Predicting Stock Market Trends Based on Moving Average Using LSTM Algorithm

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Abstract

Prediction of the stock market is highly needed to assist traders in making decisions. Many methods are used by traders to predict this such as technical analysis and moving averages. Moving averages predict stock trends based on the past data of the stock. The disadvantage of using a moving average analysis is the delay in crossover signals. As a solution, a deep learning technique known as LSTM is applied to the moving average strategy in this paper. In this research, the BBCA stock dataset spanning from 2010 to 2018 was utilized. The data was segmented into two parts: 2010-2017 for training data and 2018 for testing data. The training process employed Long Short-Term Memory (LSTM) networks, with the subsequent results being combined with moving average crossover techniques. Validation results indicate that BBCA shows a relatively minimal error. BBCA's average MAPE is 1.1%, and its RMSE is 65.402, classifying it within the "Highly Accurate Forecasting" category. Various combinations of moving average crossovers were tested during model training, with the combination of SMA05 and SMA50 for BBCA yielding the highest profit potential. Stocks that exhibit a downward trend are more likely to incur substantial losses. The model can predict the reversal of trends by predicting the trading signal given by the moving averages.

***Keywords** - LSTM, Machine Learning, Moving average, Moving average crossover, RNN, Stock Market Trend prediction*

1. INTRODUCTION

Prediction of the stock market is highly needed to assist in making decisions for investors. The stock market is a place for the buying and selling process of stocks. Stocks are defined as a form of participation or ownership of an individual or entity in a company or limited liability company. The stock price indicates company value that investors can use in valuing a stock [1]. Stocks are one of the investment instruments that individuals can use to invest their money to generate passive income. In addition to earning passive income, many investors use uncertain stock prices to engage in trading. To make a profit, buying stocks at a low price and selling them at a high price is an ideal approach. However, predicting stock price movements is not easy, whether the stock is at a low enough point to buy or high enough to sell. Therefore, many methods are used by traders to predict this, including technical analysis, market sentiment, business trends, and financial reports.

Technical analysis is the study of market action, primarily through the use of charts, to forecast future price trends [2]. One of the technical analyses used is the analysis using a moving average. A moving average is the average value of price movements over a specific period to determine the trend [3]. Traders use a moving average crossover to identify trends in stocks. The concept of the Moving Average Crossover strategy is when the short-term moving average rises above the long-term moving average, indicating a positive signal, which shows that the stock or asset value has an increasing trend. Conversely, when the short-term moving average moves down through the long-term moving average, it is a bearish indicator, indicating that the stock value has a decreasing trend.

Moving averages predict stock trends based on the past data of the stock. The disadvantage of using a moving average analysis is the lag or delay in crossover signals, as moving averages will show movement when a significant amount of data is provided. Lag results in a reduction in the potential profits obtained by the trader.

Employing deep learning was the next phase in improving prediction models with better performance. As a solution to the disadvantage of the moving average strategy, deep learning techniques applied to the moving average strategy are proposed in this paper. Deep learning techniques automatically recognize and learn patterns of changes in stock market prices in a large amount of data. This research aims to apply deep learning to predict the results of moving averages so that the lag issue in the moving average method can be overcome.

The authors in [4] attempted to compare 9 machine learning models and 2 deep learning models, namely RNN & LSTM, resulting in the conclusion that the deep learning methods RNN and LSTM are superior to the 9 machine learning models. However, the authors did not specify which one is better between RNN and LSTM. The authors in [5] conducted a study using Region Activity Identification and 4 techniques to find trend indicators, which were then trained and tested with SVM. The research concluded that the use of a trading system with a simple moving average using SVM is highly suitable. The authors in [6] compared ARIMA and LSTM models, and the results showed that LSTM outperformed ARIMA due to its lower RMSE value. The authors in [7] aimed to find an accurate modeling composition and design appropriate variables to predict future stock prices by comparing 8 machine learning and 4 different LSTM algorithm architectures. The result showed that the LSTM-based univariate model, which uses one-week prior data as input to predict the next week's open value of the NIFTY 50 stock, is the most accurate model. The authors in [8] attempted to find stocks with the lowest MAPE among LQ45 stocks using a 3-layer LSTM algorithm. The results showed that the MAPE values for BBCA and BMRI were the lowest, indicating an improvement using LSTM in prediction.

