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Predicting Bitcoin Prices Using Deep Learning

Manaf ahmed[1], Mohammed H. Adnan[2], Ali Matar[3], Faez Hlail Srayyih[4], Marwan hammoodi[5], Mathil Kamil Thamer[6], Abdulrahman Obaid Jumaah[7]

[1,2,4-7]University of Anbar, College of Administration and Economic, Iraq

[3*] Department of Financial Technology, Faculty of Business, Jadara University, P. O. Box 733, Irbid, Jordan amatar@jadara.edu.jo ORCID: 0000-0003-0599-5855

Abstract

Predicting cryptocurrency price is challenging owing to high volatility, less historical data, and the impact of external parameters like news, public sentiment, and regulatory announcements. This challenge is tackled in this research by employing models of deep learning like Recurrent Neural Network (RNN), Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU)—to predict Bitcoin's OHLC prices daily. Based on historical time-series data of Coin Codex, the research uses an autoencoder-based feature extraction method with five-day sliding window method for sequence generation. Hyperband optimization is used to tune hyperparameter of each model. The result shows that BiLSTM performs better than all the other models with minimum Mean Squared Error (MSE = 0.001183), Mean Absolute Error (MAE = 0.026090), and maximum R² score (0.980596) after optimization. The results emphasize the significance of deep learning in capturing nonlinear dynamics in time series of financial applications and bear testimony to the effectiveness of hyperparameter tuning in enhancing model accuracy. The study enhances the development of prediction tools for digital asset markets and enables more informed investment decisions.

Keywords*: Bitcoin; Deep Learning; Cryptocurrency; Neural Network; Prediction; Optimization.*

1 Introduction

Diabetes Cryptocurrency is a current development in the digital and finance sector. It is an electronic or virtual currency that relies on cryptographic techniques to secure it, hence ensuring its integrity and immutability. Cryptocurrencies diverge from conventional fiat money, which is regulated and issued by a central bank, as they employed on decentralized networks established on blockchain technology a network of computers whereby transactions are recorded on a distributed ledger system securely and transparently (Almeida and Gonçalves, 2023). Bitcoin, launched in 2009 by a mysterious individual going by the name of Satoshi Nakamoto, is the original and still the most well-known cryptocurrency. This was followed by the ecosystem around it, which witnessed a phenomenal development wave, spawning thousands of other virtual tokens, such as Ethereum, Binance Coin, Solana, and a host of altcoins. These cryptocurrencies have uses beyond just enabling peer-to-peer transactions; they are also being utilized in various areas such as smart contracts, gaming, decentralized finance (DeFi), digital identity, non-fungible tokens (NFTs) and supply chain management, (Almeida and Gonçalves, 2023).

The forecasting of cryptocurrency prices is now a very important focus area for traders, investors, researchers, and financial institutions. In comparison with conventional financial markets, where price movements are frequently determined by well-defined economic indicators and regulatory frameworks, the cryptocurrency market is extremely volatile and speculative. Daily price movements of 5% to 20% are routine, and large changes may take place within a matter of minutes. Such intense volatility presents very big opportunities along with risks for market participants (Khaniki and Manthouri, 2024). Accurate Accurate price prediction models can enable investors to produce more informed decisions on when to buy and sell. This can minimize losses and improve risk management. Also, if more people are using cryptocurrencies and institutions are investing in them, it is important to have good prediction tools for creating trading strategies, hedging products, and digital asset-based financial products (Wu et al., 2024).

Yet, predicting of cryptocurrency price comes with a multitude of challenges. Primarily, the market is plagued by intense volatility, which tends to be fuelled by speculatory trading activity, news reports, regulatory releases, and social media trend dynamics. Classical time-series prediction methods generally tend to falter under these rapidly evolving and nonlinear trends. Moreover, the crypto market is fairly nascent, with numerous coins not having ample historical data employed for effective model training (Otabek and Choi, 2024). As opposed to conventional assets like equities or fixed-income securities, cryptocurrencies are not drawn by physical assets or earnings reports, so it is difficult to determine intrinsic values. To that is included the issue of market manipulation; pump-and-dump schemes that are coordinated and the activities of "whales" (individuals or entities with large positions in a cryptocurrency) can create deceptive price action which bewilders conventional forecasting models. Further, the pseudonymous and decentralized character of blockchain networks renders it challenging to discern investor behavior and market sentiment using traditional approaches (Singh et al., 2025).

With such complexities, researchers and practitioners alike have resorted to seeking sophisticated computational approaches to enhance the accuracy of price predictions. Machine learning (ML) and artificial intelligence (AI) algorithms have demonstrated promising performance in capturing the volatile and intricate dynamics of cryptocurrency prices (Singh et al., 2025). Artificial neural networks (ANN), long short-term memory (LSTM) networks, support vector machines (SVM), and decision trees are applied to uncover complex patterns and non-linear relationships in market data. Natural language processing (NLP) applications also help in analyzing sentiments in news headlines, tweets, Reddit discussions, etc. By measuring public sentiments, the models can forecast how public sentiments may affect price trends. (Xu et al., 2024). Hybrid models, which meld technical analysis indicators such as relative strength index, moving averages, and Bollinger bands with artificial intelligence and statistical learning, provide a more complete methodology for prediction. Another new methodology is blockchain analytics, which entails analysis of the on-chain data ranging from wallet activity, transaction volume, and token balances to discern actionable insights into investor behavior and market momentum (Somayajulu and Kotaiah, 2023).

This article proposes a deep learning model that will predict Bitcoin's daily OHLC prices based on the BiLSTM, RNN, and GRU models. The proposed solution involves a detailed data preprocessing step involving feature extraction, normalization, and sequence construction using a sliding window of five days. We use an autoencoder to extract useful latent features, and the Hyperband optimization algorithm to optimize the model hyperparameters in a computationally efficient manner. Among the model pool examined, the optimized BiLSTM achieved the highest accuracy, with a great outperformance compared to other models on MSE, MAE, and R^2 score. This method offers a stable and scalable model for predicting cryptocurrency prices and has the potential to be applied to algorithmic trading and financial risk management.

2 Related Work

The formidable challenge of predicting cryptocurrency prices has spurred extensive research, evolving from classical statistical models to sophisticated hybrid deep-learning architectures. This evolution reflects a continuous effort to capture the unique blend of non-linearity, high volatility, and sensitivity to external factors that characterize markets like Bitcoin's.

Early foundational work by Ayaz et al. (2020) demonstrated the application of the ARIMA model for short-term forecasting, establishing a baseline though it highlighted gaps in long-term prediction and model comparison. The field quickly pivoted towards machine learning (ML) and deep learning (DL), with literature reviews like Kervanci and Akay (2020) and Thanvi et al. (2021) systematically cataloging this shift, noting the superior performance of ML/DL models like Support Vector Machines (SVM) and Bayesian Neural Networks (BNNs) over traditional statistical methods.

A significant strand of research has focused on architectural innovations within deep learning. Studies by Singh et al. (2021) and Singathala et al. (2023) found that bidirectional recurrent structures (Bi-GRU, BiLSTM) excelled in capturing temporal dependencies, while Freeda et al. (2021) showed RNNs' potential for longer horizons. The quest for accuracy led to comparisons of myriad models, including GRU and MLP (Al-Nefaie and Aldhyani, 2022), CNN and Random Forest (Alamery, 2023), and Linear Regression models (Liu et al., 2024), with results often contingent on the specific dataset and evaluation metrics.

