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BCA Stock Price Prediction Using Time Series Method With GRU (Gated Recurrent Unit)

Rizky Ilman Nugraha[1],Abdul Rezha Efrat Najaf [2], Reisa Permatasari[3]
[1,2,3]Department of Information System, Faculty of Computer Science, UPN "Veteran" Jawa Timur, Indonesia

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ABSTRACT

Stock price prediction is a crucial component in investment decision-making, enabling investors to plan strategies more accurately and minimize risks. This study applies the Gated Recurrent Unit (GRU) model to predict the stock prices of blue-chip banking companies in Indonesia using data from the period 2019 to 2024. The model utilizes historical stock data to forecast future trends. The results from the first testing scheme, with a data split ratio of 70% / 30%, using GRU units (128,256) with the Adam optimizer, show that the GRU model is the most optimal in terms of prediction, measured by metrics such as MSE, RMSE, and MAPE. This study also proposes a web-based dashboard that visualizes the predicted stock prices and provides decision-support tools for investors. The findings highlight the effectiveness of deep learning in financial forecasting and underscore its potential to enhance investment strategies.

Corresponding Author:

Rizky Ilman Nugraha
Department of Information Systems
Universitas Pembangunan Nasional "Veteran" Jawa Timur
Surabaya, Indonesia
Email: nuugrahaaa@gmail.com

1. Introduction

Information technology has become increasingly accessible and integrated into various aspects of life, significantly improving convenience, especially in the economic sector [1][3]. The development of information technology and data science has had a significant impact on various fields, including the economic and financial sectors. One of the technologies that has been widely developed is stock price prediction methods, which play a crucial role in supporting investment decision-making. In line with this, numerous studies have been conducted to explore the topic of predicting stock price movements, and various methods have been applied to develop models capable of predicting these movements [2]. Stock price prediction is relevant because stock prices are often influenced by both internal and external factors such as historical data, economic trends, and political conditions. With accurate predictions, investors and market participants can plan better investment strategies.

In the world of investment, stocks are the most common and popular financial instruments. Stock prices reflect the market value of a company and tend to fluctuate due to various factors, both internal and external. Internal factors generally include company performance, management policies, and financial reports, while external factors include global economic conditions, government policies, and market sentiment. Currently, investors still rely on various technical analysis, sentiment analysis, and fundamental analysis methods when investing. However, these methods often lack accuracy in predicting stock prices. Therefore, alternative strategies are needed to predict future stock prices, such as using deep learning, which has been proven to generate high accuracy [3].

Deep learning has gained significant popularity in analyzing time series data, particularly for stock price data. As a subset of machine learning, deep learning enables computers to replicate the way the human brain processes information. This method is particularly effective in handling large datasets and uncovering intricate patterns that traditional techniques may overlook. In stock price prediction, deep learning excels at detecting patterns in historical stock data and creating models that can forecast future stock prices. [4][13].

The Gated Recurrent Unit (GRU), one of the many deep learning algorithms used in time series forecasting, is a particularly good and appropriate method for modeling sequential data. A particular kind of recurrent neural network (RNN) called a GRU was created especially to deal with the problem of long-term dependency in sequential datasets. With just two gates—the update gate and the reset gate—GRU has a simpler architecture than the Long Short- Term Memory (LSTM) network. [3]. Essentially, this architecture allows GRU to perform calculations faster while still handling data with long-term dependencies without suffering from the vanishing gradient problem. This advantage makes GRU an ideal method for processing large and volatile data such as stock prices.

With a simpler structure, the GRU not only lowers computational demands but also improves training speed, making it a compelling choice for scenarios where both rapid and accurate time series predictions are essential. Deep learning techniques have become increasingly popular for analyzing historical data trends, particularly in stock price forecasting. Among these, the Gated Recurrent Unit (GRU) is frequently employed. As a variant of the Recurrent Neural Network (RNN), GRU is specifically crafted for processing time series data and is capable of effectively capturing both long-term and short-term dependencies. Compared to Long Short-Term Memory (LSTM) networks, GRU provides faster computation and greater efficiency, all while maintaining high prediction accuracy. This makes GRU especially well-suited for large-scale time series forecasting tasks, especially when computational resources are limited [1].