The authors [9] predicted the close price of GOOGLE stock from April 30th, 2017, to April 30th, 2022, with a training data range of 95%. They trained using the LSTM and ARIMA algorithms and compared the performance results of each algorithm. The results showed that LSTM outperformed ARIMA because it had better MSE, MAE, and RMSE values. The authors [10] predicted the close price of the S&P 500 using the proposed hybrid model LSTM-ARIMA compared to the forecasting library "Prophet". The results showed that the ARIMA-LSTM hybrid was better because it gave an MSE of 3.03 and RMSE of 1.74. The authors [11] predicted the close price of Google, Nifty50, TCS, Infosys, and Reliance Stocks using the LSTM algorithm. The results showed that LSTM had a prediction accuracy of over 93%. The Authors of [12] present a comparative study evaluating the performance of LSTM neural network models against SVM regression models using the Dow Jones Index (DJI) stock price dataset and an extended dataset including crude oil and gold prices. The analysis reveals that the LSTM advanced model with moving averages significantly improves stock price prediction, outperforming other models. Thus, the LSTM advanced model with moving averages is determined to be the most effective for predicting stock prices. Authors [13] focus on comparing various neural network methods and selecting the LSTM neural network, optimized with the MBGD algorithm using China's stock market. Despite some limitations, the LSTM neural network model, enhanced with an attention layer, effectively predicts stock prices by analyzing historical information and exploring internal market rules.

Authors in [14] explore future trend prediction of stock prices using deep learning techniques. Applied to stock price prediction, the LSTM model is compared with the RNN model, showing that the LSTM model has a smaller error value and better prediction accuracy. Thus, the LSTM neural network is more suitable for stock price prediction. Hasan et al, in [15] trained a system to predict Dhaka Stock Exchange (DSE) prices in graphical format using LSTM. The system is available as a live web service through Django and an Android application. Test results show a prediction accuracy of 70%. Nelson et al, in [16] explore the use of LSTM networks to predict future stock price trends based on historical prices and technical analysis indicators. The results showed that the LSTM model achieved an average accuracy of 55.9% in predicting stock price movements, outperforming baseline models in most cases. Nikhil Sawalkar et al. [17] use the LSTM model to forecast corporate growth by analyzing past stock prices. The methodology involves splitting the data into 75% for training and 25% for testing and evaluating the model using Accuracy, MSE, and Root Mean Square Error (RMSE). The results for the Reliance dataset show promising accuracy in predicting stock prices.

Deep Learning is a specialized neural network consisting of multiple layers. This network is superior to traditional neural networks in retaining information from previous states. Recurrent Neural Network (RNN) is one type of network that has a combination of networks in a loop, allowing information to persist. Each network in this loop takes input and information from the previous network, performs specified operations, and produces output while passing information to the next network [18]. LSTM is one type of RNN, which can selectively retain necessary information; this process occurs in each neuron [19]. This can improve model accuracy, making LSTM a reasonable choice for usage. The LSTM module, called the recurrent module, has four layers of neural network modules that interact with each other, as shown in Figure 1.

