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Stock Price Prediction of PT. Pertamina Geothermal Energy Tbk Using Gated Recurrent Unit (GRU) Model

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Abstract

This study aims to predict the stock price of PT. Pertamina Geothermal Energy Tbk (PGEO.JK) using the Gated Recurrent Unit (GRU) model, a neural network architecture in the Recurrent Neural Network (RNN) category that is known to be effective in handling time series data. The data used is historical stock price data from 2022 to 2024 taken from Yahoo Finance. The GRU method was chosen because of its ability to remember long-term information and overcome the vanishing gradient problem. In the research process, the data was divided into two parts, namely training data and testing data. The GRU model was trained without adjusting hyperparameters to measure its performance by default. Model evaluation was carried out using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2) metrics. The results of the study indicate that the GRU model is able to provide good prediction results with an RMSE value of 0.0271, MAE of 0.0180, MAPE of 22.25%, and an R^2 value of 0.9112. These values indicate that the GRU model is quite accurate in predicting the price of PGEO.JK shares. These findings indicate that GRU is a potential method in stock prediction analysis, especially in the renewable energy sector.

Keywords: Stock price prediction, PT. Pertamina Geothermal Energy Tbk, Gated Recurrent Unit (GRU).

1. Introduction

The financial sector is increasingly relying on technology to analyze and project market dynamics. Stock price prediction is one of the main challenges that continues to be developed through data-based approaches and intelligent algorithms (Sonkavde et al., 2023). With high market volatility and the complexity of factors that influence stock prices, conventional methods are often less able to reveal hidden patterns that are non-linear in nature. Therefore, deep learning-based approaches such as Recurrent Neural Network (RNN) and its variants are starting to be widely used in stock analysis (Ridwan et al., 2023).

One of the most promising models is the Gated Recurrent Unit (GRU), which is known to be able to handle long-term data sequences with simpler structures than LSTM (Niu et al., 2023). The GRU model has advantages in computational efficiency and training speed, while maintaining competitive accuracy in forecasting tasks (Mateus et al., 2021). These advantages are the main reasons for choosing GRU in this study, to measure the extent of its performance in the context of stock prediction in energy sector companies, especially PT. Pertamina Geothermal Energy Tbk.

PT. Pertamina Geothermal Energy Tbk is one of the main players in the renewable energy sector in Indonesia which is engaged in the development and utilization of geothermal energy (Padantya & Sudrajad, 2024). As attention to sustainability issues and clean energy transitions increases, stocks from companies such as PGE have attractive growth potential and are of interest to investors. However, to make the right investment decisions, accurate stock price predictions are needed, especially in the short term (Chang et al., 2023).

This study aims to evaluate the performance of the GRU model in predicting the stock price of PT. Pertamina Geothermal Energy Tbk. The assessment is carried out based on evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R^2 Score. The main focus of the research is not only to produce predictions, but also to analyze the ability of GRU in capturing historical patterns and its potential accuracy in real capital market situations.

The approach used in this study includes collecting historical stock price data, data normalization, forming a time series dataset, building a GRU architecture, as well as model training and evaluating results. No hyperparameter tuning is carried out in the training process, so that GRU performance can be observed purely without the influence of additional optimization. Thus, this study is expected to provide an objective picture of the initial ability of the GRU model in the task of predicting stock prices.

2. Methodology

This study uses a quantitative approach with a deep learning-based experimental method to predict the stock price of PT. Pertamina Geothermal Energy Tbk (stock code: PGEO.JK). The model used in this study is the Gated Recurrent Unit (GRU), one of the Recurrent Neural Network (RNN) architectures known to be efficient in processing time series data (Zainuddin & Hasan, 2021; Hong et al., 2022). This study aims to observe the performance of GRU in raw form (without tuning) in order to provide an initial picture of the model's capabilities in the context of stock prediction.

2.1. Data Collection

The data used in this study is historical data on the stock price of PT. Pertamina Geothermal Energy Tbk taken from Yahoo Finance. The data time range starts from early 2022 to 2025. The main variable used in the study is the Close price, which is the daily closing price that represents the final price of stock trading activities every day. The closing price visualization is presented in the form of a graph in Figure 1 to facilitate understanding of the movement of PT. Pertamina Geothermal Energy Tbk's stock price during the observation period.

