Journal of Electrical Engineering and Computer (JEECOM)
Vol. 7, No. 2 (2025), DOI: 10.33650/jeecom.v4i2
p-ISSN: 2715-0410; e-ISSN: 2715-6427

Currency Exchange Rate Prediction Using Gated Recurrent Unit (GRU) with Historical Data and Economic Factor

Muhammad Azmi Adhani [1], Kusrini [2]
[1,2] Universitas Amikom Yogyakarta, Yogyakarta, Indonesia

Article Info

Article history:

Received Agustus 8, 2025
Revised Agustus 14, 2025
Accepted Oktober 3, 2025

Keywords:

Currency Prediction
Gated Recurrent Unit
Historical Data
Economic Factors

ABSTRACT

This study presents a currency exchange rate prediction model using a Gated Recurrent Unit (GRU) with historical price data and selected economic factors. Historical data, including Open, High, Low, and Close (OHLC) prices, were obtained from Yahoo Finance. Economic factor data, including Non-Farm Payrolls (NFP), Gross Domestic Product (GDP), Purchasing Managers Index (PMI), Retail Sales, and Durable Goods Orders, were collected from Trading View. Data preprocessing involved chronological sorting, missing value handling, feature scaling, and sequence generation. Multiple experiment cases were evaluated: historical data alone, historical data combined with all economic factors, and historical data combined with each individual factor. The GRU model achieved its best performance when incorporating historical data with Durable Goods Orders, indicating that this economic indicator provides significant predictive value, as reflected by the lowest RMSE (0.0076) and MAPE (0.0054), and the highest R2 (0.9764) indicating that this economic factor provides significant predictive value. These findings highlight the importance of integrating selected economic factors into exchange rate prediction models to enhance forecasting accuracy.

Corresponding Author:
Muhammad Azmi Adhani,
Universitas Amikom Yogyakarta, Jl. Ring Road Utara, Ngringin, Condongcatur, Kec. Depok, Kabupaten Sleman, Daerah Istimewa Yogyakarta 55281, Indonesia
Email: azmi@students.amikom.ac.id

1. INTRODUCTION

The foreign exchange (forex) market represents the world's largest and most liquid financial market, facilitating currency trades in pairs like EUR/USD and USD/JPY. These transactions are essential for global trade, investment, and economic stability. Forex trading reached an average of USD 7.5 trillion per day in April 2022, representing a 14% increase from USD 6.6 trillion per day in April 2019 [1]. The rapid growth of forex trading is supported by technological advancements that have made participation accessible to a wide range of stakeholders, including governments, central banks, corporations, and individual traders [2].

Forecasting exchange rate movements is a critical task for traders, policymakers, and financial institutions. Two primary approaches are commonly used: historical analysis and economic factor analysis. Historical data generally refers to past price information such as the Open, High, Low, Close (OHLC) values and trading volume over a given period [3]. The use of historical data, particularly Open, High, Low, and Close (OHLC) prices, has been a common approach in currency exchange rate prediction. While this method effectively captures historical patterns, historical data alone is often insufficient for accurate prediction, especially in markets strongly influenced by external factors. One of the common limitations in predictive models is the lack of consideration for economic factors, such as commodity prices, inflation, public debt, and cross-currency movements, which can provide additional information for more accurate and stable forecasts [4]. Economic factor analysis addresses this limitation by considering the impact of macroeconomic indicators such as Non-Farm Payrolls (NFP), Gross Domestic Product (GDP), Purchasing Managers' Index (PMI), Retail Sales, and Durable Goods Orders, all of which have been shown to significantly influence currency volatility [5].

