Comparison of MDKA Stock Price Prediction using Multi-Layer Perceptron, Long Short-Term Memory, and Gated Recurrent Unit

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Abstract

Shares are rights owned by a person against a company due to the delivery of capital, either in part or in whole. Investors invest in stocks and try to get maximum results, but many investors are still unsure about the risks involved in investing. To minimize risk, investors need to predict stock prices with an accurate method. Several methods that can be implemented to predict stock data include Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). The research objective to be achieved in this study is to compare the performance of each algorithm in producing a more accurate stock price forecasting model by testing neurons (10, 20, 30) and epochs (50, 75, 100). The research was conducted on the stock price data of PT. Merdeka Copper Gold Tbk (MDKA) which is a mining sector share with the largest capitalization value. Tests on some of the algorithms above got the best results using 82% training data and 18% test data, namely the MLP model with 10 neurons and 100 epochs with a MAPE training data result of 2.325 and a MAPE test data of 2.014. Based on the test results, MLP can predict MDKA stock prices for the 2018-2022 period with good performance and a relatively small error rate, while tests using the LSTM and GRU methods still produce large errors. Thus, it can be concluded that MLP can predict stock prices with more accurate results.

Keywords: Prediction, Share, MLP, LSTM, GRU

Abstrak

Saham adalah hak yang dimiliki seseorang terhadap perusahaan dikarenakan penyerahan modal baik itu sebagian maupun keseluruhan. Para investor melakukan investasi saham dan berupaya untuk mendapatkan hasil secara maksimal, akan tetapi banyak investor masih ragu dengan risiko dalam berinvestasi. Untuk memperkecil risiko, investor perlu melakukan prediksi harga saham dengan metode yang akurat. Beberapa metode yang dapat diimplementasikan untuk memprediksi data saham diantaranya adalah Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), dan Gated Recurrent Unit (GRU). Tujuan penelitian yang ingin dicapai pada penelitian ini adalah membandingkan performa masingmasing algoritma dalam menghasilkan model peramalan harga saham yang lebih akurat dengan pengujian neuron (10, 20, 30) dan epoch (50, 75, 100). Penelitian dilakukan pada data harga saham PT. Merdeka Copper Gold Tbk (MDKA) yang merupakan saham sektor pertambangan dengan nilai kapitalisasi terbesar. Pengujian pada beberapa algoritma di atas mendapatkan hasil terbaik dengan menggunakan data latih 82% dan data uji sebesar 18% yakni pada model MLP dengan 10 neuron dan 100 epoch dengan hasil MAPE data latih sebesar 2,325 dan MAPE data uji sebesar 2,014. Berdasarkan hasil pengujian, MLP mampu memprediksi harga saham MDKA periode 2018-2022 dengan performa yang baik dan tingkat kesalahan yang relatif kecil, sedangkan pengujian menggunakan metode LSTM dan GRU masih menghasilkan error yang besar. Dengan demikian dapat disimpulkan bahwa MLP mampu memprediksi harga saham dengan hasil yang lebih akurat.

Kata kunci: Prediksi, Saham, MLP, LSTM, GRU

1. Introduction

Public awareness of investing in the capital market has increased since the Covid-19 pandemic. Even in 2021, 99.5% of investors in Indonesia will be retail investors dominated by millennials and Z Generation [1]. One type of investment that is currently popular in society is stock investment. Shares are a sign of the equity participation of a person or business entity in a company or Limited Liability Company [2].

In addition to the possibility of obtaining high returns, stock investment is also a somewhat risky investment. Stock prices always fluctuate due to various factors, including company performance, interest rates, inflation, exchange rates, and non-economic aspects. Therefore, stock investors need to pay attention to historical stock data in order to estimate the prospects for the company's stock price in the future

As knowledge and technology advance, future stock price estimates can be predicted using deep learning algorithms. The use of deep learning algorithms can save time and produce more measurable predictive results. Stock price predictions are included in the prediction of time series data. Several deep learning architectures that can be used to predict time series data include the MLP, GRU, and LSTM algorithms. In this study, the performance of each algorithm will be compared in predicting the stock price of PT. Merdeka Copper Gold Tbk (MDKA) based on MAPE value.

