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Research article

A Comparative Study of Temporal Convolutional Network and Gated Recurrent Unit for Predicting Ethereum Prices

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Abstract: This study compares the performance of the Temporal Convolutional Network (TCN) and Gated Recurrent Unit (GRU) models in predicting the price of Ethereum, which is important to support cryptocurrency investment strategies. With the high volatility of the cryptocurrency market, an accurate and reliable prediction model is needed. In this study, Ethereum's daily closing price data over four years was analyzed using TCN and GRU models to evaluate its predictive capabilities. Model accuracy is measured using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). The results showed that the TCN model excelled in average accuracy with lower MAE and MAPE values, while the GRU model showed excellence in reducing the impact of large errors with smaller MSE values. This reflects TCN's superiority in capturing the overall pattern of price movements, while the GRU is more responsive to short-term price fluctuations. These findings demonstrate the potential of both models in cryptocurrency price forecasting, with their respective advantages. This research provides valuable information for investors and researchers in developing predictive strategies in dynamic financial markets. A combination of TCN and GRU models can also be explored to improve prediction performance in the future.

Keywords: Ethereum, temporal convolutional network, gate recurrence unit, cryptocurrency.

1. Introduction

As information technology continues to evolve, the use of cryptocurrencies as digital financial instruments has grown rapidly across global financial markets [1], [2]. Among various cryptocurrencies, Ethereum stands out due to its wide adoption in decentralized applications and smart contracts, as well as its consistently high trading volume [3], [4], [5]. However, Ethereum's price is highly volatile, influenced by various factors such as market sentiment, regulatory developments, technological upgrades, and macroeconomic conditions [6]. This volatility poses both opportunities and risks for investors and highlights the importance of reliable forecasting techniques to support informed decision-making.

Accurate price prediction models are essential in such a dynamic environment, enabling traders, financial analysts, and automated systems to anticipate market trends and manage risks more effectively. Traditional statistical methods often fall short in capturing the nonlinear and temporal dependencies inherent in cryptocurrency price movements [7], [8]. As a result, deep learning approaches, particularly those tailored for time series forecasting, have gained significant attention [9], [10].

Two prominent deep learning models in this domain are the Temporal Convolutional Network (TCN) and the Gated Recurrent Unit (GRU). TCN leverages 1D convolutional layers with dilations to extract long-term temporal features from sequential data, offering high parallelization and stable gradients [11]. GRU, on the other hand, is a type of recurrent neural network (RNN) that incorporates gating mechanisms to control the flow of information, allowing it to effectively model sequential dependencies with relatively fewer parameters compared to LSTM [12]. Both TCN and GRU have shown promise in time series forecasting tasks, including weather prediction, stock market analysis, and energy demand forecasting [13], [14], [15]. However, comparative studies focusing specifically on their effectiveness in predicting Ethereum prices remain limited. Understanding how these models perform in real-world cryptocurrency scenarios is crucial, given the market's unpredictable behaviour.

Therefore, this study aims to compare the performance of the TCN and GRU models in predicting Ethereum prices, utilizing daily closing price data over the past four years. The models are evaluated using widely accepted metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). The goal is to determine which model offers greater predictive accuracy and stability, thereby contributing new insights into the development of robust forecasting systems for the rapidly evolving cryptocurrency landscape.

2. Materials and Methods

2.1. Dataset

The dataset used in this study comprises the daily closing prices of Ethereum collected over a span of four years. The primary source of this historical data is Yahoo Finance, supplemented by other publicly accessible and reputable financial data providers to ensure data completeness and accuracy. This dataset is representative of the high volatility and seasonality typical of cryptocurrency markets, making it suitable for time series forecasting.

Time series data, by definition, consists of sequential observations recorded at successive time intervals [16]. In this context, each data point represents the closing price of Ethereum on a specific day. Before model training, the data was cleaned to handle any missing values, and normalization was applied to scale the input features within a defined range, improving model convergence and performance. The dataset was then split into training and testing subsets, with 1120 of the data used for model training and 281 reserved for evaluation. The price data is then normalized using equation (1).

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

2.2. Methods

This study evaluates two deep learning models suitable for sequential data: i) The Temporal Convolutional Network (TCN), and ii) The Gated Recurrent Unit (GRU). Both models are trained on the same dataset and evaluated using consistent metrics.

