Journal of Theoretical and Applied Information Technology
15st June 2026. Vol.104. No.11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

HYBRID ENSEMBLE-BASED DEEP LEARNING FRAMEWORK FOR VOLATILE CRYPTOCURRENCY PRICE FORECASTING

D DAKSHAYANI HIMABINDU[1], ARCHANA KALIDINDI[2], V SRINADH[3], P JAHNAVI[4], B VASANTHA RANI[5], B KRISHNA MOHAN[6]

[1]Assistant Professor, VNR Vignana Jyothi Institute of Engineering & Technology, Department of Information Technology, Hyderabad, India
[2]Assistant Professor. Koneru Lakshmaiah Education Foundation, Department of Computer Science and Engineering, Bowrampet, Hyderabad, India
[3]Associate Professor, GMRIT Deemed to be University, Department of CSE-AIML, Rajam, Andhra Pradesh, India.
[4]Assistant Professor. SRKR Engineering College, Department of Computer Science and Engineering, Bhimavaram, India
[5] Assistant Professor. Anil Neerukonda Institute of Technology and Sciences, Department of Computer Science and Engineering (Data Science), Visakhapatnam, Andhra Pradesh., India
[6]Assistant Professor. Gokaraju Rangaraju Institute of Engineering and Technology, Department of Mechanical Engineering, Hyderabad, India
E-mail: [1] dakshayani.himabindu@gmail.com, [2] archana.buddaraju@gmail.com, [3] srinadh.v@gmrit.edu.in , [4] jahnavi.penmatsa@srkrec.edu.in, [5] badagalavasantha06@gmail.com, [6] mohan20kb@gmail.com

ABSTRACT

In today's world, cryptocurrency has emerged as a popular digital currency, which is an alternative form of payment created using encryption algorithms. Bitcoin is the most popular cryptocurrency. Bitcoin operates on a decentralized computer network or distributed ledger that tracks transactions in the cryptocurrency. Bitcoin is an innovative payment network and a new kind of money. When computers on the network verify and process transactions, new bitcoins are created, or mined. In return, for processing a transaction, networked computers or miners receive a payment in Bitcoin. Demand for Bitcoin has gone up over the past years. Bitcoin is very volatile and has multiple risks like unpredictability, losing access to one's own money, security breaches, being expensive and complex, and an uncertain future. Hence, developing a machine learning model to accurately forecast future prices of Bitcoin using machine learning algorithms is crucial. Many existing systems do not leverage the strengths of different algorithms effectively, leading to suboptimal predictive performance. This lack of diversity in model approaches often results in poor generalization to unseen data and difficulty handling Bitcoin's high volatility. The present study has developed an ensemble learning model by integrating multiple algorithms, which include BiLSTM, XGBoost Regressor, and Random Forest Regressor algorithms. The proposed ensemble model achieved an R^2 score of 99.76%, demonstrating strong predictive performance.

Keywords: *Ensemble Learning, BiLSTM, XGBoost, Random Forest, Cryptocurrency Forecasting, Volatility Analysis*

1. INTRODUCTION

Bitcoin is a type of digital money that allows people to send and receive payments over the internet. It works using blockchain, which has a public ledger that records all transactions [1]. It is the most secure way to hold records of the transactions over the internet. When someone makes a transaction (Buy something in exchange of transferring bitcoin or sell something in exchange of receiving a bitcoin), it gets verified by a network of computers, known as miners, that work together in a secured environment. This process ensures that the same Bitcoin cannot be spent twice similar to how banks uses ACID (Atomicity, Consistency, Isolation, and Durability) based transactions [2], [3]. Bitcoin is presently used as a trade to purchase various commodities or as an investment like stocks or bonds. Bitcoin is more

