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Stock Price Forecasting of PT. Bank Rakyat Indonesia (Persero) Tbk. Using Long Short-Term Memory (LSTM) Method

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Abstract

Stock price forecasting is a major challenge in financial market analysis due to the volatility and unpredictability of price movements. The limitations of traditional statistical methods in capturing nonlinear patterns and long-term temporal dependencies have encouraged the adoption of deep learning–based approaches. This research aims to predict the stock price of PT Bank Rakyat Indonesia (Persero) Tbk. (BBRI) using the Long Short-Term Memory (LSTM) method, which is effective at handling problems with fading information and identifying long-term trends in time series data. The dataset comprises historical BBRI share prices from April 16, 2015, to April 16, 2025, with 80% of the data used for training and 20% for testing. LSTM's model was trained for 10 epochs with a batch size of 32 using the Adam optimizer. The results prove that the LSTM model can effectively capture stock price movement patterns, achieving a mean absolute error (MAE) of 8.42 and a mean absolute percentage error (MAPE) of 1.50%, indicating a high level of accuracy. The visualization of the prediction results reveals a trend that closely aligns with the actual values. These findings reinforce LSTM's position as a reliable approach to stock price forecasting and highlight its potential as a strategic tool for investors and policymakers in managing market risk.

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I. INTRODUCTION

The securities market has a contributes substantially to economic growth and stability in a country's. It serves as a long-term financial platform that enables stock trading, provides funding opportunities for companies, and supports various investment activities. In countries that adhere to market economic systems, their economic progress is highly dependent on the role of the capital market because it is one of the alternative sources of funding for companies listed in it. One common type of investment in the securities market is purchasing shares of company stock (Muhajir & Canas, 2024). Stock investing has increasingly in demand and experiencing rapid development in Indonesia. Shares are financial instruments that indicate an individual's assets or organization's ownership stake in a company, typically held as proof of investment in the capital market. Value of the shares is not fixed or fluctuating, that is, it can increase or decrease. Several factors that can influence fluctuations in stock prices include the company's condition and performance, risk levels, dividend payouts, interest rate changes, overall economic conditions, government regulations, and various emerging issues or developments, inflation rates, supply and demand dynamics in the market stock (Putra et al., 2022).

Through stock investment, investors have the opportunity to make relatively fast and significant profits in a relatively short period of time, whether in a matter of days, weeks, months, or years since the investment was made ('Izzah et al., 2021). Based on statistical data from the Indonesia Stock Exchange (IDX) in 2022, the number of capital market investors has consistently increased each year. At the end of 2022, the number of investors reached 10.3 million people, an increase of 37.68% compared to the end of 2021 which amounted to 7.48 million investors (Puteri, 2023). Among a number of banking stocks listed on the IDX, one of which is PT Bank Rakyat Indonesia (Persero) Tbk shares or stock code known as BBRI, is one of the most in demand by investors. BRI is recognized as the oldest commercial bank in Indonesia, founded in 1895, and has been listed on Indonesia Stock Exchange since 2003. As part of the LQ45 index and included in the blue chip stock category, BBRI has a strong reputation, especially in terms of financing micro, small, and medium enterprises (MSMEs), and shows stable financial performance over time (Pandanan & Padang, 2021).

BRI Tbk's share price prediction is a complex challenge because its movements are not only influenced by the company's fundamental factors, but also macroeconomic conditions, monetary policy, and dynamic market sentiment. Fluctuations in stock prices that continue to change require investors to analyze historical banking data to develop the right investment strategy. This analysis is essential for enabling investors to evaluate the future potential of a company's stock price movements. In an effort to predict stock prices, Long Short-Term Memory (LSTM) is one methods of the machine learning that is considered very effective, especially for handling time series data (Pramesti et al., 2022)(Enriko et al., 2023). LSTM's are specifically developed to overcome the difficulty of capturing long-term dependencies within data, an issue that traditional methods often struggle to handle effectively (Ningrum et al., 2021). The main advantage of LSTM lies in its architecture that has internal memory units, allowing this model to store important information across a prolonged timeframe without losing the context of the previous data. This makes LSTM very suitable for studying complex patterns in historical stock price data and producing more accurate predictions (Khumaidi et al., 2020).

