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Predicting Stock Price Using Convolutional Neural Network and Long Short Term Memory (Case Study: Stock of BBCA)

Zubaidah Pangestika[1], Bony Parulian Josaphat[2*]

[1]**BPS Kabupaten Bantaeng, Sulawesi Selatan, Indonesia, zubaidah.pangestika@bps.go.id**

[2]**Politeknik Statistika STIS, Indonesia, bonyp@stis.ac.id**

Abstract. Stocks are capital market instruments capable of creating profits for investors. However, stocks have a fluctuating nature that can lead to risk, so price predictions are needed to reduce this risk. Stock price prediction can use various methods such as deep learning. This study aims to predict stock price using Convolution Neural Network (CNN) and Long Short Term Memory (LSTM), with the application carried out at the stock price of Bank Central Asia (BBCA) for the period between July 1, 2005 and December 30, 2022. Data division uses a ratio of 70% for training and 30% for testing. To maximize prediction results, we select the best hyperparameter combinations using Grid Search. The prediction results show that CNN is better to LSTM, where CNN produces RMSE values of 488.992, R^2 83.8%, and MAPE 6.5%.

Key words and Phrases: CNN, deep learning, grid search, LSTM, stock price

1. INTRODUCTION

The financial sector is an important sector in the economic growth of a nation. In general, this sectors covering the banking, capital market, and non-bank financial industry. In particular, the capital market is considered capable of improving the people's economy, one of which is through stock investment [1]. Furthermore, stocks are able to create benefits as well as risks for investors [2]. Besides having a nonlinear and volatile nature and difficulty to extract the pattern, stocks also have a fluctuating nature that can be influenced by many factors, including supply and

*Corresponding author

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demand [2, 3]. Therefore, it is necessary to predict stock price to maximize profit and minimize risk.

Stock price prediction have been carried out by several previous researchers using various methods, including by Wadi et al. [4] which uses the Autoregressive Integrated Moving Average (ARIMA) method. However, the use of the ARIMA method requires assumptions to be met and this method is unable to model nonlinear data [5]. Other authors such as Kara et al. [6], Ardyanta and Sari [7], Jange [8] and Kordonis et al. [9] predicted stock price using machine learning methods.

The traditional ARIMA and machine learning methods still have drawbacks, which are less accurate and less precise, so we need another method that is able to predict better, which is called deep learning [3]. This method is part of machine learning which has reliable and optimal performance in building models [10]. Long short term memory (LSTM) is one of the deep learning methods widely used to analyze time series data because it is capable of storing both temporal and long-term information [11]. This algorithm is a development of Recurrent Neural Network (RNN) which can overcome weaknesses, namely in terms of long-term dependence.

LSTM is often used to predict time series data with good results.. Arissinta [12] compared three methods namely ARIMA, LSTM, and Gated Recurrent Unit (GRU). The study showed that the accuracy of LSTM and GRU is superior to that of ARIMA. Bathla [3] also explained that LSTM has better accuracy than support vector regression (SVR) in predicting stock price. In addition, the convolutional neural network (CNN) is another deep learning method that is also often used to make predictions. Although CNN is more often used on image data than time series data, CNN has proven to be used effectively in predicting time series data which results in smaller mean absolute percentage error (MAPE) and root mean squared error (RMSE) than those of SARIMAX [13].

Chen and He [14] and Sayavong et al. [15] have used CNN to predict stock price, both of which showed good accuracy. Unfortunately, these two papers only used stock price history in making predictions. In fact, stock price can be influenced by many factors. According to Fitriadini et al. [2], stock price can also be influenced by demand, supply, interest rates, inflation, and company performance. Meanwhile, according to Putri and Tjahhjono [16], stock price can be influenced by both internal and external fundamental factors. Internal fundamental factors include the company's dividend distribution, general shareholders meeting, and investor's information. While external factors consist of government policies, the exchange rate of Indonesian rupiah (IDR) against US dollar (USD), inflation, and interest rates.