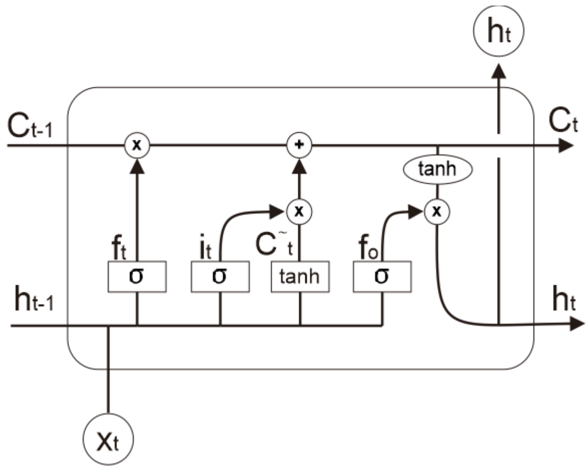

Figure 1. LSTM Algorithm Diagram

In Figure 1, there are several symbols including 'x' representing multiplication, '+' representing addition, σ representing sigmoid, and tanh representing hyperbolic tangent. The basic components of LSTM include the cell state, a line running from C_{t-1} to C_t. f_t is the value of the forget gate at the current cell is defined in Equation (1), i_t is the value of the input gate defined in Equation (2), C_{t-1} is the cell state 1 step before defined in Equation (3), C_t is the current cell state defined in Equation (4), $C^{\sim}{}_t$ it is the value of the candidate cell, f_o is the value of the output gate defined in Equation (5), W_f, W_i, W_c, W_0 are the network weights, b_f, b_i, b_c, b_o are the bias variable values, h_t is the value of the current hidden state defined in Equation (6), h_{t-1} is the value of the previous hidden state, and x_t is the new input value at the current cell. Two nonlinear activation functions are used here, namely the sigmoid activation function (σ) and the hyperbolic tangent (tanh) activation function [20]. The following are the LSTM equations:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

$$C_t^{\sim} = tanh(W_c[h_{t-1}, x_t] + b_c) \tag{3}$$

$$C_t = f_t \times C_{t-1} + b_f \times C_t^{\sim} \tag{4}$$

$$f_o = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = f_o \times tanh(C_t) \quad (6)$$

2. RESEARCH METHOD

This paper proposes the use of Deep Learning on Technical Indicators. The proposed model is Long Short Term Memory (LSTM) on the moving average to predict the moving average crossover in time. There are several stages in this study to apply the LSTM algorithm using MA. These stages include Data Collection, Preprocessing, Data Preparation, Training, Validation and Testing, Application of SMA Crossover Analysis, and Conclusion of the research results. These research stages are illustrated in a diagram in Figure 2.

Stock market data of PT. Bank Central Asia Tbk (BBCA) is collected from January 2010 – December 2018. Each row represents a day's Date, Close Price, Open Price, High Price, Low Price, and Volume. The process in pre-processing to add 2 data, namely the 5-day moving average (MA05), the 10-day moving average (MA10), the 20-day moving average (MA20), the 50-day moving average (MA50), and the 100-day moving average (MA100).

After pre-processing, creating LSTM modeling, then determining the batch size, selecting an optimizer, specifying the number of epochs, and determining the loss function. This training process will be performed using the training dataset that has been augmented with moving average data. Weights and biases will be continuously updated to obtain a suitable model.

The LSTM model will be trained in all MA that we get. When MA short rises above MA long, it indicates a positive signal, suggesting that the stock or asset value is trending upward and will get output 1. Otherwise, when MA shortfalls below MA long, suggesting that the stock value is trending downward and will get output -1. If there is no crossover, it will get output 0.

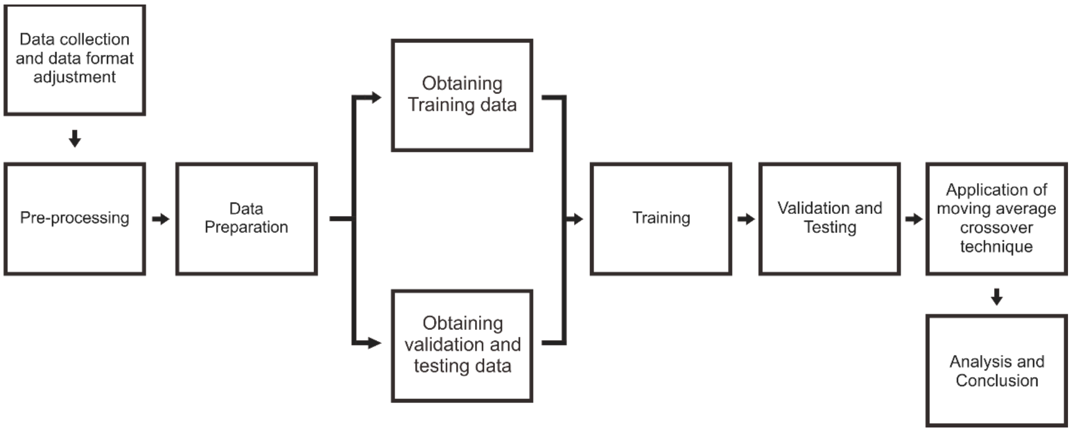

Figure 2. Flowchart of the LSTM model training process using moving average

Table 1. Show LSTM architecture for this model.

