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Comparative Analysis of LSTM, GRU, and Bi-LSTM Deep Learning Models for Time Series Cryptocurrency Price Forecasting

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Abstract: Cryptocurrency is a highly volatile digital asset that requires accurate predictive methods. This study compares the performance of three deep learning architectures LSTM, GRU, and Bi-LSTM in forecasting the prices of Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB) using univariate historical data. Evaluation was conducted through regression metrics (RMSE and MAPE) and classification of price movement into five categories, ranging from very bearish to very bullish, assessed using a confusion matrix. The results show that GRU performed best for BTC (RMSE 974.72, MAPE 1.18%), while Bi-LSTM outperformed others for ETH and BNB (RMSE 43.19 and 6.83; MAPE 1.16% and 1.08%) and achieved the highest classification accuracy (55% and 52%). However, overall classification accuracy remains low, reflecting the complexity of cryptocurrency price patterns. The study is limited by its univariate approach without incorporating external variables. Its contribution lies in combining regression and classification evaluation, and it recommends exploring multivariate and ensemble models in future research.

Keywords: Cryptocurrency Price Prediction, Deep Learning, LSTM, GRU, Bi-LSTM, Confusion Matrix.

INTRODUCTION

Cryptocurrency is an investment instrument that has experienced significant growth in popularity over the past decade, especially since the introduction of Bitcoin (BTC) in 2009. Assets such as Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB), which are among the top five in market capitalization, attract investors, companies, and governments. The main attraction lies in the blockchain technology and decentralized system that ensures transparency and security of transactions (Agrawal et al., 2024). However, high price volatility makes it difficult to predict and risky for unprepared investors (Bruzgė et al., 2023; Huang et al., 2024; Karim et al., 2023). Ethereum, in particular, is emerging as a major source of volatility transmission in the digital asset ecosystem, surpassing even Bitcoin in some aspects (Korkusuz, 2025). These dynamics underscore the importance of accurate prediction models to help investors manage risk in such volatile environments (Yang et al., 2024).

In predicting cryptocurrency prices, one important factor is technical analysis, which is analyzing historical price movements to find patterns that could repeat in the future. Recent studies show that integrating technical indicators with deep learning significantly improves prediction accuracy and trading performance in volatile markets (Cheng et al., 2025; Kang et al., 2025). Since cryptocurrency prices are highly volatile, a reliable prediction method is required. Time series with deep learning approach is a relevant solution because it can handle supervised, unsupervised, and semi-supervised learning, and has demonstrated strong performance across different forecasting scenarios (Jin & Li, 2023; Murray et al., 2023). This capability allows deep learning to analyze volatile data more accurately, supporting more precise price predictions and better-informed investment decisions (Golnari et al., 2024).

In the past few decades, deep learning has attracted considerable attention for its effectiveness in handling complex and non-linear datasets. Among its various architectures, Recurrent Neural Networks (RNNs) have emerged as a favored approach for processing sequential data like time series. However, conventional RNNs are

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limited by the vanishing gradient problem, which hampers their ability to retain information over extended sequences. To overcome this, architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM) were developed. LSTM is specifically designed to handle vanishing and exploding gradient problems (Qin et al., 2023). GRU features a simpler and more efficient structure compared to LSTM by utilizing only two gates, the update and reset gates, while still maintaining strong performance in processing sequential data (Khan et al., 2025). Meanwhile, Bi-LSTM combines two LSTMs in opposite directions, allowing for more thorough modeling of time series data and has outperformed other models in cryptocurrency price prediction (Jung et al., 2024; Rathee et al., 2023; Seabe et al., 2023). Although all three are suitable for time series data, their application in cryptocurrency price prediction is still limited. Therefore, this study compares the performance of LSTM, GRU, and Bi-LSTM in predicting cryptocurrency prices based on time series data.

Several recent studies have compared the effectiveness of deep learning architectures such as LSTM, GRU, and Bi-LSTM in cryptocurrency price prediction. (Murray et al., 2023) evaluated these models across five major cryptocurrencies (BTC, ETH, LTC, XRP, XMR) and found that LSTM achieved the best performance with an average RMSE of 0.0222 and MAE of 0.0173, outperforming GRU (RMSE 0.0284) and Bi-LSTM (RMSE 0.0321). In a real-time prediction study, (Syed et al., 2023) showed that LSTM outperformed GRU and ANN, achieving an RMSE of 1.16 and MAPE of 0.0006 for BTC, and RMSE of 0.124 and MAPE of 0.0002 for ETH. Similarly, (Koszewski et al., 2024) found that LSTM produced the lowest forecasting error in predicting one-day returns for BTC, ETH, and BNB, reporting an average RMSE of 0.0172 compared to 0.0214 for GRU and 0.0235 for Bi-LSTM. For long-term Bitcoin trend prediction, (Lee, 2024) reported that LSTM achieved a directional accuracy of 86.4% compared to 78.1% for GRU, particularly in models that incorporated historical trend indicators. Finally, (Cheng et al., 2025) used Bi-LSTM to predict BTC, ETH, and LTC and showed that Bi-LSTM achieved the best accuracy on ETH with a test RMSE of 0.047, outperforming LSTM (0.064) and GRU (0.059) when using 34 standard technical indicators.

