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Performance Evaluation of Deep Learning Models for Cryptocurrency Price Prediction using LSTM, GRU, and Bi-LSTM

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Abstract−Cryptocurrency price prediction poses a significant challenge in the digital finance landscape due to its high volatility and complex data patterns. Traditional statistical methods often fail to capture the nonlinear and temporal dependencies inherent in cryptocurrency price movements. This study addresses this issue by evaluating and comparing the performance of three deep learning architectures, namely Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM). in predicting the closing prices of Bitcoin (BTC), Ripple (XRP), and Dogecoin (DOGE). The dataset was obtained from Yahoo Finance, covering the period from January 1, 2020, to April 30, 2025. The models were evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (SMAPE), with a forecasting horizon of 30 days. The results of this study indicate that the LSTM model achieved the highest accuracy for Bitcoin and Ripple, with MAPE values of 2.58% and 4.33%, respectively. Meanwhile, the GRU model demonstrated the best overall performance for Dogecoin, with RMSE (0.0131), MAE (0.0084), MAPE (4.12%), and SMAPE (4.06%). On the other hand, the Bi-LSTM model exhibited the lowest performance across all tested cryptocurrencies. These findings highlight the importance of selecting an appropriate model for developing accurate cryptocurrency price prediction systems. This study contributes to the field by providing a detailed comparative analysis of model performance across cryptocurrencies with differing volatility patterns, offering insights for developing more robust and tailored predictive systems in volatile financial environments.

Keywords: Prediction; Cryptocurrency; LSTM; GRU; Bi-LSTM

1. INTRODUCTION

Cryptocurrency is a digital currency that utilizes cryptographic techniques based on blockchain technology. This decentralized form of currency enables users to send and receive payments in a peer-to-peer manner without the involvement of banks, governments, or other central authorities [1]. The concept was first introduced by Satoshi Nakamoto in 2008 through the creation of Bitcoin, which laid the foundation for the development of various other cryptocurrencies worldwide [2]. Today, cryptocurrency has a significant influence on global financial markets and is increasingly used in everyday life, both for speculative investment and for purchasing goods and services [3].

Despite its growing popularity, cryptocurrency is characterized by extreme price volatility. This high fluctuation is influenced by various factors such as transaction costs, market sentiment, mining difficulty, altcoin prices, market demand and supply, as well as regulatory policies across different countries. This instability presents a major challenge in cryptocurrency price prediction, which is crucial for investors to minimize risk and optimize their investment portfolios. The uncertainty of the market also drives interest among researchers, investors, and financial industry practitioners to better understand market trends and behaviors in order to support more accurate decision-making and investment strategies [4], [5].

Understanding and predicting the behavior of financial markets, including the crypto market, presents its own challenges, as it requires expertise in financial analysis and strong data interpretation skills. Over the past decades, traditional approaches such as linear statistical models have proven inadequate in addressing the nonlinear characteristics of price volatility, especially in fast-moving markets like cryptocurrency [6]. Consequently, the emergence of machine learning methods has gained popularity in financial market prediction, offering solutions to many of the limitations of traditional approaches [7]. Unlike conventional linear statistical models, machine learning techniques are capable of capturing the nonlinear aspects of cryptocurrency price fluctuations due to their inherent learning capabilities. The integration of nonlinearity into machine learning algorithms for asset price and return prediction has led to significant improvements in prediction accuracy [8], [9].

In recent years, researchers have increasingly adopted machine learning and deep learning approaches for cryptocurrency price prediction, in line with the rapid development of artificial intelligence across various sectors, including finance [10]-[13]. Numerous studies have been conducted to evaluate the effectiveness of different algorithms in predicting cryptocurrency prices. Febriansyah et al. [14] utilized the LSTM algorithm to predict cryptocurrency prices using Bitcoin price data collected from December 12, 2020, to April 14, 2024. The evaluation results on the test data showed that the model achieved an RMSE of 27,921.84 and a MAPE of 5.36%. Khoiri et al. [15] analyzed the performance of several machine learning algorithms, namely Linear Regression, Random Forest, Support Vector Machine, and LSTM in predicting the prices of three types of cryptocurrencies: Bitcoin, Ethereum, and Litecoin. Model evaluation was conducted using MAE, RMSE, and prediction accuracy metrics. The experimental results showed that the LSTM algorithm outperformed the others in terms of highest accuracy and lowest prediction error. Andromeda et al. [16] predicted Bitcoin and Ethereum prices using two deep learning algorithms: LSTM and GRU. Their findings indicated that GRU performed better than LSTM, achieving a MAPE of 0.38% for Bitcoin and 0.45% for Ethereum. Nair et al. [17] compared the performance of five deep learning algorithms in predicting Bitcoin

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prices, using Recurrent Neural Network (RNN), LSTM, GRU, Bi-LSTM, and 1D Convolutional Neural Network (Conv1D). The evaluation results showed that LSTM delivered the best performance with the lowest Mean Squared Error (MSE), RMSE, and MAE values. Hamayel et al. [18] compared GRU, LSTM, and Bi-LSTM algorithms for predicting the prices of three cryptocurrencies: Bitcoin, Litecoin, and Ethereum. The evaluation results revealed that GRU achieved the best performance among the three, with the most accurate predictions and MAPE values of 0.2454% for Bitcoin, 0.8267% for Ethereum, and 0.2116% for Litecoin. Despite the growing number of studies, limited attention has been given to evaluating deep learning model performance across cryptocurrencies with contrasting price behaviors and volatility levels, such as Ripple and Dogecoin compared to Bitcoin.

