Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 4s (2025)

Cryptocurrency Price Prediction using Deep Learning Algorithms: A Comparative Study

Pappula Ashok[1]*, D. Mallikarjuna Reddy[2], Ameen Saheb Shaik[3]
[1,3]Assistant Professor, Department of Mathematics, Anurag University, Hyderabad-500088, Telangana, India.
[2]Assosciate Professor, Department of Mathematics, GITAM University, Hyderabad- 502329, Telangana, India.
* ashokhs@anurag.edu.in, drmallikreddyd@gmail.com, ameen.maths@anurag.edu.in

Article History:

Received: *30-09-2024*

Revised: *28-11-2024*

Accepted: *09-12-2024*

Abstract:
Introduction: Due to financial technology advances, cryptocurrency is a new asset with great potential for academics. Price volatility and dynamism make Cryptocurrencies prediction difficult.

Objectives: This paper presents three Recurrent Neural Network (RNN) methods for predict Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB) prices to predict the price of Cryptocurrency.

Methods: This study uses three RNN algorithms LSTM, Bi-LSTM, and GRU to predict the prices of Bitcoin (BTC), Binance Coin (BNB), and Ethereum. (ETH)

Results: BTC, ETH, and BNB prices are predicted using three machine learning algorithms. The model's accuracy was assessed using performance metrics. We followed by comparing actual and predicted prices of models. The GRU algorithm surpassed its competitors, attaining MAPE values of 2.562795642 for BNB, 2.921155091 for ETH, and 3.363400599 for BTC.

Conclusion: The value of cryptocurrency swings regularly. Since the cryptocurrency market is nonlinear, time series data is challenging to evaluate when making price predictions. Machine learning algorithms are used in many financial and economic activities. Investors, researchers, and professionals need cryptocurrency value forecasts. In this study, GRU outperformed than LSTM and Bi-LSTM algorithms in predicting prices of BTC, ETH and BNB.

Keywords: Cryptocurrency; LSTM, Bi-LSTM GRU, BTC, ETH, BNB

1. Introduction

The monetary system relies on fiat cash, which is divisible, transferable, durable, and scarce [1]. The lack of a physical currency underpinning can lead to hyperinflation and wealth disparity [2]. Transactions are generally processed through intermediaries like financial institutions and credit card firms, which increases prices and transfer times. Current ledgers are vulnerable to manipulation and breaches. Individual data ownership may be lost. The public trusts the present financial system despite these restrictions because of government rules and legal contracts. Trust breaches, like the 1990s dot-com and 2008 real estate booms, have caused huge financial losses [3]. Creating a new framework that fosters confidence among financial system players is crucial. In October 2008, Satoshi Nakamoto released blockchain technology and the first digital currency BTC.[4]. This system enables direct monetary transactions between peers via the public internet without the involvement of middlemen. It has become a significant asset in the global market [5]. Universities, government organizations, media, and the public are studying it. Cryptocurrencies employ cryptography to secure transactions and prevent counterfeiting [6]. Because they are not issued by a central body, cryptocurrencies are independent of banks and centralized currencies. Cryptocurrencies have all blockchain properties because the blockchain is crucial. BTC allows safe pseudo-anonymous digital transactions, making it easier to identify the sender and receiver. Governments worldwide have focused on blockchain technology, calling for cryptocurrency regulation. Crime, sovereignty, and opportunities drive this government interest. However, BTC uses PoW and PoS hybrid techniques, which need substantial energy consumption to protect the network [7]. Bitcoin utilizes pow, a consensus method that requires users to calculate to validate and add transactions. ASICs and plenty of electricity are needed for mining. PoW systems' high energy usage and mining power centralization are drawbacks. In view of the worldwide movement to prevent climate change, PoW energy usage threatens the BTC network. Alternative systems like PoS employ consensus algorithms to validate transactions without computing labor. Users must stake the asset to participate in validation. PoS systems may be more energy-efficient than PoW systems because they require less processing power [8]. BTC is the most popular cryptocurrency. Its early market entry and prominence as the first cryptocurrency helped it gain importance and appeal. This has become BTC the top cryptocurrency. Ethereum, LTC, and Ripple is also popular. Ref. [9] notes that Bitcoin's rivalry with competing cryptocurrencies pushes industry improvement in technology and security. In [10], big data and cryptocurrencies are examined. Typically, this material is unstructured and difficult to handle using conventional approaches. Over the past decade, there have been substantial advancements in computer and communication platforms due to digitalization and the use of cutting-edge technologies. According to [11], this development has led to the extensive gathering and utilization of big data analytics in several areas of everyday life. The utilization of big data analytics and the IoT is revolutionizing communication infrastructure and influencing the methods by which data are processed and evaluated. Both of them depend on sophisticated technology, such as AI and ML, to handle vast quantities of data. The relationship between big data and cryptocurrencies is intimate, since blockchain technology, employed in cryptocurrency administration, utilizes big data methods for the purpose of safe and decentralized data storage and processing. Moreover, the utilization of big data analytics enables the examination of bitcoin market patterns and identification of deceitful behaviors, thereby enhancing the resilience of the cryptocurrency market. The mutual reliance between big data and cryptocurrency has favorable prospects for the advancement of both. The cryptocurrency market is very volatile, making it a profitable market for speculators. Utilizing AI and ML algorithms can assist in forecasting future cryptocurrency values, while the work remains difficult owing to the intricate and non-linear nature of the pricing. However, it is anticipated that the market value of cryptocurrencies would increase in the future, with a projected compound annual growth rate of 11.1%. Nevertheless, investors have encountered challenges in previous instances due to price bubbles resulting in an unsustainable level of volatility.

