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Implementation of Recurrent Neural Network Gated Recurrent Unit (GRU) Model for Predicting Top-Tier Bitcoin

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ABSTRACT

Cryptocurrency investments are becoming increasingly popular due to their potential as digital assets, though high price volatility poses significant challenges for investment decision-making. This study employs the Gated Recurrent Unit (GRU) model to forecast the closing prices of five prominent cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Binance Coin (BNB), and Dogecoin (DOGE), using historical data from Yahoo Finance spanning 2019 to 2024. The model's performance was assessed using evaluation metrics, including Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). The results demonstrate that BNB achieved the best performance, with a MAPE of 2.38% and RMSE of 17.03, followed by ETH and XRP, which recorded MAPEs of 2.51% and 2.64%, respectively. BTC exhibited the highest RMSE at 2280.73, highlighting its significant price volatility, while DOGE had the lowest RMSE at 0.01, despite recording the highest MAPE at 4.11%. Forecasts for the next six periods indicate that BTC and ETH are likely to experience gradual price increases, XRP and BNB are expected to stabilize, and DOGE will remain relatively stable with low volatility. The study concludes that the GRU model is effective for cryptocurrency price forecasting, but integrating it with fundamental and technical analysis could further enhance accuracy and support more informed investment decisions.

1. Introduction

Cryptocurrency is one of the latest financial technology innovations. As a digital asset, cryptocurrency functions not only as a means of payment, but also as a potential investment instrument (Hashemi Joo et al., 2020; Mikhaylov, 2020) . Its popularity continues to rise thanks to blockchain technology that supports transaction security, transparency, and efficiency. However, cryptocurrencies are highly volatile, with price movements that are often unpredictable and influenced by various factors. This characteristic volatility makes time series analysis an important approach to understanding price patterns and trends (Cao, 2023).

High crypto asset price volatility can occur in a matter of hours or even minutes, making the value of crypto assets very volatile and difficult to predict. These extreme price fluctuations provide opportunities for investors with short-term trading strategies, but also carry great risks for investors who are less experienced or do not have good risk management (Albayati et al., 2020) . With high volatility, investors often make investment decisions without conducting adequate analysis, often relying on transaction signals whose validity is not guaranteed. For this reason, a comprehensive analysis is needed to mitigate the risk of crypto asset transactions (Corbet et al., 2019)

Currently, there are five popular crypto coins out of the ten coins with the largest market capitalization globally, namely Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and DogeCoin (DOGE) (Wątorek et al., 2021) . Based on CoinMarketCap data, BTC is ranked first with the largest market capitalization (Wronka, 2024) , followed by ETH, XRP, BNB, and DOGE. Historical data shows that during 2024, these five coins experienced significant price fluctuations, with the highest prices generally recorded in November and the lowest prices in January.

The price fluctuations of crypto assets create complex movement patterns that are difficult to predict linearly. Therefore, an effective forecasting approach is needed to help investors understand price patterns and improve the quality of decision making in crypto asset trading activities (Santos, S. and Gonçalves, 2021) . Forecasting is a method to estimate future events using past data (Kumar et al., 2021; Sudipa et al., 2023) . In an investment context, forecasting helps investors to make more informed decisions and maximize profit opportunities while minimizing potential losses.

One of the superior forecasting methods for time series data analysis is the Gated Recurrent Unit (GRU). GRU is a development of Long Short-Term Memory (LSTM) designed to overcome the vanishing gradient problem in deep neural networks. With a simpler structure than LSTM, GRU uses two main gates, namely update gate and reset gate, which allows the model to store relevant information and ignore unimportant information (Inteha et al., 2022) . GRU has several advantages, such as computational efficiency and the ability to capture long-term dependencies in time series data, which is crucial for understanding the non-linear and highly volatile price movement patterns of crypto assets (Fu et al., 2024).

Based on the above explanation, this research aims to apply the GRU method in forecasting historical data of crypto coins, especially the closing price of Bitcoin. The results of this forecasting are expected to provide benefits for investors in making more informed decisions regarding crypto coin buying and selling transactions. With an effective forecasting approach, investment risks can be minimized, and profit opportunities can be maximized. Despite significant advancements in cryptocurrency forecasting, previous studies often lack comprehensive exploration of non-linear dependencies and dynamic price fluctuations. This research fills the gap by employing GRU, a model optimized for time series data, to handle the inherent complexities of cryptocurrency markets. Unlike earlier works, this study incorporates extensive hyperparameter tuning and multi-cryptocurrency analysis, offering broader insights into the volatility and trends of digital assets.

2. Literature Review

Research on forecasting with the GRU method has shown the best MAPE results, namely in research related to predicting sunspot numbers using GRU producing accuracy values with a MAPE of 7.171% (Arfianti et al., 2021) . then research using GRU for wind speed forecasting with an RMSE value of 0.031(Saini et al., 2020) . Comparative research of ARIMA and GRU to predict high-frequency data on HIMBARA crypto coins, shows the MAPE value of GRU ranges from 0.34% to 0.77% (Ridwan et al., 2023; Sudipa et al., 2024) . Other studies, such as the prediction of gold prices and Bitcoin prices, also show the superiority of GRU in producing low error values, making it an effective method for forecasting time series data (Dutta et al., 2020; Sudiatmika et al., 2024) . The implementation of a GRU model for predicting Bitcoin prices is supported by a robust body of research that underscores the model's capability to handle the complexities of cryptocurrency price movements. The combination of GRUs with other neural network architectures and the application of various evaluation metrics further enhance their predictive power, making them a viable option for financial forecasting in the cryptocurrency domain. While prior studies, such as those by Ridwan et al. (2023) and Fu et al. (2024), demonstrated GRU's effectiveness for financial forecasting, this research stands out by integrating advanced preprocessing, multi-cryptocurrency datasets, and detailed hyperparameter optimization. These enhancements address the limitations of previous models in handling volatile and non-linear time series data, offering a novel approach to cryptocurrency price prediction.