To enhance robustness, researchers have incorporated diverse data sources. Kutlu Karabiyik and Can Ergün (2021) integrated technical and economic indicators using ANFIS, while Arjmand et al. (2024) and Chatterjee et al. (2024) advanced this further by incorporating news sentiment analysis and macroeconomic factors, demonstrating their time-varying influence on price.

The most recent trend involves developing hybrid models to synergize the strengths of different architectures. Hota et al. (2024) combined LSTM and GRU, Srivastava et al. (2023) fused genetic algorithms with ARIMA, and Ateeq et al. (2023) proposed a novel LSTM-BTC variant, all reporting significant performance gains over standalone models.

Other approaches have combined different model types, such as LSTM with SARIMA and Prophet (Cheng et al., 2024), or ARIMA with GARCH (Phung Duy et al., 2024), to better capture both price and volatility dynamics.

Further studies have provided unique insights, such as using blockchain data over sentiment (Khadija et al., 2024), employing high-frequency data for futures prediction (Akyildirim et al., 2023), applying models to identify structural breaks and bubbles (Dhaku and Arumugam, 2023), and using logistic regression to challenge market efficiency (Dimitriadou and Gregoriou, 2023). Broader comparative analyses by Tiwari et al. (2021), Benjamin et al. (2022), Sonare et al. (2023), and Agrawal et al. (2023) have consistently found that AI and deep learning models, particularly LSTM and its variants, deliver superior accuracy.

The table below summarizes the core methodologies and findings of these studies, highlighting the diversity in datasets, methods, and performance metrics that define the current research landscape.

Table 1: Summary of Bitcoin Price Prediction Studies

Study	Key Methods	Key Findings / Performance
Ayaz et al. (2020)	ARIMA	Good for short-term trends; gaps in long-term forecasts.
Kervanci & Akay (2020)	Literature Review (ML/DL)	ML/DL (especially GRU, Ensemble) outperform statistical models.
Thanvi et al. (2021)	SVM, BNNs	SVM and BNNs show excellent predictive power.
Kutlu & Ergün (2021)	ANFIS	Effective with technical/economic indicators; highlights feature selection gap.
Freeda et al. (2021)	RNN	76.99% accuracy for long-term prediction, outperforming traditional ML.
Singh et al. (2021)	LSTM, Bi-LSTM, GRU, Bi-GRU	Bi-GRU achieved the highest predictive accuracy.
Tiwari et al. (2021)	ARIMA, Prophet, XGBoost	Highlights need for robust, adaptable forecasting instruments.
Akyildirim et al. (2023)	Various MLAs	MLAs surpassed ARIMA/RW in forecasting Bitcoin futures.
Al-Nefaie & Aldhyani (2022)	GRU, MLP	MLP outperformed GRU (Testing MSE: 0.000109 vs. 0.03354).
Departmental Study (2022)	12 ML Regressors	Best models achieved MSE of 0.00002, R^2 of 99.2%.

Study	Key Methods	Key Findings / Performance
Dhaku & Arumugam (2023)	ARIMA, Prophet	Prophet outperformed ARIMA; identified structural breaks.
Mittal & Geetha (2022)	GRU	GRU effective based on MAPE and RMSE.
Benjamin et al. (2022)	Linear Regression, KNN, Random Forest	Compares algorithms for crypto price pattern estimation.
Benjamin et al. (2022)	LSTM, ARIMA, SARIMA	LSTM performed best ($R^2 = 0.9702$, RMSE = 1447.648).
Sonare et al. (2023)	Various ML Models	Significance of model selection for different prediction horizons.
Agrawal et al. (2023)	AI-LSTM, ARIMA, SVM, Decision Tree	AI-LSTM had highest accuracy for daily forecasts.
Alamery (2023)	CNN, Random Forest, other ML/DL	CNN (RMSE: 0.0543) and RF (RMSE: 0.0246) performed best.
Liu et al. (2024)	OLS, LASSO, LSTM, Decision Tree	Linear regressors (OLS, LASSO) performed relatively better.
Dimitriadou & Gregoriou (2023)	Logistic Regression, SVM, Random Forest	Logistic Regression best (66% accuracy); challenges market efficiency.
Ateeq et al. (2023)	LSTM-BTC (novel variant)	Outperformed traditional models across multiple error metrics.
Singathala et al. (2023)	GRU, BiLSTM, BiGRU, LSTM	BiGRU most accurate (MAPE: 3.41).
Srivastava et al. (2023)	Genetic ARIMA	Enhanced predictability vs. standard ARIMA, especially post-COVID.
Hota et al. (2024)	LSTM-GRU Hybrid, ARIMA, Prophet, XGBoost	LSTM-GRU hybrid performed best (MAE: 0.464, RMSE: 0.323).
Khadija et al. (2024)	Deep Autoencoder, CNN-LSTM	Blockchain data most influential; external factors had limited impact.
Chatterjee et al. (2024)	Random Forest, DL models, VAR, VECM	DL and RF models superior; key predictors change over time (e.g., COVID-19).

Study	Key Methods	Key Findings / Performance
Cheng et al. (2024)	LSTM, SARIMA, Prophet	LSTM outperformed others; identified seasonal volatility patterns.
Arjmand et al. (2024)	2DCNN-GRU Hybrid, CryptoBERT	Proposed hybrid outperformed competitors, especially on MAE.
Phung Duy et al. (2024)	ARIMA-GARCH	ARIMA(12,1,12)-GARCH(1,1) provided accurate forecasts for 2021-2023.

3 Methodology

This chapter presents and discusses the research design, including the proposed system illustrated in Figure (1), in order to address the research questions and achieve the research objective.

3.1 Dataset (Missing value, consistency and normalization)

The study utilizes a comprehensive dataset of daily Bitcoin price data sourced from CoinCodex. The dataset covers the period from 1 January 2018 to 31 December 2023, comprising 2,191 daily records. For the purpose of this research, we focus on the key price features: Open, High, Low, and Close (OHLC).

The dataset was partitioned temporally, with data from 1 January 2018 to 31 December 2022 (1,826 records) used for training and validation, and data from 1 January 2023 to 31 December 2023 (365 records) reserved for testing the models. This split ensures that models are evaluated on unseen future data, simulating a real-world forecasting scenario.

The preprocessing pipeline involved two critical steps:

1. Data Consistency & Cleaning: The dataset was found to be complete with no missing values, ensuring temporal coherence and reliability for time-series analysis.
2. Normalization: To ensure all features contribute equally to the model training and to enhance convergence, the OHLC data were normalized to the [0, 1] range using Min-Max scaling. The scaling parameters were fitted solely on the training set to prevent data leakage.

The data presented on CoinCodex's Bitcoin Historical Data page has an impressive level of data consistency, with well-structured daily entries following a consistent pattern throughout the whole time spectrum. Every entry captures key market indicators, such as date, opening price, high, low, closing price, volume, and market capitalization, all aligned to the same time granularity (daily). The data maintains a chronological order free of duplicates or uneven gaps, thus guaranteeing temporal coherence. Such consistency fosters accurate time-series analysis, modeling, and comparative evaluations over different periods. In addition, the standardized formatting of numeric figures and dates enhances its usability in automated data processing, visualization, and machine learning activities.

