BAREKENG: Journal of Mathematics and Its Applications
December 2024 Volume 18 Issue 4 Page 2397–2412
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol18iss4pp2397-2412

THE IMPACT OF THE PRESIDENTIAL ELECTION ON IDX COMPOSITE PREDICTIONS USING LONG SHORT TERM MEMORY

Ashilla Maula Hudzaifa[1*], Valerie Vincent Yang[2], Defi Yusti Faidah[3]

[1,2,3]*Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran*
Jl. Ir. Soekarno km. 21, Sumedang, 45363, Indonesia

*Corresponding author's e-mail: * **ashillamlhdzf@gmail.com***

Article History:

Received: 25th, March 2024
Revised: 29th, May 2024
Accepted: 25th, July 2024
Published:14th, October 2024

Keywords:

Forecast;
IDX Composite;
Long Short Term Memory.

ABSTRACT

An analysis of the performance of Indonesia's capital market, or Indonesia Stock Exchange (IDX), shows significant growth in recent years, with market capitalization increasing dramatically from IDR 679.95 trillion in 2004 to IDR 11,674.06 trillion by 2023. The IDX plays an important role in the Indonesian economy by facilitating capital formation and providing opportunities for investors to diversify their portfolios. However, the capital market is vulnerable to political events, such as presidential elections, which can affect national stability and economic performance. An analysis of the stock index performance before the presidential election showed a significant bullish trend. Still, given the considerable impact of political events, such as presidential elections, on financial markets, this study aims to analyze and forecast the performance of the IDX Composite by examining historical data from past election years, we provide insights and predictions in highlighting how the LSTM model accommodates these political factors in its forecasts. IDX Composite closing price forecasting was conducted using the bidirectional LSTM model to anticipate the impact. The analysis results show that this model can predict the weekly closing price of the IDX Composite with an error of 1.04%, with estimated stock price fluctuations in the next 8 weeks in the range of 6619.755 to 6812.722

How to cite this article:

A. M. Hudzaifa, V. V. Yang and D. Y. Faidah., "THE IMPACT OF THE PRESIDENTIAL ELECTION ON IDX COMPOSITE PREDICTIONS USING LONG SHORT TERM MEMORY," *BAREKENG: J. Math. & App.*, vol. 18, iss. 4, pp. 2397-2412, December, 2024.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*
Research Article · Open Access

1. INTRODUCTION

A capital market is a phrase for a financial market about the trading activity encompasses funding instruments such as ETF (Exchange Traded Fund), stock market, bond market, mutual funds, shares, and other instruments that are purchased (bought and sold) and securities are issued [1] as a source for raising funds for individuals, firms, and governments. It plays a crucial role in the economy by allocating resources, enabling price discovery, and fostering economic growth. The capital market is very vulnerable/sensitive to a range of events that will impact the volatility of price and trading activity of companies across all market sectors of the capital market [2]. The stock market and bond market are the most popular and common capital markets, with the former enabling investors to trade stocks (known as shares) to gain ownership of a company, while the bond market allows investors to provide a loan (also known as credit) on behalf of a company [3].

Every country’s flourishing stock market draws in both domestic and foreign investors and is a sign of that country’s economic prosperity [4]. The Indonesian stock market, often known as the Indonesia Stock Exchange (IDX), has experienced very substantial growth in the past several years. According to the market capitalization on the Indonesia Stock Exchange (IDX), the market growth has realized 1,716.90% from 679.95 trillion Indonesian Rupiah in 2004 to 11,674.06 trillion Indonesian Rupiah as of 2023. Moreover, IDX plays a significant role in Indonesia's economy, facilitating capital formation and providing opportunities for investors to diversify their holdings [5]. As it symbolizes the state of Indonesia as a country, the IDX is also closely related to the stability of the nation.

The variation in the capital market's sectoral price index reflects the volatility of the company's stock prices across all sectors, whilst the frequency of sectoral trade indicates the trading activity of the company's shares across all sectors [2]. On the other hand, the sectoral price index has a relationship with the exchange rate, GDP growth, inflation, interest rate, and money supply [6][7]. A reflection of capital market activity in Indonesia is commonly referred to as Indeks Harga Saham Gabungan (IHSG). In the global market, IHSG known as the Indonesia Composite Index (ICI) or IDX Composite is an index that measures the price performance of all stocks listed on the Indonesia Stock Exchange (IDX). IDX Composite is determined by utilizing the Market Value Weighted Average Index which is a weighted average based on the quantity of shares traded on the exchange.

An event with important information for investors will affect price volatility and stock trading activity, giving investors a faster way to create an ideal portfolio and an overview of risk [8]. Lately in Indonesia, The General Election Commission (KPU) announced that the presidential election will be held on 14th February 2024 which is the 3rd week of February. In nations all over the world, there is a significant relationship between the performance of the stock market and political issues as both non-economic and economic factors [9]. The presidential election is regarded as one of the political events that has the most impact on national stability in any nation with a presidential system of government since it can set the course of the government for the coming years. Based on the knowledge gained from the presidential election in 2009, 2014, and 2019 showed that politics tends to influence the IDX Composite, which is also predicted to be affected by the 2024 presidential election as said by several Indonesian securities. The presidential election is one of the fascinating political issues where the stock market is most affected. There is a great deal of interest among researchers to investigate how the presidential election affects the stock market [10]. It is important to understand how the presidential election can affect the Indonesian stock market, given its significant impact on economic stability and investment. Therefore, this research will explore the potential impact of the 2024 presidential election on the volatility and trading activity of the Indonesia Composite Index (IHSG).

This study aims to investigate the impact of presidential elections on the IDX Composite and to forecast market performance using LSTM models. By utilizing historical data and LSTM's advanced sequence prediction capabilities, we seek to provide a comprehensive forecast of the IDX Composite's behavior in anticipation of Indonesia's 2024 presidential election. In this study, we employ Long Short Term Memory (LSTM) models, specifically Vanilla LSTM, Stacked LSTM, and Bidirectional LSTM, to forecast the IDX Composite's weekly closing prices. The effectiveness of these models in capturing the sequential nature of stock market data will be evaluated using historical data.

2. RESEARCH METHODS

2.1 Data

This study fits the definition of quantitative research, which is defined as utilizing statistical models to quantify data in numbers or percentages and extrapolating findings from a sample to the population of interest [11]. This research makes use of secondary data gathered from Yahoo Finance and the Indonesia Stock Exchange about the historical data of the weekly close price of IDX Composite in Indonesia Stock Exchange (IDX) starting from January 1, 2004, to February 11, 2024. The data used as a dataset will be analyzed with the *Long Short Term Memory* (LSTM) method using *vanilla*, *stacked*, and *bidirectional* models. Three categories of data will be created including train, validation, and test data. This study involves the following steps of data collection which are the historical weekly closing prices of IDX Composite, data preprocessing, the split of data into training, validation, and testing sets, model development using many models of Long Short Term Memory (LSTM), Training the model, evaluation model using RMSE, MAE, and MAPE metrics, and forecasting using the best-performing model.

2.2 Long Short Term Memory (LSTM)

LSTM is Long Short Term Memory by Sepp Hochreiter and Jurgen Schmidhuber, which was published in Neural Computation in 1977, introduced an efficient gradient method known as Long Short Term Memory (LSTM) and a corresponding gradient-based learning algorithm. LSTM was established as a solution to the vanishing gradient problem in traditional recurrent neural networks and demonstrated its effectiveness in learning long-term dependencies in sequence prediction problems [12]. Long Short Term Memory (LSTM) is a development of RNN that can handle vanishing gradient problems [13]. LSTM includes a memory unit in a network structure consisting of an input gate, a forget gate, and an output gate.

