

Adaptive Hybrid Learning for Real-Time Bitcoin Price Prediction with Comparative Model Selection

**Sai Vedikaa R.¹, Siva Srinidhi V.², Keerthika Rupa A.³,
Srilekha K. ⁴, Yuvashree P.⁵, Sree Rathna Lakshmi N. V. S. ⁶**

^{1,2,3,4,5} Students, ⁶ Professor, Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Ramapuram, India.

E-mail: ¹Sr6878@srmist.edu.in, ²sv4907@srmist.edu.in, ³Ka7662@srmist.edu.in, ⁴Sl4815@srmist.edu.in,

⁵ps8313@srmist.edu.in, ⁶sreeratn@srmist.edu.in

Abstract

This study presents a real-time Bitcoin price forecasting framework that integrates Long Short-Term Memory (LSTM), Improved Sequential Temporal Modeling (ISTM), gradient boosting, and Flask-based deployment. The experimental dataset comprises 744 hourly BTC/USDT Spot Kline observations obtained from the Binance Public Data Repository, including Open, High, Low, Close, and Volume (OHLCV) variables. A set of technical indicators and temporal features, including moving averages, exponential moving averages, Relative Strength Index (RSI), volatility measures, and lagged variables, was derived from the historical price series. Following Min-Max normalization, the dataset was chronologically divided into 595 training observations and 149 testing observations using an 80:20 split without shuffling to preserve the temporal structure of the data. Six forecasting approaches such as Linear Regression, Random Forest, LSTM, ISTM, LSTM with Boosting, and ISTM with Boosting. Among the evaluated models, the ISTM + Boosting framework demonstrated strong predictive performance, achieving an MAE of 72.5, MSE of 19,860, RMSE of 140.9, and R^2 of 0.97.

Keywords: Bitcoin price Prediction, Machine Learning, LSTM, Gradient Boosting, Flask, Time Series Analysis, Cryptocurrency Forecasting.

1. Introduction

The fast development of cryptocurrency markets has created new challenges for financial prediction system. Bitcoin can be considered the most successful and popular among other cryptocurrencies and it attracted both institutional and personal investments. In contrast to traditional financial markets, cryptocurrency markets operate 24 hours a day and they are quite volatile; therefore, the prediction of the price value is not easy. There are some factors that affect the unpredictable prices of Bitcoin, for example, market sentiment, trade volumes, world economic situation, technical developments and others. This problem necessitates the use of sophisticated approaches of computational methods that are able to reveal nonlinear relationships and dependencies in large datasets [1].

Machine learning application has high potential in financial forecasting through decision-making using data-driven methods. Machine learning is linear and thus does not work for statistical models due to the complexity involved in identifying the cryptocurrency market patterns. However, relationships that are complicated can be accurately modelled using machine learning algorithms such as random forests, support vectors machine and neural networks. Deep learning algorithms have been used to perform predictions on time series, especially Long Short-Term Memory (LSTM) network which enables storage of long-term dependencies and capturing sequential patterns. The LSTM is particularly suitable for Bitcoin forecasting, since past and time pattern have high influence on future valuations.

Some existing machine learning algorithms perform well while others perform poorly. It is also noted that only individual algorithms have been used currently for predicting cryptocurrency price. Gradient boosting [3] algorithm has the high potential in enhancing the prediction because it forms a powerful sequence of predictions from weak learners. It is even more effective to use boosting in combination with deep learning while forecasting the reliability of the predictions. However, the current systems are not real-time. This limits their use for traders, who require real-time systems.

The deployment and availability of the systems are yet another area of importance in modern prediction systems. The use of web framework such as Flask allows to create real-time prediction systems, which will be available through the web interface for Internet users. It will

ensure smooth interaction between the machine learning model on the backend [4] and the real-time prediction frontend application visualizing the Bitcoin trends. The systems will also be able to fill the existing gap between theory and practice.