Table 1. The architecture of the prediction model

Layer (type)	***Output***
LSTM_1	(None, 60, 128)
LSTM_2	(None, 64)
Dense_1	(None, 25)
Dense_2	(None, 1)

The performance of the LSTM model was conducted using several evaluation metrics, namely Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The calculation of RMSE was performed to measure the average magnitude of errors between the predicted values and the actual values. The calculation of MAPE was conducted to determine the level of error in percentage form [21]. The formulas for RMSE and MAPE are defined by equations (7) and (8) respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2} \quad (7)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_i - \hat{y}|}{y_i} \; x \; 100\% \quad (8)$$

The smaller the MAPE value, the better the predictive model. The range of values that can be used to determine the capability of a predictive model is shown in Table 2.

Table 2. Interpretation of MAPE values

MAPE	Interpretation
<10 %	Highly Accurate Forecasting
10 – 20 %	Good Forecasting
20 – 50 %	Reasonable Forecasting
>50 %	Inaccurate Forecasting

3. RESULT AND DISCUSSION

The training was conducted on BBCA stock by using several Simple Moving Averages (SMA) including SMA05, SMA10, SMA20, SMA50, and SMA100. Then, the closing prices and each SMA were trained using the LSTM deep learning model that had been created. The training process took 6 minutes for all features, with a limit of 15 epochs. Table 3 shows the data obtained after the training process.

Table 3. Training result in BBCA stock

	SMA 05	SMA 10	SMA 20	SMA 50	SMA 100
Loss	0.0001383	0.0000826	0.0000638	0.0000368	0.0000180
Val_loss	0.0004466	0.0002395	0.0001790	0.0002008	0.0000479
RMSE	88.5082807	64.3419693	55.3345744	55.1555260	26.6879644
MAPE	0.0151526	0.0113428	0.0103575	0.0097453	0.0045281
Epoch	15	15	15	10	12

Training for SMA50 and SMA100 stopped at epochs 10 and 12 because they already had MAPE below 0.01. SMA100 has the smallest error compared to the others. The visualization of the training results can be seen in Figure 3.

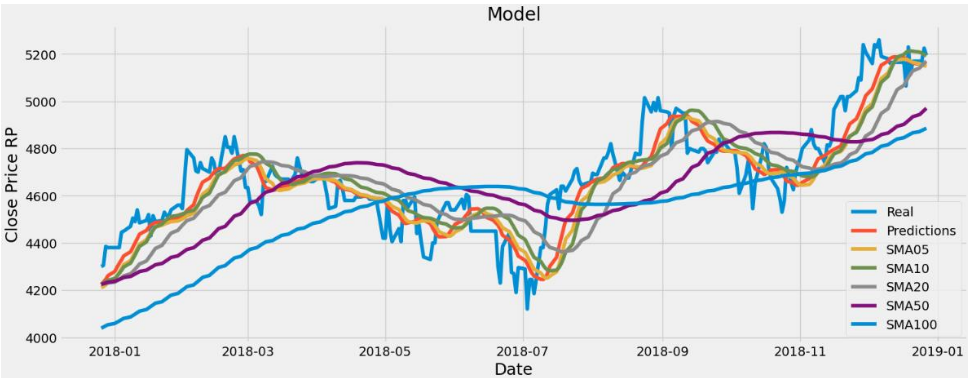

Figure 3. Training Result

The moving average crossover technique was applied to some of the obtained SMA predictions. Some combinations of SMA were analyzed, including SMA05 with SMA20, SMA05 with SMA50, SMA05 with SMA100, SMA10 with SMA50, and SMA10 with SMA100. The graph also includes SMA 100 to observe resistance to the existing trend. The analysis images for several SMA combinations can be seen in Figures 4 to 8.

