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Advanced Long Short-Term Memory (LSTM) Models for Forecasting Indonesian Stock Prices

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ABSTRACT

The Indonesian stock market is a key indicator of national economic dynamics. Blue-chip stocks, including Bank Central Asia (BBCA), Bank Rakyat Indonesia (BBRI), and Bank Mandiri (BMRI), hold significant influence due to their liquidity and impact on the market index. However, their price volatility, driven by global economic conditions, monetary policies, and market sentiment, poses challenges for accurate forecasting. This study employs the Long Short-Term Memory (LSTM) model to address these challenges. LSTM, a deep learning technique, effectively handles time series data by capturing long-term dependencies and complex price patterns. Using historical stock data from 2019 to 2024, the model was trained and optimized. Evaluation metrics, including Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), were used to assess performance. BBCA stocks achieved the best results, with a MAPE of 0.0099 and RMSE of 128.02.The findings demonstrate LSTM's robustness in forecasting stock price trends, providing investors with valuable tools for informed decision-making. This research advances predictive analytics in financial markets, particularly in emerging economies like Indonesia, and highlights LSTM's potential to improve accuracy in volatile environments.

1. Introduction

The Indonesian stock market serves as a primary indication of the national economy's dynamics. The stocks of banking institutions, especially the three largest issuers, Bank Central Asia (BBCA), Bank Rakyat Indonesia (BBRI), and Bank Mandiri (BMRI) are crucial for fostering economic stability and growth (Amimakmur et al., 2024). As blue-chip stocks, these three issuers are often referenced by investors due to their high liquidity and significant influence on the Indonesian stock market index. However, their share price movements exhibit complex volatility, which is influenced by various factors, including global economic conditions, changes in monetary policy, and market sentiment (Nasraoui et al., 2024; Tang, 2023).

This high volatility in banking stocks creates challenges for investors in making the right investment decisions (Boggavarapu et al., 2024). Unexpected price changes can provide profit opportunities, but also increase the risk of loss, especially for investors who do not have sufficient information. Under these conditions, the ability to predict stock price movements becomes very important (Zhu et al., 2023). Accurate forecasting can help investors identify future stock price trends, allowing them to better plan their investment strategies and reduce risks (Sakshi et al., 2024).

Accurate stock price forecasting is crucial not only for maximizing investment returns but also for stabilizing financial markets by providing actionable insights to investors. This research contributes to addressing these challenges by proposing an optimized LSTM model tailored to the unique volatility of Indonesia's blue-chip stocks, offering a practical solution for informed investment strategies.

To answer these challenges, this research uses the Long Short-Term Memory (LSTM) method. LSTM is a type of deep learning model specifically designed to handle time series data, such as stock price movements. The main advantage of LSTM lies in its ability to capture long-term temporal patterns in data through a unique memory mechanism. Unlike other prediction models, LSTM has the ability to overcome the vanishing gradient problem, making it capable of learning from long and complex data dependencies. By using gating-based architectures such as forget gate, input gate, and output gate, LSTM can store relevant information and ignore unnecessary information during the training process.

Various previous studies have demonstrated the superiority of LSTM in handling time series data. LSTM significantly outperforms traditional methods in predicting stock prices in global markets, thanks to its ability to identify complex data patterns (Fischer & Krauß, 2019) . In addition, research shows that LSTM is able to provide more stable forecasting results than statistical models such as ARIMA, especially on stock data with high volatility (Sudipa et al., 2024; Suryawan et al., 2024) . The use of LSTM to forecast stocks of national listed companies results in lower Mean Absolute Percentage Error (MAPE) values than other machine learning methods (Alghofaili et al., 2020) . This finding reinforces the validity of LSTM as a superior method for stock price forecasting.

While traditional methods like ARIMA are widely used, they often struggle with non-linear and volatile data patterns typical of stock markets. Hybrid approaches, such as combining ARIMA with machine learning, offer improvements but require significant computational resources. This study addresses these gaps by leveraging LSTM's strengths in capturing temporal dependencies, demonstrating its superiority over both traditional and hybrid methods in handling high-volatility datasets.

