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Comparative Analysis of LSTM and GRU Models for Predicting BBCA and BBNI Stock Prices

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Abstract

Stock price predictions always a challenging issue as the price data consists of variable, noisy, non-linear time dependence. This research aims as a testing ground to compare the performance of two deep learning algorithms, long short-term memory and gated recurrent units, in predicting the end price of PT Bank Central Asia Tbk, that is relatively stable compares to PT Bank Negara Indonesia Tbk which more volatile. Daily prices were obtained from Yahoo Finance over the previous period from January1, 2019 until Dec 1, 2025. Data cleaning, Min-Max normalization, 80:20 data split, and sequence-formation with a timestep of 60 were performed. To facilitate fair comparison and ensure that the performance differences are only due to architecture, both models were constructed with the same architecture (two layers of 50 units, 0.2 dropout, Adam optimizer, MSE loss function, and 50 epochs). It evaluated MSE, RMSE performance, MAE performance, R-squared with accuracy adjusted for a 5% tolerance range. The results suggest that GRU outperforms LSTM on both stocks. For the BBCA, GRU reached an RMSE of 101.12, MAE of 113.82, R-squared of 0.96, and tolerance accuracy of 98.52%, compared to BBNI which had an RMSE of 62.95, MAE of 71.24, R-squared of 0.92, and tolerance accuracy of 94.11%. This performance led us to realize that GRU is the numerical equivalent to this technique, and on both datasets, it was computationally faster. These results reveal that simpler GRU structure is more adaptive, especially with stocks of high volatility like BBNI.

Keywords: Stock Price Prediction, Long Short-Term Memory, Gated Recurrent Unit, Deep Learning, Time Series.

1. Introduction

Stocks are one of the most sought-after financial instruments in the capital market because they offer attractive potential returns. For companies, issuing shares is one of the main options to obtain funding, whereas for investors, stocks are a preferred investment because they can provide significant returns compared with other instruments [1] [2]. Nevertheless, the rapid and difficult-to-predict fluctuation of stock prices makes some investors hesitant to invest.

Public interest in the capital market continues to grow. Data from the Indonesian Central Securities Depository (KSEI) show that the number of capital-market investors reached 20.3 million by the end of 2025, an increase of about 37% compared with 14.8 million at the end of 2024 [3]. This growth underscores the importance of reliable analytical tools to support investment decision-making.

Stock price movements are influenced by many interrelated factors, such as global economic conditions, monetary policy, political situations, and market sentiment [4]. In addition to fluctuations that are difficult to predict, historical stock price data also contain noise and complex temporal dependencies between previous and current prices, making it difficult for investors to recognize price-movement patterns [5]. Therefore, a forecasting approach capable of handling the complexity of such time-series data is required.

The development of artificial intelligence, particularly deep learning, has become a primary choice for improving stock price prediction accuracy. Deep learning uses artificial neural networks to extract features from historical data and capture non-linear relationships that are difficult to detect using conventional methods [5]. Among various architectures, Recurrent Neural Networks (RNN) with the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) variants are widely used because of their ability to handle long-term dependencies in time-series data [6].

Stock price prediction is inherently difficult because the market is a noisy, non-parametric, non-linear, and partly chaotic system [4]. Classical time-series models are generally only able to handle relatively simple patterns and often fail to capture the random and complex behavior of stock prices. Deep learning has therefore emerged as a promising alternative for building more reliable prediction models in complex time-series cases, although deep architectures remain susceptible to vanishing- and exploding-gradient problems that require appropriate optimization techniques [5].

LSTM was designed to overcome the limitations of RNN in capturing long-term dependencies while avoiding the vanishing- and exploding-gradient problems through three gates, namely the input gate, forget gate, and output gate [7]. Meanwhile, GRU is a simplification of LSTM that uses only two gates, namely the reset gate and the update gate, so it has fewer parameters and more efficient computation

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without significantly sacrificing accuracy [8] [9].