To address these problems, market players need a credible model to capture trends and anticipate. However, government regulations, technical advances, public perception, and global events greatly impact cryptocurrency price prediction difficult. Thus, the article uses deep learning algorithms to find hidden patterns in data, combine them, and make more accurate predictions:

- Developing a framework for BTC, ETH, and BNB price predictions;
- Applying chosen DL algorithms: LSTM, Bi-LSTM, and GRU;

• Assessing prediction performance using MAPE, RMSE, MAE and MSE metrics;

In this paper, Section 2 covers the literature, Section 3 materials and methods, Section 4 experimental results, Section 5 compares our model to similar studies, and Section 6 concludes the study.

2. Literature Review

Machine learning forecasts the future using past data. Training an ML model on past data aids in future price prediction. Among other benefits over conventional forecasting models, ML and DL techniques enable the ability to produce results near to the real data points and raise accuracy. [12]. Several ML approaches are used for this purpose, such as DT, SVM and NN's. According to the authors of [13], including bitcoin into multi-asset portfolios improves portfolio performance in a variety of ways. It first increases portfolio minimal variance and raises the efficient frontier. Bitcoin assets also reduce portfolio standard deviations and increase Sharpe ratios. Several research have employed machine learning algorithms to anticipate Bitcoin values, with promising results. Machine learning techniques were applied to forecast BTC and other cryptocurrency prices. The authors [14] compared the SVM, ANN, and Deep Learning machine learning algorithms. This research attains 99% accuracy in predicting Bitcoin and Ethereum prices through the utilization of network-based characteristics and machine learning models. In [15], researchers employed ANN, KNN, gradient boosted trees, and an ensemble model to forecast the prices of nine cryptocurrencies. [16] employed an ensemble model using RF and GBM to forecast BTC, ETH, and XRP values. These forecasts' MAPE values for the ensemble model varied from 0.92% to 2.61%. Many DL-based financial time series prediction models have appeared recently. The authors of [17] created a two-stage method for forecasting Bitcoin values. Initially, they used ANN and RF to identify the elements that were essential for prediction. Subsequently, they utilized an LSTM model using the features that were identified. LSTM outscored ARIMA and SVM. LSTM and GRU networks predicted LTC and Monero prices in another research [18]. Hybrid model predicted bitcoin values better than LSTM-only. Another study used AR features in an LSTM network to anticipate daily BTC prices [19]. RMSE, MAPE, MSE and MAE were lower in the recommended LSTM-AR model than in a normal LSTM model. The study [20] uses ensemble learning, LSTM, Bi-LSTM, and CNN to make hourly predictions of coin prices that are correct and reliable. Using Random Forest (RF) and Gradient Boosting Machine (GBM), the study [21] estimates short-term bitcoin values based on past prices and technical data. Both models exhibited identical accuracy when evaluated on Bitcoin, ETH, and XRP; GBM somewhat outperformed RF in MAPE and RMSE. These models show the possibilities for automated trading systems. A WAMC was used to enhance bitcoin price prediction in Reference [22].

3. Materials and Methods

Addresses research pre-processing and modeling techniques. Prediction graphs for several cryptocurrencies are shown. Finally, we examine the study's performance and analysis. This research estimates BTC, ETH, and BNB prices using LSTM, Bi-LSTM, and GRU. Historical data for BTC, ETH, and BNB is collected, divided into training and testing datasets, and three models are trained, tested, and compared to assess each DL approach.

3.1. Dataset: The data set was obtained from web site: https://finance.yahoo.com. The dataset included four columns: Date, BTC-Close, ETH-Close, and BNB-Close. We chose Close Price to predict with Deep Learning Models. Table 1 represents dataset specifications, whereas Table 2 shows a few data points from the study's targeted cryptocurrencies.

Table 1. Specifications of dataset

Parameters of Data set	Data Description	Type of Data
Date	Date of the data	Date
Open Price	Opening price	Numeric
High	High	Numeric
Low	Low	Numeric
Close	Close	Numeric
Adj Close	Adjusted close	Numeric

This research introduces a four-layer network design for each deep learning model, comprising deep learning layers with 200 neurons. Figure 1 depicts the pre-processing techniques utilized on the dataset. We employed many preprocessing approaches on the BTC, ETH, and BNB datasets to ready them for deep learning research. After employing data imputation for removing missing values, we modified the data format to ensure compliance with the implementation of chosen models Upon analyzing the dataset, we found no missing values. Normalization is essential for ensuring the precision of model fitting and reducing bias. To address the possible problem of disparate handling of variables with varying scales, we employed feature-wise normalization methods such as MinMax Scaling before fitting the model. A study conducted recently has demonstrated that implementing data scaling techniques can enhance the efficiency of models [23]. Hence, in our inquiry, we employed MinMax Scalar to standardize the data. We utilized an 80:20 training: test split methodology to ensure the uniformity of attributes for each Cryptocurrency. The training dataset covers the time period from 1 January 2020 to 31 December 2023, representing appropriatly80% of the available data. The testing dataset comprises appropriately 20% of the data and encompasses the period from 1 January 2024 to 30 June 2024. Daily closing prices of BTC, ETH, and BNB are shown in Figures 2–4 for training and testing datasets.

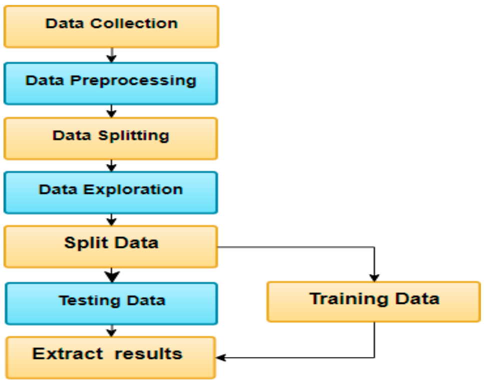

Fig.1 Processing of data set and model selection

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 4s (2025)

Fig.2 Train and test- data set of BTC.