3. Research Methods

3.1. Research Data Sources

This research uses the main data that researchers get from the site https://finance.yahoo.com/ in the form of time series data in the form of BTC, ETH, XRP, BNB, and DOGE crypto coin history data from November 30, 2019 to November 29, 2024.

3.2. Research Stages

In this research, the analysis process uses the GRU method and is assisted by the Python programming language. The following are the steps of applying the GRU method.

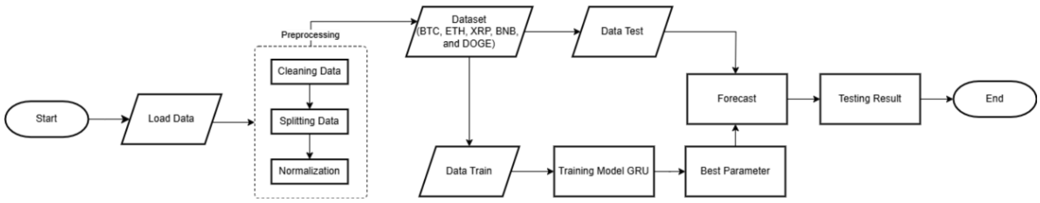

Fig. 1. Procedure Flowchart GRU

In this research, the GRU method is carried out through several stages, including the following:

Load Data

The first step in data analysis using Python is to load the data into the working environment. To do so, we can use the pandas library with the pd.read_csv() command to import data from a CSV-formatted file.

Data Preprocessing

In this research, the data preprocessing stage is carried out to prepare the dataset before it is used in modeling. It is done in three stages as follows:

a. Cleaning data

In the data cleaning stage, the date column is converted to datetime data type to enable accurate processing of time-based data. This process ensures that each data is recorded at the correct time and organized chronologically. This step is important to maintain data validity in time-based analysis. Next, the data is sorted by the date column to ensure that the analysis and forecasting process is done in the correct time order. This aims to minimize potential errors in temporal analysis that depend on data chronology. Only the date and close columns are retained in the dataset, as they are considered to be the main relevant variables for cryptocurrency price prediction modeling. Meanwhile, other columns with no immediate relevance were removed to reduce data complexity while improving efficiency in the modeling process.

b. Normalization

In the normalization stage, the MinMaxScaler method is used to convert the values in the close column into a uniform range, which is between 0 and 1. This process is done using the following formula:

$$x' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Description: when x' = Normalized result

X_i = Data at index (i)
X_{min} = Data with minimum value
X_{max} = data with maximum value

Using this formula, each value in the close column will be mapped into a range of 0 to 1, which helps to reduce the scale difference between features and makes the model more stable and efficient in the training process.

c. Splitting Data

After the data processing is complete, the next step is to divide the dataset into two subsets, namely training data and testing data. In this research, the dataset division is done with a ratio of 80:20, where 80% of the data is used to train the model, while the remaining 20% is allocated to measure the performance of the model in the testing stage.

Training Model GRU

The GRU training model consists of an input layer that receives data, several hidden layers to identify patterns in historical data, and an output layer that generates crypto coin price predictions for future periods. The processed data is used to train the model, where the training process involves adjusting the model's weights and biases to improve prediction accuracy. The model architecture used in this study consists of three GRU layers with 50 neuron units in each layer. The first and second GRU layers use return_sequences=True to forward the entire output sequence, while the third GRU layer uses return_sequences=False to only generate the output at the last step. Each GRU layer is followed by a dropout layer with a rate of 0.2 to prevent overfitting. The final layer is a Dense layer with 1 output unit that serves to generate the final predicted value.

Best Parameter Selection

Optimal parameter selection in the GRU model is performed using the Grid Search method, which tests combinations of various predefined hyperparameter values, such as epochs and batch size. In this study, two epochs values (50 and 100) and four batch size values (16, 32, 64, and 128) were tested. Each parameter combination was evaluated by calculating the loss value using the Mean Squared Error (MSE) (Pradnyani et al., 2024) , which measures the difference between the predicted and actual values in the training data. The evaluation results were then saved and sorted based on the smallest loss value, where the model with the lowest loss was selected as the best model.

3.5. Forecasting

The forecasting stage can be carried out if the best parameter combination of the GRU model has been obtained and all residual assumptions have been met.

3.6. Testing Results

Testing the results is done using testing data that has been previously separated. The purpose of this test is to assess the model's ability to predict cryptocurrency prices on data that has never been seen before. At this stage, the model that has gone through the training process is applied to the testing data to produce cryptocurrency price predictions, so that its performance can be measured objectively.

The prediction results are then compared with the actual values on the testing data to calculate two key performance metrics, namely Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R-squared (R^2).

1. MAPE

   Measures the relative error between predicted and actual values in percentage terms. MAPE gives a clear picture of how much the error is relative to the actual value, where the smaller the MAPE value, the better the model performance in terms of predictions that are closer to the actual value (Suryadana & Sarasvananda, 2024).