This research focuses on forecasting the stock prices of issuers BBCA, BBRI, and BMRI, using an optimized LSTM approach. Historical stock price data of these three issuers is used to train the model, with the aim of producing accurate predictions of future stock price movement trends. The main objective of this research is to develop an optimized LSTM model to predict the stock prices of these three issuers with a high degree of accuracy. This research also aims to analyze the forecasting results to provide a clear picture of the trend of stock price movements, so that it can help make investment decisions in the Indonesian stock market.

2. Literature Review

The application of advanced Long Short-Term Memory (LSTM) models for forecasting Indonesian stock prices has garnered significant attention due to their ability to handle financial time series data effectively. LSTM networks, a specialized type of recurrent neural network (RNN), excel in capturing temporal dependencies, making them ideal for modeling complex stock price movements (Fischer & Krauß, 2019). Their architecture mitigates the vanishing gradient problem, enabling the analysis of long data sequences like historical stock prices (Yang et al., 2023). Studies such as (Wahab, 2024) have highlighted LSTM's superior performance over traditional statistical methods, particularly in volatile markets like Indonesia's, also optimized LSTM's hidden layers and activation functions to enhance prediction accuracy.

Recent research explores integrating technical indicators, like moving averages and Bollinger Bands, into LSTM models to provide richer context and improve performance (Babu & Sathyanarayana, 2023). Comparative analyses of LSTM variants, such as Stacked and Bidirectional LSTMs, have shown their potential to outperform standard configurations. Hybrid models combining LSTM with other techniques, like convolutional neural networks (CNNs), further enhance predictive capabilities by capturing both temporal and spatial patterns. Additionally, incorporating external factors, such as sentiment analysis, has proven to significantly boost forecasting accuracy (Lu et al., 2020; Yan, 2023).

Previous studies using ARIMA models highlighted limitations in handling complex, non-linear patterns and adapting to rapid market changes. Hybrid approaches improve accuracy but introduce computational inefficiencies and overfitting risks. This research differentiates itself by employing GridSearchCV for hyperparameter optimization, ensuring the LSTM model is fine-tuned for accuracy and generalizability in volatile markets like Indonesia. Recent research, such as (Lu et al., 2020; Yan, 2023), underscores the potential of LSTM in emerging markets, where high volatility and sparse data present unique challenges. Building on these insights, this study applies advanced LSTM configurations to Indonesia's blue-chip stocks, offering novel contributions to predictive analytics in emerging economies.

This study builds on existing literature by applying advanced LSTM models to forecast Indonesian stock prices, leveraging their ability to capture financial time series complexities. The ongoing exploration of hybrid approaches and external factors promises further advancements in stock price prediction for dynamic markets like Indonesia's.

3. Research Methods

3.1. Research Stages

In this research, there are stages of research to facilitate the explanation of each process at the beginning of data collection to produce forecasts of Indonesian stocks.

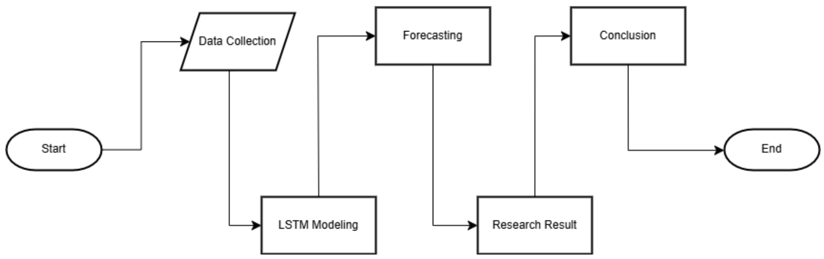

Fig 1. Research Stages

The research begins with an initial study stage to understand the problems related to the analysis of BBCA, BBRI, and BMRI stocks. At this stage, this research uses a case study to forecast the closing price of BBCA, BBRI, and BMRI stocks using the Long Short-Term Memory (LSTM) method. The main data source that researchers get from the site https://finance.yahoo.com/ is in the form of time series data in the form of BBCA, BBRI, and BMRI stock history data from 2019 to 2024. After the data is collected, modeling is carried out using LSTM with Python to find the model that best suits the characteristics of the stock dataset.