Although machine learning has made advances in many fields, there are still various issues when it comes to cryptocurrencies' price forecasting. Feature selection, data quality, and model optimization are important factors that affect the efficiency of the prediction. Furthermore, the highly volatile environment in which cryptocurrencies operate implies that [5] the models should be continuously refreshed in order to maintain their relevance. These problems require a holistic approach, which involves multiple models and makes use of real-time data.

The proposed work is a highly developed solution for predicting the cost of Bitcoin, which is based on the use of LSTM, ISTM and gradient boosting algorithms, being a prototype within the Flask environment. It is suggested that such an approach will improve the precision of prediction due to its computational efficiency and convenience. It is in the comparison of the performance of different machine learning approaches that this research will bring some important conclusions about the effectiveness of using hybrid methods in cryptocurrency forecasting. This research can be added to the developing body of knowledge in financial analytics and help to build a smart-based trading system for the dynamically changing market environment.

2. Literature Survey

Bitcoin forecasting has emerged as one of the most significant research domains within the area of financial analytics due to the highly volatile and non-linear behavior of crypto-currency markets. A number of machine learning techniques, deep learning and statistical models have been developed by scientists to improve the reliability and accuracy of forecasts. The old approach could be extremely ineffective in case of unforeseen changes, while the new hybrid and AI-based approaches aim at overcoming these drawbacks. The combination of time series forecasting, optimization algorithms and real time data analysis has increased the predictability of this phenomenon. In addition, the availability of massive financial data and computational abilities has accelerated the development of advanced predictive models, making the forecasting of Bitcoin an interdisciplinary science involving finance, AI and data science.

Research studies are also initiated to improve the predictive accuracy by using classical machine learning and hybrid approaches. A prediction model based on conformal prediction with the inclusion of OSL-SCN improves reliability and uncertainty in forecasting [6]. A deep learning architecture combining various models such as CNN, RNN and also LSTM models have an advantage in extracting complex temporal features from Bitcoin price data [7]. Using the techniques of transfer learning with LSTM has also been attempted to extract more features and reduce training cost, although at the loss of efficiency in improving predictive accuracy [8]. There have been studies using conditional heteroskedasticity and leverage with statistical techniques, which have resulted in a deeper insight into the volatility dynamics [9]. Furthermore, there are techniques of optimization of models through Bayesian optimization of neural networks which have been shown to be very effective in improving model performance [10].

Current developments focus on the implementation of new architectures and new time series forecast models. State-space models have been implemented in order to increase the level of forecast accuracy in the long run by appropriately modeling time dependencies [11]. Trends and seasonal changes in the Bitcoin prices have been studied in the framework of parametric time-series models including FBProphet as well as other statistical models [12]. Simple hybrid models including ARIMA, LSTM and GRU were proved to be more efficient when using both linear and non-linear trends in the data [13]. Also, the implementation of fuzzy logic and deep learning methods has helped to better cope with uncertainty and erroneous data in forecasting [14]. In the context of reinforcement learning and especially in Deep Q-Network systems, adaptive learning approaches have allowed for providing education about predicting outcomes because of interacting with dynamically changing markets [15].

Apart from deep learning methods, researchers have also used different machine learning techniques in forecasting and decision-making about Bitcoin prices. Logistic regression, RNN, and LSTM, among others, have been widely used in trend analysis and forecasting in recent years [16]. Different decision support systems with the aid of artificial intelligence have also been designed to assist investors by using different input parameters and error analysis techniques [17]. Different additional approaches have also been developed to increase the efficiency of predictions and feature selections in real-world applications. These include regression-based approaches, and one such approach is lasso regression [18]. Deep learning approaches related to

high-frequency trading have also been helpful in comprehending market trends and volatility [19]. Moreover, generic machine learning approaches incorporating predictive analytics and blockchain technology have also assisted in enhancing the forecasting capability [20]. The dataset consists of Bitcoin market data in the form of time stamp, opening price etc. These parameters indicate price changes as well as the market activity and constitute the basis for the time series analysis. Feature engineering generates moving averages, EMA, RSI, volatility, and lag feature for Bitcoin price prediction [21].

