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Modification of the LSTM Model in Time Series Data Prediction

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Abstract

Accurate stock price forecasting is crucial in supporting investment decision-making, especially during stock price fluctuations. This research aims to improve the accuracy of stock price prediction on time series data through modification of the Long Short-Term Memory (LSTM) model. The modification is done by simplifying the hyperparameters, adding dense layers, and applying the Adam optimizer. In addition, this research also aims to compare the prediction error rate of the LSTM model with several other methods using the Mean Absolute Percentage Error (MAPE) metric. The results show that the modified LSTM model produces lower MAPE on different stock data, namely 3.51% (train) and 1.65% (test) for ANTM.JK, 2.24% (train) and 1.69% (test) for BBRI.JK, 2.17% (train) and 1.52% (test) for BBCA.JK, and 3.06% (train) and 1.43% (test) for BBNI.JK. This model outperforms the LSTM method before modification and other methods such as RNN, CNN, SES, WMA, and Facebook Prophet. This finding shows that LSTM modification significantly improves the accuracy of stock price prediction.

Keywords: *Modification, Long Short-Term Memory (LSTM), MAPE, Accuracy, Stocks, Time Series*

1. Introduction

Stocks are essential in the global financial world and are a key element in economics and investment. As dynamic and complex investment instruments, stock prices are often volatile and influenced by various factors, such as global economic conditions, political events, and company performance[1]. Erratic changes in stock prices make investors worry about the losses they experience, so stock price forecasting becomes very important in making better investment decisions because highly volatile changes in stock prices create uncertainty for investors.

The stock market is basically a dynamic, non-linear, unstable, and full of disturbances system [2]. One of the stock market issuers often affected is the shares of PT Aneka Tambang Tbk (ANTM.JK). Based on Yahoo finance data, the historical closing price of ANTM.JK, from the beginning of 2019 to January 2024, continues to experience significant changes, especially during the COVID-19 pandemic, which resulted in a decline in share prices. The lowest price was recorded at 348 on March 23, 2020. In contrast, the highest price was reached on January 20, 2021, at 3,190, caused by the Russian invasion of Ukraine. Over the next few years, ANTM.JK's share price continued to experience significant fluctuations. To overcome stock price fluctuations, it can be minimized by forecasting [3]. Accurate stock price forecasting is essential to ensure future stock prices. In addition, forecasting can also help decision-making and minimize the risk of investment losses [4].

In the context of this research, the forecasting accuracy of a method in making predictions is critical to avoid investment losses. Several prediction methods, such as regression, moving average, and exponential smoothing, have been widely applied in making predictions[5]. However, these methods still have limitations, such as less precise accuracy results and cannot capture complex patterns in stock prices. For example, prediction methods such as weighted moving average (WMA) are less accurate against unstable data and cannot anticipate seasonal patterns, as in research[6], using time series data produces predictive values that are still less stable, with MAE 36.07 accuracy and MSE 1833.07. Then, the simple exponential smoothing (SES) method, which has limitations in capturing trends and seasonal patterns and selecting the proper smoothing parameters to produce accurate predictions, as in research [7], produces the highest forecasting accuracy with alpa 0.1 of 7.14 (MAD) and 9.17 (MAPE), and the lowest value with alpa 0.9 of 2.89 (MAD), and 3.54 (MAPE), the selection of alpa in the method greatly affects the forecasting results. While the Facebook prophet method has weaknesses in adjusting the appropriate hyperparameters to produce good accuracy and requires a long time, such as research conducted by [8].

Based on this problem, an accurate method is needed to make predictions. One method that can be applied is the deep learning method. The deep learning method is a machine learning model widely used today because of its high ability to solve problems such as regression, classification, and prediction. Part of deep learning that has a unique ability to predict is the Long Short-Term Memory (LSTM) algorithm [9]. LSTM is an artificial neural network that has proven effective in predicting time series data. LSTM can learn patterns and dependencies of data in the long term, producing more accurate predictions. However, the LSTM architecture used so far still produces poor accuracy when used on different data. Thus, modifications are needed in the LSTM model's architecture to improve forecasting accuracy.

Modifications that can be made include simplifying the model hyperparameters, adding dense layers, and applying Adam optimization. These model modifications aim to optimize model training and produce more accurate forecasting accuracy despite using different data. Modifying the model hyperparameters and optimizing the LSTM algorithm can be an attractive alternative because the LSTM method has high adaptive capabilities in facing the challenges of complexity and uncertainty in time series data such as stock prices. In assessing the accuracy of the modified and optimized LSTM model, a comprehensive evaluation of the model's performance error rate is required. This evaluation tests the model's ability to produce accurate stock price predictions. One evaluation method that can be used is Mean Absolute Percentage Error (MAPE) [5].

Based on this background, this research will focus on modifying the model hyperparameters, adding two dense layers, and applying Adam's optimization technique to the LSTM model architecture to improve forecasting accuracy. In addition, this research will compare the prediction error rate of the modified and optimized LSTM model with methods such as the RNN, CNN, WMA, SES, and Facebook Prophet methods in producing the best forecasting method, especially in stock forecasting by considering the resulting MAPE error rate.

