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Multivariate Time Series Stock Price Data Prediction in The Banking Sector in Indonesia Using Bidirectional Long Short-Term Memory (BiLSTM)

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ABSTRACT

The capital market is a place for individuals or business entities to carry out investment activities, especially in the banking sector, one of the sectors in the LQ45 stock index which is in great demand by investors in Indonesia. In the capital market, one of the investments that can be made is stock investment, but investors will be faced with uncertainty by fluctuations in stock prices caused by several factors, one of which is macroeconomic factors. Therefore, a predictive analysis of stock prices is needed to prevent uncertainty and minimize losses. Accurate prediction models can use deep learning algorithm methods. In the prediction of stock price movements, the data used is historical data on stock prices which is time series type data. This study conducted stock price predictions using the Bidirectional Long Short-Term Memory (biLSTM) method. biLSTM is another variation of the LSTM model. The object of this study uses the variables open, close, adj close, low, high, volume, value, buying rate, selling rate. The data that has been obtained will be preprocessing. Next build a prediction model using hyperparameter tuning with Genetic Algorithm (GA), train the model and evaluate the model. Data testing was carried out using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) with 4 data from the banking sector in Indonesia including Bank BRI, Bank BNI, Bank BCA, and Bank Mandiri. Based on the data testing that has been carried out, the results of the biLSTM algorithm can predict stock prices accurately because it has a relatively low RMSE value with a MAPE value below 10%.

1. Introduction

The capital market plays an important role in a country's economic growth. Because the capital market performs two functions. First, as a means of financing business entities, the proceeds from community investment can be used to grow and expand businesses, increase capital, and other investments. Second, the capital market as an intermediary for investment activities in long-term or short-term financial instruments [1]. In the capital market, there are various long-term and short-term financial instruments that are traded such as bonds, stocks, mutual funds, derivative instruments and other instruments. In the capital market, one form of investment that can be traded is investment in the form of shares. Shares are a form of participation in the capital ownership of an individual or business entity that carries out investment activities in the capital market. Stocks in the capital market experience a price movement, the movement of the price of this stock can increase or decrease [2], measuring the performance of price movements on a group of stocks requires an indicator, the indicator is called a stock index. Stock indices that are in great demand by investors, one of which is the LQ45 stock index on the Indonesian stock exchange [3].

The LQ45 stock index is a stock index consisting of 45 large companies in Indonesia that have good business prospects for investors who have high liquidity and large market capitalization and are supported by good company fundamentals. At the LQ45 share price, there is a banking sector. The banking sector has a significant influence on capital market activities in Indonesia, as almost one-third of the total composite stock price index belongs to the financial sector of 1 million investors, 300 of whom choose to invest in the banking sector and have a high market capitalization, indicating that the value of stocks in this sector is getting better and is in great demand by investors [4]. According to Forbes 2000 The World Biggest Companies which contains more than 2000 of the largest public companies in the world there are Indonesian companies in the banking sector that enter [5]. Companies in the banking sector are owned by the government and the private sector. The banking sectors included in Forbes 2000 are Bank Rakyat Indonesia, Bank Central Asia, Bank Mandiri, and Bank Negara Indonesia.

In investing in stocks, investors are required to have a good understanding of the rate of return for profit and risk management because later investors will experience or receive profits that are not in line with expectations, resulting in problems that are often referred to as uncertainty [6]. Investing in stock prices carries risks because one of the stock prices is fluctuating [7]. Fluctuations in the stock price index can be caused by several factors, one of which is macroeconomic factors. These macroeconomic factors come from abroad as well as domestically [8]. Macroeconomic factors are economic factors outside the company that influence the ups and downs of the company's performance [9]. Macroeconomics from abroad include changes in the rupiah exchange rate, fluctuations in world gold prices and world oil prices. Meanwhile, the domestic macroeconomics includes inflation, interest rates. These macroeconomic factors that partially affect the LQ45 stock price index and the stock price of the banking sector are the rupiah exchange rate [10][11]. Therefore, a prediction with a good analytical method is needed to prevent uncertainty and minimize losses by considering the factors that affect the LQ45 stock price index and the stock price of the banking sector.

