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Empirical analysis of Bitcoin investment strategy: a comparison of machine learning and deep learning approach

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ABSTRACT

A digital currency known as a cryptocurrency uses blockchain technology to record transactions electronically, guaranteeing security and transparency. Cryptocurrencies, in contrast to conventional hard currency, are virtual or soft currencies; that do not exist in the actual world like coins or banknotes. Since all transactions occur digitally, cryptocurrencies are decentralized and frequently stand-alone from conventional financial institutions. Peer-to-peer transfers, increased anonymity, and often quicker transaction processing without middlemen are made possible by this. In this study, two machine learning models; autoregressive integrated moving average (ARIMA), extreme gradient boosting (XGBoost), and two deep learning models; long short-term memory (LSTM), bidirectional LSTM (Bi-LSTM) were compared. By employing past Bitcoin data from 2012 to 2020, we evaluated the models' mean absolute error (MAE) and root mean squared error (RMSE). Compared to other models, the Bi-LSTM model yields minimal RMSE scores of 67.18 and MAE scores of 24.73. This aids in capturing all temporal correlations, which are important for forecasting the price of Bitcoin.

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1. INTRODUCTION

Bitcoin has garnered a lot of interest from investors and the media due to its novel qualities, namely its traceability and decentralization. The price of Bitcoin fluctuates greatly because it is a decentralized digital currency rather than a sovereign one that is not guaranteed by any government [1]. The value of Bitcoin varies unexpectedly, yet similar to a stock. It differs from typical flat currencies in that it is open, whereas there is no comprehensive data on either cash or flat currencies. The first cryptocurrency to be implemented was Bitcoin, which became popular in 2012. It was initially introduced in 2009. Cryptocurrency consists solely of codes with a certain degree of financial calculation. Despite being the world's first decentralized digital money, Bitcoin is not controlled by any national or international authority.

Liu *et al.* [2] employ a graph meta-path network to represent a heterogeneous information network, and it is capable of being transformed to acquire mixed meta-pathways, which cram the tracks among multi-hop connection nodes. Because the model does not require manual assignment of a meta-path, its efficiency is enhanced. Value expectation is determined using a variety of computations using stock market data. Nevertheless, the factors upsetting Bitcoin are discrete. Therefore, to make wise speculating decisions, it is critical to anticipate Bitcoin's future value. The projection of Bitcoin is independent of market conditions or intervening authorities, unlike stock market advertising. In this way, Rizwan *et al.* [3] suggested long short-term memory (LSTM), gated recurrent unit (GRU), and reccurrent neural network (RNN) models that were implemented. It was revealed that the total variable and dataset may affect the outcome. The prior model, which was created with RNN and LSTM, had a projected accuracy of about 52%. A GRU result accuracy of 94.70% is predicted by the optimal model. A 42.3% accuracy improvement is shown by the suggested model. In this work, many variables influence the Bitcoin market, and bidirectional LSTM (BiLSTM's) bidirectionality enables it to interpret price data in both sequential and complicated ways across time. By considering Bitcoin dataset, BiLSTM's bidirectional sequence processing capability reduces the inaccuracy associated with short-term predictions.

2. MATERIALS AND METHOD

Globally, Bitcoin is a popular digital payment method and cryptocurrency that is utilized by many people. The program came into being in the early 2010s and was made accessible as open-source. We use historical Bitcoin data over the last eight years, from September 2020 to January 2012 [4]-[7]. Firstly, we preprocess the data and ensure that it is balanced. bitstamp.set_index("Timestamp") establishes the index as the "Timestamp" column. By doing bitstamp.isnull().sum(), the total amount of missing values for every column in the dataset is determined. By differentiating the series, autoregressive integrated moving average (ARIMA) can successfully capture both short- and long-term variations and trends in non-stationary data. Extreme gradient boosting (XGBoost) works effectively in noisy data situations because of its regularization algorithms (L1 and L2), which serve to minimize overfitting. Long-term relationships in the data could be remembered by LSTMs, unlike simpler models such as ARIMA or conventional neural networks. This helps anticipate the price of Bitcoin based on historical price fluctuations. The capacity of BiLSTM to learn from both past and future contexts gives it an advantage over ordinary LSTM networks when it comes to predicting Bitcoin prices [8], [9].