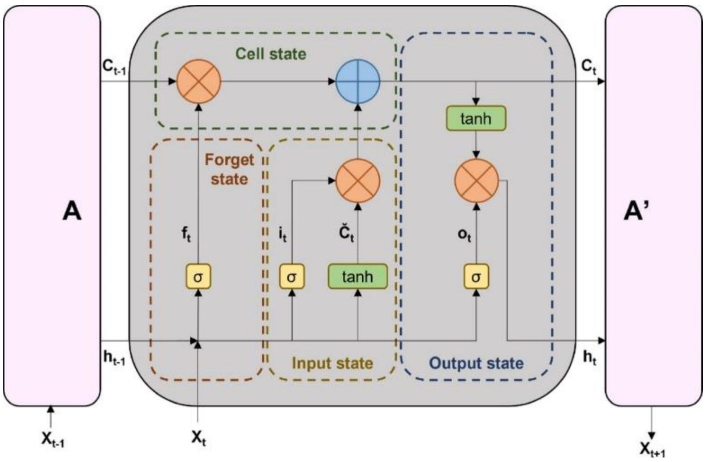

Figure 1. Representation of LSTM cell [15]

Figure 1, LSTM is formed by four neural networks and several memory blocks referred to as cells in a chain structure. A standard LSTM unit consists of a cell state (C_t), previous state (C_{t-1}), input gate with the previous time step (X_{t-1}), hidden state (h_t), previous hidden state (h_{t-1}), candidate value $(\tilde{C}_t)$, and a function (tanh) that plays a role in giving weight to the data. In addition, it includes combining the output gate (o_t) with the next time step (X_{t+1}) and a function (tanh) whose role is to determine the value that will be skipped to the next time step. In the end, there is a forget gate (f_t). All these gates are governed by a sigmoid function (σ) to determine whether to allow the incoming value to be 0 or 1.

Input state (i_t) determines which input value will be used to update the cell state which controls the amount of information allowed into the cell [14]. The same information is conveyed through the hyperbolic tangent, resulting in the value of the candidate value. After that, the results of the input state and the candidate value are combined to update the cell state. Forget state (f_t) determines the information from the previous cell state that should be retained or ignored. Output state (o_t) manages the output of the current block based on the input and memory gate. Hidden state (h_t) is then calculated by applying the tanh activation function to the current cell state and multiplying it element-wise with the output state (o_t). Output states allow the

LSTM model to generate relevant outputs based on sequential data. These outputs can serve as predictions for the current time step or as input for the next time step [15].

Each LSTM model's architecture consists of input features (historical closing prices) and outputs (predicted future prices). The Vanilla LSTM uses a single layer, the Stacked LSTM uses multiple layers to capture hierarchical information, and the Bidirectional LSTM processes data in both forward and backward directions to enhance context understanding.

2.3 LSTM Model

2.3.1. Vanilla Long Short Term Memory (VLSTM)

VLSTM is the basic model of LSTM without any additional layers and is called the original model of LSTM. In other words, VLSTM is a standard LSTM with one layer. VLSTM has been widely used [16][17][18] in many domains and applications. VLSTM consists of one hidden layer and an output feed-forward standard layer. **Figure 2** shows the inner structure of the VLSTM [19].

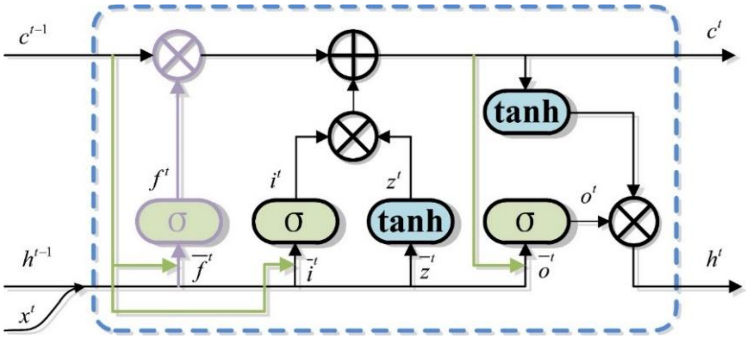

Figure 2. Vanilla LSTM structure [19]

The vanilla LSTM structure, also known as a basic LSTM architecture, consists of a single hidden layer of LSTM units and an output layer used to make a prediction. It is a simple and commonly used LSTM architecture for various applications, including time series forecasting and sequence classification problems [20].

2.3.2. Stacked Long Short Term Memory (Stacked LSTM)

Stacked LSTM is an LSTM model consisting of several layers that are stacked one on top of another [21]. In this structure, the output of the first LSTM layer becomes the input for the second LSTM layer [22]. This allows the model to utilize the hierarchical representation of the data. The way the stacked LSTM works is that the output from the first hidden layer will be the input of the last hidden layer.

2.3.3. Bidirectional Long Short Term Memory (Stacked Bi-LSTM)

Bidirectional Long Short Term Memory (Bi-LSTM) or bidirectional LSTM is a model extension of LSTM. The way Bi-LSTM works is that it has input sequences in both directions, namely backward (future to past) and forward (past to future). The structure of Bi-LSTM is shown in **Figure 3**.

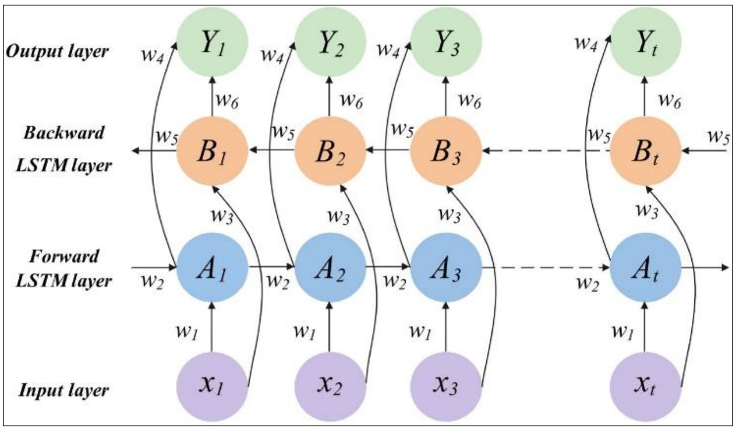

Figure 3. Bidirectional LSTM Structure [23]

A Bi-directional LSTM (Bi-LSTM) structure is an extension of the standard LSTM architecture, where the input sequence flows in both forward and backward directions [24]. It consists of two LSTM layers, one taking the input in a forward direction and the other in a backward direction. This architecture effectively increases the amount of information available to the network, improving the context available to the algorithm.

Suppose $x_1, x_2, x_3, \ldots, x_t$ denotes the corresponding input data for each moment $t_1 \sim t_i$. Then there are $A_1, A_2, A_3, \ldots, A_t$ and $B_1, B_2, B_3, \ldots, B_t$ which denote the corresponding forward and backward iterations from the LSTM hidden state. $Y_1, Y_2, Y_3, \ldots, Y_t$ are the output data generated and $\omega_1, \omega_2, \omega_3, \ldots, \omega_t$ are the weights of each layer.

$$A_i = f_1(\omega_1 x_i + \omega_2 A_{i-1}) \quad (1)$$

$$B_i = f_2(\omega_3 x_i + \omega_5 B_{i+1}) \quad (2)$$

$$Y_i = f_3(\omega_4 A_i + \omega_6 B_i) \quad (3)$$

with f_1, f_2, and f_3 being the activation functions between the different layers.