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

Information:

($\hat{y}_{(1)}$) = predicted value
(y_i) = Actual value
(n) = number of data

2. RMSE
   Measures how much difference there is between the predicted value and the actual value by giving more weight to larger errors. A smaller RMSE indicates a more accurate prediction.

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

   Information:
   ($\hat{y}_{(1)}$) = predicted value
   (y_i) = Actual value
   (n) = number of data

3. MAE
   Measures the average absolute value of the difference between predicted and actual values. MAE gives an idea of how much the average prediction error is in the same unit as the original data. The smaller the MAE value, the better the model's performance in producing predictions that are close to the actual value.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (3)$$

   Information:
   ($\hat{y}_{(1)}$) = predicted value
   (y_i) = Actual value
   (n) = number of data

4. R-squared (R^2).
   R-squared (Coefficient of Determination) measures how well the model can explain variations in actual data. R^2 values range from 0 to 1, where values close to 1 indicate that the model has a good ability to predict the actual data. A high R^2 value means that the model can explain most of the variability in the data.

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

   Information:
   ($\hat{y}_{(1)}$) = predicted value
   (y_i) = Actual value
   ($\bar{y}$) = Average actual value
   (n) = number of data

4. Results and Discussions

The results demonstrate that the GRU model effectively forecasts cryptocurrency prices, supported by preprocessing techniques such as normalization and dataset splitting. For instance, BTC's high RMSE (2280.73) reflects its significant volatility, while DOGE's low RMSE (0.01) indicates greater stability. This variation emphasizes the model's adaptability to different price characteristics, driven by tailored hyperparameter configurations and robust data preprocessing methods.

4.1. Load Data

The data loaded using python amounted to 1827 time series data on each of the BTC, ETH, XRP, BNB, and DOGE crypto coins.

Table 1. BTC Sample Data

Date	Adj Close	Close	High	Low	Open	Volume
11/30/2019	7569.63	7569.63	7836.102	7515.85	7764.057	1.72E+10
12/01/2019	7424.292	7424.292	7571.616	7291.342	7571.616	1.87E+10
12/02/2019	7321.988	7321.988	7474.819	7233.399	7424.036	1.71E+10
12/03/2019	7320.146	7320.146	7418.859	7229.357	7323.976	1.48E+10
12/04/2019	7252.035	7252.035	7539.785	7170.923	7320.125	2.17E+10
:	:	:	:	:	:	:
11/29/2024	97461.52	97461.52	98693.17188	95407.88281	95653.9531	5496868247

Table 2. ETH Sample Data

Date	Adj Close	Close	High	Low	Open	Volume
11/30/2019	152.5397	152.5397	156.6913	151.2253	155.2864	6.57E+09
12/01/2019	151.1857	151.1857	152.4919	147.0679	152.4919	7.1E+09
12/02/2019	149.0592	149.0592	152.117	147.6068	151.1755	6.67E+09
12/03/2019	147.9564	147.9564	150.3104	146.0017	149.0582	6.2E+09
12/04/2019	146.7477	146.7477	150.6808	145.0009	147.9184	7.87E+09
:	:	:	:	:	:	:
11/29/2024	3593.494	3593.494	3647.264	3538.447	3579.911	2.76E+10

Table 3. XRP Sample Data

Date	Adj Close	Close	High	Low	Open	Volume
11/30/2019	0.226474	0.226474	0.233615	0.224546	0.230232	1.16E+09
12/01/2019	0.225333	0.225333	0.226525	0.220253	0.226466	1.18E+09
12/02/2019	0.219581	0.219581	0.227203	0.217283	0.225386	1.19E+09
12/03/2019	0.21987	0.21987	0.223179	0.216675	0.219516	1.02E+09
12/04/2019	0.216348	0.216348	0.22177	0.212603	0.219824	1.43E+09
:	:	:	:	:	:	:
11/29/2024	1.796731	1.796731	1.811531	1.527908	1.541334	1.47E+10

Table 4. BNB Sample Data

Date	Adj Close	Close	High	Low	Open	Volume
11/30/2019	15.71595	15.71595	16.3707	15.53915	16.2635	2.13E+08
12/01/2019	15.49634	15.49634	15.74318	15.05423	15.74318	2.03E+08
12/02/2019	15.19186	15.19186	15.70717	15.15254	15.50936	2.01E+08
12/03/2019	15.30956	15.30956	15.55317	15.04867	15.19186	2.2E+08
12/04/2019	15.27998	15.27998	15.69059	15.00968	15.34843	2.38E+08
:	:	:	:	:	:	:
11/29/2024	654.8098	654.8098	663.3247	649.1632	654.3618	2.1E+09

Table 5. DOGE Sample Data

Date	Adj Close	Close	High	Low	Open	Volume
11/30/2019	0.00232	0.00232	0.002474	0.002314	0.002456	89565611
12/01/2019	0.002292	0.002292	0.002394	0.002257	0.00232	77007809
12/02/2019	0.002235	0.002235	0.002312	0.002204	0.002293	66782510
12/03/2019	0.002217	0.002217	0.002256	0.002167	0.002234	62508732
12/04/2019	0.002208	0.002208	0.002241	0.002165	0.002217	73151442
:	:	:	:	:	:	:
11/29/2024	0.425839	0.425839	0.437086	0.399992	0.402019	6.77E+09

4.2. Data Preprocessing

In the data preprocessing stage, the first step is data cleaning. At this stage, the date column is converted to datetime data type to ensure that time-based data can be processed correctly. This step is important so that each data entry is recorded at the right time and organized accurately. Next, the data is sorted by the date column to maintain the accuracy of the time sequence in analysis and forecasting. Only the date and close columns were retained, as they were considered to be the main relevant features for cryptocurrency price prediction modeling. Other irrelevant columns were removed to reduce data complexity and improve processing and modeling efficiency.