Several studies showed the capability of deep learning models in financial forecasting. For example, Long Short-Term Memory (LSTM) have achieved high accuracy in predicting USD/JPY exchange rates, although such studies often rely solely on historical data without incorporating economic factors such as Gross Domestic Product (GDP) or Non-Farm Payrolls (NFP), which significantly influence exchange rate movements [6]. Comparative studies of deep learning models, specifically LSTM and GRU, have produced consistent findings across various datasets. A recent evaluation comparing both models for forex prediction using daily EUR/USD data from 2003–2022 found that while both achieved high accuracy, the GRU model delivered slightly better performance, achieving an RMSE of 0.054, a MAPE of 0.037, and an R2 of 97% [7]. Gated Recurrent Unit (GRU) models have been found to outperform LSTM and Linear Regression models in stock price prediction due to their superior handling of the vanishing gradient problem [8].

Integrating fundamental and technical data in models such as BERTFOREX has also yielded higher accuracy than using either data type alone, with cascading aggregation allowing the model to capture latent relationships between fundamental and technical data [9].

Although several deep learning approaches such as LSTM and GRU have shown strong performance in exchange rate forecasting, most prior research either focused solely on historical data or lacked a detailed investigation of the individual impact of economic factors. Furthermore, while some studies have combined technical and fundamental data, limited work has systematically compared the predictive contribution of each economic factor when integrated with GRU models. This study addresses that gap by developing a GRU-based forecasting model that not only incorporates historical data but also evaluates the incremental predictive value of key economic factors (NFP, GDP, PMI, Retail Sales, and Durable Goods Orders) both individually and collectively. The novelty of this research lies in its comparison of economic factor contributions, enabling a clearer understanding of which economic factors most significantly enhance model performance. By doing so, this study aims to provide a more targeted and efficient input selection strategy for exchange rate prediction models.

2. METHOD

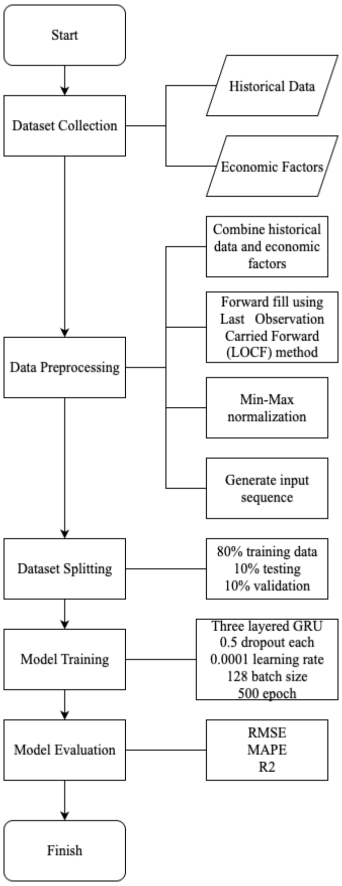

Figure 1. Predicted vs actual exchange rate values for the GRU model using historical data only

The methodology implemented in this study consists of five major stages as shown in Figure 1: dataset collection, data preprocessing, dataset splitting, model training, and model evaluation. The first stage involves retrieving historical exchange rate data and selected economic indicators relevant to currency volatility. The preprocessing phase prepares the raw data by handling missing values, normalizing feature values, and generating sequences suitable for time-series forecasting using a sliding window approach. After preprocessing, the dataset is partitioned into training, validation, and test sets to ensure robust model evaluation. The forecasting model is built using a Gated Recurrent Unit (GRU) architecture with optimized hyperparameters, followed by model evaluation using three standard metrics (RMSE, MAPE, and R2). Each step is explained in more detail in the following subsections.

2.1. Dataset Collection

The dataset used in this study consisted of two primary sources. Historical data, such as Open, High, Low, and Close (OHLC) values, was obtained from Yahoo Finance. Economic factors were collected from Trading View, consisting of Non-Farm Payrolls (NFP), Purchasing Managers Index (PMI), Gross Domestic Product (GDP), Retail Sales, and Durable Goods Orders. These economic factors were selected due to their recognized influence on currency volatility [5].