2.1. Visualizing using KDEs

Kernel density estimation (KDE) plots provide a smoothed distribution that makes it easier to see the fundamental probability density of the price of Bitcoin without being unduly impacted by noise or data spikes. Where Bitcoin values tend to be clustered and where they invested the most time during a specific period may be easily shown using KDE graphs [10], [11]. We may graphically examine the changes in Bitcoin price distributions over time by charting KDEs for various time intervals (e.g., annually, quarterly). Figure 1 shows the KDE plot, which provides us a smoothed-out representation of a histogram, which makes it easier to see how data points are distributed. Data on Bitcoin is frequently skewed or heavy-tailed, or not distributed regularly. Compared to parametric techniques like fitting normal distributions, KDE is more adaptable and more accurate in capturing the actual form of the data. By showing the spread of variation and any multi-modal behavior, KDE plots can shed light on the volatility of Bitcoin values. To present a more thorough picture of Bitcoin price patterns and dispersion across various periods, KDE plots coupled with other plots such as time series or scatter plots [12].

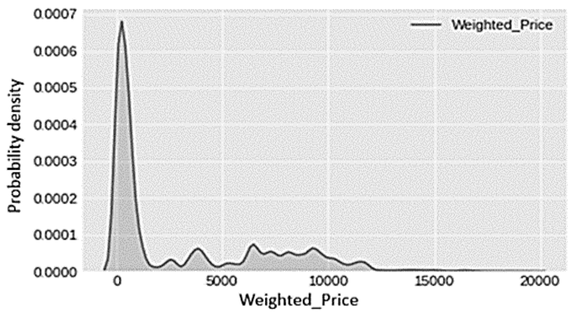

Figure 1. Visualizing missing values using KDE

2.2. Kwiatkowski-Phillips-Schmidt-Shin test

One important statistical test for determining if a time series is stationarity is the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, which is cast-off to estimate the price of Bitcoin [13]. A time series' stationaryity, or the degree to which its statistical characteristics (variance and mean) remain constant across time, may be ascertained using the KPSS test. The assumption of stationarity is crucial for several forecasting models. You can efficiently use standard time series models and improve forecast accuracy by making sure the Bitcoin price series is stationary. Model outputs might become unreliable due to non-stationary data. When looking for deterministic trends in data a non-random pattern that has the potential to influence Bitcoin values over time KPSS is very helpful. The right kind of model to employ for predicting Bitcoin prices may be chosen with the help of the KPSS test. Data transformation can be required if the test shows that the time series is not stationary. In the event of regime shifts, forecasting models may become more accurate if we identify structural breakdowns in the data and divide them into segments that are useful for prediction. To comprehend a time series' basic structure, a time series decomposition plot dissects it into its essential elements [14], [15]. The time series decomposition plot is shown in Figure 2.

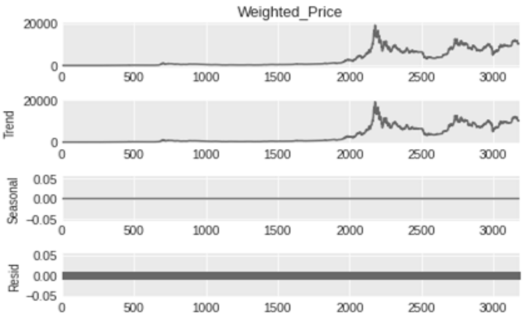

Figure 2. Time series decomposition plot

2.3. Imputation techniques

Time series datasets, including those about Bitcoin, employ imputation techniques to address missing data. Data collection difficulties, API problems, and market outages can all result in missing numbers [16]. Since deficiencies are not appropriately addressed, a lot of models that deal with missing variables either crash or yield inaccurate conclusions. Models are better able to correctly identify the underlying patterns when missing values are imputed, keeping the dataset entire. Predictions of Bitcoin prices become more accurate and less biased as a result [17]. Data loss is a serious consequence of certain approaches, such as deleting rows that have missing values. Due to the extreme volatility and recurrent price fluctuations of Bitcoin, datasets including this information may contain many data points that are critical for research.

In prediction models, replacing missing values in a Bitcoin dataset using forward fill ('ffill' or 'pad') and backward fill ('bfill' or 'backfill') can have several advantages, especially when working with time series data. It is easy to use forward and backward filling in the Bitcoin dataset since they are straightforward imputation techniques that need little processing. Since the latest observed price trend keeps moving forward, forward fill (or "ffill") maintains the most recently recorded Bitcoin price, which may be helpful if the data points that are absent are within a small range. When projecting into the future, backward fill (or "bfill") might be helpful since it allows gaps in data to be filled in using the next recorded value [18], [19]. Figure 3 shows different imputation techniques for time series and non time series data.