With the rapid development of technology and information, especially in the field of intelligent systems, it can complete tasks such as data prediction. Therefore, the intelligent system can be used also for stock price prediction. Intelligent systems to accurately predict can use deep learning. Because, deep learning is able to use past data to inform decisions to be made to predict and in performance is proven to have better accuracy and performance than other algorithms, namely machine learning [12]. Deep learning in predicting stock prices can use historical data on stock prices.

In the economic world, there have been many studies that have been carried out related to prediction using machine learning and deep learning methods. The first research conducted research on stock price prediction using the Support Vector Machine (SVM) and Multilayer Percepton (MLP) algorithms with the results of the Multilayer Perceptron (MLP) algorithm showing a better level of prediction accuracy than the Support Vector Machine (SVM) algorithm with an accuracy value of 92.5% [13]. In the second study, namely stock price prediction using the moving average (MA) algorithm, exponential moving average (EMA), support vector machine (SVM), LSTM with the results of the LSTM algorithm has the smallest RMSE value on the 200-day prediction performance of 16.7404 [14]. The third study of consumer price prediction using Multilayer Perceptron, LSTM, and bidirectional LSTM algorithms compared 3 deep learning algorithm methods, with the results of bidirectional LSTM having the best level of accuracy compared to other deep learning algorithms with an RMSE value of 3,519 using 10 neurons and an epoch of 2000 [15].

Long short-term memory (LSTM) is a variation of the renewal form of RNN. The purpose of this update is intended to address the issue where the gradient value used to update the new weight will be zero (vanishing gradient) on the long-term dependence of the RNN [16]. RNN is a repetitive artificial neural network architecture developed from ANN that aims to process sequential data so that it is commonly used to complete tasks on time series type data. RNN was developed to address the problem that exists in the markov assumption which is essentially the problem with ann memory, as it only remembers sequence data in a limited way [17]. There are two types of LSTM, namely undirectional LSTM and bidirectional LSTM. Unidirectional LSTM or usually referred to as LSTM alone is a model that in its input uses one direction, namely forward (past to future). Meanwhile, bidirectional LSTM is an LSTM model that in the process of sequential input uses two directions, namely forward (past to future) and backwards (future to past).

2. Metode Research

The stages in the study are carried out sequentially. This research step is useful for obtaining the right research results in accordance with the assessment of the problems that have been described. The flow of research can be seen in Fig. 1.

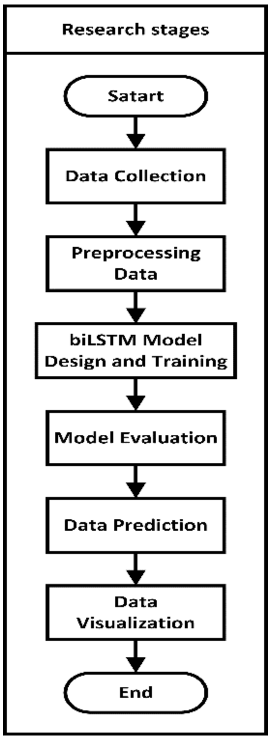


Fig. 1. Research flow

2.1. Data Collection

The first stage is to collect stock price data that will be used in research. Researchers collect data and collect data in the form of historical stock prices in the banking sector and the rupiah exchange rate in Indonesia.

Table 1. Collection of stock price data

No	Data	Period	Number of sample data	Data Retrieval Sources
1.	Bank BRI	2 January 2015 – 21 December 2021	1746	Source: finance.yahoo.com
2.	Bank BNI	2 January 2015 – 21 December 2021	1746	Source: finance.yahoo.com
3.	Bank BCA	2 January 2015 – 21 December 2021	1746	Source: finance.yahoo.com
4.	Bank Mandiri	2 January 2015 – 21 December 2021	1746	Source: finance.yahoo.com
5.	Rupiah Exchange Rate against US Dollar (USD)	2 January 2015 – 21 December 2021	1719	Source: bi.go.id

2.2. Preprocessing Data

The data that has been collected is still in the form of raw data, so that the data used has a better quality, it is necessary to preprocess the data first. The stages of data preprocessing include combining data, data correlation, checking data whether there are missing values if there are replacing missing values with interpolation, then choosing what features to use, then normalizing using MinMaxScaler with vulnerable values of 0 to 1, converting data series to supervised learning, creating data sharing for training, validation and testing, and finally create a dataset.