Based on the explanation above, this study aims to predict stock price using LSTM and CNN methods. The variables we use are stock price, the exchange rate of IDR against USD (the Indonesia rupiah exchange rate), interest rates, technical indicators, and foreign stock price indexes. The case study of this research is the stock price of Bank Central Asia (BBCA). The reasons for implementing banking stocks for case study is that banking is included in a country's economic drive, both directly and indirectly [17]. Banking stocks as part of the financial sector are also a major contributor to the Composite Stock Price Index [18]. Furthermore, banking stocks play a significant role in suppressing the Jakarta Stock Exchange Composite (JKSE), such as the decline in the JKSE on 19 February 2016 due to the weakening of stocks of BBNI, BMRI, BBRI and BBCA [19].

Bank BCA is a private bank that is included in the LQ45 group, namely the group that has the largest capitalization value in Indonesia [20]. This group consists of 45 companies on the Indonesia Stock Exchange with the highest liquidity, large market capitalization value, and other predetermined criteria. The stock of BCA (BBCA) has the largest capitalization value in Indonesia with a value of IDR 1,034.31 trillion on January 31, 2023 [21]. This value is higher than the value of stocks of other banks, such as BBRI, BMRI, and BBNI. In addition, BBCA is one of the stocks that has been traded on the capital market for a longer time horizon than the stocks of the other 10 companies with the largest capitalization, so it has a longer historical data. This is especially useful in making predictions using deep learning methods because the more patterns a model can learn, the better the resulting accuracy.

The rest of the paper is organized as follows. Section 2 presents preliminaries including deep learning, convolutional neural network, and long short term memory. Section 3 presents methodology, Section 4 presents the empirical results and conclusion is shown in Section 5.

2. PRELIMINARIES

2.1. **Deep Learning.**

Deep learning is a part of machine learning that has optimal performance in model building [10]. This method can extract complex information using hierarchical learning and has a way of working that mimics the human brain in drawing conclusions about a task. Based on the architecture and techniques, deep learning is divided into three groups [10], namely:

(1) Unsupervised learning
This method has no labeled target data, works by capturing high-level correlations from the data to be analyzed, and is able to model a set of input data automatically. One example of unsupervised learning is clustering.

(2) Supervised learning
This method has labeled target data, both labeled directly and indirectly. Supervised learning can be used to do classification and regression. Furthermore, this method generates a function to map input data to output based on the label it has.

(3) Hybrid Deep Network
This method combines unsupervised learning with supervised learning, where some data has labels and some others are not labeled.

2.2. Convolutional Neural Network.

Convolutional Neural network (CNN) is a model initiated in 1998 by Lecun et al. [22]. This is a feed forward neural network model that has good performance in image processing as well as natural language processing [23]. Although CNN is more often used on image data, the model has also proven to be used effectively for forecasting time series data [13].

CNN architecture consists of input, hidden, and output layers. Generally, the hidden layer contains the convolution layer, pooling, normalization layer, ReLU, fully connected layer, and loss layers [24]. In addition, to avoid overfitting the model, a dropout is added. The convolution layer is the first and main layer for performing convolution operation where this layer has filters that are learned randomly in convolution with the aim of extracting features from the input [25]. Furthermore, this layer has four hyperparameters consisting of the number of filters (K), spatial extent (F), stride (s), and zero padding (p) [26]. The basic architecture of CNN is shown in the Figure 1.

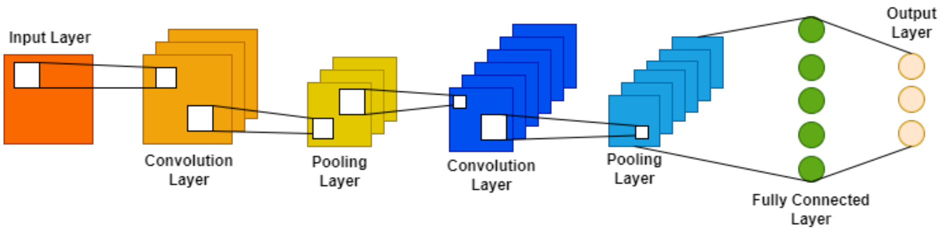

FIGURE 1. The basic architecture of CNN

2.3. Long Short Term Memory.

Long short term memory (LSTM) LSTM was initiated by Sepp Hochreiter and Jurgan Schmidhuber in 1997 [27]. This method is the development of a Recurrent Neural Network which is able to overcome long-term dependence (vanishing gradient). Furthermore, this method is widely used for time series analysis because it is superior to other algorithms [28]. The architecture is shown in Figure 2. LSTM has three gates, namely forget, input, and output gates. Forget gate serves to eliminate unnecessary information using sigmoid function. Input gate works for enter information that is important and still needed. While the output gate is a gate that produces information about the data.