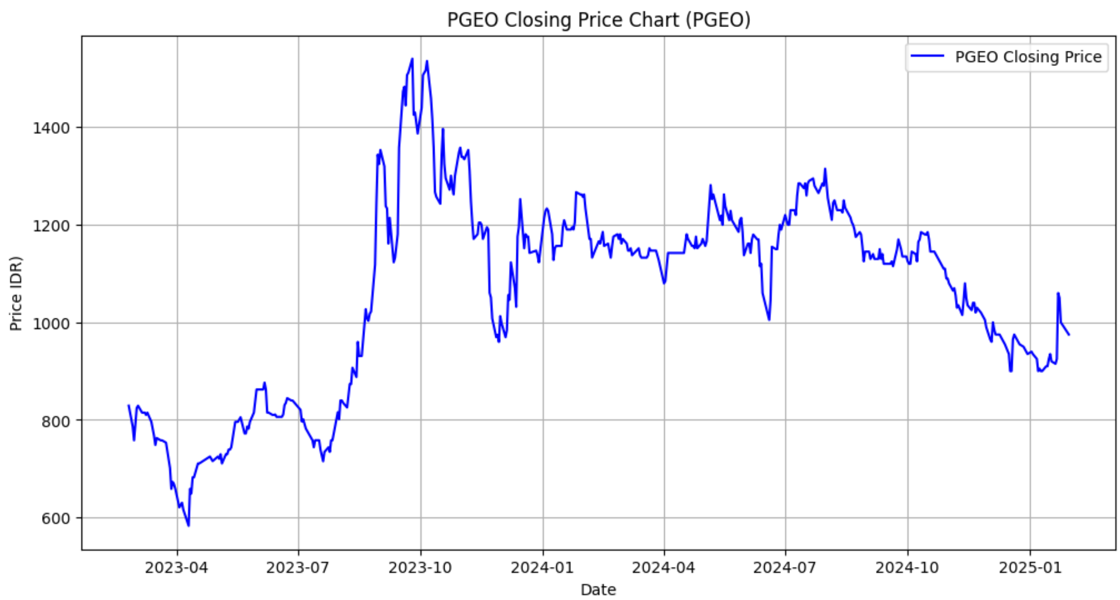

Figure 1: PGEO stock closing price (2020–2025)

As seen in Figure 1, the closing price of PT. Pertamina Geothermal Energy Tbk shares showed a significant upward trend in the period from July to October 2023. This increase reached the highest price point throughout the year before finally experiencing a sharp decline towards the end of 2023. Entering 2024 to approaching the beginning of 2025, the movement of stock prices tended to decline gradually. Although this decline continues, the level of decline is not as significant as what happened at the end of the previous year.

2.2. Data Pre-Processing

The initial step is to normalize the data using the Min-Max Scaling method to change the stock price value into a scale between 0 and 1. This aims to speed up the model training process and avoid the dominance of large numeric values in the learning process. Furthermore, the data is formed in a time series window format, namely grouping historical data into input forms and prediction targets with a certain time window, for example 60 days of historical data to predict prices on the 61st day.

2.3. Model Development and Training

The stock price prediction model is built using the Gated Recurrent Unit (GRU) architecture, a variant of the Recurrent Neural Network (RNN) designed to handle time series data such as stock prices. In this study, the model architecture consists of two GRU layers. The first layer uses 224 units and is set to return the entire data sequence (using return_sequences=True), which is then passed on to the next layer. This layer is also equipped with a dropout of 0.2 to reduce the risk of overfitting. Furthermore, the second GRU layer has 256 units and is set to only return the last output (using return_sequences=False). This layer is also accompanied by a dropout of 0.5 as an additional form of regularization. Finally, the results of the GRU will be processed by the output layer in the form of a Dense layer with one neuron, which functions to produce predictions of the closing price of the stock.

