Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 6, Number 2, April 2022
DOI : https://doi.org/10.33395/sinkron.v7i2.11405
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Predict stock prices using the Generative Adversarial Networks

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Submitted : Apr 20, 2022 | **Accepted** : Apr 25, 2022 | **Published** : Apr 27, 2022

Abstract: Predicting the price of a stock is very difficult. Due to very volatile prices. Many traders incorrectly predict stock prices, forex or trading commodities. It takes an analysis of each price movement. The purpose of the analysis is to predict price movements. One of them is the use of indicators that seek to help predict prices. Currently the development of Artificial Intelligence (AI) has grown very rapidly. Machine learning which is part of AI is also used to predict prices. Stocks are data that are related to time. Just like the weather. If the stock is analyzed then the suitable method is the time series method. The method used is Deep Learning, namely Recurrent Neural Network (RNN). Recurrent Neural Network is the same as Artificial Neural Network (ANN). ANN performs processing of sequential data. RNN does not discard past problem data information, but will also enter past information as input. This is what distinguishes RNN and ANN. In the Recurrent Neural Network there is a Long Short Term Memory Algorithm, Gated Recurrent Unit (GRU). One of the algorithms that can be used to predict stock prices is the Generative Adversarial Network. This algorithm was modified before being used. In the GAN algorithm there are Generators and Discriminators. Because stock is a process that is carried out in the presence of time or time series, the Generative is modified with Long Short Term Memroy and Discriminator uses Long Short Term Memory.

Keywords: Generative Adversarial Networks; Longs Short Term Memory; Gated Recurrent Unit; Stock; Recurrent Neural Network;

INTRODUCTION

In shaping the economy of a country, the market capital is one component that is sufficient Importantly, many instruments can be transacted such as bonds, mutual funds and stocks. In addition to getting fast fresh funds from the wider community, capital market provide benefits to the company, consideration portfolio and liquidity, changes in owner's capital and investor recognition, which is the reason why the company makes an initial public election offering (IPO) (Waluyo & Parasetya, 2021).

One model of ANN that is quite popular in the prediction and classification of time series data is Recurrent Neural Networks (RNN). RNN is suitable for use in time series datasets because this model has the ability to study data sequences where the network output depends on the amount that changes from the previous input. RNN can be a useful model for making predictions of irregular time series, especially in making multi-step predictions (Rashid et al., 2019). However, RNN has a weakness in dealing with predictions with a fairly long time frame, this problem is better known as long memory dependency. Because the RNN will experience problems called Vanishing Gradient and Gradient Exploding if the RNN handles prediction problems with a long time range (Wang et al., 2019). The Gated Recurrent Unit (GRU) comes as a further development of the conventional RNN unit which has the ability to handle prediction and classification cases without the problems of Vanishing Gradient and Gradient Exploding (Wang et al., 2019). GRU is an RNN unit which is a machine learning model which is a development of the Long Short Term Memory (LSTM) unit. GRU is a simplification of the LSTM in the form of reducing gates and parameters to speed up training time and simplify implementation (Althelaya et al., 2018).

LSTM is used to overcome vanishing gradients or situations where the gradient value is 0 or close to 0 with a gate mechanism (Pulver & Lyu, 2017). LSTM is another way to calculate hidden state. The memory in the LSTM is called cells which take input from the previous state (ht-1) and the current input (xt). The set of cells decides what to keep in memory and when to delete it from memory. LSTM combines the previous state, current memory, and input. LSTM is very efficient for recording long-term dependencies.

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LSTM has 3 gates, the first gate is a forget gate to determine the information to be removed from the cell using a sigmoid layer. The activation function used is Relu. The second gate is the input gate which of the sigmoid layer will be updated and the tanh layer will be created as a vector of the updated values (Le Calvez & Cliff, 2019). The third gate is the output gate to expose the contents of the memory cell to the LSTM output. The LSTM is treated as a black box given the current input and the previous hidden state to calculate the next hidden state. The memory used in the LSTM is called cells which take input from the previous state (ht-1) and the current input (xt). LSTM is very suitable for learning long-term dependencies.