The initial step in data analysis with Python is to import the data into the working environment. We may utilize the pandas library with the pd.read_csv() function to import data from a CSV file. This research involves a data preprocessing phase to ready the dataset for modeling, which includes data cleaning; specifically, the date column is changed to the datetime data type to ensure accurate processing of time-related data. This method is essential to guarantee that all data is documented accurately and in chronological sequence. The data is thereafter organized by the date column to guarantee that the analysis and forecasting occur in the appropriate chronological sequence. Only the date and close columns are preserved, as they are the primary pertinent aspects for stock price forecasting modeling, while other extraneous columns are eliminated to decrease data complexity and enhance modeling efficiency. Subsequent to the normalization phase, the MinMaxScaler technique is employed to transform the values in the near column into a standardized range of 0 to 1. This procedure is executed utilizing the subsequent formula:

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

Information:
x' = Normalized result
X_i = Data at index (i)
X_{min} = Data with minimum value
X_{max} = data with maximum value

Subsequent to data processing, the next phase involves partitioning the dataset into two segments: training data and testing data. This research employs an 80:20 ratio for data split, utilizing 80% for model training and the remaining 20% for performance testing. The use of an 80:20 data split ensures sufficient training data for the model while preserving enough unseen data for robust testing. GridSearchCV was employed to systematically explore hyperparameter combinations, minimizing model bias and enhancing reproducibility. This approach distinguishes the current research from prior studies by ensuring the optimal LSTM configuration for high-volatility stocks.

LSTM Model Training

Training an LSTM model consists of an input layer that receives data, several hidden layers to identify patterns in historical data, and an output layer that generates stock price predictions for future periods. The processed data is used to train the model, where the training process involves adjusting the weights and biases of the model to improve prediction accuracy.

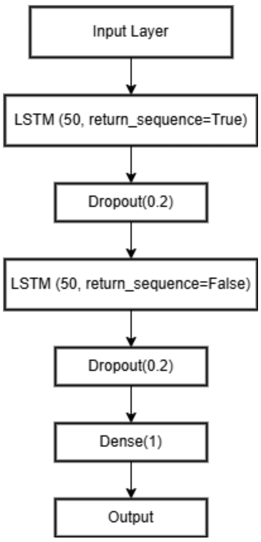

Fig. 2. Flowchart of LSTM Structure

The structure of the LSTM model used consists of several layers: first, the Input Layer which receives processed stock price data, such as date and close data. The data is then processed through hidden layers that serve to identify patterns in historical data and store long-term information needed for prediction. Each of these LSTM layers assists the model in maintaining important temporal memory. After that, the results from the LSTM layers are passed to the Dense Layer, which connects the hidden layers with the output. Finally, the Output Layer generates stock price predictions for the upcoming period.

Hyperparamater Value Selection

GridSearchCV is employed to identify optimal parameters in the LSTM model by evaluating combinations of several specified hyperparameter values, including epochs and batch size. This study investigated two epoch values (50 and 100) and four batch sizes (16, 32, 64, 128). Each parameter combination was assessed according to the loss determined by the Mean Squared Error (MSE) between the predicted and actual values in the training dataset. The evaluation results were recorded and organized by the minimal loss value, with the model with the lowest loss designated as the optimal model.

Model Evaluation

Assessment of the model with previously partitioned test data. This evaluation aims to assess the model's ability to anticipate previously unseen stock prices. In the assessment phase, the trained model is utilized on the testing data to produce stock price forecasts. The anticipated outcomes are subsequently juxtaposed with the actual values from the testing data to compute two principal performance metrics: Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

1. RMSE
   Quantifies the disparity between the expected value and the actual value by assigning greater significance to larger discrepancies. A reduced RMSE signifies a more precise prediction.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (2)$$

   Information:
   ($\hat{y}_{(1)}$) = predicted value
   (y_i) = Actual value
   (n) = number of data

2. MAPE
   Quantifies the relative error between expected and actual values as a percentage. MAPE provides a definitive assessment of the inaccuracy in relation to the actual value; a smaller MAPE indicates superior model performance, reflecting predictions that are more closely aligned with the actual value.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \qquad (3)$$

   Information:
   ($\hat{y}_{(1)}$) = predicted value
   (y_i) = Actual value
   (n) = number of data

The selected LSTM model is then used to perform stock price forecasting in the future. The final stage of this research is drawing conclusions based on the forecasting results obtained, as well as interpreting graphs and forecasting values to analyze the trend of BBCA, BBRI, and BMRI stock prices in the future period.