In forget gate, information is selected from the previous cell memory, namely whether (C_{t-1}) is discarded or retained. This gate reads the previous order output value (h_{t-1}) and the current input vector (x_t). Furthermore, the use of the sigmoid activation function produces a value of 0 or 1. When the value is 0 the information is discarded, whereas when the value is 1 the information is retained. The forget gate equation is as follows,

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

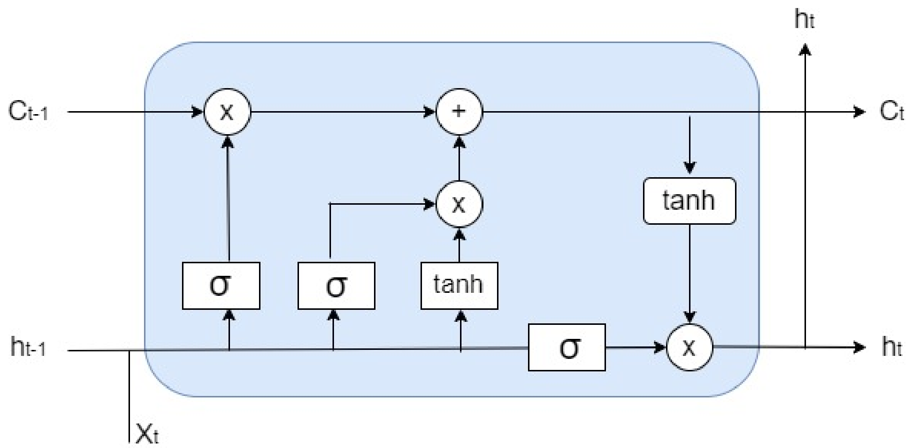

FIGURE 2. The architecture of LSTM

where:

h_{t-1}: previous hidden state
σ : sigmoid activation function
W_f : weight matrix associated with the forget gate
x_t : current input
b_f : bias with the forget gate
f_t : forget gate.

Input gate is useful for specifying information to be added to C_t. This gate consists of two layers, namely a layer to determine the value that is updated using the sigmoid function and a layer to create a new vector saved in the memory cell. The input gate equation is as follows,

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i),$$
$$\tilde{C}_t = \tanh(W_c * [h_{t-1}, x_t] + b_c),$$

where:

tanh : hyperbolic tangent activation function
f_i : input gate
W_i : weight matrix associated with the input gate
b_i : bias with the input gate
$\tilde{C}_t$: candidate cell state
W_c : weight matrix associated with the cell state
b_c : bias with the cell state.

In cell gate, the information contained in memory from previous cell is replaced with a new memory cell obtained from the forget and input gates. The new cell gate equation is as follows,

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t,$$

where:

C_{t-1} : previous cell state
C_t : new cell state
$\tilde{C}_t$: candidate cell state

The output gate has two layers. The first layer discards the memory cell value using the sigmoid activation function and inputs its output to the second layer , namely the hyperbolic tangent layer. Then the two layers are merged to generate the LSTM output. The output gate equation is as follows,

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o),$$

where:

o_t : output gate
W_o: weight matrix associated with the output gate
b_o : bias with the output gate,

Thus, the resulting output value equation is as follows,

$$h_t = o_t * \tanh(C_t),$$

where:

h_t: hidden state
o_t: output gate
C_t: cell state

3. METHODOLOGY

The research flowchart can be seen in Figure 3. We first collected data of BBCA from Yahoo Finance [29], then we preprocessed the data. Preprocessing consists of creating technical indicator variables and combining them with all the research data. The research data is then divided into 2 parts including training and test data., data standardization is carried out using min max normalization so that it has the same range, which is between 0 and 1. Then, we applied CNN and LSTM models to the data to predict BBCA price. We then evaluate the models by calculating the RMSE, MAPE, and R^2 values to find the best model among them.