Multi-Layer Perceptron (MLP) is the development of a single-layer perceptron so that there is a hidden layer in its architecture [3]. There are three types of layers that make up MLP, namely an input layer, one or more hidden layers, and an output layer [4]. Multi-Layer Perceptron is a deep learning architecture with a feed-forward system and uses a fully connected configuration [5]. Based on research [6], the MLP algorithm produces higher accuracy than the Support Vector Machine (SVM) algorithm in predicting stock prices. The MLP algorithm also shows good performance in recognizing training data patterns [7].

Long Short-Term Memory (LSTM) is an evolution of the RNN architecture which was first introduced by Hochreiter & Schmidhuber (1997). Until this research was conducted, many researchers have continued to develop the LSTM architecture in various fields such as forecasting. LSTM can overcome the problem of disappearing gradients in the RNN because of its ability to manage memory for each input using memory cells and gate units. In predicting stock prices, the LSTM algorithm can produce higher accuracy than the Support Vector Machine (SVM) algorithm because

of its ability to overcome long-term dependencies [8]. Meanwhile, in the prediction of stock prices for 2019-2021 by [9] it was found that the GRU algorithm has the best performance compared to LSTM using a time series model.

Gated Recurrent Unit (GRU) is a revolution of the LSTM method. GRU is an architecture created by Kyung Hun Cho in 2014 [10]. In GRU, there are two information control components, namely the reset gate and the update gate. The reset gate determines how to combine new input with past information, while the update gate determines how much information will be stored. The main goal of creating a GRU is for each recurrent unit to adaptively capture dependencies on different timescales.

With the discovery of various kinds of algorithms for predicting stock prices along with the advantages and disadvantages of each, it is necessary to study further about the performance comparison between each of these algorithms so that the best deep learning algorithm architectural model is obtained which can produce the highest accuracy.

The discovery of the best architectural model is expected to be a reference for investors, especially investors in PT Merdeka Copper Gold Tbk (MDKA) in predicting stock prices to minimize possible risks.

2. Methodology

Stock data was obtained from Yahoo Finance by taking data on shares of PT Merdeka Copper Gold Tbk (MDKA) for the period May 2018 to May 2022. The data obtained includes the date column, opening stock price, highest price, lowest price, closing price, and adj close or closing price including dividends and stock split, and volume. Based on this data, it will enter data grouping or commonly known as pre-processing. After these steps are completed, the Multi-Laver Perception (MLP) model is designed, LSTM which is part of the Recurrent Neural Network (RNN), and Gated Recurrent Unit (GRU). Then the data is entered into the model design and the training process and data testing process are carried out with a data sharing ratio of 82% and 18%.

2.1. Data collection

Data on shares in the mining and mineral sector came from Yahoo Finance, the issuer taken was PT MDKA shares. Stock data taken includes column date, open, close, high, low, adj close, and volume. This study uses close data or stock closing prices.

The display of the MDKA stock data set can be seen in Figure 1.

| | Date | 0pen | High | Low | Close | Adj Close | Volume |
|-----|------------|-------------|-------------|-------------|-------------|-------------|-----------|
| 0 | 2018-05-14 | 460.408234 | 464.244995 | 454.653137 | 460.408234 | 460.408234 | 559850 |
| 1 | 2018-05-15 | 460.408234 | 468.081726 | 460.408234 | 464.244995 | 464.244995 | 181925 |
| 2 | 2018-05-16 | 460.408234 | 462.326630 | 460.408234 | 460.408234 | 460.408234 | 364893 |
| 3 | 2018-05-17 | 464.244995 | 468.081726 | 460.408234 | 460.408234 | 460.408234 | 59946 |
| 4 | 2018-05-18 | 466.163361 | 466.163361 | 456.571503 | 456.571503 | 456.571503 | 159510 |
| | *** | | Con. | *** | *** | *** | *** |
| 993 | 2022-05-09 | 5150.000000 | 5250.000000 | 4930.000000 | 4950.000000 | 4950.000000 | 104434800 |
| 994 | 2022-05-10 | 4800.000000 | 4840.000000 | 4620.000000 | 4830.000000 | 4830.000000 | 107238100 |
| 995 | 2022-05-11 | 4830.000000 | 4950.000000 | 4800.000000 | 4860.000000 | 4860.000000 | 47129700 |
| 996 | 2022-05-12 | 4850.000000 | 4850.000000 | 4520.000000 | 4600.000000 | 4600.000000 | 108059600 |
| 997 | 2022-05-13 | 4560.000000 | 4570.000000 | 4280.000000 | 4380.000000 | 4380.000000 | 107786800 |