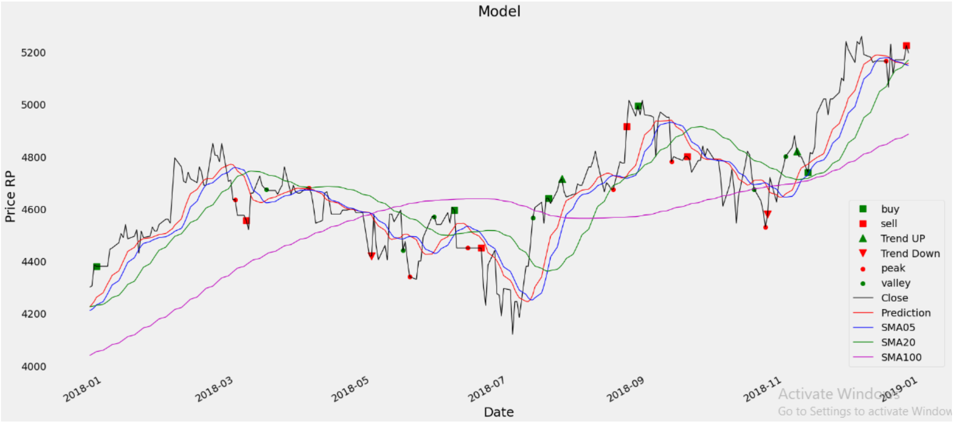

Figure 4. Visualization of SMA 05 graph with SMA 20 against real data

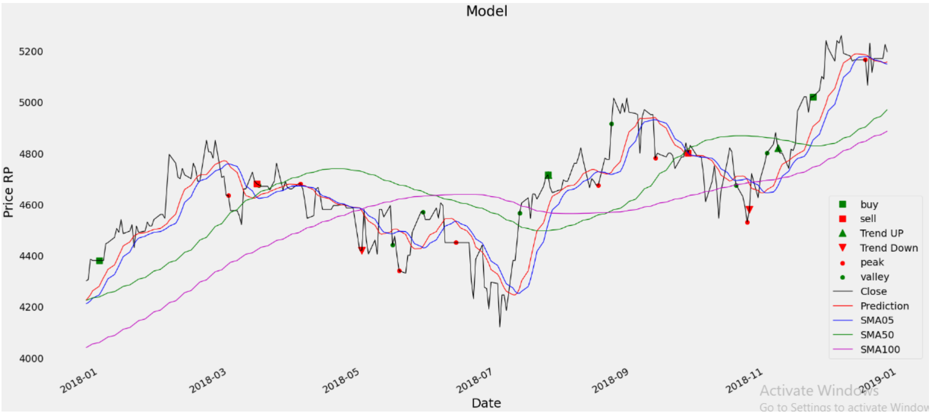

Figure 5. Visualization of SMA 05 graph with SMA 50 against real data

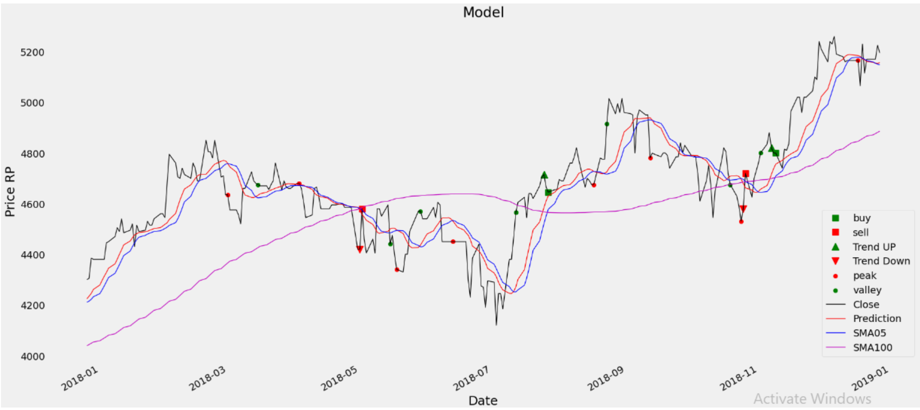

Figure 6. Visualization of SMA 05 graph with SMA 100 against real data

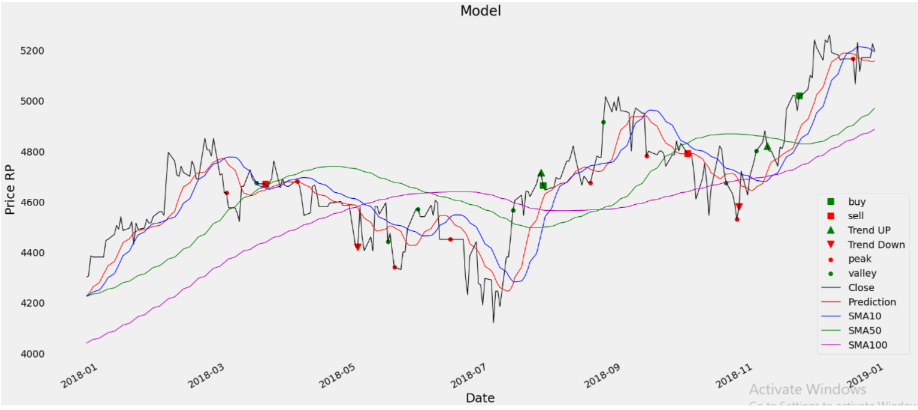

Figure 7. Visualization of SMA 10 graph with SMA 50 against real data

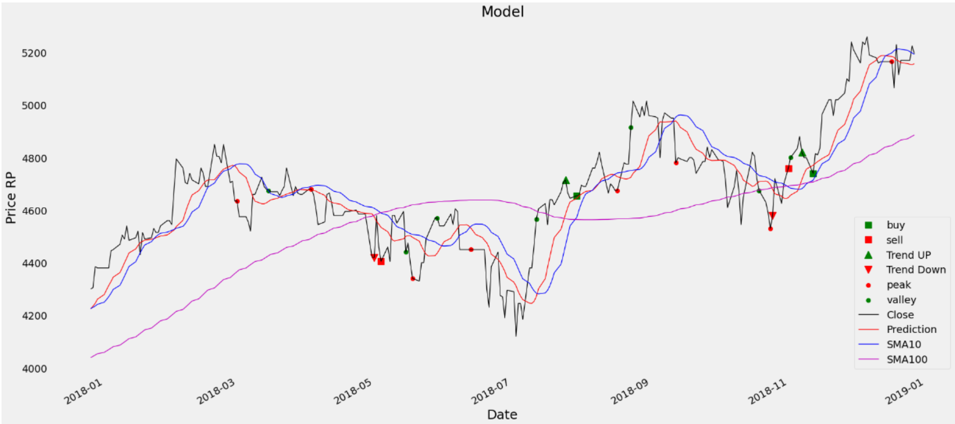

Figure 8. Visualization of SMA 10 graph with SMA 100 against real data

Details of the crossovers generated from several simple moving average crossovers can be seen in Table 4 to Table 8.

Table 4. Crossover SMA 05 & SMA 20

Crossover SMA 05 & SMA 20							
Date	Close	SMA05	SMA10	SMA20	SMA50	SMA100	Position
29/12/2017	4380	4232.26	4241.6	4230.54	4233.5	4053.55	Buy
01/05/2018	4420	4581.38	4606.8	4645.59	4727.88	4580.55	Sell
07/06/2018	4595	4501.55	4491.42	4501.28	4623.02	4636.19	Buy