4. Results and Discussions

3.1 Load Data

The data loaded using python amounted to 1213 time series data on each of BBCA, BBRI, and BMRI stocks.

Table 1. BBCA Sample Data

Date	Adj Close	Close	High	Low	Open	Volume
2019-11-11	5627.959961	6295	6340	6265	6335	70207000
2019-11-12	5601.13916	6265	6280	6220	6220	47635500
2019-11-13	5614.550293	6280	6285	6265	6265	40083500
2019-11-14	5605.609863	6270	6280	6210	6265	37862000
2019-11-15	5610.080078	6275	6290	6255	6280	47138000

Table 2. BBNI Sample Data

Date	Adj Close	Close	High	Low	Open	Volume
2019-11-11	3266.637	3775	3825	3750	3800	29695800
2019-11-12	3288.27	3800	3800	3725	3750	43277200
2019-11-13	3180.104	3675	3800	3675	3800	47613000
2019-11-14	3158.47	3650	3712.5	3587.5	3687.5	59175600
2019-11-15	3223.37	3725	3775	3650	3675	34211400

Table 3. BMRI Sample Data

Date	Adj Close	Close	High	Low	Open	Volume
2019-11-11	2803.373	3525	3550	3487.5	3537.5	45212000
2019-11-12	2793.432	3512.5	3550	3462.5	3500	52900800
2019-11-13	2733.785	3437.5	3500	3387.5	3500	75148400
2019-11-14	2733.785	3437.5	3450	3350	3437.5	66698600
2019-11-15	2763.609	3475	3512.5	3462.5	3462.5	47017200

3.2 Data Preprocessing

The initial phase in the data preprocessing stage is data cleaning. The MinMaxScaler method is employed to normalize the data following the data cleaning procedure. This method ensures that all values are on a uniform scale without substantially altering the data distribution by transforming the values in the close column into a range of 0 to 1. The objective of this normalization is to enhance the model's performance during the training procedure.

The final stage of preprocessing involves the partition of the dataset into two components: training data (80%) and test data (20%). The total number of training data is 970, while the total number of test data is 243. The model is trained using the training data, and its efficacy on data that has never been seen before is evaluated using the test data. The model is anticipated to be capable of making precise predictions and generalizing effectively to new data as a result of this division.

3.3 LSTM Model Training

The LSTM model is trained on pre-dispersed training data in an 80:20 ratio, comprising normalized date and closing characteristics. Throughout the training phase, multiple combinations of hyperparameters, including the number of epochs and batch size, were evaluated to identify the ideal configuration with GridSearchCV. Epochs denote the total number of complete iterations executed by the model throughout the entire dataset, whereas batch size indicates the magnitude of the data subset employed to adjust the model parameters during each iteration. The subsequent table presents the outcomes of the parameter combination:

Table 4. BBCA Hyperparameter Training Results

Epochs	Batch Size	Loss
100	16	12217.76111
100	64	12673.84499
50	16	12823.06687

100	32	12998.3658
50	32	14073.48178
50	64	14921.98379
100	128	15474.34861
50	128	18678.05182

Table 5. BBNI Hyperparameter Training Results

Epochs	Batch Size	Loss
100	32	4900.263354
50	32	5391.364154
100	16	5679.486943
50	16	6441.900401
100	128	6456.577158
50	64	6514.362083
100	64	7638.639818
50	128	8119.376805

Table 6. BMRI Hyperparameter Training Results

Epochs	Batch Size	Loss
100	16	6035.057024
100	64	6837.839998
50	32	7195.141071
100	32	7829.133731
100	128	7942.670222
50	64	11601.86758
50	128	13270.97955
50	16	14176.69939

3.4 Forecasting Results

3.4.1 Three Period Forecasting Plot

The results of forecasting BBCA shares for the next three periods with the LSTM epoch 100 model, batch size 16 show that the trend of BBCA shares starting from November 2024 to January 2025 tends to experience a slight decrease with the highest closing price value at 9939.544 which is likely to occur in November 2024. BBCA stock forecasting values and charts for the next three periods can be seen in Table 7 and Figure 3.

