (Joseph et al., 2022).

The first process is the forget gate, this process decides which information will be deleted or stored in the cell, using equation 4.

$$f_t = \sigma\,(W_f.[h_{t-1}, x_t] + b_f) \tag{4}$$

Input gate is a gate used to decide the value of the input to be stored in the state memory. This process can be done using equation 5, and after the input gate is obtained, the next memory cell is calculated to get a new candidate memory using equation 6.

$$i_t = \sigma\,(W_i.[h_{t-1}, x_t] + b_i) \tag{5}$$

$$\tilde{C}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{6}$$

After these steps are completed, the memory cell is then updated by combining the information from the forgate gate and input gate, using equation 7.

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{7}$$

The last process is the output gate which is used to decide what will be produced according to the input and memory in the cell. This process can be done using equation 8, and after getting the gate output value ($\boldsymbol{o_t}$) the actual output value ($\mathbf{h}_t$) is calculated using equation 9.

$$o_t = \sigma \left(W_o . [h_{t-1}, x_t] + b_o\right) \quad (8)$$

$$\mathrm{h}_t = o_t \odot \tanh(c_t) \quad (9)$$

E. Testing Model

After the model is trained, the stored model is then tested using data that has never been seen during the training process. The data used to test the model is validation data. The purpose of testing this model using validation data is to check how well the model functions during training, and help in choosing hyperparameters and avoiding overfitting, if forecasting is done on the latest data. After the model is tested, the model is then evaluated for accuracy to ensure that the model that has been built is the best model.

F. Prediction Using Model

This stage applies stock price forecasting using the best LSTM method that has been tested previously in the training and validation stages. Forecasting is done using testing data, where this data is data that has never been seen before during the model training and validation process.

G. Denormalization

After obtaining the forecasting results, the prediction results are denormalized to convert the data into the original scale, because the forecasting results are still in interval form at the time of normalization. The purpose of denormalization is to make it easier to read the resulting output, as well as to allow proper comparison with the original data when calculating the model accuracy evaluation. Denormalization of this data is done using equation 10 (Kurniawati et al., 2023).

$$x = x'(\max(x) - \min(x)) + \min(x) \quad (10)$$

Where, $\boldsymbol{x}$ is the denormalized result, $\boldsymbol{x'}$ is the denormalized value, ***min(x)*** is the smallest value, and ***max(x)*** is the largest value.

H. Model Accuracy Evaluation

The model accuracy evaluation stage is carried out to determine the best architecture or method parameters, and validate the prediction performance that has been carried out. The evaluation process is carried out using the MAPE (mean absolute percentage error) method (Ensafi et al., 2022) and RMSE (Root Mean Square Error) (Abumohsen et al., 2024). The MAPE process can be done using equation 11 (Pangaribuan et al., 2023), and RMSE in equation 12 (Zhang et al., 2024).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| * 100\% \quad (11)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \quad (12)$$

Where, $\boldsymbol{Y_i}$ is the actual value, $\hat{Y}_i$ is the forecast value, and $\boldsymbol{n}$ is the number of data tested. In MAPE analysis, a value of ≤10% indicates highly accurate accuracy, 11% to 20% is considered accurate, 21% to 50% is moderately accurate, and >50% indicates inaccurate accuracy (Arkadia et al., 2022).

RESULT AND DISCUSSION

A. Data Collection and Preprocessing

This research uses quantitative data with secondary data taken from yahoo finance *(https://finance.yahoo.com/)*. This study uses the ANTM.JK stock time series dataset for the last 5 years on a daily basis from April 30, 2019 to April 30, 2024, with a total of 1221 datasets and 7 features (Date, Open, High, Low, Close, Adj Close, Volume). After the data is collected, the dataset is then preprocessed by deleting data that is not used in the study, such as Open, High, Low, Adj Close, and Volume. Meanwhile, the remaining datasets, such as Date and Close are used as materials in this study. In the Date feature, the data transformation stage is carried out by converting the data form into an index. The results of the cleaning and data transformation stages in the research can be seen in Figure 3 and the visualization of stock price movements on the data used is shown in Figure 4.