A new framework for estimating a generative model through an adversarial process, which simultaneously trains two models: a G generative model that captures the distribution of the data, and a D discriminatory model that estimates the probability that the sample comes from training data rather than G. The training procedure for Gi is to maximize probability of D making a mistake. This framework is suitable for two player minimax game (Goodfellow et al., 2014). The purpose of this study is to predict stock prices with the Generative Adversarial Network by modifying the Generator and Discriminator using Long Short Term Memory and Gated Recurrent Units.

LITERATURE REVIEW

In previous studies discussing stock predictions, various methods have been used, such as Long Short Term Memory, Gated Recurrent Units, and other time series methods. Several methods have produced very good prediction models. Therefore, this study uses a different method from previous studies.

Table. 1 Previous research in predicting stock prices

Author	Topic	Advantage	Disadvantage
(Dwiyanto et al., 2019)	Stock Price Prediction using the Recurrent Neural Network Method	Discussion of stock price predictions using the Recurrent Neural Network method, the average accuracy results reach 90%	The weakness of this research is that it does not use other algorithms such as Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM) and Generative Adversarial Network (GAN).
(Afrianto et al., 2022)	Stock Price Prediction Using BiLSTM with Public Sentiment Factor	Discussion about stock price prediction, using BiLSTM is good.	The weakness of the research is not comparing with similar algorithms such as Gated Recurrent Unit (GRU) or using Generative Adversarial Network (GAN).
(Hastomo et al., 2021)	Deep Learning Optimization for Stock Predictions during the Covid-19 Pandemic	The discussion on stock prediction uses the LSTM-GRU-LSTM-GRU method. The method used combines LSTM and GRU.	The weakness of this research is that it does not use the Generative Adversarial Network as comparison material. The challenge in making predictions is the problem of epoch values.
(Khalis Sofi et al., 2021)	Stock Price Prediction using Time Series Model by Comparing Linear Regression, LSTM and GRU Algorithm	Discussion on stock price prediction using Linear Regression, Long Short Term Memory and Gated Recurrent Unit (GRU). Produce good models.	The weakness of this study is that it does not use other algorithms, for example by using the Generative Adversarial Network by modifying the Generative using Long Short Term Memory, while the Discriminator uses Long Short Term Memory.

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(Althelaya et al., 2018)	Stock Market Forecast Using Multivariate Analysis with Bidirectional and Stacked (LSTM, GRU)	Discussion about price predictions from the stock market, using multivariate analysis using LSTM and GRU and getting models from both LSTM and GRU algorithms, where the results are very good.	This study has the disadvantage of not building a model with the Generative Adversarial Network (GAN) algorithm. GAN indeed cannot be used for stock prediction analysis, but if you modify the Generator and Discriminator with LSTM or with GRU, it will be able to predict stock prices.

Many previous studies that discussed stock price predictions conducted research using the Recurrent Neural Network (RNN) algorithm, because stocks are a dataset that has a relationship with previous prices. This causes the analysis to use the Recurrent Neural Network. One of the widely used RNN algorithms is LSTM and GRU. The state-of-the-art of this study discusses the Deep Learning Generative Adversarial Network (GAN) algorithm used in analyzing stock prices. Generative Adversarial Network has two parts, namely Generator and Discriminator. One of them is by modifying the Generator and Discriminator with the LSTM and GRU algorithms. The purpose of this study is to analyze stocks using Generative Adversarial Networks which have been modified in the Generator and Discriminator sections with Long Short Term Memory or with modified Gated Recurrent Units (GRU).

METHOD

The method used for this research is to use the Generative Adversarial Network which in the Generator uses Long Short Term Memory (LSTM), Discriminator uses Longs Short Term Memory (LSTM). The research proposal is in figure 1 research proposal.