This model is compiled using the Adam optimizer with a learning rate of 0.001 and a loss function of Mean Squared Error (MSE), which is commonly used for regression problems. After the architecture is completed, the training process is carried out using training data (X_train, y_train) for a maximum of 50 epochs with a batch size of 16. In addition, validation data (X_test, y_test) is also used to monitor model performance in each epoch. To improve training efficiency and prevent overfitting, two callbacks are used, namely EarlyStopping and ReduceLROnPlateau. EarlyStopping will automatically stop training if there is no improvement in the validation loss value in 5 consecutive epochs, and will return the best weights of the model. Meanwhile, ReduceLROnPlateau will reduce the learning rate value by 50% if there is no improvement in model performance in 3 epochs, with a minimum learning rate limit of 0.00001.

2.4. Evaluation

The evaluation is conducted using four common metrics in regression modeling, namely Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and R-Squared Score (R^2). The following is an explanation and formula for each metric:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \tilde{y}_i| \tag{1}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \tag{2}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \tilde{y}_i}{y_i}\right| \tag{3}$$

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y}_i)^2} \tag{4}$$

where y_i is the actual value and $\tilde{y}_i$ is the predicted value (Majumder et al., 2022). These metrics are used to assess how close the model predictions are to the actual data and to what extent the GRU model can explain the variation in stock price data.

3. Results and Discussion

3.1. Model Performance Evaluation

The evaluation of the performance of the GRU model in predicting the stock price of PT. Pertamina Geothermal Energy Tbk shows quite satisfactory results.

Table 1: GRU Model performance evaluation results

Evaluation method	Value
RMSE	0.0271
MAE	0.0180
MAPE	22.25%
R^2 Score	0.9112

Based on the evaluation table above, the Root Mean Squared Error (RMSE) value obtained is 0.0271. This value illustrates how far the model's prediction results deviate from the actual value in the same units as the original data. In addition, the Mean Absolute Error (MAE) value of 0.0180 indicates that the average absolute error of the prediction against the actual data is relatively small, which indicates good prediction accuracy. The Mean Absolute Percentage Error (MAPE) value of 22.25% indicates that the average percentage error of the prediction is still within the tolerance limit for stock price analysis. Meanwhile, the coefficient of determination (R^2 Score) value of 0.9112 indicates that around 91.12% of the variability of stock price data can be explained by the model. In other words, the GRU model is able to capture historical data patterns quite accurately. Overall, the four evaluation metrics provide an overview that the GRU model has good performance in predicting time series on PGEO.JK shares.

3.2. Model Training Process

The results during model training in the learning process will be shown in Figure 2.