2.3. biLSTM Model Design and Training

At the stage of designing the biLSTM model, a design is made in order to produce the right model to predict. This design includes considering what parameters will be used, to make it easier to find the right parameters in a model, hyperparameter tuning is carried out. The hyperparameter tuning method uses sklearn-deap using the Genetic Algorithm (GA). After the model is designed, then the model is trained to determine whether the model is suitable or not in a problem.

2.4. Model Evaluation

After the data is trained the next stage evaluates the loss values and metrics on the model. The data used is test data. This evaluation will return loss values and metrics.

2.5. Data Prediction

At this stage the evaluated biLSTM model will be used to predict using the new test data. New data testing using data with a period of 22 December 2021 – 30 August 2022. After the data is predicted, the data goes through preprocessing first and then denormalized. Denormalization is carried out so that the predicted results are normalized to their original form. Then finally, evaluate the predicted results using RMSE and MAPE. The smaller the error value, the prediction result is close to the original.

2.6. Data Visualization

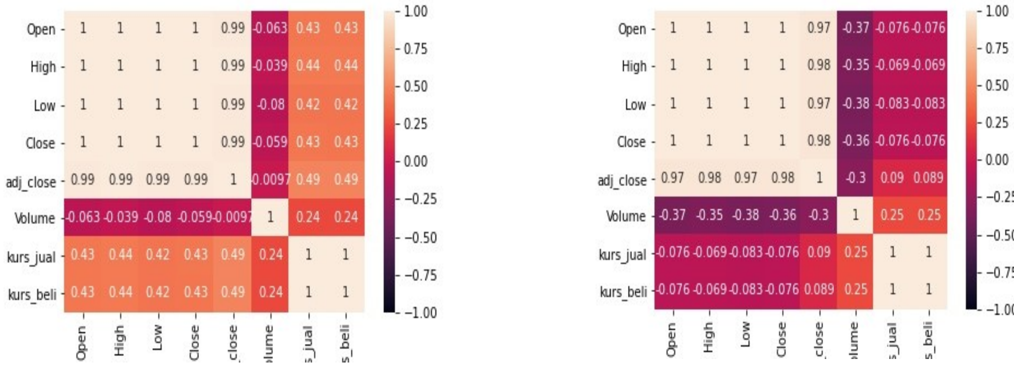
3. Results and Discussion

3.1. Data Collection

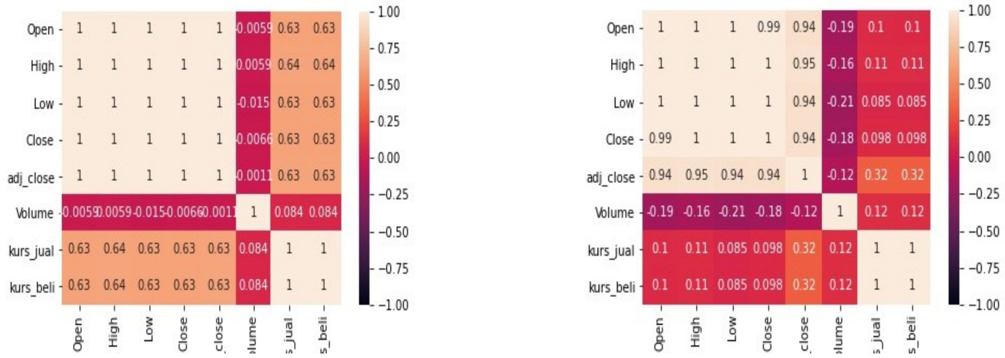
The data used in the prediction is data on the share price of Bank BRI, Bank BNI, Bank BCA, Bank Mandiri and rupiah exchange rate data obtained from the yahoo finance and Bank Indonesia website pages. The data includes parameters including open, close, adj close, low, high, and volume parameters for stock price data. Value, buying rate, and selling rate for rupiah exchange rate data.

3.2. Preprocessing Data

Data merging is used to combine two data or more data sets originating from different sources as can be seen in the Fig. 2.