Although deep learning methods such as LSTM, GRU, and Bi-LSTM have been widely utilized in price prediction tasks, direct comparative studies of these three methods specifically applied to cryptocurrency price data, particularly BTC, ETH, and BNB, remain limited. Additionally, research exploring parameter optimization to enhance prediction accuracy within the cryptocurrency context is scarce. Therefore, the gap addressed by this study lies in the lack of comprehensive comparative analyses that incorporate parameter optimization among LSTM, GRU, and Bi-LSTM models for cryptocurrency price prediction. Meanwhile, the novelty of this research is the comprehensive evaluation of all three models simultaneously, employing MAPE, RMSE, and Confusion Matrix metrics to identify the most accurate prediction model and determine the optimal combination of parameters specifically tailored to BTC, ETH, and BNB datasets.

METHOD

This methodology section discusses in detail the dataset used in the development of the prediction model as well as the model layer architecture design. In addition, the preprocessing stage on the dataset and the overall workflow in the implementation of this research are also explained.

Figure 1 shows the research flow starting from the cryptocurrency price data collection stage (BTC, ETH, and BNB), followed by preprocessing which includes data cleaning, data division into training data and test data, and normalization using the Min-Max Scaling method. The processed data is then used to build three prediction models, namely LSTM, GRU, and Bi-LSTM. Each model is trained using training data and tested using test data. The final stage of this process is the evaluation of model performance to measure the level of prediction accuracy, so that the effectiveness of each architecture can be compared in predicting cryptocurrency prices.

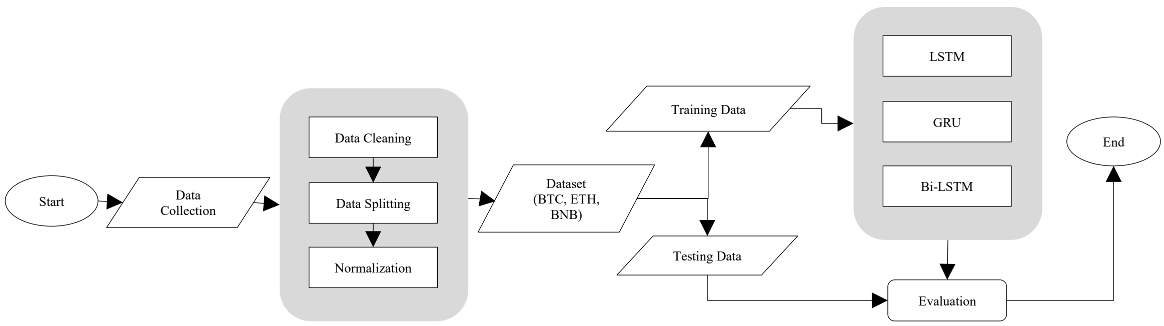

Figure 1. Research Flow Stages

Data Description

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This study uses cryptocurrency price data obtained from the https://finance.yahoo.com platform. The three types of crypto assets used in this study are Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB), each in csv format. The time span of the analyzed data covers a five-year period, starting from November 11, 2019 to November 11, 2024, with the same number of entries in each dataset, which is 1828 data. Each dataset contains several important columns of information, including: Date which records the trading date and time, Open as the opening price, High and Low which show the daily high and low prices, and Close as the closing price. In addition, there is an Adj Close column that represents the closing price that has been adjusted for certain events such as token distribution or other technical adjustments, and a Volume column that reflects the total number of coin units traded on that day.

Table 1. Sample Dataset (BTC)

Date	Close	Adj Close	High	Low	Open	Volume
2019-11-11	8757.788	8757.788086	9081.279	8700.608	9056.918	2.03E+10
2019-11-12	8815.662	8815.662109	8853.769	8685.428	8759.752	2.03E+10
2019-11-13	8808.263	8808.262695	8836.842	8761.651	8812.033	1.75E+10
2019-11-14	8708.095	8708.094727	8826.943	8692.552	8811.937	1.91E+10
2019-11-15	8491.992	8491.992188	8730.873	8484.844	8705.708	2.18E+10

Data Cleaning

Data cleaning is the first step in preprocessing that aims to ensure the cryptocurrency dataset is clean and relevant for further processing. At this stage, columns that do not contribute significantly to the analysis process or are redundant are removed to simplify the dataset structure. For example, the "Adj Close" column was removed because it had the same identical value as the "Close" column, and removed the "Volume" column because this research only focuses on features that represent the price value of crypto coins. So its existence does not add additional information. This step aims to improve the efficiency of data analysis and reduce computational complexity in the model training process.