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

volatile, and is similar to or even more risky than small cap stocks [4]. With its quick rise as a revolutionary digital currency, it has provided an alternative to regular currency controlled by banks or central agencies [5]. Bitcoin has shown a new way to make transactions in the current economy. With Bitcoin, users may send and receive money directly without the assistance and meddling of middlemen like banks. This has paved the way for new financial models as well as other crypto currencies while also improving transaction efficiency [4]. In recent years, there has been a notable increase in interest in Bitcoin, accompanied by notable changes in its price. Therefore, traders and investors face the challenging task of predicting its prices accurately [6]. Many traditional prediction models fail to explain the details of the behavior of Bitcoin and usually do not update frequently with new information or perhaps when market conditions change. As a result, there is growing interest in the use of machine learning to enhance the accuracy of predictions. Traditional models of prediction are often incapable of capturing the highly dynamic and volatile nature of Bitcoin, leading to incorrect forecasts. To reduce these shortcomings, machine learning (ML) algorithms have gained popularity, providing the capacity to critically analyze historical information and detect patterns [6], [7]. Notwithstanding, there exist some limitations to using individual machine learning algorithms to address the irregular changes permissible in Bitcoin's market. To address these concerns, an alternative and efficient method, named the ensemble method, utilizing multiple machine learning techniques, has been found to work well [8]. With this strategy, utilizing the strengths of algorithms such as BiLSTM, XGBoost Regressor, and Random Forest Regressor, there is potential to enhance overall prediction accuracy and its reliability. Our result model has reported significant accuracy, reflected in an R^2 score of 94.92% and 95.17% on test and training datasets, respectively, outperforming other models in predicting Bitcoin prices.

Despite significant advancements in cryptocurrency forecasting, existing prediction models often suffer from limited generalization capability, poor handling of Bitcoin's extreme volatility, and dependency on single-model architectures. Many traditional machine learning and deep learning approaches fail to effectively capture nonlinear market behavior and temporal dependencies simultaneously. Therefore, there is a need for a robust ensemble-based framework that integrates the strengths of multiple predictive models to improve forecasting accuracy and stability in Bitcoin price prediction

2. LITERATURE REVIEW

Narayanan [9] describe Bitcoin as an electronic payment system that is decentralized. It eradicates double-spending using cryptography and a peer-to-peer network.

Limba et al. [10] investigated the disruptive effect of Bitcoin on the global financial system, with its decentralized character and rarity contributing to its value despite lacking the potential to substitute traditional currencies. Studies indicate the potential associated with Bitcoin and tried to estimate its price employing sophisticated approaches based on machine learning. Yousuf Javed et al [11] investigated the significance of Bitcoins in the Indian market, operating without any control from the governing authorities, and notes its growing importance despite fluctuations. Bonneau et al [12] presented an extensive discussion on the economic development of Bitcoin since its inception in 2009, with its advantages and shortcomings associated with the process of growing Bitcoin's network size. Sudhakaran et al. [13] investigated the potential of applying Recurrent Neural Networks (RNN) models and its variant, Long Short-Term Memory (LSTM) models, which are acclaimed for its efficacy in extracting long-term dependencies within sequential data (data in which order is significant). Having analyzed the data extracted from Kraken Exchange, including transaction volume and Google search trends, it can be concluded that the LSTM model works incredibly well in price prediction. By focusing on the importance of sequential data to improve prediction accuracy, this research suggests that future work should be done on dataset extension and the inclusion of more external factors. A comparative analysis by Dimitriadou & Gregoriou [14] assesse logistic regression, Support Vector Machines (SVM), and Random Forest algorithms in the application of machine learning for Bitcoin price prediction. Among these, the best results were obtained from logistic regression, which achieved 66% accuracy over SVM and Random Forest. This again hints at the fact that while macroeconomic elements may affect Bitcoin little, its course may still be valued using machine learning models. Logistic regression's capability in efficiently anticipating market changes clearly identifies its usability for short-term forecasting, although it might not portray market changes perfectly. Further study [15] regarding models in predictions determines that Random Forest Regression marginally outperforms LSTM models in their accuracy, although their

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

performance is not significantly different in a Diebold and Mariano Test. Analysis clearly identifies that stock markets along with Cryptocurrencies like Ethereum affect the markets of Bitcoin. Nonetheless, accuracy regarding recent values for exploratory variables presented in Random Forest Regression clearly identifies usability within the scope of Efficient Market Hypothesis (EMH), within which only recent information characterizes market changes perfectly.