Several related studies have been conducted by Rendy Saputra et al. (2024) regarding the prediction of Tesla stock price using the LSTM algorithm (Saputra et al., 2024). This research uses historical data on Tesla's stock price from 2020 to 2024 which has been processed using the Standard Scaler normalization. The test results showed that the model with two layers of LSTM and 50 neurons achieved the best performance, with an RMSE value of 0.0417 and MAPE of 0.1866. Visualization of prediction results shows a significant match between the actual value and the predicted value. Based on these results, LSTM can predict stock prices with a good level of accuracy and relatively small prediction errors. In addition, the research by Moch Farryz Rizkilloh and Sri Widiyanesti (2022)

(Rizkilloh & Widiyanesti, 2022). Regarding cryptocurrency price predictions, the LSTM method is used. The test was carried out with a variation of the number of epochs of 1, 10, and 20, developed with the ADAM optimizer. Based on the results of the evaluation with RMSE metrics, the best performance was obtained on the DOGE price prediction with the number of 20 epochs which resulted in an RMSE value of 0.0544. These results show that LSTM is effective for predicting the price of crypto assets with volatility and relatively low prices.

The results of the research are relevant amid the growing public interest in stock investment in Indonesia. The high level of accuracy of the model is a potential solution for investors in dealing with the changing dynamics of the stock market. The rapid growth of the stock market has contributed to a rising number of investors participating in stock trading, making it important to exercise caution to prevent potential losses in stock transactions. Based on this, this study was conducted to predict stock prices by applying the Recurrent Neural Network (RNN) method using the LSTM approach on stock closing prices. This research has high urgency because it provides practical contributions for investors and financial analysts in investment decision-making based on stock price prediction as an indicator of future value (Budiprasetyo et al., 2023). In addition, the study is also relevant in the context of financial marketing, financial institutions can leverage predictive results to develop more competitive investment strategies (Wu, 2021). From an academic perspective, this research adds to the existing of knowledge on the implementation of deep learning techniques in stock market analysis, with a particular focus on the banking sector in Indonesia. Therefore, this study is expected to provide theoretical and practical benefits for investors, financial analysts, financial institutions, and academics who are interested in developing a deep learning-based stock price prediction model.

II. METHODS

2.1 Data Source

This research utilizes the stock price data of PT. BRI (Persero) Tbk, with the stock code BBRI, in Rupiah currency units, from April 16, 2015, to April 16, 2025, as obtained from the official BRI website, accessible through the following URL: https://www.ir-bri.com/historical_price.html.

2.2 Research Procedure

The research phase involves a methodical, organized, and systematic approach to achieve certain goals (Borman et al., 2020). The scheme of the research stages can be described as follows:

1. **Data Collection**
   The BBRI stock dataset has several columns; the dataset provides date, open, close, high, low, adjusted close, and volume values. Only the daily closing price is considered. The software used in this study is Google Colaboratory with the Python programming language.
2. **Pre-Processing of Data**
   At this stage, the process of feature scaling and data sharing is performed using the Python programming language. Python is one of the most popular programming languages and is widely used by developers due to its simple and easy-to-understand syntax (Candra, 2025). The stages of data preprocessing include:
   a. Feature scaling
   The feature scaling process is a process of normalizing data so that all values have a uniform range (Oktasia Nasution, 2022). The technique used in feature scaling is min-max normalization, where the actual data is converted into a range of values between 0 to 1

before being further processed by the LSTM model. The formula of min-max normalization can be explained by the equation below:

$$x_{norm,i} = \frac{X_i - X_{min}}{X_{max} - X_{min}} ; \ i = 1,2,3, \ldots, t \quad (1)$$

where xnorm is the normalization value, and is the maximum and minimum value.

b. Split data

Refers to the act of allocating portions of the dataset for training and testing purposes (Kholifatullah & Prihanto, 2023). In this research, 80% of the data was designated for training purposes, while the remaining 20% was used for testing.

3. LSTM Model Design

At this point, the design process for the LSTM model is undertaken, which encompasses structural configurations such as the hidden layer's neuron count, dropout ratio, and the structural design of the LSTM layers. LSTM extends the RNN framework, aiming to resolve the vanishing gradient issues frequently observed in RNNs (Sidiq & Nurzaman, 2024). During the design process, it is essential to configure several key components, such as dropout, dense layers, activation functions, and the total number of neurons incorporated in the model.