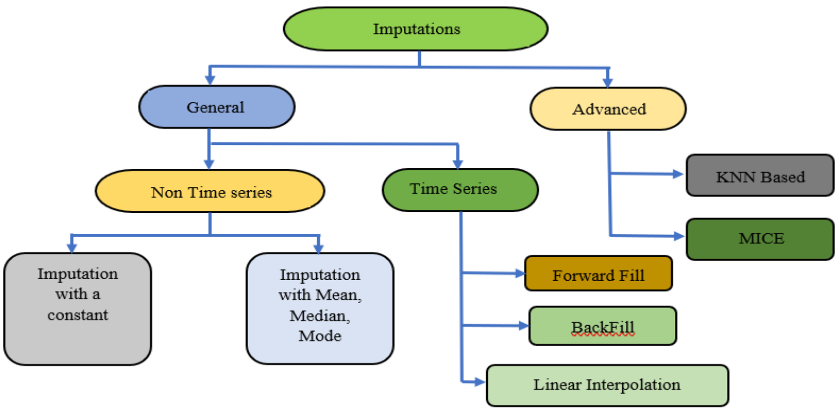

Figure 3. Different imputation techniques for time series and non time series data

3. PROPOSED MODEL

This work aims to forecast Bitcoin values using various machine learning and deep learning algorithms, which is a powerful approach given the volatility and complexity of cryptocurrency markets. To make certain that those gaps were filled in a way that reduces bias and increases the accuracy of the model, we used the linear interpolation approach for data imputation in this study. This dataset's test data spans the months of January 2020 through September 2020. The complete workflow diagram of this work is given in Figure 4.

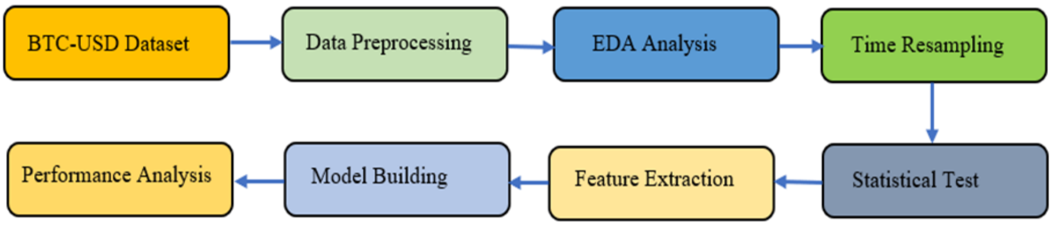

Figure 4. Workflow diagram

3.1. ARIMA

ARIMA offers a straightforward and efficient method of making future price predictions from previous data without the need for intricate feature engineering [20]. The ARIMA model is signified as ARIMA (p, d, q), where p denotes to the figure of lagged observations, d represents the number of times the data is differenced, and q accounts for the rapport among an remark and a remaining error. It can be written in (1) to (4). Figure 5 shows the ARIMA predicted BTC price. Bitcoin prices are frequently non-stationary, which means that over time, trends or seasonality may have an impact on their statistical characteristics. By differencing the data to create a stationary series, ARIMA models address non-stationarity. Because of this property, ARIMA may be used to Bitcoin prices with good results, regardless of whether the data exhibits patterns or fluctuating degrees of volatility over time [21].

$$X_t = c + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \epsilon_t \tag{1}$$

$$Y_t = X_t - X_{t-d} \tag{2}$$

$$X_t = \mu + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{3}$$

$$X_t = c + \emptyset_1 X_{t-1} + \cdots + \emptyset_p X_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{4}$$