(a) Bank BRI (b) Bank BNI



(c) Bank BCA (b) Bank Mandiri

Fig. 2. Missing data on bank data (a) Bank BRI, (b) Bank BNI, (c) Bank BCA, (b) Bank Mandiri

The next stage determines the missing values or values that are missing some information that is often encountered during data collection. These, missing values can be resolved by the mean. The first step ascertains on the data whether any values are missing by checking the data with the is null () function. There is missing data on BRI, BNI, and Mandiri bank data. Furthermore, the missing data is filled with interpolated values on each of these data. The interpolation method used because the data is of the time series type. In stock price data before making a selection on the features to be used, data correlation is carried out first. This data correlation is carried out in order to find out the relationship between one variable and another.

The features used in this study are open, high, low, close, adj close, selling rate, buying rate. In BCA bank variable volume is not used in the selected feature. Because, it has a less strong correlation. In BNI, BRI, and Mandiri banks with variable volume, the buy/sell rate is not used in the selected feature. Because, it has a less strong correlation.

In some datasets there is a different range of values in each attribute. Because of the difference in the range of values for each attribute, attributes with a value that is much smaller than the other attributes will not work. Normalization is performed to balance the range of values on each attribute with a specific scale. Before normalizing the data must be of type float. Normalization of stock price data is scaled at a range of 0 to 1 using MinMaxScaler, which is shown in Table 2.

Table 2. Bank data correlation variable

Data	Variables that have a strong correlation
Bank BRI	Open, High, Low, Close, adj_close
Bank BNI	Open, High, Low, Close, adj_close
Bank BCA	Open, High, Low, Close, adj_close, selling_rate, buying_rate
Bank Mandiri	Open, High, Low, Close, adj_close

Before converting, first know what time series and supervised learning type data looks like. A time series is a sequence of numbers sorted by time index. Meanwhile, supervised learning consists of input (x) and output (y) patterns, so that an algorithm can learn how to predict the output patterns of input patterns.

After converting the number of framing stock price prediction data generated amounts to 14, to select the desired prediction target using the drop() function. Before choosing a prediction target, the close feature should be in the var1 position. The prediction target is the close feature. After the conversion of the data series to supervised learning, then the division of data which will be divided into training data, validation data and test data.

Training data is data used during training, validation data is data that is taken a little from the training data for use at the time of the validation process, and test data is data used for model testing, this data should never be seen by the model before. Data sharing uses 80% for training data, 10% for validation data, and 10% for test data. In training and testing datasets, data is divided into input and output variables. In creating a dataset, the input is reshaped into 3D consisting of samples, timesteps, features using the reshape () function. Samples is the number of sample data to be used, timesteps are how long it takes for each sample, features are the number of dimensions used at each time step. In the training and testing input variables, the training samples numbered 1396, the validation amounted to 174 and the tests numbered 175, the timesteps on each input variable used 1-time or one-step, features on each input variable using 7 dimensions including the close, open, high, low, adj close, selling rate, buying rate. The output variable uses one feature, namely close with 1396 training data, 174 validation data and 175 test data.

3.3. BiLSTM Model Design and Training

At the design stage of the biLSTM model, hyperparameter tuning is carried out first, so that it is easy to find out which parameters are appropriate to use. The hyperparameter tuning method uses the sklearn-deap framework using the Genetic Algorithm (GA) algorithm.

Table 2. Parameter biLSTM model design and training

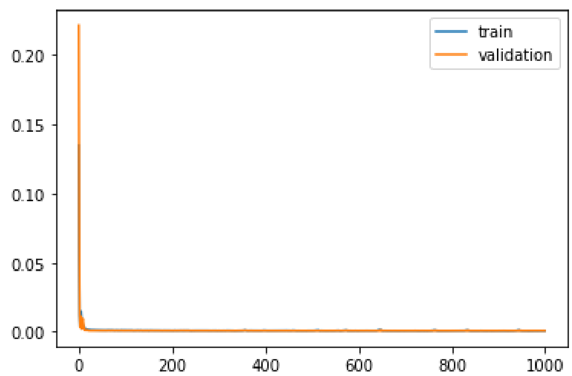
No	Parameter Name	Parameters used
1.	Units Bidirectional LSTM	range(30, 160)
2.	Units Dense	range(40, 120)
3.	Activation	[relu, tanh, sigmoid]
4.	Learning rate	[0.0001, 0.0005]
5.	batch_size	[250, 350, 450]
6.	Epochs	[500, 1000]

Hyperparameter tuning with genetic algorithms using 374400 parameter combinations, the more combinations the resulting process time of finding the best parameters will be longer. After performing hyperparameter tuning on the model and getting the best parameters from the hyperparameter optimization (HPO) algorithm with Genetic Algorithm (GA), the results are implemented into the model.