Data Splitting

The dataset is partitioned into two segments, with 80% allocated for training and the remaining 20% for testing (Iftikhar et al., 2024; Qureshi et al., 2024; Syed et al., 2023). The training set is utilized to help the model learn underlying patterns, while the testing set serves to assess the model's performance on previously unseen data. This approach is intended to evaluate the model's ability to generalize and reduce the likelihood of overfitting. Each cryptocurrency dataset BTC, ETH, and BNB contains 1,828 records, resulting in 1,462 entries for training and 366 for testing after the split, thereby maintaining uniformity throughout the training and evaluation phases.

Normalization

Normalization plays a crucial role in the preprocessing stage by adjusting the range of data values to a standard scale, typically between 0 and 1. In this study, the Min-Max Scaling technique is applied to avoid the disproportionate influence of features with large values such as cryptocurrency prices over those with smaller magnitudes like trading volume. This process enhances the efficiency of model training, promotes faster convergence, and contributes to more consistent and accurate prediction results. The normalization formula is presented below (Santosa et al., 2024).

$$x_i' = \frac{x_i - min_x}{max_x - min_x} \quad (1)$$

Description:
(x') = Normalized value
(x_i) = Data at index (i)
(x_{min}) = Data with minimum value
(x_{max}) = Data with maximum value

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a specialized type of artificial neural network developed to handle long-range dependencies within time series data. Originally introduced by Hochreiter and Schmidhuber in 1997, LSTM has evolved through numerous enhancements and is now widely adopted in tasks involving sequential data, such as price forecasting, natural language processing, and other temporal analyses. One of LSTM's key strengths lies in its ability to preserve relevant information across long sequences while filtering out unimportant data. Its core structure includes three essential gates: the forget gate, which discards non-essential information; the input gate, which stores new information into memory; and the output gate, which produces results based on the current memory state. This gating mechanism enables LSTM networks to regulate information flow effectively, making

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them particularly well-suited for models that require contextual understanding of historical data. The diagram below depicts the standard architecture of an LSTM unit (Kong et al., 2024).

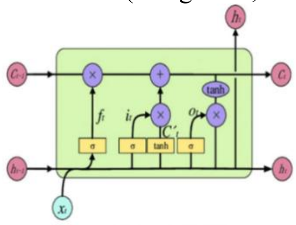

Figure 2. LSTM Architecture

Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU), introduced by KyungHyun Cho in 2014, is a simplified variant of the Recurrent Neural Network (RNN) designed to address the vanishing gradient issue in long sequential data. Unlike LSTM, GRU employs a more streamlined architecture consisting of just two primary gates: the update gate and the reset gate. It eliminates the need for an output gate and operates solely with a hidden state rather than a separate cell state. The update gate regulates how much information from the previous time step is retained, while the reset gate determines which parts of the previous state to discard. By applying a combination of linear transformations, sigmoid functions, and the tanh activation, GRU computes candidate hidden states, which are then merged element-wise to produce the final output at each time step (h_t). Thanks to its reduced number of parameters, GRU offers greater computational efficiency and is particularly effective when working with smaller datasets (Thor & Postek, 2024) . The following figure illustrates the basic architecture of GRU.

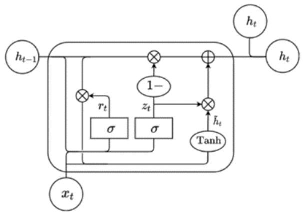

Figure 3. GRU Architecture

Bidirectional Long Short-Term Memory (Bi-LSTM)

Bidirectional Long Short-Term Memory (Bi-LSTM) is an extension of the standard LSTM architecture that processes input data in two temporal directions: forward (from start to end) and backward (from end to start). This dual-processing approach enables the model to access both past and future context at each time step, similar to the narrative technique of flashbacks in storytelling. By incorporating information from both directions simultaneously, Bi-LSTM enhances the model's ability to understand the full context of sequential data. Unlike the traditional LSTM, which captures patterns only in a single direction, Bi-LSTM provides a more comprehensive representation, making it especially effective for tasks that require deeper contextual awareness (Gopali et al., 2024; Mounir et al., 2023). The following figure illustrates the basic architecture of GRU.