2.2.1. Temporal Convolutional Network

The Temporal Convolutional Network is a type of deep convolutional neural network designed for processing sequential data. TCN applies causal convolutions, ensuring that the prediction at time *t* is only influenced by inputs from time *t* and earlier. It also uses dilated convolutions to expand the receptive field, allowing the model to capture long-range dependencies without requiring many layers.

The architecture includes multiple stacked convolutional layers, each followed by non-linear activation functions (e.g., ReLU), dropout layers to prevent overfitting, and residual connections to facilitate stable training. Key hyperparameters include:

- Filter size: Determines the kernel width for each convolution
- Dilation rate: Controls the spacing between kernel elements
- Sequence length: Number of historical data points considered in each input sample
- Dropout rate: Used to regularize the model

TCNs have been shown to outperform traditional RNNs in terms of parallelism and training stability, particularly in long-range sequence modeling tasks [17], [18].

2.2.2. Gate Recurrent Unit

The Gated Recurrent Unit is a recurrent neural network variant designed to efficiently model temporal dependencies in sequential data. Unlike traditional RNNs, GRU introduces update and reset gates to manage information flow within the network. These mechanisms help the GRU retain relevant information over longer sequences while avoiding the vanishing gradient problem.

GRU has fewer parameters than LSTM but can achieve comparable performance in many forecasting tasks. The model was implemented with:

- An input layer accepting time series data sequences
- A GRU layer with optimized units
- Dropout regularization
- A fully connected output layer for prediction

GRU is well-suited for capturing short- to medium-term dependencies, making it a viable candidate for highly dynamic financial data [19].

2.3. Model Evaluation

To assess the performance of the TCN and GRU models, three commonly used error metrics in regression tasks were employed: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). The most effective model was selected based on the lowest values on all three metrics in the test data.

MAE is the average of the absolute difference between the actual value and the predicted value [20]. MAE is formulated in Equation (2).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}| \tag{2}$$

where *yi* is the actual values and *yi* is the predicted values.

MAPE is a percentage of the average absolute difference between actual and predicted values [21]. MAPE is shown in equation (3).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} |\frac{y_i - \widehat{y_i}}{y_i}| \times 100\% \tag{3}$$

MSE is the average of the squared error between the actual value and the predicted value [20]. MSE is described in equation (4).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (4)$$

The model that achieved the lowest values across all three metrics on the test dataset was considered the most accurate and robust for Ethereum price prediction.

3. Results and Discussion

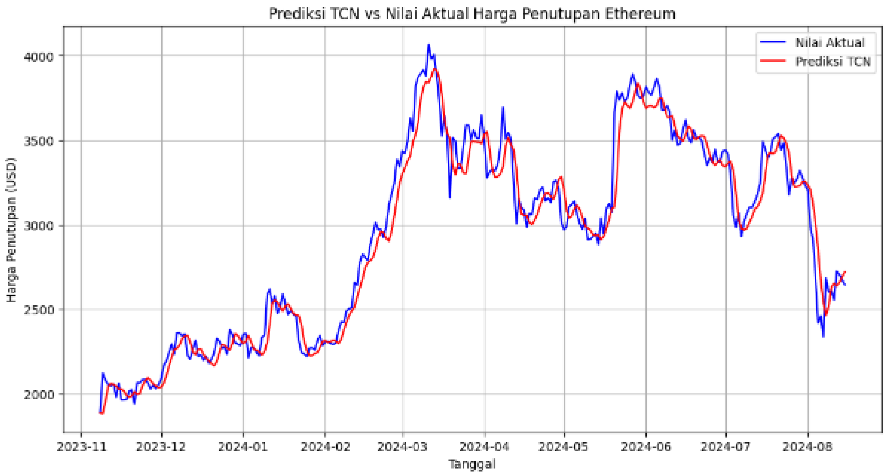
This section presents the outcomes of the training and evaluation of the Temporal Convolutional Network (TCN) and Gated Recurrent Unit (GRU) models for predicting Ethereum's daily closing price. The models were assessed using three standard regression metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). Visualizations of the predictions compared to actual values are also included to support quantitative findings.

