
| RESEARCH ARTICLE

Analysis and Prediction of Indonesia Stock Exchange (IDX) Stock Prices Using Long Short Term Memory (LSTM) Algorithm

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| ABSTRACT

Stock investment is now a popular choice for many individuals and business entities. To optimize profits in investing, a deep understanding of price movements, timing, and accurate predictions in trading is required. The Long Short-Term Memory (LSTM) algorithm, a type of neural network suitable for time series data such as stock prices, can recognize complex temporal patterns in financial data. This algorithm has the potential to help investors and financial analysts predict BBRI stock prices more accurately. The purpose of this research is to predict the closing price of BBRI stock using the LSTM algorithm. This system can also conduct technical analysis with various indicators to understand the characteristics of the financial market. The research data includes BBRI stock prices from January 2006 to the present, with closing prices as the main variable. The research results show good model performance with a Mean Squared Error (MSE) of 0.000279, Mean Absolute Error (MAE) of 0.0133, and Root Mean Squared Error (RMSE) of 0.0167 on the training data. This reflects the model's level of accuracy against the training data. Although there is a slight increase in the validation data, these values remain within an acceptable level, indicating the model's ability to recognize data patterns that have not been seen before.

| KEYWORDS

Stock, Prediction; LSTM; Technical Analysis; BBRI.

| ARTICLE INFORMATION

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1. Introduction

In recent years, investing in the stock market has become increasingly popular in Indonesian society. This investment avenue offers attractive return opportunities but is also accompanied by significant risks. In this context, the Indonesia Stock Exchange (IDX) plays a crucial role as a platform for people to invest, serving as one of the alternative capital investment options (Syahfutris et al., 2023). Investors often attempt to predict the movement of stock prices on the Indonesia Stock Exchange (IDX) in hopes of gaining profits or managing their investment risks. However, the challenge faced by investors lies in the difficulty of accurately predicting stock price movements, given that the stock market can be influenced by various external and internal factors that are often unpredictable. This uncertainty complicates making informed investment decisions, thus requiring analytical tools and strategies to better manage risks (Isra Miraltamirus et al., 2023).

At the same time, the digital revolution and advancements in information technology have transformed how individuals and business entities interact with the stock market. Information on stock price movements, economic news, and company financial data can be accessed quickly through online platforms. With this development, there is an increasing need for sophisticated analytical tools to understand stock market dynamics and make smarter investment decisions (Strader et al., 2020).

One increasingly popular analytical tool is the Long Short-Term Memory (LSTM) algorithm, which is a type of artificial neural network capable of addressing issues in modeling time series data, such as stock price movements. With its ability to recognize

complex temporal patterns in financial data, the LSTM algorithm may have the potential to enable investors and financial analysts to make more accurate predictions about stock prices on the Indonesia Stock Exchange (IDX). Based on previous research, such as the study titled "Prediction of Trends in the Movement of PT Bank Central Asia Tbk Stock Prices Using Long Short Term Memory (LSTM) Algorithm" (Wathani et al., 2023), experimental results have yielded values including a Mean Absolute Error (MAE) of 96.92, Mean Squared Error (MSE) of 16185.22, and Root Mean Squared Error (RMSE) of 127.22 (Wathani et al., 2023).

2. Literature Review

2.1 Stocks

Literature on stocks explains that stocks represent tangible ownership in a company, granting shareholders the right to participate in decision-making and receive dividends or capital gains. Stocks reflect the involvement of shareholders in the company as well as the rights and responsibilities inherent in ownership. Research by (Hakim et al., 2023) outlines the advantages of owning stocks, including long-term profit potential, ownership rights to participate in company decision-making, dividends as a source of passive income, high liquidity, portfolio diversification, and the right to receive company information periodically. This knowledge underscores the diverse role of stocks beyond just investment instruments, shaping shareholder engagement and corporate governance dynamics.

2.2 Indonesian Stock Exchange (IDX)

Indonesian Stock Exchange (IDX) is the official stock exchange in Indonesia where trading of stocks, bonds, and other financial instruments takes place. IDX plays a crucial role as a platform for the public to engage in investment activities, offering an alternative avenue for capital investment. Additionally, IDX is instrumental in regulating and supervising the capital market in Indonesia and provides companies with access to additional capital through the issuance of shares or other securities, commonly known as going public. This process involves issuers (companies going public) offering shares to the public in accordance with regulations stipulated in the Capital Market Law and relevant regulations.