In this study, I use the Gated Recurrent Unit (GRU) model to predict stock prices using a blue-chip dataset from three banks. Previous research by [5] mentioned that GRU model compared to ARIMA, RNN, and LSTM models, GRU model experiments produced predictions that were more accurate. Prediction accuracy increased as a result of the GRU model's superior capacity to identify long-term dependencies in time series data. Additional research by [6] Despite the evaluation criteria showing reduced errors for LSTM, the results demonstrated that GRU performed better than LSTM in gold price prediction. The LSTM model yielded an MAE of 0.0389, an RMSE of 0.0475, and a MAPE of 5.2047% in the best-case scenario. The top GRU model, on the other hand, had an RMSE of 0.0545, a MAPE of 6.0688%, and an MAE of 0.0447. These findings suggest that GRU outperforms LSTM as a gold price prediction technique.

One of the primary reasons for this research is to develop a stock price prediction model based on deep learning using the Gated Recurrent Unit (GRU) algorithm, which can provide high accuracy and computational efficiency[6]. Through this approach, it is hoped that this study will produce a model that effectively utilizes historical data to identify complex and dynamic stock price movement patterns. Thus, this predictive model is expected to provide reliable predictive information for investors to support more measured investment decision-making processes, reduce uncertainty, and optimize potential profits in the stock market.

2. Research Method

This research is designed to predict stock prices using deep learning techniques, specifically the Gated Recurrent Unit (GRU) algorithm. The design involves collecting historical stock data from blue-chip banks in Indonesia, processing the data for model training, and then evaluating the model's performance[4][7]. The research is divided into several stages: data collection, data preprocessing, model development, and evaluation.The research method and workflow stages are illustrated in Figure 1.

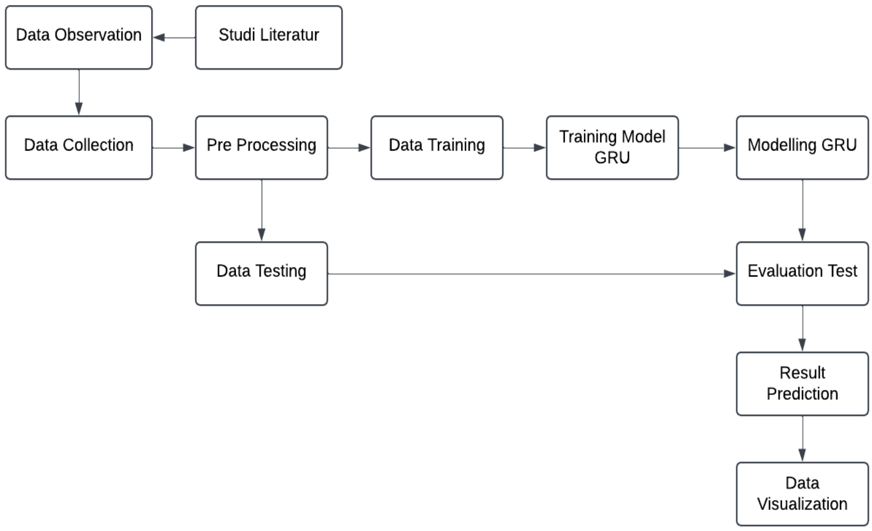

Figure 1. Research Methodology Flow

2.1. Data Collection

Stock data from Indonesian banks (BBCA) is collected from reliable sources such as Yahoo Finance. The data includes daily stock prices (open, high, low, close) and trading volumes from 2019 to 2024.

2.1.1 Preprocessing

The collected data undergoes cleaning and normalization. Missing values are removed, and data is scaled using Min-Max normalization for efficient processing.