Figure 2 shows the selected data on the Bitcoin (BTC) closing price. The closing price increased progressively until 2021, when it suddenly climbed to 67566.8281 USD at its time series peak.

Fig.3 Train and test – data set of ETH

Figure 3 shows the selected data on the Ethereum (ETH) closing price. The closing price increased progressively until 2021, when it suddenly climbed to 4812.0874 USD at its time series peak.

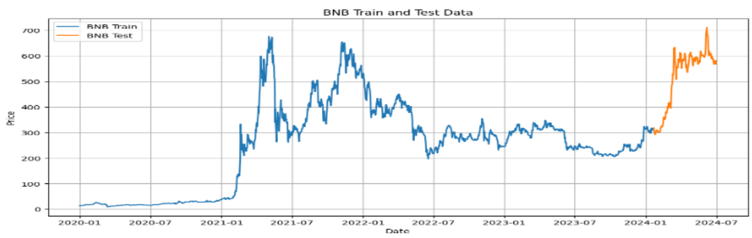

Fig.4 Train and test- data set of BNB.

Figure 4 shows the BNB price at the end of the collection. It shows that the closing price went up slowly until the end of 2021. After that, it went up quickly and reached a high of 675.6841 USD. Understanding the flow of data and activity via a reliable and relevant chart helps communicate its meaning. Figure 5 shows targeted Bitcoin, Ethereum and Binance distribution from January 1, 2020, to June 30, 2024. The closing price determines the price rise and interval.

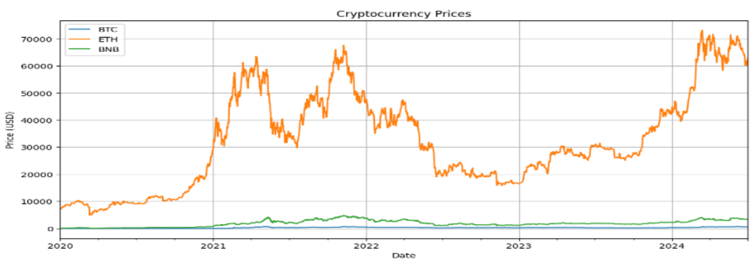

Fig. 5 Time series of BTC, ETH, & BNB closing prices

Table 2: Displays a few data points from the BTC, ETH, and BNB: Close prices.

Date	BTC	ETH	BNB
1-Jan-20	7200.174	130.802	13.68908
2-Jan-20	6985.47	127.4102	13.02701
3-Jan-20	7344.884	134.1717	13.66045
4-Jan-20	7410.657	135.0694	13.89151

Figure 6 shows the chosen cryptocurrencies' Pearson correlation coefficient. BTC, BNB, and ETH the closing price are positively correlated via the correlation matrix. If the value of one currency changes, so will the others.

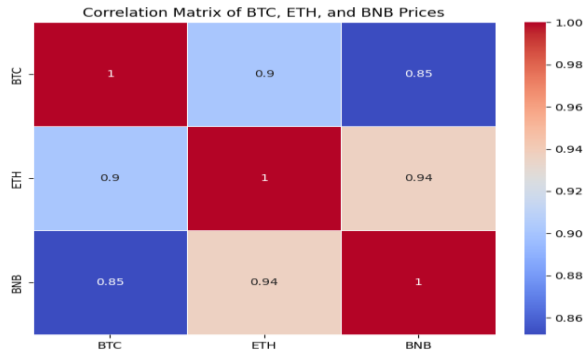

Fig.6 BTC, BNB, & ETH correlations matrix**.**

3.2.Deep Leaning Methods:

3.2.1. LSTM: LSTM is advanced RNN. These approaches are designed to prevent long-term reliance and address the vanishing gradient problem with a system that modulates information for long-term storage [24]. The LSTM architecture comprises of memory blocks linked by recurrent subnetworks. Memory blocks maintain the network's state and manage cell-to-cell communication. Figure 8 shows the LSTM architecture. The input gate selects critical cell status information, while the output gate determines what to send.

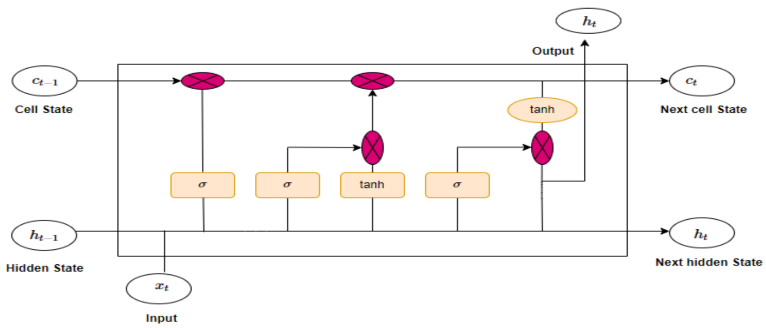

Fig.7 LSTM algorithm structure

An LSTM network is trained by below equations [25]:

$$i_t = \sigma(W_i [h_{t-1}, x_t] + b_t) \quad (1)$$

$$f_t = \sigma(W_f [h_{t-1}, x_t] + b_t) \quad (2)$$

$$C_t = f_t * C_{t-1} + i_t * tanh(W_c [h_{t-1}, x_t] + b_c) \quad (3)$$

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 4s (2025)

$$O_t = \sigma(W_o\,[h_{t-1},x_t\,] + b_o) \qquad (4)$$

$$h_t = O_t * tanh(C_t) \qquad (5)$$

where x_t Input, h_t Hidden state, C_t Cell state, i_t Input gate, f_t Forget gate, O_t Output gate, t Time step, W Weight matrices, b Bias vectors.The sigmoid function limit output to 0 and 1, The Tanh limit output to -1 and 1.