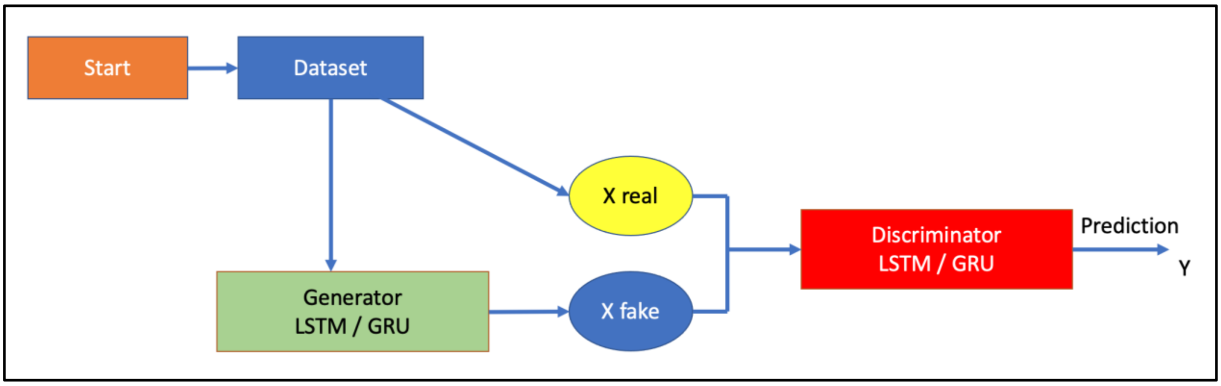

Figure. 1 Usulan penelitian
Source : researcher property

The proposed use of the Adversarial Network Generator, the Generator is from the Long Short Term Memory method, the dataset is directly used using the LSTM and the Discriminator uses the LSTM as well, the result is predicting stock prices. The process in figure 1 shows that the Adversarial Network Generator is a combination of Convolutional Neural Network (CNN) if you want to process images. But Generative Adversarial Networks not only process images but can also process text. So the Generator Adversarial Network can do processing using text, in this research proposal as an example of GAN to predict stock prices.

Long Short Term Memory (LSTM)

The initial model of machine learning based on neural networks is RNN (Recurrent Neural Network). The inability of the RNN to relate long information (Hochreiter & Schmidhuber, 1997), causes the problem of vanishing gradient values in the iterative process in the neural network (backpropagation neural network). To overcome this problem, a new model was created, namely LSTM (Long Short Term Memory). The LSTM is in the form of a cell containing a series of 4 gates and 5 activation functions which are quite complicated. Although

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the LSTM is successful in storing long and interrelated information with the data before and after it (time series data), the complexity of the circuit makes the LSTM require a larger processing time. To improve the LSTM, a simpler model was designed, namely the GRU (Gated Recurrent Unit) model. GRU is a cell with 2 gates and 3 activation functions. With this minimal gate and activation function, of course, it will speed up the processing of data which is generally very large. GRU capabilities are designed to be better than LSTM, especially for small datasets (Chung et al., 2014).

Constant error backpropagation in memory cells results in the ability of the LSTM to bridge very long time lags in the case of problems similar to those discussed above. For long lag time problems as discussed in this paper, LSTM can handle noise, distributed representation, and continuous values. In contrast to end-state automata or hidden Markov models, LSTM does not require a priori selection of a number of states. In principle, it can handle an unlimited number of countries. For the problem discussed in this paper, LSTM generalizes well | even if the position is widely separately, the relevant input in the input order does not matter. In contrast to the previous approach, we quickly learn to distinguish between two or more events that are far apart from certain elements in the input sequence, without relying on the corresponding short time lag training example. It seems that there is no need to set the new parameter. LSTM works well over a wide range of parameters such as learning speed, input gate bias, and output gate bias. For example, some of the reading levels of learning used in our experiments may seem large. However, a big learning rate pushes the output gate towards zero, thus automatically countering it own negative effects (Hochreiter & Schmidhuber, 1997).