19/06/2018	4450	4503.14	4543.15	4513.8	4598.45	4639.02	Sell
19/07/2018	4640	4376.82	4333.92	4361.65	4497.58	4576.84	Buy
25/07/2018	4715	4521.15	4466.81	4384.76	4496.56	4567.16	Sell
28/08/2018	4995	4742.97	4761.16	4740.68	4589.49	4571.01	Buy
25/10/2018	4580	4695.63	4711.77	4762.74	4866.95	4685.21	Sell
12/11/2018	4740	4729.14	4713.85	4716.37	4848.27	4707.01	Buy

Table 5. Crossover SMA 05 & SMA 50

Crossover SMA 05 & SMA 50							
Date	Close	SMA05	SMA10	SMA20	SMA50	SMA100	Position
01/01/2018	4380	4244.79	4249.69	4234.3	4237.13	4058.66	Buy
14/03/2018	4680	4626.28	4687.72	4735.84	4637.39	4421.07	Sell
25/07/2018	4715	4521.15	4466.81	4384.76	4496.56	4567.16	Buy
27/09/2018	4800	4801.23	4854.95	4910.78	4816.01	4632.14	Sell
23/11/2018	5020	4850.53	4852.11	4773.45	4828.68	4745.21	Buy

Table 6. Crossover SMA 05 & SMA 100

Crossover SMA 05 & SMA 100							
Date	Close	SMA05	SMA10	SMA20	SMA50	SMA100	Position
01/05/2018	4420	4581.38	4606.8	4645.59	4727.88	4580.55	Sell