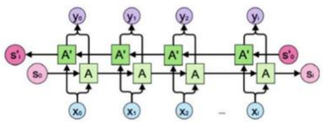

Figure 4. Bi-LSTM Architecture

Price Prediction Using LSTM/GRU/Bi-LSTM

To evaluate the model's long-term predictive capabilities, Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are employed.

Root Mean Squared Error (RMSE)

RMSE represents the deviation between the model's predicted values and the actual observed data. A lower RMSE indicates a more accurate model, especially when compared to others that yield higher RMSE scores. Here is the equation.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (2)$$

Description:
(P_i) = Value predicted by the model at data point (i)
(O_i) = Observed value at data point (i)

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(n) = Total number of data points

MAPE

MAPE is a statistical measure used to assess the accuracy of predictions by expressing the error as a percentage. It is computed by taking the average of the absolute percentage differences between actual and predicted values, relative to the actual values. A smaller MAPE value reflects a more accurate forecasting model. One of the key advantages of MAPE is its interpretability, as the error is expressed in a clear percentage format. Additionally, since it uses absolute values, it avoids the issue of errors canceling each other out due to opposing signs. Here is the equation.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - P_i}{O_i}\right| \times 100 \quad (3)$$

Description:
(Pi) = Value predicted by the model at data point (i)
(Oi) = Observed value at data point (i)
(n) = Total number of data points

Price Movement Classification Using Confusion Matrix

In contrast, the Confusion Matrix is utilized to assess how well the model captures short-term or daily fluctuations in the data.

Confusion Matrix

A confusion matrix is a commonly used tool for evaluating the effectiveness of classification models. It provides a detailed breakdown of how well the model's predicted classifications align with the actual labels. This matrix organizes the results into four categories: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). From these values, key evaluation metrics such as accuracy, precision, recall, and F1-score can be derived to assess overall model performance.

Before evaluating the confusion matrix, labeling and classification will first be carried out on actual data and predicted data from the model, first the actual data will be given five labels, namely, very bearish, bearish, neutral, bullish, and very bullish. This labeling is done by finding the daily change value first and then calculating the average price of bullish and bearish on the daily change of each coin, then given a neutral price tolerance of 10% of the average. Here is the daily price difference equation.

$$\Delta P_t = P_t - P_{t-1} \quad (4)$$

Description:
(ΔP_t) = difference in price change on day (*t*),
(P_t) = the closing price of the cryptocurrency on day (*t*),
(P_{t-1}) = the closing price of the cryptocurrency on the previous day (*t-1*).

After calculating the daily price change difference, the(ΔP_t) values are separated into two groups. If($\Delta P_t > 0$) , then the price is increasing (Bullish). If($\Delta P_t < 0$) , then the price is decreasing (Bearish). Here is the equation to calculate the average bullish and bearish price.

$$\overline{P_{\text{bullish}}} = \frac{\Sigma(\Delta P_t \mid \Delta P_t > 0)}{N_{\text{bullish}}} \quad (5)$$

Description:
($\sum(\Delta P_t \mid \Delta P_t > 0)$) = the sum of all positive price changes.
(N_{bullish}) = the total number of days on which prices have increased.

The bearish equation is also the same as equation 5, but the difference is that it uses the sum of all negative price changes.

$$T_{bullish} = 10\% \times |\overline{P_{bullish}}| \quad (6)$$

$$T_{bearish} = 10\% \times |\overline{P_{bearish}}| \quad (7)$$

($T_{bullish}$) and($T_{bearish}$) are the upper and lower tolerance limits for Neutral, which are calculated as 10% of the average of *bullish* and *bearish* price changes.($\overline{P_{bullish}}$) and($\overline{P_{bearish}}$) are the average of price changes on days with *bullish* and *bearish* increases. Thus, the Neutral range is defined as:

$$-T_{\text{bearish}} \leq \Delta P_t \leq T_{\text{bullish}} \quad (8)$$

Description:
(ΔP_t) = difference in daily price change.
$-T_{bearish}$ = lower limit of the Neutral category

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$T_{bullish}$ = upper limit of the Neutral category

After obtaining the average value of the price change and the Neutral tolerance limit, the classification category is determined as follows:

$C_1: \Delta P_t < \overline{P_{\text{bearish}}} \quad = \text{(Very Bearish)}$
$C_2: \overline{P_{\text{bearish}}} \leq \Delta P_t < -T_{\text{bearish}} \quad = \text{(Bearish)}$
$C_3: -T_{\text{bearish}} \leq \Delta P_t \leq T_{\text{bullish}} \quad = \text{(Netral)}$
$C_4: T_{\text{bullish}} < \Delta P_t \leq |\overline{P_{\text{bullish}}}| \quad = \text{(Bullish)}$
$C_5: \Delta P_t > |\overline{P_{\text{bullish}}}| \quad = \text{(Very Bullish)}$

After labeling the actual data manually, labeling will then be carried out on the predicted data from the three LSTM, GRU, and Bi-LSTM models using internal DL (softmax) for the classification model, this is done so that the categorization rules on the prediction model results are the same as the actual data. Then the last stage after all the data is labeled, a confusion matrix evaluation will be carried out to measure the performance of the prediction model in capturing the pattern of daily price changes.