3.1. **Model of Long Short Term Memory.**

The LSTM model was built using one input layer, several hidden layers, and one output layer compiled using Adam optimization and a loss function in the form of mean of squared error (MSE). Apart from that, the model is also added with a dropout layer which is useful for avoiding overfitting [30].

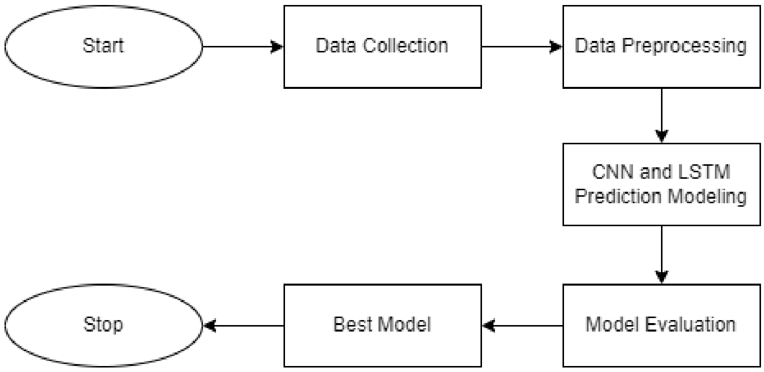

FIGURE 3. Research flowchart

The LSTM input layer has a 3-dimensional size consisting of samples, timesteps, and features [31]. Samples indicate the amount of research data. Timesteps show the number of previous days' data used to predict the t-day. While features are the number of variables we use as input. In the study, the samples used are 4,340 with 5 timesteps and 13 features because there were 13 variables consisting of closing data, rupiah exchange rates, interest rates, five technical indicators, and five foreign stock price indices.

The model architecture consists of two LSTM layers, two dense layers, and a unit dense output layer. Each LSTM layer has a dropout layer to avoid overfitting. The hyperparameter determination of the model is searched using Grid Search to obtain the best hyperparameter that produces the smallest error value. Hyperparameters to be selected include the amount of dropout, LSTM unit, and dense layer. This study uses a batch size of 32 similar to the research of Afrianto et al. [32] and the number of epochs as many as 100 referring to the results of the research of Sunny et al. [33] This study uses a batch size of 32 similar to the research of Afrianto et al. and the number of epochs as many as 100 referring to the results of the research of Sunny et al.

3.2. **Model of Convolutional Neural Network.**

In CNN modeling, the architecture composed of convolution layer, pooling layer, flatten layer, two dense layers and dropout. In the convolution stage, a kernel of size two and the activation function is ReLU. The next layer is the pooling layer. The pooling layer used is maxpooling with size two. Just like the LSTM model, the hyperparameter selection uses Grid Search. The hyperparameters include the filter size of the convolution layer, dense layer, and dropout.

3.3. **Grid Search.**

Grid Search is a way to find the best parameters of the model. Grid Search builds and evaluates the model by trying all combinations of parameters so that the most suitable parameters are obtained [34]. Selection of the best parameters is a combination of parameters with the smallest error value.

3.4. **Model Evaluation.**

(1) Root mean square error
Root mean square error (RMSE) is one of the measures for evaluating model. A small RMSE value indicates the better and more accurate the model. RMSE calculates the value of the error or difference between the prediction data. The formula of RMSE is as follows,

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

where:

y_i : actual value
$\hat{y}_i$: predicted value
n : sample size

(2) R^2
R^2 is one of the measures for model evaluation. A high value of R^2 is a good model. R^2 describes the amount of response variation that can be explained by the model. The formula of R^2 is as follows,

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{(y_i - \hat{y}_i)^2}{(y_i - \bar{y}_i)^2} \quad (1)$$

where:

SSE : Sum of squares error
SST : Sum of squares total
$\bar{y}_i$: Mean value of a sample

(3) Mean Absolute Percentage Error
Mean Absolute Percentage error (MAPE) is a measure that expresses the absolute average percentage error to see the prediction accuracy. MAPE provides information on the magnitude of the prediction error compared to the actual value. The smaller the value, the more accurate the results obtained. The MAPE value can be categorized as shown in Table 1.