This study uses two datasets from the financial sector with different stability characteristics. BBCA was chosen as a representation of a blue-chip stock with the largest market capitalization in Indonesia, which tends to be stable [10], whereas BBNI was chosen as a comparison because it is a state-owned bank whose price movements tend to be more dynamic [11]. The selection of these two stocks aims to test the robustness of the models and to examine whether there are significant performance differences between LSTM and GRU when faced with data of different stability levels.

Several previous studies have compared stock price prediction algorithms. Study [1] found that GRU outperformed Linear Regression and LSTM on the KEJU stock, whereas [12] obtained the opposite result, in which Linear Regression was superior for Coca-Cola stock. Another study compared the statistical ARIMA model with GRU and demonstrated the superiority of the deep learning approach [13]. Several studies have applied GRU for stock prediction, both on BBCA stock [14] and on emerging markets by integrating exogenous variables [15], whereas research on BBNI generally still uses LSTM [16]. Most of these studies tested the algorithms on only a single stock, so a direct comparison between LSTM and GRU on two stocks with different volatility levels remains limited. Based on the above description, the objective of this study is to compare the performance of the LSTM and GRU algorithms in predicting the closing prices of BBCA and BBNI stocks using the RMSE, MSE, MAE, R-squared, and tolerance-accuracy metrics, and to provide a recommendation on the most effective algorithm according to the volatility characteristics of each stock.

2. Research Method

This study uses a quantitative approach with an experimental method that focuses on modeling and predicting time-series data that are complex and non-linear, such as stock prices [17]. The methodology flow is presented in Figure 1.

Figure 1. Research Methodology Flowchart

The research stages were arranged sequentially, starting from problem identification and literature study, data collection, preprocessing, data splitting, the parallel development and training of the LSTM and GRU models, comparison of evaluation results, analysis, and drawing conclusions.

The data were obtained from Yahoo Finance, namely the daily time-series stock price data of BBCA (ticker BBCA.JK) and BBNI (ticker BBNI.JK) listed on the Indonesia Stock Exchange. The data were retrieved automatically using the *yfinance* library in Python for the period of 1 January 2019 to 31 December 2025. This range was chosen to cover several economic cycles, including the periods before, during, and after the COVID-19 pandemic, and to provide a sufficient amount of data for training the deep learning models. The prediction target variable is the closing price (Close Price).

Data cleaning was performed by handling missing values using linear interpolation to maintain data continuity, and by identifying outliers using the Interquartile Range (IQR) method. The data were then normalized using Min-Max Scaling into the range of 0 to 1. Normalization was chosen because it is suitable for neural networks, preserves the original data distribution, and accelerates convergence during training. The data were subsequently split based on time order into 80% training data and 20% testing data to avoid data leakage. Because RNN models do not predict based on a single data point but rather on a sequence of preceding data, the data were transformed into sequences using a sliding-window approach with a timestep length of 60 trading days. Each 60-day sequence was used to predict the price of the following day.

To ensure a fair comparison, the LSTM and GRU models were built with identical structures. Each model consists of two recurrent layers of 50 units with 0.2 dropout to prevent overfitting, followed by one Dense layer as the output. The main difference lies only in the type of recurrent cell used. All training hyperparameters were kept the same, as listed in Table 1, so that any performance difference is purely due to the effectiveness of each algorithm's internal structure. The use of a two-layer structure and dropout to prevent overfitting refers to the model-configuration practices in similar studies [18] [19].

The Adam (Adaptive Moment Estimation) optimizer was selected because it dynamically adjusts the learning rate based on previous gradients, thereby accelerating convergence and improving accuracy. The Mean Squared Error (MSE) loss function was used because it strongly penalizes large prediction errors, which is appropriate for the regression nature of stock price prediction. Training was conducted for 50 epochs with a batch size of 32, while the validation set was monitored to detect potential overfitting during the learning process. Next Hyperparameter Configuration on Table 1.