2. Research Methods

This research was conducted in several stages. The stages of the research are illustrated in the flow chart presented in Figure 1. The following is an explanation or review of the process of each stage of the research procedure carried out:

2.1. Literature Study

The first stage is a literature study, namely, the process of searching and collecting information related to research that has been done before in the field of forecasting, such as theories, methods, techniques, and others. Literature studies are carried out to build ideas and strengthen the theory so that the truth of the research is not in doubt. The theories used include stock forecasting, Long Short-Term Memory (LSTM), Adam optimization, time series data, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Weight Moving Average (WMA), Simple Exponential Smoothing (SES), Facebook Prophet, and Mean Absolute Percentage Error (MAPE).

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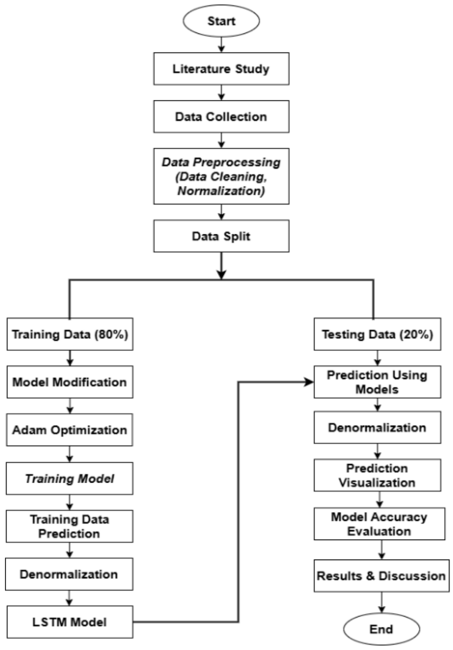

Figure 1. Research Procedure

2.2. Data Collection

The second stage is data collection, which aims to obtain valid, accurate, and representative data so that this study's main objectives can be fulfilled.

2.3. Data Preprocessing

The data preprocessing stage is carried out by cleaning the data, changing the data format, and normalizing the data. Data cleaning is done by deleting data that is not used in forecasting such as open, high, low, adj close, and volume data. Changing the data format is done by changing the date data variable to Index. The normalization stage is carried out by equalizing the value of all data with a uniform scale into the range -2.0 and 1.0 or 0.0 and 1.0. This process is done using the Min-Max Scaling method.

Normalization starts by calculating the actual value (x) minus the smallest data value (min(x)), then divided by the result of reducing the largest data value (max(x)) by the smallest data value (min(x)), as shown in the equation (1)[10].

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

2.4. Data Split

Data split is divided into two, namely training data and testing data, using the holdout method, namely by dividing the ratio of 80:20 or 80% train and 20% test[11]. Data division of training and testing data can be done using modified equations such as equations (2) and (3)[12].

$$Total\ Training\ Data = \lceil Training\ Data\ Proportion * N \rceil \tag{2}$$
$$Total\ Testing\ Data = N - Total\ Training\ Data \tag{3}$$

With the training data proportion being a ratio of 80 or 80% and N being the total number of data and ⌈ ⌉ being a rounding-up function.

Training data is data that is used for the model training process. While testing data is data used for the testing process, this process is carried out after the data training stage is complete.

2.4.1. Model Modification

Modifying the Long Short-Term Memory (LSTM) method is done by simplifying the model's hyperparameters so that the model is easier to manage and optimize and produce a quality model. The simplified hyperparameters are the number of LSTM layer units, Number of Neurons, Epoch, Batch size, Random seed, and the addition of two Dense layers. The purpose of the simplification is to improve model performance and increase better forecasting accuracy.

2.4.2. Adam Optimization

The modified LSTM model in this study applies Adam's optimization and Mean Absolute Error (MAE) loss function. The Adam's process starts with a forward pass, which flows the input data through the model to produce a prediction output. Then, a loss function is calculated to measure the difference between the prediction and the target. After the loss function is calculated, a backward pass is performed to estimate the loss gradient on each weight through backpropagation through time (BPTT), which is formulated as equation (4)[13].

$$\mathrm{g}_t = \nabla_\theta \mathrm{f}_t(\theta_{t-1}) \tag{4}$$

Here, g_t is the gradient at time $\boldsymbol{t}$, $\mathbf{f}_t$ is the loss function at that time, and $\boldsymbol{\theta}_{t-1}$ represents the model parameters before the update.

The calculated gradient is then used by Adam to update the model weights by adaptively adjusting the learning rate based on the exponential average of the gradient (first moment) and the square of the gradient (second moment). With this approach, Adam accelerates convergence and improves stability without the need for manual learning rate adjustment. The parameter updating process in Adam can be done as equations (5) to (8)[13].

a. Calculating first-moment bias.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\mathrm{g}_t \tag{5}$$

With m_t is the average of the first moment, β_1 is the beta value of the first moment, and gt is the current gradient.

b. Calculating second-moment bias.