Based on that background, this study aims to evaluate and compare the performance of three deep learning algorithms: LSTM, GRU, and Bi-LSTM in predicting the prices of three cryptocurrencies: Bitcoin, Ripple, and Dogecoin. The evaluation was conducted using various performance metrics, including RMSE, MAE, MAPE, and SMAPE. Through this approach, the study is expected to contribute to the development of more accurate and reliable cryptocurrency price prediction models, thereby supporting better decision-making for investors, researchers, and industry stakeholders in the digital asset sector. By evaluating multiple deep learning architectures across cryptocurrencies with varying characteristics, the study provides a more comprehensive understanding of model suitability and performance in diverse market conditions.

2. RESEARCH METHODOLOGY

2.1 Research Stages

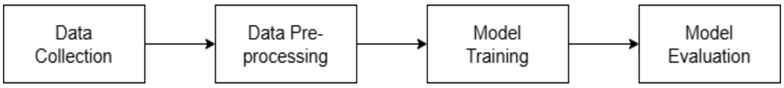

Figure 1. Research stages

Figure 1 illustrates the research stages in this study, starting from data collection, data pre-processing, model training, to model evaluation. A more detailed explanation of each stage is described in Sections 2.2 to 2.5.

2.2 Data Collection

In this study, data collection was conducted using web scraping techniques from Yahoo Finance, a globally trusted platform that provides financial market data, including historical cryptocurrency prices. The collected data includes three types of cryptocurrencies: Bitcoin, Ripple, and Dogecoin, covering the period from January 1, 2020, to April 30, 2025. The data used for cryptocurrency price prediction is the close price, which represents the final trading price of a crypto asset at the end of each daily session. The closing price is often considered the most relevant indicator of an asset’s value as it reflects the market consensus at the end of the trading period.

2.3 Data Pre-processing

In the preprocessing stage, several steps were performed to prepare the data before model training. First, data normalization was applied using the min-max scaling technique. Since the dataset contained only the Close price column, data normalization was applied solely to this column. This step is essential to enhance the model’s stability and performance during training. The min-max scaling method adjusts each feature in the dataset so that its values fall within a specified range, typically between 0 and 1 or -1 and 1. The formula is shown in Equation (1).

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Where x represents the original value of the feature, x_{min} is the minimum value, x_{max} is the maximum value, and x_{new} is the normalized value of the feature [19].

Next, the normalized data was transformed into a sequential format with a sequence length of 30. This means the model learns from the previous 30 data points to predict the price at the next time step. In this process, the data was split into two parts: X as the input features and y as the prediction targets.

Following this, the sequential data was divided into training and testing datasets, with 80% allocated for training and 20% for testing. This division allows the model to learn from the majority of the data while being evaluated on unseen data to assess its generalization performance.

2.4 Model Training

In this study, model training was conducted using three different deep learning algorithms, namely LSTM, GRU, and Bi-LSTM. These three algorithms are part of the RNN family, which is specifically designed to handle sequential data such as time series. The selection of these three models is based on their ability to capture temporal patterns and long-term dependencies in historical data, which are very important in the context of cryptocurrency price prediction. Each model has different architectural characteristics and internal mechanisms, which will be explained further in sections 2.4.1-2.4.3.

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2.4.1 Long Short-Term Memory

LSTM is a type of RNN developed to handle long-term dependencies in sequential data. It addresses the main limitation of conventional RNNs, namely the vanishing gradient problem, which often arises when processing long sequences. LSTM utilizes a special structure consisting of a cell state and three main layers: the input layer, hidden layer, and output layer. These layers control what information should be stored, discarded, or output from long-term memory, allowing LSTM to effectively manage the flow of information [20], [21]. The specific architecture used in this study is described in Section 3.2.1.

2.4.2 Gated Recurrent Unit

GRU is a simplified variant of RNN that effectively handles long-term dependencies while offering a more efficient architecture compared to LSTM. It combines and simplifies the gates found in LSTM into two main gates: the update gate and the reset gate. The update gate controls what information is carried forward to the next time step, while the reset gate determines how much past information should be forgotten. This structure makes GRU computationally lighter and faster to train without compromising prediction performance [22], [23]. The specific architecture used in this study is described in Section 3.2.2.

