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Predicting the Share Price of Bank Syariah Indonesia Using the GRU (*Gated Recurrent Unit*) Algorithm

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A R T I C L E I N F O

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A B S T R A C T

This scientific paper uses three different models, namely the baseline model, hyperparameter tuning with 4 layers, and hyperparameter tuning with 5 layers, to evaluate the effectiveness of GRU in predicting future stock prices. The performance of each model was measured using Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The baseline model, configured with 50 GRU units, 100 lookbacks, 100 timestamps, batch size 64, and 50 epochs, showed the best performance, achieving MSE 5601.44, MAE 54.06, RMSE 74.84, and MAPE 1.90%. In comparison, the 4-layer model showed slightly higher errors, with MSE 10842.89, MAE 79.65, RMSE 104.13, and MAPE 2.77%, while the 5-layer model produced higher errors, with MSE 14687.76, MAE 91.94, RMSE 121.19, and MAPE 3.22%.

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INTRODUCTION

In recent years, stock price predictions have become a major concern in research in the fields of finance and technology. Advances in machine learning methods and neural networks have given birth to advanced models such as the Gated Recurrent Unit (GRU). As one of the variants of the recurrent neural network (RNN), the GRU is specifically designed to process sequential data. Its ability to handle complex temporal information, such as stock price movement data, makes it a highly effective tool in stock market analysis and prediction (Oni et al., 2023). In this context, the use of GRU in stock price prediction offers a more adaptive and responsive approach to rapid market fluctuations

The main advantage of GRU lies in its ability to overcome the problem of vanishing gradient which is often an obstacle in conventional RNN models. By utilizing the gating mechanism, the GRU is able to retain important information from previous time steps. This is crucial in stock price prediction which involves various external and internal factors as its influence (Saud & Shakya, 2019).

Research conducted by Oni reveals the success of the GRU model in predicting the prices of various commodities in traditional markets, highlighting its flexibility and effectiveness in processing diverse data (Oni et al., 2023). In addition, Wu in his study showed that GRU is able to provide accurate predictions for stock prices during times of uncertainty, such as during the COVID-19 pandemic (Wu & Huang, 2023). These findings confirm that GRU not only excels in stable market conditions, but is also able to adapt well in uncertain situations.

Overall, the application of GRU in predicting stock prices has given promising results. This model is able to process complex temporal data with a higher level of accuracy than conventional methods. With the continuous development and integration of new techniques, such as combinations with other models and more advanced feature processing, GRU has the potential to be an invaluable tool for future financial market analysis ("Predicting TSLA Stock Price Based on LSTM and GRU Models," 2023).

LITERATURE REVIEW

Stock Price Prediction in Financial Markets

Stock price prediction has long been a central topic in financial research due to its importance for investment decision-making and risk management. Stock prices are inherently non-linear, noisy, and volatile, influenced by historical price movements, macroeconomic conditions, and market sentiment. Traditional statistical approaches such as Moving Average, Autoregressive Integrated Moving Average (ARIMA), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been widely applied

Deep Learning Approaches for Stock Price Forecasting

Deep learning models have demonstrated strong performance in modeling complex, non-linear relationships in large-scale data. Common architectures applied in financial time series analysis include Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). Among these, RNN-based models are particularly well-suited for sequential data because they retain information from previous time steps.

Gated Recurrent Unit (GRU) for Time Series Prediction

The Gated Recurrent Unit (GRU) is a type of recurrent neural network that simplifies the LSTM architecture by combining memory and gating mechanisms into two primary components: the update gate and the reset gate. This simplified structure allows GRU models to train faster and require fewer parameters, while still maintaining the capability to model long-term temporal dependencies.