Vol. 1, No. 3, December 2024, pp. 153-168

After the data cleaning process is complete, the next step is normalization using the MinMaxScaler method. This method converts the values in the close column into a range of 0 to 1 to ensure that all values are on a uniform scale without significantly changing the data distribution. This normalization is done to improve the performance of the model during the training stage.

The final stage in preprocessing is dividing the dataset into two parts, namely training data (80%) and test data (20%), with each consisting of 1437 data for training and 360 data for testing. Training data is used to train the model, while test data is used to evaluate the model's performance on data that has never been seen before. This division is expected to produce models with accurate predictions and good generalization capabilities to new data.

The dataset underwent rigorous preprocessing to address challenges such as missing values and outliers. Missing data were handled using linear interpolation, ensuring temporal continuity, while outliers were identified and mitigated through robust statistical thresholds. These steps, combined with normalization, enhanced the dataset's quality and ensured reliable model training.

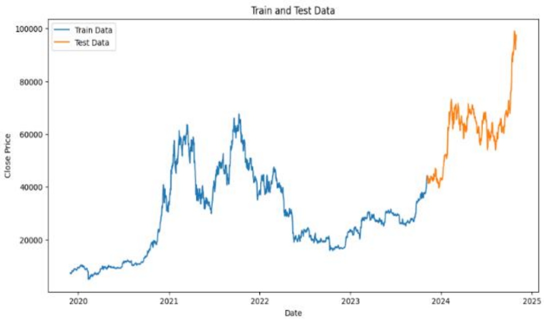

Fig. 2. BTC Train Data and Test Data

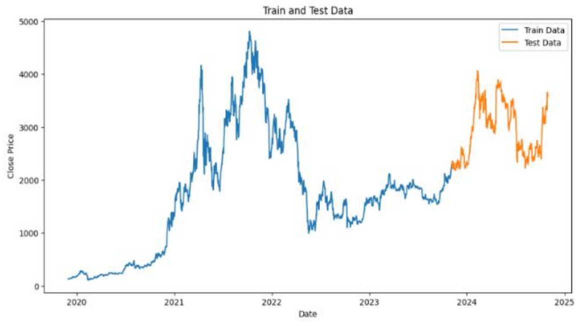

Fig. 3. ETH Train Data and Test Data

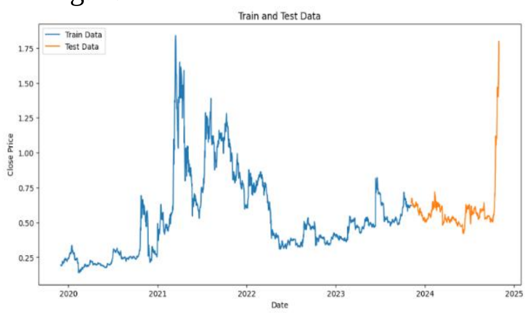

Fig. 4. XRP Train Data and Test Data

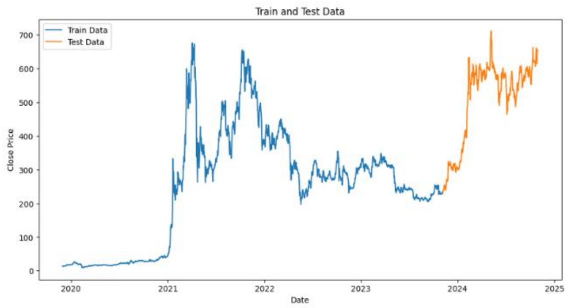

Fig. 5. BNB Train Data and Test Data

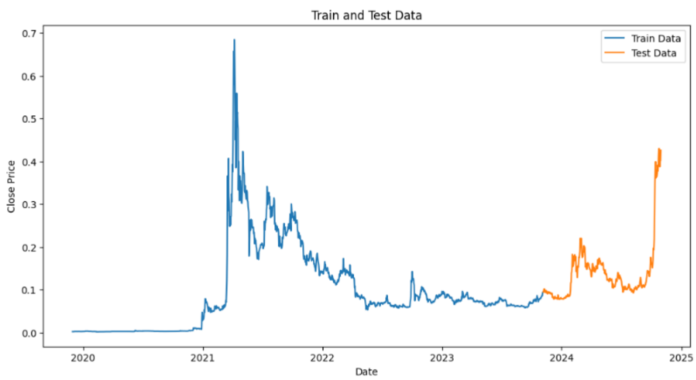

Fig. 6. DOGE Train Data and Test Data

4.3. LSTM Model Training

The GRU model is trained using pre-separated training data with a ratio of 80:20, where the date and close features have gone through a normalization process. During the training process, various combinations of hyperparameters, such as the number of epochs and batch size, are tested to find the best configuration using the Grid Search method. Epochs refer to the number of full cycles in which the model learns the entire dataset, while batch size refers to the size of the data subset used to update the model parameters in each iteration. The following table shows the results of the various parameter combinations tested:

Table 6. BTC Hyperparameter Training Results

Epochs	Batch Size	Loss
100	**32**	**1562732**
50	32	1574403
100	64	1858053
50	16	1902294
100	16	2218571
50	64	2259787
100	128	2348444
50	128	2598810

Table 7. ETH Hyperparameter Training Results

Epochs	Batch Size	Loss
100	**64**	**9267.442**
50	32	9451.996
100	32	10479.82
50	64	10561.18
100	128	10578.01
50	16	11414.23
50	128	14023.28
100	16	16440.01

The results in Table 7 highlight the loss values obtained from different hyperparameter combinations for Ethereum (ETH). The best performance is achieved with 100 epochs and a batch size of 64, yielding the lowest loss value of 9267.442. This suggests that moderate batch sizes combined with longer training cycles improve the model's ability to capture ETH's price movement patterns.