2.4.3 Bidirectional Long Short-Term Memory

Bi-LSTM is an extension of the LSTM model that processes sequential data in both forward and backward directions. With this approach, Bi-LSTM can capture a broader temporal context, enhancing prediction accuracy. Several studies have shown that Bi-LSTM is effective in financial analysis tasks, such as stock price forecasting, due to its ability to understand patterns more comprehensively [24]. The specific architecture used in this study is described in Section 3.2.3.

2.5 Model Evaluation

After the model is trained, model evaluation is conducted to assess the performance of the developed prediction model. This evaluation aims to measure how accurately the model predicts cryptocurrency prices based on historical data. Several evaluation metrics are employed in this study, including RMSE, MAE, MAPE, and SMAPE. These metrics are selected as they provide a comprehensive representation of the magnitude and proportion of prediction errors generated by each model.

RMSE measures the average magnitude of the error between predicted and actual values in the model [25]. MAE calculates the average of the absolute differences between the actual values and the predicted values produced by the model [26]. The smaller the RMSE and MAE values, the more accurate the model's predictive performance. Meanwhile, MAPE assesses the relative error in the prediction results. It computes the average percentage difference between the predicted and actual values of the observed data [27]. On the other hand, SMAPE is a metric similar to MAPE but is symmetric, treating positive and negative errors equally. SMAPE remains valid when actual values are zero but tends to be more sensitive to outliers, as it calculates the error based on the ratio of the absolute difference to the sum of actual and predicted values [28]. The formulas for each evaluation metric are presented in Equations (2-5).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|X_i - Y_i| \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|X_i - Y_i|}{Y_i} \times 100\% \tag{4}$$

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{2|X_i - Y_i|}{|Y_i| + |X_i|} \times 100\% \tag{5}$$

Where n denotes the number of data points, X_i represents the actual value, and Y_i represents the predicted value.

3. RESULT AND DISCUSSION

3.1 Data Collection Results

The data collected through the web scraping process from Yahoo Finance consists of 1,946 rows for each of the three selected cryptocurrencies, namely Bitcoin, Ripple, and Dogecoin. The retrieved data includess only two columns: Date and Close. The Date column records the specific date of each trading session, while the Close column represents the asset's closing price at the end of each day's trading activity. This closing price is commonly used in financial analysis as it reflects the final consensus value determined by the market at the close of the trading day. The selection of only the Close price was based on its relevance and consistency as a reference point in time-series modeling. Sample

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data for each cryptocurrency is presented in Tables 1–3, which display the top five rows within the specified time range.

Table 1. Sample data of Bitcoin

Date	Close
2020-01-01	7200.174316
2020-01-02	6985.470215
2020-01-03	7344.884277
2020-01-04	7410.656738
2020-01-05	7411.317383

Table 2. Sample data of Ripple

Date	Close
2020-01-01	0.192667
2020-01-02	0.188043
2020-01-03	0.193521
2020-01-04	0.194355
2020-01-05	0.195537

Table 3. Sample data of Dogecoin

Date	Close
2020-01-01	0.002033
2020-01-02	0.002009
2020-01-03	0.002145
2020-01-04	0.002241
2020-01-05	0.002419

Figures 2-4 display the historical close price graphs of Bitcoin, Ripple, and Dogecoin over the period from January 1, 2020, to April 30, 2025. These figures illustrate the long-term price fluctuations of each cryptocurrency and provide a visual representation of market volatility, including major upward and downward trends.

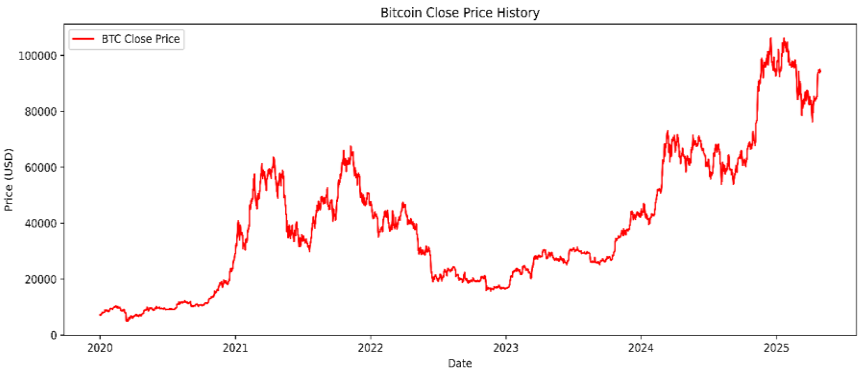

Figure 2. Close price graph of Bitcoin

Figure 2 shows the historical closing price trend of Bitcoin, where a significant surge occurred between late 2023 and early 2025. This fluctuation illustrates Bitcoin's volatility and forms the basis for the predictive modeling in this study. The upward and downward movements in this period highlight the challenges in capturing long-term trends and short-term noise in price forecasting.