2.2. Data Preprocessing

The preprocessing stage began with sorting the data chronologically to maintain temporal order. Historical data economical combined by its date. Missing values were handled using the Last Observation Carried Forward (LOCF) method to preserve the structure of the time series [10]. All numerical features were normalized using Min-Max scaling to ensure better convergence during model training, as normalization helps maintain consistent feature ranges and enhances model performance [11]. Recurrent Neural Networks (RNNs), such as GRU, require sequential data to learn temporal patterns. To generate input sequences, this study employed a sliding window approach, where each sequence of T consecutive days is used to predict the value on day T+1. For example, with a sequence length of 40, the model takes the previous 40 days of data to forecast the 41st day's value [12].

2.3. Dataset Splitting

To ensure the model's applicability across various scenarios, the dataset was divided into training, validation, and testing subsets during the training process [13]. To be able to evaluate model performance on unseen data, the dataset splitted into training and testing sets where the dataset was divided using an 80:10:10 ratio for training, testing, and validation, respectively [7].

2.4. Model Training

The prediction model was implemented using a Gated Recurrent Unit (GRU) architecture. The model consisted of three GRU layers, each with 64 units and a tanh activation function. The first two GRU layers returned sequences, while the third did not. A dropout rate of 0.5 was applied to each layer to reduce overfitting. The output layer was a dense layer with a single unit representing the predicted exchange rate. The model was trained using a learning rate of 0.0001, a batch size of 128, and 500 epochs [7].

2.5. Model Evaluation

Performance evaluation of the model uses three widely adopted time-series forecasting metrics: Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R2).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{1}$$

Root Mean Square Error (RMSE) is used to measure the predicted values and actual observations difference, with lower RMSE values signifying greater predictive accuracy [14].

$$MAPE = \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times \frac{100}{N} \tag{2}$$

MAPE calculate the difference of mean percentage between predicted and real (actual) values [15]. In MAPE, smaller values reflect better prediction accuracy [16].

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{1}$$

The R2 metric shows how effectively the model captures and explains variations in the target variable. A value near 1 implies the model closely aligns with the actual data, signifying a strong fit [17].

ISSN: 2715-6427

These metrics were applied to all experimental cases to assess prediction accuracy, percentage error, and explanatory power of the GRU model across different input configurations.

3. RESULTS AND DISCUSSION

The GRU model was evaluated under seven different scenarios: Historical Data alone, Historical Data combined with all Economic Factors, and Historical Data combined individually with each Economic Factors. The model performance was assessed using RMSE, MAPE, and R2 score.

The results indicate variation in model accuracy across the different configurations. The combination historical data with Durable Goods Orders achieved the best performance with the lowest RMSE (0.0076), MAPE (0.0054), and the highest R2 value (0.9764). The combination of OHLC with Retail Sales also produced strong performance, closely following Durable Goods Orders. Interestingly, Historical Data combined with all economic factors showed slightly lower performance than the best individual combinations, suggesting that adding multiple factors simultaneously may introduce redundancy or noise.

Table 1. Evaluation results across scenarios

Scenario	**RMSE**	**MAPE**	**R2**
Historical data only	0.0084	0.0063	0.9709
Historical data with all economic factors	0.0098	0.0072	0.9610
Historical data + NFP	0.0095	0.0073	0.9629
Historical data + GDP	0.0095	0.0074	0.9629
Historical data + PMI	0.0096	0.0074	0.9618
Historical data + Retail Sales	0.0077	0.0056	0.9758
Historical data + Durable Order Goods	0.0076	0.0054	0.9764

Table 1 summarizes the evaluation metrics for all experimental configurations, presenting RMSE, MAPE, and R2 values side by side. These results form the basis for selecting configurations to visualize in the subsequent figures. For better illustration, predicted versus actual exchange rate plots are provided for the baseline configuration and the highest-performing configuration, as shown in Figures 1, 2, and 3.