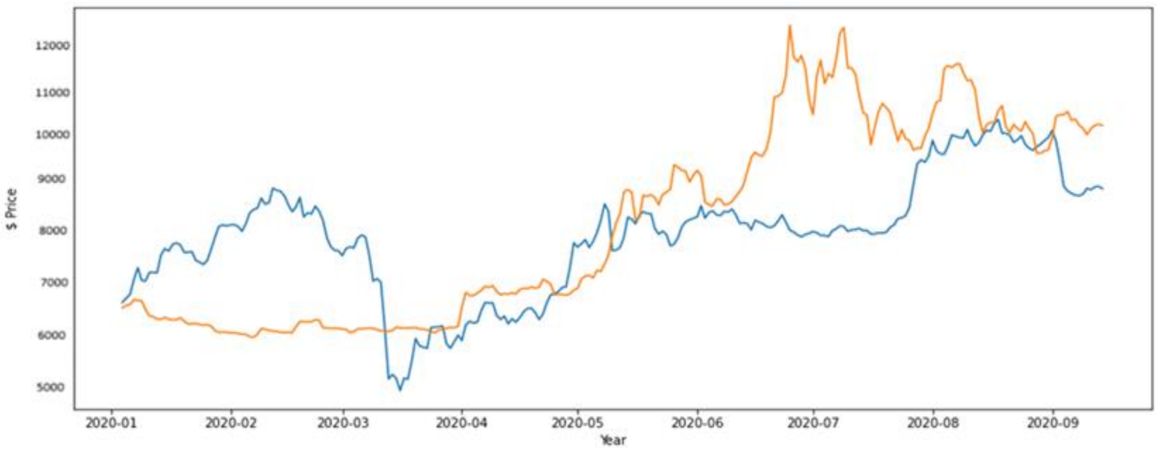

Figure 5. ARIMA predicted BTC price

3.2. XGBoost

By automatically determining the appropriate imputation approach for missing data, XGBoost handles missing values natively. This is quite helpful for predicting Bitcoin when there may be missing or insufficient data, especially when combining data from several sources. Figure 6 shows the XGBoost predicted BTC price. The XGBoost model is simplified as given in (5) to (9). Time series data be modeled by XGBoost in conjunction with feature engineering. Rather than depending just on autoregressive techniques like ARIMA, it captures temporal interdependence by using past price data as features. With the help of past prices, and various other pertinent data, XGBoost can manage Bitcoin time series data and produce precise forecasts based on previous patterns and trends without requiring specialized time series models [22].

$$\delta(\theta)=\sum_{i=1}^{n} L\,(y_i\hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{5}$$

$$\mathrm{L}(y_i, \hat{y}_i) = (y_i - \hat{y}_i)^2 \tag{6}$$

$$\mathrm{L}(y_i, \hat{y}_i) = -[y_i \log\big(\sigma(\hat{y}_i)\big) + (1 - y_i)\log(1 - \sigma(\hat{y}_i))] \tag{7}$$

$$\hat{y}_t = \hat{y}_{t-1} + f_t(x) \tag{8}$$

$$\hat{y}_t = \hat{y}_{t-1} + \eta f_t(x) \tag{9}$$

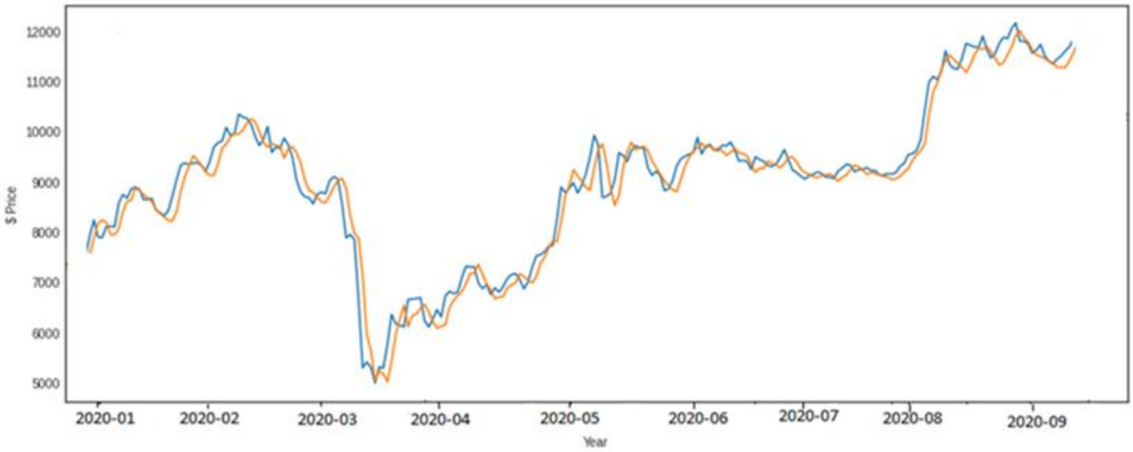

Figure 6. XGBOOST predicted BTC price

3.3. LSTM

The digital currency market is a dynamic space where things shift quickly. Because LSTMs can continually learn from fresh data, the model can regulate to new market patterns and regime transitions. Figure 7 shows the LSTM projected BTC price. The LSTM model is expressed as in (10) to (14). LSTM models are useful for remembering and learning from long-term information, which enhances prediction accuracy when it comes to Bitcoin values because past data spanning months or even years might impact present pricing [23], [24].