2.4 Evaluation Metrics

In every prediction/forecasting situation, there is a level of uncertainty called error. Deviations in prediction do not only come from the error element but are also influenced by the limited ability of the prediction model to recognize other elements in the dataset. The amount of deviation in prediction is influenced by these factors. To evaluate the accuracy and predictive performance of different models, this study uses three evaluations as follows:

- Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(R_i - \hat{R}_i\right)^2} \quad (4)$$

- Average Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|R_i - \hat{R}_i\right|^2 \quad (5)$$

- Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|PE_i| = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \quad (6)$$

3. RESULTS AND DISCUSSION

Market capitalization on the Indonesian Stock Exchange (IDX) from 2004 to 2023 is depicted in the following chart.

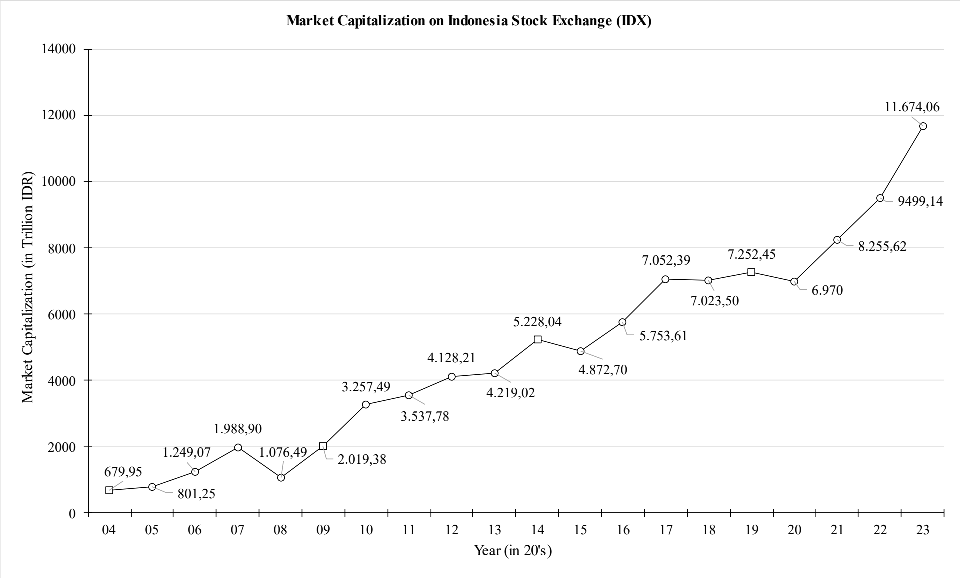

Figure 4. Market Capitalization on Indonesia Stock Exchange (IDX)

Market capitalization has fluctuated in the last 20 years and 2023 the highest value was obtained at IDR 11674.06 trillion. The analysis was conducted on weekly IDX historical data to see whether or not there is a match between the IDX Composite and the presidential election period in Indonesia.

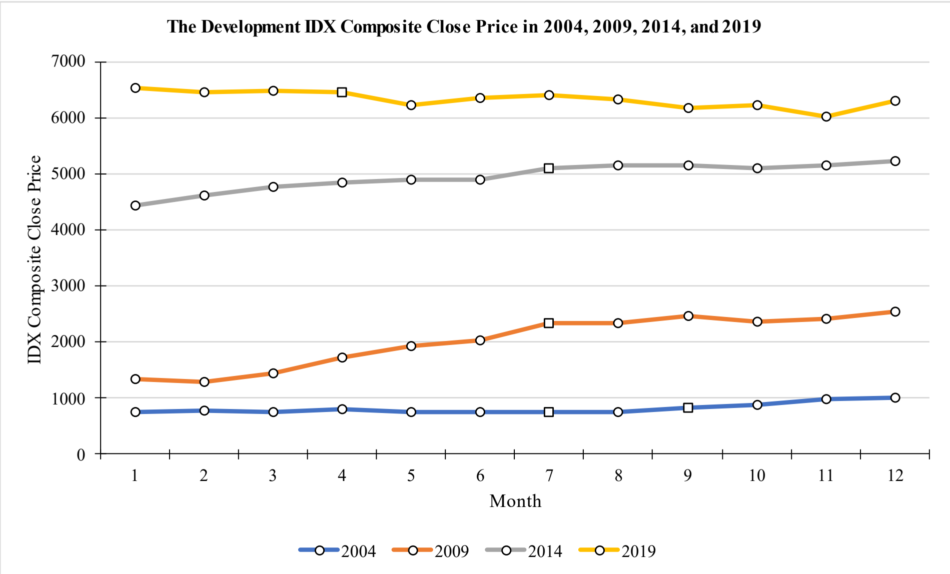

Figure 5. The Development IDX Composite Close Price in 2004, 2009, 2014, and 2019

According to **Figure 5**, the development of IDX Composite price in 2004, 2009, and 2014 before the month of the presidential election shows a significant bullish trend, the increase reached 3.36% and 8.67% in July and September 2004, 14.63% in July 2009, and 4.31% in July 2014 compared to the previous month consecutively. However, in the year of 2019 drags down 0.21% in April 2019 compared to the previous month. Undeniably, especially on the day of the presidential election, investors seek higher returns in exchange for the availability of uncertainty in the stock market. Based on the previous knowledge in 2004, 2009, 2014, and 2019, this study is conducted to forecast the performance of the stock market, especially IDX Composite price on the 2024 Indonesia presidential election.

The data used in this study are historical data of the weekly close price of IDX Composite stocks for the last twenty years from January 1, 2004, to February 13, 2024.

3.1 Statistics Analysis Descriptive

Descriptive statistical analysis on historical data of the weekly stock close price of IDX Composite (^JKSE) in IDR units can be seen in **Table 1**.

Table 1. Descriptive Statistics

	Minimum	Maximum	Mean	Standard Deviation
IDX *Close Price*	699.756	7297.669	4187.152	1980.171

Based on **Table 1**, it is shown that the minimum price of IDX Composite shares in the last twenty years is IDR 699.756 occurred on June 17, 2004, and the maximum price of IDR 7297.669 occurred on February 8, 2024. The average monthly closing stock price is IDR 4187.152 with a fairly high diversity with a standard deviation value of 1980,171. This shows that the closing price of IDX Composite shares in the last 20 years varies.

3.2 Plot Data

A plot of the weekly close price data of IDX Composite stocks is shown in **Figure 6**.

Figure 6. Plot Data of IDX Composite Weekly Stock Close Price

Based on **Figure 6**, there has been an upward trend in the IDX Composite share price over the past 20 years.

3.3 Split Data

In this research, the dataset is divided into train, validation, and test data with a percentage of 70%, 20%, and 10% respectively with the data comparison plot shown in **Figure 7**.