METHODOLOGY

This scientific work will apply a quantitative approach, which starts with establishing basic assumptions. After that, the relevant variables will be determined and analyzed using valid methods, especially those that are in accordance with the quantitative approach (Ali et al., n.d.). This scientific paper will use the Gated Recurrent Unit (GRU) deep learning algorithm to analyze and classify stock data from PT Bank Syariah Indonesia Tbk. The main purpose of this scientific work is to predict future stock value movements and evaluate model performance through a number of metrics, namely Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

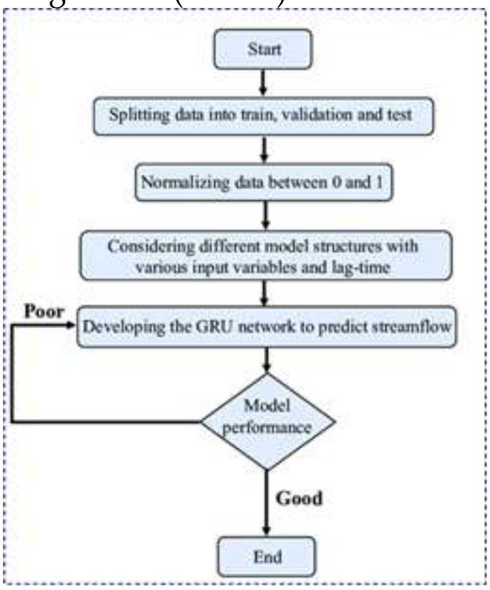


Figure 1. Stages of Study

Pre-processing data

The data that has been collected in advance will be divided into 80% training data and 20% test data

1. Data Normalization
   After the data is divided into training data and test data, the next step is to carry out the normalization process. Normalization aims to reduce excessive data variation, as high variations can affect the accuracy of prediction results. The method used in this process is the Min-Max Scaler, where this method applies linear transformations to the original data. This transformation results in a balance of value between the data, both before and after normalization, thus supporting more stable and accurate model performance (Azzahra Nasution et al., 2019).
2. Parameter Model
   The next stage is to determine the model parameters to be applied in the Gated Recurrent Unit (GRU) deep learning algorithm to achieve optimal performance, such as improved accuracy and evaluation of other aspects. This scientific paper will use three types of models, namely baseline model, hyperparameter tuning with 4 layers, and hyperparameter tuning with 5 layers. Once the model with the best parameters is successfully identified, it will be used to make predictions or forecasts in real time

Gated Recurent Unit (GRU)

The Gated Recurrent Unit (GRU) model is a derivative of the improved Recurrent Neural Network (RNN) model. The GRU model has a simpler structure that only has an update gate and a reset gate. Despite having fewer gates and a simpler structure, the GRU model provides predictive accuracy comparable to other deep learning models. The reset gate has a function to choose from the information that should be reset or deleted, while the update gate has a function to select the information that should be retained. After that, calculate the hidden state that serves to store the relevant information previously by using the update gate.