Table 8. XRP Hyperparameter Training Results

Epochs	Batch Size	Loss
100	**128**	**0.001841**
50	32	0.001849
100	64	0.001907
100	16	0.002015
50	16	0.002016
50	64	0.00202
100	32	0.002484
50	128	0.002768

In Table 8, the lowest loss value for XRP (0.001841) is achieved with 100 epochs and a batch size of 128. This indicates that a higher batch size facilitates better generalization for XRP's relatively stable price movements.

Table 9. BNB Hyperparameter Training Results

Epochs	Batch Size	Loss
50	**32**	**221.1978**
100	32	225.0056
100	64	225.2302
100	128	264.8087
50	64	268.2721

50	16	323.2442
100	16	346.4733
50	128	383.8497

The results in Table 9 demonstrate that the optimal hyperparameters for Binance Coin (BNB) are 50 epochs and a batch size of 32, resulting in the lowest loss value of 221.1978. This configuration balances training time with model performance, effectively capturing BNB's stable price trends.

Table 10. DOGE Hyperparameter Training Results

Epochs	Batch Size	Loss
100	**128**	**0.000189**
100	64	0.000197
50	64	0.000211
100	16	0.00023
50	16	0.000245
50	32	0.000251
100	32	0.000274
50	128	0.000279

Table 10 shows that Dogecoin (DOGE) achieves the best loss value (0.000189) with 100 epochs and a batch size of 128. This result reflects the GRU model's ability to handle DOGE's low volatility with higher batch sizes and extended training.

4.4. Forecasting Results

Plot of Actual Data and Forecasting Data

Figures 7-11 show the comparison between actual data (blue line) and forecasted data (orange line) for BTC, ETH, XRP, BNB, and DOGE crypto coins. The GRU model is generally able to follow the price movement pattern well on all five charts. On the BTC chart, the model successfully captured the upward and downward price trends although there was a slight deviation on extreme price spikes. The ETH chart showed high agreement between predictions and actual data, especially on significant trends. Meanwhile, the XRP chart showed good accuracy with small differences in the final spikes. The BNB chart shows a stable performance, where the up and down price trends are well replicated by the model. On the DOGE chart, the model was able to capture the price movement pattern although it lagged slightly in some parts, but remained accurate in the period of significant spikes at the end. Overall, the GRU model performed well in predicting crypto coin prices with varying accuracy, especially in handling high price fluctuations.