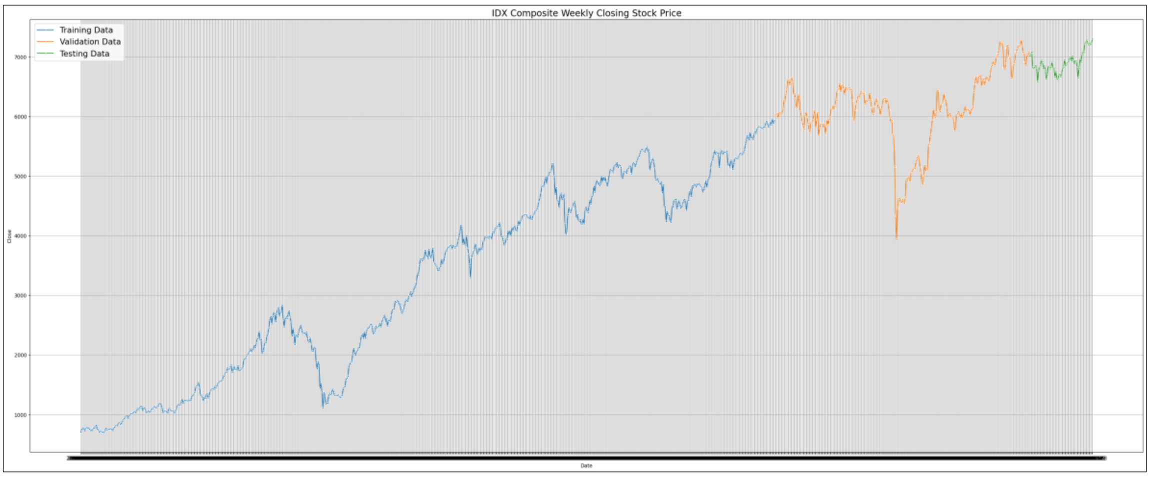

Figure 7. Split Dataset

3.4 Long Short Term Memory (LSTM)

In this study, a dataset with 720 train data observations, 264 validation data observations, and 51 test data observations is used. Then, modeling using LSTM with several models for comparison, namely vanilla LSTM, stacked LSTM, and stacked Bi-LSTM. The LSTM model used has 8 neurons in the hidden layer with ReLU activation function to add non-linearity. To prevent overfitting, L2 regularization is applied with a value of 0.01. The optimizer used is Adam with a learning rate of 0.0001 to adjust the model weights. The loss function chosen was Huber, which is more tolerant of outliers. The training process was conducted for 1000 epochs with the training data divided into batches of size 8. This configuration was designed to provide a balance between model complexity and the capacity to understand complex patterns in time series data.

3.4.1. Vanilla LSTM

The comparison graph of the training model and validation loss is used to evaluate the model and identify the possibility of overfitting the model.

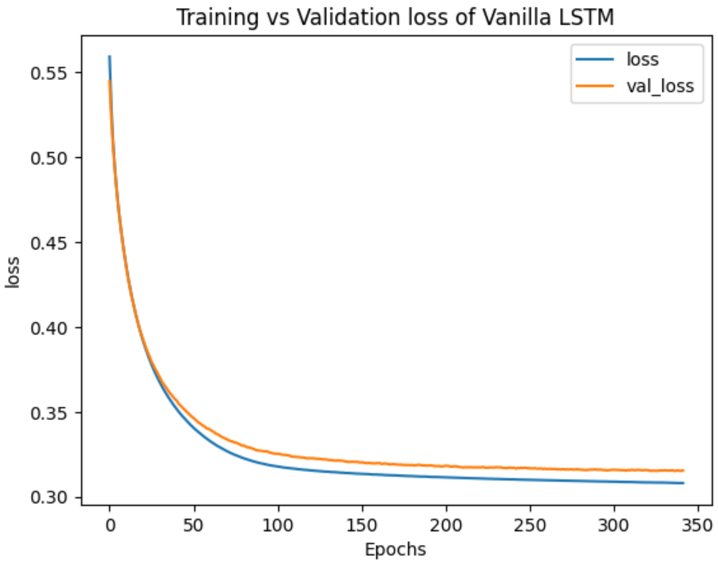

Figure 8. Graphic of Vanilla LSTM Model Training vs Validation Loss

Based on **Figure 8**, the training against validation loss graph shows good results with the loss and validation loss curves almost coinciding. This shows that the performance of the model is close to each other and can be interpreted that in the Vanilla LSTM model, the model is effective in learning the pattern of the train data and is also effective in performing good generalization on data that has never been seen before. In addition, the closeness of the curves could be an indication that the model is not significantly overfitting. **Figure 9** shows a graph of actual data and predicted results.

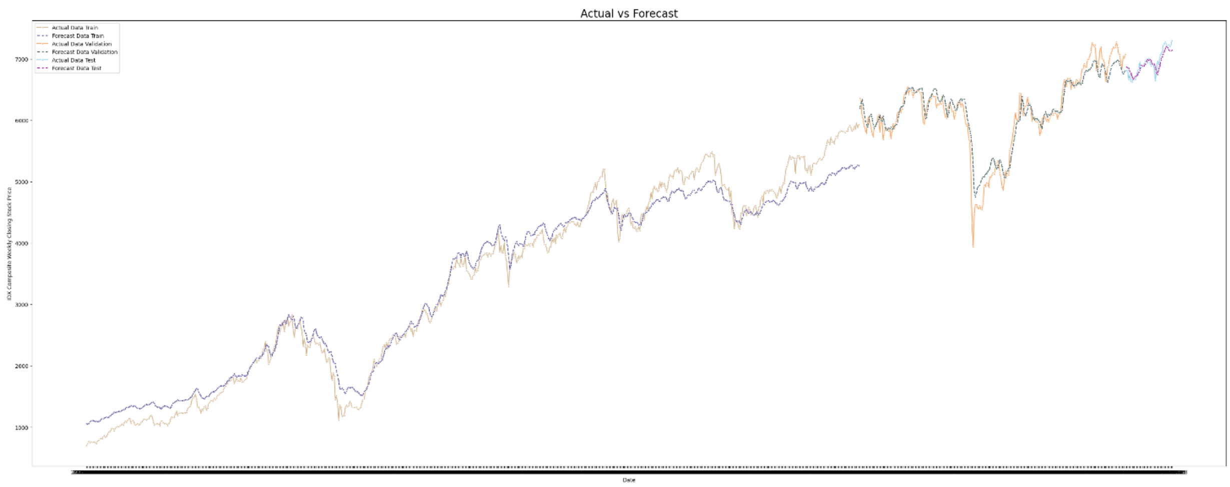

Figure 9. Graphic of Actual and Prediction Data Vanilla LSTM model

The graph shows the comparison between training data, validation data, and test data on actual and forecast. The results show that the graph of the forecast data follows the actual data although the graphs do not coincide.

Table 2. Vanilla LSTM Model Evaluation

Data	RMSE	MAE	MAPE
Training	246.77	196.48	7.34
Validation	211.2	146.72	2.46
Testing	91.97	73.98	1.07

Based on **Table 2**, the Mean Absolute Percentage Error (MAPE) generated shows results <10% on validation data and test data so that the model formed can predict with minimal error. As for the MAPE value on the test data model prediction, it shows a value of 1.07% which is quite good at predicting.

3.4.2. 2-Stacked LSTM

The comparison graph of the training model and validation loss is used to evaluate the model and identify the possibility of overfitting the model.