2.3 Forecasting

Forecasting is a method used in the planning and production control stages with the aim of anticipating and addressing uncertainties that may arise in the future. An essential part of this technique is to project and predict trends and price changes that may occur in the stock market, which significantly impact decision-making in stock investment and trading strategies. This technique becomes increasingly relevant and crucial in situations where stock price movements become key factors in economic and investment decision-making (Ruhail & Prashar, 2023).

Forecasting is an approach used to anticipate or predict changes based on historical data used as the main input, with the aim of determining patterns or future movement directions. The fundamental function of forecasting techniques is to provide guidance supporting companies in making optimal and efficient policies and decisions for the future (Huang et al., 2021).

There are many types of forecasting, including financial forecasting, sales forecasting, and stock market forecasting. Financial forecasting relates to predicting financial aspects such as revenue, costs, and company profits. Sales forecasting predicts demand and sales of products or services in the future, which helps companies plan production and inventory. Meanwhile, stock market forecasting focuses on predicting stock price movements and stock values in the financial market. Each type of forecasting plays a crucial role in assisting companies and individuals in making better and more informed decisions for the future (Afrizal et al., 2023).

2.4 Long Short Term Memory

LSTM (Long Short-Term Memory) is a type of neural network that is effective for processing sequential data, such as text or time series. Its main advantage lies in its ability to overcome long-term dependencies in sequential data, making it suitable for natural language processing and time series prediction (Le et al., 2019). In this study, the type of Recurrent Neural Network (RNN) method used is Long Short Term Memory (LSTM).

LSTM is designed to address the issue of information propagation over long sequences of sequential data. This algorithm enables the neural network to efficiently "remember" and "forget" information. LSTM utilizes several key components, including the input gate, forget gate, memory cell state, and output gate. The input gate regulates how much new information will be inputted into the memory cell state, while the forget gate controls how much old information will be discarded. The output gate regulates how much information will be conveyed to the next layer (Van Houdt et al., 2020).

Here are the equations used in LSTM :

2.4.1. Input Gate (i_t)

The input gate (i_t) is responsible for controlling how much new information will be inputted into the cell memory at a specific time (t). This is done by controlling how much information from the current input (x_t) and the output from the previous time step (ht_{t-1}) will be forwarded to the cell memory (Khalil et al., 2021). In the formula, i_t is computed using the sigmoid function of the combination of the current input (x_t), the output from the previous time step (ht_{t-1}), and the corresponding weights and biases. The equation for the input gate is shown below.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

2.4.2. Candidate Cell State (C_t)

The candidate cell state (C_t) is the candidate value considered for updating the cell memory at a specific time (t). This value is computed using the hyperbolic tangent function of the combination of the current input (x_t), the output from the previous time step (ht_{t-1}), and the corresponding weights and biases (Sherif et al., 2023). The candidate cell state is a potential value for updating the cell memory, but the final decision for updating will be controlled by the forget gate and the input gate. The equation for the candidate cell state is shown below.

$$C_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$

2.4.3. Forget Gate (f_t)

The forget gate (f_t) is responsible for controlling how much old information will be forgotten or retained in the cell memory at a specific time (t). This is done by controlling how much information from the previous cell memory (C_{t-1}) will be retained or discarded (Zhang et al., 2020). The forget gate makes this decision using the sigmoid function of the combination of the current input (x_t), the output from the previous time step (ht_{t-1}) and the corresponding weights and biases. The equation for the forget gate is shown below.

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

2.4.4. Memory Cell State (C_t)

The memory cell state (C_t) is the actual value of the cell memory at a specific time (t). This value is updated based on the candidate cell state (C_t), the input gate (i_t), and the forget gate (f_t). In the formula (C_t) is calculated by considering the values of the candidate cell state and the previous memory cell state (Su, 2020). This allows the memory cell to remember relevant information and forget irrelevant information over time. The equation for the memory cell state is shown below.

$$C_t = i_t \cdot C_t + f_t \cdot C_{t-1}$$

2.4.5. Output Gate (o_t)

The output gate (o_t) is responsible for controlling how much information from the cell memory at a specific time (t) will be conveyed to the next layer as output. This is done by controlling how much information from the cell memory will be forwarded after being processed through the hyperbolic tangent function. The output gate makes this decision using the sigmoid function of the combination of the current input (x_t), the output from the previous time step (ht_{t-1}), and the corresponding weights and biases. The equation for the output gate is shown below.