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)\mathrm{g}_t^2 \tag{6}$$

Where v_t is the mean of the second moment, β_2 is the beta value of the second moment, and g_t^2 is the square of the current gradient

c. First and Second-moment bias correction.

$$\widehat{m}_t = \left(\frac{m_t}{1-\beta_1^t}\right), \hat{v}_t = \left(\frac{v_t}{1-\beta_2^t}\right) \tag{7}$$

$\widehat{m}_t$ is the first-moment bias correction, and β_1^t is the beta value of the first moment at iteration t. $\hat{v}_t$ is the second-moment bias correction, and β_2^t is the second-moment beta value at iteration t.

d. Parameter update.

$$\theta_{t+1} = \theta_t - \alpha \frac{\widehat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \tag{8}$$

θ_{t+1} is the new parameter, θ_t is the current model parameter, α is the learning rate, $\widehat{m}_t$ is the first-moment bias correction, $\hat{v}_t$ is the second-moment bias correction, and ∈ is the epsilon value.

2.4.3. Training Model

The modified LSTM model is then trained with previously prepared training data to recognize patterns and relationships in the data. This process involves iterating over the data in multiple epochs until the model achieves optimal performance. In model training, modifications are made by simplifying the hyperparameters of the number of epochs and batch size to run model training.

The LSTM model is expected to produce better training and more accurate forecasting accuracy by simplifying the epoch and batch size.

2.4.4. Prediction Using Models

This stage carries out the prediction of stock sales prices using the modified and pre-trained LSTM method. Forecasting is done using data that has never been seen before during model training, namely testing data.

2.4.5. Denormalization

After obtaining the prediction results, the resulting forecasting requires denormalization to convert the data into its original form, because the prediction results are still in interval form at the time of data normalization. This denormalization aims to make the resulting output easy to read and understand and allow proper comparison with the original data when calculating the evaluation of the model error rate. Denormalization of this data can be done by using the equation (9)[10].

$$x = x'(\max(x) - \min(x)) + \min(x) \tag{9}$$

x is the denormalized value, $x'$is the denormalized data value, *max(x)* and *min(x)* are the largest and smallest data values.

2.4.6. Prediction Visualization

Predictions are visualized by displaying a comparison graph between actual values and predicted results on training, validation, and testing data to facilitate analysis and interpretation of results.

2.4.7. Model Error Evaluation

The evaluation process is carried out to determine the best method architecture and validate the prediction performance that has been carried out. The evaluation process uses the MAPE (mean absolute percentage error) method[5]. MAPE is a measure of the average percentage absolute error between the predicted value and the actual value, which shows how accurate the prediction is in percentage form regardless of the direction of the error. The MAPE process can be done using equation (10)[14].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| * 100\% \tag{10}$$

Where Y_i is the actual value, $\hat{Y}_i$ is the forecasting value, and n is the number of data tested. In MAPE analysis, a value of ≤10% indicates a highly accurate error rate of the method, between 11% and 20% is considered accurate, 21% to 50% is moderately accurate, and >50% indicates inaccurate performance[15].

3. Result and Discussion

This research produces a stock price prediction model using a modified LSTM architecture optimized with Adam optimization and uses the MAPE method to evaluate the prediction model error rate. The research begins with data processing and preprocessing to ensure its quality. Then the LSTM model is modified by simplifying the hyperparameters, such as the number of epochs, batch size, number of neurons in the LSTM layer, Dense layer, and Random Seed.

In addition, the forecasting error rate of the modified LSTM model will be compared with several methods such as Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Weighted Moving Average (WMA), Single Exponential Smoothing (SES), and Facebook Prophet. This comparison aims to assess each method's advantages and disadvantages based on the resulting prediction error rate. This evaluation comparison can provide a deeper understanding of the effectiveness of the modified LSTM in improving forecasting accuracy.

3.1. Data Collection and Preprocessing.

This type of research data is secondary data. The dataset used is the time series data of PT Aneka Tambang Tbk, PT Bank Rakyat Indonesia (Persero) Tbk, PT Bank Central Asia Tbk, and PT Bank Negara Indonesia (Persero) Tbk shares. The dataset was taken from the Yahoo Finance

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site (https://finance.yahoo.com/) and used the search code ANTM.JK, BBRI.JK, BBCA.JK, BBNI.JK. Dataset information includes daily data for the last 5 years, from April 30, 2019, to April 30, 2024, with each stock having 1221 data, with seven features: Date, Open, High, Low, Close, Adj Close, and Volume.
The dataset that has been collected is preprocessed, such as by removing unused features and transforming the data. The features used in this study are date and close features. The results of the data are presented in Table 1.

Table 1. Stock Closing Price Data

	ANTM.JK	BBRI.JK	BBCA.JK	BBNI.JK
Date	Close	Close	Close	Close
30/04/2019	865	2997	5140	4056
01/05/2020	865	2997	5140	4056
…	…	…	…	…
29/04/2024	1615	4616	9751	5225
30/04/2024	1640	4781	9751	5250

Based on the data in Table 1, the dataset is then normalized using the MinMaxScaler technique from scikit-learn. The results of data normalization are shown in Table 2.