3.1. Model Training

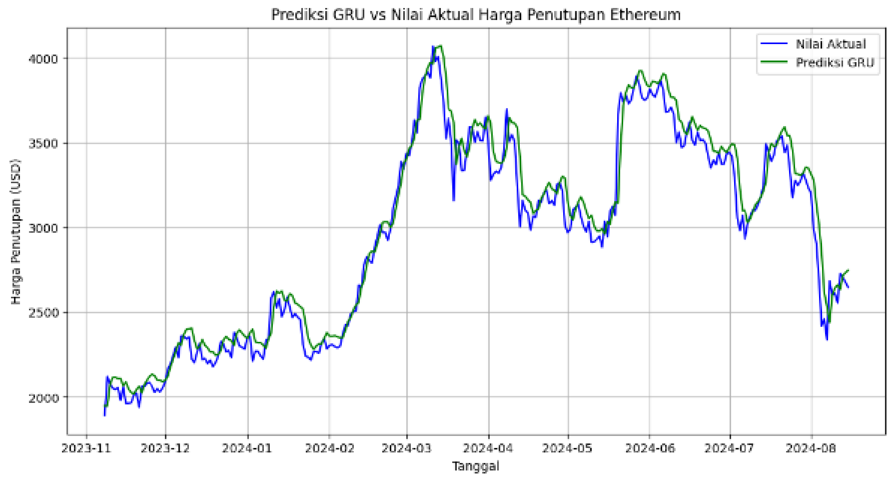
The model training process involves several key steps. First, Ethereum price data is taken and divided into training data and testing data, with the data covering 1120 samples of training data and 281 samples for testing data. The price data is then normalized using equation (1). The TCN and GRU models are trained using optimized parameters, including the number of epochs, batch sizes, and activation functions. The training process is carried out using the backpropagation method using the Adam optimizer to reduce prediction errors, and the model is saved after achieving the desired accuracy. After the training is complete, the model is evaluated using test data to calculate evaluation metrics.

Figures 1 and 2 show the comparison between actual Ethereum prices and the predictions made by the TCN and GRU models, respectively. Visually, both models closely follow the actual price trend, demonstrating strong predictive capability.

Figure 1. Model training results: **(a)** TCN, **(b)** GRU.



(a)



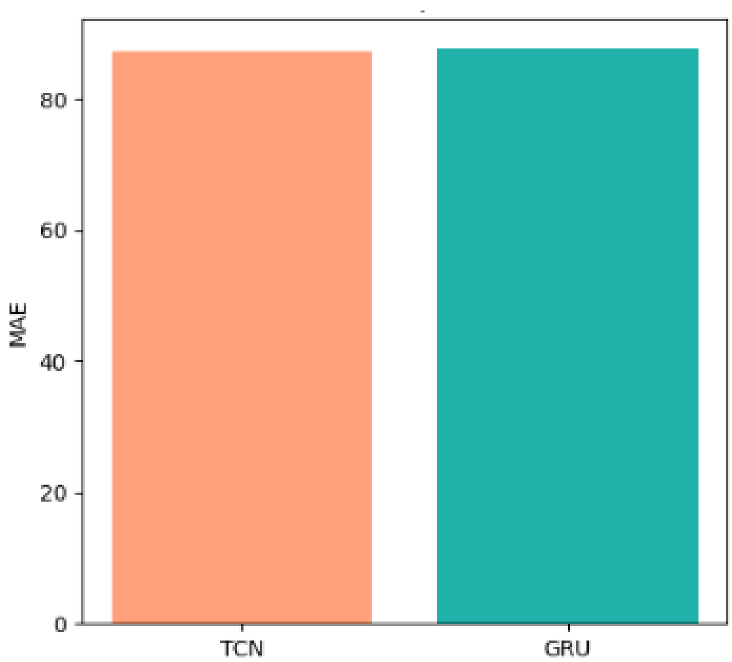
(b)

Figure 1 shows the TCN prediction (red line) and the actual Ethereum price (blue line). The two curves align well, particularly during steady upward and downward trends. Figure 2 presents the GRU prediction (green line) alongside the actual price (blue line), also demonstrating good adherence to market trends, though slight deviations are observed during sharp fluctuations. These visualizations confirm that both models are capable of modeling the non-linear and temporal nature of cryptocurrency price movements.