3.2.2. Gated Recurrent Unit: GRUs are RNNs created by [26] in 2014 to improve LSTM networks. LSTMs and GRUs examine input sequences of any length while storing past information. GRUs use one update gate and a reset gate to decide which information to preserve and discard, unlike LSTMs, which use several gates and an internal memory cell. This makes GRUs easier to train than LSTMs and performs similarly on many tasks [27]. GRUs outperformed LSTMs in Penn Tree bank language modeling. A NLP model research [28] found GRUs similar to LSTMs and CNNs on several benchmarks. Long-range associations in sequential data are better detected by GRUs than RNNs. Based on input and network state, a GRU's update and reset gates can maintain or forget earlier information. For language translation, GRUs are good for recalling and applying knowledge from long sequences.
Figure 9 shows the hidden state at time t, h_t, updated by the following equations [29]:

$$u_t = \sigma(W_u\,[h_{t-1},x_t\,]) \qquad (6)$$

$$r_t = \sigma(W_r[h_{t-1},x_t\,]) \qquad (7)$$

$$h_t = (1-u_t) * h_{t-1} + u_t * tanh(W_u\,[r_t * h_{t-1},u_t\,]) \qquad (8)$$

where u_t update gate, r_t reset gate.

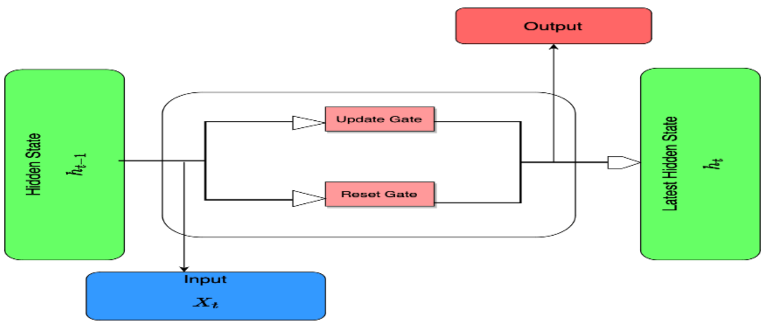

Fig. 8 GRU cell diagram

3.2.3. Bi-Directional LSTM: Recurrent Neural Networks, such as Bi-LSTMs, evaluate sequential input in both forward and backward directions (Figure 9). This enables the network to forecast or classify based on historical and prospective inputs. This is particularly advantageous for roles where antecedent and subsequent events influence the current circumstances. A Bi-LSTM or Bi-GRU has four layers of LSTM or GRU cells, with one layer processing data in a forward direction and the other in a backward direction. The research "Bi-directional Recurrent Neural Networks" [30] first presented the concept of integrating a forward and backward LSTM to capture both past and future context for speech signal processing tasks in 1997. Since that time, Bi-LSTMs have been employed in sentiment analysis, text classification, and language translation. Multiple research [31,32] have shown that Bi-

LSTMs can proficiently forecast time series. The Bi-LSTM yielded advantageous outcomes in several studies. References [33] established a Bi-LSTM model, showcasing its enhanced efficacy.

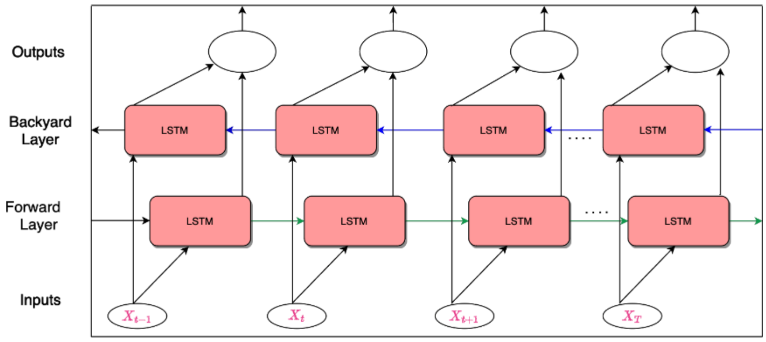

Fig.9 Structure of a Bi-LSTM algorithm

3.3. Hyperparameter Tuning: Machine learning system performance depends on hyperparameter adjustment. The best hyperparameters can improve the algorithm's performance and give more accurate predictions [34]. To get the best results, optimize the hyperparameters before running the deep learning algorithm. This study optimized hyperparameters such layer neuron count, epoch size, and batch size. Each epoch represents a full dataset iteration during model execution, including forward and backward passes. A single forward/backward run uses a certain number of samples, called the batch size. It determines the number of samples sent across the network to update weights in one iteration. A model's performance and training time depend on batch size. While reducing batch size increases weight updates, it may hinder convergence. Increasing batch size may hasten convergence but require more computer resources. Batch sizes were 16, 32, 64, and 120 for the trials. However, the best hyperparameter value of 32 was chosen since it yielded more accurate results across all prediction models in this study.

3.4. Performance Metrics: MAPE, RMSE, MAE, and MSE were the metrics that we applied in order to evaluate the efficacy of the deep learning algorithms

$$\text{MAPE}=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t-F_t}{A_t}\right| \quad (9)$$

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t-F_t)^2} \quad (10)$$

$$\text{MAE}=\frac{1}{n}\sum_{t=1}^{n}|A_t-F_t| \quad (11)$$

$$\text{MSE}=\frac{1}{n}\sum_{t=1}^{n}(A_t-F_t)^2 \quad (12)$$

where F_t and A_t are the predicted and tested prices, and n is the no of time steps

The smaller the MAPE, the RMSE, the MAE and the MSE values, the better the prediction model performance

4. Results: The outcomes of using these models to forecast BTC, ETH, and BNB are shown in Table 3, whereby the model exhibiting the lowest error values is identified as the most efficient. Figures 10-21 provide a comparison between actual and forecasted values for various currencies. The anticipated values closely align with the actual ones; nonetheless, minor differences exist. The differences are illustrated by the performance measures presented in Table 3.

Table 3. Proposed model performance.