Table 7. BBCA Stock Forecasting Results 3 Periods Ahead

Month	Forecasting Results
November 2024	9939.544
December 2024	9830.06
January 2025	9762.634

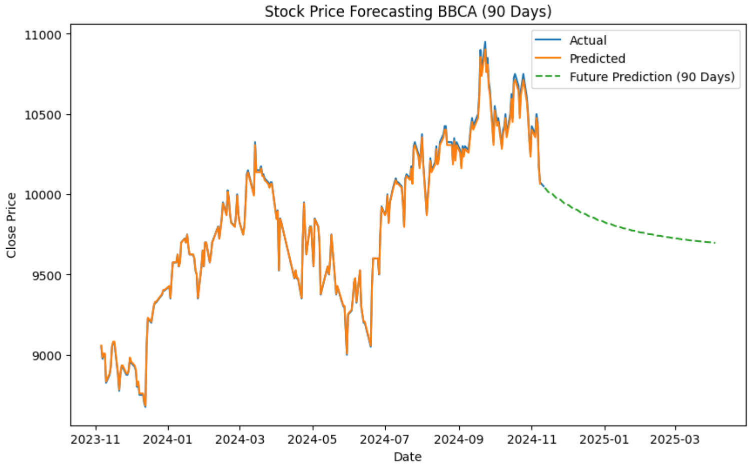

Fig. 3. BBCA Stock Forecasting Chart Three Periods Ahead

In BBNI shares, the forecasting results for the next three periods with the LSTM epoch 100 model, and batch size 32 show that the trend of BBNI shares starting from November 2024 to January 2024 tends to experience a slight decline and then experience sideways with the highest closing price value at 4945,834 which is likely to occur in November 2024. BBNI stock forecasting values and charts for the next three periods can be seen in Table 8 and Figure 4.

Table 8. BBNI Stock Forecasting Results for the Next 3 Periods

Month	Forecasting Results
November 2024	4945.834
December 2024	4893.2847
January 2025	4853.8813

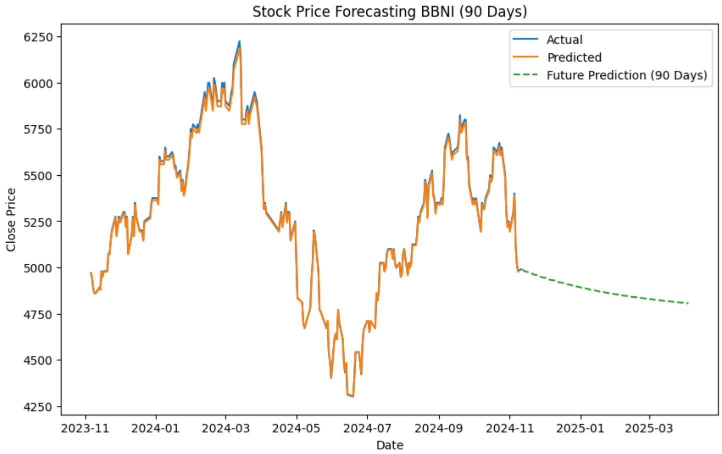

Fig. 4. BBNI Stock Forecasting Chart Three Periods Ahead

Meanwhile, the results of BMRI stock forecasting for the next three periods with the LSTM epoch 100 model, and batch size 16 show that the trend of BMRI shares starting from September 2024 to January 2024 will also experience a periodic decline with the highest closing price value at 6293,232 which is likely to occur in September 2024. BMRI stock forecasting values and graphs for the next three periods can be seen in Table 9 and Figure 5.