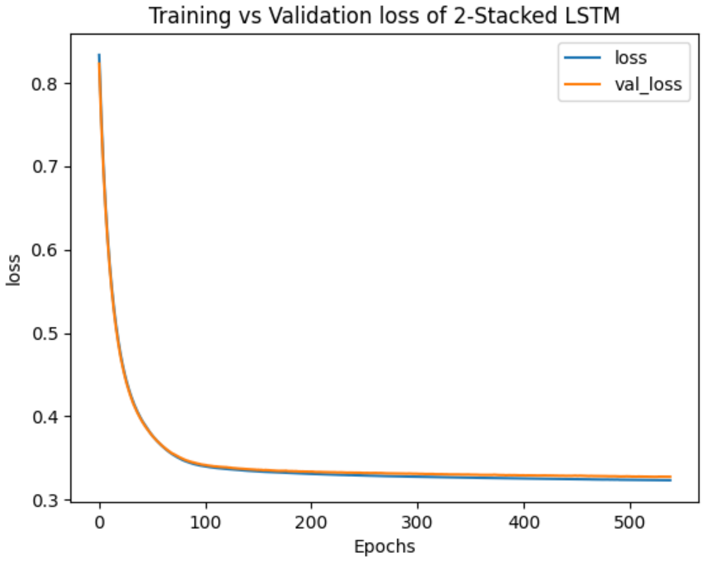

Figure 10. Graphic of 2-stacked LSTM model training vs validation loss

Based on **Figure 10**, the training vs validation loss graph shows good results with the loss and validation loss curves almost coinciding. This shows that the performance of the model is close to each other and it can be interpreted that in the 2-Stacked LSTM model, the model is effective in learning the train data pattern and also effective in performing good generalization on data that has never been seen before. In addition, the closeness of the curves could be an indication that the model is not significantly overfitting. **Figure 11** shows the graph of actual data and predicted results.

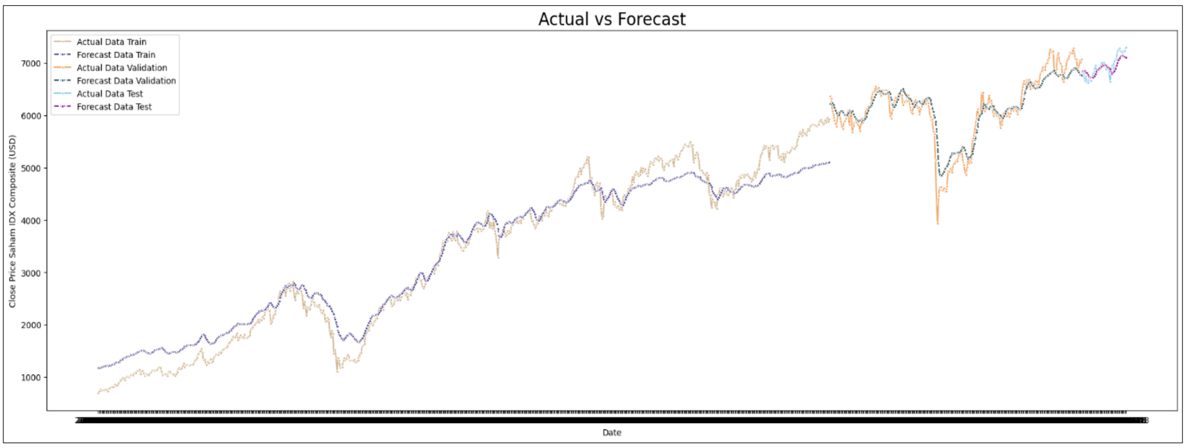

Figure 11. Graphic of Actual and Prediction Data 2-stacked LSTM model

The graph shows the comparison between training data, validation data, and test data on actual and forecast. The results show that the graph of the forecast data follows the actual data although the graphs do not coincide.

Table 3. 2-Stacked LSTM Model Evaluation

Data	RMSE	MAE	MAPE
Training	375.49	298.31	10.87
Validation	266.69	190.04	3.17
Testing	113.25	89.29	1.29

Based on **Table 3**, the Mean Absolute Percentage Error (MAPE) generated shows results <10% on validation data and test data so that the model formed can predict with minimal error. As for the MAPE value on the test data model prediction, it shows a value of 1.29% which is quite good at predicting.

3.4.3. 3-Stacked LSTM

The comparison graph of the training model and validation loss is used to evaluate the model and identify the possibility of overfitting the model.

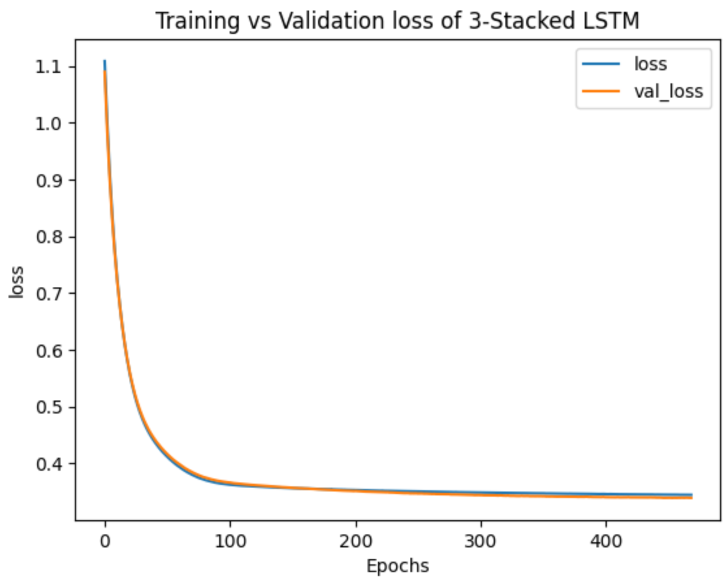

Figure 12. Graphic of 3-Stacked LSTM Model Training vs Validation Loss

Based on **Figure 12**, the training vs validation loss graph shows good results with the loss and validation loss curves almost coinciding. This shows that the performance of the model is close to each other and it can be interpreted that in the 3-Stacked LSTM model, the model is effective in learning the train data pattern and also effective in performing good generalization on data that has never been seen before. In addition, the closeness of the curves could be an indication that the model is not significantly overfitting. **Figure 13** shows a graph of the actual data and the predicted results.

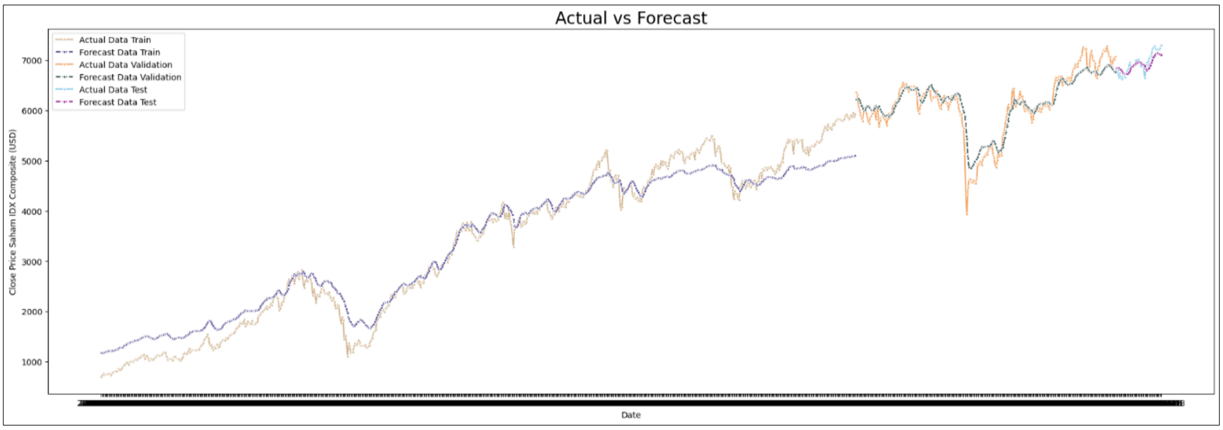

Figure 13. Graphic of Actual and Prediction Data 3-stacked LSTM model

The graph shows the comparison between training data, validation data, and test data on actual and forecast. The results show that the graph of the forecast data follows the actual data although the graphs do not coincide.