The models of deep learning are also promising for predicting the price of the bitcoin. Ferdiansyah et al. [16] compared the efficacy of both models of Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) for predicting the price of the bitcoin. The findings show inference to the effect that the former (GRU) is superior to the latter (LSTM) not only in accuracy but also in processing speed. This research highlights the need for incorporating other factors such as political events and market sentiment with the aim of increasing the volatility of trends to make it superior to other models of cryptocurrencies. In light of the successes of LSTM models for the prediction of the price of the bitcoin, Maheshwari et al. [17] enhanced it further by introducing variables such as market capitalization and market volume to make their model superior to than other models and. result indicates that LSTM is more effective in reducing prediction error. They recommend exploring sentiment analysis and more complex neural network architectures to push the boundaries of prediction accuracy. Chen et al. [18] proposed a new approach called sample dimension engineering. This approach optimizes Bitcoin price prediction through aligning model complexity and feature selection with the arrangement and frequency of the information. To accomplish the prediction of daily price, high-dimensional features such as trading, network, investor attention, and gold spot price are used. The simpler statistical models of Logistic Regression and Linear Discriminant Analysis achieve an accuracy of 66%. Complex machine learning models such as LSTM and XGBoost are used for high-frequency 5-minute interval data and achieved 67.2% prediction accuracy. Omole & Enke [19] compared various state-of-the-art neural models for the prediction of direction of bitcoin pricing, using combinations of on-chain data and feature selection methods that can promise great capability to solve issues of high-dimensional data. The CNN-LSTM model paired with Boruta feature selection did turn out best with an accuracy of 82.44%. There were remarkable profits in backtesting where a long-and-short trading strategy generated a whopping 6654% annual return, demonstrating how powerful models can dissolve into a lucrative channel to trade cryptocurrencies. Ji et al. [20] compared Deep Learning models for the purpose of predicting Bitcoin price: DNN, LSTM, CNN, ResNet, and combinations of CNN-RNN. In terms of accuracy for regression tasks, the highest was achieved by LSTM; while DNN, in this case, performed best in classifying the task, a right direction predicted. For algorithmic trading applications, classification models outperformed deep learning counterparts, with DNN achieving 53.06% price movement predictions; overall, deep learning models retain promise, especially in classification tasks, to be more powerful compared to classical models. Verma et al. [21] examined the prediction of Bitcoin prices using two machine learning models: Random Forest Regression and LSTM. Bitcoin is a highly volatile asset, and its price prediction is both challenging and useful for risk management in investments. The authors tested both models on data ranging from 2015 to 2022, dividing it into two periods (before and after 2018) to capture changes in the behavior of Bitcoin. They concluded that Random Forest performed slightly better overall, with a lower error rate, while LSTM's accuracy changed depending on the period. The key drivers of Bitcoin's price included its own recent trading data, U.S. stock indices, and Ethereum. The findings of this study indicate that using only recent data, such as 1-day lag, improves prediction accuracy. This agrees with the fact that the price of Bitcoin is mostly driven by its recent activity. Such a model could enable investors to predict the prices of Bitcoin and consequently avoid some risks. The underlying reason for choosing ML and deep learning approaches in this paper is the high volatility of the currency. Ho et al. [22] tested two main models: one traditional ML approach, linear regression, and one deep learning model, Long Short-Term Memory (LSTM). Data from August 2017 to August 2020 is used; the features under consideration are "open," "high," "low," and "close" prices of Bitcoin. The results of the linear regression model indicated 99.87% accuracy, while that of LSTM resulted in a minimum error of 0.08%, hence a little more accurate. In addition, visualization libraries such as Pandas and Seaborn were used to gain intuition of feature importance, while Python packages simplified the process of data handling and model implementation. A simple GUI using Tkinter has been developed for entering key values for obtaining predictions. It is found that the deep learning model, particularly LSTM, gives more accurate outcomes for Bitcoin prediction, though

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

However, additional features might serve to further improve accuracy. Drawbacks lie in the crypto market's volatility and inefficiency compared to the established payments system VISA. Akyildirim et al. [23] discussed the accuracy of Bitcoin prediction models based on machine learning algorithms. With December 2014 to July 2019 data, the paper examines 24 features ranging from other cryptocurrencies to macroeconomic factors for predicting Bitcoin price variations. Three models were employed: logistic regression, Support Vector Machine (SVM), and Random Forest. Of the models used, logistic regression proved to be the most accurate at 66%. While the models were not 100%, it is because the Bitcoin market is volatile and inefficient compared to the established markets. The paper concludes that Bitcoin is not related to standard market factors but instead offers the possibility of being an inflation hedge or interest rate hedge.