Table 1. Hyperparameter Configuration

Configuration	Value
Optimizer	Adam
Loss Function	MSE
Epochs	50
Batch Size	32
Timestep	60

Model performance was measured using several error and goodness-of-fit metrics that are commonly used in stock price prediction research [20] [21]. Mean Absolute Error (MAE) measures the average absolute error, Mean Squared Error (MSE) measures the average squared error, and Root Mean Squared Error (RMSE) is the square root of MSE with the same unit as the target variable. The coefficient of determination (R-squared) measures the proportion of the variance in the actual data that can be explained by the model. The formulas for these metrics are presented in Equation (1).

$$\begin{aligned} MAE &= (1/n)\,\Sigma\,|y_i - \hat{y}_i| \\ MSE &= (1/n)\,\Sigma\,(y_i - \hat{y}_i)^2 \\ RMSE &= \sqrt{[(1/n)\,\Sigma\,(y_i - \hat{y}_i)^2]} \\ R^2 &= 1 - [\Sigma\,(y_i - \hat{y}_i)^2 / \Sigma\,(y_i - \bar{y})^2] \end{aligned} \tag{1}$$

In addition, a Tolerance Accuracy metric was used to assess the practical success of the model by considering an acceptable error margin. A prediction is considered successful if its value falls within ±δ of the actual price, with δ set at 5% of the actual price. Accuracy is calculated as the percentage of predictions that fall within this tolerance band relative to the total number of predictions. The higher the value, the more reliable the model is for use in investment decision-making.

3. Result and Discussion

The BBCA dataset consists of 1,621 rows of daily price data over the study period, with a comparable number of rows for BBNI. Figure 2 and Figure 3 show the original closing-price movements of the two stocks. Visually, BBCA exhibits a relatively consistent upward trend, whereas BBNI shows a more fluctuating movement pattern over the same period.

Figure 2. Research Methodology Flowchart

Figure 3. Original Stock Price Movement of BBNI

After handling missing values through linear interpolation and identifying outliers, the data were normalized using Min-Max Scaling into the 0–1 range and then split into 80% training data and 20% testing data. Figure 4 and Figure 5 shows the preprocessing result of the stock data, ready to be used as model input.

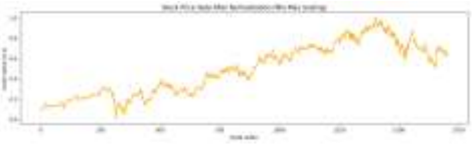


Figure 4. Stock Data Preprocessing Result (Min-Max Scaling) of BBCA

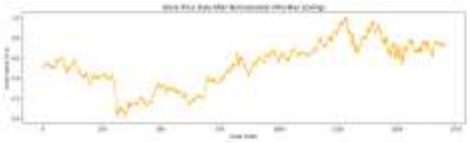
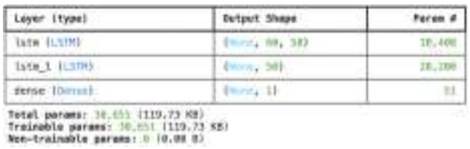


Figure 5. Stock Data Preprocessing Result (Min-Max Scaling) of BBNI

Based on the model summary, the LSTM architecture produced a total of 30,651 parameters, whereas GRU produced only 23,301 parameters. This difference occurs because GRU has only two gates (reset and update gates) compared with LSTM, which has three gates (input, forget, and output gates). The simpler structure makes GRU more computationally efficient. The summaries of both architectures are shown in Figure 6 and Figure 7.



```
Layer (type)          Output Shape           Param #
lstm (LSTM)           (None, 60, 50)          10,400
lstm_1 (LSTM)         (None, 50)              20,200
dense (Dense)         (None, 1)                   51
Total params: 30,651 (119.73 KB)
Trainable params: 30,651 (119.73 KB)
Non-trainable params: 0 (0.00 B)
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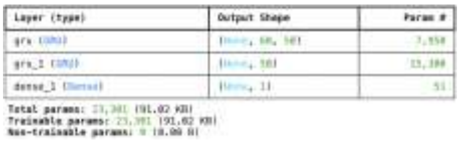
Figure 6. LSTM Model Architecture Summary



```
Layer (type)          Output Shape           Param #
gru (GRU)             (None, 60, 50)           7,950
gru_1 (GRU)           (None, 50)              15,300
dense_1 (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 7. GRU Model Architecture Summary

During 50 epochs of training, both models showed a stable decrease in loss with no significant indication of overfitting, marked by a relatively small and consistent gap between training loss and validation loss. The GRU model tended to converge slightly faster, with a more stable validation loss in the later epochs. The loss curves of both models are shown in Figure 8 and Figure 9.