27/07/2018	4645	4577.9	4540.25	4409.98	4499.23	4564.91	Buy
26/10/2018	4720	4686.58	4706.79	4756.5	4866.12	4686.78	Sell
09/11/2018	4800	4709.23	4700.1	4713.24	4850.68	4704.08	Buy

Table 7. Crossover SMA 10 & SMA 50

Crossover SMA 10 & SMA 50							
Date	Close	SMA05	SMA10	SMA20	SMA50	SMA100	Position
01/05/2018	4420	4581.38	4606.8	4645.59	4727.88	4580.55	Sell
26/07/2018	4665	4551.18	4504.36	4396.25	4497.62	4565.84	Buy
25/10/2018	4580	4695.63	4711.77	4762.74	4866.95	4685.21	Sell
22/11/2018	5020	4829.2	4836.68	4761.81	4829.5	4739.66	Buy

Table 8. Crossover SMA 10 & SMA 100

Crossover SMA 10 & SMA 100							
Date	Close	SMA05	SMA10	SMA20	SMA50	SMA100	Position
01/05/2018	4420	4581.38	4606.8	4645.59	4727.88	4580.55	Sell
30/07/2018	4655	4601.11	4572.83	4425.42	4501.42	4564.29	Buy
01/11/2018	4760	4645.58	4688.45	4728.76	4861.66	4692.25	Sell
12/11/2018	4740	4729.14	4713.85	4716.37	4848.27	4707.01	Buy

From the above transaction data, some data can be extracted, and the analysis can be seen in Table 9.

Table 9. Crossover Combination Trade Analysis

	SMA 05 vs SMA 20	**SMA 05 vs SMA 50**	**SMA 05 vs SMA 100**	**SMA 10 vs SMA 50**	**SMA 10 vs SMA 100**
Amount trade	4	2	1	1	1
Winning Trade	2	2	1	0	1
Losing Trade	2	0	0	1	0
Winning Trade Percentage	50%	100%	100%	0%	100%
Losing Trade Percentage	50%	0%	0%	100%	0%
Average of profit per trade (%)	2.624%	8.786%	1.712%	0%	2.396%
Average of Losing per trade (%)	-12.779%	0%	0%	-1.940%	0%
Loss / Profit (%)	-10.155%	8.786%	1.712%	-1.940%	2.396%

Table 8 shows that BBCA experienced 4 trades using the combination of SMA05 and SMA20 with a 50% winning trade and 50% loss trade percentage. In the SMA05 and SMA20 combination, there was a loss of 10.155%. SMA05 vs SMA50 obtained an average profit of 8.786% on 2 trades that occurred. SMA05 vs SMA100 and SMA10 vs SMA100 both experienced 1 trade and obtained profits of 1.712% and 2.396% respectively. Meanwhile, in SMA10 vs SMA50, there was a loss of 1.940%. The largest profit that can be obtained in BBCA stock is by using the combination of SMA05 and SMA50, namely using the medium term in 2018. we can conclude that the SMA crossover combination between SMA5 and SMA50 can generate a profit of 8.786%, which is larger than other SMA crossovers. Therefore, the LSTM deep learning model with the simple moving average crossover technique between SMA5 and SMA50 is highly suitable for BBCA stock.

4. CONCLUSION

The prediction model is trained using the BBCA dataset, which includes blue-chip stocks within the range of 2010 - 2018. By selecting a specific dataset, researchers can evaluate the performance of the model being studied without external factors, such as recessions, wars, and other events, that could cause anomalies in stock price changes. The validation results show that BBCA has small errors with an average MAPE of 1.1% and RMSE of 65.4017078. The average MAPE obtained from this prediction model is 1.1%, which falls into the category of "Highly Accurate Forecasting". From the model training results, several combinations of SMA crossovers are taken, and the largest potential profit is obtained in the SMA05 & SMA50 combination. The results of this study are relevant for BBCA stocks, as they are generally stable with relatively flat price movements. This research can assist investors in forecasting stock trends, enabling them to identify which stocks are more dependable for investment.

In the future, researchers will develop this stock market prediction model by adding variations of moving averages to observe the prediction results and compare them with the moving average methods that have already been applied. The development of the prediction model using technical analysis of support and resistance, as well as incorporating market sentiment variables, can be done to improve the accuracy of predictions.

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