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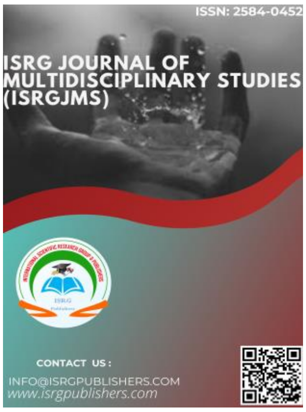

Gated Recurrent Unit (GRU) Method in Predicting Stock Prices of PT Astra Agro Lestari Tbk. on the Indonesia Stock Exchange (IDX)

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Abstract

Gated Recurrent Unit (GRU) is one of Recurrent Neural Network (RNN) algorithm architecture that is considered effective in processing sequential data and processing high-frequency data such as stock data. The study was conducted to assess the performance of the GRU model in forecasting daily stock prices and short-term predictions for 30 days. Hyperparameter tuning is applied to optimize the number of hidden layer units, dense layers, batch size, and also droplets to improve accuracy and prevent overfitting. From the results of the study, the best model was built using 64 units of dense layer, 16 units of hidden layer, 16 batch size, and 0.1 dropout with an RMSE value of 0.013 and MAPE of 0.03 where the accuracy reached 99.97%. It can be concluded that the model shows good performance in predicting stock prices based on the evaluation of the model and forecasting results that are not too far from the latest actual data.

Keywords: *GRU, Machine Learning, MAPE, RMSE, Stock, Time Series.*

1. INTRODUCTION

Gated Recurrent Unit (GRU) is a type of artificial neural network architecture Recurrent Neural Network (RNN) which developed to handle the problems commonly faced by traditional RNNs in training long-term data sequence [1]. GRU applies a similar gating concept to LSTM, but with a simpler system where GRU only has two gates, update gate and reset gate. Even so, GRU showed great performance equally as good as LSTM [2, 3].

GRU is able to see patterns in data and adapt to data movement well [4]. This makes GRU one of the methods used in processing high-frequency data that has fast movement, such as stock prices.

High-frequency data is generally found in stock data, where data is collected in very short intervals (seconds or milliseconds). This leads to the creation of high-frequency trading, where stock

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exchanges use computers to process stock prices in real-time, improve trading efficiency, and provide detailed analysis [5].

Stock forecasting is one of forecasting type that can be challenging because stock prices most likely change due to internal and external factors, such as policy changes or stock market movements [6].

Based on the above explanation, this study will discuss about GRU to forecast stock prices of PT Astra Agro Lestari Tbk's stock prices on the Indonesia Stock Exchange (IDX) which model performance and accuracy will be evaluated using RMSE and MAPE.

2. LITERATURE REVIEW

Gated Recurrent Unit (GRU) is one of the methods that is often used to conduct forecasting analysis. In addition, GRU is also one of the solutions in overcoming vanishing gradients and exploding gradients that are often experienced by traditional RNNs.

2.1 Recurrent Neural Network

Recurrent Neural Network (RNN) is a form of development of Artificial Neural Network (ANN) that is specifically designed to handle sequential data [7]. RNN has the basic mathematical formula shown as:

$$h_t = \tanh(W_h h_{t-1} + W_x x_t + b_h) \qquad (2.1)$$

and

$$y_t = W_y h_t + b_y \qquad (2.2)$$

where h_t is hidden state at t-time, $x_t$is the input at t-time, W_h is the weight for the previous hidden state, W_x is the weight for the current input, W_y is the weight for the output, b_h is the bias for the hidden state, and b_y is the bias for the output.

RNNs are able to retain information from the previous time step to be reprocessed at the next time step. Unfortunately, RNN only works well with short-term sequence because RNN tend to fails to retain the information from long-term sequences [8]. This problem happened due to vanishing gradient and exploding gradient.

2.2. Gated Recurrent Unit

Gated Recurrent Unit (GRU) implements two system gates, update gate and reset gate. Update gate act as a determinant of the amount of information that needs to be retained from the previous state, while reset gate act as a controller of the amount of information that needs to be forgotten from the previous state before being combined with the information from the new input [9]. This system allows GRU to capture dependencies, where dependency refers to the ability of the model to view and retain relevant information, from long-term sequential data [10].

The formula of update gate written as follows:

$$z_j = \sigma\big([W_z x]_j + [U_z h_{\langle t-1\rangle}]\big) \qquad (1)$$

then, for the reset gate it is formulated as follows:

$$r_j = \sigma\left([W_r x]_j + [U_r h_{\langle t-1\rangle}]_j\right) \qquad (2)$$

with the candidate hidden state as:

$$\tilde{h}_j^{\langle t\rangle} = tanh\left([Wx]_j + [U(r \odot h_{\langle t-1\rangle}]_j\right) \qquad (3)$$

then the current final hidden state formulated as:

$$h_j^{\langle t\rangle} = z_j h_j^{\langle t-1\rangle} + (1-z_j)\tilde{h}_j^{\langle t\rangle} \qquad (4)$$

where z is the update gate, r is the reset gate, $\tilde{h}_j^{\langle t\rangle}$ is the candidate hidden state, h_j is the final hidden state, $h_{\langle t-1\rangle}$ is the previous hidden state, x is the data input, σ is the sigmoid activation function, W, W_z, and W_r is the weight value for x and U, U_z, and U_r is the weight value for $h_{\langle t-1\rangle}$.