TABLE 1. The MAPE value category

MAPE (%)	Interpretation
≤ 10	Highly
10 - 20	Good
20 - 50	Reasonable
≥ 50	Inaccurate

The formula of MAPE is as follows,

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100.$$

4. EMPIRICAL RESULTS

4.1. **Data.**

The data we use is BBCA stock price data for the period between July 1, 2005 and December 30, 2022. This data totals 4,340 observations which are divided into training and testing data. Training data is useful for making models, while testing is used to measure the model accuracy. The distribution of the data uses a comparison of 7:3. 70% of the data is used for testing data, while the 30% of data is testing data. The training data contains observations from 1 July 2005 to 31 October 2017, while data testing from 1 November 2017 to 30 December 2022.

Bank Central Asia (BCA) was established in February 21, 1957. in Indonesia, bank BCA is the largest private bank. Bank BCA conducted its initial public offering on May 11, 2000 [35]. The BBCA stock price fluctuated from 1 July 2005 to 30 December 2022. However, in general, BBCA stock price have a positive trend as shown by price increases from year to year as shown in Figure 4.

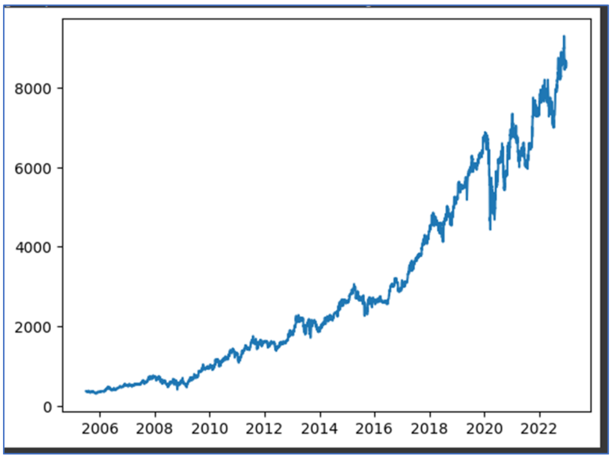

FIGURE 4. Historical closing price of BBCA

In 2020, there was a decline in BBCA's share price since the beginning of the year and continued to decline until March 23, 2020. After that, the price tends to rise again even though it has experienced a downward trend several times as well. This trend is partly due to the Covid-19 outbreak which creates economic uncertainty[36].

TABLE 2. Descriptive statistics of BBCA stock

Statistics	Value
Mean	2,799.01
Standard deviation	2,368.70
Minimum	177.5
Quartile 1	691.25
Median	2,070
Quartile 3	4,605
Maximum	9,300

BCA stocks have the largest market capitalization in Indonesia with a value of IDR 1,597,524,315,000 as of 27 January 2023. This value is higher than those of other banks, including BRI, Mandiri, and BNI. Based on the stock price history obtained from the yahoo finance website for the period June 8, 2004 to December 30, 2022, the lowest price per stock of BCA bank was IDR 177.5 on June 8, 2004. While the highest price was IDR 9,300 per stock on November 30, 2022 (see Table 2). The average stock price during this period was IDR 2,956.47.

According to Ardyanta and Sari [7], a combination of sentiment, technical, and fundamental analysis is required in predicting stock prices. In their research, the variables of the rupiah exchange rate against the United States dollar and the foreign stock price index produced a higher accuracy of 11.78%. The research is in line with Mensi et al. [37] which suggests that the movement of the stock price index in a country can affect the movement of stock prices in other countries. On the other hand, the use of the rupiah exchange rate and interest rates in the research of Goh et al. [38] had quite good results with a coefficient of determination of 71.9%. Maurina [39] also successfully showed that the rupiah exchange rate and interest rates significantly affect stock prices. The use of technical analysis is often used in predicting stock prices. This is because the previous price can affect the next price. Technical analysis is calculated using open, close, high, and low price data within a certain period. Moreover, Wu et al. [40] combined sentiment, technical and stock price indicators in predicting stock prices. The study produced a predicted value that was close to the actual value with an MSE value of 2.39.