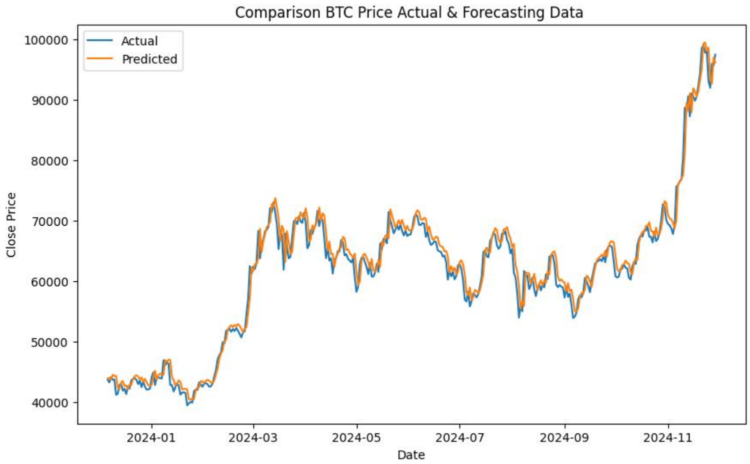

Fig.7 . Graph of Actual Data and Forecasting Data of BTC Crypto Coin

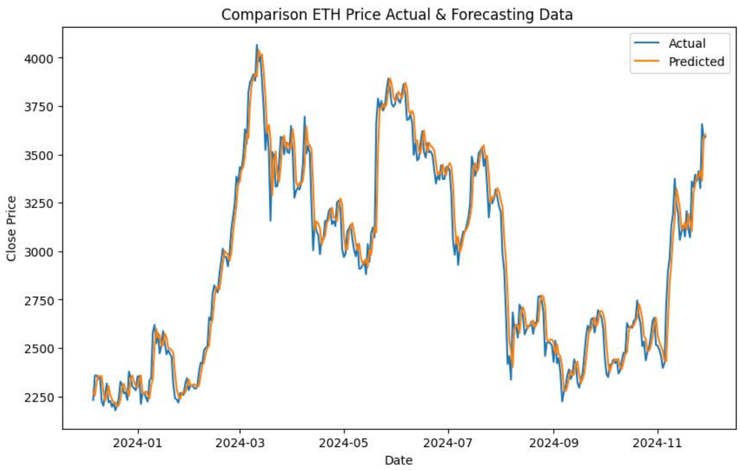

Fig. 8. Graph of Actual Data and Forecasting Data of ETH Crypto Coin

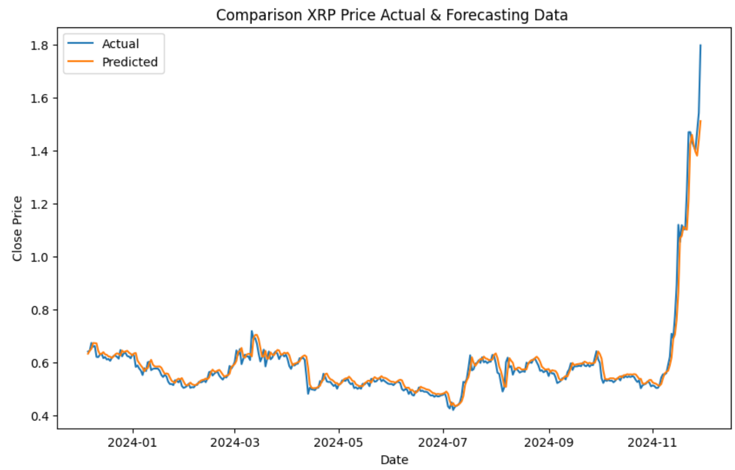

Fig. 9. Graph of Actual Data and Forecasting Data of XRP Crypto Coin

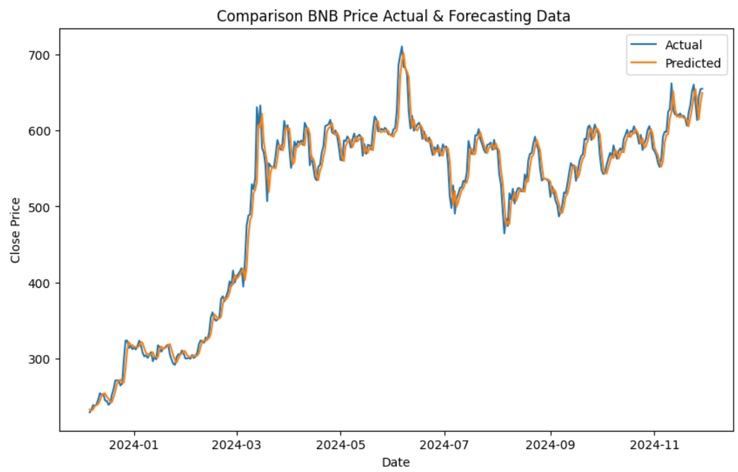

Fig. 10. Graph of Actual Data and Forecasting Data of BNB Crypto Coin

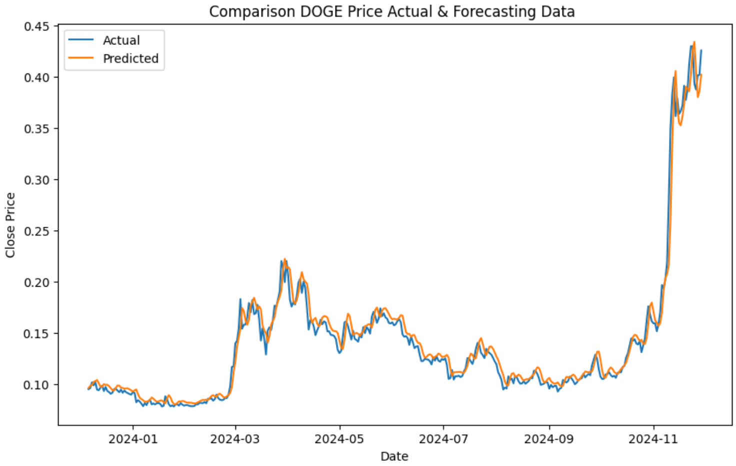

Fig. 11. Graph of Actual Data and Forecasting Data of DOGE Crypto Coin

Six Period Forecasting Plot

The results of BTC crypto coin forecasting for the next six periods using the GRU model with 100 epochs and batch size 34 show that the price trend of BTC coins tends to increase and then move sideways. Based on Table 17, the BTC closing price forecasting value is predicted to increase from 114114.5 in December 2024 to 118956.9 in April 2025. This increase is clearly visible in Figure 14, where the future prediction line shows a trend that tends to flatten after reaching the highest level around 118956.9. The BTC crypto coin forecasting values and graphs for the next six periods can be seen in Table 17 and Figure 14.

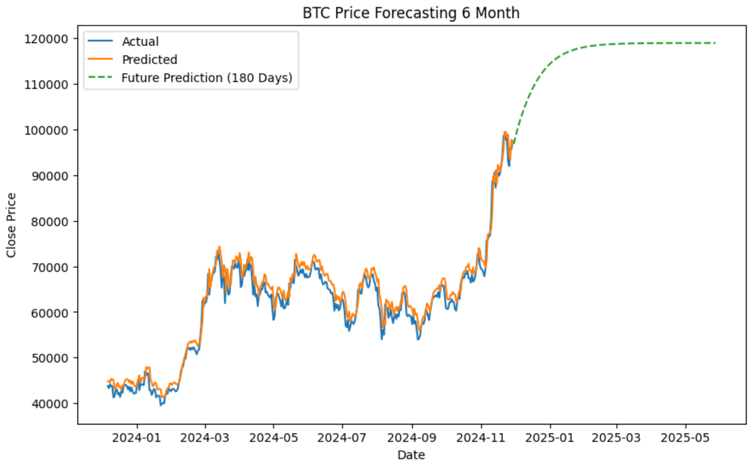

Fig.12. BTC Crypto Coin Forecasting Chart Six Periods Ahead

The results of forecasting ETH crypto coins for the next six periods using the GRU model with 100 epochs and batch size 64 show a consistent upward trend until April 2025. Based on Table 18, the closing price of ETH is predicted to increase from 3707.808 in December 2024 to 4376.107 in April 2025. This trend is visible in Figure 15, where the future prediction line shows a steady upward pattern after a fluctuating period throughout the previous year. The graph indicates that ETH price movements are likely to increase sustainably in the coming six months at a more stable growth rate.