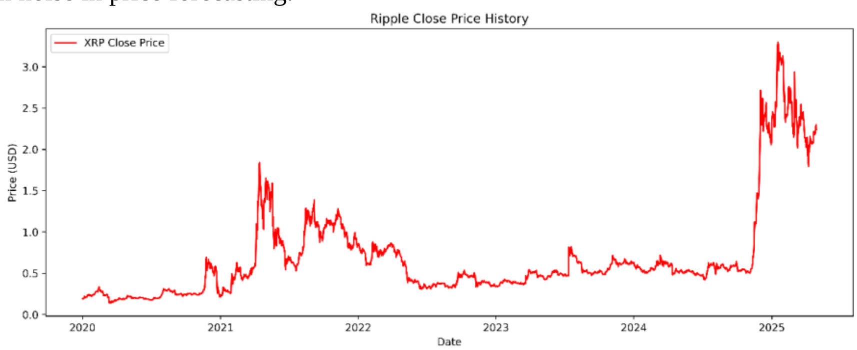

Figure 3. Close price graph of Ripple

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Figure 3 shows the historical closing price trend of Ripple, which experienced multiple sharp spikes, particularly in early 2025. These fluctuations highlight the erratic nature of XRP's price movements, underscoring the challenge in accurately forecasting its future values.

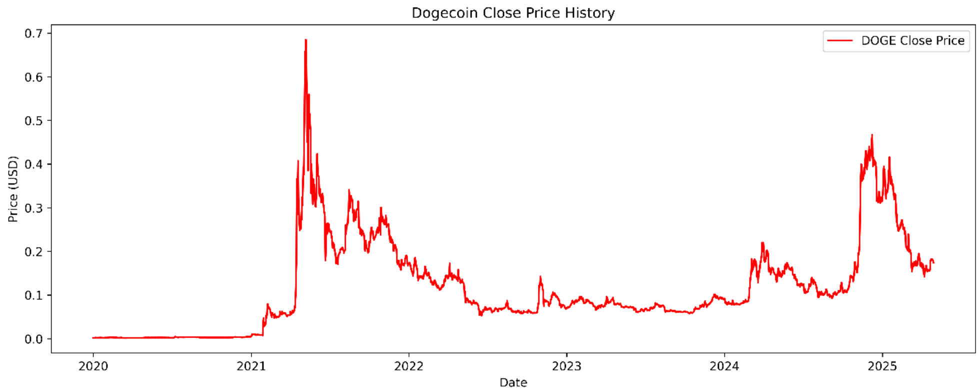

Figure 4. Close price graph of Dogecoin

Figure 4 presents the historical closing price trend of Dogecoin, which exhibited rapid surges around early 2021 and late 2024. The pronounced volatility seen in DOGE's price reflects its sensitivity to market sentiment and speculative activity, making it a compelling case for deep learning-based prediction.

3.2 Model Training Results

Each deep learning model used in this study was trained using same parameters to ensure consistency in evaluation results. All models were compiled using the Adam optimizer and MSE as the loss function. To prevent overfitting and enhance training efficiency, two types of callbacks were applied: EarlyStopping and ReduceLROnPlateau. EarlyStopping was used to automatically stop training if the validation loss did not decrease after 30 consecutive epochs, with the option to restore the best weights. Meanwhile, ReduceLROnPlateau served to reduce the learning rate by 50% if there was no improvement in validation loss over 10 consecutive epochs. The training process was conducted for a maximum of 100 epochs with a batch size of 32. The same model architecture was used for all three cryptocurrencies (Bitcoin, Ripple, and Dogecoin). The architecture of each model and the corresponding training results are described in detail in Sections 3.2.1-3.2.3.

3.2.1 LSTM

The LSTM model architecture used in this study consists of six layers, including two LSTM layers with 50 units each, two Dropout layers with a dropout rate of 20%, one Dense layer with 25 units, and one output Dense layer with a single unit. The LSTM layers use the default *tanh* activation function, while the output Dense layer uses a linear activation function. The total number of trainable parameters in this model is 31,901. The complete architectural structure is presented in Table 4.

Table 4. LSTM model architecture

Layer	Output Shape	Parameter
LSTM	(None, 30, 50)	10,400
Dropout	(None, 30, 50)	0
LSTM	(None, 50)	20,200
Dropout	(None, 50)	0
Dense	(None, 25)	1,275
Dense	(None, 1)	26

During training, the LSTM model for Bitcoin stopped at epoch 96, while the models for Ripple and Dogecoin stopped at epochs 72 and 100, respectively. The higher number of epochs required for Dogecoin and Bitcoin indicates that the model needed more iterations to reach convergence and optimal performance on those datasets. A detailed summary of the evaluation metrics for this model is presented in Table 5.