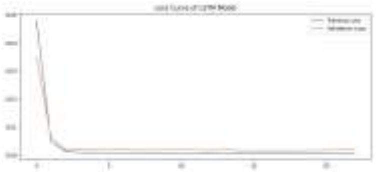


Figure 8. LSTM Model Loss Curve for BBCA

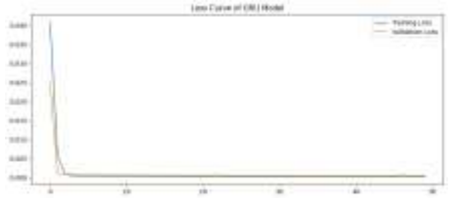


Figure 9. GRU Model Loss Curve for BBCA

A comparison of the loss curves across the two stocks indicates a consistent convergence pattern. The initial loss was around 0.04 and decreased sharply within the first few epochs before stabilizing at a low value below 0.01 by the 50th epoch, while the gap between training and validation loss remained narrow throughout training, confirming that the models generalize well despite the higher volatility of BBNI. The GRU model converged slightly faster and reached a more stable validation loss (below 0.008) than LSTM in the later epochs, suggesting a better generalization capability resulting from its simpler structure, which reduces the risk of overfitting on relatively consistent data patterns.

In terms of efficiency, GRU completed training faster than LSTM on both datasets, as shown in Table 2. On BBCA, GRU was about 15% faster, whereas on BBNI it was about 26% faster. This is due to GRU's smaller number of parameters, which makes the matrix multiplication and gradient computation during backpropagation lighter. GRU's training time was also relatively stable across datasets, whereas LSTM was more sensitive to variations in data characteristics. Next Computation Time Comparison on Table 2.

Table 2. Computation Time Comparison

Algorithm	Time (BBCA)	Time (BBNI)
LSTM	18,47 s	21,88 s
GRU	16,04 s	16,14 s

A visual comparison between the actual prices and the prediction results for the last 100 days of both stocks is shown in Figure 10 and Figure 11. Visually, GRU's predictions are more responsive to daily fluctuations and capture price turning points more accurately, whereas LSTM sometimes produces slightly lagging predictions.

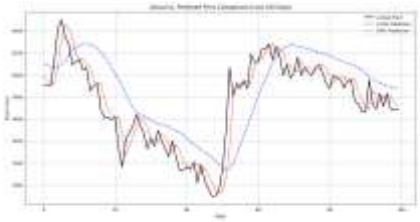


Figure 10. Comparison of the Last 100 Days Prediction for BBCA

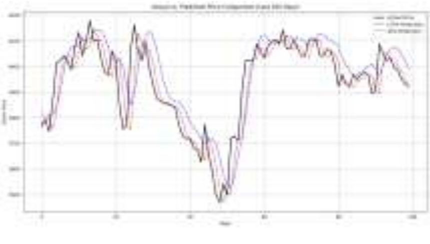


Figure 11. Comparison of the Last 100 Days Prediction for BBNI

The accuracy evaluation with a ±5% tolerance band is presented in Figure 12 and Figure 13. On BBCA, GRU achieved a tolerance accuracy of 98.52%, well above LSTM's 90.58% (a difference of 7.94 percentage points). On BBNI, GRU achieved 94.11% compared with LSTM's 82.35% (a difference of 11.76 percentage points). The larger margin of GRU's superiority on BBNI indicates that the GRU architecture is more adaptive to stocks with high volatility.