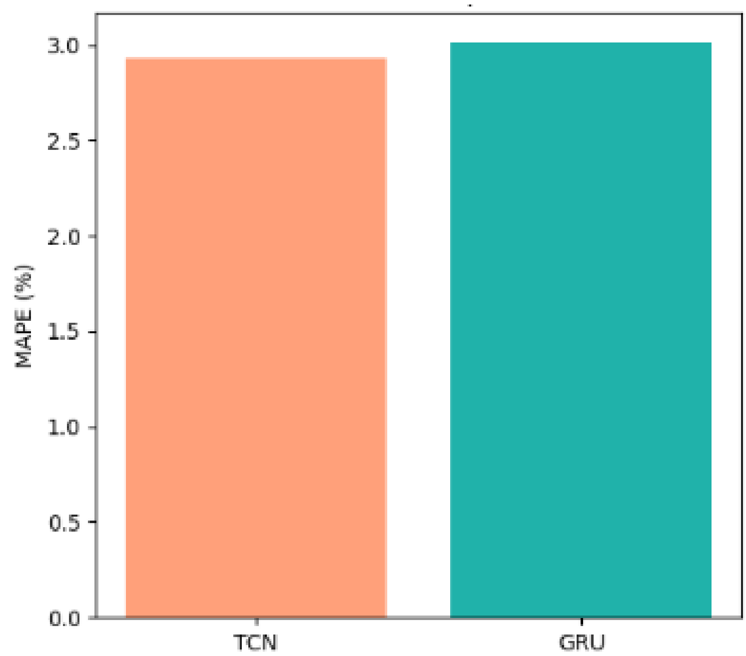
3.2. Evaluation Metrics

Figure 2 displays the comparative performance of both models across MAE, MAPE, and MSE metrics.

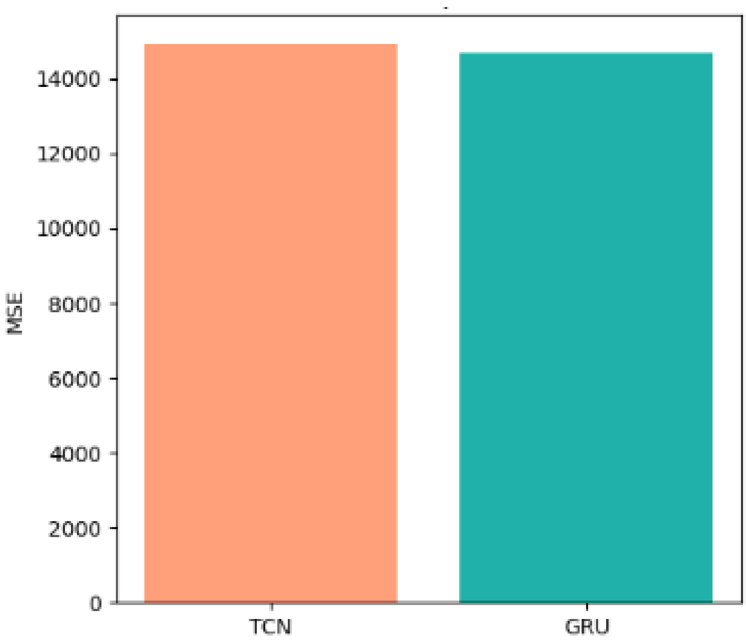
Figure 2. Comparative performance of TCN vs GRU: **(a)** MAE, **(b)** MAPE, **(c)** MSE.



(a)



(b)



(c)

The results showed that the TCN model produced an MAE of 87,189, while the GRU model produced an MAE of 87,795. TCN has a slightly lower MAE, indicating marginally more accurate predictions in terms of average absolute error. Similar to MAE, TCN also shows better performance in MAPE, with a lower relative error percentage. The GRU model has an MAPE of 3.01%, while the TCN model has an MAPE of 2.93%. This result suggests that TCN has a more consistent prediction accuracy relative to actual values. Interestingly, GRU outperforms TCN in MSE. The results showed that the TCN model produced an MSE of 14,940, and the GRU model produced an MSE of 14,663. This indicates that while TCN is more accurate on average, GRU may handle large deviations better, indicating better stability during volatile price swings.