Table 2. Data Normalization Results

	ANTM.JK	BBRI.JK	BBCA.JK	BBNI.JK
Date	Close (Normalized)	Close (Normalized)	Close (Normalized)	Close (Normalized)
30/04/2019	0,18191414	0,31051949	0,19237937	0,58303468
01/05/2019	0,18191414	0,31051949	0,19237937	0,58303468
…	…	…	…	…
29/04/2024	0,44581281	0,67062911	0,95205644	0,84035825
30/04/2024	0,45460943	0,70722586	0,95205644	0,84586314

The following process is that the dataset is divided into 80% (training) and 20% (testing). The dataset that has been separated is then changed in a format that is suitable for the LSTM model, namely by using windowing techniques. The window size used is 25 timesteps. The dataset that has been divided and formed, then taken back as much as 20%, to be used as validation data. The dataset taken is the training dataset that has been formed. The goal is to ensure the model can be trained with most of the data and the rest as evaluation and testing. The results of the data division are shown in Table 3.

Table 3. Data Sharing Result

Total Dataset (*N*)	Window Size	Training Data	Validation Data	Testing Data
1221	25	761	191	244

3.2. LSTM Model Modification and Optimization.

The Long Short-Term Memory (LSTM) model was modified to improve the accuracy of stock price prediction on time series data. Modifications include simplifying hyperparameters, adding two dense layers, and using Adam's algorithm to speed up training and stabilize model convergence.

Default hyperparameters, such as three layers of LSTM with 50-100 neurons per layer, batch size of 32-128, and number of epochs of 50-200, were adopted based on standard practices in the literature [16], [17], [18], [19], [20] as well as recommendations from popular libraries such as TensorFlow and Keras. Architectural simplifications, such as reducing the number of layers and neurons, were made to improve efficiency without sacrificing prediction performance.

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The modification results show that the LSTM model significantly improves the model's accuracy. Details of the modifications made are presented in Table 4, and the model architecture is shown in Figure 2.

Table 4. LSTM Model Hyperparameter Modification

Hyperparameter	Value Before Modification	Value After Modification
LSTM Layer	3	2
Neuron per layer LSTM	50 or 100	25
Dense Layer	1	2
Neuron per layer Dense	1	15 and 1
Epoch	50, 100, 200	7
Bacth Size	32, 64, 128	3
Loss	MSE	MAE
Optimizer	RMSprop or SGD	Adam
Random Seed	-	2

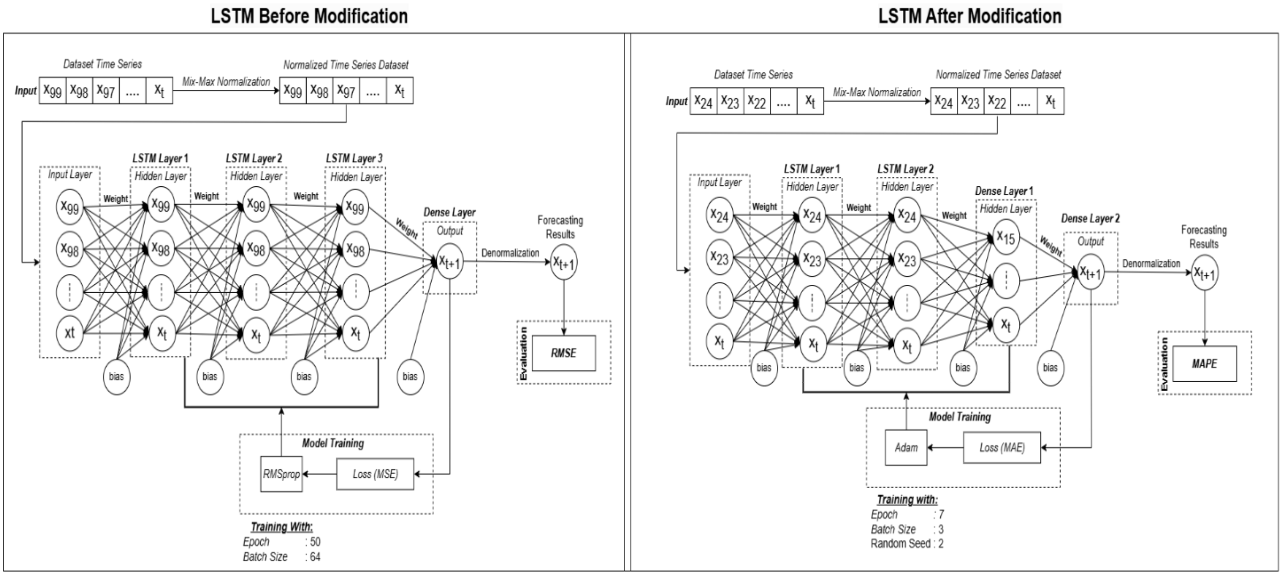

Figure 2. LSTM Model Architecture

3.3. Prediction Using the LSTM Method

The modified and optimized LSTM method shows highly accurate prediction results on training, validation, and testing data. These results indicate that the modified LSTM method is able to provide better prediction performance than other methods on time series data. The prediction results obtained for each training, validation, and testing data, including actual and predicted values, are presented in Table 5.