RESULT

Price Prediction using LSTM/GRU/Bi-LSTM

Model training is conducted by testing hyperparameters including batch sizes of 32, 64, and 128, with a maximum of 500 epochs and an early stopping mechanism set at 15 epochs. Grid Search method is employed for systematically identifying optimal hyperparameters. To ensure validity and robustness, walk-forward validation is implemented, maintaining the chronological order of data and avoiding data leakage from future observations. Detailed training results for each model are presented in Table 2.

Table 2. Best Grid Search Hyperparameter Results of Each Model

Cryptocurrency	Model	Epoch Set	Stopped Epoch	Batch Size	Best Val Loss
BTC	LSTM	**500**	**58**	**32**	**0.000449**
		500	23	64	0.000470
		500	28	128	0.000471
	GRU	**500**	**52**	**32**	**0.000427**
		500	24	64	0.000481
		500	22	128	0.000497
	Bi-LSTM	500	19	32	0.000469
		500	**63**	**64**	**0.000435**
		500	38	128	0.000472
ETH	LSTM	500	50	32	0.000456
		500	**143**	**64**	**0.000429**
		500	111	128	0.000460
	GRU	500	34	32	0.000446
		500	86	64	0.000425
		500	**110**	**128**	**0.000421**
	Bi-LSTM	500	56	32	0.00043
		500	**104**	**64**	**0.00042**
		500	96	128	0.00044
BNB	LSTM	500	49	32	0.000524
		500	**90**	**64**	**0.000503**
		500	34	128	0.000563
	GRU	**500**	**71**	**32**	**0.000490**
		500	42	64	0.000513
		500	84	128	0.000497
	Bi-LSTM	**500**	**73**	**32**	**0.000483**
		500	42	64	0.000529
		500	91	128	0.000504

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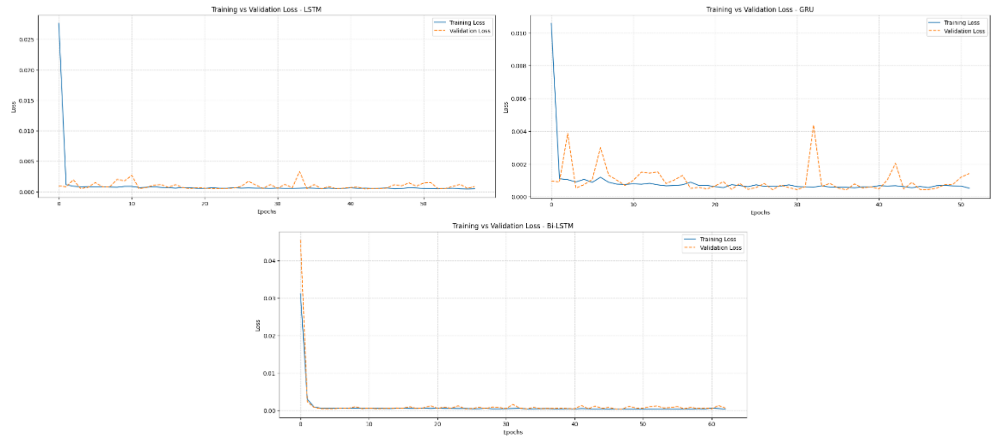