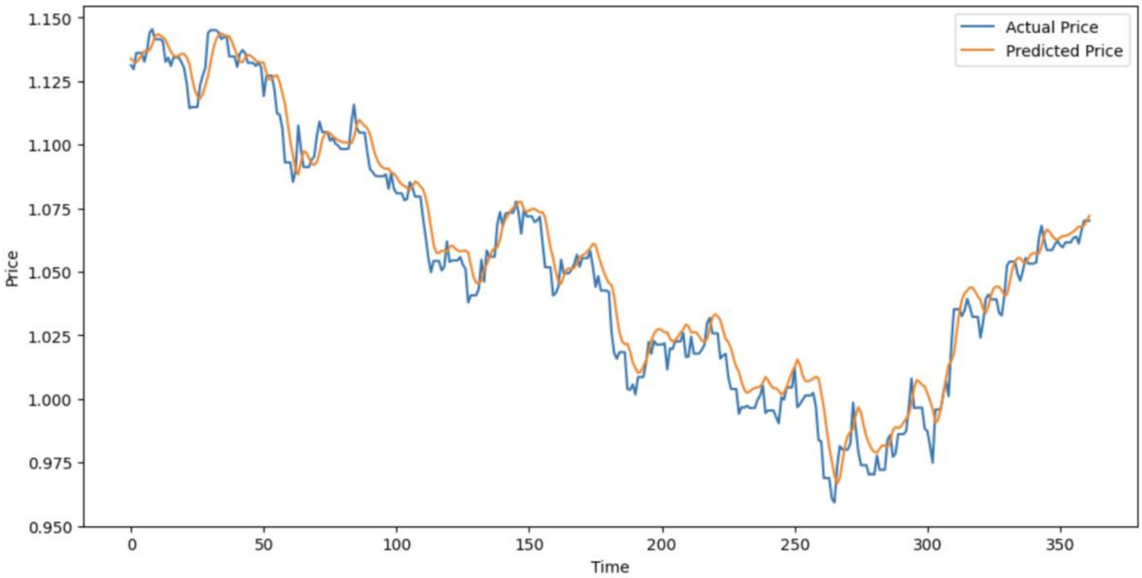

Figure 2. Predicted vs actual exchange rate values for the GRU model using historical data only

The results in Table 1 show that the baseline GRU model using only Historical Data achieved strong performance (RMSE = 0.0084, MAPE = 0.0063, R2 = 0.9709), confirming the effectiveness of OHLC for exchange rate prediction. However, the integration of certain economic factors enhanced predictive accuracy.

Figure 2 illustrates the predicted versus actual exchange rate values for the baseline model using only Historical Data. The prediction line closely follows the actual value trend, indicating that the GRU model successfully captured the general movement of the exchange rate. Minor deviations were observed during periods of sharp volatility, which is expected due to the inherent challenges of modeling sudden market shocks using technical data alone.