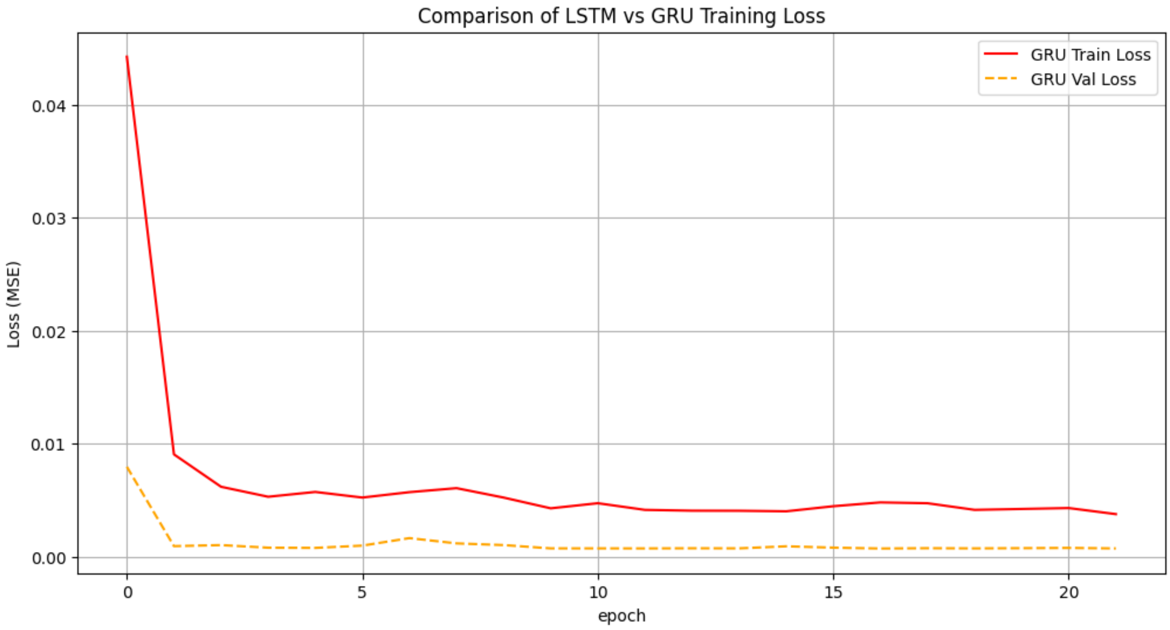

Figure 2: GRU Model training process (Loss vs. Val_Loss)

In the first epoch, the model still showed quite high loss and val_loss values, namely 0.0892 and 0.0028 respectively. However, as the training progressed, the model was able to reduce the loss value significantly. This was seen in the 3rd and 4th epochs, where val_loss dropped to 0.0008, indicating that the model was getting better at learning data representation.Interestingly, in the 5th epoch there was a slight increase in val_loss to 0.0022, which likely indicated the potential for momentary overfitting. However, the model stabilized again with a consistent decrease in val_loss to 0.0007 in the 9th epoch. This decrease in val_loss also coincided with a decrease in loss on the training data, indicating that the model was able to learn well from the available data without losing generalization.

At epoch 10, the ReduceLROnPlateau callback system starts to reduce the learning rate to 0.0005 because there is no significant decrease in val_loss. However, the model performance remains quite stable with relatively small fluctuations in val_loss values between epochs 11 to 14. This learning rate adjustment helps maintain training stability, so that the model does not learn too aggressively, but still maintains the quality of its predictions.

3.3. Comparison of Prediction and Actual

The comparison between the actual stock price and the predicted results of the GRU (Gated Recurrent Unit) model will be shown in Figure 3.

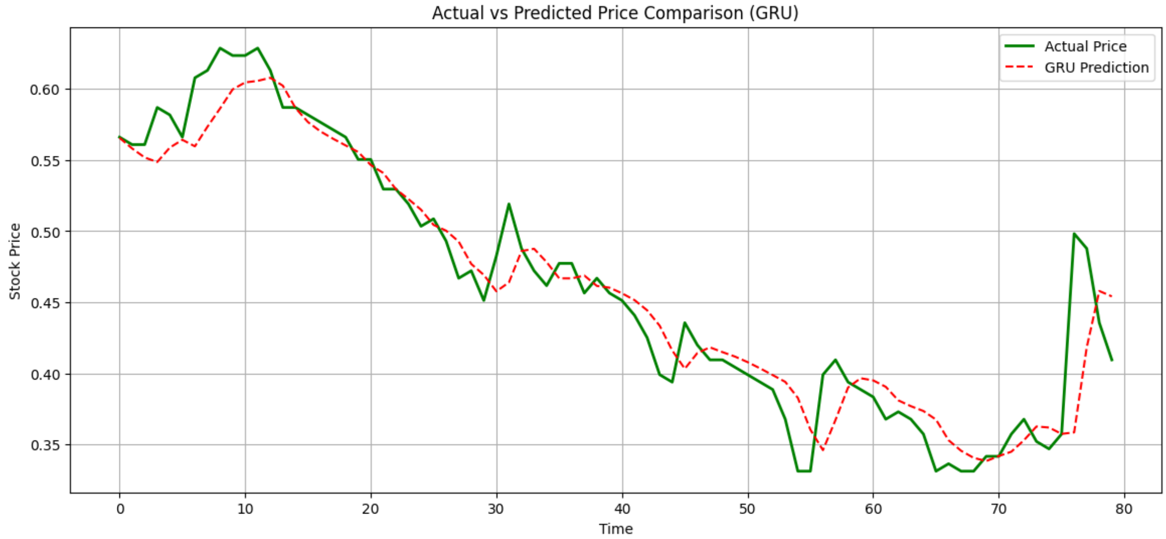

Figure 3: Comparison of actual stock prices and GRU model predictions

The green line represents the actual stock price, while the red dotted line shows the predicted results of the GRU model. In general, it can be seen that the GRU model is able to follow the stock price movement pattern quite well. Price fluctuations, both uptrends and downtrends, can be captured by the model with a relatively high level of accuracy. Although there is a slight deviation between the predicted line and the actual value at some points, especially at the end of the graph around the 75th to 80th time points, the model still successfully projects the overall price movement direction. This shows that the model has good generalization ability to the test data, although there are limitations in capturing sharp price spikes. Overall, this visualization strengthens the results of the previous metric evaluation which showed quite optimal performance of the GRU model in predicting stock prices based on historical data.