Table 5. Prediction of Training, Validation, and Testing Data

Stocks	Date	Actual Training	Predict Training	Date	Actual Validation	Predict Validation	Date	Actual Testing	Predict Testing
ANTM	4/6/19	725	712,12	13/7/22	1720	1737,79	13/4/23	2130	2069,93
	12/7/22	1740	1730	12/4/23	2110	2056,42	30/4/24	1640	1591,75
BBRI	4/6/19	2912	2835,96	13/7/22	3509	3578,56	13/4/23	4574	4537,93
	12/7/22	3552	3571,31	12/4/23	4528	4509,85	30/4/24	4781	4861,96
BBCA	4/6/19	5203	5122,05	13/7/22	6617	6649,91	13/4/23	8639	8407,45
	12/7/22	6782	6645,19	12/4/23	8615	8352,25	30/4/24	9751	9645,69
BBNI	4/6/19	3634	3653,18	13/7/22	3305	3505,28	13/4/23	4473	4508,05
	12/7/22	3408	3527,94	12/4/23	4461	4508,87	30/4/24	5250	5275,05

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The prediction results show that the performance of the modified LSTM model is able to follow the pattern of stock price movements well in terms of training, validation, and testing data, especially in periods with significant price fluctuations, as shown in Figure 3.

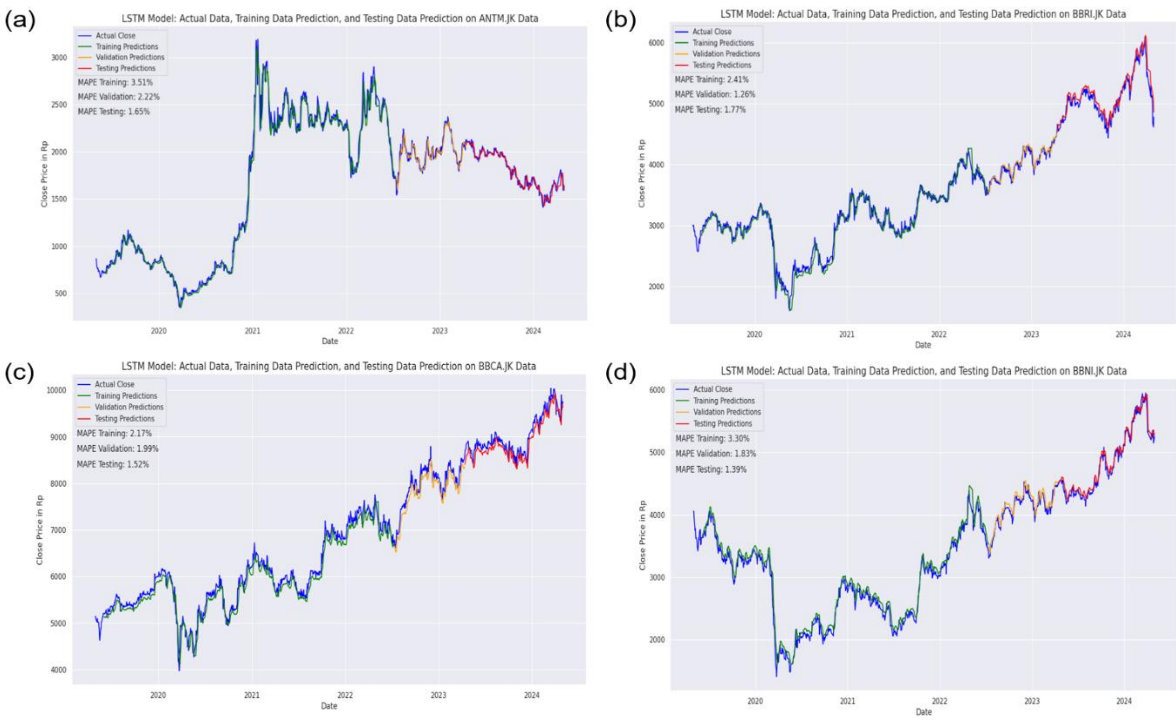

Figure 3. LSTM Model Prediction Graph on ANTM (a), BBRI (b), BBCA (c), and BBNI (d) Data

The prediction results and forecasting movement graphs shown in Table 5 and Figure 3 for the modified LSTM model, result in a MAPE error evaluation with very accurate performance compared to the LSTM method before modification, as shown in Table 6.

Table 6. MAPE Evaluation Results

Stocks	Model	Hyperparameter Values	MAPE		
			Train	Val	Test
ANTM	LSTM	L3-NL100-D1-ND1-E50-BS64-MSE-RMSprop	7,64%	3,85%	2,65%
	LSTM Modification	L2-NL25-D2-ND15&1-E7-BS3-MAE-Adam-RS2	3,51%	2,22%	1,65%
BBRI	LSTM	L3-NL100-D1-ND1-E50-BS64-MSE-RMSprop	3,61%	4,14%	5,29%
	LSTM Modification	L2-NL25-D2-ND15&1-E7-BS3-MAE-Adam-RS2	2,41%	1,26%	1,17%
BBCA	LSTM	L3-NL100-D1-ND1-E50-BS64-MSE-RMSprop	3,75%	5,30%	5,72%
	LSTM Modification	L2-NL25-D2-ND15&1-E7-BS3-MAE-Adam-RS2	2.17%	1,99%	1,52%
BBNI	LSTM	L3-NL100-D1-ND1-E50-BS64-MSE-RMSprop	4,29%	5,25%	5,88%
	LSTM Modification	L2-NL25-D2-ND15&1-E7-BS3-MAE-Adam-RS2	3,30%	1,83%	1,39%