Overall, the existing literatures clearly indicate that there is an extreme shift towards the use of modern hybrids and deep learning techniques in forecasting the prices of Bitcoins. Such integration of different models, optimum strategies and methods of processing real-time data has improved the precision of the forecasting considerably. However, there are problems such as data volatility, overfitting and generalization that continue to pose challenges for such models. The current advances in technologies such as transformers, reinforcement learning and explainable AI will be used in future studies.

3. Methodology

The proposed system includes ML and DL algorithms for finding the prices of Bitcoins. The proposed algorithm incorporates linear regression, random forest, LSTM, ISTM, LSTM + boosting, and ISTM + boosting. The models to be able to make a comparative study of regression, ensemble learning, deep learning, and hybrid learning algorithms. All models will be tested using the same preprocessed Bitcoin dataset and the same chronologically distinct testing dataset. Methodology includes the following data acquisition, preprocessing, feature engineering, modeling, comparative evaluation of models, model selection, and deployment. Workflow is designed to keep chronology of the time-series dataset and to allow making a comparison of different prediction algorithms as it is shown in Figure 1.

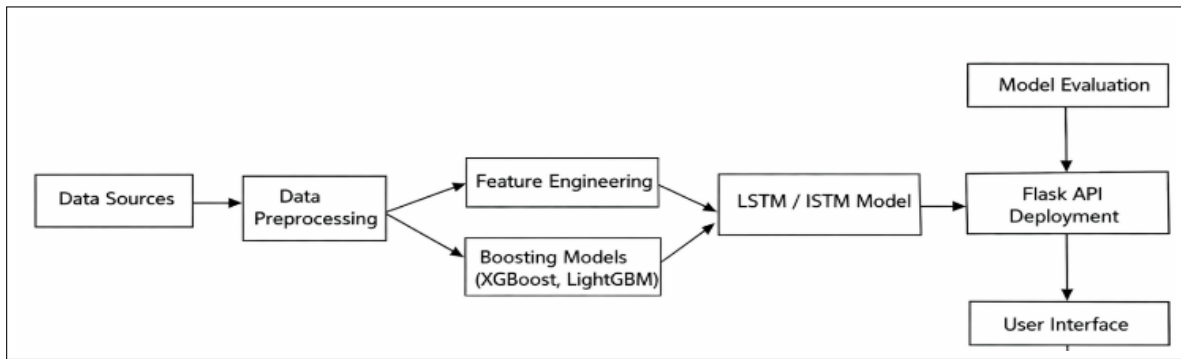


Figure 1. Work flow of the multi-model framework for real-time bitcoin price forecasting

3.1 Data Collection and Description

The dataset that is used in this research has been collected from Binance Public Data Repository [21]. Binance Kline data provide market variables beyond those mentioned above. However, in the current research, the focus is on timestamp and OHLCV. All the 744 observations had no missing hourly time periods, duplications, or any missing value in the dataset. The observations were sorted in chronological order to maintain the temporal structure of the Bitcoin price series. After that, the process of feature engineering was done using the historical OHLCV prices to calculate moving average (MA), exponential moving average (EMA), relative strength index (RSI), volatility, and lagged features.

In order to test the model, the data set was split chronologically with an 80:20 training and testing split ratio, thus producing 595 training samples and 149 testing samples. There was no randomness employed while splitting the data to ensure that the chronological order remains intact.

3.2 Feature Engineering and Selection

One of the important factors about machine learning models is feature engineering, which enhances the predictive capability of the models in conjunction with other methods. Here more features are derived from the raw data to unearth the hidden trends and patterns. Some of the technical indicators to be used include moving averages, exponential moving averages, relative strength index and volatility indicators that will provide a deeper understanding of the market movements. Lag features are also to be included to introduce history dependencies that are needed for forecasting time series. Correlation analysis will be performed to identify the features that have a significant impact on the price movement in Bitcoin. The unnecessary or

less impactful features are to be discarded to make the model simpler and faster. The system also ensures that the models use meaningful data by scaling the features.