Long Short Term Memory (LSTM) network was created with the aim of overcoming the hidden layer problem. The key in the LSTM design is to incorporate non-linear, data-dependent controls into RNN cells [10], which can be trained to ensure that the gradient of the objective function takes account of the signal (quantity is directly proportional to the update of the parameters calculated during training by Gradient Descent) does not disappear.

Gated Recurrent Unit (GRU)

The goal of the Gated Recurrent Unit (GRU) is to solve the missing gradient problem using a standard iterative neural network. The GRU is a variation of Long Short Term Memory (LSTM) because the LSTM and GRU are of the same design and, in some cases, produce equally good results (Cho et al., 2014).

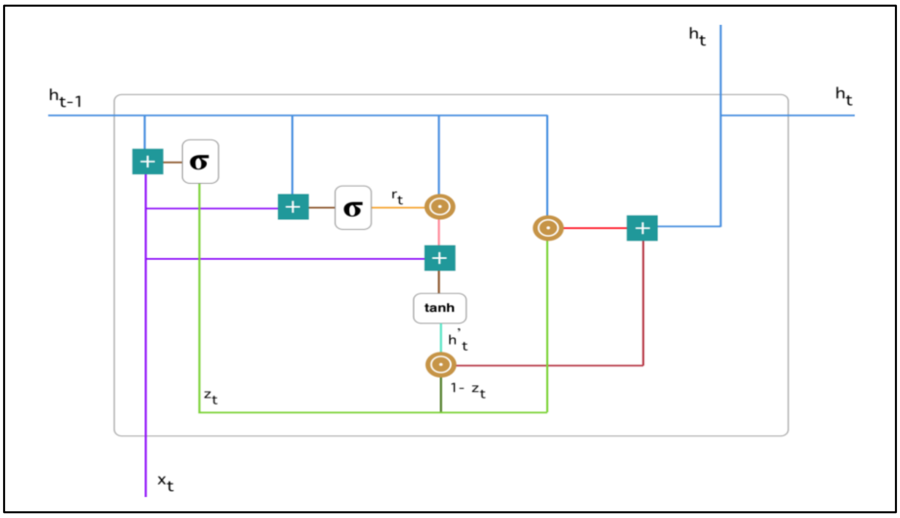

Figure. 2 Gated Recurrent Unit (GRU)
Source code : Google Image

Update gate

How to calculate the update gate z_t for time t with the formula:

$$Z_{(t)} = a(W^{(z)}\, x_1 + U^{(z)}\, h_{t-1}) \quad (1)$$

When x_t is plugged into the Gate network unit, it is then W(z) weighted. The value of h_(t-1) stores the information for the previous unit t-1 and is then multiplied by the weight U(z). The two results are added together and a sigmoid activation function is applied to suppress the result between 0 and 1. The update gate is used by the model in determining how much past information needs to be passed into the future. That's very powerful because the model can decide to copy all the information from the past and eliminate the risk of disappearing gradient problems.

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Reset gate
Basically, these gates are used from the model to decide how much past information should be forgotten. Here's the formula for reset gated.

$$r_t = a(W^{(r)} X_t + U^{(r)} h_{t-1}) \quad (2)$$

This formula is the same as the formula for the renewal gate. The difference lies in the weight and use of the gate. The reset gate is at h_(t-1) — the blue line and x_t — the purple line, multiply by the appropriate weight, add up the result then apply it with the sigmoid function.