Evaluation of prediction errors in the LSTM model before and after modification shows that modification of the LSTM model by simplifying hyperparameters such as Layer LSTM from 3 to 2 (L3, L2), Neuron LSTM 100 to 25 (NL100, NL25), Epoch 50 to 7 (E50, E7), Batch Size 64 to 3 (BS64, BS3), and the addition of two dense layers (D2), with 15&1 neurons (ND15&1), and

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Random Seed (RS2) successfully improved the model's ability to capture complex patterns from time series data. The Adam optimization and loss function application also helped the model become more efficient with faster training time.

3.4. Method Prediction

This research applies several prediction methods, such as the Recurrent Neural Network (RNN) method, Convolutional Neural Network (CNN), Weighted Moving Average (WMA), Single Exponential Smoothing (SES), and Facebook Prophet which are used as a comparison in predicting stock prices with the modified and optimized LSTM method. The comparison is done based on the error rate of the MAPE metric generated by the forecasting methods.

The prediction method is implemented based on historical stock data with a dataset division of 80% training data and 20% testing data without any validation data division, as in the LSTM model. This approach is taken to maintain the focus of research in modifying the LSTM model to provide a clear basis for comparing prediction error rates between methods.

a. Prediction Using the RNN Method.
The prediction of the RNN method is made by capturing sequential patterns in time series data, which allows the model to predict future stock prices based on past trends. In this research, the RNN model uses SimpleRNN architecture with 50 units, time step of 10, epoch of 10, batch size of 32, Adam optimizer, and loss function using mean squared error. The prediction results generated by this method for four types of stock data are presented in graphical form, which can be seen in Figure 4.

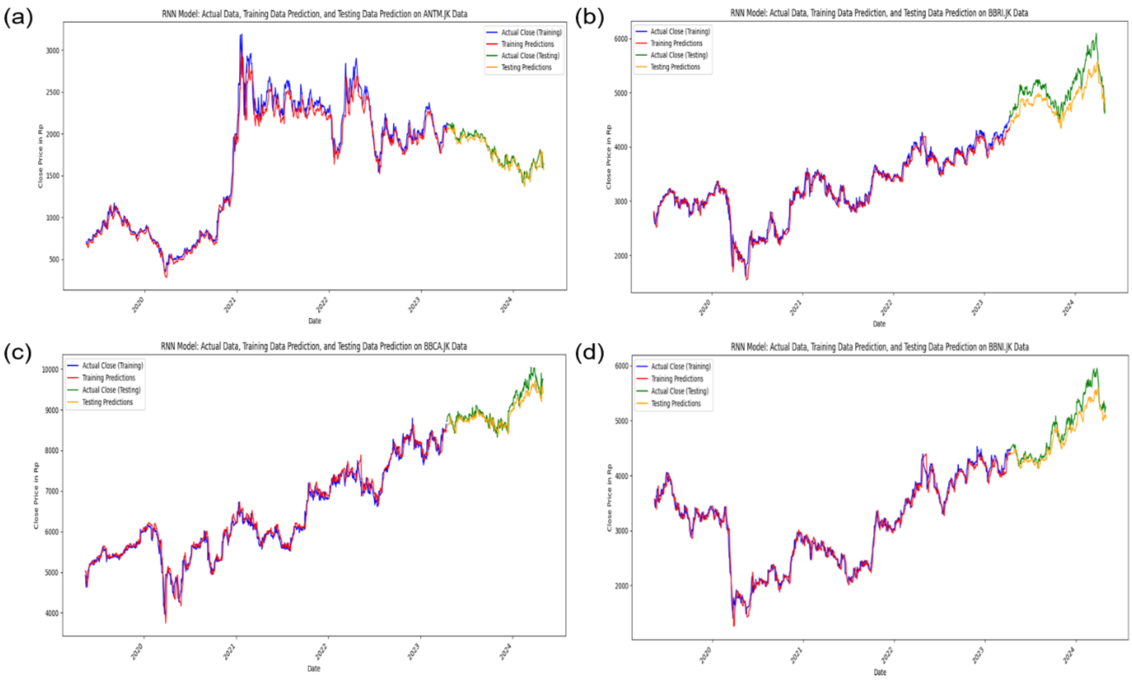

Figure 4. RNN Model Prediction Graph on ANTM (a), BBRI (b), BBCA (c), and BBNI (d) Data

b. Prediction Using the CNN Method.
CNN method prediction is done by utilizing spatial patterns in time series data to predict future stock prices based on information from previous data sets. In this study, the CNN model uses the Conv1D architecture with two convolution layers, followed by a max-pooling layer to extract essential features from the data, and flatten and dense layers to generate predictions. The model was trained with 10 epochs, batch size 32, and Adam's optimizer and loss mean squared error function. The prediction results for training and testing data are presented in the form of a graph which can be seen in Figure 5.