Table 5. Evaluation results of the LSTM model

Coin	Evaluation Metrics				Epoch
	RMSE	MAE	MAPE (%)	SMAPE (%)	
Bitcoin	2659.6989	1996.1041	2.58%	2.59%	96
Ripple	0.1227	0.0701	4.33%	4.43%	72
Dogecoin	0.0139	0.0089	4.27%	4.25%	100

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3.2.2 GRU

The GRU model architecture employed in this study consists of seven layers: two GRU layers with 128 and 64 units respectively, one Batch Normalization layer, two Dropout layers with a dropout rate of 20%, one Dense layer with 32 units, and one output Dense layer with a single unit. Both GRU layers use the *tanh* activation function, while the Dense layers use the *ReLU* and linear activation functions, respectively. The total number of trainable parameters in this model is 90,177. The complete architectural structure is presented in Table 6.

Table 6. GRU model architecture

Layer	**Output Shape**	**Parameter**
GRU	(None, 30, 128)	50,304
BatchNormalization	(None, 30, 128)	512
Dropout	(None, 30, 128)	0
GRU	(None, 64)	37.248
Dropout	(None, 64)	0
Dense	(None, 32)	2,080
Dense	(None, 1)	33

In the GRU model, training was completed more quickly compared to LSTM. For Bitcoin, the training stopped at epoch 85, while for Ripple and Dogecoin it stopped at epochs 64 and 67, respectively. This indicates the GRU model’s efficiency in recognizing data patterns and achieving optimal performance in a shorter amount of time. Thus, GRU tends to adapt more rapidly to the characteristics of each dataset. A full evaluation of the model's performance is provided in Table 7.

Table 7. Evaluation results of the GRU model

Coin	Evaluation Metrics				Epoch
	RMSE	MAE	MAPE (%)	SMAPE (%)	
Bitcoin	2785.4067	2268.5570	3.02%	3.00%	85
Ripple	0.1141	0.0665	4.56%	4.60%	64
Dogecoin	0.0131	0.0084	4.12%	4.06%	67

3.2.3 Bi-LSTM

The Bi-LSTM model architecture utilized in this study consists of seven layers: two Bidirectional LSTM layers with 128 and 64 units respectively, one Batch Normalization layer, two Dropout layers with a dropout rate of 30%, one Dense layer with 64 units, and one output Dense layer with a single unit. Both Bidirectional LSTM layers use the *tanh* activation function, while the Dense layers use *ReLU* and linear activation functions, respectively. The total number of trainable parameters in this model is 306,817. The complete architectural structure is presented in Table 8.

Table 8. Bi-LSTM model architecture

Layer	Output Shape	Parameter
Bidirectional	(None, 30, 256)	133,120
BatchNormalization	(None, 30, 256)	1,024
Dropout	(None, 30, 256)	0
Bidirectional	(None, 128)	164,352
Dropout	(None, 128)	0
Dense	(None, 64)	8,256
Dense	(None, 1)	65

The Bi-LSTM model required a relatively long training process, with training stopping at epoch 92 for Bitcoin, epoch 90 for Ripple, and epoch 79 for Dogecoin. Although the number of epochs reflects the model’s effort to thoroughly learn from the data, its evaluation results were unable to surpass the accuracy and stability achieved by the LSTM and GRU models. Detailed evaluation metrics for the Bi-LSTM model are provided in Table 9.

Table 9. Evaluation results of the Bi-LSTM model

Coin	Evaluation Metrics				Epoch
	RMSE	MAE	MAPE (%)	SMAPE (%)	
Bitcoin	6011.6541	4495.4412	5.15%	5.33%	92
Ripple	0.3799	0.2412	11.53%	12.72%	90
Dogecoin	0.0165	0.0115	5.59%	5.44%	79

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3.3 Discussion

The performance comparison of the three algorithms and their evaluation results for each cryptocurrency are presented in Table 10.

Table 6. Comparison of LSTM, GRU, and Bi-LSTM model evaluation results

Model	Coin	Evaluation Metrics			
		RMSE	MAE	MAPE (%)	SMAPE (%)
LSTM	Bitcoin	2659.6989	1996.1041	2.58%	2.59%
	Ripple	0.1227	0.0701	4.33%	4.43%
	Dogecoin	0.0139	0.0089	4.27%	4.25%
GRU	Bitcoin	2785.4067	2268.5570	3.02%	3.00%
	Ripple	0.1141	0.0665	4.56%	4.60%
	Dogecoin	0.0131	0.0084	4.12%	4.06%
Bi-LSTM	Bitcoin	6011.6541	4495.4412	5.15%	5.33%
	Ripple	0.3799	0.2412	11.53%	12.72%
	Dogecoin	0.0165	0.0115	5.59%	5.44%

Based on the evaluation using four performance metrics, the results indicate that each deep learning model exhibits varying levels of predictive performance depending on the specific cryptocurrency. The best-performing metrics for each model and coin are highlighted in bold in Table 10.