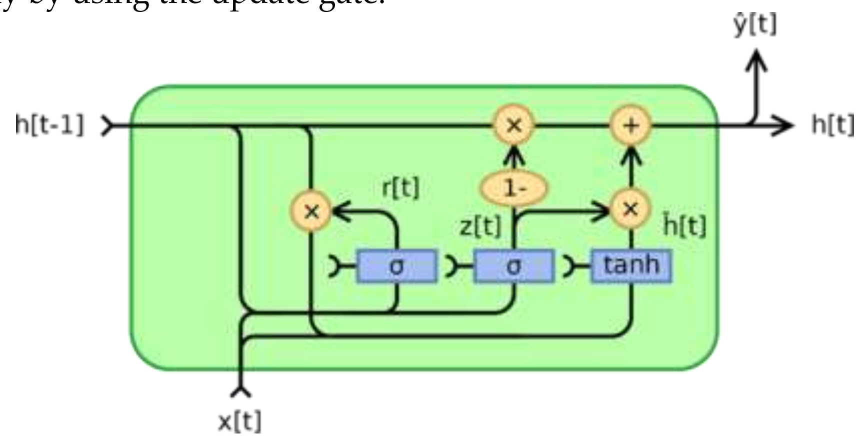


Figure 2. Gated Recurrent Unit (GRU) Architectural Model

RESEARCH RESULT AND DISCUSSION

Data Collection

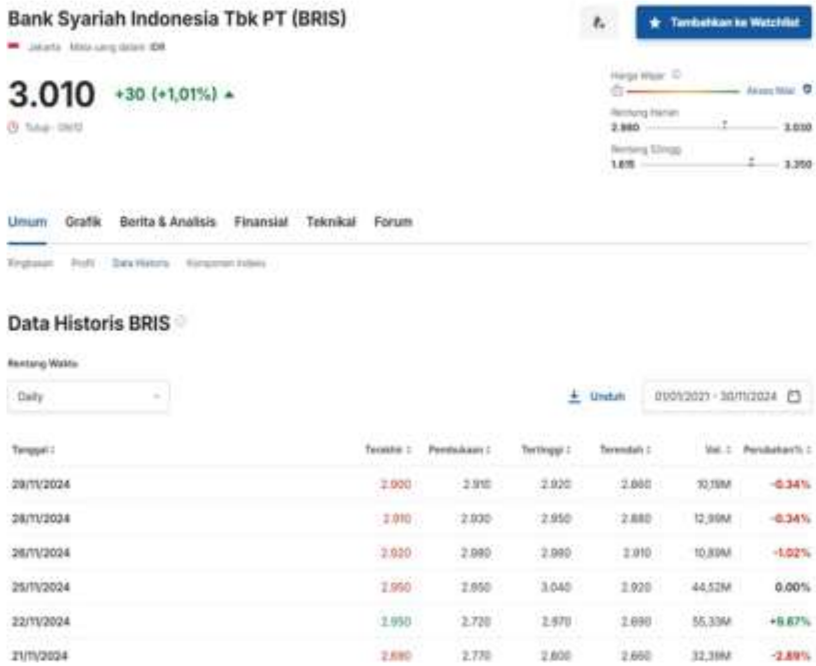
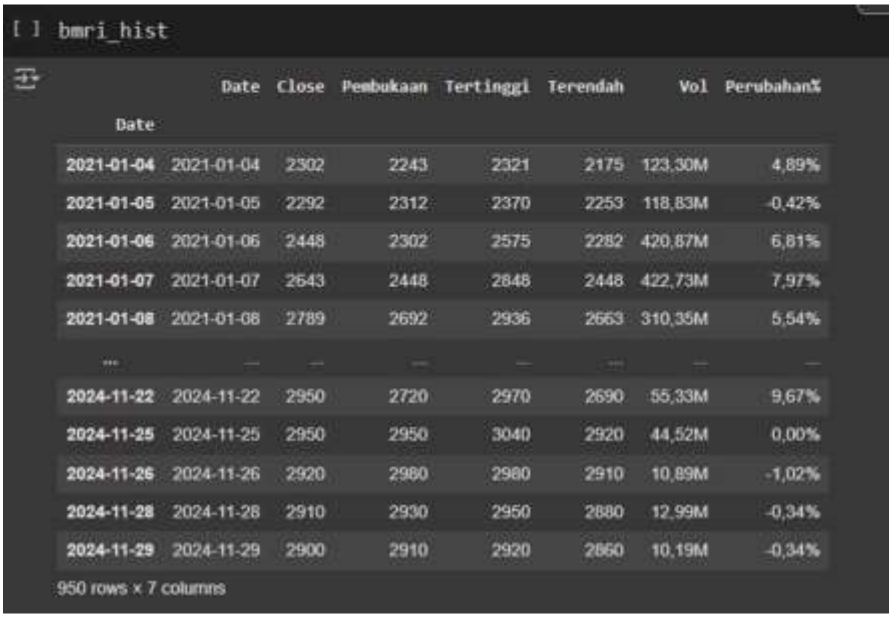


Figure 3. Website Display

https://id.investing.com/equities/bank-brisyariah-historical-data



[ ] bmri_hist

Date	Date	Close	Pembukaan	Tertinggi	Terendah	Vol	Perubahan%
2021-01-04	2021-01-04	2302	2243	2321	2175	123,30M	4,89%
2021-01-05	2021-01-05	2292	2312	2370	2253	118,83M	-0,42%
2021-01-06	2021-01-06	2448	2302	2575	2282	420,87M	6,81%
2021-01-07	2021-01-07	2643	2448	2848	2448	422,73M	7,97%
2021-01-08	2021-01-08	2789	2692	2936	2663	310,35M	5,54%
...	...	...	...	...	...	...	...
2024-11-22	2024-11-22	2950	2720	2970	2690	55,33M	9,67%
2024-11-25	2024-11-25	2950	2950	3040	2920	44,52M	0,00%
2024-11-26	2024-11-26	2920	2980	2980	2910	10,89M	-1,02%
2024-11-28	2024-11-28	2910	2930	2950	2880	12,99M	-0,34%
2024-11-29	2024-11-29	2900	2910	2920	2860	10,19M	-0,34%