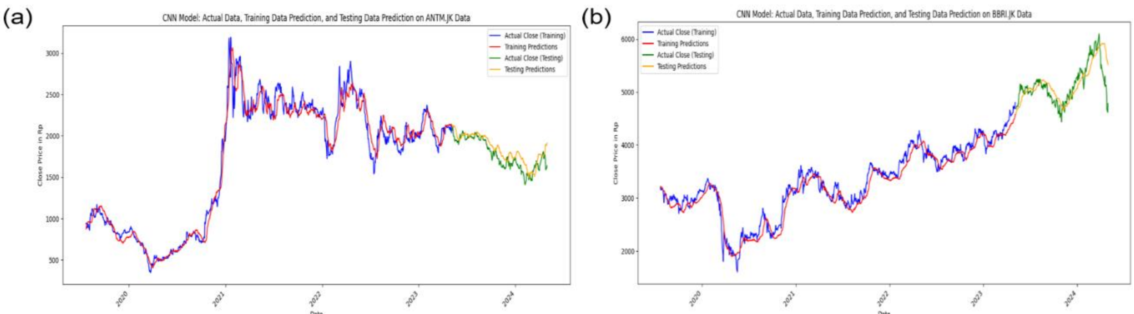

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Figure 5. CNN Model Prediction Graph on ANTM (a), BBRI (b), BBCA (c), and BBNI (d) Data

c. Prediction Using the WMA Method.
The WMA method prediction is done by giving greater weight to the most recent data, resulting in predictions that are more responsive to price changes. This method uses a window of 50 with weights that increase linearly from window 1 to 50. The prediction results will be compared with the actual data. The prediction graphs of the four types of stocks can be seen in Figure 6.

Figure 6. WMA Model Prediction Graph on ANTM (a), BBRI (b), BBCA (c), and BBNI (d) Data

d. Prediction Using the SES Method
The SES method's predictions are made by giving greater exponential weight to the most recent data, resulting in predictions that are more responsive to price changes. The model uses an α (alpha) value, which determines the speed at which the model adjusts to changes in the data. In this analysis, the α value used is 0.2. The prediction results that

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have been obtained will be compared with the actual data. The prediction chart of 4 types of stocks can be seen in Figure 7.

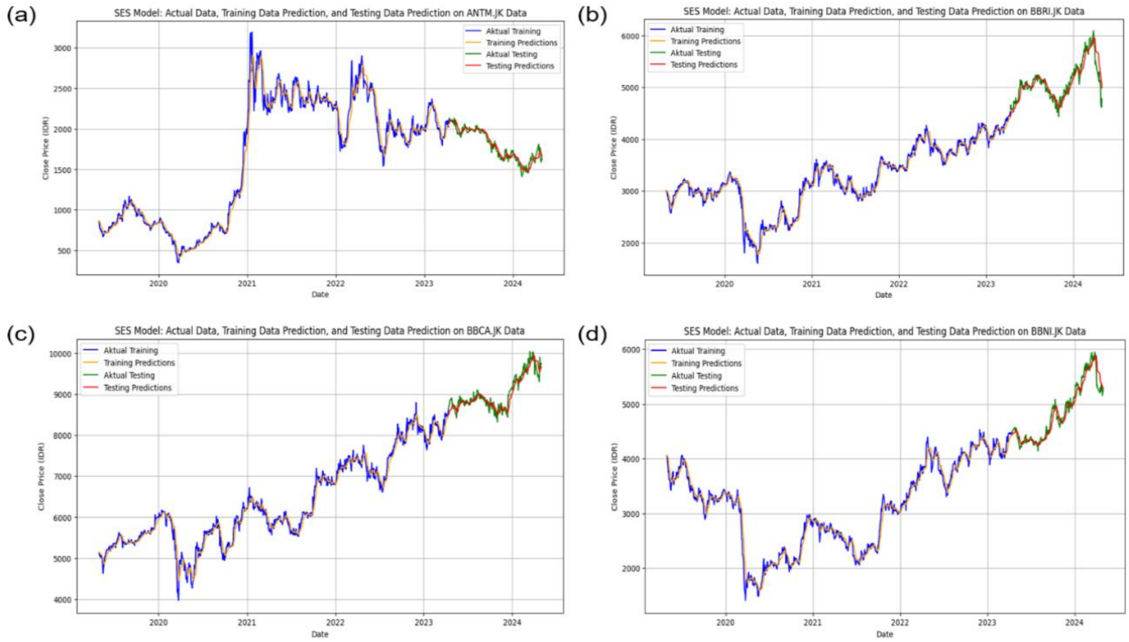

Figure 7. SES Model Prediction Graph on ANTM (a), BBRI (b), BBCA (c), and BBNI (d) Data

e. Prediction Using the Facebook Prophet Method
Predictions using the Prophet method are made without considering the holiday component, but the model utilizes the effects of trends and seasonality on the data. In the application of the Prophet method, stock price data is prepared in column format ds for date and y for closing price. The prediction results generated by this method will be compared with the actual data. The prediction graphs of the four types of stocks in this model can be seen in Figure 8.