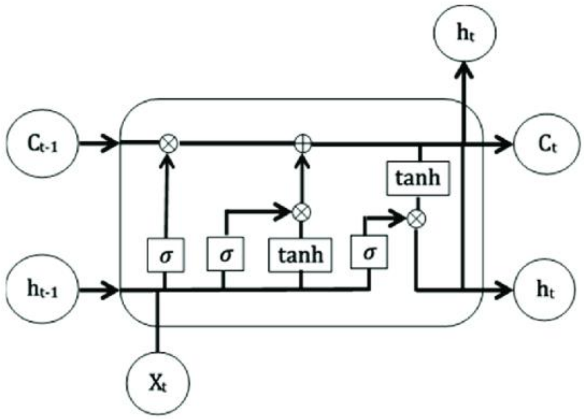

Figure 1. Long-Short Term Memory (LSTM) Architecture
Source: Nur Faid Prasetyo et al (2025)

Figure 1 this illustrates the operational workflow of memory cells within each LSTM neuron. Each input neuron comprises four activation function processes known as gate units. This illustrates the operational workflow of memory cells within each LSTM neuron. Each input neuron comprises four activation function processes known as gate units.

At the forget gate, every piece of data from the input is evaluated to ascertain which will be preserved and which will be removed from the memory cell. This evaluation employs the sigmoid activation function, yielding an output that ranges from 0 to 1. An output value nearing 1 signifies that the information is completely retained, whereas a value approaching 0 indicates that the information has been overlooked or eliminated. This evaluation is expressed by the following equation. With the following equation:

$$f_t = \sigma_1 \left(w_f \, x_t + U_{f \, C_{t-1}} + b_f \right) \quad (2)$$

At the input gate, the process consists of two stages. Initially, the information to be updated is identified through the sigmoid activation function. Subsequently, a new value vector, intended to be kept in the memory cell, is created using the tanh activation function. The outcomes of these two stages are then merged to refresh the memory cells. With the following formula (Roondiwala et al., 2017):

$$i_{t=\sigma_1}\left(w_i x_t + U_{i\,C_{t-1}} + b_i\right) \quad (3)$$
$$C'_{t=}\,tanh\,(w_c\ * [h_{t-1,}x_t\ ]\ +\ b_c\ ) \quad (4)$$

At the cell gate, the content of the previous memory cell is updated with the current value from the new memory cell. This new value is derived from the outcome of merging the outputs of the forget gate and the input gate. With the following formula (Arfan & ETP., 2019):

$$c_{t=}f_t\ *\ c_{t-1}\ +\ i\ *\ \sigma_i(w_c x_1 +\ b_c) \quad (5)$$

At the output gate, two stages are performed. Initially, the specific portion of the memory cell to be ejected is identified through the sigmoid activation function. Additionally, the values within the memory cells undergo processing via the tanh activation function. Ultimately, the outcomes of both processes are multiplied to generate the final output.

$$O_{t=}\,\sigma_1\left(w_o\,x_t\ +\ U_{o\,C_{t-1}}\ +\ b_0\right) \quad (6)$$
$$h_{t=}\,o_t\ *\ \sigma_2(c_t\,) \quad (7)$$

At time t, xt is the input vector, ht is the output vector, and ct signifies the memory cell state. Meanwhile, it, ft, and ot denote the vectors for the input gate, forget gate, and output gate. The weight on the tissue is expressed by the matrix W and U, while b expresses bias. The activation function used is sigmoid, denoted by the symbol σ.

4. **LSTM Model Training**

The model training process utilizes ADAM (Adaptive Moment Estimation), which is one of the optimizers offered within the Hard Framework. The ADAM Optimizer is a development of the classic Stochastic Gradient Descent (SGD) algorithm, with the ability to update weights more adaptively through a combination of momentum and exponential gradient averages. When training an LSTM model with ADAM, several important parameters need to be configured to maximize model performance. Among them are the learning rate of 0.001, the loss function used batch size of 32, and the number of training epochs. is 10 times. Several stages are involved in the training process of the LSTM model, including:

1. Initializing the initial weights using the Xavier (Glorot) Initialization method.
2. Feeding the training data into the model.
3. Performing LSTM computations on each input, starting with the forget gate, followed by the input gate, cell state updates, and lastly the output gate functions.
4. Calculating the error by measuring the difference between the LSTM output and the target output.
5. Computing the gradients to update the weight values, aiming to minimize the loss almost 0
6. Repeat to step two as many times as the specified epoch.