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

2.4.6. Output

The output (h_t) is the final result of LSTM at a specific time (t), which will be forwarded to the next layer or used for specific tasks, such as prediction or classification. This output is influenced by the information from the cell memory at that time (C_t), which has been controlled and filtered through the output gate (o_t). The output (h_t) is calculated by multiplying the output gate (o_t) by the value of the cell memory at that time (C_t) which has been processed through the hyperbolic tangent function. The output gate controls how much information from the cell memory will be forwarded, while the hyperbolic tangent function transforms the cell memory value into a broader range, preserving or highlighting important features of the stored information. The equation for the output can be seen below.

$$h_t = o_t \cdot \tanh(C_t)$$

3. Methodology

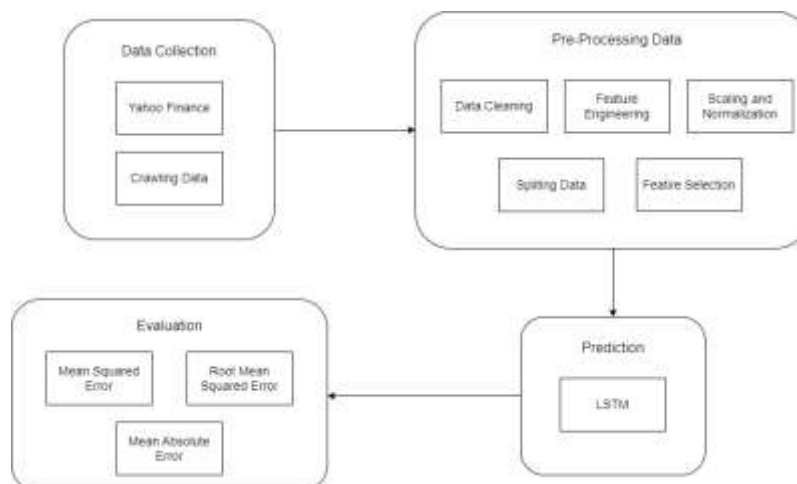


Figure 1 Research Stages

3.1 Dataset

Stock price movement data for research purposes can be accessed through Yahoo Finance, a financial website provided by Yahoo. Yahoo Finance provides news and financial-related information, as well as stock price data for companies listed on the stock exchange; this research only utilizes stock price data as the primary information source. In the study, to obtain data on BBRI stock movements for the period January 2006 to December 2023, mplfinance in Python is used. The main steps involve downloading historical BBRI stock data and then processing it into a format suitable for mplfinance. Afterward, mplfinance can be used to plot the BBRI stock price movement graphs as required for the research.

Table 1 Dataset Saham Bursa Efek Indonesia (BEI)

Date	Open	High	Low	Close	Volume
2006-01-02	149.386063	150.630939	149.386063	149.386063	47619822
2006-01-03	149.386079	158.100266	149.386079	158.100266	400379415
2006-01-04	159.345143	166.814453	159.345143	166.814453	577795979
2006-01-05	166.814446	166.814446	163.079800	164.324677	176894055
2006-01-06	164.324672	166.814441	163.079795	165.569565	111783930

Table 1 is an example of data downloaded from Yahoo Finance, consisting of seven columns: Date, Open, High, Low, Close, adj. Close and Volume. In developing the program for this research, the author only requires two columns: the Date column containing dates and the Close column containing stock closing prices.

3.2 Data Preprocessing

Data Preprocessing is a critical process in data analysis aimed at ensuring that the data used in a model or analysis is accurate, consistent, and reliable (Fan et al., 2021). The steps in Data Preprocessing help identify, correct, or remove errors, anomalies, and inconsistencies in the dataset so that the data is ready for analysis or other purposes.

3.3 Data Cleaning

Data cleansing is the first step in Data Preprocessing, involving the identification and handling of missing values, outliers, or invalid data in the dataset. In the context of stock prices, this may involve identifying and addressing missing values, which may arise due to input errors, sensor failures, or other reasons. If there are missing values, the next step is to decide whether to fill in the missing values using techniques such as interpolation or imputation or to delete rows or columns containing these values. Additionally, outliers or invalid data should also be identified and appropriately handled, either by removing them or using techniques such as winsorization or logarithmic transformation.

3.4 Feature Engineering

Feature engineering is the process of creating additional features based on existing data. In the context of stock price prediction, this could mean creating indicators such as moving averages, relative strength index (RSI), or various other technical indicators that can provide additional insights into stock price behavior. By adding these additional features, we can enhance the model's ability to capture patterns and trends that may not be apparent using only raw stock price data.