Figure 1. The View of the MDKA stock dataset

2.2. Pre-processing

In the data preprocessing process, normalization will be carried out, division of split data, and creation of supervised learning data sets. Normalized the data without changing the original value of the data using a min-maxscler with a range of 0 to 1, then divide the training data by 818 lines and the test data by 180 lines based on the closing price of the stock price. Then the data is made into a new data set or supervised learning data, this aims so that the training on the model can be supervised by the machine.

2.3. Modelling

The closing price of the stock will be predicted using three different algorithms, namely Multi-Layer Perceptron (MLP), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM). The three algorithms use the ADAM optimizer and the default batch size. In each algorithm, 9 (nine) different model variations are applied based on the number of neurons in the hidden layer and the number of epochs. The variations used are as follows:

- a. The number of neurons in the hidden layer is varied to 10, 20, and 30 neurons.
- b. The number of epochs is varied to 50, 75, and 100.

From the results of the 9th training model variations in each algorithm, the predicted values are generated which will be evaluated with MAPE. Next, the best model of each algorithm will be determined. The best model of each algorithm will be compared again so that the best model of the entire algorithm is obtained.

2.4. Evaluation

The model prediction results will be denormalized first so that the value which was originally in the form of a range [0,1] will return to its true value. Then, the predicted results that have been returned to their true values will be evaluated with actual data. The evaluation was carried out using MAPE parameters. MAPE (Mean Average Percentage Error) is a measure of relative accuracy that is used to determine the percentage deviation of prediction results. MAPE indicates how much the prediction error is compared to the real value [11]. MAPE is calculated by the following formula:

$$MAPE = \sum \left| \frac{Y - Y'}{Y'} \right| \times 100\% \tag{1}$$

where:

Y : Actual valueY' : Prediction value

3. Results and discussion

After going through the data preprocessing stage, training and testing were carried out on 9 model variations of each algorithm. These model variations are formed from a combination of the number of neurons (10, 20, 30) and the number of epochs (50, 75, 100).

3.1. Multi-Layer Perceptron (MLP)

The results of MDKA's stock price prediction are divided according to the variations carried out. Table 1 below shows the MAPE value of all MLP variations in predicting MDKA stock prices.

Table 1. MLP Model MAPE

| M. J.1 | Number | Number | MAPE | MAPE |
|---------------|---------|--------|----------|---------|
| Model Code | of | of | training | testing |
| Code | neurons | epochs | data | data |
| A | 10 | 50 | 2,005 | 2,097 |
| В | 10 | 75 | 1,998 | 7,832 |
| \mathbf{C} | 10 | 100 | 2,315 | 2,104 |
| D | 20 | 50 | 2,089 | 4,535 |
| E | 20 | 75 | 2,01 | 7,258 |
| F | 20 | 100 | 1,974 | 5,218 |
| G | 30 | 50 | 1,985 | 2,963 |
| Н | 30 | 75 | 2,134 | 5,839 |
| I | 30 | 100 | 1,951 | 3,997 |

Based on Table 1, it was found that almost all MAPE values in the training data were smaller than the MAPE values in the test data. This condition indicates the possibility of overfitting the model. However, there is a model where the MAPE value of the training data is greater than the MAPE value of the test data, namely the MLP C model with 10 neurons and 100 epochs. In this variation of the

model, it can be said that the model has a good fit so it can be concluded that the best variation of the MLP model in predicting MDKA stock prices is MLP with 10 neurons and 100 epochs.

Then in the Figure 2 shows a graphic comparison between the actual data and the predicted data from the MLP model.

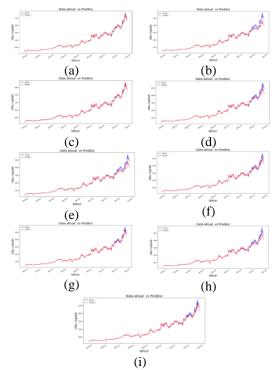


Figure 2. Comparison of predicted data and actual data: (a) MLP A (b) MLP B (c) MLP C (d) MLP D (e) MLP E (f) MLP F (g) MLP G (h) MLP H (i) MLP I

Figure 2 shows that sub-image (c), namely MLP C with 10 neurons and 100 epochs, has a denser graph than all other sub-images. This shows that the stock price predicted by the model is very close to the actual price.