$$f_t = \sigma(P_f.[q_{t-1}, x_t] + s_f) \tag{10}$$

$$i_t = \sigma(P_i.[q_{t-1}, x_t] + s_i) \tag{11}$$

$$o_t = \sigma(P_o.[q_{t-1}, x_t] + s_o) \tag{12}$$

$$\hat{c}_t = \tanh\,(P_c.[q_{t-1}, x_t] + s_c) \tag{13}$$

$$q_t = o_t.\tanh(c_t) \tag{14}$$

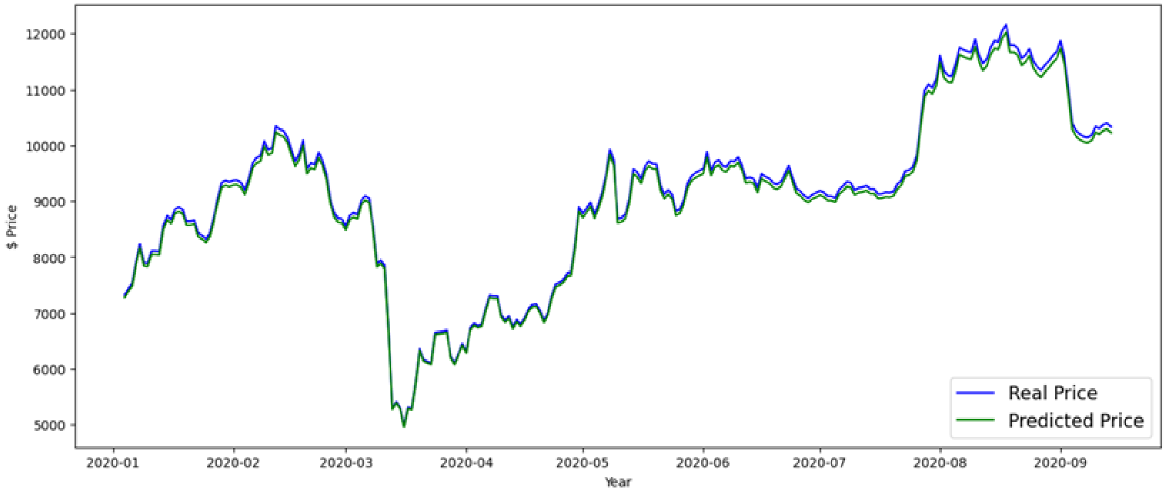

Figure 7. LSTM predicted BTC price

3.4. BiLSTM

The dual perspective of the BiLSTM model is helps forecast Bitcoin since it provides information about future market movements that improves our comprehension of current patterns and increases forecast accuracy. Figure 8 shows the Bi-LSTM predicted BTC price. The Bi-LSTM model is simplified as in (15) to (18). The gating mechanisms and cell state of the LSTM architecture are specially engineered to retain long-term dependence. This suggests that Bi-LSTMs can acquire and remember pertinent knowledge from a very distant past, knowledge that may have an impact on the price of Bitcoin today. Bi-LSTMs are naturally optimized to handle sequential data, such as time series. Since Bitcoin prices are logical, the sequence in which observations are made is significant [25]-[27].

$$\vec{h}_t=LSTM_{forward}(x_t,\vec{h}_{t-1}) \tag{15}$$

$$\overleftarrow{h}_t = LSTM_{backward}(x_t,\overleftarrow{h}_{t+1}) \tag{16}$$

$$\vec{h}_t=\sigma(W_{x\vec{h}}x_t + W_{\vec{h}\vec{h}}\overrightarrow{h_{t-1}} + b_{\vec{h}}) \tag{17}$$

$$\overleftarrow{h}_t = \sigma(W_{x\overleftarrow{h}}x_t + W_{\overleftarrow{h}\overleftarrow{h}}\overleftarrow{h_{t-1}} + b_{\overleftarrow{h}}) \tag{18}$$