Currency	Model	MAPE	RMSE	MAE	MSE
BTC	LSTM	5.74517992	4476.194874	3688.774618	20036320.55
	Bi-LSTM	5.34301493	3826.955086	3308.275949	14645585.23
	GRU	3.36340059*	2603.043999*	2084.982958*	6775838.062*
ETH	LSTM	3.90121391	157.7434218	124.2988898	24882.98712
	Bi-LSTM	3.20296604	137.8613613	101.8942603	19005.75493
	GRU	2.92115509*	121.2087421*	91.11290297*	14691.55915*
BNB	LSTM	3.002507352	21.1590163	14.69491963	447.704
	Bi-LSTM	2.743532156	19.49814094	14.01106665	380.1775
	GRU	2.562795642*	19.98837011*	13.28685417*	399.5349*

***Represents the high accuracy of GRU model**

4.1. Results for BTC: Table 6 indicates that the GRU model forecasts BTC prices more accurately, exhibiting the lowest RMSE, MSE, MAE, and MAPE values. Figure 12 verifies that the forecasts of the GRU model align with actual prices. GRU forecasts BTC trends more effectively than LSTM and Bi-LSTM, with a negligible difference. The Bi-LSTM model ranks second for BTC, with somewhat elevated RMSE, MSE, MAE, and MAPE. These findings show that bidirectional RNN networks forecast BTC prices better than conventional ones. BTC Figures 10–12 compare testing data set and predicted dataset prices for the three models.

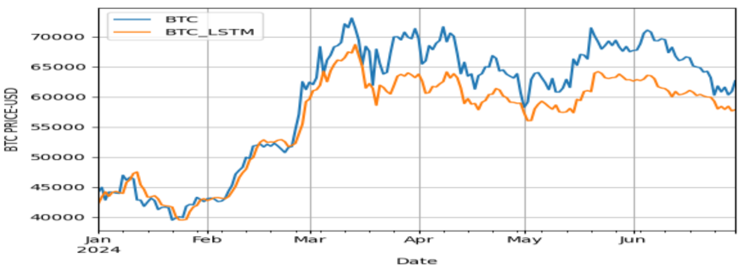

Fig.10 Actual and forecasted BTC prices using LSTM

.

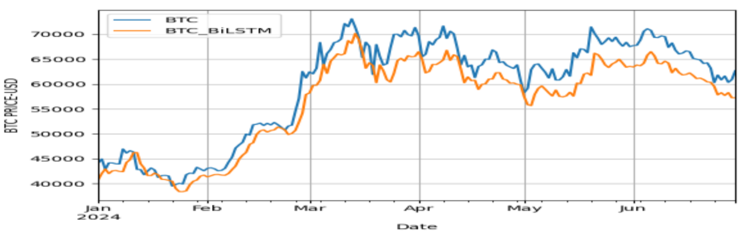

Fig.11 Actual and forecasted BTC prices using Bi-LSTM model.

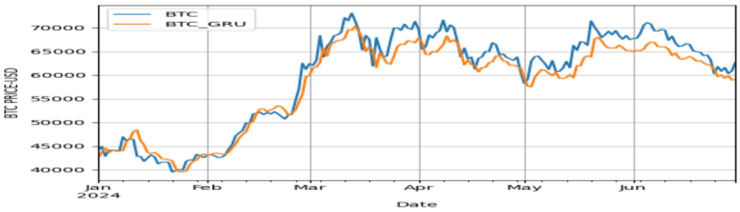

Fig.12 Actual and forecasted BTC prices using GRU model.

4.2. Results for ETH: Table 3 indicates that the GRU model forecasts ETH prices more accurately, exhibiting the lowest RMSE, MSE, MAE, and MAPE. Figure 15 verifies that the forecasts of the GRU model align with actual prices. GRU forecasts BTC trends more well than LSTM and Bi-LSTM, with a negligible difference. The Bi-LSTM model ranks second for ETH, exhibiting somewhat elevated RMSE, MSE, MAE, and MAPE. These data indicate that bidirectional RNN networks predict ETH prices more well than traditional models. Ethereum Figures 13–15 juxtapose the testing dataset prices with the anticipated dataset prices for the three models.

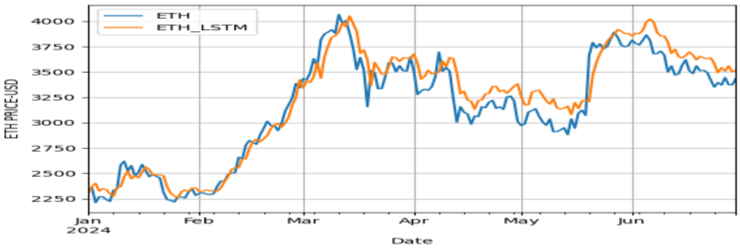

Fig.13 Actual and forecasted ETH prices using the LSTM model.

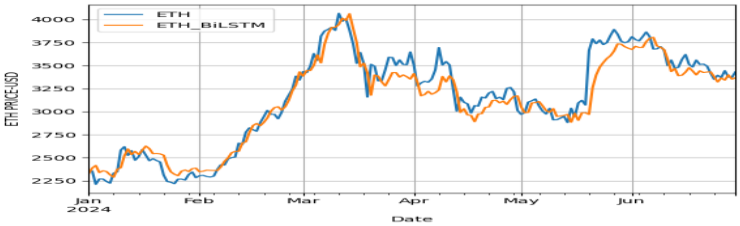

Fig.14 Actual and forecasted ETH prices using the bi-LSTM model.