Table 4. 3-Stacked LSTM Model Evaluation

Data	RMSE	MAE	MAPE
Training	526.87	443.34	15.59
Validation	365.09	268.25	4.45
Testing	152.13	125.8	1.82

Based on **Table 4**, the Mean Absolute Percentage Error (MAPE) generated shows results <10% on validation data and test data so that the model formed can predict with minimal error. As for the MAPE value on the test data model prediction, it shows a value of 1.82% which is quite good at predicting.

3.4.4. Bi-LSTM

The comparison graph of the training model and validation loss is used to evaluate the model and identify the possibility of overfitting the model.

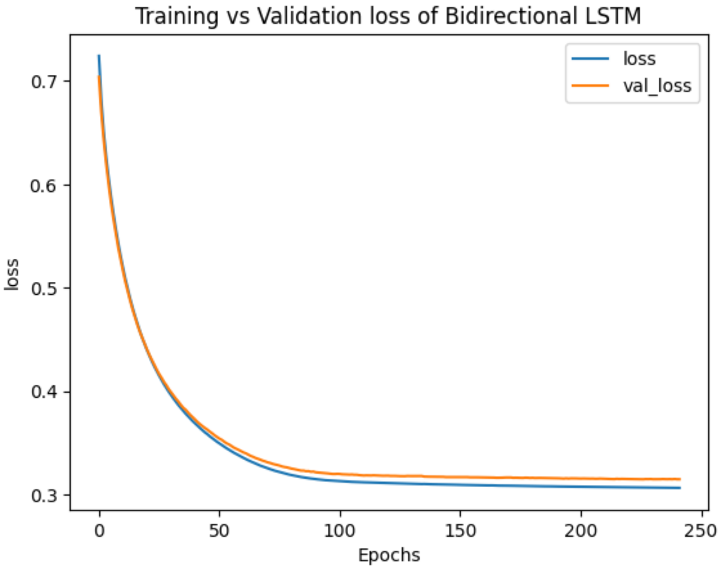

Figure 14. Graphic of Bi-LSTM Model Training vs Validation Loss

Based on **Figure 14**, the training vs validation loss graph shows good results with the loss and validation loss curves almost coinciding. This shows that the performance of the model is close to each other and can be interpreted that in the Bi-LSTM model, the model is effective in learning the pattern of the train data and is also effective in performing good generalization on data that has never been seen before. In addition, the closeness of the curves could be an indication that the model is not significantly overfitting. **Figure 15** shows the graph of actual data and predicted results.

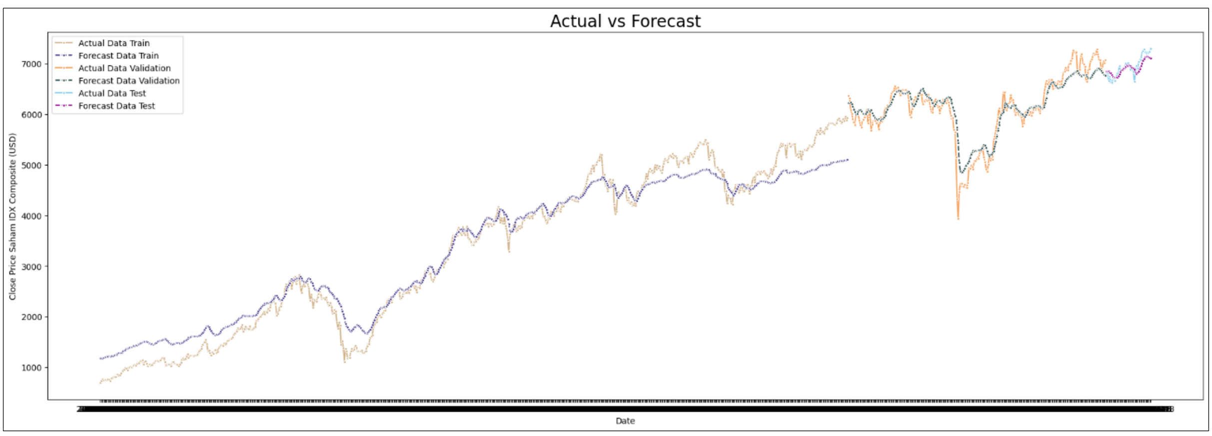

Figure 15. Graphic of Actual and Prediction Data Bi-LSTM Model

The graph shows the comparison between training data, validation data, and test data on actual and forecast. The results show that the graph of the forecast data follows the actual data although the graphs do not coincide.

Table 5. Bi-LSTM Model Evaluation

Data	RMSE	MAE	MAPE
Training	241.7	192.7	7.29
Validation	207.26	144.92	2.43
Testing	90.26	72.23	1.04

Based on Table 5, the Mean Absolute Percentage Error (MAPE) generated shows results <10% on validation data and test data so that the model formed can predict with minimal error. As for the MAPE value on the test data model prediction, it shows a value of 1.04% which is quite good at predicting.

3.4.5. 2-Stacked Bi-LSTM

The comparison graph of the training model and validation loss is used to evaluate the model and identify the possibility of overfitting the model.

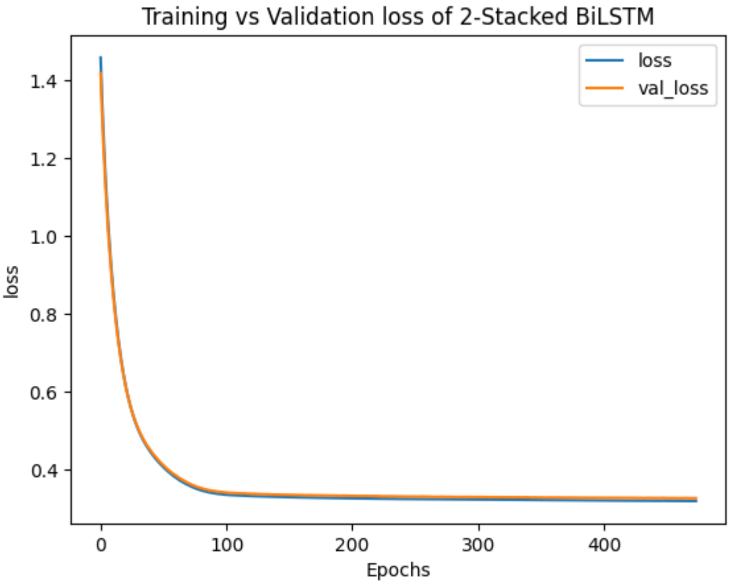

Figure 16. Graphic of 2-stacked Bi-LSTM Model Training vs Validation Loss

Based on Figure 16, the training vs validation loss graph shows good results with the loss and validation loss curves almost coinciding. This shows that the performance of the model is close to each other and it can be interpreted that in the 2-Stacked Bi-LSTM model, the model is effective in learning the train data pattern and also effective in performing good generalization on data that has never been seen before. In addition, the clustered curves could be an indication that the model is not significantly overfitting. Figure 17 shows the graph of actual data and predicted results.