Figure. 5 Visualization Loss Best Parameter Model BTC

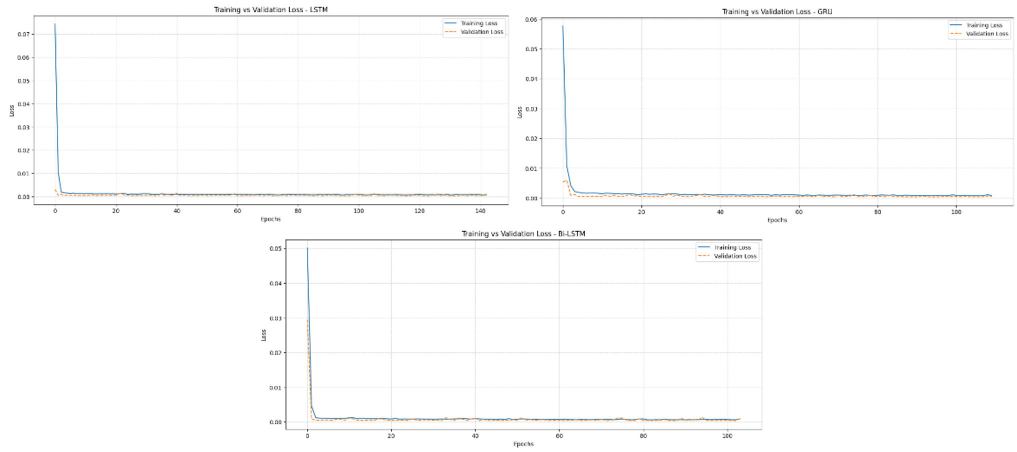

Figure. 6 Visualization Loss Best Parameter Model ETH

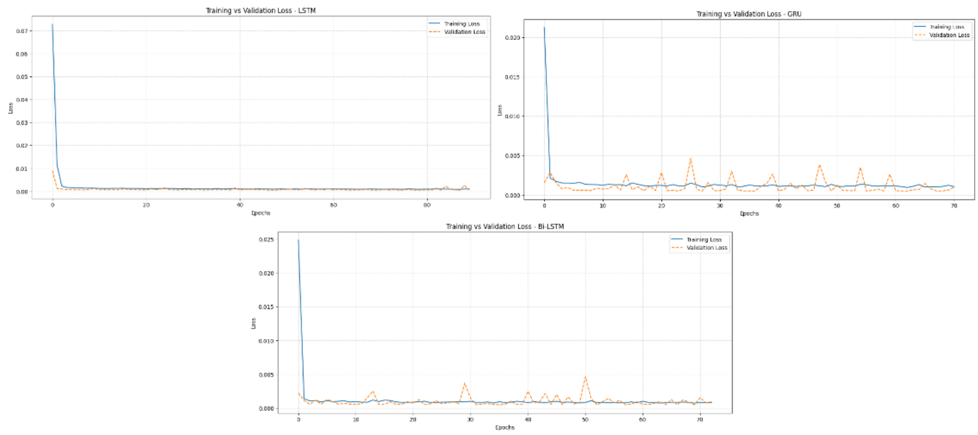

Figure. 7 Visualization Loss Best Parameter Model BNB

Model Performance Evaluation

The following are the evaluation results of each best model, which are then tested using test data and presented in Table 3 below.

Table 3. Results of Evaluating the Error Value of Each Model

Cryptocurrency	Model	RMSE	MAPE%
BTC	LSTM	1118.20	1.31%
BTC	**GRU**	**974.72**	**1.18%**
BTC	Bi-LSTM	1016.26	1.16%
ETH	LSTM	47.39	1.30%

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Cryptocurrency	Model	RMSE	MAPE%
ETH	GRU	44.55	1.21%
ETH	**Bi-LSTM**	**43.19**	**1.16%**
BNB	LSTM	7.52	1.26%
BNB	GRU	6.95	1.16%
BNB	**Bi-LSTM**	**6.83**	**1.08%**

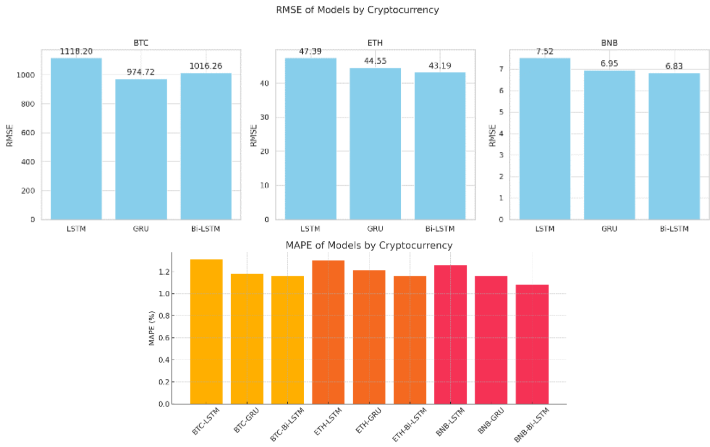

Figure 8. Comparison of Model Performance Using RMSE And MAPE Metrics Across Three Cryptocurrencies.

Table 3 summarizes the model evaluation using RMSE and MAPE metrics. Overall, the GRU and Bi-LSTM models demonstrated superior performance compared to LSTM across all three cryptocurrencies. Specifically, GRU achieved the lowest error for BTC, with an RMSE of 974.72 and MAPE of 1.18%. Meanwhile, Bi-LSTM provided the best predictions for ETH (RMSE: 43.19, MAPE: 1.16%) and BNB (RMSE: 6.83, MAPE: 1.08%). These results indicate that GRU and Bi-LSTM are more effective and reliable than LSTM in capturing patterns in cryptocurrency price time series data, with Bi-LSTM exhibiting superior performance on ETH and BNB, and GRU being optimal for BTC. Additionally, a visual comparison between actual and predicted values is provided to further illustrate model performance.