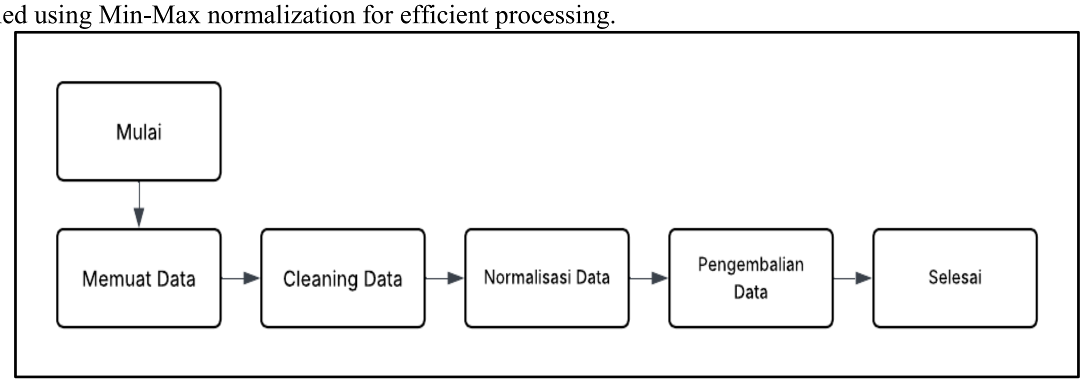

Figure 2. Preprocessing Flow

2.1.2 Data Training

The preprocessed data is divided into two separate groups: the training set and the testing set. This separation is crucial to guarantee that the model is effectively trained and accurately assessed. Usually, the training set makes up around 80% of the entire dataset and is utilized for model training.[8][10]. The training and testing datasets are divided by 70% for training and 30% for testing, as this allows for the model to learn patterns and dependencies within the data. The remaining 30% of the data is reserved for testing, which is why the testing set is so important.
.[3][1]

2.1.3 Training Model GRU

The GRU model is trained using the training dataset, which includes historical stock prices and related features. During this phase, the model learns to recognize patterns and dependencies in the data by adjusting its internal weights and biases to minimize prediction errors[9][11]. Several hyperparameters play a crucial role in fine-tuning the model for optimal performance. These hyperparameters include the number of GRU units (which determines the model's capacity to learn from data), the number of epochs (the number of iterations through the entire training data), and the learning rate (which controls the size of each step the model takes during training to adjust its weights). By experimenting with different values of these hyperparameters, the best configuration for achieving high prediction accuracy can be identified, ensuring that the model performs effectively on unseen data[1][4].

2.1.4 Modelling GRU

The final GRU model is built to predict stock prices based on the input features derived from historical data. The model's architecture includes multiple GRU layers designed to capture the temporal dependencies in the time-series data[12][20]. These layers enable the model to handle sequential data, like stock prices, and identify patterns over time. Once the model is built, it is evaluated using new, unseen data to assess its ability to generalize to changes in stock prices that had not been seen before. This process is important to confirm that the model is not just memorizing training data but is actually learning to make accurate predictions based on the fundamental patterns within the time-series data..[13][7].