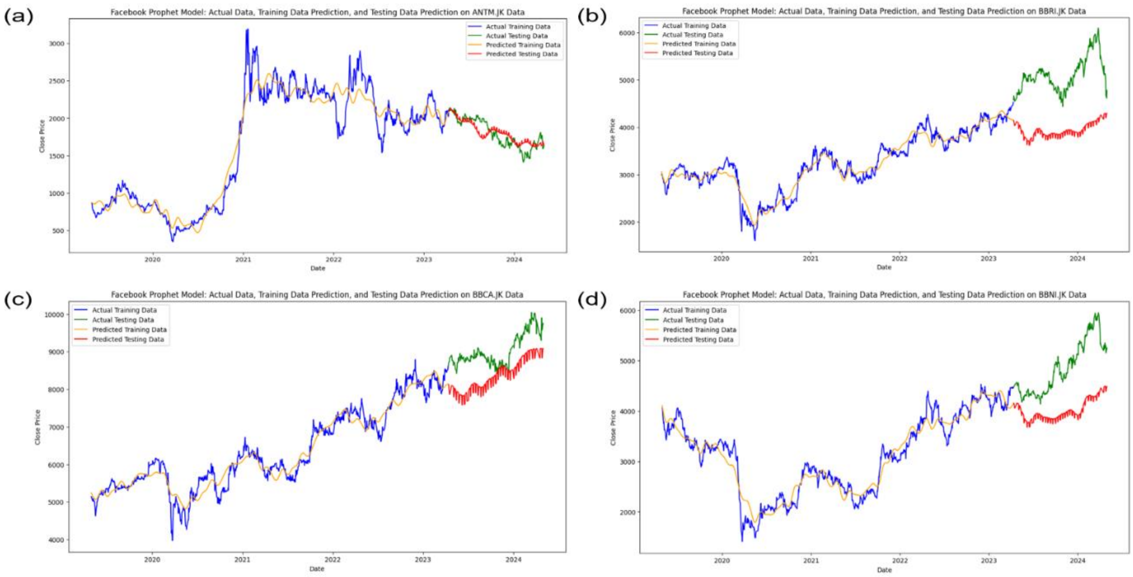

Figure 8. Facebook Prophet Method Prediction Results on Training and Testing Data

3.5. Performance Comparison of Prediction Models

This research measures the prediction model's performance by evaluating the resulting forecasting error rate. This evaluation compares prediction models and determines the best model to predict stock prices on time series data. The prediction models used include LSTM before and after modification, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Weighted Moving Average (WMA), Single Exponential Smoothing (SES), and Facebook Prophet. The error rate of the methods in this study is measured using the Mean Absolute Percentage Error (MAPE) metric. The evaluation results of each method are shown in Table 7.

Table 7. Comparison of Prediction Model Error Rates

No	Method	MAPE							
		ANTM.JK		BBRI.JK		BBCA.JK		BBNI.JK	
		Train	Test	Train	Test	Train	Test	Train	Test
1.	LSTM Before Modification	7,64%	2,65%	3,61%	5,29%	3,75%	5,72%	4,29%	5,88%
2.	**LSTM After Modification**	**3,51%**	**1,65%**	**2,24%**	**1,69%**	2,17%	1,52%	3,06%	**1,43%**
3.	SES	4,30%	2,10%	2,37%	1,90%	**1,77%**	**1,10%**	2,87%	1,64%
4.	RNN	4,83%	2,55%	2,56%	4,83%	1,87%	1,54%	**2,80%**	3,06%
5.	CNN	5,59%	4,85%	3,78%	3,24%	2,51%	2,49%	3,95%	3,14%
6.	WMA	8,73%	3,63%	4,65%	4,10%	3,34%	1,93%	5,91%	3,19%
7.	Prophet	10,04%	5,53%	4,25%	22,85%	3,33%	7,26%	5,83%	16,96%

Table 11 shows the results of comparing the error rates of each method. The modified Long Short-Term Memory (LSTM) model shows the lowest average MAPE value in most of the data, both in training and testing data. This indicates that the modified LSTM method has better prediction performance and is more accurate than most other methods in predicting stock prices on time series data.

4. Conclusion

The Long Short-Term Memory (LSTM) model is modified by simplifying hyperparameters, such as the number of layers, neurons per layer, epoch, batch size, adding two dense layers, and applying the Adam optimizer. This study uses the Mean Absolute Percentage Error (MAPE) evaluation metric to assess the level of prediction error produced by the method.

Based on the MAPE evaluation results, the modified LSTM model recorded the lowest average prediction error rate on most stock data, both in training and testing data. The model also consistently outperformed other methods, including LSTM before modification, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Weighted Moving Average (WMA), Single Exponential Smoothing (SES), and Facebook Prophet.

This research proves that the modified LSTM architecture can more effectively capture complex patterns in time series data, especially during periods of significant price fluctuations. This modification not only improves the efficiency of the training process but also provides superior prediction accuracy, making it a highly effective method for stock price prediction in time series data.

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