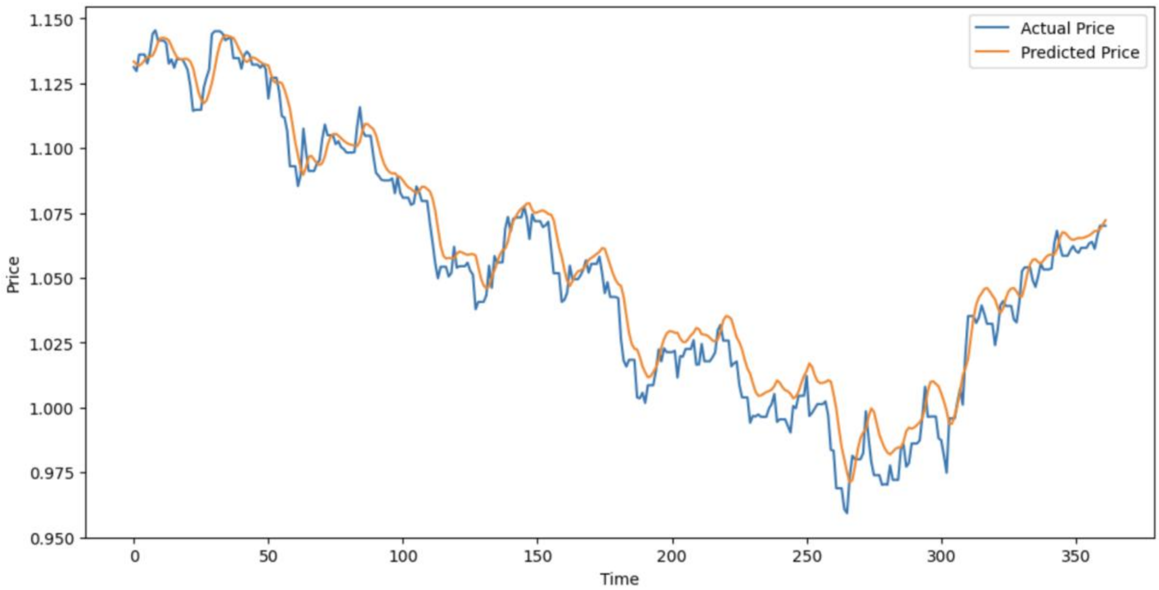

Figure 3. Predicted vs actual exchange rate values for the GRU model using Historical Data with all economic factors

The combinations of Historical Data with NFP, GDP, PMI, Retail Sales, and Durable Goods Orders in Table 1 showed minor improvements over the baseline. The slightly lower performance of historical data combined with all economic factors (RMSE = 0.0097, MAPE = 0.0072, R2 = 0.9610) suggests that adding all factors simultaneously may introduce noise or redundancy, thereby reducing generalization.

Figure 3 displays the predicted versus actual exchange rate values for the GRU model that incorporates both historical data and all economic factors. While the overall trend alignment remains consistent with the actual values, the prediction line shows slightly more fluctuation compared to the best-performing configuration. This suggests that although the integration of multiple economic indicators contributes additional information, it may also introduce noise or redundancy, which slightly reduces the model's ability to generalize. Nevertheless, the model still captures key trend movements and reflects reasonable predictive capability, supporting the idea that economic factors have a measurable influence on exchange rate behavior when combined with technical data.

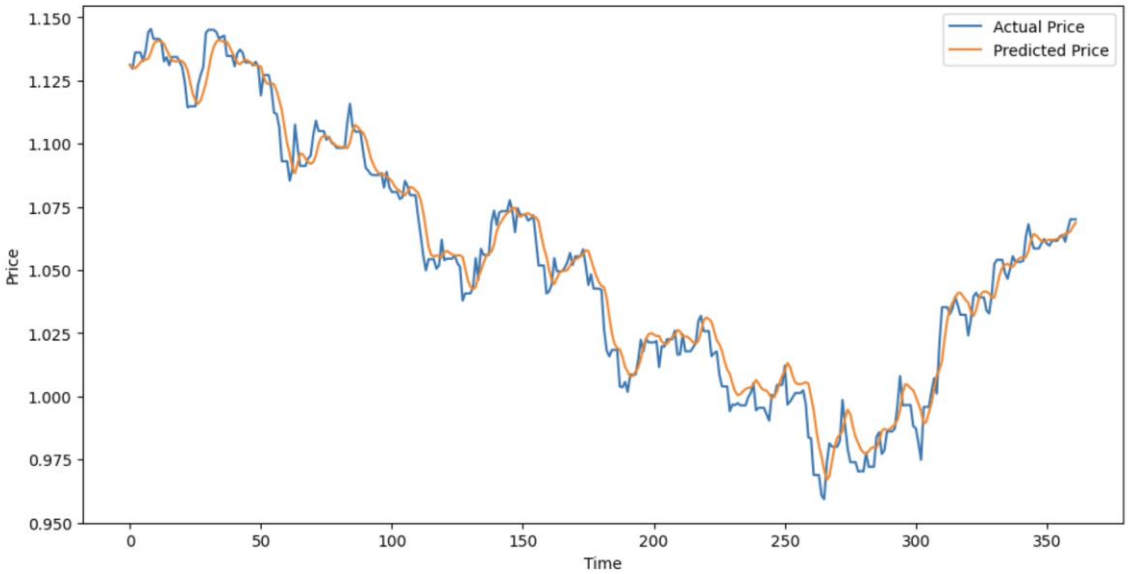

Figure 4. Predicted vs actual exchange rate values for the GRU model using historical data durable goods orders