Memory content
How the gate will affect the final result. First, the use of the reset gate, introduces new memory content that will use the reset gate to store relevant information from the past.

$$h_t = \tanh(Wx_t + r_t \, O \, U \, h_{t-1}) \quad (3)$$

1. Multiply input x_t by weight W and h_(t-1) by weight U.
2. Calculate between the reset gates r_t and Uh_(t-1). That will determine the information that should be deleted in the previous step. The assignment vector r_t approaches 0, eliminating the past and focusing only on the last information.
3. Add up the results of step 1 and step 2.
4. Apply the nonlinear activation function tanh.

Generative Adversarial Networks (GAN)
GAN is an algorithm that has two parts, Generator and Discriminator. Generator as a generate image, while the discriminator as a classification to determine the real class and fake class. In this study, to predict stock prices or forex, using a modified Generative Adversarial Network. The generator will be modified using Long Short Term Memory (LSTM) or Gated Recurrent Unit (GRU) and the Discriminator will also be modified using Long Short Term Memory (LSTM) or Gated Recurrent Unit (GRU), like figure 3 Generative Adversarial Network.

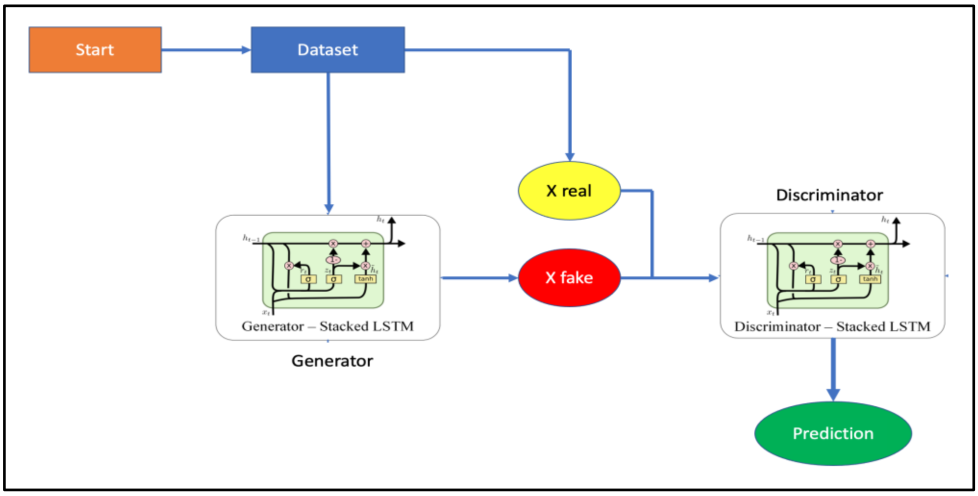

Figure. 3 Generative Adversarial Network with LSTM
Source : researcher property

RESULT

Experimental results using python and datasets from Yahoo (Yahoo, 1994). The results of the Generative Adversarial Network using Long Short Term Memory (LSTM). There is still a difference between the real stock price and the predicted stock price, as in figure 4.