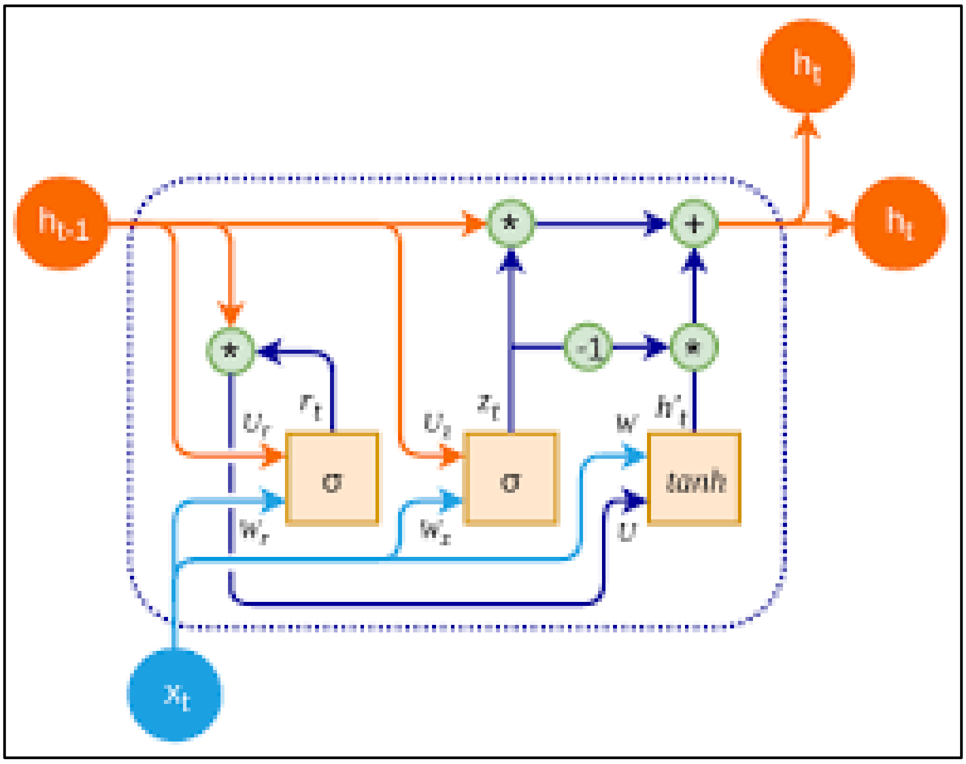

Figure 3. GRU Architecture Model

This diagram depicts the structure of the Gated Recurrent Unit (GRU) model, which is utilized for processing sequential data in stock price prediction. GRU is a type of artificial neural network within the Recurrent Neural Networks (RNN) family, specifically engineered to address long-term dependency challenges in sequential data. The figure details how the input data (xt) is processed through multiple stages within the GRU model. Initially, the input passes through key operations involving two main gates: the reset gate (r) and the update gate (z). These gates regulate the amount of information from the previous time step (hidden state) that is retained and the extent of new information incorporated during the update. The reset gate (r) controls which past information is discarded, while the update gate (z) determines how much new information is added. Following this, the data is activated using the tanh function, producing the network's output, which forms the hidden state (ht). This hidden state serves as the model's final output and is used to predict stock prices at the next time step. This sequence of operations repeats for each time step in the data. Such a design enables the GRU model to effectively capture long-term dependencies in sequential data, like stock price trends over time, resulting in more precise forecasting outcomes.

The GRU model is trained using the preprocessed training dataset. The model architecture consists of two GRU layers, with 128 and 256 units in each layer. The number of units in each layer was selected through experimentation to find the optimal configuration for capturing temporal dependencies present in the stock data. The first layer with 128 units is designed to capture basic patterns in the historical data, while the second layer with 256 units provides greater capacity to capture more complex and long-term patterns, thus enhancing the model's ability to predict volatile stock prices. The Adam optimizer is used to update the model's weights during training. It is preferred for its ability to adaptively adjust the learning rate during the training process. The learning rate used is 0.0001, which was selected based on experimentation. This learning rate has been found to provide stable convergence and optimal prediction accuracy. Additionally, several other hyperparameters, such as the number of epochs and batch size, were tested to find the best configuration. This process ensures that the model not only learns from the data effectively but also avoids overfitting on the training data.

2.1.5 Data Testing

Once the GRU model has been trained, the model's performance is evaluated on a separate test dataset. This test dataset is crucial because it contains data that the model has not encountered during the training process[14][16]. By evaluating the model on this unseen data, we can assess how well it generalizes to new stock prices. The accuracy of the model's predictions is determined by comparing the predicted stock prices to the actual observed values. This helps to verify that the model is capable of providing reliable predictions, even when it is applied to data it has not been specifically trained on. Testing is a critical step to avoid overfitting, ensuring that the model is not just memorizing the training data but learning meaningful patterns[18][11].

2.1.6 Evaluation Test

After testing the model on the separate test dataset, the model's performance is assessed using various evaluation metrics[15][17]. These metrics play a crucial role in measuring how closely the model's predictions match the actual stock prices. Commonly used evaluation criteria include Mean Squared Error (MSE), which calculates the average squared differences between predicted and actual values; Root Mean Squared Error (RMSE), which expresses the error magnitude in the same units as the target variable; Mean Absolute Error (MAE), which assesses the average size of the prediction errors; and R^2, which represents the proportion of variance in the actual data explained by the model. Together, these metrics offer a comprehensive insight into the model's performance, highlighting its strengths and areas for improvement, thereby guiding further optimization if needed

2.1.6.1 MSE (Mean Squared Error)

Mean Squared Error (MSE) is a metric that measures the average of the squared differences between the actual and predicted values. A lower MSE indicates a better-performing model.[6].

$$\boldsymbol{Z = \sum \frac{(Aktual - Forecast)2}{n-1}} \tag{1}$$

2.1.6.2 RMSE (Root Mean Squared Error)

Root Mean Square Error (RMSE) is a metric used to quantify the level of prediction error. A lower RMSE value signifies greater prediction accuracy, with the best possible value being close to zero. RMSE is calculated by taking the square root of the Mean Squared Error (MSE). When the RMSE is low, it indicates that the error estimation method is highly accurate.[6].