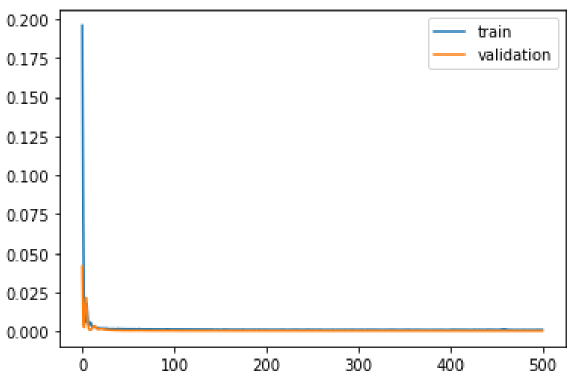
Table 3. Results of hyperparameter tuning

Data Name	Parameter Name						MSE
	Units biLSTM	Units Dense	Activation	Learning Rate	Batch Size	Epochs	
Bank BRI	127	115	tanh	0.0005	350	1000	0.00036
Bank BNI	127	115	tanh	0.0005	350	500	0.00038
Bank BCA	104	95	relu	0.0005	250	1000	0.00037
Bank Mandiri	89	66	tanh	0.0005	350	500	0.00053

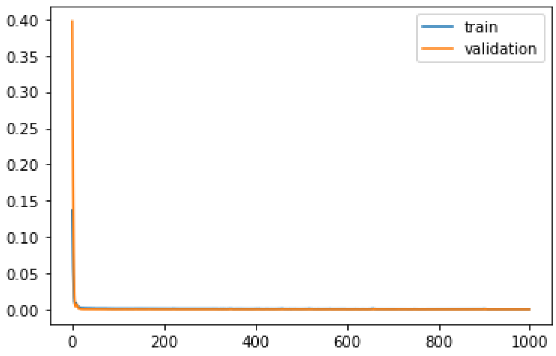
Then, the model is trained to know whether the model that has been designed is suitable or not in a problem. Incompatibility in a model can occur overfitting and underfitting which can affect the prediction results to be less than optimal. Overfitting is a condition where the model studies the data too well while underfitting is the opposite. The solution to the problem of underfitting is to increase the complexity of the model by adding the number of parameters and adding epochs. Instead, the solution is to deal with the problem of overfitting by lowering the complexity of the model.



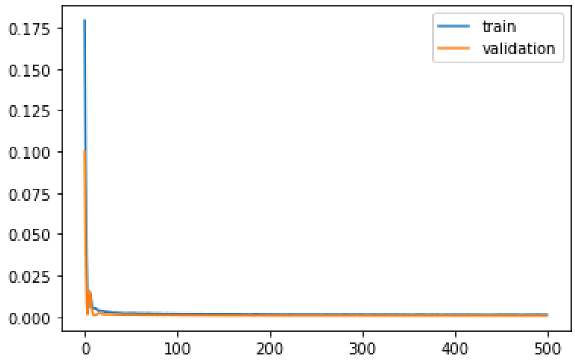
(a) Bank BRI



(b) Bank BNI



(c) Bank BCA



(d) Bank Mandiri

Fig. 3. Graph of the results of training the biLSTM model

3.4. Model Evaluation

After the data is trained, the model is evaluated using test data that was not included at the time of training. Model evaluation is done to find out whether the model has been trained is good using data that has not been seen before. The performance of the model will be said to be good if the loss of test data is almost the same as that of the training data. At the time of evaluation, the system will return loss values and metrics for the model. Where is the loss to optimize the model and metrics to assess the performance on the model.

3.5. Data Prediction

Next, the data is predicted using the new test data. In data prediction, the function used to predict is predict(). Because, this function will return a prediction result for each data from the test X in the form of an array.