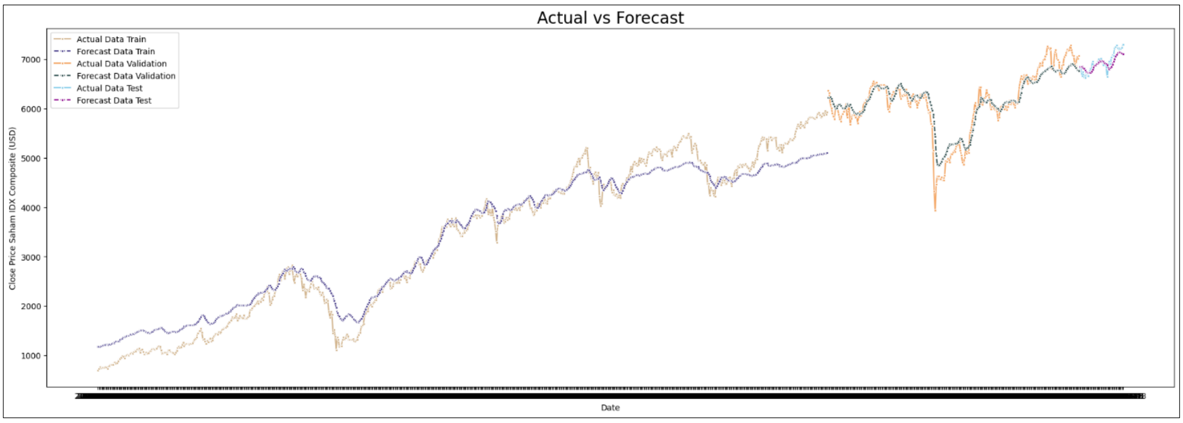

Figure 17. Graphic of Actual and Prediction data 2-stacked Bi-LSTM model

The graph shows the comparison between training data, validation data, and test data on actual and forecast. The results show that the graph of the forecast data follows the actual data although the graphs do not coincide.

Table 6. 2-Stacked Bi-LSTM Model Evaluation

Data	RMSE	MAE	MAPE
Training	292.15	234.29	8.87
Validation	228.14	161.67	2.7
Testing	100.31	78.85	1.14

Based on Table 6, the Mean Absolute Percentage Error (MAPE) generated shows results <10% on validation data and test data so that the model formed can predict with minimal error. As for the MAPE value on the test data model prediction, it shows a value of 1.14% which is quite good at predicting.

3.4.6. 3-Stacked Bi-LSTM *3-Stacked* Bi-LSTM

The comparison graph of the training model and validation loss is used to evaluate the model and identify the possibility of overfitting the model.

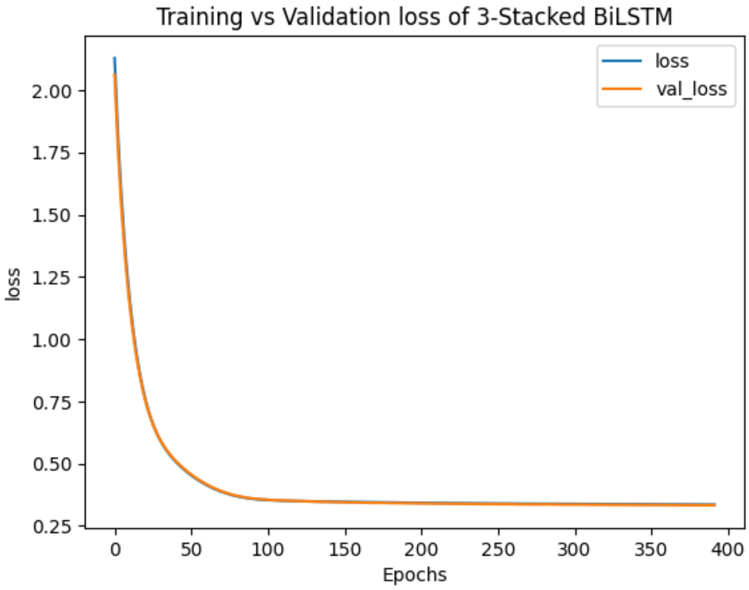

Figure 18. Graphic of 3-stacked Bi-LSTM Model Training vs Validation Loss

Based on Figure 18, the training vs validation loss graph shows good results with the loss and validation loss curves almost coinciding. This shows that the performance of the model is close to each other and it can be interpreted that in the 3-Stacked Bi-LSTM model, the model is effective in learning the train data pattern and also effective in performing good generalization on data that has never been seen before. In addition, the clustered curves could be an indication that the model is not significantly overfitting. Figure 19 shows the graph of actual data and predicted results.

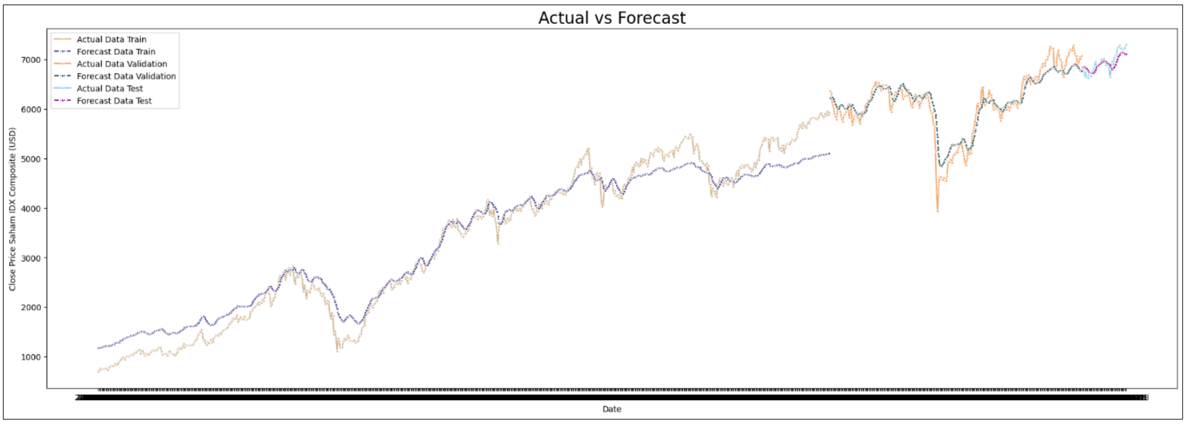

Figure 19. Graphic of Actual and Prediction Data 3-stacked Bi-LSTM Model

The graph shows the comparison between training data, validation data, and test data on actual and forecast. The results show that the graph of the forecast data follows the actual data although the graphs do not coincide.

Table 7. **3-Stacked Bi-LSTM Model Evaluation**

Data	RMSE	MAE	MAPE
Training	320.3	254.94	9.95
Validation	242.16	171.08	2.84
Testing	112.12	89.07	1.29

Based on **Table 7**, the Mean Absolute Percentage Error (MAPE) generated shows results <10% on validation data and test data so that the model formed can predict with minimal error. As for the MAPE value on the test data model prediction, it shows a value of 1.29% which is quite good at predicting.

3.5 Forecasting

Determination of the best model based on the evaluation results shows that the Bi-LSTM model has a better accuracy value on the test data, which is 1.04%. Therefore, forecasting the weekly closing price of IDX Composite (JKSE) shares for the next 8 weeks is carried out as follows.

Table 8. **Forecasting**

Bulan	Forecast (IDR)
February 15, 2024	6812.722
February 22, 2024	6811.905
February 29, 2024	6663.114
March 7, 024	6745.804
March 14, 2024	6633.261
March 21, 2024	6619.755
March 28, 2024	6699.717
April 4, 2024	6702.625

The forecast results show a fluctuating IDX Composite in the next 8 weeks with the lowest value of 6619.755 for the forecast period of March 21, 2024. A significant increase occurred in the 7th week after the election. In previous research with different methods of observing the effect of elections on stock returns in Indonesia, it was found that there were abnormal stock returns on the 10 days before and after the election **[25]**.