Date	Close
2019-04-30	865.0
2019-05-01	865.0
2019-05-02	820.0
2019-05-03	790.0
2019-05-06	760.0
...	...
2024-04-24	1680.0
2024-04-25	1590.0
2024-04-26	1595.0
2024-04-29	1615.0
2024-04-30	1640.0

1221 rows × 1 columns

Figure 3. ANTM stock closing price data

Figure 4. Closing price movement of ANTM shares

The next stage is that the dataset is normalized using the MinMaxScaler technique in accordance with equation 1. The results of this normalization are shown in table 1.

Table 1. Data normalization results

No.	***Date***	***Close***	
		Actual	***Normalization***
1	30-04-2019	865	0,18191414
2	1-05-2019	865	0,18191414
…	….	….	….
4	29-04-2024	1615	0,44581281
5	30-04-2024	1640	0,45460943

B. Data Split

After the preprocessing stage is complete, the dataset is then divided into 2 with a range of 80:20 or 80% training and 20% testing. After the dataset is divided, the dataset is then transformed into a form that is suitable for the LSTM model. This transformation process uses a windowing technique with a size of 100. After the data is in accordance with the LSTM format, Training data, then 20% data is taken to be used as validation data. The results of this dataset division are shown in table 2.

Table 2. dataset sharing results

No.	*Total Data*	*Window Size*	*Training Data*	*Validation Data*	*Testing Data*
1	1221	100	701	176	244

C. LSTM Model

This stage is to build an LSTM model to train the model in forecasting stock price time series data using training data. The LSTM model is built using one input layer that receives data of 100 timesteps as an input sequence, three hidden layers in the form of LSTM layers, where each LSTM layer has 100 neurons to learn long-term patterns in time series data, and one dense layer that produces prediction output. The hyperparameters of the model, such as epochs are set with a size of 50 and batch size of 64. To accelerate convergence during model training, the RMSprop algorithm is used as the optimizer, and Mean Squared Error (MSE) as the loss function. The model training process is visualized as in Figure 5 and the forecasting results using the training data are shown in Table 3.

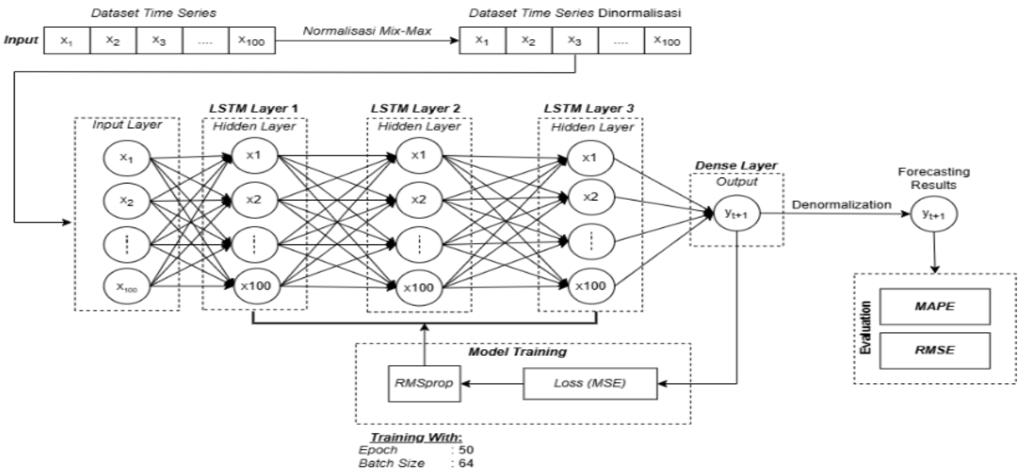

Figure 5. LSTM model process

Table 3. LSTM model forecasting results on training data

No.	*Date*	*Close*	
		Actual	*LSTM*
1	17-09-2019	1050	1134
2	18-09-2019	1065	1123
…	….	….	….
4	01-08-2022	2080	1815
5	02-08-2022	1995	1871

D. Testing Model

After the model has finished applying training, the LSTM model is then tested for forecasting using validation data to evaluate how well the model functions before being applied to new data and to ensure that the resulting model is the best model. This process is carried out without affecting the updating of the weights and hyperparameters of the model. The results of the forecasting trials on the validation data are shown in table 4, and the accuracy evaluation results are shown in table 6.