This research uses 13 variables taken from various sources from Ardyanta & Sari [7], Sunny et al. [33], Wu et al. [40], Maurina [39], Maretha & Prasetya [41], and Goh et al. [38], namely:

(1) The stock price of BCA obtained from Yahoo Finance [29].
(2) The rupiah exchange rate against the United States dollar obtained from Investing.com [42].
(3) BI interest rate obtained from Bank Indonesia [43].
(4) Technical indicators. Technical indicators are values calculated using open, close, high, and low price data with a certain time period. The technical

indicators of this study are selected based on the research of Wu et al. [40], Marchha and Prasetya [41], and Mndawe et al. [44], namely:

(a) Moving Average. Moving Average (MA) is an indicator that is easy to use and analyze. MA is used to detect trends in stock price movements such as signaling a new trend or confirming an ongoing trend reversal. In general, MA is divided into Simple Moving Average (SMA), Weighted Moving Average (WMA), and Exponential Moving Average (EMA). This index is given in the following,

$$EMA_{today} = \left(\text{Price}_{today} \times \left(\frac{\text{Smoothing}}{(1+\text{Days})}\right)\right) + (EMA_{yest} \times \left(1 - \frac{\text{Smoothing}}{(1+\text{Days}))}\right),$$

where:
Smoothing : 2
Days : Number of time periods
Price_{today} : Current price.

(b) Moving Average Convergance Divergence. Moving Average Convergance Divergence (MACD) is an indicator that is obtained by looking at the deviation between two exponential moving averages (EMA) with different periods. This index is given in the following,

$$MACD = EMA_{12}(t) - EMA_{26}(t),$$

where:
EMA_{12} : 12-period exponential moving average
EMA_{26} : 26-period exponential moving average

(c) Relative Strength Index. The Relative Strength Index (RSI) is a technical indicator that has a value on a scale of 0 to 100. If the value is more than 70 it is declared as overbought, while if it is less than 30 it is declared as oversold. This index is given in the following,

$$RSI = 100 - \frac{100}{1 + \left(\frac{\sum_0^{13} Up_{t-1}}{14}\right) + \left(\frac{\sum_0^{13} Dw_{t-1}}{14}\right)},$$

where:
Dw_{t-1} : downward price change at i-th time
Up_{t-1} : upward price change at i-th time

(d) William %R. William %R is a technical indicator that has a value with a vertical scale of -100 to 0. If the value is above -20, it is declared as overbought, while below -80 is declared as oversold. It is declared an extreme area (danger zone) when the value is below the -80 level and above -20 [45]. This indicator formula is given in the following,

$$\%R = \frac{HH_{t-14} - C_t}{HH_{t-14} - LL_14}$$

where:
HH_{t-14} : Highest high for the 14th period
LL_{t-14} : Lowest low for the 14th period
C_t : Current close price

(e) Stochastic Oscillator. The Stochastic indicator depicts two oscillator lines namely %K and %D. Each line has a vertical scale of 0 to 100. If the value is more than 80, it is declared as overbought, while if it is less than 20, it is declared as oversold. The signal line is %K so it can be stated that the line is the main and most important line, which is given as follows [45],

$$\%K = \frac{C_t - LL_{t-14}}{HH_{t-14} - LLt - 14} \times 100$$

(5) Foreign stock price index obtained from Yahoo Finance. Selection of technical indicators based on research by Ardyanta and Sari [13] by selecting 5 stock indices that have the highest correlation. The index consists of :
(a) Dow Jones Industrial Average
The Dow Jones Industrial Average (DJI) is one of the oldest indices in the United States, published on May 26, 1896 by Charles Dow and Edward Jones (Investing, 2023) consisting of 30 major listed companies. The Dow Jones is measured arithmetically, which is based on the price of one share of each company in it, not on its capitalization value.
(b) Financial Times Stock Exchange (FTSE 100 Index)
The FTSE 100 Index is a stock index introduced in January 1984. The FTSE 100 comprises the 100 companies listed on the London Stock Exchange with the highest market capitalization. The index is widely used as a leading indicator of market performance and is seen as a measure of prosperity in the UK.
(c) Indeks Standard & Poor's 500 (S&P 500)
The S&P 500 is an index consisting of 500 stocks of the biggest companies in the United States. The stocks included in this index have criteria as companies with large stock capitalization value, liquidity level, finance, and others. S&P500 is the dominant index so that it can represent the state of the stock exchange in the United States.
(d) National Association of Securities Dealers (NASDAQ)
MASDAQ is a US stock index founded on February 8, 1971. NASDAQ consists of 2,500 stocks of companies that focus on technology. The calculation of the weight of this index uses market capitalization, which is multiplying the number of stocks by their stock price.
(e) Nikkei 225 Index (N225)
The Nikkei 225 Index is an index that has been around since September 1990. It is an average price index consisting of 225 leading stocks (blue chips) of the Tokyo Stock Exchange. To date, the Nikkei 225 is