950 rows × 7 columns

Figure 4. Dataset Collection Results

Pre-Processing

The data that has been obtained will be divided into 80% training data and 20% test data. In Figure 5, the blue line shows 760 training data and the yellow line shows 190 test data

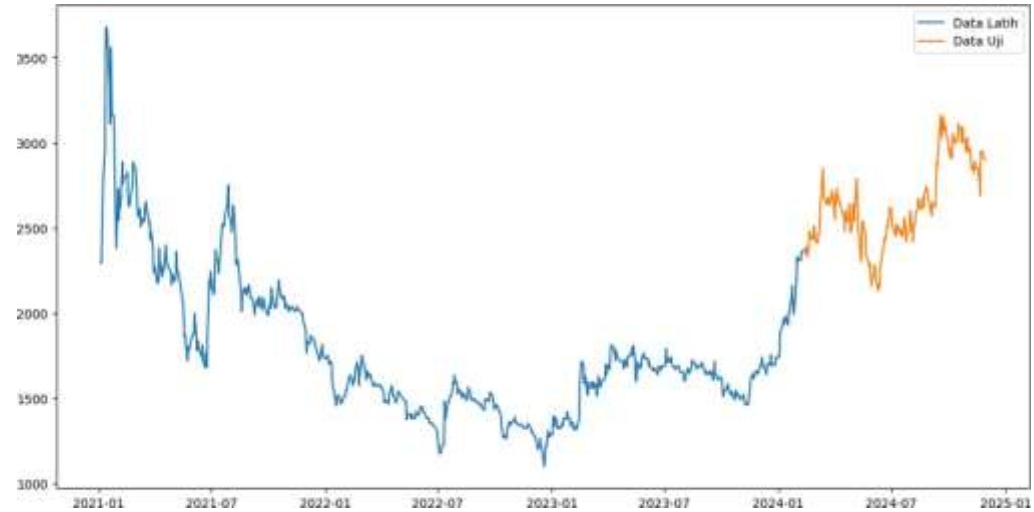


Figure 5. Dataset Sharing Results

After the data is divided into training data and test data, the next step is to implement the normalization process using the Min-Max Scaler method. This normalization aims to change the values in the dataset to be within a certain range, usually between 0 and 1, so as to reduce the large-scale influence on the data. With this normalization, the deep learning model used will be more stable and able to capture patterns more accurately, as the difference in scale between features has been minimized. This process also helps to improve efficiency in model training and produce more consistent prediction results.

Normalization Result of the Min Max Scaler in the "Close" Column

```
print(bmri_hist2[:10]) #10 Data Pertama

[[0.46643384]
 [0.46255336]
 [0.52308886]
 [0.59875825]
 [0.65541327]
 [0.72370974]
 [0.99611952]
 [1.        ]
 [0.99611952]
 [0.96197128]]
```

Figure 6. Min-Max Scaler Results First 10 Data

```
print(bmri_hist2[-10:]) #10 Data Terakhir

[[0.67908421]
 [0.67908421]
 [0.65192084]
 [0.64804036]
 [0.61699651]
 [0.71788902]
 [0.71788902]
 [0.70624757]
 [0.70236709]
 [0.69848661]]
```

Figure 7. Min-Max Scaler Results Last 10 Data

Gated Recurrent Unit (GRU)

In this scientific paper, the construction of the Gated Recurrent Unit (GRU) deep learning model was carried out using the Python TensorFlow library. Leveraging the capabilities of TensorFlow, the model architecture is designed using a sequential model approach. This approach allows the sequentialization of neural network layers, making the model development process more structured and manageable. The TensorFlow library was chosen because of its advantages in handling complex numerical computations, flexibility in deep learning implementations, and its availability of features that support model optimization, such as hyperparameter adjustment and efficient data processing. The results of this sequential model can be seen in Figure 8, Figure 9, and Figure 10.