Table 4. LSTM model testing forecasting results on validation data

No.	*Date*	*Close*	
		Actual	*LSTM*
1	03-08-2022	1970	1924
2	04-08-2022	1970	1967
…	….	….	….
4	11-04-2023	2110	2086
5	12-04-2023	2110	2086

E. Forecasting Model LSTM

This process applies stock price forecasting using the best LSTM model. Forecasting results using the best LSTM method is done using data that has never been seen at all by the LSTM model during the training and validation process, namely by using testing data. This step is done to measure the final performance of the model on actual data that will reflect the capabilities of the model in the real world. The forecasting results are shown in table 5.

Table 5. LSTM model forecasting results on testing data

No.	*Date*	*Close*	
		Actual	*LSTM*
1	13-08-2023	2130	2086
2	14-0802023	2110	2087
…	….	….	….
4	29-04-2024	1615	1744
5	30-04-2024	1640	1717

F. Evaluation Model

Based on the prediction results, it shows that the performance of the LSTM model that has been built produces accurate prediction results, both in prediction on training data, validation, and testing data. This is evidenced by the results of the model accuracy evaluation based on the MAPE and RMSE values, as shown in table 6. In addition, based on the visualization of predicted stock movements, the LSTM model built can learn the overall pattern of stock price movements and produce predictions that are close to the actual closing price, although there are some small differences, as shown in figure 6.

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Table 6. LSTM model accuracy evaluation results

No.	***Dataset***	***MAPE***	***RMSE***
1	Training	6,17%	138,51
2	Validation	2,95%	76,90
3	Testing	2,52%	54,64

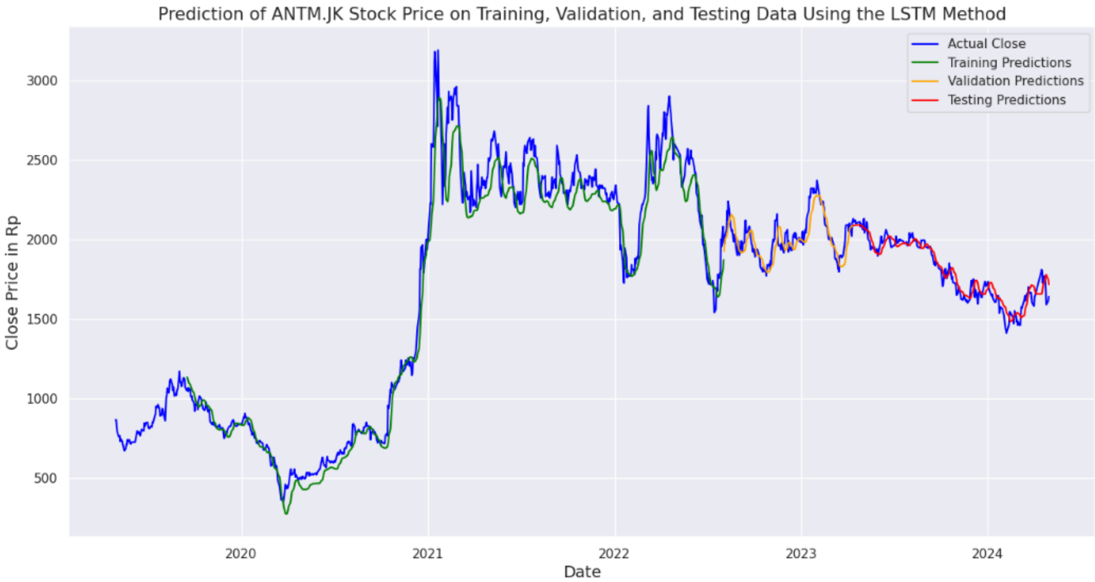

Figure 6. Visualization of forecasting results

CONCLUSION

Research on the application of the Long Short-Term Memory (LSTM) model and performance evaluation using the MAPE and RMSE methods in predicting stock prices on time series data provides good results. This is evidenced based on the results of the MAPE evaluation with an accuracy of 2.52% and RMSE of 54.64 on testing data or data that reflects the ability of the overall model. These results show that the LSTM model built is effective in capturing time series data patterns on stock prices and can be a solution to the need for more accurate forecasting and investment decision making. However, although the model produces accurate MAPE and RMSE values, this model can still be developed again by modifying the hyperparameters of the LSTM model to produce more accurate predictions and a fast and efficient model training process. Future research is expected to pay attention to the hyperparameter value of the LSTM model and improve model training by selecting the right optimization, so as to improve forecasting accuracy.

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