3.2. Long Short-Term Memory

The results of MDKA's stock price prediction are divided according to the variations carried out. Table 2 below shows the MAPE value of all LSTM variations in predicting MDKA stock prices.

Table 2. LSTM Model MAPE

| Model Code of neurons of epochs training data testing data A 10 50 4,53 2,99 B 10 75 2,36 3,60 C 10 100 1,92 3,98 D 20 50 3,31 2,95 E 20 75 2,04 2,77 F 20 100 3,00 3,00 G 30 50 2,63 2,25 H 30 75 2,17 3,07 | Model | Number | Number | MAPE | MAPE |
|--|-------|---------|--------|----------|---------|
| A 10 50 4,53 2,99 B 10 75 2,36 3,60 C 10 100 1,92 3,98 D 20 50 3,31 2,95 E 20 75 2,04 2,77 F 20 100 3,00 3,00 G 30 50 2,63 2,25 | | of | of | training | testing |
| B 10 75 2,36 3,60 C 10 100 1,92 3,98 D 20 50 3,31 2,95 E 20 75 2,04 2,77 F 20 100 3,00 3,00 G 30 50 2,63 2,25 | Code | neurons | epochs | data | data |
| C 10 100 1,92 3,98 D 20 50 3,31 2,95 E 20 75 2,04 2,77 F 20 100 3,00 3,00 G 30 50 2,63 2,25 | A | 10 | 50 | 4,53 | 2,99 |
| D 20 50 3,31 2,95 E 20 75 2,04 2,77 F 20 100 3,00 3,00 G 30 50 2,63 2,25 | В | 10 | 75 | 2,36 | 3,60 |
| E 20 75 2,04 2,77 F 20 100 3,00 3,00 G 30 50 2,63 2,25 | C | 10 | 100 | 1,92 | 3,98 |
| F 20 100 3,00 3,00 G 30 50 2,63 2,25 | D | 20 | 50 | 3,31 | 2,95 |
| G 30 50 2,63 2,25 | E | 20 | 75 | 2,04 | 2,77 |
| | F | 20 | 100 | 3,00 | 3,00 |
| H 30 75 2,17 3,07 | G | 30 | 50 | 2,63 | 2,25 |
| | Н | 30 | 75 | 2,17 | 3,07 |
| I 30 100 3,57 3,04 | I | 30 | 100 | 3,57 | 3,04 |

Based on Table 2, it is found that the LSTM models A, D, F, G, and I are good-fit models because they have a higher MAPE value of the training data than the MAPE value of the test data. As for other models, it can be indicated that there is overfitting in the model. Among the five good-fit LSTM models, it was found that the LSTM G model with 30 neurons and 50 epochs was the best LSTM model because it had the smallest MAPE value of the test data. Figure 3 shows a comparison graph between the actual data and the predicted data from the LSTM model.

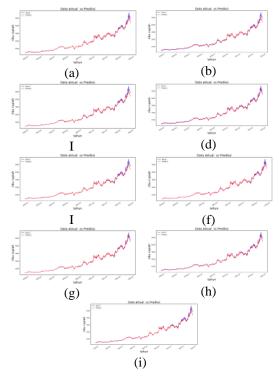


Figure 3. Comparison of predicted data and actual data: (a) LSTM A (b) LSTM B (c) LSTM C (d) LSTM D I LSTM E (f) LSTM F (g) LSTM G (h) LSTM H (i) LSTM I

Based on Figure 3, sub-image (g), namely LSTM G with 30 neurons and 50 epochs, has a denser graph than all other sub-images. This shows that the stock price predicted by the model is very close to the actual price.

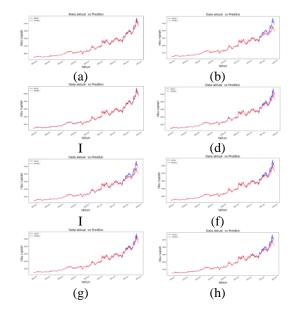
3.3. Gated Recurrent Unit (GRU)

The results of MDKA's stock price prediction are divided according to the variations carried out. Table 3 below shows the MAPE value of all GRU variations in predicting MDKA stock prices.