Model: "sequential"

Layer (type)	Output Shape	Param #
gru (GRU)	(None, 100, 50)	7,950
gru_1 (GRU)	(None, 50)	15,300
dense (Dense)	(None, 1)	51

Total params: 23,301 (91.02 KB)
Trainable params: 23,301 (91.02 KB)
Non-trainable params: 0 (0.00 B)

Figure 8. Baseline Model

Model: "sequential_1"

Layer (type)	Output Shape	Param #
gru_3 (GRU)	(None, 100, 50)	7,950
gru_4 (GRU)	(None, 100, 100)	45,600
gru_5 (GRU)	(None, 100)	60,600
dense_1 (Dense)	(None, 1)	101

Total params: 114,251 (446.29 KB)
Trainable params: 114,251 (446.29 KB)
Non-trainable params: 0 (0.00 B)

Figure 9. Hyperparameter Tuning Layer 4

Model: "sequential_1"

Layer (type)	Output Shape	Param #
gru_4 (GRU)	(None, 100, 200)	121,800
gru_5 (GRU)	(None, 100, 150)	158,400
gru_6 (GRU)	(None, 100, 100)	75,600
gru_7 (GRU)	(None, 150)	113,400
dense_1 (Dense)	(None, 1)	151

Total params: 469,351 (1.79 MB)
Trainable params: 469,351 (1.79 MB)
Non-trainable params: 0 (0.00 B)

Figure 10. Hyperparameter Tuning Layer 5

Gated Recurrent Unit (GRU) Model Classification

a. Processing data

The next test was conducted using the Gated Recurrent Unit (GRU) deep learning model, using the same dataset but with variations in data sharing and different parameter configurations. In this test, the baseline model was run for 50 epochs with a data division of 80% for training data and 20% for test data. The model with hyperparameter tuning using 4 layers was also tested for 50 epoches with the same data distribution, namely 80% training data and 20% test data. In addition, the model with hyperparameter tuning uses 5 layers following a similar arrangement, i.e. 50 epochs with training data sharing and tests of 80% and 20%. This setting is done to evaluate the performance of each model consistently in various parameter configurations.

Table 1. GRU Model Test Results

Model GRU	Data	Epoch	Look back	Timestamp	MSE	MAE	RMSE	MAPE
Baseline model	Latih	50	100	100	5601.44	54.06	74.84	1.90
Baseline model	Uji	50	100	100	5601.44	54.06	74.84	1.90
Hyperparameter tuning layer 4	Latih	50	100	100	10842.89	79.65	104.13	2.77
Hyperparameter tuning layer 4	Uji	50	100	100	10842.89	79.65	104.13	2.77
Hyperparameter tuning layer 5	Latih	50	100	100	14687.76	91.94	121.19	3.22
Hyperparameter tuning layer 5	Uji	50	100	100	14687.76	91.94	121.19	3.22

b. Model Comparison

From Table 1, it can be seen that the baseline model is the model that has the best performance compared to other models. The baseline model produces MSE, MAE, RMSE, and MAPE values. Baseline is able to provide lower error values based on evaluation metrics such as MSE, MAE, RMSE, and MAPE, thus proving its ability to predict data more accurately. The model manages to efficiently capture complex patterns in datasets, making it an excellent choice for use in future predictions.