For Bitcoin price prediction, the LSTM model achieved the lowest MAPE (2.58%) and SMAPE (2.59%) among all models, indicating superior relative accuracy in capturing price movements. While the RMSE and MAE values for LSTM remain relatively high, this is expected due to Bitcoin's significantly larger price scale compared to Ripple and Dogecoin. In this context, relative metrics such as MAPE and SMAPE provide a more meaningful assessment of prediction accuracy for high-value assets.

In the case of Ripple, LSTM again delivered the best relative performance, with a MAPE of 4.33% and SMAPE of 4.43%. However, the GRU model produced lower RMSE and MAE values, suggesting that its predictions were closer to the actual prices in absolute terms. For Dogecoin, GRU demonstrated the most consistent and accurate performance across all metrics, achieving the lowest RMSE (0.0131), MAE (0.0084), MAPE (4.12%), and SMAPE (4.06%). This implies that GRU is more effective at capturing the underlying price patterns of Dogecoin, leading to more stable and reliable forecasts.

On the other hand, Bi-LSTM showed the worst performance across all coins, particularly on Ripple, with a MAPE of 11.53% and SMAPE of 12.72%. These findings suggest that despite its architectural complexity, Bi-LSTM does not necessarily outperform simpler models, especially when dealing with highly volatile and nonlinear time series data such as cryptocurrency prices.

Next, visualizations were generated to illustrate the comparison between the actual close prices and the predicted values from the three models. Furthermore, 30-day ahead forecasts were made and are displayed in Figures 5-7. These visualizations provide a clearer picture of the prediction patterns of each model and the projected price trends over the next 30 days. Observing the alignment and deviation between the actual and predicted curves helps demonstrate the reliability and consistency of each model's forecasting capability.

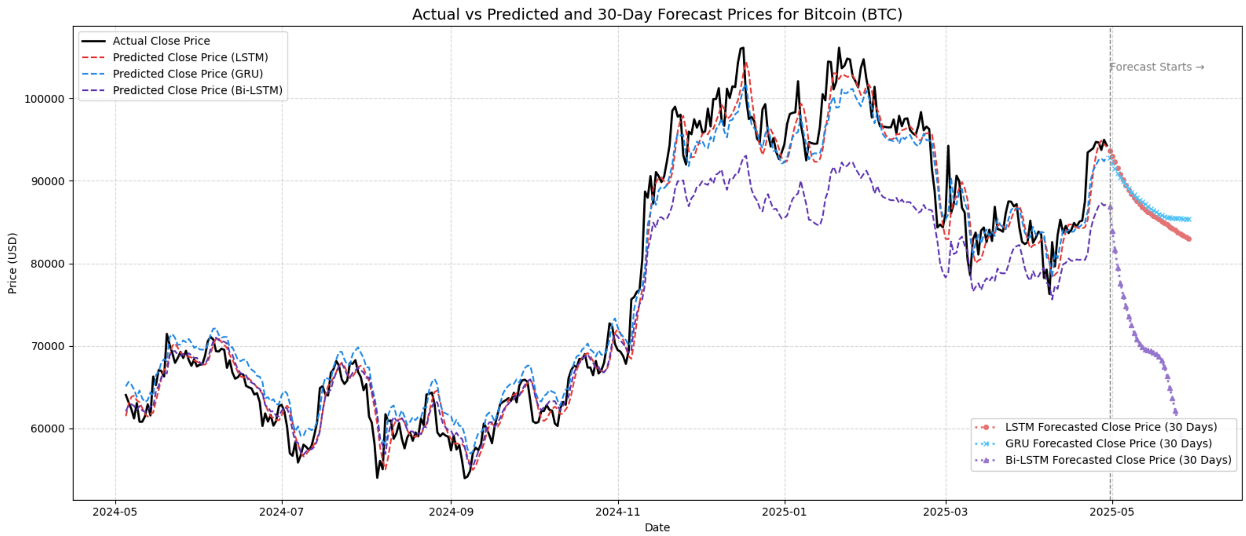

Figure 5. Comparison actual close price, predicted close price, and 30-day forecast for Bitcoin

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As shown in Figure 5, the LSTM model produces prediction lines closest to the actual price line, indicating strong alignment with real price movements throughout the observed period. GRU also performs similarly, albeit with slightly larger deviations at certain points, particularly during short-term fluctuations. On the other hand, Bi-LSTM predictions deviate more significantly, particularly during downward trends, where the predicted curve tends to underestimate the actual price. In the forecast section, both LSTM and GRU estimate a reasonable price decline over the next 30 days that remains consistent with recent trends. In contrast, Bi-LSTM projects a steep and rapid drop, which appears less realistic based on the historical price pattern. This suggests that LSTM and GRU are more stable in anticipating near-future price movements for Bitcoin.