3.5 Scaling and Normalization

Scaling and normalization are steps to adjust the scale of stock price data so that the model can interpret it properly. This is important because some algorithms, including LSTM, can be sensitive to differences in scale between features. By adjusting the scale of the data, we can ensure that all features have a balanced influence on prediction formation without allowing features with larger value ranges to dominate the learning process.

3.6 Feature Selection

Feature selection is the process of choosing the most relevant and significant subset of features to use in a prediction model. In the context of stock price prediction, this could mean selecting features that are most correlated with stock price movements or most influential in the model. Choosing the right features can help reduce data dimensions, improve model performance, and avoid overfitting.

3.7 Long Short Term Memory

This research employs the Long Short-Term Memory (LSTM) algorithm, a type of Recurrent Neural Network (RNN) specifically designed to model and predict sequential data patterns. LSTM networks are particularly well-suited for time series prediction due to their ability to capture long-term dependencies and remember information over extended sequences. The implementation of the LSTM model in this study involves several key steps, as outlined below.

The LSTM model is built using the Sequential API from Keras. The architecture starts with an LSTM layer containing 50 units, with `return_sequences` set to True to ensure that the output of the layer returns the full sequence to the next LSTM layer. This is followed by another LSTM layer, also with 50 units, but with `return_sequences` set to False, which means it will return only the last output of the sequence. Next, a Dense layer with 25 neurons is added, followed by a final Dense layer with a single neuron, representing the predicted output.

The model is compiled with the Adam optimizer and uses Mean Squared Error (MSE) as the loss function, which is suitable for regression tasks such as stock price prediction. The training process involves fitting the model to the training data (`x_train` and `y_train`) with a batch size of 128 and running for 72 epochs.

3.7 Evaluation

1. Root Mean Squared Error (RMSE): is a commonly used evaluation metric in statistics and machine learning to measure how close the model's prediction results are to the actual or target values in regression tasks (Boursalie et al., 2022). RMSE is a variant of Mean Squared Error (MSE) that has the advantage that its measurement unit corresponds to the measurement unit of the original target due to the square root of MSE.

$$RMSE = \sqrt{(1/n) * \sum (y_i - \hat{y}_i)^2}$$

Description:

RMSE: Root Mean Squared Error.

n: the number of samples or data points in the dataset.

y_i : the actual target value for the i-th data point.

\hat{y}_i : the model's prediction for the i-th data point.

2. Mean Squared Error (MSE): in the context of evaluating statistical or machine learning models, is a metric used to measure how close the model's prediction results are to the actual or target values (Bukhari et al., 2021). MSE measures the average squared error between the model's predictions and the target values. It is one of the most commonly used metrics for regression tasks.

$$MSE = (1/n) * \sum (y_i - \hat{y}_i)^2$$

Description:

MSE: Mean Squared Error.

n: the number of samples or data points in the dataset.

y_i : the actual target value for the i-th data point.

\hat{y}_i : the model's prediction for the i-th data point.

3. Mean Absolute Error (MAE): Mean Absolute Error (MAE) is an evaluation metric used in statistics and machine learning to measure the absolute error between the model's predicted values and the actual or target values (Ding & Qin, 2020). MAE measures the average of the absolute differences between each model prediction and the actual value, regardless of the direction of the error.

$$MAE = (1/n) * \sum (y_i - \hat{y}_i)$$

Description:

MSE: Mean Squared Error.

n: the number of samples or data points in the dataset.

y_i : the actual target value for the i -th data point.

\hat{y}_i : the model's prediction for the i -th data point

4. Results and Discussion

In this study, we conducted a training process on a Long Short-Term Memory (LSTM) neural network to predict the stock prices of Bank Rakyat Indonesia (BBRI). The implementation of the model training process in this system aims to train the data to gain insights from the available information. After the training is completed, the results of the trained data will display several evaluation metrics that measure the effectiveness of the LSTM model used. The LSTM model architecture is designed as follows.

```

model = Sequential([LSTM(50, input_shape=(1, 1), return_sequences=True),
                    LSTM(50),
                    Dense(25, activation='relu'),
                    Dense(1)])

optimizer = tf.keras.optimizers.Adam(learning_rate=0.0001)
model.compile(optimizer=optimizer,
              metrics=["mae"],
              loss=tf.keras.losses.Huber())
    
```

Figure 2 LSTM model architecture

After the training process is completed, the next step is to evaluate the model. This evaluation aims to determine the performance of the LSTM model in predicting the next data points in a time series, in this case, the stock prices of BBRI from January 2006 to December 2023. In this study, the performance of the LSTM model was evaluated using three key metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The results of the evaluation matrix can be seen in Table 2.