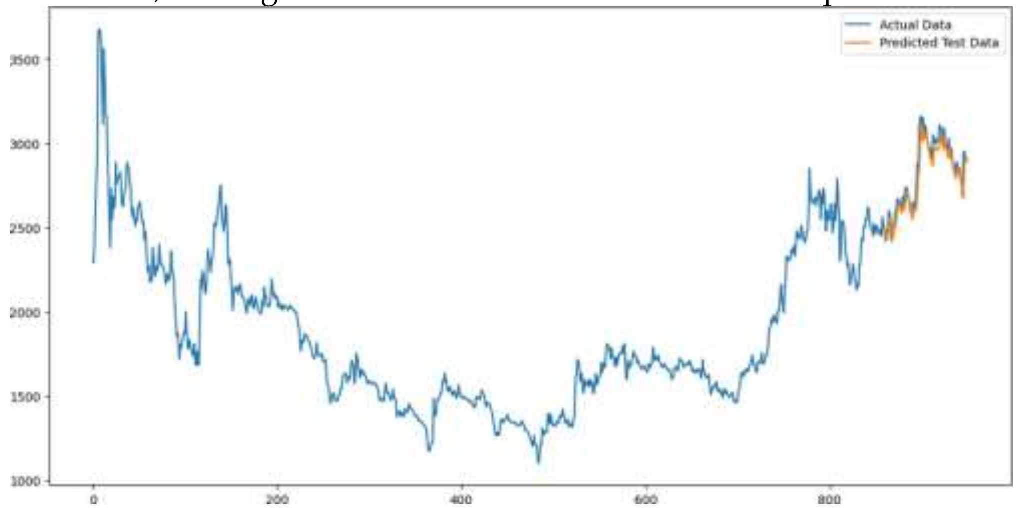


Figure 11. Baseline Model

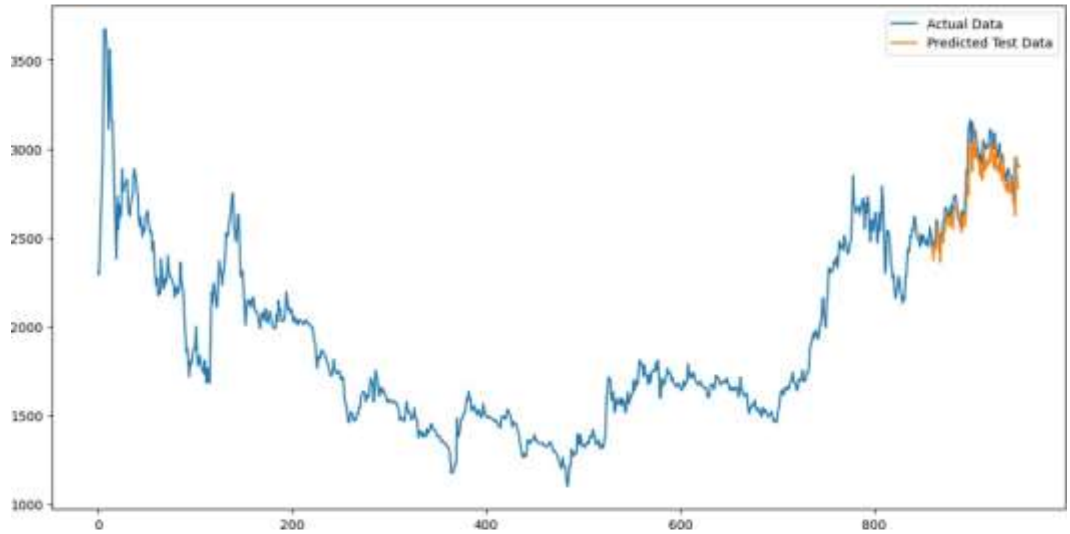


Figure 12. Hyperparameter Tuning 4 Layer

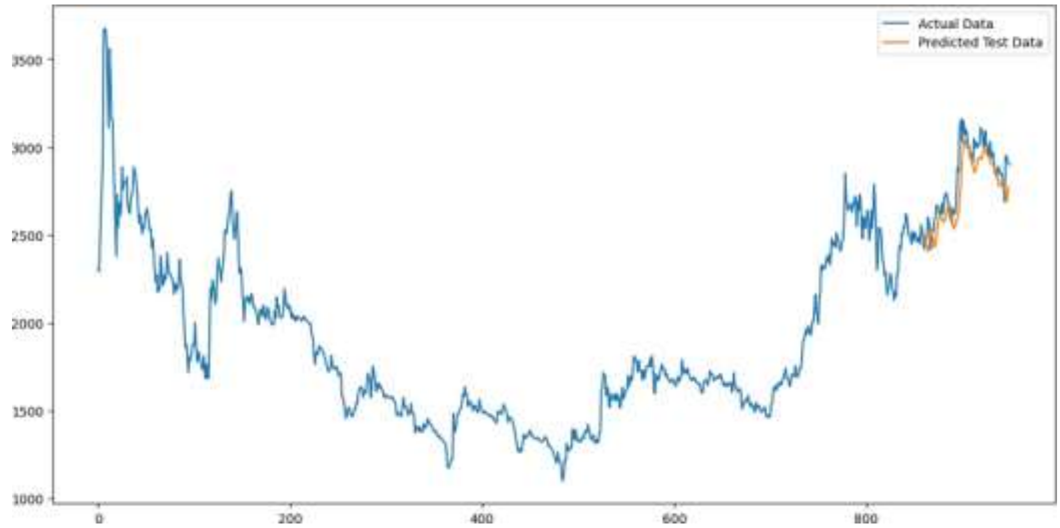


Figure 13. Hyperparameter Tuning 5 Layers

BSI Stock Close Price Data Prediction (Baseline Model)

Next, the prediction stage continues by initializing a blank matrix to accommodate the prediction results. After that, visualization is carried out to compare the closing price of the stock over the last 100 days with the prediction of the closing price for the next 30 days generated by the baseline model.