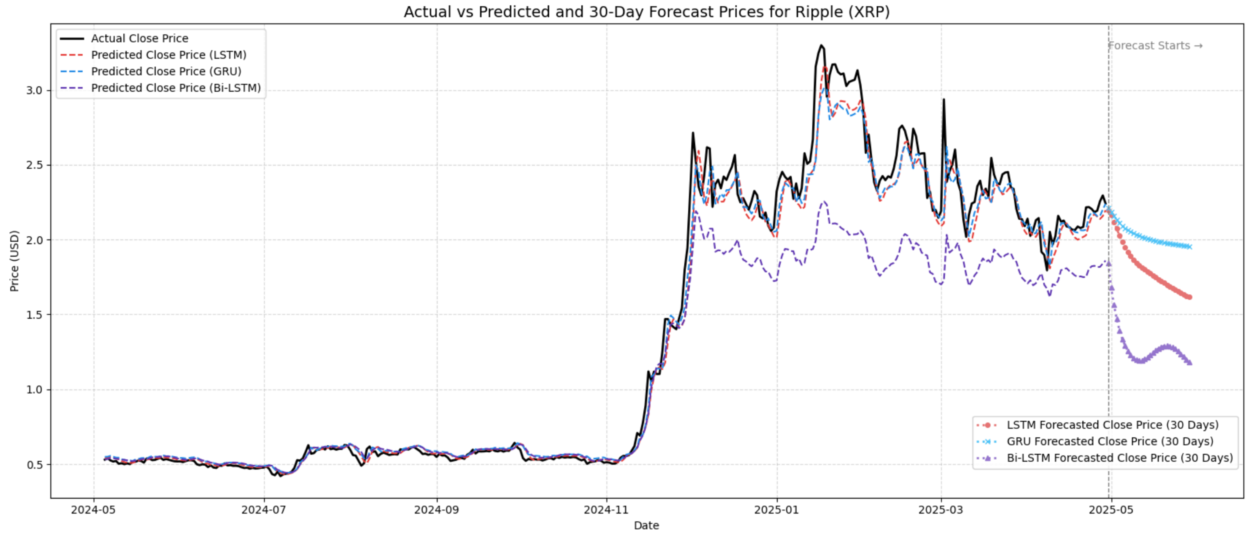

Figure 6. Comparison actual close price, predicted close price, and 30-day forecast for Ripple

Figure 6 illustrates Ripple's prediction performance. Both LSTM and GRU successfully follow the actual price trend, with prediction lines closely aligned to the real prices, albeit with minor deviations that are more noticeable during price spikes. Bi-LSTM again shows less accurate results, especially during periods of sharp price fluctuations, as the model tends to consistently underestimate the price, resulting in a flatter prediction curve. For the 30-day forecast, LSTM and GRU predict a gradual and realistic downward trend that remains within the recent historical range, whereas Bi-LSTM exhibits unstable and less interpretable results with a lower baseline and inconsistent fluctuation, reflecting its lower reliability for Ripple price forecasting.

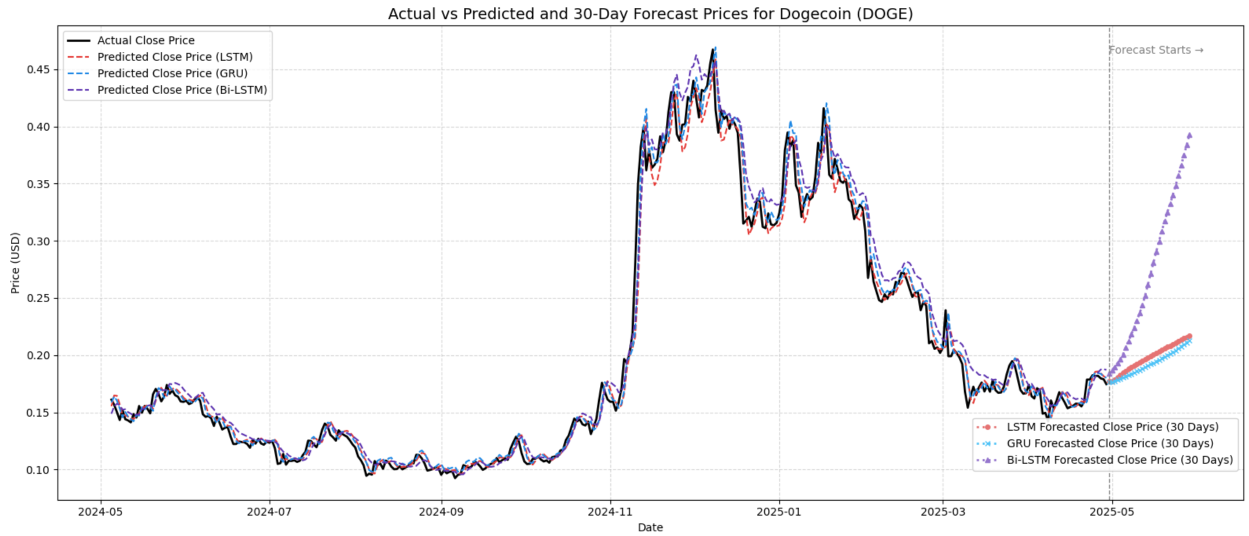

Figure 7. Comparison actual close price, predicted close price, and 30-day forecast for Dogecoin