Table 4. Results from predictive data

Date	Current	Predictions	RMSE	MAP
		Bank BRI		
12/23/2021	4100	4064.12	35.87	0.87 %
12/24/2021	4070	4104.72	35.30	0.86 %
…..	…..	…..	…..	…..
8/29/2022	4250	4290.18	75.05	1.20 %
8/30/2022	4260	4263.45	74.82	1.20 %
		Bank BNI		
12/23/2021	6650	6669.90	19.90	0.29 %
12/24/2021	6725	6666.87	43.44	0.58 %
…..	…..	….	….	…..
8/29/2022	8200	8288.40	160.34	1.41 %
8/30/2022	8425	8175.57	161.03	1.42 %
		Bank BCA		
12/23/2021	7300	7314.44	14.44	0.19 %
12/24/2021	7300	7280.09	17.39	0.23 %
…..	…..	…..	…..	…..
8/29/2022	8150	8033.20	114.25	1.10 %
8/30/2022	8175	8117.41	113.99	1.10 %
		Bank Mandiri		
12/23/2021	7075	7094.08	19.08	0.26 %
12/24/2021	7050	7098.05	36.56	0.47 %
…..	…..	…..	…..	…..
8/29/2022	8550	8541.71	143.93	1.22 %
8/30/2022	8650	8517.56	143.86	1.22 %

Table 5. Results of predictive data testing

Data Name	Accuracy Results	
	RMSE	**MAP**
Bank BRI	74.82	1.2 %
Bank BNI	161.04	1.43 %
Bank BCA	114	1.1 %
Bank Mandiri	143.87	1.23 %

3.6. Visulisasi Data

Prediction results are analyzed using a graph so that the resulting results can be easily understood the pattern between actual data and prediction data. Visualization of predictions using data with a period of December 23, 2021 – August 30, 2022.