considered to be the best indicator of price movements and represents the overall performance of the Tokyo Stock Exchange. The Nikkei 225 Index represents the rebuilding and industrialization of Japan after the Second World War.

4.2. Predictions of the LSTM Model.

The LSTM model is formed using 2 LSTM layers with 128 units, each of which has a dropout layer of 0.1 and 2 dense layers with 16 units and 1 dense output layer. Furthermore, the model is compiled using adam optimizer and MSE loss function. The hyperparameters are determined by the Grid Search process. The summary of the formed LSTM model is shown in Figure 5. The model results show RMSE value of 1,277,582 and MAPE value of 15.2% which means that the results are not good enough. The prediction line is far below the actual line. Figure 5 shows a comparison between the predicted lines and the actual lines formed using the LSTM model.

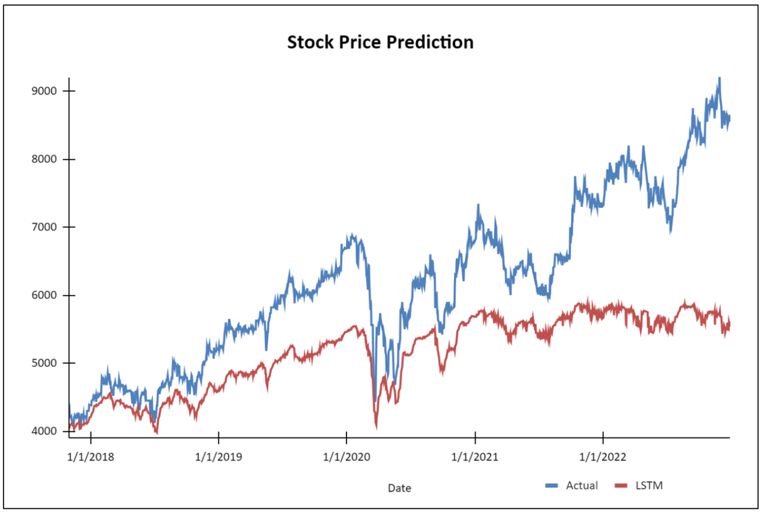

FIGURE 5. LSTM Prediction Result

4.3. Predictions of the CNN Model.

The CNN model is composed of convolution layer with 128 filters and 2 kernels, maxpooling layer with pool size of 2, flatten layer, dense layer of 16 units, dropout layer 0.25, and dense layer unit 1 as the output model. The CNN model results in predicting stock price have an RMSE value of 488,992. The MAPE value of the resulting CNN model is 6.5%. These results are better than with the LSTM model. The R^2 value generated by the model is 0.838, which means 83.8% of the independent variables can explain the dependent variable. The CNN model prediction line pattern follows the actual stock price line quite well. Figure 7 shows a comparison between the predicted lines and the actual lines formed using the CNN model.