3. METHODOLOGY

The data used for this research was obtained from https://investing.com/ about daily closing stock price data of PT Astra Agro Lestari Tbk in the period from July 3rd, 2021 to August 30th, 2024 (n=765). First, the data is visualized with a line graph to observe price movements. Then, the data is processed first by scaling and splitting the data with a ratio of 80:20 with K Fold = 5.

Furthermore, to build the model, Hyper-parameter Tuning was applied to choose the best parameters and then measured using RMSE and MAPE to evaluate the performance of the model. Latter most, the stock prices forecasted for 30 days using the best model.

4. RESULT AND DISCUSSION

Data visualization aims to see the shape and pace of stock price movements over the past three years. The graph obtained is as follows:

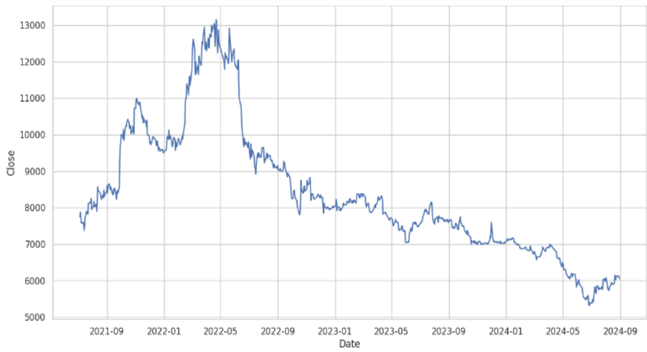

Fig. 1. Stock price chart

As can be seen from Fig 1, the stock price fluctuated in the middle of 2021 and soared up as it approached the end of the year. The stock price was seen to decline in early 2022 but then experienced a significant increase when approaching May 2022. Afterwards, the stock prices experienced a fairly drastic decline from mid-September 2022 and continue to fluctuate with a downward trend that lasted until mid-2024. Eventually, the stock prices increased starting from June 2024 to the end of August 2024.

Furthermore, pre-processing stage started with normalizing the data using MinMax Scaler, where the data value is changed to a range between 0 and 1. The formula written as follows:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (5)$$

where X' is the result of scaled data, X is the value of the data to be scaled, X_{min} is the minimum value of the overall data, and X_{max} is the maximum value of the entire data.

After being successfully scaled, the data divided into data train and test data, with the distribution scale used being 80% data train and 20% test data with KFold=5. The data that has been shared is then used to perform hyperparameter tuning to select the best parameter by trying multiple values at once. The parameters used are as follows:

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able 1. Hyperparameter Tuning Value

Hyperparameter	Value
Epoch	100
Loss function	Mean Squared Error
Hidden Neuron	16, 32, 64
Batch size	16, 32, 64
Dropout	0.1, 0.2

From the process, the following results were obtained:

Table 2. Hyperparameter Tuning Results

Hyperparameter	Value
Epoch	100
Hidden neuron	GRU unit: 16 Dense unit: 64
Batch size	16
Dropout	0.1
MSE	0.000526

Table 2 shows that hyperparameter tuning has obtained the best model with the smallest MSE score, namely 0.000526, is found in 16 units of GRU layer, 64 units of dense layer, and 16 units of batch size with a dropout of 0.1. Furthermore, the GRU model was built and used to train the data train. The model then applied to the data test to make prediction. The results was shown as follows:

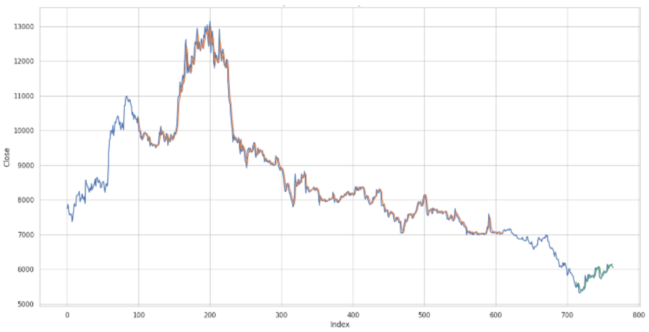

Fig 2. Prediction Result

Based on Fig 2, the graph for the original data is shown with a blue line, an orange line for the prediction results using the train data, and a green line for the prediction results using the test data. Result shows that the prediction line shows similar pattern as original data. This can be concluded that the model has great performance and able to work well.

Furthermore, to show more definite result, the model is evaluated to find out the percentage of the accuracy and how much error is generated. The metrics used are MAPE and RMSE as shown below:

Table 3. Model Evaluation Results

Evaluator	Value
RMSE	0.013
MAPE	0.03

It can be seen that the RMSE score obtained is 0.013 and the MAPE value obtained is 0.03, which shows that the error obtained is 3%. From the results of MAPE, it can also be concluded that the accuracy of the model prediction reaches 99.97%.