Figure 14. Bank Syariah Indonesia Stock Price Prediction for the Next 30 Days

Analysis of Gated Recurrent Unit (GRU) Algorithm Prediction Results

In tests with the baseline model, which used parameter configurations such as 50 GRU units, 100 lookback, 100 timestamps, 64 batch sizes, and 50 epochs with the Adam optimizer, the model showed excellent performance on the tested data. The results of the evaluation of the metric showed an MSE value of 5601.44, which indicates that this model has a fairly low squared error in the stock price prediction. In addition, the MAE of 54.06 shows that the average difference between the predicted and actual value is about 54 points, which is still good for applications in stock price prediction. The RMSE of 74.84 gives an idea that the model's prediction error is within reasonable limits, while the MAPE of 1.90% indicates that the rate of prediction error in the form of a percentage is very minimal, reflecting the model's ability to produce predictions that are close to the actual value.

Further testing was carried out with hyperparameter tuning using 4 layers, which is expected to capture more complex patterns in the data. The results of the metric evaluation for this model showed an MSE value of 10842.89, which is higher than the baseline model. This indicates that although the 4-layer model is able to capture some of the more complex patterns, there is a significant increase in square error. The MAE of 79.65 also shows that the average difference between the prediction and the actual value is greater compared to the baseline model. The RMSE of 104.13 further confirms that this model has a greater prediction error. Meanwhile, the MAPE of 2.77% indicates that the prediction error rate is also slightly higher compared to the baseline. Although these 4-layer models can learn more complex patterns, higher results on evaluation metrics suggest that adding layers does not necessarily result in better predictions in this context.

In a model with hyperparameter tuning using 5 layers, which is expected to capture deeper and more complex patterns, the evaluation results show that although this model is more in-depth, its performance is not much different from the previous model. The MSE of 14687.76 shows a larger squared error compared to the two previous models, both baseline and 4-layer models. This indicates that the model with 5 layers does not provide better results, even showing a higher increase in errors. The MAE of 91.94 and the RMSE of 121.19 confirm that this model has a greater prediction error than the previous two models. The MAPE of 3.22% shows that the percentage error rate is also higher compared to the baseline and 4-layer models. These results suggest that while adding layers can provide more capacity to learn more complex features, in these cases, adding layers does not provide a significant performance improvement. The success of the model in predicting stock prices is likely to be more influenced by other factors such as more precise hyperparameter settings and more appropriate architectures.

CONCLUSIONS AND RECOMMENDATIONS

From the series of tests that have been carried out, it can be concluded that deep learning can be applied to predict stock prices using the Gated Recurrent Unit (GRU) method. This scientific paper shows various results in the prediction of the share price of PT. Bank Syariah Indonesia Tbk and also make it possible to determine the most effective model in making predictions. In addition, the purpose of this scientific paper is to improve the quality of the classification of the GRU method in predicting future stock prices, focusing on the analysis of the results obtained from variations in the use of parameters such as lookback, timestamp, and epoch, which can produce the best data training, where the baseline model produces an MSE value of 5601.44, MAE of 54.06, RMSE of 74.84, and MAPE of 1.90. Then the model with Hyperparameter Tuning 4 Layer produces an MSE value of 10842.89, MAE of 79.65, RMSE of 104.13, and MAPE of 2.77. And the last model with 5 Layer Hyperparameter

Tuning produces an MSE value of 14687.76, MAE of 91.94, RMSE of 121.19, and MAPE of 3.22

The prediction results using the baseline model (the best-performing model based on the MSE, MAE, RMSE, and MAPE values) show a declining performance against its share price in the next 30 days. But keep in mind, the prediction results are not 100% the Absolute Truth.

ADVANCED RESEARCH

Further studies are needed regarding the implementation of the results of Bank Syariah Indonesia's share price prediction using the Gated Recurrent Unit (GRU) algorithm.

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