Koo & Kim [24] proposed a hybrid model using LSTM for predicting the price of Bitcoin with help of Singular Spectrum Analysis (SSA) and Centralized Clusters Distribution (CCD) filtering to address the extreme bimodality of Bitcoin. This method, with WES loss formulation embedded in it, shows an overall prediction increase of only 11.5% and in the tails of 22.5%, respectively, while being able to outperform the baseline models. Bâra & Oprea [25] proposed an ensemble learning method (ELM) for 7-day Bitcoin Price Prediction, relying on historical data, volatility indicators, and trend classification(s); testing out combinations between a Random Forest model and Extreme Gradient Boosting, their ELM method improved the accuracy by 26% compared to individual methods obtaining a MAE of 319 over a 2021 volatile trading period. Awoke et al. [26] compared two deep learning architectures, specifically LSTM and GRU, in the context of the volatility of Bitcoin prices and market demand. These models were trained on daily price data from 2014 to 2018, and RMSE and MAPE have been used as metrics to evaluate their predictive accuracy. This model proved faster convergence and error levels for short time horizons of forecasts but LSTM was only slightly more efficient at certain sizes.The work by Vujicic et al. [27] explains block chain technology especially as it tells about ethereum. Parekh et al. [28] speaks about Blockchain in which all the transactions are stored in the form of immutable blocks, which ensures data integrity and transparency. Using cryptographic hashing, we can detect any attack on the block data and discard it. Blockchain ensures security and authenticity with the help of a distributed ledger and cryptographic protocols [28-30].

3. DATASET DESCRIPTION

The dataset consists of 50009 observations and 8 variables (Table 1) of different days [31].

Table 1: Dataset Description.

Column Name	Description
Id	Unique identifier for each record (integer).
date	Date of the trading day in DD-MMM-YY format (string).
Open	Opening price of the stock for the day (string).
High	Highest price of the stock reached on that day (string).
Low	Lowest price of the stock reached on that day (string).
close	Closing price of the stock at the end of the trading day (string).
Vol.	Trading volume for the day, which indicates the total quantity of stock traded (string, with potential suffixes like 'K' for thousands).
Change %	Percentage change in the stock's closing price compared to the previous day's close (string, formatted with a % symbol).

Date refers to the date of the survey, in the format "DD-MM-YYYY." Open refers to the price of the Bitcoin at the start of the trading day. High refers to the highest price of the day. Low refers to the lowest price of the day. Close refers to the price of the Bitcoin at the end of the trading day. Apart from the prices, the dataset has another column known as 'Volume (Vol.).' This is the number of Bitcoins that are traded in the market each day. Finally, the last column, 'Change %,' shows the relative percentage change in the Bitcoin price compared to the last trading day. This is the amount of percentage fluctuation in the Bitcoin price within the given time period.

4. PROPOSED METHODOLOGY

The research design of this study consists of five major phases: dataset collection, preprocessing, feature engineering, model development, and performance evaluation. Historical Bitcoin price data obtained from Kaggle was preprocessed using

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

normalization and missing-value handling techniques. Feature engineering techniques such as rolling averages, lag features, and volatility indicators were applied. Subsequently, BiLSTM, XGBoost, and Random Forest models were trained individually and integrated using a Voting Regressor ensemble framework. The models were evaluated using MAE and R^2 metrics to compare predictive performance.

4.1 Pre-Processing

It is important to process data before it is used for analysis and modeling. Data was prepared for effective feature extraction and model training. Data Cleaning was done by removal of null values and missing data points. Ensure that there are no null values to avoid inconsistencies in the data. Only feature variables like Open, Close, High, Low prices, and Volume are preserved. Date-Time Formatting was performed which formats the date columns as datetime for time-series analysis. MinMaxScaler was applied to normalize data such that all features will fall between 0 and 1, large values do not bias the model's predictions for large input values. The dataset was split into training and test sets to generalize the performance of the model with unseen data, which is usually 80-20 split.

4.2 Feature Construction

Feature engineering enhances predictive power by deriving new features or transforming existing ones. Temporal Features like day and month, would be extracted from date variables, thus including temporal patterns into the Bitcoin price variations. Rolling averages and standard deviations are computed to follow the developments of prices and volatility overtime.

Technical Indicators like MACD, RSI, Bollinger Bands, and many more techniques were utilized in the real application of financial forecasting. Lag Features like the closing price the day before are included to help the model capture time dependence by providing historical context. Feature engineering uses historical data to improve the model's aptness at discovering patterns and movements for value of price of Bitcoin.