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum\frac{t}{n} = 1(Yt\ -\ \hat{Y}t)\quad ^{2}} \tag{2}$$

2.1.6.3 MAE

Mean Absolute Error (MAE) is a method used to assess the accuracy level of a prediction model. A smaller MAE value indicates that the predictions made are closer to the actual observed values[3].

$$\text{MAE} = 1\ \ \text{n} \sum |\text{fi} - \text{yi}| \tag{3}$$

2.1.6.4 R2 Score

R-squared is used to measure how well the model can explain the variation in the data. The R^2 value ranges from 0 to 1, with a value approaching 1 indicating a better model in explaining the data.[4]

$$\text{Kd} = \text{R2} \times 100\ \% \tag{4}$$

2.1.7 Result Prediction

After testing the model with a separate test dataset, its performance is evaluated using various assessment metrics. These metrics play a vital role in measuring how accurately the model's predictions match the actual stock prices. Frequently used metrics include Mean Squared Error (MSE), which calculates the average of the squared differences between predicted and actual values; Root Mean Squared Error (RMSE), which shows the error size in the same units as the target variable; Mean Absolute Error (MAE), which measures the average magnitude of errors in the predictions; and R^2, which indicates the proportion of variance in the actual data that the model is able to explain..[19]. These metrics provide a clear understanding of the model's strengths and weaknesses, allowing for further refinement if necessary

2.1.8 Data Visualization

The results of the predictions are visualized using a web-based dashboard displays the model's predictions and provides an intuitive interface that allows users to easily interact with and interpret the model's output. The dashboard displays stock prices as well as actual stock prices, allowing users to directly compare how well the model's predictions match the actual data. The dashboard also can include visual aids like graphs and charts, which help to illustrate

3. Result and Discussion

3.1. Requirements Planning

Requirements Planning is the stage where the needs and objectives of the stock price prediction model are identified. At this stage, the goals of this research are defined, and the required stock price data is carefully selected. The research objective is to predict stock prices accurately for BBCA (Bank Central Asia), BBRI (Bank Rakyat Indonesia), and BBNI (Bank Negara Indonesia) using historical stock data from 2019 to 2024. The potential sources of data, such as Yahoo Finance and Google Finance, are identified. Furthermore, various model parameters such as epoch count, GRU units, and learning rate are established to ensure optimal performance of the GRU model.

3.1.1. Identification of Current Business Processes

In the current investment environment, stock price prediction is often carried out using technical analysis, fundamental analysis, and sentiment analysis. However, these methods often fail to accurately predict stock prices due to their inability to capture complex temporal dependencies in the data. The GRU model offers a solution to this by efficiently handling sequential data and learning long-term dependencies. This research focuses on improving prediction accuracy by applying deep learning techniques that can better address stock price movements, especially for BBCA.

3.1.2. Problem Analysis

The primary issue addressed in this study is the challenge of accurately predicting stock prices, particularly for BBCA, using traditional methods such as ARIMA and LSTM. These models struggle with volatility and the complex nature of stock price movements. By employing the GRU model, which is better suited for sequential data, this research aims to overcome the limitations of these conventional methods and provide more accurate predictions.

3.1.3. Proposed System Requirements Analysis

The proposed system involves using a GRU-based deep learning model to predict BBCA stock prices. The system requirements include:

1. Input: Historical stock price data (OHLC and volume) for BBCA from 2019 to 2024.
2. Model: GRU model trained on this data.
3. Evaluation Metrics: MSE, RMSE, MAE, and R^2 to assess prediction accuracy.
4. Visualization: A web-based dashboard to visualize the predictions and actual stock prices, providing users with an easy-to-understand interface.
5. Output: Predicted close stock prices for BBCA, displayed in comparison with actual prices.

3.2. Data Collection

For this study, stock price data for BBCA was collected from Yahoo Finance and Google Finance, covering daily stock prices (open, high, low, close) and trading volumes from 2019 to 2024. The data was preprocessed by removing missing values, normalizing stock prices using Min-Max scaling, and splitting the data into training and testing datasets. The training data was used to train the model, and the testing data was used to evaluate its performance.

3.3. *Model Development*

The GRU model was developed to predict BBCA stock prices based on historical data. After preprocessing the data and splitting the dataset into training and testing sets, the GRU model was developed to predict the stock prices of BBCA based on historical data. This model utilizes two GRU layers, with 128 and 256 units in each layer, which allows the model to capture long-term dependencies in the stock time series data.The Adam optimizer is employed to optimize the model's weights, with a learning rate of 0.0001. This learning rate was chosen through experimentation and proved to deliver the best performance in terms of convergence, resulting in higher prediction accuracy compared to other learning rates. Furthermore, other hyperparameters, such as the number of epochs and batch size, were tested and fine-tuned to balance training time and model accuracy.