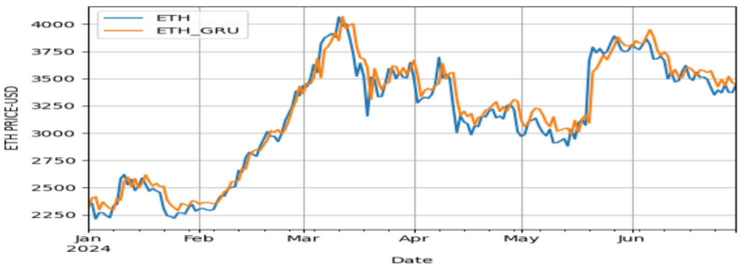

Fig. 15. Actual and forecasted ETH prices using the GRU model.

4.3. Results for BNB: Table 3 shows the GRU model predicts BNB prices better with the lowest RMSE, MSE, MAE and MAPE. Figure 18 confirms that GRU model projections match real prices. GRU predicts BTC trends better than LSTM and Bi-LSTM, with a minor difference. With slightly higher RMSE, MSE, MAE and MAPE, the Bi-LSTM model is second-best for BNB. These findings show that bidirectional RNN networks forecast BNB prices better than conventional ones. BNB Figures 16–18compare testing data set and predicted dataset prices for the three models.

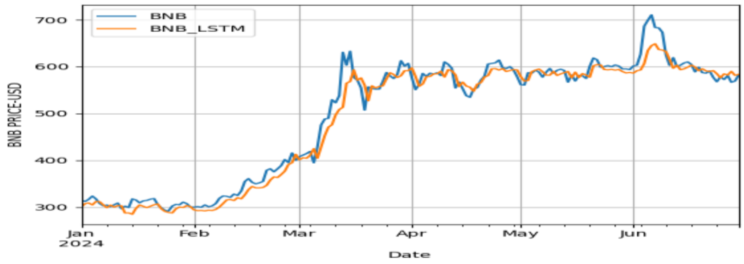

Fig.16 Actual and forecasted BNB prices using the LSTM model.

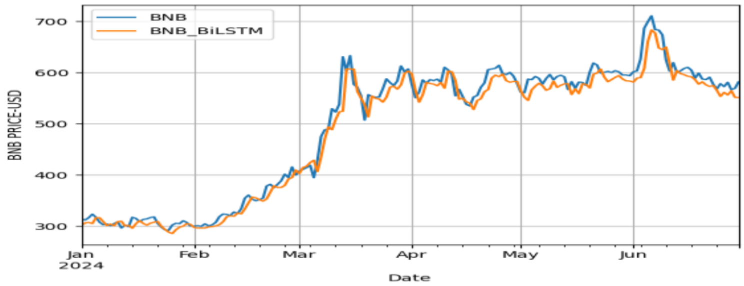

Fig.17 Actual and forecasted BNB prices using the bi-LSTM model.

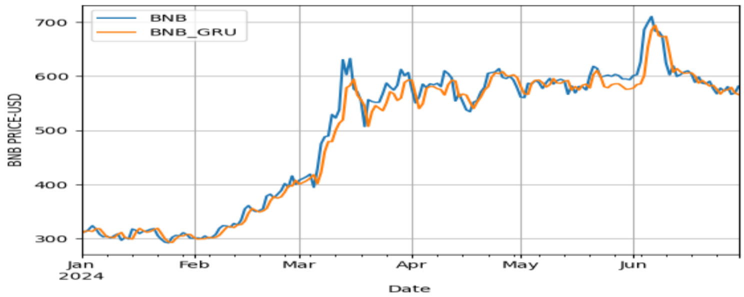

Fig.18 Actual and forecasted BNB prices using the GRU model.

The GRU model surpasses conventional LSTM and Bi-LSTM networks in forecasting bitcoin prices. Figure 19-21 depicts the disparity between the actual and projected values of BTC, ETH, and BNB using the LSTM, Bi-LSTM, and GRU models. The predicted prices and the actual prices are very close, as shown by the error measures such as MAPE, RMSE, MAE, and MSE. This signifies that the GRU model demonstrated enhanced accuracy in its predictions compared to LSTM and Bi-LSTM.

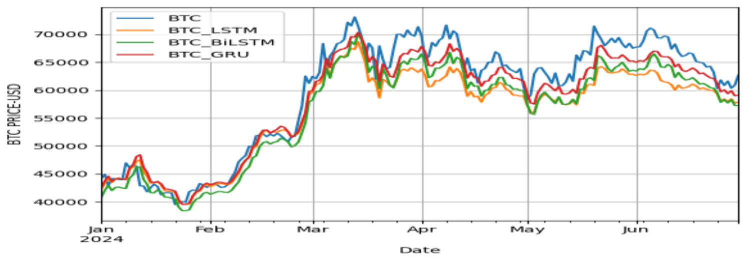

Fig.19 Actual data set and predicted data set - Bitcoin prices using the LSTM, Bi-LSTM and GRU models.

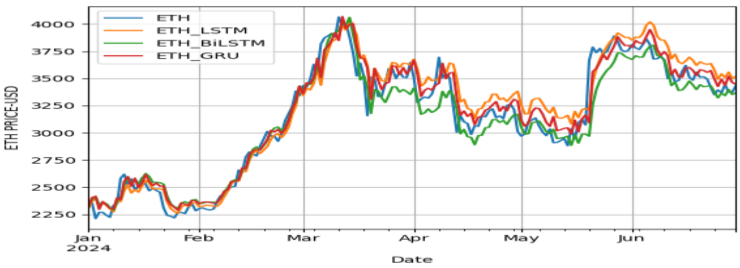

Fig.20 Actual data set and predicted data set - Ethereum prices using the LSTM, Bi-LSTM and GRU models.