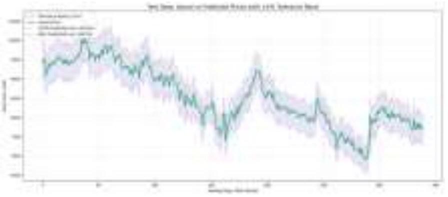


Figure 12. Accuracy Visualization with Tolerance Band for BBCA

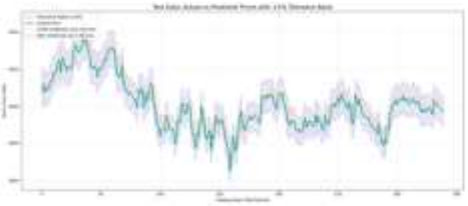


Figure 13. Accuracy Visualization with Tolerance Band for BBNI

A summary of the quantitative performance of both models across all metrics is presented in Table 3. Consistently on both stocks, GRU produced lower MSE, RMSE, and MAE values as well as higher R-squared and tolerance accuracy than LSTM. Next Evaluation Metrics Comparison on Table 3.

Table 3. Evaluation Metrics Comparison

Metric	LSTM (BBCA)	GRU (BBCA)	LSTM (BBNI)	GRU (BBNI)
MSE	66499,43	22195,42	22901,92	9093,25
RMSE	168,27	101,12	101,29	62,95
MAE	211,26	113,82	118,03	71,24
R²	0,88	0,96	0,80	0,92
Accuracy (5%)	90,58%	98,52%	82,35%	94,11%

The R-squared values close to 1 for both models indicate that both are able to explain the variance in stock prices well. However, quantitatively, GRU is superior in minimizing prediction error. BBCA's relatively smooth movement pattern and BBNI's more fluctuating yet still structured pattern make the gating mechanism in GRU more optimal in filtering relevant information without the additional complexity present in LSTM. GRU's advantage is also evident in its ability to capture price turning points more accurately. During periods of correction or sudden rallies, GRU's predictions tend to be closer to the actual values. This phenomenon is consistent with the characteristic of GRU's update gate, which is more adaptive in responding to changes in the latest data patterns. From a practical perspective, GRU's high tolerance accuracy provides a sufficient level of confidence for investors to use the model as a decision-support tool for determining entry and exit points in medium- to long-term investment strategies.

These findings are consistent with several previous studies that demonstrated the superiority of GRU in time-series stock price prediction [1] [8], and they complement studies that previously tested LSTM or GRU separately on a single stock [2] [14] [16]. From a practical standpoint, the difference in accuracy between GRU and LSTM has significant implications for investment decision-making, where each additional percentage point of accuracy can contribute to reducing the risk of incorrectly determining entry or exit points. With a tolerance accuracy of 98.52% on BBCA and 94.11% on BBNI, GRU can serve as a reliable technical decision-support tool for medium- to long-term investment strategies. Nevertheless, investors should still complement its use with thorough fundamental analysis, given the highly complex and dynamic nature of the stock market, as well as the influence of external factors that are not captured by historical price data alone.

4. Conclusion

Based on the research results, the Gated Recurrent Unit (GRU) algorithm has superior performance compared with Long Short-Term Memory (LSTM) in predicting stock prices for both tested issuers. For BBCA, GRU recorded an MSE of 22,195.42, RMSE of 101.12, MAE of 113.82, and R-squared of 0.96, whereas for BBNI it obtained an MSE of 9,093.25, RMSE of 62.95, MAE of 71.24, and R-squared of 0.92. All evaluation metrics of GRU were consistently better than those of LSTM. In terms of computational efficiency, GRU proved to be faster on both datasets, namely 16.04 seconds on BBCA (15% faster than LSTM) and 16.14 seconds on BBNI (26% faster), owing to its simpler internal structure with only two gates. With a 5% tolerance band, GRU achieved an accuracy of 98.52% on BBCA and 94.11% on BBNI, whereas LSTM achieved only 90.58% and 82.35%. The larger margin of GRU's superiority on BBNI shows that the GRU architecture is more adaptive to stocks with higher volatility. Future research is suggested to add exogenous variables such as news sentiment, global market indices, or macroeconomic indicators, to test multi-layer or hybrid architectures, and to perform hyperparameter optimization using methods such as Grid Search or Random Search to improve prediction accuracy.

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