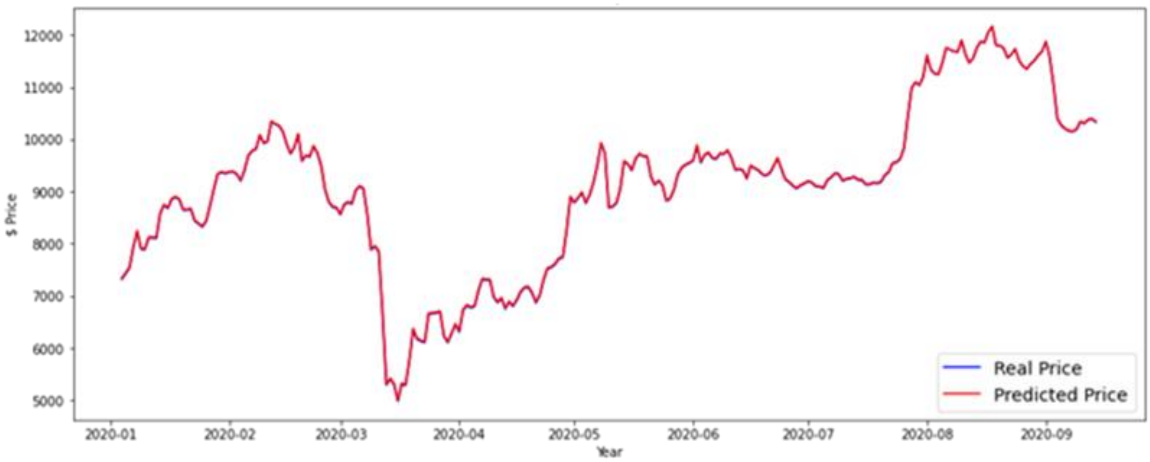

Figure 8. Bi-LSTM predicted BTC price

4. RESULT ANALYSIS

The ability of deep learning models to automatically extract characteristics from unprocessed data is one of its major advantages. Important trends in Bitcoin price data get automatically identified by deep learning models, eliminating the need for manually-engineered features. Future movements and past tendencies both have an impact on the price of Bitcoin. Through full-time series consideration, BiLSTM can capture both short- and long-term price dependence.

According to Table 1 the MAE and RMSE score of different models. The ARIMA model gets higher error metrics with an MAE score of 1035.41 and an RMSE score of 1733.71. In contrast, the XGBOOST shows notable improvement with an MAE score of 225.36 and an RMSE score of 617.91. Moving to deep learning models the LSTM model shows prominent perfection with an MAE score of 113.56 and an RMSE score of 214.37. The Bi-LSTM model maintains the performance with the lowest MAE score 24.73 and RMSE score of 67.18. Figure 9 shows the bar diagram of the MAE and RMSE scores of different models. Once trained, deep learning models are used for real-time prediction. This is especially helpful for high-frequency Bitcoin trading, where choices need to be made in milliseconds based on quickly shifting market information.

Table 1. MAE and RMSE score of different models

Model name	MAE	RMSE
ARIMA	1035.41	1733.71
XGBOOST	225.36	617.91
LSTM	113.56	214.37
Bi-LSTM	24.73	67.18