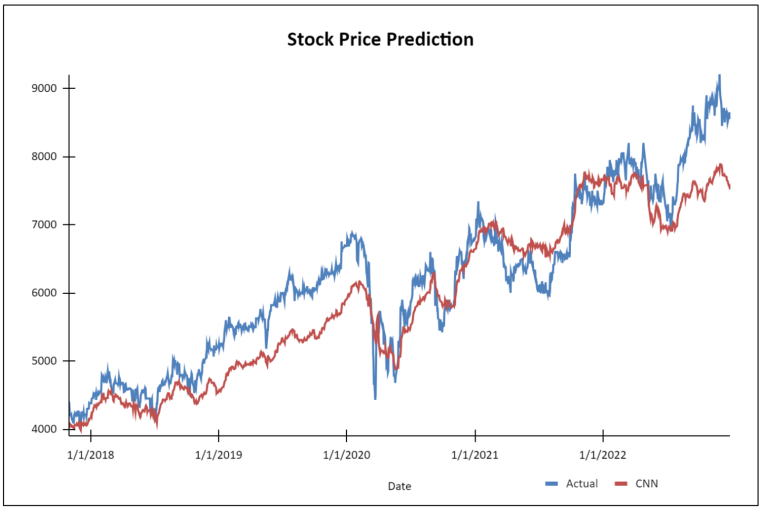

FIGURE 6. CNN Prediction Result

4.4. **Comparison of prediction results.**

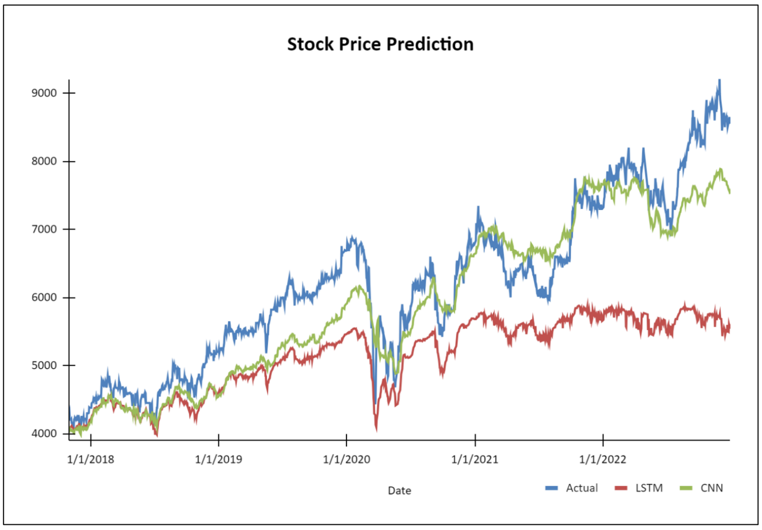

FIGURE 7. Comparison of Prediction Result

Stock price prediction models with different methods than based on RMSE, MAPE, and R^2 values. A good RMSE and MAPE value is a value close to 0, while a good R^2 value is a value close to 1. A comparison of the value of each model is provided in Table 3.

TABLE 3. Model Evaluation Result

Metode	RMSE	R^2	MAPE(%)
CNN	488.992	0.838	6.5
LSTM	1,277.582	-0.103	15.2

The best model with the smallest RMSE and MAPE values and the largest R^2 is the CNN model. The CNN model shows a higher R^2 value than the LSTM. The R^2 of the LSTM model is -0.103. In machine learning, the R^2 ranges from 0 to 1 [46]. The closer R^2 is to 1, the better the model performance. R^2 can be less than 0 when the MSE of the designed model is greater than the MSE of the base model that only predicts the average value. In other words, the prediction results using machine learning is worse than the original data, so R^2 can become negative. An increase in the value of R^2 means that the CNN model is able to predict stock prices better. When both models are compared according to the MAPE values, the CNN model has a value of less than 10% which means the model is included in the excellent category.

5. CONCLUSION

Stock price prediction needs to be done to reduce the risk of losses experienced by investors. This paper describes stock price prediction using LSTM and CNN. Based on the obtained results shown in Table 3, we conclude that prediction using CNN is better than LSTM in predicting BBCA stock price because it has lower RMSE and MAPE values and higher R^2. CNN has an RMSE value of 488.992, an R^2 of 83.8%, and a MAPE of 6.5%. This can be obtained due to inappropriate hyperparameter selection or insufficiently long data periods so that the performance of LSTM, which should be able to predict better due to its ability to store long-term information, actually gets worse results than CNN. Oyedare and Park's research proved that increasing the size of training data can reduce RMSE and increase R^2 [47]. In addition, hyperparameter selection is very important to produce optimal performance [48]. One way that can be done is hyperparameter tuning which can improve training efficiency and model performance [49]. Suggestions for future research are to use other machine learning and deep learning methods such as BiLSTM, SVR, Neural Network, and others. Selection of more appropriate parameters or increasing the size and period of research data so as to be able to provide more optimal results.

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