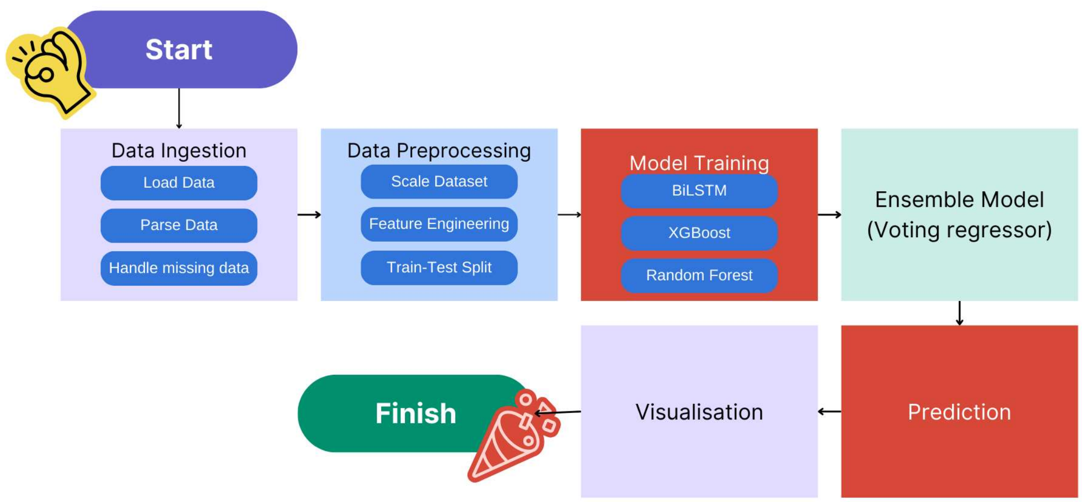

Figure1: Proposed Architecture

4.3 Models of Machine Learning

The present study discusses how different machine learning algorithms were used to predict Bitcoin prices. Each of the algorithms has its own distinct characteristics, thus providing a basis for comparison of their performance that have been depicted in figure1.

4.3.1 XGBoost regression framework

The XGBoost Regression model is a high-performance algorithm on gradient boosting. It learns from residuals of previous models, yielding an iterative and always-improving model for better prediction accuracy. In order to improve the model's performance and efficiency, only relevant features were selected with care and given as input, which would also minimize over fitting and save computational costs. The precision was further optimized through tuning relevant hyper parameters like learning rate, max depth, and number of estimators, employing methods of grid or randomized search. The predictive capability of the model was assessed on grounds of Mean Squared Error-MSE, Mean Absolute Error-MAE, and R-squared - R^2 metrics, and all of them reflected lower values, hence confirming high predictive accuracy.

4.3.2 Random forest regression framework

The Random Forest Regression model is an ensemble method of decision trees. This would provide better stability and reduce the variance in forecasting due to the averaging of the outcome from multiple trees. For example, in Bitcoin price forecasting, Bootstrap sampling was used to generate random subsets of data that could allow the model to learn various patterns and avoid overfitting. Some important hyperparameters such as the number of trees and a tree's depth were optimized for better model performance. The Random Forest algorithm showed the best performance, especially regarding the minimization of variance, although sometimes it failed to learn sharp increases in price.

4.4 Deep Learning Architecture

More complex patterns had to be identified for analysis through deep learning techniques like RNNs for discovering time-dependent trends for the Bitcoin prices.

4.4.1 Bidirectional long short-term memory model

The Bidirectional LSTM is a type of RNN, which encaptures the temporal dependencies while processing the data in both the forward and backward passes. This assists in context understanding, where past and future values in the time series can be related:

The architecture consists of several layers of LSTMs followed by dense layers for obtaining the output for prediction, with dropout to prevent overfitting. Being a bidirectional model helps in leveraging both historical and forward-looking perspectives for trend identification in complex time series in finance. During training:

Mean Squared Error function was employed as the loss function, and the prediction errors were optimized using the Adam optimizer. The Bidirectional LSTM outperformed conventional approaches in identifying overall trends, although the training time taken by the Bidirectional LSTM was much higher because of its complexity.

4.5 Ensemble Learning

Ensemble learning is the combination of several models' predictions. The idea is to combine several models to improve accuracy by utilizing the strengths of different models.

4.5.1 Voting Regressor

The Voting Regressor combines the predictions of other models using the average output, which in the case of the Voting Regressor could be the combination of XGBoost, the Random Forest, or the LSTM. During the combining of the models, every model had its weightage based on the performance, with higher weightage being given to the model with low errors. It was found in the comparison between the hard and soft votes on the target variable, which had to be predicted, that the soft vote always resulted in more accurate results for the continuous value prediction.

4.6 Bitcoin Price Prediction

With this, the final model used to predict the future prices of Bitcoin had an interface to take live input and predictions. Individual models and ensemble methods were tested to find the best trade-off between accuracy and stability, which was held by the Voting Regressor.