3.4. Residual plot

The residual plot depicting the distribution of errors between the actual and predicted values of the GRU model is shown in Figure 4.

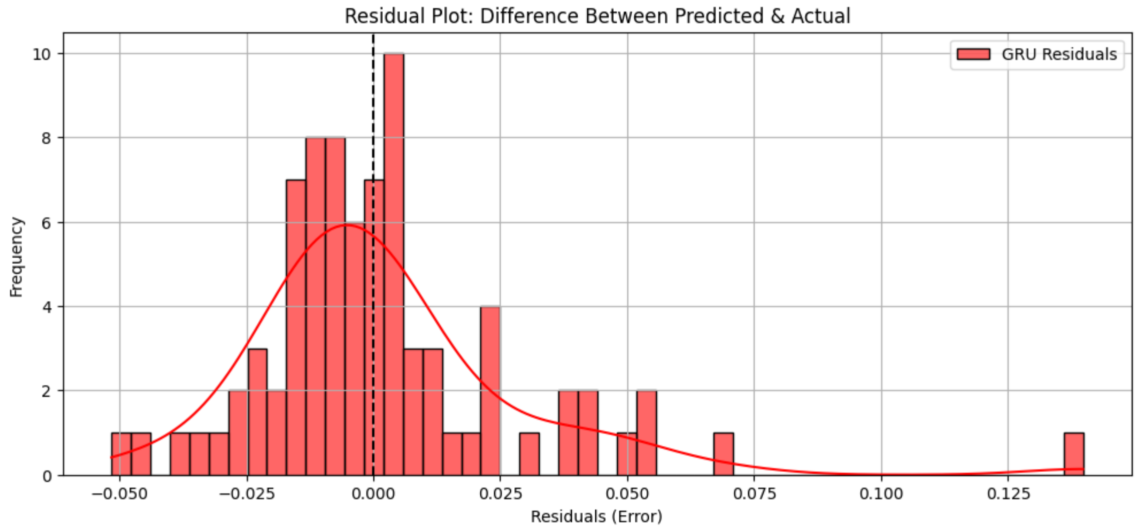

Figure 4: Histogram of GRU model residuals against the difference between predicted and actual values

The horizontal axis shows the residual values, while the vertical axis shows the frequency of occurrence of each residual value. Most of the residual values refer to around zero, which is indicated by the high frequency of residual values approaching zero. This indicates that the GRU model tends to provide fairly accurate predictions, with small errors that do not deviate far from the actual value. The red curve in the plot represents the normal distribution of the resulting errors. Although the residual distribution is not completely symmetrical, it is still visible that the error distribution tends to lead to a distribution that is close to normal. The slight asymmetry, especially in the positive error section, indicates that the GRU model sometimes experiences errors in the form of underestimation, which is predicting values that are lower than the actual value. In addition, the residual distribution does not show a large number of extreme outliers, which means that the model does not make large errors too often. Overall, this residual distribution indicates that the GRU model has a fairly stable and accurate prediction performance in predicting stock prices based on the data provided.

4. Conclussion

This study shows that the Gated Recurrent Unit (GRU) model is able to provide reliable stock price predictions for PT. Pertamina Geothermal Energy Tbk (PGEO.JK). Through a deep learning-based approach, the GRU model can capture historical patterns of stock price movements well even without making parameter adjustments (hyperparameter tuning). The evaluation results show an RMSE value of 0.0271, MAE of 0.0180, MAPE of 22.25%, and an R^2 value of 0.9112. These values indicate that the GRU model has a high level of accuracy in making predictions. This proves that GRU has strong potential in handling time series data in the financial sector, especially stocks in the renewable energy sector. In conclusion, the GRU model is a promising method for stock price prediction tasks and can be used as a reference in further research.

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