But, For the scope of this research, only the pertinent features Open, High, Low, and Close prices were picked from the data set, as they give enough information for analyzing Bitcoin's price patterns and conducting technical analysis. To make all the chosen features contribute equally to the analysis and enhance machine learning model performance, Min-Max normalization was performed on the data. It is a technique that rescales the values of every feature to a common range, usually [0,1]. The Hyperband optimization algorithm is an efficient hyperparameter optimization approach that aims to maximize model performance with minimal computational effort. It is inspired by the principles of multi-armed bandits and extends the Successive Halving algorithm. Hyperband adaptively assigns resources to a huge number of hyperparameter configurations by training them with limited resources (e.g., fewer epochs or a fraction of data) and iteratively pruning poor-performing configurations. The algorithm operates by searching a large hyperparameter space with numerous small budgets and increasing the budget for the most promising ones. In this way, Hyperband achieves a good trade-off between exploration (trying many configurations) and exploitation (fine-tuning the best ones), which makes it highly suitable for settings with vast search spaces and scarce resources.

Hyperband is so beneficial over standard grid or random search techniques since it can deliver similar or superior results using considerably fewer evaluations, enhancing both effectiveness and efficiency in hyper parameter optimization applications.

4 Results

This section presents the empirical findings of our study, which aimed to forecast Bitcoin's OHLC (Open, High, Low, Close) prices using deep learning models enhanced by hyperparameter optimization. The models were trained on data from 1 January 2018 to 31 December 2022 and evaluated on the subsequent unseen test period of 1 January 2023 to 31 December 2023, constituting an approximate 83/17 temporal split. Model performance was assessed using three standard metrics: Mean Squared Error (MSE), which heavily penalizes larger errors; Mean Absolute Error (MAE), which provides a linear score for average error magnitude; and the Coefficient of Determination (R^2 Score), which indicates the proportion of variance in the target variable that is predictable from the input features.

4.1 Training without Optimization

The performance of the deep learning (BiLSTM, RNN, and GRU) models MAE, MSE and the Coefficient of Determination (R^2 Score). The results for predicting Open, High, Low, and Close prices of cryptocurrency before optimization are summarized in table (1) below. Figure (2) represent the training and validation loss for BiLSTM model before optimization.

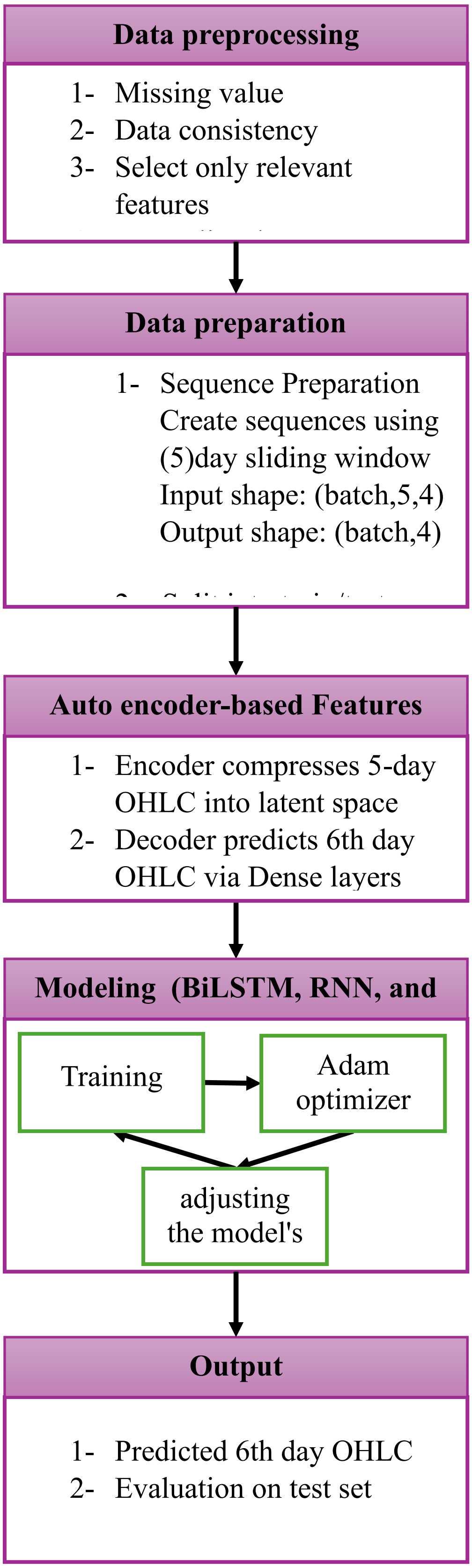

Figure 1 the proposed system.

Table 1 performance measures for the prediction models before optimization

Model	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	R^2 Score
BiLSTM	0.0014	0.0267	0.9777
GRU	0.0057	0.0572	0.9066
RNN	0.0046	0.0525	0.9249

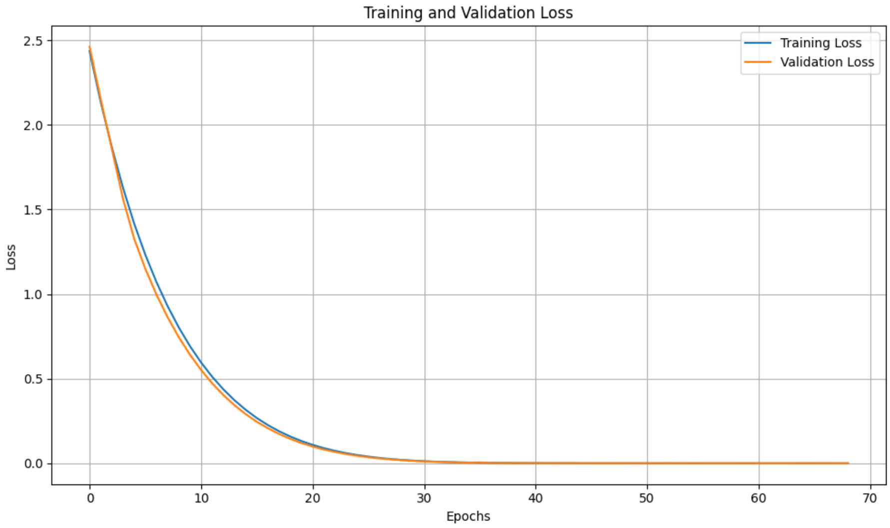

Figure 2 training and validation loss for BiLSTM model

Figure (3) represent the training and validation loss for GRU model before optimization.

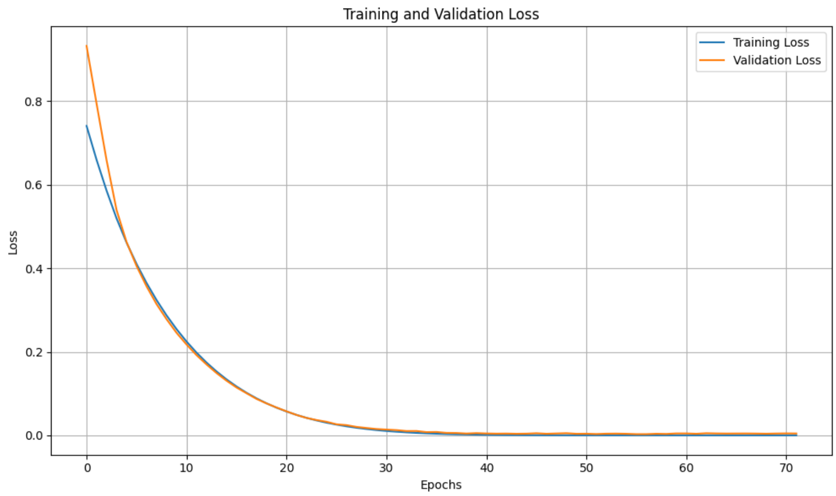

Figure 3 training and validation loss for GRU model

Figure (4) represent the training and validation loss for RNN model before optimization.