5. **Evaluation of Model Accuracy**

During the testing phase, an assessment is conducted by juxtaposing the predicted outputs of the LSTM model against the actual data derived from the testing dataset within a specified time period. To determine the model's accuracy, two evaluation techniques were employed: Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). MAE serves as a popular approach to quantify forecasting accuracy by averaging the absolute differences between real and predicted values. The formula for MAE is presented as follows:

$$\text{MAE} = \frac{\sum_{i=1}^{n} | y_i - \hat{y}_i |}{n} \tag{8}$$

The MAPE is a technique employed to determine the average of the absolute percentage errors in a forecast. The MAPE value provides insight into the extent of deviation or error in the predictions compared to the actual values of a time series (Rahmawati et al., 2021). Equation of MAPE is formulated as follows:

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} |\frac{y_i - \hat{y}_i}{y_i}| \times 100\% \tag{9}$$

III. RESULTS AND DISCUSSION

Figure 2 presents the closing price data for BRI Tbk stock for the period from April 16, 2015, to April 16, 2025.

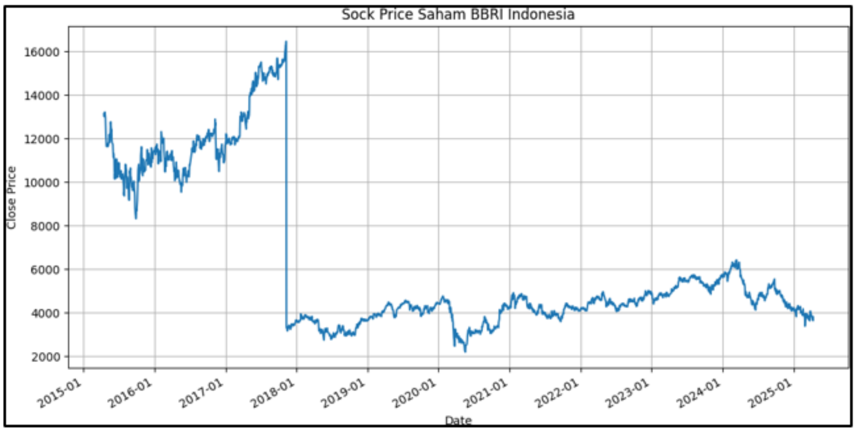

Figure 2. Actual Stock Data of Bank BRI

Figure 2 displays the actual data from the dataset utilized in this study. In the figure, the y-axis represents the stock's closing price, while the x-axis indicates the time span of the years analyzed. Based on the historical closing price data of PT BRI (Persero) Tbk (stock code: BBRI) from 2015 to 2025, it is evident that the stock experienced a significant drop in early 2018. The closing price, which had been in the range of Rp14,000 to Rp16,000 at the end of 2017, suddenly plummeted to around Rp3,000 at the beginning of 2018.

This sharp decline was not caused by fundamental factors such as the company's financial performance or macroeconomic conditions, but due to corporate actions in the form of stock splits carried out by BBRI in 2018. Stock splits aim to increase stock liquidity by lowering the price per share, so that the stock becomes more affordable for retail investors without changing the total value of their investment. Thus, the lowest share price recorded in the period occurred in early 2018, coinciding with the implementation of the stock split. Furthermore, several stages of analysis are carried out as follows.

3.1. Pre-Processing Data

The data preprocessing stage was carried out by performing feature scaling first. Feature scaling is done to normalize the data so that it has the same range of values. After performing feature scaling, the data splitting stage continues. At the stages of data splitting, the data is divided into 2, namely training data with a ratio of 80% and testing data with a ratio of 20%. The distribution of the data is presented in Table 1.

Table 1. Data Composition

Data Composition	Frequency	Period of project
Data Training	1931	16 April 2015 – 20 March 2023
Data Testing	483	24 March 2023 – 16 April 2025

3.2. LSTM Model Design

The LSTM network was trained using the following parameters: 2, 3, 4, 5, and 6 hidden layers; 50 neurons per hidden layer; 10 epochs; and a batch size of 32. Each parameter combination was tested five times, as the initial weights are randomly assigned; therefore, a single run cannot reliably represent actual performance. Repeated testing prevents results from appearing unduly good or bad purely by chance. The model design was carried out by experimenting with the number of parameters with hidden layers 2, 3, 4, 5, and 6, as shown in Table 2.