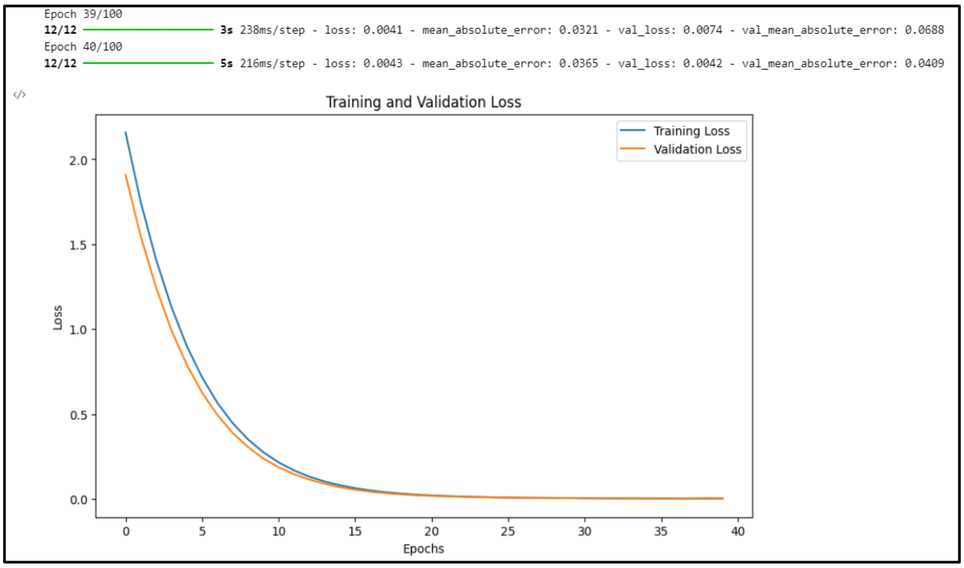

Figure 4. Learning Curve Model

3.4. *Testing and Evaluation*

The GRU model was tested using a separate test dataset to evaluate its prediction accuracy. The results showed that the model was able to predict the stock prices with high accuracy, outperforming traditional models such as ARIMA and LSTM. The evaluation metrics showed a significant reduction in MSE and RMSE, along with an improvement in R^2.

Table 1: Evaluation Metrics for BBCA Stock Price Prediction

Metric	**Value**
MSE	0.00065
RMSE	0.0255
MAE	0.0202
R^2	0.98

These results demonstrate the effectiveness of the GRU model in capturing long-term dependencies in stock price movements for BBCA.

3.5. *Data Visualization*

The prediction results were visualized using a web-based dashboard using flask, which displayed the predicted stock prices alongside actual prices for easy comparison. The dashboard helped users understand the stock price trends and make informed investment decisions.