The results indicate that both TCN and GRU models are effective for forecasting Ethereum prices. TCN slightly edges out GRU in MAE and MAPE, reflecting its strength in reducing average and percentage errors. This can be attributed to the TCN's ability to capture long-term temporal dependencies effectively through dilated convolutions.

However, GRU shows a lower MSE, meaning it better manages large prediction errors, which is an important quality in highly volatile financial markets like cryptocurrency. This suggests GRU may be better suited for use in scenarios where occasional large price swings occur, such as during news-driven market events.

Overall, the performance gap between the two models is relatively small, indicating that both approaches are viable. The choice between them could depend on the specific forecasting requirements, whether prioritizing average prediction accuracy (favoring TCN) or robustness to extreme fluctuations (favoring GRU).

4. Conclusions

This study compared the performance of two deep learning models—Temporal Convolutional Network (TCN) and Gated Recurrent Unit (GRU)—in predicting the daily closing price of Ethereum. The evaluation was based on three key performance metrics: MAE, MAPE, and MSE. The results indicate that each model offers distinct advantages. The TCN model achieved lower MAE and MAPE values, demonstrating higher average and relative prediction accuracy. This suggests TCN's strength in capturing consistent temporal patterns and minimizing typical forecasting errors. On the other hand, the GRU model achieved a lower MSE, indicating superior robustness in handling larger deviations, which are common in the highly volatile cryptocurrency market.

These findings suggest that TCN is preferable for stable and accurate forecasting in average conditions, while GRU may be better suited for scenarios involving high volatility where larger prediction errors are more likely. Thus, both models are effective, but their application may depend on the specific forecasting goals. For future work, it is recommended to explore hybrid architectures that combine the strengths of both TCN and GRU, potentially leveraging TCN's accuracy with GRU's adaptability. Furthermore, extending the prediction horizon and applying these models to other cryptocurrencies or financial assets could help validate and generalize the findings, contributing to more robust and scalable predictive systems.

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References

[1] A. Chandra Mudhol, "The Future of Digital Currency: Implications for Global Financial Systems and Trade," *International Journal of Innovative Science and Research Technology (IJISRT)*, pp. 2315–2321, Sep. 2024, doi: 10.38124/ijisrt/IJISRT24AUG1660.

[2] M. Wątorek, J. Kwapień, and S. Drożdż, "Cryptocurrencies Are Becoming Part of the World Global Financial Market," *Entropy*, vol. 25, no. 2, p. 377, Feb. 2023, doi: 10.3390/e25020377.

[3] A. Yunizar, T. Rismawan, and D. M. Midyanti, "Penerapan Metode Recurrent Neural Network Model Gated Recurrent Unit Untuk Prediksi Harga Cryptocurrency," *Coding Jurnal Komputer dan Aplikasi*, vol. 11, no. 1, pp. 32–41, May 2023, doi: 10.26418/coding.v11i1.58073.

[4] N. Aslanidis, A. F. Bariviera, and Ó. G. López, "The link between cryptocurrencies and Google Trends attention," *Financ Res Lett*, vol. 47, p. 102654, Jun. 2022, doi: 10.1016/j.frl.2021.102654.

[5] K. Wu, Y. Ma, G. Huang, and X. Liu, "A first look at blockchain-based decentralized applications," *Softw Pract Exp*, vol. 51, no. 10, pp. 2033–2050, Oct. 2021, doi: 10.1002/spe.2751.

[6] Y. Sovbetov, "Factors Influencing Cryptocurrency Prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero," *Journal of Economics and Financial Analysis*, vol. 2, no. 2, pp. 1–27, 2018.

[7] J. J. Sega, Shivam, Y. Gautam, and K. D. Yadav, "Improving the Prediction and Fine-Grained Approach for Predicting and Forecasting Cryptocurrency Price Using ARIMA," in *2023 4th International Conference on Intelligent Technologies (CONIT)*, IEEE, Jun. 2024, pp. 1–7. doi: 10.1109/CONIT61985.2024.10627511.

[8] L. Pan, "Cryptocurrency Price Prediction Based on ARIMA, Random Forest and LSTM Algorithm," *BCP Business & Management*, vol. 38, pp. 3396–3404, Mar. 2023, doi: 10.54691/bcpbm.v38i.4313.