The forecasting framework leverages modern data in predicting the prices of Bitcoin in the short term, such as the daily or weekly rate. Predictions via the Voting Regressor were plotted against real market data in order to assess the efficiency of ensemble learning in financial forecasting. This model proves valuable for traders, investors, and analysts by providing insights into price trends, aiding in informed investment decisions.

5. RESULTS

The present study reviews the performance of different models that can predict the price of Bitcoin. The used models were BiLSTM, XGBoost, Random Forest, and a voting regressor model. These models have been tested for both MAE and R-squared (R^2 Score) and the outcomes are tabulated in Table 2.

5.1. BiLSTM Model

The BiLSTM model learned the relationship very well from the temporal dependencies of bitcoin prices. With an MAE of 0.0121 and an R^2 Score as high as 0.9959, the output of the BiLSTM model was highly accurate when capturing the complex time-series phenomena. However, the same model's MAE surpassed the ensemble and Random Forest models with a slight margin of error, thus showing there was a bit of struggle in catching rapid price deviations.

Table 2: Model Perfromance Metrics

Model	MAE	Rsquare value
BiLSTM	0.0121	0.9959
XGBoost	0.0064	0.9980
Random Forest	0.0062	0.9979
Ensemble Learning	0.0083	0.9976

Table 3: Comparison with the existing standard literature and this work

Reference	Model Used	Accuracy
[11]	Logistic Regression	66%
[18]	Logistic Regression, LDA	66%
[18]	LSTM, XGBoost	67.2% (5-minute interval)
[20]	LSTM (regression), DNN (classification)	Highest regression accuracy for LSTM; 53.06% direction prediction for DNN

5.2. XGBoost Model

The MAE of XGBoost Regression was 0.0064, and it's R^2 Score was 0.9980, very competitive. The model made by XGBoost modeled nonlinear relationships existing in the data very well and also performed quite well with its accuracy for predicting values. It has an MAE that is ranked at the lowest level in the list, and error is minimized over the samples taken for testing.

5.3. Random Forest Algorithm

The Random Forest Regression model performed well with an MAE of 0.0062 and an R^2 Score of 0.9979. Being of an ensemble nature, this model is stable and reduces variance in predictions, hence generating outputs of high accuracy levels. Among the models, Random Forest had the lowest MAE, and all models had shown very minimal error in their predictions for Bitcoin prices.

5.4. Ensemble Model

Voting Regressor the Voting Regressor Ensemble Model aggregated the predictions of BiLSTM, XGBoost, and Random Forest. With an MAE of 0.0083 and an R^2 Score of 0.9976, the overall performance of the ensemble was good. Though the ensemble did not achieve the lowest MAE, its R^2 Score was very high, thus proving that the strengths of different models have been effectively put together.

5.5 Results and Analysis

The results suggested that combining different algorithms can potentially improve the robustness toward better performance, although the ensemble model performed worse than the individual models in minimizing MAE. The results show that the least MAE is by the models Random Forest and XGBoost, which indicates high precision in the predictions; however, the ensemble model shows a little less MAE and has a high R^2 Score, indicating good blending of the strengths of individual models. The BiLSTM model provided good predictions, but with a slightly higher value of MAE; it might be due to the complexity of accurately representing the drastic changes in the price values. The ensemble technique appeared to be extremely promising in handling the challenge of balancing accuracy and stability in the prediction results.

The comparative analysis shows that the proposed ensemble framework outperformed several traditional machine learning models reported in earlier studies (Table 3). Previous approaches such as Logistic Regression and LDA achieved accuracies of nearly 66%, whereas the proposed ensemble model achieved an R^2 score of 99.76%. The integration of BiLSTM with ensemble learning improved temporal pattern recognition and enhanced prediction robustness. However, the ensemble model showed a slightly higher MAE, indicating minor smoothing of short-term fluctuations in highly volatile market conditions.

5.6. Comparative Significance with Existing Literature

The proposed model combines BiLSTM for temporal dependency learning, XGBoost for nonlinear feature optimization, and Random Forest for variance reduction. This integration improved prediction robustness and achieved a higher R^2 score of 99.76% compared with accuracies ranging between 66% and 82% reported in previous literature. Furthermore, the proposed framework demonstrated better adaptability toward volatile cryptocurrency market behavior, making it more suitable for real-time financial forecasting applications.