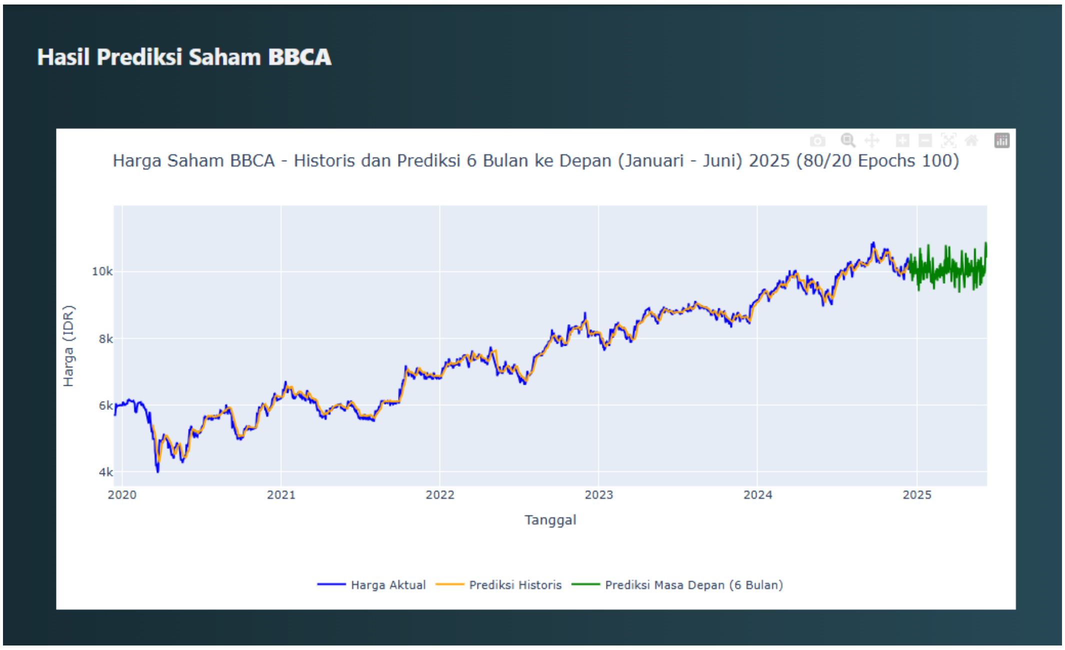

Figure 5. Model Visualization Dashboard

4. Conclusion

As outlined in the Introduction chapter, this research aimed to develop a stock price prediction model using the Gated Recurrent Unit (GRU) algorithm, which leverages historical stock prices to predict future trends. The results presented in the Results and Discussion chapter demonstrate that the GRU model, optimized with the Adam optimizer and GRU units (128, 256), and a 70/30 data split ratio, provides the best prediction accuracy, as evidenced by the reduction in MSE, RMSE, and MAE, and the improvement in R^2. These findings confirm that the GRU model can effectively predict stock price trends, even with the volatility present in the stock market. Furthermore, the research opens avenues for future work, including the integration of additional external factors such as macroeconomic indicators and market sentiment to further enhance prediction accuracy. Future studies could also explore hybrid models combining different machine learning techniques to improve forecasting capabilities. Ultimately, this research not only meets its objective of stock price prediction but also contributes to the development of data-driven investment decision-making tools, providing valuable insights for future studies in financial forecasting.

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References

[1] I. A. Saputra, A. V. Vitianingsih, Y. Kristyawan, A. L. Maukar, and J. F. Rusdi, “Forecasting Model of Export and Import Value of Oil and Gas Using Gated Recurrent Unit Method,” Teknika, vol. 13, no. 2, pp. 239–243, Jun. 2024, doi: 10.34148/teknika.v13i2.861.

[2] J. A. Ripto and H. Heryanto, “Penerapan Gated Recurrent Unit untuk Prediksi Pergerakan Harga Saham pada Bursa Efek Indonesia”.

[3] K. Prayogi, W. Gata, and D. P. Kussanti, “Prediksi Harga Saham Bank Central Asia Menggunakan Algoritma Deep Learning GRU,” Jutisi J. Ilm. Tek. Inform. Dan Sist. Inf., vol. 13, no. 1, p. 647, May 2024, doi: 10.35889/jutisi.v13i1.1910.

[4] Avrijsto Amandri Achyar, Ali Muhammud Olow, Muhammad Rizky Perdana, Andika Sundawijaya, and Aaqila Dhiyaanisafa Goenawan, “Identifikasi Ras Wajah dengan Menggunakan Metode Deep Learning Model Keras,” J. Tek. MESIN Ind. ELEKTRO DAN Inform., vol. 1, no. 1, pp. 29–37, Mar. 2022, doi: 10.55606/jtmei.v1i1.779.

[5] A. Arwansyah, S. Suryani, H. Sy, U. Usman, A. Ahyuna, and S. Alam, “Time Series Forecasting Menggunakan Deep Gated Recurrent Units,” Digit. Transform. Technol., vol. 4, no. 1, pp. 410–416, Jun. 2022, doi: 10.47709/digitech.v4i1.4141.

[6] A. P. Meriani and A. Rahmatulloh, “PERBANDINGAN GATED RECURRENT UNIT (GRU) DAN ALGORITMA LONG SHORT TERM MEMORY (LSTM) LINEAR REFRESSION DALAM PREDIKSI HARGA EMAS MENGGUNAKAN MODEL TIME SERIES,” J. Inform. Dan Tek. Elektro Terap., vol. 12, no. 1, Jan. 2024, doi: 10.23960/jitet.v12i1.3808.