Durable Goods Orders had the most significant impact, producing the lowest RMSE and MAPE values and the highest R2. The best results were obtained by combining Historical Data with Durable Goods Orders (RMSE = 0.0076, MAPE = 0.0054, R2 = 0.9764) and Historical Data with Retail Sales (RMSE = 0.0077, MAPE = 0.0056, R2 = 0.9758). This suggests that consumer spending and manufacturing investment factor provide additional predictive value, likely due to their direct relationship with economic growth expectations and monetary policy decisions.

Figure 4 shows the predicted versus actual values for the best-performing model, which combines Historical Data with Durable Goods Orders. The prediction line in this configuration aligns even more closely with the actual values compared to the baseline model. The inclusion of Durable Goods Orders appears to improve the model's responsiveness to trend reversals and reduce lag in volatile market periods. This improvement is reflected in the higher

4. CONCLUSION

This study developed a currency exchange rate prediction model using a Gated Recurrent Unit (GRU) by integrating historical OHLC data with selected economic indicators. The results confirmed the initial hypothesis: while historical data alone yielded strong predictive performance, incorporating specific economic factors significantly improved accuracy. The best performance was achieved when combining historical data with Durable Goods Orders, resulting in an RMSE of 0.0076, a MAPE of 0.0054, and an R^2 of 0.9764. This outperformed all other scenarios, including the combination of historical data with all economic indicators, which slightly decreased accuracy due to possible feature redundancy.

These findings reinforce the importance of selective feature integration, especially focusing on influential macroeconomic variables like Durable Goods Orders and Retail Sales to enhance model generalization and responsiveness. This aligns with previous studies emphasizing targeted input selection over excessive feature inclusion.

Future work may explore additional indicators such as sentiment analysis or central bank signals, utilize advanced deep learning architectures like Transformer or Temporal Fusion Transformer (TFT), and apply the methodology across various currency pairs. The resulting model offers promising potential as a practical tool for analysts, traders, and policymakers seeking reliable exchange rate forecasts.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to Universitas AMIKOM Yogyakarta for providing the academic support and resources necessary for the completion of this research. Grateful acknowledgment is also given to Prof. Dr. Kusrini, M.Kom., for her exceptional guidance, insightful suggestions, and continuous encouragement during the course of this research.