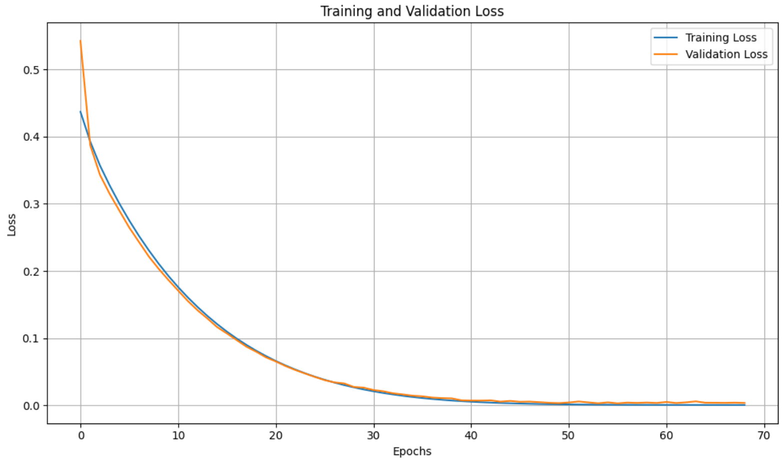

Figure 4 training and validation loss for RNN model

Figure (5) represent the predicted and actual for OHLC for the BiLSTM model

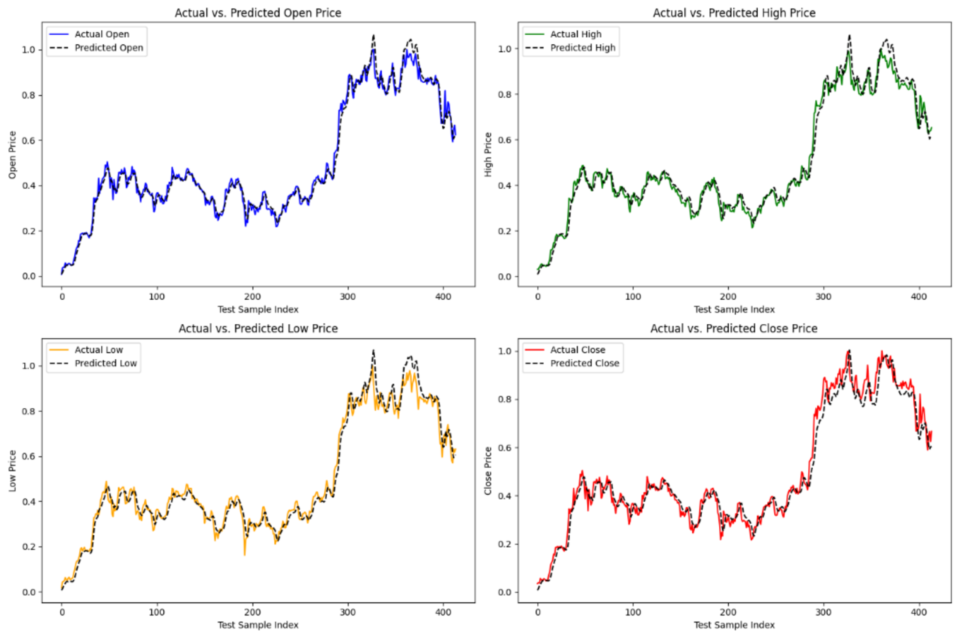

Figure 5 the predicted and actual for OHLC for the BiLSTM model

Figure (6) represent the predicted and actual for OHLC for the GRU model

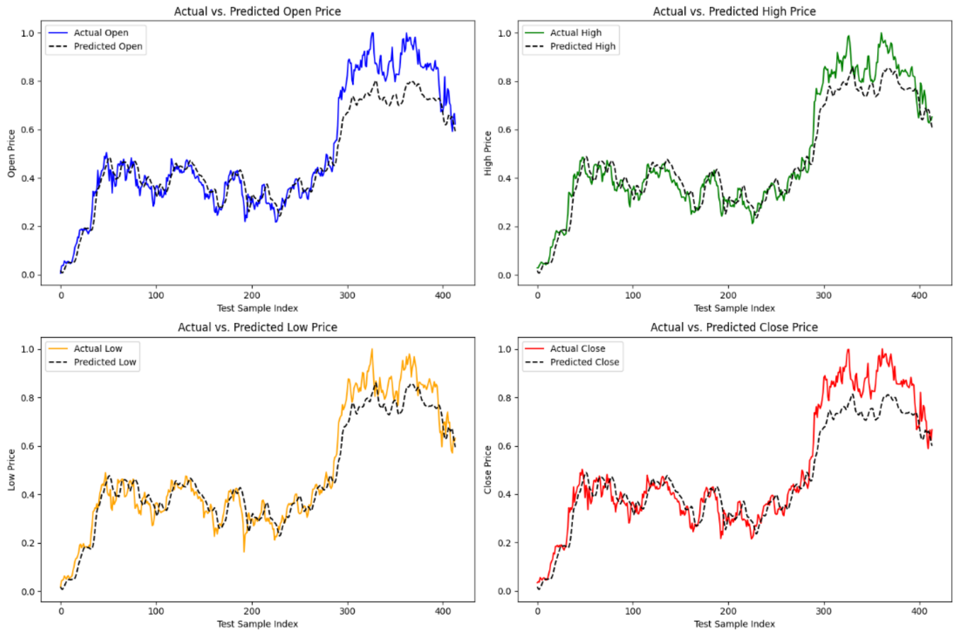

Figure 6 the predicted and actual for OHLC for the GRU model

Figure (7) represent the predicted and actual for OHLC for the RNN model

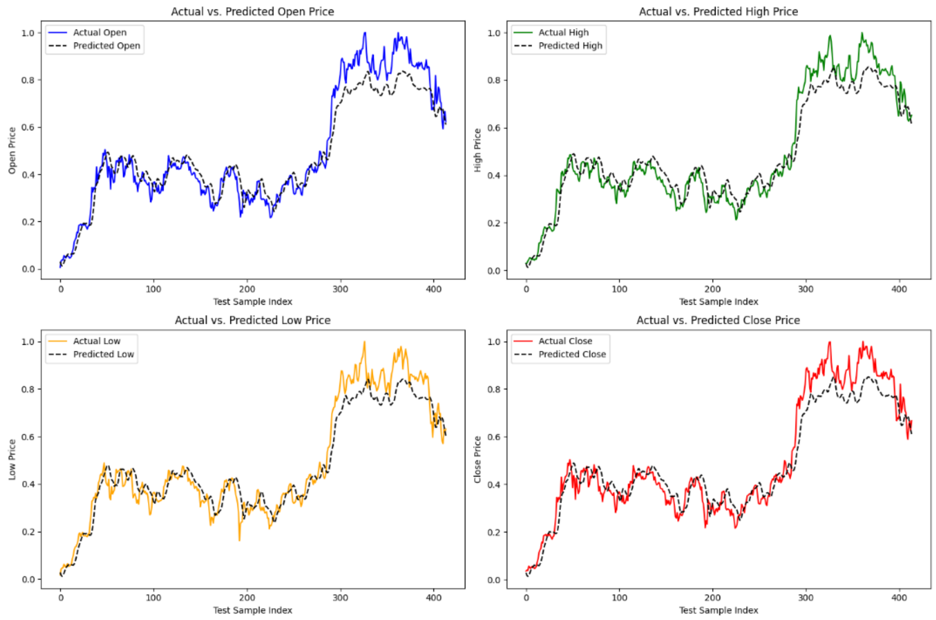

Figure 7 the predicted and actual for OHLC for the RNN model

4.1 Training with optimization

The performance of the deep learning (BiLSTM, RNN, and GRU) models after the optimization will help to choose the best parameter for training to obtain the best result. MAE, MSE and the Coefficient of Determination (R^2 Score). The results for predicting Open, High, Low, and Close prices of cryptocurrency listed as below:

Table 2 performance measures for the prediction models after optimization

Model	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	R^2 Score
BiLSTM	0.001183	0.026090	0.980596
GRU	0.003163	0.042862	0.948185
RNN	0.002976	0.042767	0.951263

The comparation between table 1 and table 2 shows a significant improvement in performance measures that because the optimization technique through the training process.