[9] G. Pavani, K. S. Vyshnavi, M. Samhitha, and A. T, "Cryptocurrency Price Prediction using LSTM with Self Attention," in *2024 3rd International Conference on Sentiment Analysis and Deep Learning (ICSADL)*, IEEE, Mar. 2024, pp. 306–311. doi: 10.1109/ICSADL61749.2024.00056.

[10] N. Tripathy, S. Hota, D. Mishra, S. K. Nayak, S. S. Dalai, and J. Tripathy, "Cryptocurrency Price Prediction: A Comprehensive Analysis of High-dimensional Features with Deep Learning Techniques," in *2024 International Conference on Intelligent Computing and Sustainable Innovations in Technology (IC-SIT)*, IEEE, Nov. 2024, pp. 1–6. doi: 10.1109/IC-SIT63503.2024.10862895.

[11] Y. Pei, C.-J. Huang, Y. Shen, and M. Wang, "A Novel Model for Spot Price Forecast of Natural Gas Based on Temporal Convolutional Network," *Energies (Basel)*, vol. 16, no. 5, p. 2321, Feb. 2023, doi: 10.3390/en16052321.

[12] R. Dey and F. M. Salem, "Gate-variants of Gated Recurrent Unit (GRU) neural networks," in *2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS)*, IEEE, Aug. 2017, pp. 1597–1600. doi: 10.1109/MWSCAS.2017.8053243.

[13] M. S. Abdullah, A. Selamat, N. Q. Do, M. A. Abu, K. C. Lim, and O. Krejcar, "Rainfall Prediction based on Time-series Data and Temporal Convolutional Network for Flood Forecasting in Malaysia," in *2024 IEEE International Conference on Computing (ICOCO)*, IEEE, Dec. 2024, pp. 404–409. doi: 10.1109/ICOCO62848.2024.10928210.

[14] H. Liu, Z. Zhao, and S. Zhao, "Temporal Convolutional Network-Based Model for Precision Time-Series Forecasting in Marine Fisheries," in *2024 4th International Conference on Communication Technology and Information Technology (ICCTIT)*, IEEE, Dec. 2024, pp. 425–429. doi: 10.1109/ICCTIT64404.2024.10928443.

[15] H. Qin, "Comparison of Deep learning models on time series forecasting : a case study of Dissolved Oxygen Prediction," arXiv. [Online]. Available: https://arxiv.org/abs/1911.08414

[16] E. Darnila, R. K. Dinata, and S. Ramadani, "Prediksi Harga Pasar Komoditi Tanaman Pangan di Aceh Utara pada Masa Pandemi COVID-19 dengan Metode Fuzzy Time Series Model Chen," *JTIK (Jurnal Teknik Informatika Kaputama)*, vol. 7, no. 1, pp. 17–26, Jan. 2023, doi: 10.59697/jtik.v7i1.26.

[17] P. Hewage *et al.*, "Temporal convolutional neural (TCN) network for an effective weather forecasting using time-series data from the local weather station," *Soft comput*, vol. 24, no. 21, pp. 16453–16482, Nov. 2020, doi: 10.1007/s00500-020-04954-0.

[18] Y. He and J. Zhao, "Temporal Convolutional Networks for Anomaly Detection in Time Series," *J Phys Conf Ser*, vol. 1213, no. 4, p. 042050, Jun. 2019, doi: 10.1088/1742-6596/1213/4/042050.

[19] J. A. Ripto, "Penerapan Gated Recurrent Unit untuk Prediksi Pergerakan Harga Saham pada Bursa Efek Indonesia," Institut Teknologi Harapan Bangsa, Bandung, 2022.

[20] Khalis Sofi, Aswan Supriyadi Sunge, Sasmitoh Rahmad Riady, and Antika Zahrotul Kamalia, "Perbandingan Algoritma Linear Regression, LSTM, dan GRU dalam Memprediksi Harga Saham dengan Model Time Series," *SEMINASTIKA*, vol. 3, no. 1, pp. 39–46, Nov. 2021, doi: 10.47002/seminastika.v3i1.275.

[21] I. Nabillah and I. Ranggadara, "Mean Absolute Percentage Error untuk Evaluasi Hasil Prediksi Komoditas Laut," *JOINS (Journal of Information System)*, vol. 5, no. 2, pp. 250–255, Nov. 2020, doi: 10.33633/joins.v5i2.3900.