Table 2 Matrix Evaluation (MSE, RMSE, MAE)

Mean Squared Error (MSE)	0.0002791007279173775
Root Mean Squared Error (RMSE)	0.01670630802772945
Mean Absolute Error (MAE)	0.013317640008720497

These metrics indicate a relatively low error rate, suggesting that the model performs well in predicting the stock prices of BBRI. An MSE of 0.000279 and an RMSE of 0.0167 indicate that the model's predictions are very close to the actual values. Additionally, an MAE of 0.0133 indicates a small average deviation, which reinforces the model's accuracy.

To further evaluate the model's performance, we compared the predicted stock prices with the actual stock prices over a specific period. Hasilnya ditunjukkan pada Figure 3 and Figure 4.

Date	Actual	Predicted
2020-04-17 00:00:00+07:00	2158.078613	1952.450195
2020-04-20 00:00:00+07:00	2119.950195	2121.921631
2020-04-21 00:00:00+07:00	2074.195801	2083.215088
2020-04-22 00:00:00+07:00	2127.575928	2036.914917
2020-04-23 00:00:00+07:00	2135.201660	2090.947754
...
2023-12-05 00:00:00+07:00	5172.854004	5158.245117
2023-12-06 00:00:00+07:00	5149.125000	5108.968262
2023-12-07 00:00:00+07:00	5196.582520	5084.372070
2023-12-08 00:00:00+07:00	5101.667969	5133.592773
2023-12-11 00:00:00+07:00	5030.481934	5035.268066

[888 rows x 2 columns]

Figure 3 Comparison of Predicted Prices and Original Prices



Figure 4 Graph Comparison

This comparison shows that the predicted stock prices closely follow the trend of the actual prices, although there are some deviations, especially during sharp fluctuations. These discrepancies could be attributed to the inherent volatility in stock prices, which may not be fully captured by the LSTM model. Overall, the LSTM model demonstrates significant potential for stock price prediction, showing a strong ability to capture the direction and significant movements in stock prices.

5. Conclusion

Based on the overall process of analysis, design, and implementation in creating the Stock Price Analysis and Prediction System Using Long Short Term Memory (LSTM) Algorithm, the following conclusions are drawn. Firstly, the system is able to predict stock price movements based on closing prices (Close) of Bank Rakyat Indonesia (BBRI) stock and the Indonesia Stock Exchange (IDX) by applying the Long Short Term Memory (LSTM) algorithm method. Secondly, the results of the prototype show excellent performance with a Mean Squared Error (MSE) value of 0.000279, Mean Absolute Error (MAE) of 0.0133, and Root Mean Squared Error (RMSE) of 0.0167 on the training data, reflecting the model's accuracy level against the training data. Although there is a slight increase in validation data, these values remain at an acceptable level, indicating the model's ability to generalize sequential patterns to unseen data. Thirdly, this system can conduct technical analysis of stocks on the Indonesia Stock Exchange (IDX) using several indicators such as moving averages, MACD, RSI, and other indicators to assist investors in making better investment decisions.

Although this study has yielded positive results, there are several limitations that need to be acknowledged. First, despite the dataset covering the period from January 2006 to December 2023 and encompassing various variables such as opening price, highest price, lowest price, closing price, and volume, the complexity of stock market dynamics might not be fully captured. While the LSTM model has advantages in handling time series data, it cannot account for sudden market anomalies or unexpected macroeconomic events. The results of this study are also specific to BBRI stocks and may not be well generalized to other stocks or markets without further validation. Additionally, the LSTM model's hyperparameters in this study were selected based on limited experiments, leaving room for optimization to improve model performance.

To enhance this research, several considerations can be added. First, expanding the dataset to include more diverse stock indices and incorporating other financial indicators such as trading volume, market sentiment, and macroeconomic variables can provide a more comprehensive analysis. Moreover, exploring other machine learning algorithms and hybrid models that combine LSTM with other techniques, such as ARIMA or reinforcement learning, can improve prediction accuracy. Optimizing hyperparameters using techniques like grid search or Bayesian optimization can also further enhance model performance. Lastly, validating the model across various sectors and global markets can provide insights into the model's generalization and robustness.

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