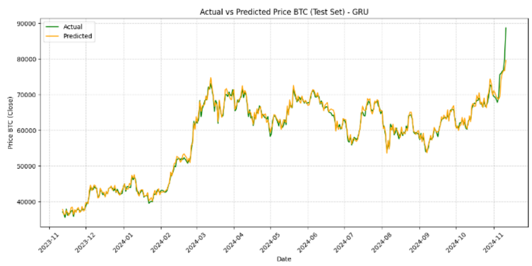

Figure 9. Visualization of Actual Data Comparison Results with Best BTC Model Prediction Results

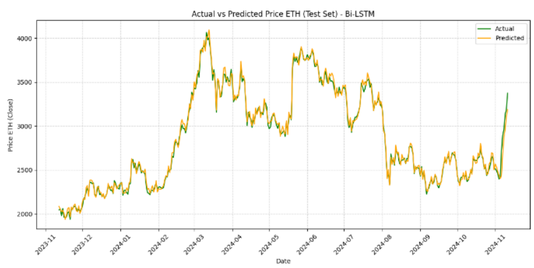

Figure 10. Visualization of Actual Data Comparison Results with Best ETH Model Prediction Results

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Figure 11. Visualization of Actual Data Comparison Results with Best BNB Model Prediction Results

Price Movement Classification Using Confusion Matrix

The following evaluation measures the performance of each model in predicting or capturing the pattern of daily price changes.

Table 3. BTC Data Testing Evaluation

Model	Accuracy	Precision	Recall	F1-Score
LSTM	48%	47%	48%	46%
GRU	50%	48%	50%	48%
Bi-LSTM	50%	49%	50%	49%

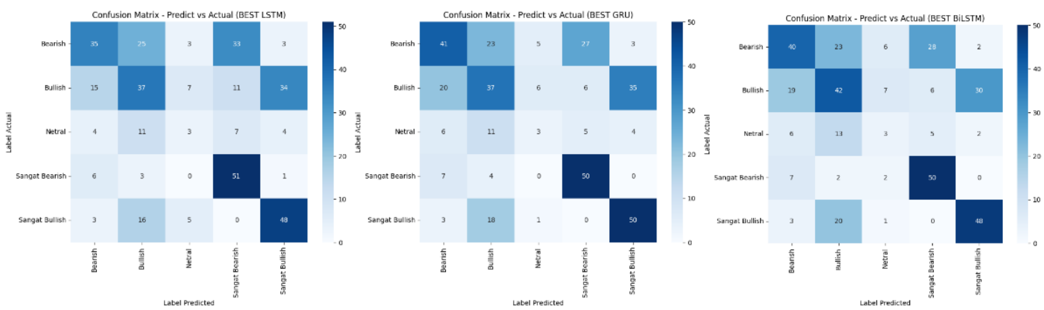

Figure 12. Confusion Matrix Evaluation of BTC Data

Table 4. ETH Data Testing Evaluation

Model	Accuracy	Precision	Recall	F1-Score
LSTM	54%	52%	54%	52%
GRU	54%	53%	54%	52%
Bi-LSTM	55%	54%	55%	54%

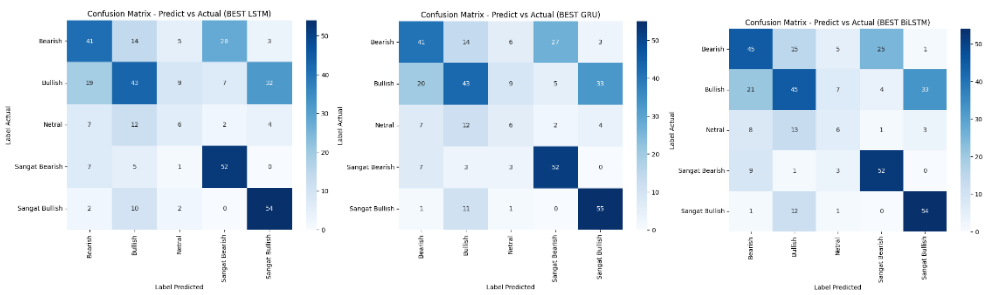

Figure 13. Confusion Matrix Evaluation of ETH Data

Table 5. BNB Data Testing Evaluation

Model	Accuracy	Precision	Recall	F1-Score
LSTM	50%	48%	50%	49%
GRU	51%	50%	51%	50%
Bi-LSTM	52%	50%	52%	51%