Here in after, the stock price forecast will be carried out for the next 30 days. The forecast results are displayed as follows:

Table 4. Forecasting Results

Date	Forecast	Actual
30/08/2024	6168	6050
02/09/2024	6221	6150
03/09/2024	6275	6125
04/09/2024	6328	6025
05/09/2024	6382	6375
06/09/2024	6435	6625
09/09/2024	6488	6450
10/09/2024	6541	6450
11/09/2024	6594	6350
12/09/2024	6646	6450
13/09/2024	6698	6350
17/09/2024	6750	6400
18/09/2024	6801	6350
19/09/2024	6853	6475
20/09/2024	6904	6625
23/09/2024	6955	6725
24/09/2024	7006	6725
25/09/2024	7056	6725
26/09/2024	7106	6775
27/09/2024	7156	6700
30/09/2024	7206	6600
01/10/2024	7256	6725
02/10/2024	7305	6700
03/10/2024	7354	6700
04/10/2024	7404	6600
07/10/2024	7453	6700
08/10/2024	7501	6650
09/10/2024	7550	6600
10/10/2024	7598	6525
11/10/2024	7647	6575

Based on the table above, it can be seen that the results of the stock price prediction and the actual share price from August 30th, 2024 to October 11th, 2024 are not too different. This indicates the model is producing good performance. In addition, the stock price is

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expected to experience a significant increase as shown in the following chart:

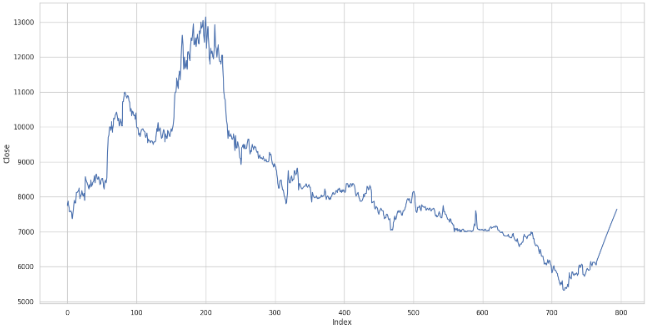

Fig 3. Forecasting Result

5. CONCLUSION

Based on the results and discussion, a conclusion was obtained, namely the best model with a score of -0.000526, where the model used a number of neurons of 64 neurons for the dense layer, 16 neurons for the hidden layer, dropout of 0.1 or 10%, and 16 data processed for each iteration. In addition, the accuracy level produced from this model is 99.97% where the RMSE value obtained is 0.013 and the MAPE value obtained is 0.03. Furthermore, from the model owned, the stock price of PT Astra Agro Lestari Tbk is forecasted for 30 days, namely August 30th, 2024 to October 11th, 2024, where it is known that the share price will decrease.

References

1. Cho, K., Merriënboer, B. V., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. 2014. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 1725-1734. Association for Computational Linguistics, Doha, Qatar.
2. Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. 2014. *Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling*. Presented in NIPS 2014 Deep Learning and Representation Learning Workshop.
3. Happy Nur Azizah, H.N., Herawati, N., Sutrisno, A., Widiarti Study Study of Gated Recurrent Unit (GRU) and Extreme Gradient Boosting (XGBoost) Methods in Predicting the Closing Price of Garudafood Putra Putri Jaya Tbk., Indonesia. International Journal of Multidisciplinary Research and Publications (IJMRAP). **7**(1),199-202.
4. Ridwan, M., Sadik, K., & Afendi, F. M. 2024. Comparison of ARIMA and GRU Models for High-Frequency Time Series Forecasting. *Scientific Journal of Informatics*. **10**(3): 389-400.
5. Zhang, X., Huang, Y., dan Xing, L. 2023. Novel Modelling Strategies for High-Frequency Stocsk Trading Data. *Financial Innovation*. **9**(32)
6. Hamzah, Chrismawan, P. E. E., Winardi, S., & Tambunan, R. 2023. Robust Stock Price Prediction using Gated Recurrent Unit. *International Journal of Informatics and Computation (IJICOM)*. **5**(1): 29-38.
7. Goodfellow, I., Bengio, Y., & Courville, A. 2016. *Deep Learning*. MIT Press, Massachusetts.
8. Das, S., Tariq, A., Santos, T., Kantareddy, S. S., & Banerjee, I. 2023. Recurrent Neural Networks (RNNs): Architectures, Training Tricks, and Introduction to Influential Research. Protocol. 197: 117-138
9. Onyekpe, U., Palade, V., Kanarachos, S., & Christopoulos, S. R. G. 2021. A Quaternion Gated Recurrent Unit Neural Network for Sensor Fusion. Information. **12**(3) 117-132
10. Mienye, I. D., Swart, T. G., and Obaido, G. 2024. Recurrent Neural Networks: A Comprehensive Review of Architectures, Variants, and Applications. *Information*. **15**(9).

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