Table 2. Hidden Layer Parameter Combinations

Hidden Layer	Neuron	Batch Size	Epoch	MAE	MAPE
2	**50**	**32**	**10**	**8.4237**	**1.4605**
3	50	32	10	8.5053	1.5084
4	50	32	10	9.1964	1.7698
5	50	32	10	8.5599	1.5311
6	50	32	10	9.8807	1.9494

Table 2 is obtained by the hidden layer on the 2nd hidden layer, showing the lowest MAE and MAPE results, which indicates the most optimal prediction performance. Although the differences between configurations are relatively small, this combination provides the best balance between the level of accuracy and the efficiency of training time.

The LSTM model was trained using historical stock price data that had been formatted as a time series sequence. ADAM optimizer was employed with a learning rate of 0.0001 to facilitate faster convergence. During the training phase, the model was run for 10 epochs with a batch size of 32. This parameter configuration was selected to balance computational efficiency while allowing the model to effectively learn historical patterns.

The training process lasted for 10 epochs, as presented in Figure 3. Based on the visualization in Figure 3, at the beginning of the training, the loss value was relatively high because the model had not yet studied the sequential patterns of the data. However, as the epoch increases, losses consistently show a decline, signaling that the model is beginning to understand the temporal relationship between time steps.

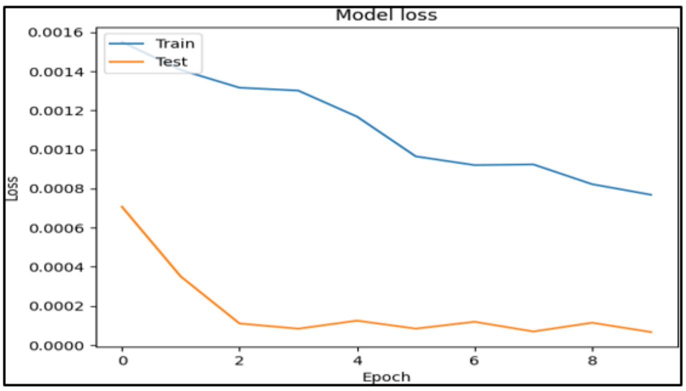

Figure 3. Loss Epoch 10 Chart

Figure 3 illustrates the loss values for both training and testing over 10 epochs. At the beginning, the training loss starts at a relatively high value, indicating that the model had not yet captured the sequential dependencies within the data. As the number of epochs increases, both training and testing losses demonstrate a consistent downward trend, showing that the model gradually learns the temporal relationships and improves its performance. The reduction of loss values approaching zero suggests that the model successfully minimizes errors, with stable convergence achieved before the final epoch.

3.3. Evaluation of Model Accuracy

The model evaluation based on the Mean Absolute Error (MAE) produced a value of 8.4237, while the Mean Absolute Percentage Error (MAPE) was 1.4605%, as shown in Table 3. The relatively low MAPE value suggests that the model has a low percentage error compared to the actual values, indicating that the predictions are fairly accurate. Although the MAE value is 8.42, this level of error is still considered acceptable given that BBRI's stock price is typically in the range of several thousand rupiah. Thus, the absolute prediction error is still relatively low and not practically significant. Overall, the model has performed well with the ability to capture historical patterns of stock prices and produce fairly precise predictions. The combination of low MAE and MAPE values reinforces that this model is feasible for stock price forecasting purposes in the context of the data used.

Table 3. Model Accuracy Evaluation Results

Evaluation Matrix	Value
MAE	8.4237
MAPE	1.4605%

The following is a comparison of the original data graph with the prediction data graph presented in Figure 4.

Figure 4. Prediction Results in Data Testing with Epoch 10

In Figure 4, actual stock prices are shown by the blue line, model predictions for the training set are represented by the green line, and predictions for the testing set are illustrated by the red line. Visually, the model appears to effectively track the stock price trends, as indicated by the relatively small gap between the predicted and actual values. This suggests that the model successfully captures the temporal patterns in historical stock data and demonstrates good generalization to previously unseen data.

IV. CONCLUSION

Based on the results of the research, it can be concluded that the LSTM model is effective in predicting the share price of PT BBRI. The model is able to capture historical patterns of stock data well and provide accurate predictions, as shown by an MAE value of 8,4237 and a very low MAPE, which is 1.4605%. The prediction results show that the prediction line follows the actual price trend with a small deviation. This proves that LSTM has the potential to be a reliable tool for investors and analysts in making investment decisions in the stock market. Going forward, this model can be further developed, taking into account other external variables such as macroeconomic conditions or market sentiment, to enhance prediction accuracy and make predictions more precise

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