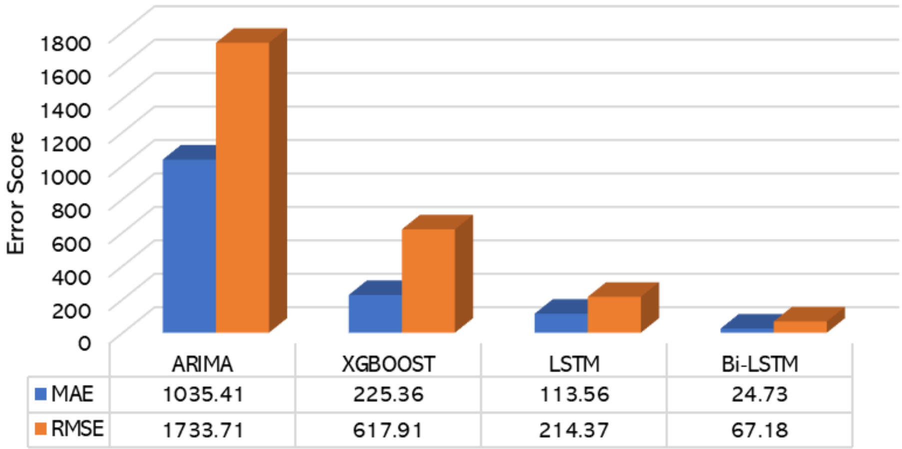

Figure 9. Performance analysis of different models

5. CONCLUSION

The market for cryptocurrencies, particularly Bitcoin, is very volatile. To capture the bidirectional character of market reactions, BiLSTM not only analyses historical price changes but also takes into account what occurs following certain market moves. The model works effectively at capturing the general trend and pattern that governs the movement in the price of Bitcoin and can help traders find possible chances to purchase or sell. It is vital to comprehend that the volatility of the Bitcoin price poses a problem to the production of precise projections. Further research into other methods to lessen the effect of volatility and enhance the predictability of the model will be beneficial. Furthermore, adding outside variables like macroeconomic statistics, regulatory developments, and market emotion might increase the precision of Bitcoin price projections. A greater knowledge of the Bitcoin market and the facilitation of decision-making processes will result from ongoing study and forecasting model improvement.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Nrusingha Tripathy	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
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Rajesh Kumar Ghosh	✓		✓	✓		✓			✓		✓		✓	
Biswajit Dash														
Archana Rout					✓		✓			✓		✓		
Nirmal Keshari Swain			✓							✓		✓		
Subrat Kumar Nayak					✓			✓				✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

kaggle/input/bitcoin-historical-data/bitstampUSD_1-min_data_2012-01-01_to_2020-09-14.csv. The authors confirm that the data supporting the findings of this study are available within the link

REFERENCES

[1] P. Monamo, V. Marivate, and B. Twala, “Unsupervised learning for robust Bitcoin fraud detection,” in *2016 Information Security for South Africa - Proceedings of the 2016 ISSA Conference*, Aug. 2016, pp. 129–134, doi: 10.1109/ISSA.2016.7802939.

[2] L. Liu, W. T. Tsai, M. Z. A. Bhuiyan, H. Peng, and M. Liu, “Blockchain-enabled fraud discovery through abnormal smart contract detection on Ethereum,” *Future Generation Computer Systems*, vol. 128, pp. 158–166, Mar. 2022, doi: 10.1016/j.future.2021.08.023.

[3] M. Rizwan, S. Narejo, and M. Javed, “Bitcoin price prediction using deep learning algorithm,” in *MACS 2019 - 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics, Proceedings*, Dec. 2019, pp. 1–7, doi: 10.1109/MACS48846.2019.9024772.

[4] N. Tripathy, S. Hota, D. Singh, B. M. Acharya, and S. K. Nayak, “A comprehensive analysis of Bitcoin volatility forecasting using time-series econometric models,” *Applied Soft Computing*, vol. 113, Art. no. 113339, May 2025.

[5] S. K. Nayak, A. K. Nayak, S. Mishra, P. Mohanty, N. Tripathy, and K. S. Chaudhury, “Exploring speech emotion recognition in tribal language with deep learning techniques,” *International Journal of Electrical and Computer Engineering Systems*, vol. 16, no. 1, pp. 53–64, Jan. 2025.

[6] E. Jung, M. Le Tilly, A. Gehani, and Y. Ge, “Data mining-based ethereum fraud detection,” in *Proceedings - 2019 2nd IEEE International Conference on Blockchain, Blockchain 2019*, Jul. 2019, pp. 266–273, doi: 10.1109/Blockchain.2019.00042.

[7] M. Bartoletti, S. Lande, A. Loddo, L. Pompianu, and S. Serusi, “Cryptocurrency scams: analysis and perspectives,” *IEEE Access*, vol. 9, pp. 148353–148373, 2021, doi: 10.1109/ACCESS.2021.3123894.

[8] N. Tripathy *et al.*, “A comparative analysis of exponential smoothing method and deep learning models for bitcoin price prediction,” *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 14, no. 2, p. 1401, Apr. 2025, doi: 10.11591/ijai.v14.i2.pp1401-1409.

[9] T. Ashfaq *et al.*, “A machine learning and blockchain based efficient fraud detection mechanism,” *Sensors*, vol. 22, no. 19, p. 7162, Sep. 2022, doi: 10.3390/s22197162.

[10] H. Kanezashi, T. Suzumura, X. Liu, and T. Hirofuchi, “Ethereum fraud detection with heterogeneous graph neural networks,” *arXiv preprint arXiv:2203.12363*, 2022.

[11] A. A. Amponsah, A. F. Adekoya, and B. A. Weyori, “A novel fraud detection and prevention method for healthcare claim processing using machine learning and blockchain technology,” *Decision Analytics Journal*, vol. 4, p. 100122, Sep. 2022, doi: 10.1016/j.dajour.2022.100122.

[12] N. Tripathy, S. K. Nayak, and S. Prusty, “A comparative analysis of Silverkite and inter-dependent deep learning models for bitcoin price prediction,” *Frontiers in Blockchain*, vol. 7, May 2024, doi: 10.3389/fbloc.2024.1346410.

[13] Y. Kumar, “AI techniques in blockchain technology for fraud detection and prevention,” in *Security Engineering for Embedded and Cyber-Physical Systems*, CRC Press, 2022, pp. 207–224.