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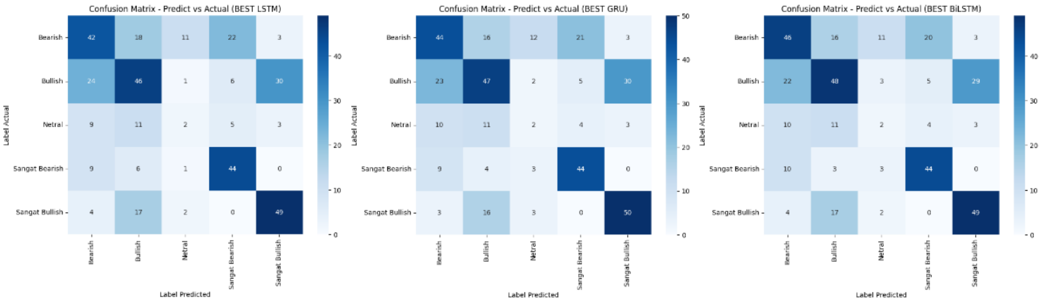

Figure 14. Confusion Matrix Evaluation of BNB Data

DISCUSSIONS

The results of this study indicate that among the three deep learning architectures evaluated LSTM, GRU, and Bi-LSTM both GRU and Bi-LSTM consistently outperformed LSTM in predicting cryptocurrency prices. GRU achieved the lowest error in Bitcoin (BTC) prediction, with an RMSE of 974.72 and a MAPE of 1.18 percent. Meanwhile, Bi-LSTM delivered the most accurate results for Ethereum (ETH) with an RMSE of 43.19 and MAPE of 1.16 percent, and for Binance Coin (BNB) with an RMSE of 6.83 and MAPE of 1.08 percent. These findings differ from a previous study by (Murray et al., 2023), which concluded that LSTM was the most accurate model across several cryptocurrencies. In contrast, this study found that Bi-LSTM surpassed both LSTM and GRU in two out of the three assets, demonstrating its superior ability to capture contextual patterns in more stable cryptocurrencies.

The advantage of GRU in BTC forecasting is likely due to its simpler and more efficient architecture, consisting of only two gates: the update gate and the reset gate. This structure enables GRU to handle high-volatility data effectively while minimizing overfitting and maintaining computational efficiency. This aligns well with the nature of BTC, which exhibits frequent and sharp price fluctuations. On the other hand, Bi-LSTM's bidirectional processing allows it to analyze both past and future sequences simultaneously, providing a broader context for time series data. This makes Bi-LSTM particularly effective for ETH and BNB, which tend to display more structured and predictable trends compared to BTC.

From a practical perspective, these findings offer valuable insights for financial analysts and market participants in selecting appropriate models based on the volatility profile of specific assets. GRU may be better suited for highly volatile assets like BTC, while Bi-LSTM appears more appropriate for assets with less erratic movements such as ETH and BNB. Theoretically, this study contributes to the field by presenting a comprehensive comparative evaluation of three popular deep learning models, using both regression metrics (RMSE and MAPE) and classification metrics (accuracy, precision, recall, and F1-score). For instance, Bi-LSTM achieved the highest classification accuracy for ETH at 55 percent and for BNB at 52 percent in the five-class price movement labeling scheme. Moreover, the implementation of hyperparameter tuning and walk-forward validation in this research enhances model reliability and ensures that the evaluation remains chronologically sound and free from data leakage.

CONCLUSION

This study concludes that the choice of deep learning architecture has a significant impact on the accuracy of cryptocurrency price prediction using time series data. GRU emerged as the most suitable model for predicting Bitcoin, achieving an RMSE of 974.72 and a MAPE of 1.18 percent, likely due to its computational efficiency and ability to generalize on highly volatile data. In contrast, Bi-LSTM yielded the most accurate predictions for Ethereum and Binance Coin, with RMSE and MAPE values of 43.19 and 1.16 percent for ETH, and 6.83 and 1.08 percent for BNB, respectively, while also recording the highest classification accuracies of 55 percent for ETH and 52 percent for BNB. These findings suggest that model selection should be aligned with the volatility characteristics of the target asset. The main scientific contribution of this study lies in its comprehensive comparative analysis of three state-of-the-art deep learning architectures, supported by hyperparameter tuning and sequential validation techniques that maintain data integrity throughout the process. However, the study has certain limitations, particularly in its reliance on univariate time series without considering external variables such as trading volume, technical indicators, or sentiment analysis. Future studies are encouraged to explore multivariate time series models and ensemble approaches to enhance predictive performance and robustness in the face of increasingly complex market conditions.

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