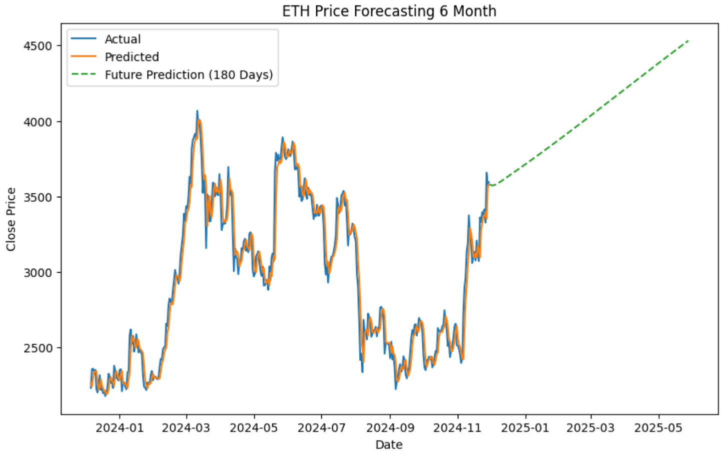

Fig. 13. Forecasting Chart of ETH Crypto Coin Six Periods Ahead

The results of forecasting XRP crypto coins for the next six periods using the GRU model with 100 epochs and batch size 128 show that the price trend of XRP crypto coins will experience a gradual increase after a sharp spike at the end of 2024. Based on Table 19, the closing price is predicted to increase from 1.614019 in December 2024 to 1.651406 in April 2025. Figure 16 shows the future prediction pattern, which shows a steady upward trend after a significant spike at the end of 2024. This indicates that despite the previous sharp spike, the price movement of XRP is predicted to move up gradually in the next six months.

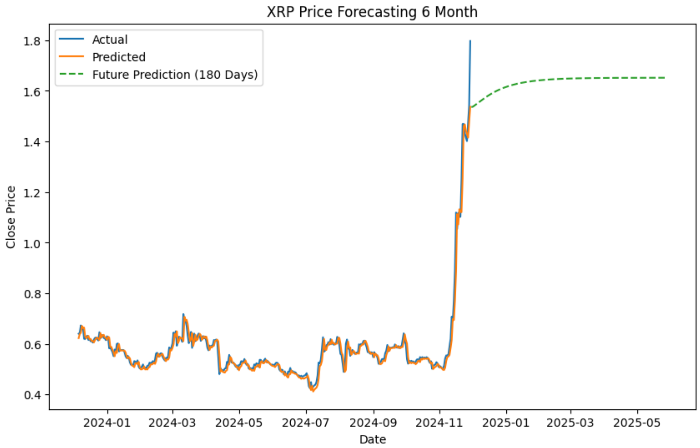

Fig. 14. XRP Crypto Coin Forecasting Chart Six Periods Ahead

The results of forecasting BNB crypto coins for the next six periods using the GRU model with 50 epochs and batch size 34 show that the price trend of BNB crypto coins tends to experience a gradual increase until April 2025. Based on Table 20, the closing price is predicted to increase from 796.7341 in December 2024 to 883.9632 in April 2025. This increase can be seen in Figure 17, where the future prediction line shows a stable trend after experiencing a consistent increase. This indicates the potential for price movements to gradually increase and then move sideways towards the end of the forecasting period.

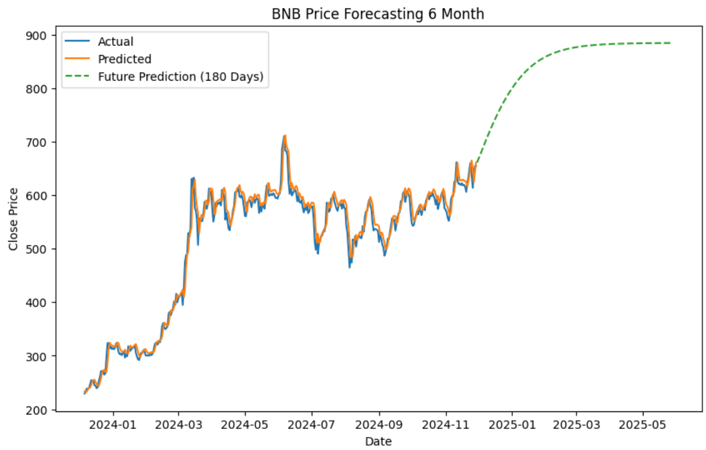

Fig. 15. BNB Crypto Coin Forecasting Chart Six Periods Ahead

Meanwhile, the results of forecasting DOGE crypto coins for the next six periods using the GRU model with 100 epochs and batch size 128 show that the price trend will tend to stabilize with a slight increase from December 2024 to April 2025. Based on Table 20, the closing price is predicted to increase from 0.444847 in December 2024 to 0.476409 in April 2025. Figure 17 shows a flat pattern of future prediction lines after a significant spike at the end of 2024. This indicates that the price movement of DOGE is predicted to enter a sideways phase with very little upward trend and low volatility during the forecasting period.