4. CONCLUSIONS

The capital market is a financial market that involves the trading of funding instruments such as stocks, bonds, and others, as well as securities issued to raise funds. The role of capital markets is crucial in resource allocation, price formation, and promoting economic growth. In Indonesia, the Indonesia Stock Exchange (IDX) displays significant growth in market capitalization, reflecting the country's economic prosperity. Presidential elections are considered to have a major impact on national stability and can affect the performance of the stock market, as happened in previous presidential elections. Previous research shows a bullish trend before presidential elections. Therefore, an analysis was conducted to forecast the performance of the stock market, especially the JCI, in Indonesia's 2024 presidential election.

The Bi-LSTM model showed good predictive ability with a MAPE value on the testing data of 1.04%. This indicates that the model can explain variations in the observed data and provide relatively accurate predictions of closing stock prices. The results of the weekly IDX Composite forecast after the presidential election showed fluctuating values up to 5 weeks after the election, and backup since March 28.

This study demonstrates that LSTM models, particularly the Bidirectional LSTM, can effectively forecast the IDX Composite's weekly closing prices in the context of presidential elections. These findings underscore the significant impact of political events on stock market performance and provide valuable insights for investors anticipating the 2024 presidential election.

REFERENCES

[1] S. P. Kothari, “Capital markets research in accounting,” *Journal of Accounting and Economics*, vol. 31, no. 1–3, pp. 105–231, Sep. 2001, doi: 10.1016/S0165-4101(01)00030-1.

[2] A. Wibowo and S. Darmanto, “Saudi Journal of Business and Management Studies Impact of Quick Count Result of President Election on Stock Prices and Trade Activities in the Indonesian Capital Market,” *Saudi J Bus Manag Stud*, 2019, doi: 10.36348/sjbms.2019.v04i06.002.

[3] N. Kirana and R. Sembel, “THE EFFECT OF POLITICAL EVENT ON THE INDONESIAN STOCK MARKET: AN EVENT STUDY OF PRESIDENTIAL ELECTION ON LQ45 INDEX STOCKS,” *International Journal of Business, Economics and Law*, vol. 19, p. 1, 2019.

[4] H. Murtaza, M. Abrar, and R. Ali, “Impact of Major Political Events on Stock Market Returns of Pakistan,” 2015. [Online]. Available: www.iiste.org

[5] S. Hidayatulloh and P. Yulianti, “Investigate the Financial Instruments Trade on the Indonesia Stock Exchange.”, Jurnal Ilmiah Manajemen Ubhara, 2023.

[6] H. P. Koapaha, “The Impact of Macroeconomics Factors on the Jakarta Composite Index,” *East Asian Journal of Multidisciplinary Research*, vol. 1, no. 10, pp. 2161–2172, Nov. 2022, doi: 10.55927/eajmr.v1i10.1898.

[7] R. A. F. Tumiwa, A. R. Rooroh, and S. A. lasut, “Determinants of The Indonesia Composite Index Movement in The Covid-19 Pandemic Era,” *SHS Web of Conferences*, vol. 149, p. 02045, 2022, doi: 10.1051/shsconf/202214902045.

[8] A. Wibowo, S. Darmanto, and J. Pawiyatan Luhur Bendan Dhuwur, “Reaction of Indonesian Capital Market Investors to the Implementation of Tax Amnesty,” 2017. [Online]. Available: http://jurnal.unmer.ac.id/index.php/jkdp

[9] F. S. Chien, K. Y. Chau, M. Sadiq, and C. C. Hsu, “The impact of economic and non-economic determinants on the natural resources commodity prices volatility in China,” *Resources Policy*, vol. 78, Sep. 2022, doi: 10.1016/j.resourpol.2022.102863.

[10] Wen-Wen Chien, Roger W. Mayer, and Zigan Wang, “Stock Market, Economic Performance, And Presidential Elections,” *Journal of Business & Economics Research* , vol. 2, pp. 159–170, 2014.

[11] Shalonda Skidmore and Devin Kowalczyk, “Research Methodologies: Quantitative, Qualitative & Mixed Method.”, May 2016.

[12] Madhuri Yerukala, “What is LSTM.”

[13] S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” *Neural Comput*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[14] B. Sasya and D. Pradana, “ABSTRACT FORECASTING TIME SERIES DATA ON FOOD COMMODITY PRICES USING THE LONG SHORT TERM MEMORY (LSTM) METHOD (Case Study: Closing Prices of United States Soybeans).”, Universitas Lampung.

[15] A. Picornell *et al.*, “A deep learning LSTM-based approach for forecasting annual pollen curves: Olea and Urticaceae pollen types as a case study,” *Comput Biol Med*, vol. 168, Jan. 2024, doi: 10.1016/j.compbiomed.2023.107706.

[16] E. Kanjo, E. M. G. Younis, and C. S. Ang, “Deep learning analysis of mobile physiological, environmental and location sensor data for emotion detection,” *Information Fusion*, vol. 49, pp. 46–56, Sep. 2019, doi: 10.1016/j.inffus.2018.09.001.

[17] J. Liu, T. Li, P. Xie, S. Du, F. Teng, and X. Yang, “Urban big data fusion based on deep learning: An overview,” *Information Fusion*, vol. 53, pp. 123–133, Jan. 2020, doi: 10.1016/j.inffus.2019.06.016.

[18] J. Liu, Z. Wang, and M. Xu, “DeepMTT: A deep learning maneuvering target-tracking algorithm based on bidirectional LSTM network,” *Information Fusion*, vol. 53, pp. 289–304, Jan. 2020, doi: 10.1016/j.inffus.2019.06.012.

[19] W. Fang, R. Zhu, and J. C. W. Lin, “An air quality prediction model based on improved Vanilla LSTM with multichannel input and multiroute output,” *Expert Syst Appl*, vol. 211, Jan. 2023, doi: 10.1016/j.eswa.2022.118422.

[20] G. Van Houdt, C. Mosquera, and G. Nápoles, “A review on the long short-term memory model,” *Artif Intell Rev*, vol. 53, no. 8, pp. 5929–5955, Dec. 2020, doi: 10.1007/s10462-020-09838-1.

[21] F. Sains and D. Teknologi, “RANCANG MODEL ALGORITMA LONG SHORT TERM MEMORY DENGAN METODE ROLLING WINDOWS CROSS VALIDATION: Studi Kasus Nilai Tukar Rupiah Terhadap Dollar Amerika PROGRAM STUDI TEKNIK INFORMATIKA.”, Repository UIN Syarif Hidayatullah, August 2023.

[22] A. Satyo Bayangkari Karno, J. K. Noer Ali, and K. Bekasi, “Prediksi Data Time Series Saham Bank BRI Dengan Mesin Belajar LSTM (Long ShortTerm Memory),” *Journal of Information and Information Security (JIFORTY)*, vol. 1, no. 1, pp. 1–8, 2020, [Online]. Available: http://ejurnal.ubharajaya.ac.id/index.php/jiforty

[23] Y. Xu, T. Liu, and P. Du, “Volatility forecasting of crude oil futures based on Bi-LSTM-Attention model: The dynamic role of the COVID-19 pandemic and the Russian-Ukrainian conflict,” *Resources Policy*, vol. 88, Jan. 2024, doi: 10.1016/j.resourpol.2023.104319.

[24] G. Liu and J. Guo, “Bidirectional LSTM with attention mechanism and convolutional layer for text classification,” *Neurocomputing*, vol. 337, pp. 325–338, Apr. 2019, doi: 10.1016/j.neucom.2019.01.078.

[25] H. Manurung, “PENGARUH PEMILU SERENTAK TERHADAP RETURN SAHAM DI INDONESIA (Studi Kasus Saham LQ-45 di Bursa Efek Indonesia)”, Journal for Business and Entrepreneurship, 2019. [Online]. Available: www.journal.uta45jakarta.ac.id