Figure (8) represent the training and validation loss for BiLSTM model after optimization.

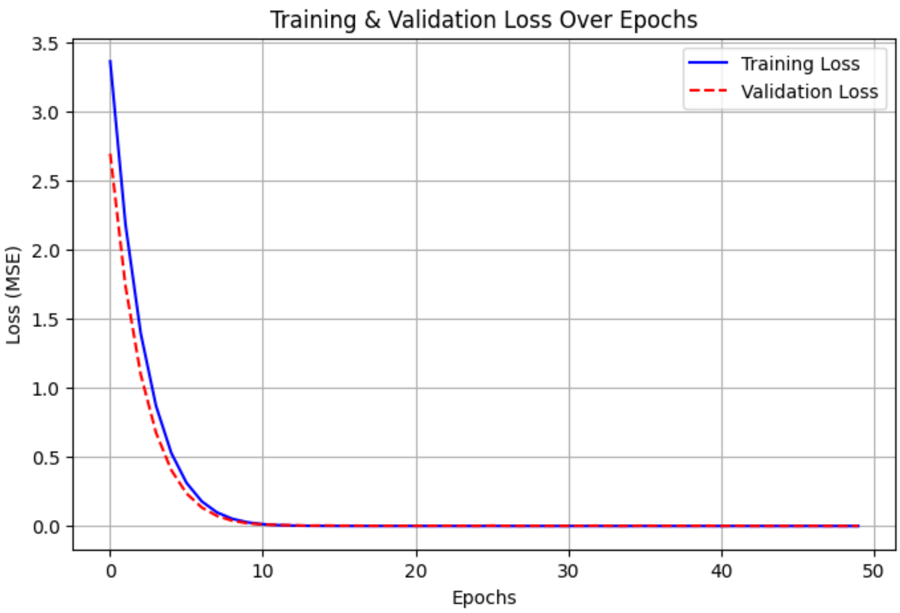

Figure 8 the training and validation loss for BiLSTM model after optimization

Figure (9) represent the training and validation loss for GRU model after optimization.

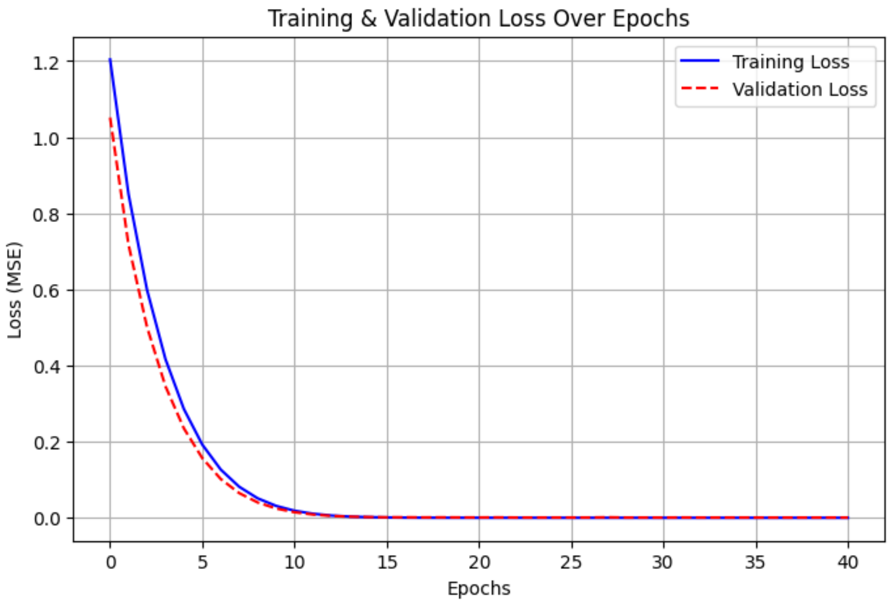

Figure 9 the training and validation loss for GRU model after optimization

Figure (10) represent the training and validation loss for RNN model after optimization.

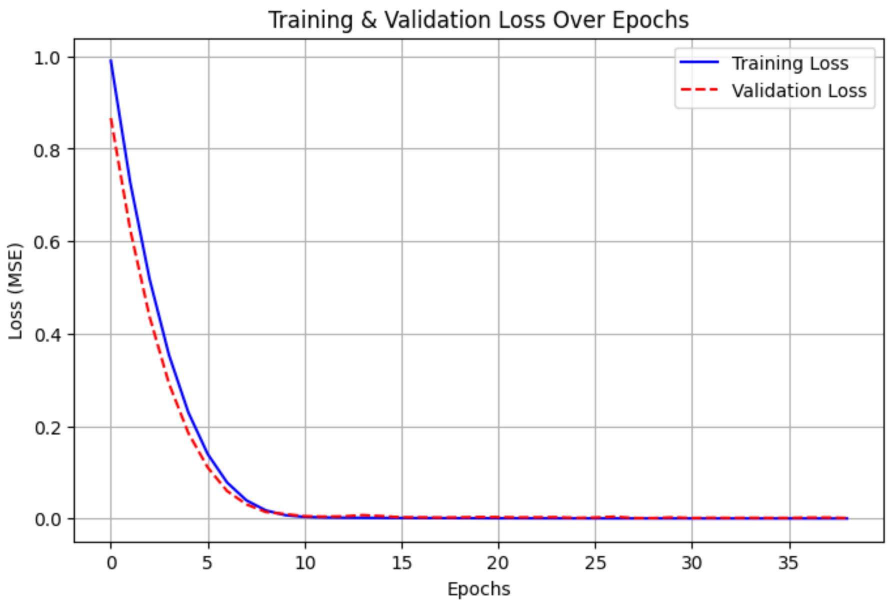

Figure 10 the training and validation loss for RNN model after optimization

From figures 8, 9, and 10 notice that the training loss and validation loss close to be the same the reason of that because in optimization process choses the best parameters for training therefore the prediction modes will obtain the best results than the previous models without optimization.

Figure (11) represent the predicted and actual for OHLC for the BiLSTM model after optimization.