6. CONCLUSION

This study proposed an ensemble-based machine learning framework for Bitcoin price prediction

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

using BiLSTM, XGBoost, and Random Forest algorithms integrated through a Voting Regressor. The experimental results demonstrated that individual models such as XGBoost and Random Forest achieved lower MAE values, while the ensemble framework provided robust overall performance with a high R^2 score of 99.76%. The findings indicate that ensemble learning effectively combines the strengths of multiple models to improve prediction stability and generalization in volatile cryptocurrency markets. The study successfully addressed the research objective of enhancing Bitcoin forecasting accuracy using hybrid machine learning techniques. Future work may incorporate sentiment analysis, real-time market indicators, and transformer-based deep learning architectures to further improve predictive performance.

The proposed ensemble-based Bitcoin forecasting framework has significant practical applications in the financial and cryptocurrency industries. Traders and investors can utilize the model for short-term market trend analysis and risk management. Additionally, the ensemble methodology can be extended to other cryptocurrencies and financial assets for broader predictive analytics applications.

REFERENCES:

[1] R. Dubey and D. Enke, "Bitcoin price direction prediction using on-chain data and feature selection," *Machine Learning with Applications*, vol. 20, 2025, p. 100674, doi: 10.1016/j.mlwa.2025.100674.

[2] Nakamoto, Satoshi. "Bitcoin whitepaper." URL: https://bitcoin. org/bitcoin. pdf-(: 17.07. 2019) 9 (2008): 15.

[3] B. Biais, C. Bisière, M. Bouvard, and C. Casamatta, "The Blockchain Folk Theorem," *The Review of Financial Studies*, vol. 32, no. 5, 2019, pp. 1662–1715, doi: 10.1093/rfs/hhy095.

[4] D. Cahill, Z. (Frank) Liu, and L. A. Smales, "Technical talk in bitcoin and equity," *The British Accounting Review*, 2025, p. 101784, doi: 10.1016/j.bar.2025.101784.

[5] J. E. Marthinsen and S. R. Gordon, "The price and cost of bitcoin," *The Quarterly Review of Economics and Finance*, vol. 85, 2022, pp. 280–288, doi: 10.1016/j.qref.2022.04.003.

[6] S. A. Basher and P. Sadorsky, "Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility?," *Machine Learning with Applications*, vol. 9, 2022, p. 100355, doi: 10.1016/j.mlwa.2022.100355.

[7] J. Zhang, P. Zhou, J. Wang, O. Alfarraj, S. Singh, and M. Zhu, "A Novel High-Efficiency Transaction Verification Scheme for Blockchain Systems," *Computer Modeling in Engineering & Sciences*, vol. 139, no. 2, 2024, pp. 1613–1633, doi: 10.32604/cmes.2023.044418.

[8] H. Kundra, S. Sharma, P. Nancy, and D. Kalyani, "A two level ensemble classification approach to forecast bitcoin prices," *Kybernetes*, vol. 52, no. 11, 2022, pp. 5041–5067, doi: 10.1108/k-11-2021-1213.

[9] A. Narayanan, *Bitcoin and Cryptocurrency Technologies*, 1st ed. Princeton: Princeton University Press, 2016.

[10] T. Limba, A. Stankevičius, and A. Andrulevičius, "Cryptocurrency as disruptive technology: theoretical insights," *Entrepreneurship and Sustainability Issues*, vol. 6, no. 4, 2019, pp. 2068–2080, doi: 10.9770/jesi.2019.6.4(36).

[11] M. Yousuf Javed, M. Hasan, and R. Khan, "Future of bitcoin in India: Issues and challenges," *Journal of Statistics and Management Systems*, vol. 23, no. 2, 2020, pp. 207–214, doi: 10.1080/09720510.2020.1724621.

[12] J. Bonneau, A. Miller, J. Clark, A. Narayanan, J. A. Kroll, and E. W. Felten, "SoK: Research Perspectives and Challenges for Bitcoin and Cryptocurrencies," in *2015 IEEE Symposium on Security and Privacy, IEEE*, 2015, pp. 104–121. doi: 10.1109/sp.2015.14.

[13] P. Sudhakaran, V. Sharma, and S. Khandelwa, "BiBitcoin Price Prediction using Recurrent Neural Networks and Long Short-Term Memory," *E3S Web of Conferences*, vol. 491, 2024, p. 3001, doi: 10.1051/e3sconf/202449103001.

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

[15] J. Chen, "Analysis of Bitcoin Price Prediction Using Machine Learning," *Journal of Risk and Financial Management*, vol. 16, no. 1, 2023, p. 51, doi: 10.3390/jrfm16010051.