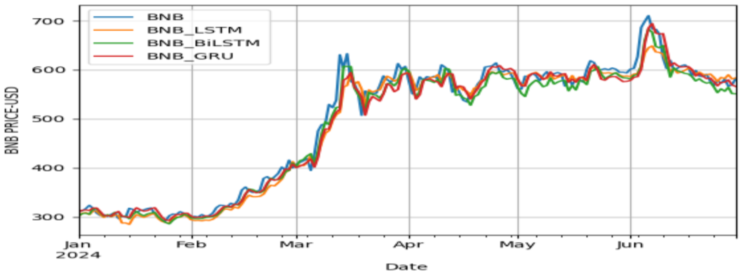

Fig.21 Actual data set and predicted data set - Binance prices using the LSTM, Bi-LSTM and GRU models.

5. Discussion: The suggested strategy for predicting future bitcoin prices is evaluated against previous models in the literature [35,36] to determine its performance. These models are considered reliable and appropriate based on the assessment techniques and outcomes. Nevertheless, it is important to acknowledge that these models possess many constraints that might affect their precision in forecasting bitcoin prices. LSTMs, GRUs, and Bi-LSTMs may not capture all of the linkages that affect cryptocurrency values, leading in poor projections. These models also overfit, especially when trained on small datasets, resulting in poor performance on novel data. These models also struggle to capture basic trends since cryptocurrency prices fluctuate and are unstable. Table 4 contrasts study RMSE and MAPE outcomes. The three strategies are successful and equivalent to literary methods. MAPE results show that the GRU outperformed the standard Bi-LSTM and LSTM models in predicting the prices of all three cryptocurrencies studied.

Table 4. Relative comparison with similar studies

Author's	Cryptocurrency	Method's	MAPE	RMSE
[35]	BTC - USD	LSTM	4.2	2518.02
		Bi-LSTM	3.8	2222.74
		GRU	3.5	1777.31
[35]	ETH -USD	LSTM	6.4	150.09
		Bi-LSTM	6.0	147.85
		GRU	5.7	151.62
[36]	BTC - USD	LSTM	4.0	2350.53
		Bi-LSTM	3.3	1992.88
		GRU	5.3.	3223.01

[36]	ETH -USD	LSTM	4.7	18384
		Bi-LSTM	4.2	16860
		GRU	4.7	18103
[36]	XRP -USD	LSTM	6.3	98
		Bi-LSTM	4.8	79
		GRU	7.2	104
Proposed approach	BTC - USD	LSTM	5.74517992	4476.194874
		Bi-LSTM	5.34301493	3826.955086
		GRU	**3.36340059**	**2603.043999**
Proposed approach	ETH -USD	LSTM	3.90121391	157.7434218
		Bi-LSTM	3.20296604	137.8613613
		GRU	**2.92115509**	**121.2087421**
Proposed approach	BNB-USD	LSTM	3.002507352	21.1590163
		Bi-LSTM	2.743532156	19.49814094
		GRU	**2.562795642**	**19.98837011**

6. Conclusion:

This study predicts BTC, ETH, and BNB values using three deep learning algorithms. Tables 3 display model performance metrics. We then compared Test and Predicted data set pricing. GRU outperformed the other algorithms with BTC, ETH, and BNB MAPE values of 2.859813, 2.51626, and 4.327951. Metrics imply the proposed GRU model is more accurate. The LSTM and Bi-LSTM models also performed better. This study shows that deep learning models can anticipate cryptocurrency prices, but further research is needed. Advanced hyperparameter tweaking, adding macroeconomic variables or blockchain metrics, and using hybrid models like GRU-LSTM to improve accuracy may be future research. Applying the method to additional cryptocurrencies, creating real-time prediction systems for trading, and using explainability methods like SHAP or LIME to increase model interpretability seem promising.

References

[1] J. Melitz, *DP178 Monetary Discipline, Germany, and the European Monetary System*, National Bureau of Economic Research (NBER) Working Paper No. 2319, National Bureau of Economic Research (NBER), Cambridge, MA, USA, 1987. [Online]. Available: https://ssrn.com/abstract=884539 [Accessed: Sep. 24, 2022].

[2] A. Bulír, "Income inequality: Does inflation matter?" *IMF Staff Papers*, vol. 48, pp. 139–159, 2001.

[3] S. Basco, "Globalization and financial development: A model of the Dot-Com and the Housing Bubbles," *J. Int. Econ.*, vol. 92, pp. 78–94, 2014.

[4] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," *Decentralized Bus. Rev.*, vol. 21260, 2008. [Online]. Available: https://bitcoin.org/bitcoin.pdf [Accessed: Oct. 19, 2022].

[5] P. N. Sureshbhai, P. Bhattacharya, and S. Tanwar, "KaRuNa: A blockchain-based sentiment analysis framework for fraud cryptocurrency schemes," in *Proc. 2020 IEEE Int. Conf. Commun. Workshops (ICC Workshops)*, Dublin, Ireland, Jun. 2020, pp. 1–6.

[6] C. Rose, "The evolution of digital currencies: Bitcoin, a cryptocurrency causing a monetary revolution," *Int. Bus. Econ. Res. J. (IBER)*, vol. 14, pp. 617–622, 2015.

[7] L. Badea and M. C. Mungiu-Pupăzan, "The economic and environmental impact of bitcoin," *IEEE Access*, vol. 9, pp. 48091–48104, 2021.

[8] H. Vranken, "Sustainability of bitcoin and blockchains," *Curr. Opin. Environ. Sustain.*, vol. 28, pp. 1–9, 2017.

[9] M. Iwamura, Y. Kitamura, and T. Matsumoto, "Is bitcoin the only cryptocurrency in the town? Economics of cryptocurrency and Friedrich A. Hayek," *SSRN Electron. J.*, 2014.

[10] H.Hassani, X. Huang, and E. Silva, "Big-crypto: Big data, blockchain and cryptocurrency," *Big Data Cogn. Comput.*, vol. 2, p. 34, 2018.

[11] K. Hwang and M. Chen, *Big-Data Analytics for Cloud, IoT and Cognitive Computing*, Hoboken, NJ, USA: John Wiley & Sons, 2017.