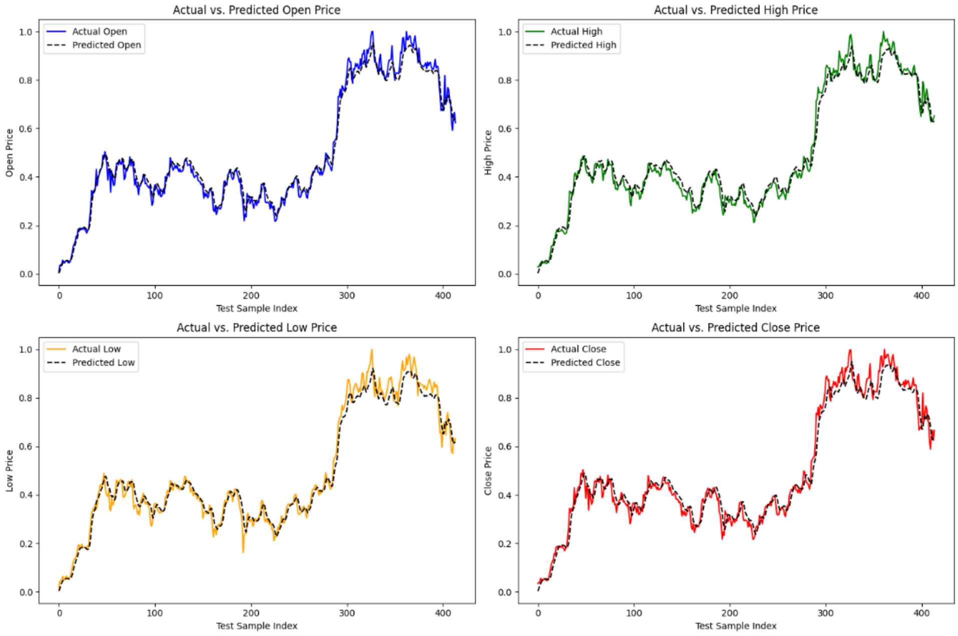

Figure 11 the predicted and actual for OHLC for the BiLSTM model after optimization.

Figure (12) represent the predicted and actual for OHLC for the GRU model after optimization.

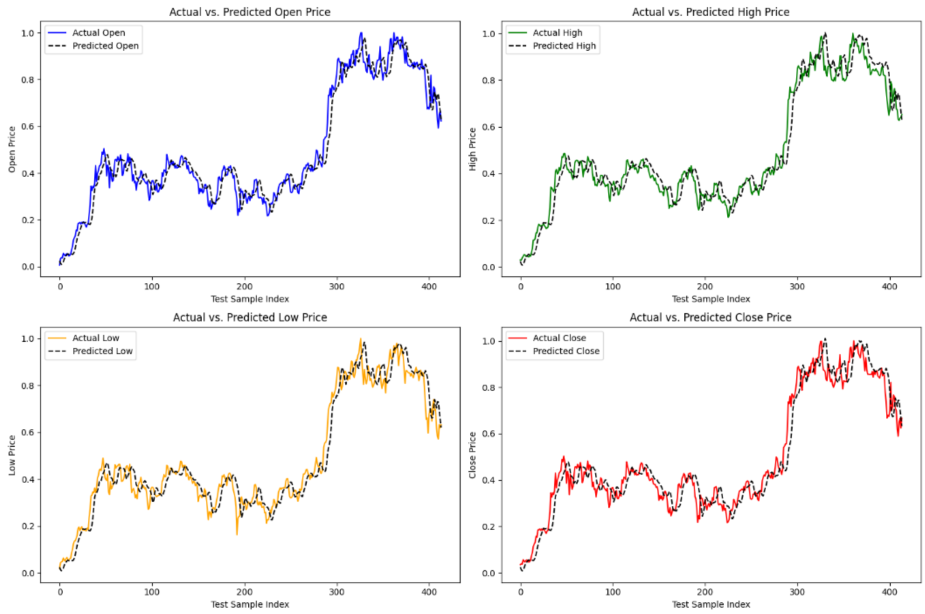

Figure 12 the predicted and actual for OHLC for the GRU model after optimization.

Figure (13) represent the predicted and actual for OHLC for the RNN model after optimization.

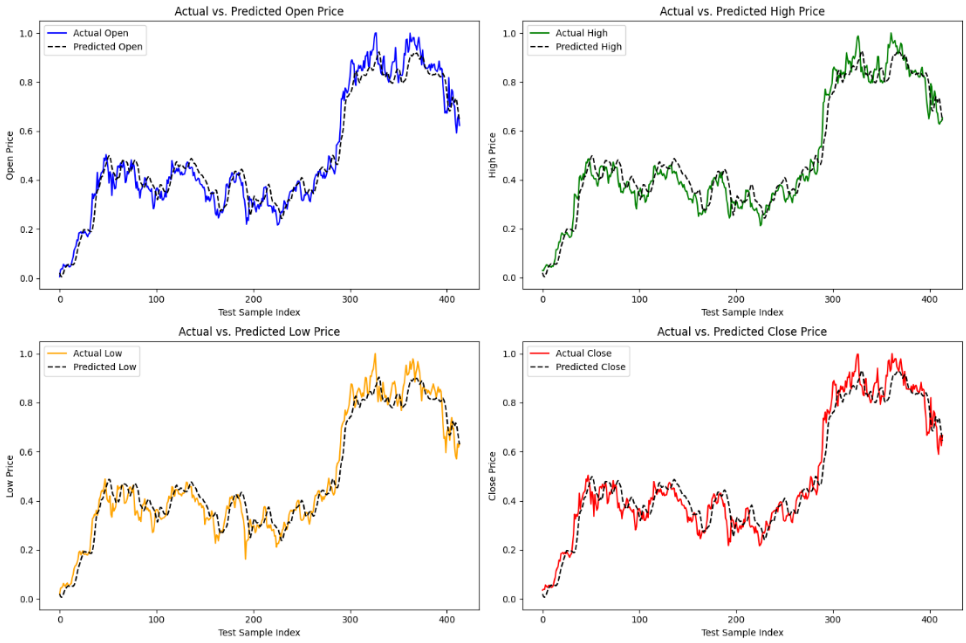

Figure 13 the predicted and actual for OHLC for the RNN model after optimization.

The performance measures in table (1) and table (2) with figures of performance before and after the optimization show that the performance measures have been enhanced obviously.

4.3. Comparative Analysis with Benchmark Models

To contextualize the performance of our proposed model, we compare our best-performing optimized BiLSTM with recent benchmark models from the literature, as summarized in Table 3. The metrics reported in the cited studies have been selected for their closeness to our own (MSE, MAE, R^2).

Table 3. Quantitative performance comparison with recent benchmark studies.

Study (Model)	**Key Performance Metrics**	**Comparative Note**
Our Study (Optimized BiLSTM)	**MSE: 0.001183, MAE: 0.0261, R^2: 0.981**	**Reference for comparison.**
Al-Nefaie & Aldhyani (2022) - MLP	MSE: 0.000109, R^2: ~0.99 (Testing)	Reported lower MSE but on a different, potentially less volatile test period (2021-2022). Our model demonstrates robust performance on 2023 data.
Alamery (2023) - CNN	RMSE: 0.0543, MAE: 0.0324	Our model's MAE (0.0261) is **~19% lower**, indicating higher prediction accuracy.

Study (Model)	Key Performance Metrics	Comparative Note
Hota et al. (2024) - LSTM-GRU Hybrid	MAE: 0.464, RMSE: 0.323	Our model's errors are an order of magnitude lower, though direct comparison is complex due to potential differences in data scaling.
Ateeq et al. (2023) - LSTM-BTC	Reported lower MSE/MAPE on multi-frequency data.	Highlights the competitive performance of our single-model, daily-frequency approach against specialized architectures.

This comparative analysis demonstrates that our optimized BiLSTM model delivers state-of-the-art performance. It achieves a very high R^2 value, explaining over 98% of the variance in Bitcoin prices on a challenging, recent out-of-sample test set (2023). The model's low error rates are highly competitive with, and in several cases superior to, other advanced deep learning and hybrid models reported in the contemporary literature. This confirms the efficacy of our methodology, particularly the strategic use of the Hyperband algorithm for model optimization.