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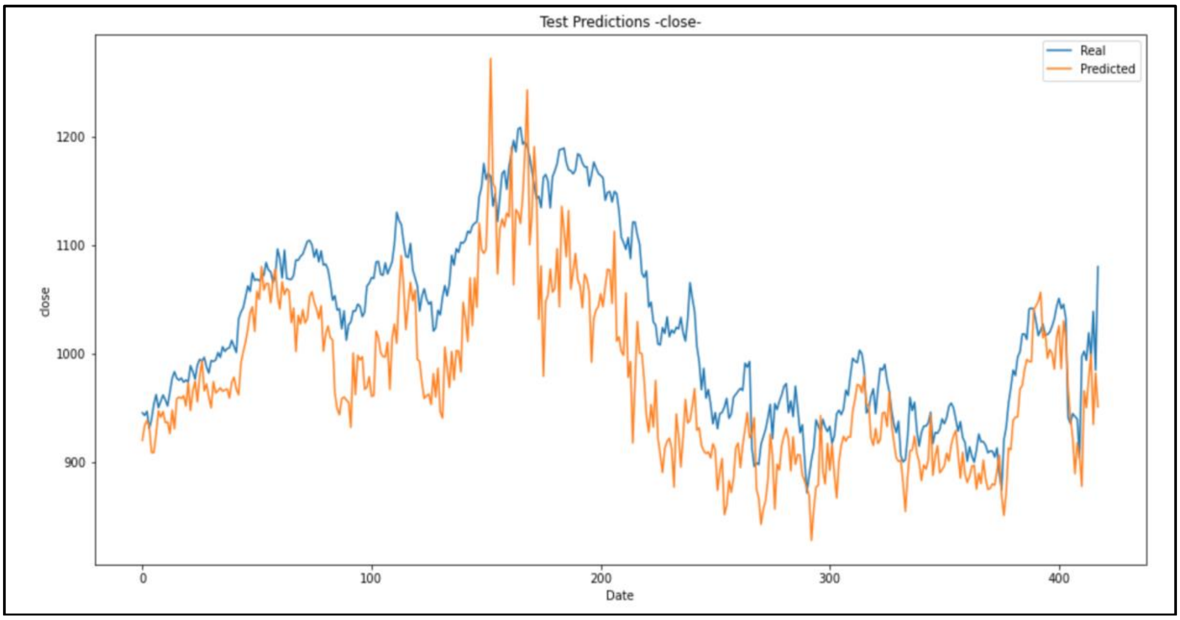

Figures. 4 Test Prediction Istanbul stock price Delayed Price Currency in TRY
Source : researcher property