[12] N. A. Hitam, A. R. Ismail, R. Samsudin, and E. H. Alkhammash, "The effect of kernel functions on cryptocurrency prediction using support vector machines," in *Proc. Int. Conf. Reliable Inf. Commun. Technol.*, Cham, Switzerland, 2022, pp. 319–332.

[13] Y. Andrianto and Y. Diputra, "The effect of cryptocurrency on investment portfolio effectiveness," *J. Financ. Account.*, vol. 5, pp. 229–238, 2017.

[14] M. Saad, J. Choi, D. Nyang, J. Kim, and A. Mohaisen, "Toward characterizing blockchain-based cryptocurrencies for highly accurate predictions," *IEEE Syst. J.*, vol. 14, pp. 321–332, 2019.

[15] R. Chowdhury, M. A. Rahman, M. S. Rahman, and M. Mahdy, "An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning," *Phys. A Stat. Mech. Its Appl.*, vol. 551, p. 124569, 2020.

[16] V. Derbentsev, V. Babenko, K. Khrustalev, H. Obruch, and S. Khrustalova, "Comparative performance of machine learning ensemble algorithms for forecasting cryptocurrency prices," *Int. J. Eng.*, vol. 34, pp. 140–148, 2021.

[17] W. Chen, H. Xu, L. Jia, and Y. Gao, "Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants," *Int. J. Forecast.*, vol. 37, pp. 28–43, 2021.

[18] M. M. Patel, S. Tanwar, R. Gupta, and N. Kumar, "A deep learning-based cryptocurrency price prediction scheme for financial institutions," *J. Inf. Secur. Appl.*, vol. 55, p. 102583, 2020.

[19] C. H. Wu, C. C. Lu, Y. F. Ma, and R. S. Lu, "A new forecasting framework for bitcoin price with LSTM," in *Proc. 2018 IEEE Int. Conf. Data Mining Workshops (ICDMW)*, Singapore, Nov. 2018, pp. 168–175.

[20] I. E. Livieris, E. Pintelas, S. Stavroyiannis, and P. Pintelas, "Ensemble deep learning models for forecasting cryptocurrency time-series," *Algorithms*, vol. 13, p. 121, 2020.

[21] V. Derbentsev, N. Datsenko, V. Babenko, O. Pushko, and O. Pursky, "Forecasting cryptocurrency prices using ensembles-based machine learning approach," in *Proc. 2020 IEEE Int. Conf. Problems Infocommun. Sci. Technol. (PIC S&T)*, Kharkiv, Ukraine, Oct. 2020, pp. 707–712.

[22] Z. Zhang et al., "Forecasting cryptocurrency price using convolutional neural networks with weighted and attentive memory channels," *Expert Syst. Appl.*, vol. 183, p. 115378, 2021.

[23] M. M. Ahsan et al., "Effect of data scaling methods on machine learning algorithms and model performance," *Technologies*, vol. 9, p. 52, 2021.

[24] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, pp. 1735–1780, 1997.

[25] N. Ayoobi et al., "Time series forecasting of new cases and new death rates for COVID-19 using deep learning methods," *Results Phys.*, vol. 27, p. 104495, 2021.

[26] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," *arXiv*, 2014, arXiv:1412.3555.

[27] S. Yang, X. Yu, and Y. Zhou, "LSTM and GRU neural network performance comparison study: Taking Yelp review dataset as an example," in *Proc. 2020 Int. Workshop Electron. Commun. Artif. Intell. (IWECAI)*, Shanghai, China, Jun. 2020, pp. 98–101.

[28] X. Wang, W. Jiang, and Z. Luo, "Combination of convolutional and recurrent neural network for sentiment analysis of short texts," in *Proc. 26th Int. Conf. Comput. Linguistics: Tech. Papers (COLING)*, Osaka, Japan, Dec. 2016, pp. 2428–2437.

[29] R. Dey and F. M. Salem, "Gate-variants of gated recurrent unit (GRU) neural networks," in *Proc. 2017 IEEE 60th Int. Midwest Symp. Circuits Syst. (MWSCAS)*, Boston, MA, USA, Aug. 2017, pp. 1597–1600.

[30] M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," *IEEE Trans. Signal Process.*, vol. 45, pp. 2673–2681, 1997.

[31] S. Lai, C. Ye, and H. Zhou, "Chinese stock trend prediction based on multi-feature learning and model fusion," in *Proc. 2021 IEEE Int. Conf. Smart Data Services (SMDS)*, Chicago, IL, USA, Sep. 2021, pp. 18–23.

[32] A. Singh, A. Kumar, and Z. Akhtar, "Bitcoin price prediction: A deep learning approach," in *Proc. 2021 8th Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Noida, India, Aug. 2021, pp. 1053–1058.

[33] K. A. Althelaya, E. S. M. El-Alfy, and S. Mohammed, "Stock market forecast using multivariate analysis with bidirectional and stacked (LSTM, GRU)," in *Proc. 2018 21st Saudi Comput. Soc. Nat. Comput. Conf. (NCC)*, Riyadh, Saudi Arabia, Apr. 2018, pp. 1–7.

[34] Z. Na et al., "Subcarrier allocation based simultaneous wireless information and power transfer algorithm in 5G cooperative OFDM communication systems," *Phys. Commun.*, vol. 29, pp. 164–170, 2018.

[35] S. Hansun, A. Wicaksana, and A. Q. Khaliq, "Multivariate cryptocurrency prediction: Comparative analysis of three recurrent neural networks approaches," *J. Big Data*, vol. 9, p. 1, 2022.

[36] S. O. Birim, "An analysis for cryptocurrency price prediction using LSTM, GRU, and the bi-directional implications," in *Developments in Financial and Economic Fields at the National and Global Scale*, M. Cömert and A. E. Şimşek, Eds., Ankara, Türkiye: Gazi Kitabevi, 2022, pp. 377–392