As seen in Figure 7, all three models managed to capture Dogecoin's historical patterns reasonably well, with predicted lines closely following the actual closing price throughout most of the timeline. However, LSTM and GRU generated predictions that remained more consistently aligned with the actual price, particularly during periods of high volatility. Bi-LSTM showed more fluctuation and less accuracy than the other two models, often deviating during price dips and peaks. In the forecast section, Bi-LSTM indicated a sharp and unrealistic price surge, suggesting potential overfitting or sensitivity to recent price movements. In contrast, the LSTM and GRU forecasts appeared

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more stable and consistent with the recent trend, reflecting better generalization and reliability for short-term price forecasting.

Table 7. Close price prediction for May 1–5, 2025

Date	Coin	Close Price Prediction		
		LSTM	**GRU**	**Bi-LSTM**
2025-05-01	Bitcoin	92992.77	92109.72	83938.08
	Ripple	2.162681	2.183646	1.679428
	Dogecoin	0.177412	0.176751	0.186648
2025-05-02	Bitcoin	92287.19	91439.48	81631.21
	Ripple	2.118851	2.156485	1.564375
	Dogecoin	0.178711	0.177492	0.189737
2025-05-03	Bitcoin	91558.24	90900.66	79481.29
	Ripple	2.072384	2.132011	1.469655
	Dogecoin	0.180492	0.178388	0.192903
2025-05-04	Bitcoin	90839.01	90434.66	77604.82
	Ripple	2.027187	2.110534	1.393828
	Dogecoin	0.182446	0.179373	0.196207
2025-05-05	Bitcoin	90152.48	89989.98	76075.00
	Ripple	1.985436	2.092087	1.335575
	Dogecoin	0.184394	0.180412	0.200779

Following the visualization of prediction and 30-day forecasting, Table 11 presents a sample of the predicted values for the first five days (May 1-5, 2025). The table shows that each model produces different predictions, consistent with the unique characteristics of each cryptocurrency. For instance, on May 1, 2025, the LSTM model predicted Bitcoin's price at $92,929, while GRU predicted $92,109, and Bi-LSTM predicted a lower value of $83,938. Similar variations were observed for Ripple and Dogecoin. Over the five-day period, GRU produced the most stable predictions, while Bi-LSTM tended to produce more fluctuating outputs, especially for Ripple and Bitcoin.

This further reinforces the finding that although Bi-LSTM is theoretically capable of learning from bidirectional sequences, in practice, it does not always offer a significant advantage, particularly when applied to highly dynamic financial time series. The complexity of Bi-LSTM can instead lead to overfitting and difficulty in generalizing when faced with unstable price patterns, as reflected by the model's tendency to produce extreme forecasts.

In contrast, GRU consistently performed well across all three cryptocurrencies. It not only produced predictions closely aligned with actual trends but also achieved better training efficiency. GRU models converged more quickly and maintained stable performance despite the varying characteristics of the data. LSTM also performed competitively, especially in predicting Bitcoin's relatively more stable long-term trends.

The alignment between the visualizations and the metric-based evaluation confirms that GRU and LSTM are more suitable choices for cryptocurrency price forecasting in this study. The presented forecasts and five-day sample predictions provide practical insights into how algorithmic differences impact prediction outcomes, offering valuable guidance for both practitioners and researchers in the domain.

4. CONCLUSION

In this study, three deep learning models: LSTM, GRU, and Bi-LSTM were applied to predict the prices of Bitcoin, Ripple, and Dogecoin using historical closing price data from January 1, 2020 to April 30, 2025. The models were evaluated using RMSE, MAE, MAPE, and SMAPE metrics, and a fixed 30-day forecast horizon was implemented to assess their predictive capabilities. The LSTM model achieved the best performance for Bitcoin with a MAPE of 2.58% and SMAPE of 2.59%, and also showed strong results for Ripple with a MAPE of 4.33% and SMAPE of 4.43%. The GRU model performed best on Dogecoin, achieving a MAPE of 4.12% and SMAPE of 4.06%, and it also recorded the lowest RMSE (0.1141) and MAE (0.0665) for Ripple, indicating strong absolute accuracy. In contrast, the Bi-LSTM model consistently showed the highest error across all cryptocurrencies, particularly for Ripple, which had a MAPE of 11.53% and SMAPE of 12.72%. These findings suggest that model performance is highly influenced by the volatility and characteristics of each cryptocurrency. However, this study is limited by its reliance solely on closing prices and specific model architectures and hyperparameters that may not be optimal. Future research could enhance performance by incorporating additional features and explore multivariate or hybrid models to increase forecasting robustness and overall effectiveness.

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