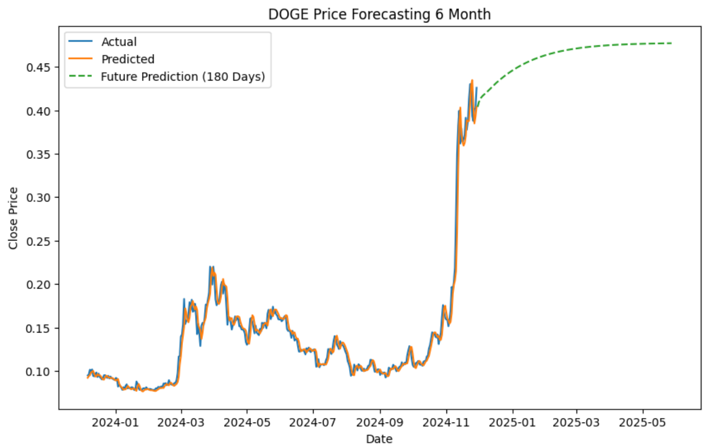

Fig. 16. Forecasting Chart of DOGE Crypto Coin Six Periods Ahead

4.5. Testing Results

This research uses MAPE and RMSE as metrics for testing results and evaluating the performance of the GRU model. Table 11 shows the performance results of the GRU model on the five cryptocurrency data.

Table 11. Model Evaluation

Cryptocurrency	MAPE	MAPE Percentage	RMSE	MAE	R2
BTC	0.0310	3.10%	2280.73	1858.84	0.9637
ETH	0.0251	2.51%	105.96	73.70	0.9564
XRP	0.0264	2.64%	0.03	0.02	0.9634
BNB	0.0238	2.38%	17.03	12.07	0.9804
DOGE	0.0411	4.11%	0.01	0.01	0.9750

To enhance interpretability, confidence intervals were added to the actual vs. predicted value graphs. These intervals illustrate the model's prediction reliability, with narrower bands observed for

ETH and BNB, reflecting higher accuracy. In contrast, wider intervals for BTC indicate greater variability, aligning with its higher volatility.

The GRU model's ability to achieve a MAPE of 2.38% for BNB and 2.51% for ETH underscores its robustness in handling stable and moderately volatile cryptocurrencies. This research introduces novel preprocessing steps and hyperparameter configurations that significantly enhance GRU's forecasting accuracy compared to traditional methods. Additionally, the study's focus on multi-cryptocurrency analysis broadens its applicability, providing a versatile framework for diverse financial contexts.

The results of testing five cryptocurrency data sets showed that BNB performed best with a MAPE of 0.0238 (2.38%) and an RMSE of 17.03, indicating the lowest prediction error rate. ETH recorded a MAPE of 0.0251 (2.51%) and an RMSE of 105.96, indicating good accuracy. XRP had a MAPE of 0.0264 (2.64%) with an RMSE of 0.03, indicating a small prediction error in absolute terms. Meanwhile, BTC had a MAPE of 0.0310 (3.10%) and the highest RMSE of 2280.73, indicating higher price volatility. DOGE recorded the highest MAPE of 0.0411 (4.11%) with the smallest RMSE of 0.01, indicating a larger proportion of error but small magnitude. These results show that the performance of the GRU model varies according to the price fluctuation characteristics of each cryptocurrency. GRU's superior performance for BNB and ETH can be attributed to their relatively stable price trends, allowing the model to capture consistent patterns. Conversely, BTC's higher volatility poses challenges for GRU, highlighting the need for additional techniques such as dynamic feature extraction or ensemble methods to improve accuracy for highly volatile assets.

5. Conclusion

Based on the results, the GRU model is able to forecast the closing prices of BTC, ETH, XRP, BNB, and DOGE cryptocurrencies with varying degrees of accuracy. The BNB coin performed best with a MAPE of 2.38% and an RMSE of 17.03, reflecting a minimal and stable prediction error rate, followed by ETH with a MAPE of 2.51% and an RMSE of 105.96, and XRP with a MAPE of 2.64% and an RMSE of 0.03, indicating a small absolute prediction error. BTC has a MAPE of 3.10% and the highest RMSE of 2280.73, indicating significant price volatility, while DOGE has the highest MAPE of 4.11%, but with the smallest RMSE of 0.01, indicating a low magnitude of prediction error. The forecasting trend for the next six periods shows BTC and ETH experiencing a gradual increase in price, while BNB and XRP show a flattening pattern after an increase, and DOGE moves in a stable pattern with low volatility. This study shows that the GRU model is effective in capturing the complex price movement patterns of crypto assets, but these prediction results should be complemented with more comprehensive fundamental and technical analysis to improve the accuracy and reliability of predictions. The GRU model demonstrated robust performance across cryptocurrencies, particularly excelling with Binance Coin (BNB) and Ethereum (ETH). For BNB, the model achieved a MAPE of 2.38% and RMSE of 17.03, reflecting its ability to capture relatively stable trends. Similarly, ETH displayed strong results with a MAPE of 2.51% and RMSE of 105.96, highlighting the model's capability in handling moderate price fluctuations. These results underline the GRU model's suitability for diverse cryptocurrency forecasting scenarios. This study presents a novel application of the GRU model, combining advanced preprocessing, hyperparameter optimization, and multi-cryptocurrency analysis. By addressing limitations in existing studies, the proposed approach offers a more accurate and scalable solution for forecasting highly volatile digital assets

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