[14] A. Sallam, T. Rassem, H. Abdu, H. Abdulkareem, N. Saif, and S. Abdullah, “Fraudulent account detection in the ethereum’s network using various machine learning techniques,” *International Journal of Software Engineering and Computer Systems*, vol. 8, no. 2, pp. 43–50, Jul. 2022, doi: 10.15282/ijsecs.8.2.2022.5.0102.

[15] N. Tripathy, S. Hota, D. Mishra, B. Dash, S. K. Nayak, and J. Tripathy, “Empirical analysis of digital currency herding and contagion effect using deep learning approaches,” in *3rd Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology, ODICON 2024*, Nov. 2024, pp. 1–6, doi: 10.1109/ODICON62106.2024.10797617.

[16] V. Patel, L. Pan, and S. Rajasegarar, "Graph deep learning based anomaly detection in ethereum blockchain network," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12570 LNCS, Springer International Publishing, 2020, pp. 132–148.

[17] N. Tripathy, S. Hota, D. Mishra, S. K. Nayak, S. S. Dalai, and J. Tripathy, "Cryptocurrency price prediction: a comprehensive analysis of high-dimensional features with deep learning techniques," in *Proc. International Conference on Intelligent Computing and Sustainable Innovations in Technology (IC-SIT),* Nov. 2024, pp. 1–6

[18] A. Viswam and G. Darsan, "An efficient bitcoin fraud detection in social media networks," in *Proceedings of IEEE International Conference on Circuit, Power and Computing Technologies, ICCPCT 2017*, Apr. 2017, pp. 1–4, doi: 10.1109/ICCPCT.2017.8074262.

[19] N. Tripathy, S. Hota, S. Prusty, and S. K. Nayak, "Performance analysis of deep learning techniques for time series forecasting," in *2023 International Conference in Advances in Power, Signal, and Information Technology, APSIT 2023*, Jun. 2023, pp. 639–644, doi: 10.1109/APSIT58554.2023.10201734.

[20] R. Tan, Q. Tan, P. Zhang, and Z. Li, "Graph neural network for ethereum fraud detection," in *Proceedings - 12th IEEE International Conference on Big Knowledge, ICBK 2021*, Dec. 2021, pp. 78–85, doi: 10.1109/ICKG52313.2021.00020.

[21] O. I. Jacinta, A. E. Omolara, M. Alawida, O. I. Abiodun, and A. Alabdultif, "Detection of Ponzi scheme on Ethereum using machine learning algorithms," *Scientific Reports*, vol. 13, no. 1, Oct. 2023, doi: 10.1038/s41598-023-45275-0.

[22] N. Nayyer, N. Javaid, M. Akbar, A. Aldegheishem, N. Alrajeh, and M. Jamil, "A new framework for fraud detection in bitcoin transactions through ensemble stacking model in smart cities," *IEEE Access*, vol. 11, pp. 90916–90938, 2023, doi: 10.1109/ACCESS.2023.3308298.

[23] N. Tripathy *et al.*, "Bitcoin volatility forecasting: a comparative analysis of conventional econometric models with deep learning models," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 15, no. 1, pp. 614–623, Feb. 2025, doi: 10.11591/ijece.v15i1.pp614-623.

[24] K. Rathan, S. V. Sai, and T. S. Manikanta, "Crypto-currency price prediction using decision tree and regression techniques," in *Proceedings of the International Conference on Trends in Electronics and Informatics, ICOEI 2019*, Apr. 2019, vol. 2019-April, pp. 190–194, doi: 10.1109/icoei.2019.8862585.

[25] M. Ali and S. Shatabda, "A data selection methodology to train linear regression model to predict bitcoin price," in *2020 2nd International Conference on Advanced Information and Communication Technology, ICAICT 2020*, Nov. 2020, pp. 330–335, doi: 10.1109/ICAICT51780.2020.9333525.

[26] J. Tripathy, R. Dash, B. K. Pattanayak, D. Mohapatra, N. Tripathy, and S. K. Nayak, "An improved model for gene expression data analysis using combined feature reduction and ELM approaches," in *Proc. 3rd Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology (ODICON),* Nov. 2024, pp. 1–6.

[27] B. Chen, F. Wei, and C. Gu, "Bitcoin theft detection based on supervised machine learning algorithms," *Security and Communication Networks*, vol. 2021, pp. 1–10, Feb. 2021, doi: 10.1155/2021/6643763.

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