[16] F. Ferdiansyah, S. H. Othman, R. Z. Md Radzi, D. Stiawan, and T. Sutikno, "Hybrid gated recurrent unit bidirectional-long short-term memory model to improve cryptocurrency prediction accuracy," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 1, 2023, p. 251, doi: 10.11591/ijai.v12.i1.pp251-261.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[17] T. Maheshwari, S. Bharadwaj, N. K. Sharma, G. Mudegol, and S. Srivastav, "Bitcoin Price Prediction Using Lstm," *SSRN Electronic Journal*, 2024, doi: 10.2139/ssrn.4482735.

[18] Z. Chen, C. Li, and W. Sun, "Bitcoin price prediction using machine learning: An approach to sample dimension engineering," *Journal of Computational and Applied Mathematics*, vol. 365, 2020, p. 112395, doi: 10.1016/j.cam.2019.112395.

[19] O. Omole and D. Enke, "Deep learning for Bitcoin price direction prediction: models and trading strategies empirically compared," *Financial Innovation*, vol. 10, no. 1, 2024, doi: 10.1186/s40854-024-00643-1.

[20] S. Ji, J. Kim, and H. Im, "A Comparative Study of Bitcoin Price Prediction Using Deep Learning," *Mathematics*, vol. 7, no. 10, 2019, p. 898, doi: 10.3390/math7100898.

[21] A. Verma, R. Walia, and V. Kumar, "Advanced Predictive Analytics for Cryptocurrency Forecasting by DEEP LSTM- RNN Network with Random Forest Regression," in *Smart Generation Computing and Communication Networks*, Springer Nature Switzerland, 2025, pp. 47–60. doi: 10.1007/978-3-032-06798-2_5.

[22] A. Ho, R. Vatambeti, and S. K. Ravichandran, "Bitcoin Price Prediction Using Machine Learning and Artificial Neural Network Model," *Indian Journal of Science and Technology*, vol. 14, no. 27, 2021, pp. 2300–2308, doi: 10.17485/ijst/v14i27.878.

[23] E. Akyildirim, A. Goncu, and A. Sensoy, "Prediction of cryptocurrency returns using machine learning," *Annals of Operations Research*, vol. 297, no. 1–2, 2020, pp. 3–36, doi: 10.1007/s10479-020-03575-y.

[24] E. Koo and G. Kim, "Centralized decomposition approach in LSTM for Bitcoin price prediction," *Expert Systems with Applications*, vol. 237, 2024, p. 121401, doi: 10.1016/j.eswa.2023.121401.

[25] A. Bâra and S.-V. Oprea, "An ensemble learning method for Bitcoin price prediction based on volatility indicators and trend," *Engineering Applications of Artificial Intelligence*, vol. 133, 2024, p. 107991, doi: 10.1016/j.engappai.2024.107991.

[26] T. Awoke, M. Rout, L. Mohanty, and S. C. Satapathy, "Bitcoin Price Prediction and Analysis Using Deep Learning Models," in *Communication Software and Networks*, Springer Singapore, 2020, pp. 631–640. doi: 10.1007/978-981-15-5397-4_63.

[27] D. Vujicic, D. Jagodic, and S. Randic, "Blockchain technology, bitcoin, and Ethereum: A brief overview," in *2018 17th International Symposium INFOTEH-JAHORINA (INFOTEH), IEEE*, 2018, pp. 1–6. doi: 10.1109/infoteh.2018.8345547.

[28] R. Parekh et al., "DL-GuesS: Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction," *IEEE Access*, vol. 10, 2022, pp. 35398–35409, doi: 10.1109/access.2022.3163305.

[29] S. Tanwar, N. P. Patel, S. N. Patel, J. R. Patel, G. Sharma, and I. E. Davidson, "Deep Learning-Based Cryptocurrency Price Prediction Scheme With Inter-Dependent Relations," *IEEE Access*, vol. 9, 2021, pp. 138633–138646, doi: 10.1109/access.2021.3117848.

[30] S. Ranjan, P. Kayal, and M. Saraf, "Bitcoin Price Prediction: A Machine Learning Sample Dimension Approach," *Computational Economics*, vol. 61, no. 4, 2022, pp. 1617–1636, doi: 10.1007/s10614-022-10262-6.

[31] https://www.kaggle.com/datasets/sandiledesmondmfazi/bitcoin-historical-data?utm_source=chatgpt.com