5 Conclusion

This The findings of this research confirm that deep learning models, namely BiLSTM, are highly effective in predicting Bitcoin OHLC prices. Without hyperparameter tuning, the three models BiLSTM, GRU, and RNN displayed an adequate amount of predictive accuracy, with BiLSTM displaying the maximum R^2 value (0.9777), thereby reflecting a proper fit for the data. However, the application of Hyperband optimization enhanced the performance of the models significantly, especially BiLSTM, where it achieved an R^2 score of 0.980596, MSE of 0.001183, and MAE of 0.026090. This demonstrates that hyperparameter tuning is a central aspect of enhancing model robustness as well as reducing prediction error.

Compared to traditional statistical models like ARIMA or SARIMA, which often struggle in handling non-stationary and fluctuating data, deep learning models provide a more flexible framework that can efficiently learn to identify subtle temporal patterns. Moreover, the use of an autoencoder for feature learning enabled the creation of more compact and meaningful representations of the five-day input sequences, thus improving forecasting accuracy.

Notably, although the GRU and RNN had comparable performance levels, they were marginally less effective compared to the BiLSTM in handling long dependencies and volatility in the highly volatile Bitcoin market. This observation is consistent with current research that emphasizes the processing of bidirectional temporal information by BiLSTM, which is highly relevant in financial contexts where recent and moderately older historic information may influence future price movements.

The study also validates the need for data preprocessing like normalization, feature selection, and sequence preparation for enhancing performance in deep learning models for time-series forecasting. The absence of any missing values in the dataset and consistent structure also assisted in enhancing model stability.

In spite of the promising outcomes, the study has some limitations. The models were trained using OHLC data only, refraining from adding sentiment analysis, macroeconomic factors, or blockchain metrics, which in earlier studies have proved to have an impact on the fluctuations of cryptocurrency prices. Moreover, the study focuses on a single cryptocurrency (Bitcoin), potentially narrowing the applicability of the findings to other digital currencies.

Future research may advance this work by integrating different multi-modal data sources, implementing real-time predictive models, and exploring ensemble and hybrid deep learning models. Further, expanding the model to other cryptocurrencies and evaluating its performance over wider temporal horizons can render it more applicable in live trading setups.

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References

[1] D. Aggarwal, S. Chandrasekaran, and B. Annamalai, "A complete empirical ensemble mode decomposition and support vector machine-based approach to predict Bitcoin prices," Journal of Behavioral and Experimental Finance, vol. 27, p. 100335, 2020, doi: 10.1016/j.jbef.2020.100335.

[2] A. Agrawal, M. Mani, and S. Varshney, "Bitcoin Forecasting Performance Measurement: A Comparative Study of Econometric, Machine Learning and Artificial Intelligence-Based Models," Journal of International Economics, Commerce and Policy, vol. 14, p. 2350008, 2023, doi: 10.1142/S1793993323500084.

[3] E. Akyildirim, O. Cepni, S. Corbet, and G. S. Uddin, "Forecasting mid-price movement of Bitcoin futures using machine learning," Annals of Operations Research, vol. 330, pp. 553–584, 2023, doi: 10.1007/s10479-021-04205-x.

[4] F. M. S. Alamery, "Cryptocurrency analysis using machine learning and deep learning approaches," Journal of Computer, Electrical, Electronics and Engineering Science, vol. 1, pp. 29–33, 2023, doi: 10.51271/JCEEES-0007.

[5] J. Almeida and T. C. Gonçalves, "A systematic literature review of investor behavior in the cryptocurrency markets," Journal of Behavioral and Experimental Finance, vol. 37, p. 100785, 2023, doi: 10.1016/j.jbef.2022.100785.

[6] A. H. Al-Nefaie and T. H. H. Aldhyani, "Bitcoin Price Forecasting and Trading: Data Analytics Approaches," Electronics, vol. 11, no. 24, p. 4088, 2022, doi: 10.3390/electronics11244088.

[7] M. Arjmand, S. Kazeminia, and H. Sajedi, "Bitcoin price prediction based on financial data, technical indicators, and news headlines sentiment analysis using CNN and GRU deep learning algorithms," in 2024 Third International Conference on Distributed Computing and High Performance Computing (DCHPC), Tehran, Iran, 2024, pp. 1-7, doi: 10.1109/DCHPC60845.2024.10454082.

[8] K. Ateeq, A. A. A. Zarooni, A. Rehman, and M. A. Khan, "A Mechanism for Bitcoin Price Forecasting using Deep Learning," International Journal of Advanced Computer Science and Applications, vol. 14, no. 8, 2023, doi: 10.14569/IJACSA.2023.0140849.

[9] Z. Ayaz, J. Fiaidhi, A. Sabah, and M. A. Ansari, "Bitcoin Price Prediction using ARIMA Model," 2020, doi: 10.36227/techrxiv.12098067.

[10] J. J. Benjamin, R. Surendran, and T. Sampath, "A professional strategy for Bitcoin and Ethereum using Machine Learning for Investors," in 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2022, pp. 798-804, doi: 10.1109/ICIRCA54612.2022.9985532.

[11] M. Gupta and R. Srivastava, "A Comparative Analysis and Prediction over Bitcoin Price Using Machine Learning Technique," Financial and Political Analysis, pp. 31-41, 2021, doi: 10.54216/FPA.050103.

[12] I. Chatterjee, S. Chakraborti, and T. Tono, "A comparative study of bitcoin price prediction during pre-Covid19 and whilst-Covid19 period using time series and machine learning models," Discover Analytics, vol. 2, no. 1, p. 19, 2024, doi: 10.1007/s44257-024-00024-z.

[13] J. Cheng, S. Tiwari, D. Khaled, M. Mahendru, and U. Shahzad, "Forecasting Bitcoin prices using artificial intelligence: Combination of ML, SARIMA, and Facebook Prophet models," Technological Forecasting and Social Change, vol. 198, p. 122938, 2024, doi: 10.1016/j.techfore.2023.122938.

[14] S. K. Ibrahim and P. Singh, "Bitcoin Price Prediction Using Machine Learning Techniques," Journal of Information, Electrical, and Electronics Engineering, vol. 3, no. 1, pp. 1-9, 2022, doi: 10.54060/JIEEE/003.01.005.

[15] C. R. Dhaku and S. K. Arumugam, "Forecasting Bitcoin Price During Covid-19 Pandemic Using Prophet and ARIMA: An Empirical Research," in Intelligent Systems Design and Applications, A. Abraham et al., Eds. Cham: Springer Nature, 2023, pp. 487-495, doi: 10.1007/978-3-031-35510-3_46.

[16] A. Dimitriadou and A. Gregoriou, "Predicting Bitcoin Prices Using Machine Learning," Entropy, vol. 25, no. 5, p. 777, 2023, doi: 10.3390/e25050777.

[17] M. Fernandes, S. Khanna, L. Monteiro, A. Thomas, and G. Tripathi, "Bitcoin Price Prediction," in 2021 International Conference on Advances in Computing, Communication, and Control (ICAC3), Mumbai, India, 2021, pp. 1-4, doi: 10.1109/ICAC353642.2021.9697202.

[18] S. E. Freeda, T. C. E. Selvan, and I. G. Hemanandhini, "Prediction of Bitcoin Price using Deep Learning Model," in 2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2021, pp. 1702-1706, doi: 10.1109/ICECA52323.2021.9676048.