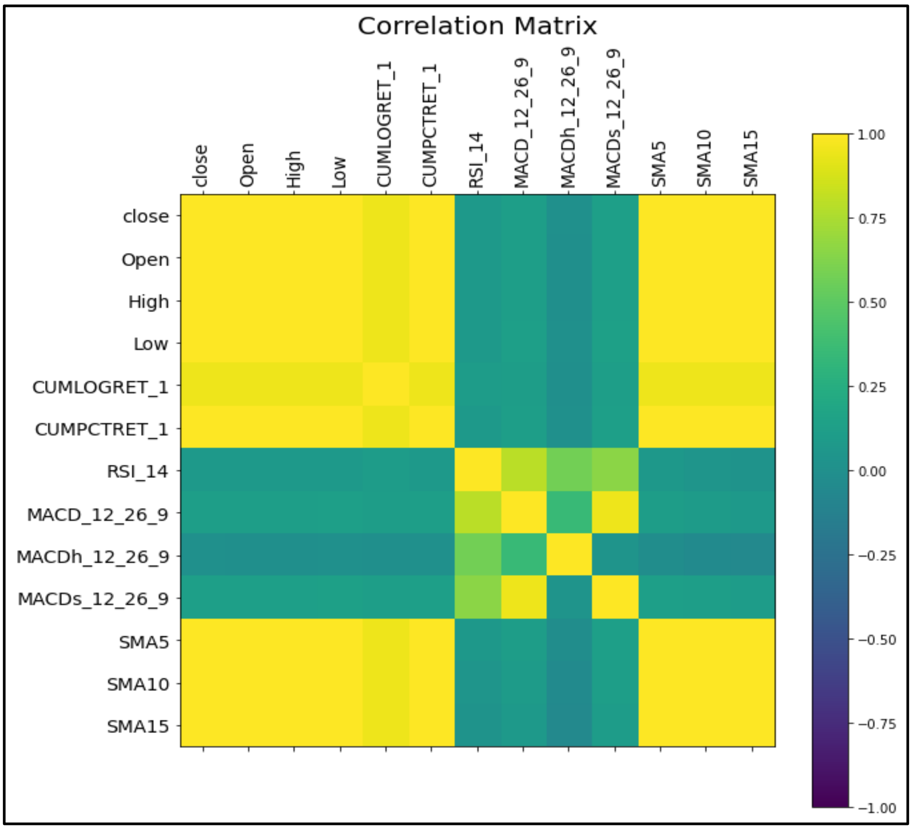

Figure. 5 Correlation Matrix
Source : researcher property

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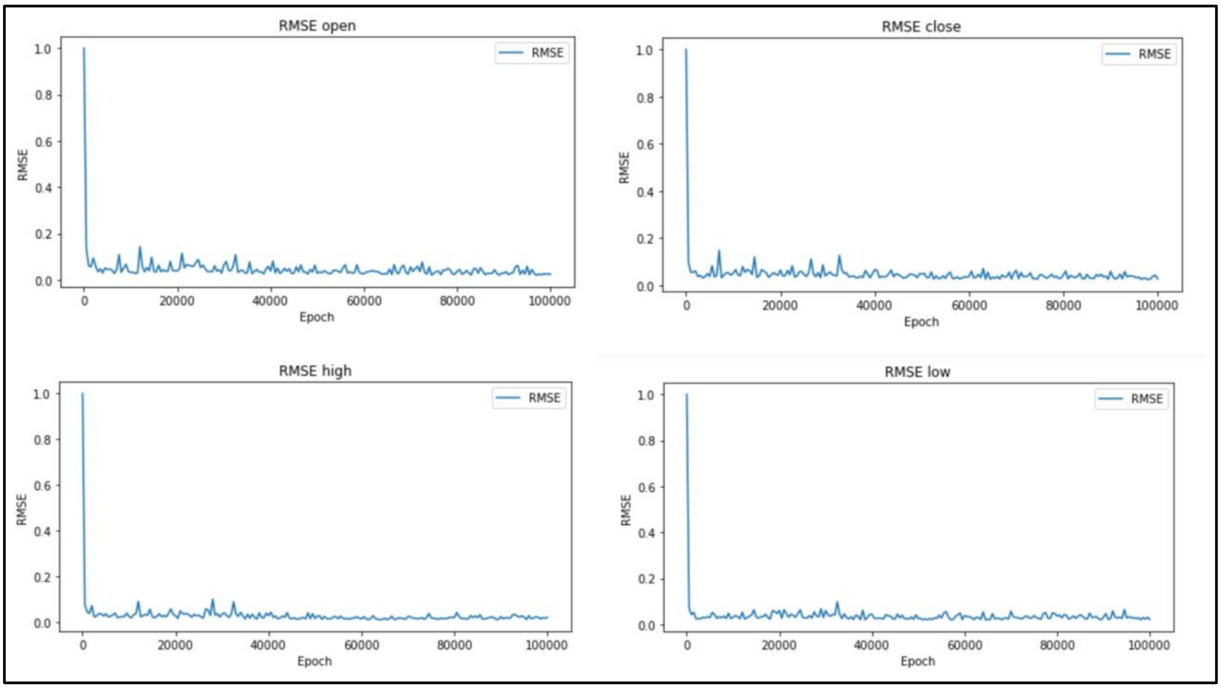

Figure 6. Root Mean Square Error (RMSE)
Source : researcher property

Root Mean Square Error (RMSE), the value of the open price rmse, close price, high price and low price, have something in common. So that it can be said to have a balanced value.

DISCUSSIONS

Discussion about the Generative Adversaril Network used to predict stock prices is very possible, considering that the contents of the generator and discriminator are filled with Long Short Term Memory. This is reasonable because in a modified GAN, you can predict stock prices or forex.

CONCLUSION

From the results of stock price prediction research using Generative Adversarial Networks by modifying the Generator and Discriminator with Long Short Term Memory or Gated Recurrent Units, the price prediction results are very good. But there is still a difference or difference between the real price and the predicted price. Overall stock price predictions are close to the real stock prices.

SUGGESTION

This research can be continued by examining the Generative Adversarial Network which has been modified using the Gated Recurrent Network.

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