Table 9. BMRI Stock Forecasting Results for the Next 3 Periods

Month	Forecasting Results
November 2024	6293.232
December 2024	6251.843

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January 2025	6235.1543

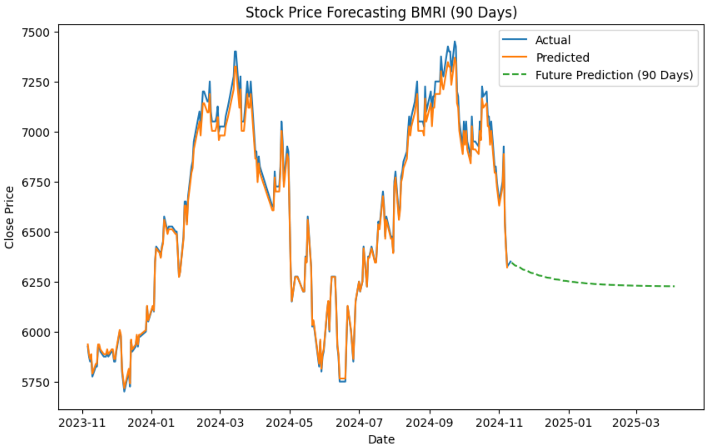

Fig. 5. BMRI Stock Forecasting Chart Three Periods Ahead

3.5 Model Evaluation

This study uses MAPE and RMSE as metrics to evaluate the performance of the LSTM model. Table 10 shows the results of the LSTM model performance evaluation on the three stock data.

Table 10. Model Evaluation

Stock Data	MAPE	RMSE
BBCA	0.0099	128.0208
BBNI	0.0135	94.2724
BMRI	0.0138	119.8012

Of the three stock data analyzed, BBCA stock shows the best performance with a MAPE value of 0.0099 and RMSE of 128.0208, indicating a relatively low level of prediction error compared to other stocks. BBNI shares have a MAPE value of 0.0135, RMSE is 94.2724. While BMRI shares have a MAPE value of 0.0138 with an RMSE of 119.8012. These results illustrate that the LSTM model is able to provide varied prediction performance depending on the characteristics of the stock data used.

The superior performance of BBCA, as indicated by a MAPE of 0.0099 and RMSE of 128.02, reflects the stock's relatively stable price trends, allowing the LSTM model to capture patterns more effectively. Conversely, the higher RMSE for BMRI (119.80) suggests greater volatility, highlighting the challenges in forecasting highly dynamic stocks.

These forecasting results can guide investors in identifying potential price trends and adjusting their portfolio strategies accordingly. For instance, the stable trends observed for BBCA make it an attractive option for risk-averse investors, while the volatility of BMRI may appeal to those seeking high-risk, high-return opportunities.

This research highlights the novelty of combining GridSearchCV with LSTM to optimize forecasting for volatile markets, demonstrating improved accuracy compared to conventional methods. The focus on Indonesian blue-chip stocks adds a unique perspective, addressing a gap in the literature.

5. Conclusion

Based on the results of the analysis of forecasting the closing prices of BBCA, BBRI, and BMRI stocks using the LSTM model, it can be concluded that the resulting forecasting pattern is close to the actual data graph. In the period September 2024 to January 2024, BBCA shares are predicted to experience a slight decline, with the highest closing price of 9939.544 which is expected to occur in November 2024. Meanwhile, BBRI and BMRI stocks show a relatively stable movement trend with a slight decline (sideways), where the highest closing prices are projected to be at 4945,834 for BBNI and 6293,232 for BMRI, respectively, which is estimated to occur in September 2024. The applied

LSTM model shows a high level of accuracy, as indicated by the good MAPE and RMSE values. These forecasting results can be used as a consideration in making investment decisions in the stock market. However, it is recommended to combine these prediction results with fundamental, technical, and sentiment analysis to improve the accuracy and validity of investment decisions. Future research could incorporate external factors, such as market sentiment and macroeconomic indicators, to further enhance forecasting accuracy. Exploring hybrid architectures that combine LSTM with attention mechanisms may also improve the model's ability to focus on critical patterns in highly volatile data.

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