[19] S. Hota, D. Mishra, P. Satapathy, S. K. Nayak, and N. Tripathy, "Empirical Forecasting Analysis of Bitcoin Prices: A Comparison of Machine learning, Deep learning, and Ensemble Learning Model," International Journal of Electrical and Computer Engineering Systems, vol. 15, no. 1, pp. 21-29, 2024, doi: 10.32985/ijeces.15.1.3.

[20] I. S. Kervanci and F. Akay, "Review on Bitcoin Price Prediction Using Machine Learning and Statistical Methods," Sakarya University Journal of Computer and Information Sciences, vol. 3, no. 3, pp. 272-282, 2020, doi: 10.35377/saucis.03.03.774276.

[21] M. Khadija, B. R. Fahmi, and B. R. Syrine, "Prediction of Bitcoin Prices Based on Blockchain Information: A Deep Reinforcement Learning Approach," Advances in Artificial Intelligence and Machine Learning, vol. 4, pp. 2416-2433, 2024, doi: 10.54364/AAIML.2024.43141.

[22] M. K. Salman and A. A. Ibrahim, "Price Prediction of Different Cryptocurrencies Using Technical Trade Indicators and Machine Learning," in IOP Conference Series: Materials Science and Engineering, vol. 928, 2020, p. 032007, doi: 10.1088/1757-899X/928/3/032007.
[23] M. A. L. Khaniki and M. Manthouri, "Enhancing Price Prediction in Cryptocurrency Using Transformer Neural Network and Technical Indicators," 2024, doi: 10.48550/ARXIV.2403.03606.
[24] B. Kutlu Karabiyik and Z. Can Ergün, "Forecasting Bitcoin Prices with the ANFIS Model," Dicle University Journal of Economics and Administrative Sciences*, vol. 11, no. 22, pp. 295-315, 2021, doi: 10.53092/duiibfd.970900.
[25] S. Liu, K. Wu, C. Jiang, B. Huang, and D. Ma, "Financial Time-Series Forecasting: Towards Synergizing Performance And Interpretability Within a Hybrid Machine Learning Approach," 2024, doi: 10.48550/ARXIV.2401.00534.
[26] J. Luo, "Bitcoin price prediction in the time of COVID-19," in 2020 Management Science Informatization and Economic Innovation Development Conference (MSIEID), Guangzhou, China, 2020, pp. 243-247, doi: 10.1109/MSIEID52046.2020.00050.
[27] M. Mittal and G. Geetha, "Predicting Bitcoin Price using Machine Learning," in 2022 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2022, pp. 1-7, doi: 10.1109/ICCCI54379.2022.9740772.
[28] S. Otabek and J. Choi, "From Prediction to Profit: A Comprehensive Review of Cryptocurrency Trading Strategies and Price Forecasting Techniques," IEEE Access, vol. 12, pp. 87039-87064, 2024, doi: 10.1109/ACCESS.2024.3417449.
[29] M. M. Patel, S. Tanwar, R. Gupta, and N. Kumar, "A Deep Learning-based Cryptocurrency Price Prediction Scheme for Financial Institutions," Journal of Information Security and Applications, vol. 55, p. 102583, 2020, doi: 10.1016/j.jisa.2020.102583.
[30] Q. P. Duy, O. Nguyen Thi, P. H. Le Thi, H. D. Pham Hoang, K. L. Luong, and K. N. Nguyen Thi, "Estimating and forecasting bitcoin daily prices using ARIMA-GARCH models," Banks and Bank Systems, vol. 45, no. 1, pp. 11-23, 2024, doi: 10.1108/BAJ-05-2024-0027.
[31] E. Pintelas, I. E. Livieris, S. Stavroyiannis, T. Kotsilieris, and P. Pintelas, "Investigating the Problem of Cryptocurrency Price Prediction: A Deep Learning Approach," in Artificial Intelligence Applications and Innovations, I. Maglogiannis, L. Iliadis, and E. Pimenidis, Eds. Cham: Springer International Publishing, 2020, pp. 99-110, doi: 10.1007/978-3-030-49186-4_9.
[32] G. Serafini et al., "Sentiment-Driven Price Prediction of the Bitcoin based on Statistical and Deep Learning Approaches," in 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, United Kingdom, 2020, pp. 1-8, doi: 10.1109/IJCNN48605.2020.9206704.
[33] I. H. Shakri, "Time series prediction using machine learning: a case of Bitcoin returns," Studies in Economics and Finance, vol. 39, no. 3, pp. 458-470, 2022, doi: 10.1108/SEF-06-2021-0217.
[34] H. Singathala, J. Malla, J. Jayashree, and J. Vijayashree, "A Deep Learning based Model for Predicting the future prices of Bitcoin," in 2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN), Vellore, India, 2023, pp. 1-4, doi: 10.1109/ViTECoN58111.2023.10157841.

[35] A. Singh, A. K. Jha, and A. N. Kumar, "Prediction of cryptocurrency prices through a path dependent Monte Carlo simulation," Communications in Statistics - Simulation and Computation, pp. 1-20, 2025, doi: 10.1080/03610918.2025.2480211.

[36] A. Singh, A. Kumar, and Z. Akhtar, "Bitcoin Price Prediction: A Deep Learning Approach," in 2021 8th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2021, pp. 1053-1058, doi: 10.1109/SPIN52536.2021.9565988.

[37] M. V. N. S. S. R. K. S. Somayajulu and B. Kotaiah, "A Survey on Cryptocurrency Price Prediction using Hybrid Approaches of Deep Learning Models," in 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2023, pp. 1322-1327, doi: 10.1109/ICIRCA57980.2023.10220894.

[38] B. Sonare et al., "Analysis of Various Machine Learning and Deep Learning Algorithms for Bitcoin Price Prediction," in *2023 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI), Chennai, India, 2023, pp. 1-5, doi: 10.1109/RAEEUCCI57140.2023.10134467.

[39] V. Srivastava, V. Kumar Dwivedi, and A. Kumar Singh, "Prediction of Bitcoin Price using Optimized Genetic ARIMA Model and Analysis in Post and Pre Covid Eras," in 2023 3rd International Conference on Smart Data Intelligence (ICSMDI), Trichy, India, 2023, pp. 143-148, doi: 10.1109/ICSMDI57622.2023.00033.

[40] A. Thanvi et al., "Bitcoin Exchange Rate Price Prediction Using Machine Learning Techniques: A Review," in Information Management and Machine Intelligence, D. Goyal et al., Eds. Singapore: Springer Singapore, 2021, pp. 635-642, doi: 10.1007/978-981-15-4936-6_69.

[41] R. G. Tiwari, A. K. Agarwal, R. K. Kaushal, and N. Kumar, "Prophetic Analysis of Bitcoin price using Machine Learning Approaches," in 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC), Solan, India, 2021, pp. 428-432, doi: 10.1109/ISPCC53510.2021.9609419.

[42] L. Vaddi, "Predicting Crypto Currency Prices Using Machine Learning and Deep Learning Techniques," International Journal of Advanced Trends in Computer Science and Engineering, vol. 9, no. 4, pp. 6603-6608, 2020, doi: 10.30534/ijatcse/2020/351942020.

[43] J. Wu, X. Zhang, F. Huang, H. Zhou, and R. Chandra, "Review of deep learning models for crypto price prediction: implementation and evaluation," 2024, doi: 10.48550/ARXIV.2405.11431.

[44] Z. Xu, W. Zhang, Y. Sun, and Z. Lin, "Multi-Source Data-Driven LSTM Framework for Enhanced Stock Price Prediction and Volatility Analysis," 2024, doi: 10.5281/ZENODO.14291972.