[7] D. Anjeli, S. T. Faulina, and A. Fakih, “Sistem Informasi Perpustakaan Sekolah Dasar Negeri 49 OKU Menggunakan Embarcadero XE2 Berbasis Client Server,” vol. 13, no. 2, 2022.

[8] W. L. Seventeen and S. D. Shinta, “Pengaruh Economic Value Added dan return On Equity (ROE) Terhadap Harga Saham pada perusahaan Investasi yang Terdaftar Di BEI Tahun 2016-2019.,” JAZJurnal Akunt. Unihaz, vol. 4, no. 1, p. 138, Aug. 2021, doi: 10.32663/jaz.v4i1.2094.

[9] G. A. Saputri and A. Suharsono, “Analisis Value at Risk (VaR) pada Investasi Saham Blue Chips dengan Pendekatan Copula”.

[10] S. Samsudin, A. M. Harahap, and S. Fitrie, “IMPLEMENTASI GATED RECURRENT UNIT (GRU) UNTUK PREDIKSI HARGA SAHAM BANK KONVENSIONAL DI INDONESIA,” JISTech J. Islam. Sci. Technol., vol. 6, no. 2, Dec. 2021, doi: 10.30829/jistech.v6i2.11058.

[11] S. Mulyani, D. Hayati, and A. N. Sari, “ANALISIS METODE PERAMALAN (FORECASTING) PENJUALAN SEPEDA MOTOR HONDA DALAM MENYUSUN ANGGARAN PENJUALAN PADA PT TRIO MOTOR MARTADINATA BANJARMASIN,” vol. 14, no. 1, 2021.

[12] M. A. Ridla, N. Azise, and M. Rahman, “Perbandingan Model Time Series Forecasting Dalam Memprediksi Jumlah Kedatangan Wisatawan Dan Penumpang Airport,” SIMKOM, vol. 8, no. 1, pp. 1–14, Jan. 2023, doi: 10.51717/simkom.v8i1.103.

[13] Febby Wilyani, Qonaah Nuryan Arif, and Fitri Aslimar, “Pengenalan Dasar Pemrograman Python Dengan Google Colaboratory,” J. Pelayanan Dan Pengabdi. Masy. Indones., vol. 3, no. 1, pp. 08–14, Mar. 2024, doi: 10.55606/jppmi.v3i1.1087.

[14] “Karimah Tauhid, Volume 2 Nomor 1 (2023), e-ISSN 2963-590X,” vol. 2, 2023.

[15] E. Retnoningsih and R. Pramudita, “Mengenal Machine Learning Dengan Teknik Supervised Dan Unsupervised Learning Menggunakan Python,” BINA INSANI ICT J., vol. 7, no. 2, p. 156, Dec. 2020, doi: 10.51211/biict.v7i2.1422.

[16] P. A. Nugroho, I. Fenriana, R. Arijanto, and M. Kom, “IMPLEMENTASI DEEP LEARNING MENGGUNAKAN CONVOLUTIONAL NEURAL NETWORK (CNN) PADA EKSPRESI MANUSIA,” vol. 2, no. 1, 2020.

[17] “Recurrent Neural Network (RNN) dan Gated Recurrent Unit (GRU).” Accessed: Jan. 06, 2025. [Online]. Available: https://socs.binus.ac.id/2017/02/13/rnn-dan-gru/

[18] W. Hastomo, A. S. B. Karno, N. Kalbuana, E. Nisfiani, and L. Etp, “Optimasi Deep Learning untuk Prediksi Saham di Masa Pandemi Covid-19,” J. Edukasi Dan Penelit. Inform. JEPIN, vol. 7, no. 2, p. 133, Aug. 2021, doi: 10.26418/jp.v7i2.47411.

[19] D. Suluh, D. E. Herwindiati, and J. Hendryli, “Peramalan Pertumbuhan Jumlah Outlet Menggunakan Metode Gated Recurrent Unit (Studi Kasus: PT XYZ),” Comput. J. Comput. Sci. Inf. Syst., vol. 8, no. 1, pp. 62–72, Apr. 2024, doi: 10.24912/computatio.v8i1.21234.

[20] V. R. Danestiara, E. Setiana, I. Akbar, and T. Hidayah, “Algoritma Gated Recurrent Unit untuk Prediksi Harga Indeks Penutupan Saham LQ45,” J. Account. Inf. Syst. AIMS, vol. 7, no. 1, pp. 1–8, Mar. 2024, doi: 10.32627/aims.v7i1.814.

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