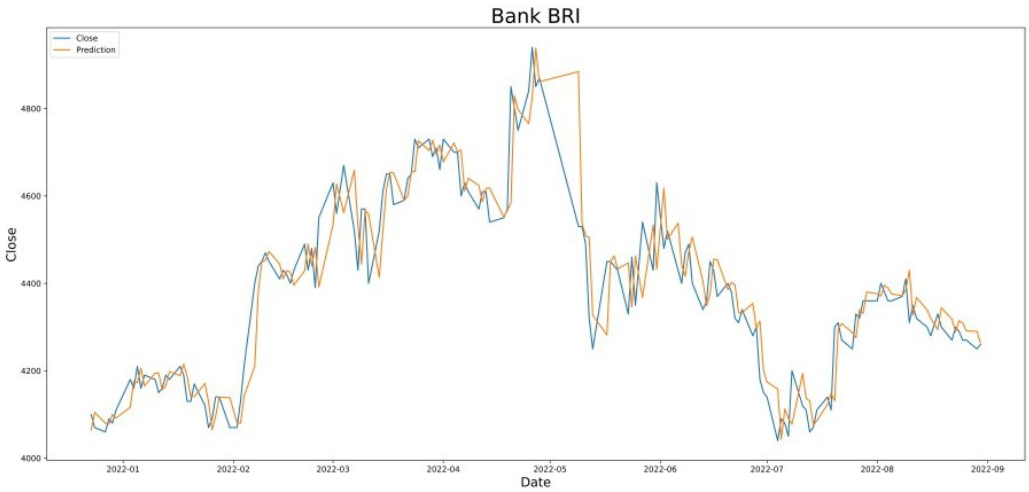


Fig. 4. Visualization of prediction Bank BRI

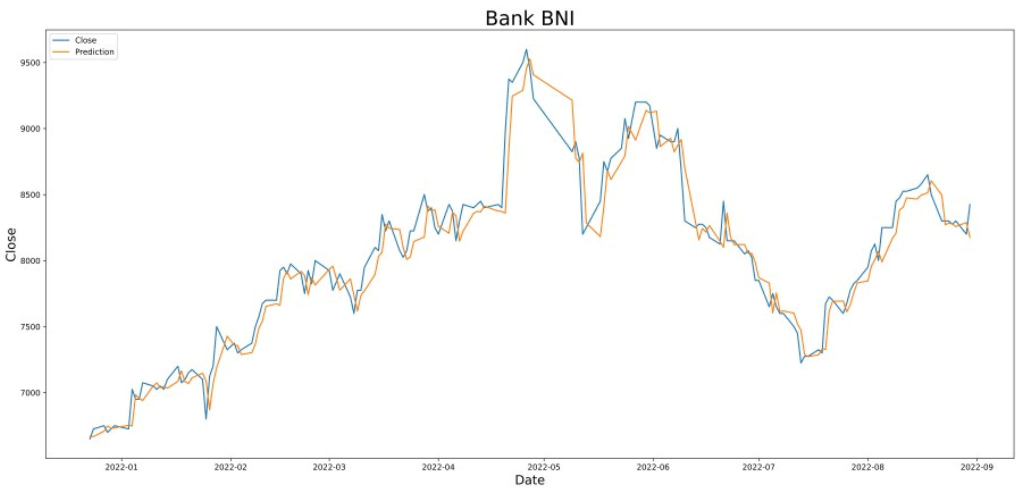


Fig. 5. Visualization of prediction Bank BNI

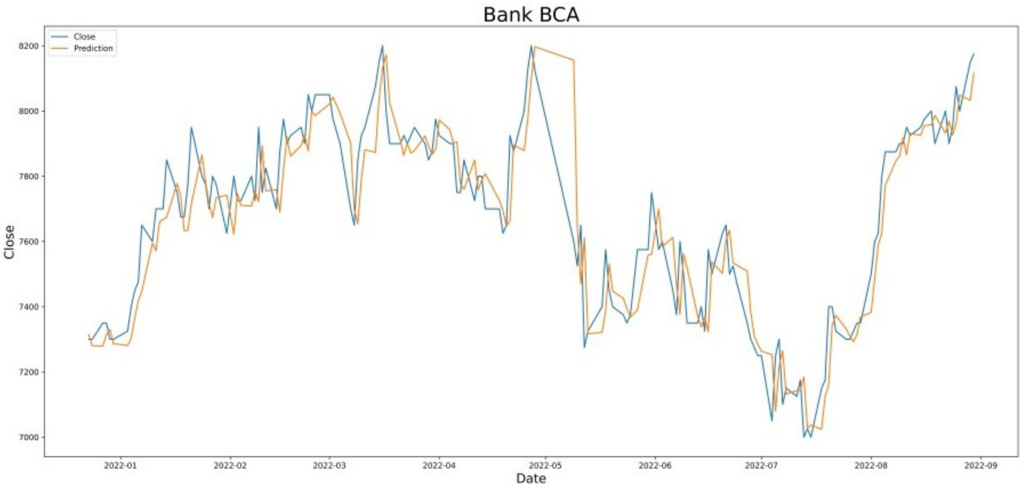


Fig. 6. Visualization of prediction Bank BCA

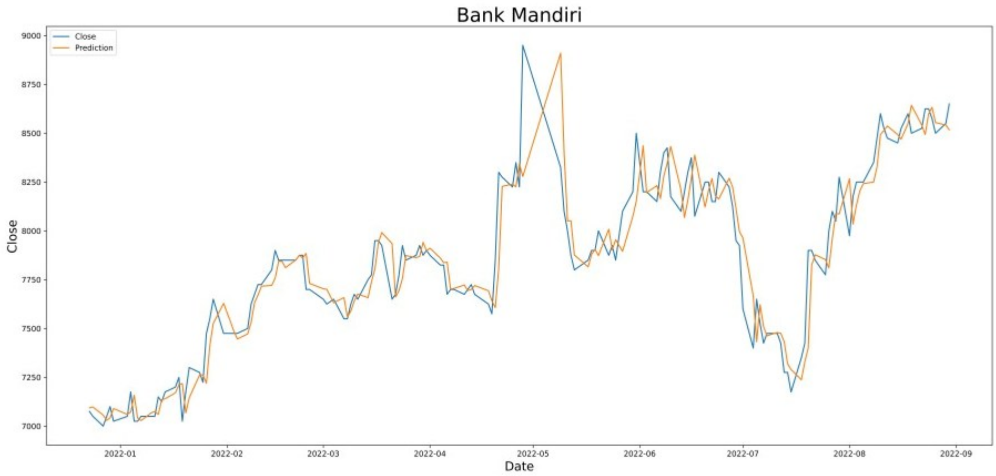


Fig. 7. Visualization of prediction Bank Mandiri

4. Conclusion

Based on the results of research that has been carried out to analyze stock price predictions in the banking sector with Multivariate Time Series data using the Bidirectional Long Short-Term Memory (biLSTM) algorithm, the biLSTM algorithm can predict stock prices accurately because it has a relatively low RMSE value with a MAPE value below 10%.

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