Table 3.
GRU Model MAPE

| Model | Number | Number | MAPE | MAPE |
|-------|---------|--------|----------|---------|
| Code | of | of | training | testing |
| Code | neurons | epochs | data | data |
| A | 10 | 50 | 2,606 | 2,854 |
| В | 10 | 75 | 1,912 | 2,746 |
| C | 10 | 100 | 2,529 | 2,785 |
| D | 20 | 50 | 1,949 | 3,447 |
| E | 20 | 75 | 2,606 | 2,854 |
| F | 20 | 100 | 5,413 | 2,476 |
| G | 30 | 50 | 4,495 | 2,852 |
| Н | 30 | 75 | 1,919 | 3,277 |
| I | 30 | 100 | 2,983 | 2,437 |

Based on Table 3, it is found that the GRU F, G, and I model are good-fit models because they have a higher MAPE value of the training data than the MAPE value of the test data. As for other models, it can be indicated that there is overfitting in the model. Among the three existing good-fit GRU models, it was found that the GRU I model with 30 neurons and 100 epochs was the best GRU model because it had the smallest test data MAPE value.



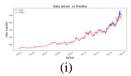


Figure 4. Comparison of predicted data and actual data: (a) GRU A(b) GRU B (c) GRU C (d) GRU D I GRU E (f) GRU F (g) GRU G (h) GRU H (i) GRU I

Figure 4 displays a comparison graph between actual data and predicted data using the GRU model. Sub-Figure (i), namely GRU I with 30 neurons and 100 epochs, has a denser graph than all other sub-Figures. This shows that the stock price predicted by the model is very close to the actual price.

3.4. Best Model Comparison

To find out the best model of all the algorithms tested, the following is a summary of the best models for each algorithm:

Table 4.

| The Best Mode | el of Each Algori | thm |
|-------------------------------|-------------------|---------|
| Architectural | MAPE | MAPE |
| Models | training | testing |
| WIOUCIS | data | data |
| MLP 10 neurons and 100 epochs | 2,315 | 2,104 |
| LSTM 30 neurons and 50 epochs | 2,63 | 2,25 |
| GRU 30 neurons and 100 epochs | 2,983 | 2,436 |
| | | |

From Table 4 it is found that the MLP model with 10 neurons and 100 epochs produces the smallest MAPE value among the three existing models, so it can be concluded that this model is the best model in predicting the closing price of MDKA stocks tested in this study.

Table 5.

| Stock Closing Price Prediction Results from the Best Model | | | | |
|--|---|--|--|--|
| Actual Price | Predicted Price | | | |
| (Rp) | (Rp) | | | |
| 460,408 | 478,159 | | | |
| 464,245 | 481,161 | | | |
| 460,408 | 478,159 | | | |
| 460,408 | 478,159 | | | |
| 456,572 | 475,157 | | | |
| | ••• | | | |
| 5300 | 5263,126 | | | |
| 5300 | 4922,110 | | | |
| 4950 | 4805,189 | | | |
| 4830 | 4834,419 | | | |
| 4860 | 4581,093 | | | |
| | Actual Price (Rp) 460,408 464,245 460,408 460,408 456,572 5300 5300 4950 4830 | | | |

Table 5 shows the results of closing stock price predictions with the best model, namely the 10 neuron and 100 epoch MLP model.

4. Conclusion

Based on the research, it was found that the MLP, LSTM, and GRU algorithms were able to predict the stock price of PT. Merdeka Copper Gold Tbk (MDKA) for the 2019 – 2022 period with good performance. From each algorithm, 9 variations of the model were carried out with variations in the number of neurons in the hidden layer and the number of epochs. The number of neurons varied was 10, 20, and 30. Meanwhile, the number of epochs was 50, 75, and 100. Of all the variations of the models tested, the best prediction results were obtained, namely from the MLP model with 10 neurons and 100 epochs with split training data: test data of 82.18. In the best model, the training MAPE data is 2.325 and the test MAPE data is 2.014. In this study, the prediction of stock closing prices is only influenced by the previous closing price variable without considering other variables. Therefore, future research is expected to be able to consider other variables besides the closing price variable so that the model obtained can be more complex and more representative of the real conditions that occur.

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