REFERENCES

[1] Bank of International Settlements, “OTC Foreign Exchange Turnover in April 2022,” Bank for International Settlements, Basel, Switzerland, Statistical Release Triennial Central Bank Survey 2022, 2022.
[2] H. Hartono, N. Nersiwad, M. Muslimin, F. Asj’ari, and M. Martins, “Risk management analysis and investment strategy on forex online trading,” *JPPI*, vol. 10, no. 2, p. 616, Jun. 2024, doi: 10.29210/020242657.
[3] W. Pongsena, P. Sitsayabut, N. Kerdprasop, and K. Kerdprasop, “Development of a Model for Predicting the Direction of Daily Price Changes in the Forex Market Using Long Short-Term Memory,” *IJMLC*, vol. 11, no. 1, pp. 61–67, Jan. 2021, doi: 10.18178/ijmlc.2021.11.1.1015.
[4] S. W. Agung, K. S. W. Rianto, and A. Wibowo, “Comparative Study of Forecasting Models for Forex Predictions with the Impact of Different Currencies,” *IJETAE*, vol. 12, no. 1, pp. 11–22, Jan. 2022, doi: 10.46338/ijetae0122_02.
[5] E. Kocenda and M. Moravcová, “Intraday Effect of News on Emerging European Forex Markets: An Event Study Analysis,” 2018.
[6] M. Jannah, W. Fuadi, and Z. Fitri, “Application of Long Short-Term Memory (LSTM) Algorithm in Predicting Forex Trading Price Movements on the USD/JPY Pair,” in *The 2nd International Conference on Multidisciplinary Engineering (ICOMDEN)*, in ICOMDEN Proceedings, vol. 2. Lhokseumawe, Indonesia: Faculty of Engineering, Universitas Malikussaleh, 2024, pp. 1–7.
[7] M. R. Pahlevi, K. Kusrini, and T. Hidayat, “Comparison of LSTM and GRU Models for Forex Prediction,” *SinkrOn*, vol. 8, no. 4, pp. 2254–2263, Oct. 2023, doi: 10.33395/sinkron.v8i4.12709.
[8] M. O. Rahman, S. Hossain, T.-S. Junaid, S. A. Forhad, and M. K. Hossen, “Predicting Prices of Stock Market using Gated Recurrent Units (GRUs) Neural Networks,” *International Journal of Computer Science and Network Security (IJCSNS)*, vol. 19, no. 1, pp. 213–222, 2019.
[9] A. Pornwattanavichai, S. Maneeroj, and S. Boonsiri, “BERTFOREX: Cascading Model for Forex Market Forecasting Using Fundamental and Technical Indicator Data Based on BERT,” *IEEE Access*, vol. 10, pp. 23425–23437, 2022, doi: 10.1109/ACCESS.2022.3152152.
[10] M. Alwateer, E.-S. Atlam, M. M. A. El-Raouf, O. A. Ghoneim, and I. Gad, “Missing Data Imputation: A Comprehensive Review,” *JCC*, vol. 12, no. 11, pp. 53–75, 2024, doi: 10.4236/jcc.2024.1211004.
[11] B. G. Chepino, R. R. Yacoub, A. Aula, M. Saleh, and B. W. Sanjaya, “EFFECT OF MINMAX NORMALIZATION ON ORB DATA FOR IMPROVED ANN ACCURACY,” *J3EIT*, vol. 11, no. 2, p. 29, Aug. 2023, doi: 10.26418/j3eit.v11i2.68689.
[12] I. P. G. A. Sudiatmika and I. M. A. W. Putra, “Comparison of LSTM and GRU Models Performance in Forecasting Gold Prices: A Case Study Using Historical Data from Yahoo Finance,” *ARRUS J. Eng. Tech.*, vol. 4, no. 1, Jul. 2024, doi: 10.35877/jetech2760.
[13] Nisha Wankhade, “An Statistical Analysis of Gated Recurrent Unit Based Predictive Modelling for Dynamic Obstacle Avoidance in Autonomous Aerial Vehicles,” *cana*, vol. 31, no. 2s, pp. 360–372, Jun. 2024, doi: 10.52783/cana.v31.654.
[14] C. Chen, L. Xue, and W. Xing, “Research on Improved GRU-Based Stock Price Prediction Method,” *Applied Sciences*, vol. 13, no. 15, p. 8813, Jul. 2023, doi: 10.3390/app13158813.
[15] I. W. R. Pinastawa, M. G. Pradana, D. S. Setiawan, and A. Izzety, “Comparison of ARIMA and GRU Methods in Predicting Cryptocurrency Price Movements,” *SinkrOn*, vol. 9, no. 1, pp. 96–105, Jan. 2025, doi: 10.33395/sinkron.v9i1.14235.
[16] R. Rizky, M. Ula, and Z. Yunizar, “Evaluating GRU Algorithm and Double Moving Average for Predicting USDT Prices: A Case Study 2017-2024,” *SISFOKOM*, vol. 14, no. 1, pp. 107–113, Jan. 2025, doi: 10.32736/sisfokom.v14i1.2328.
[17] J. Dip Das, R. K. Thulasiram, C. Henry, and A. Thavaneswaran, “Encoder–Decoder Based LSTM and GRU Architectures for Stocks and Cryptocurrency Prediction,” *JRFM*, vol. 17, no. 5, p. 200, May 2024, doi: 10.3390/jrfm17050200.