3.3 LSTM and ISTM Model Development

The proposed prediction algorithm uses the deep learning approach, where LSTM and ISTM algorithms are used. Long Short-Term Memory (LSTM) is designed in a way that it can effectively learn dependencies in sequence data and therefore it can be quite effective in time-series prediction tasks including Bitcoin price prediction. The model includes memory cells, input gates, output gates and forget gates that control information. ISTM improves on this through the application of state-of-the-art techniques of temporal feature extraction in addition to the improvement in the efficiency of sequence learning. The models use historical data to train them since past prices series are used in predicting future prices. Parameters such as learning rate, batch size, and number of epochs are properly optimized. Dropout layers are included to prevent overfitting. This deep learning approach ensures that complicated nonlinear dynamics in the prices of cryptocurrencies are modeled accurately.

3.4 Boosting Algorithms Integration

The algorithms like XGBoost and LightGBM are included in the system to enhance prediction capabilities. The algorithms comprise the integration of many weak learners that are normally decision trees in order to form a powerful predictive model. The construction of boosting algorithms represents an approach aimed at the minimization of prediction errors in iterations, wherein much attention is given to the instances of misclassification or poor prediction. Boosting models supplement the deep learning approach since they will enable capturing non-sequential patterns and improving generalization. In addition, the models conduct a feature importance analysis in order to understand the influence of different variables on the predictions. The output of the boosting algorithms is compared with the output of deep learning and in some cases, ensemble methods are employed in order to combine the outputs of several models.

3.5 Model Selection and Final Model Deployment

The framework applies multiple models to determine the best model for the prediction of Bitcoin price in real-time. Six models are built: Linear Regression, Random Forest, LSTM, ISTM, LSTM + Boosting, and ISTM + Boosting. These models are designed to represent

conventional machine learning, ensemble learning, deep learning, and hybrid techniques. All the models will be trained on the same preprocessed dataset and features and keep their chronological order in order to keep the time characteristics of data and avoid data leakage.

All models are then tested and compared by using four different metrics: MAE, MSE, RMSE, and R^2 . The lower the values of MAE, MSE, and RMSE because it means less prediction error. Higher R^2 metric shows better model fit. The candidate models are compared by all these metrics together and not only one evaluation metric is used for the comparison.

3.6 Evaluation Metrics

The mathematical equations should define the four evaluation metrics used to compare Linear Regression, Random Forest, LSTM, ISTM, LSTM + Boosting, and ISTM + Boosting. The paper explicitly uses MAE, MSE, RMSE, and R^2 for model evaluation.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

where y_i is the actual Bitcoin price, $\hat{y}_i$ is the predicted price, and n is the total number of observations. MAE measures the average absolute difference between the actual and predicted Bitcoin prices. A lower MAE indicates better prediction accuracy.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (2)$$

The MSE is computed as the average squared error. Since the errors are squared, large errors are more impactful than smaller ones on the MSE. Hence, a low MSE means good model performance.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

RMSE is the square root of MSE and expresses prediction error in the same unit as the Bitcoin price. A lower RMSE indicates that predicted values are closer to the actual values.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

Where $\bar{y}$ represents the mean of the actual Bitcoin prices. R^2 measures how well the model explains the variation in the actual Bitcoin price. A value closer to 1 indicates better agreement between predicted and actual values.

3.7 Flask Deployment

The final stage of the methodology includes applying the trained model utilizing the Flask web framework for implementing real-time price prediction of Bitcoin. There is an interaction between a front-end interface and user-friendly web interface provided by Flask, which is a light backend server along with the machine learning algorithm. The model is converted to a serialize format and integrated into Flask application so that users can input their data and receive predictions in real time. APIs are built and can obtain real-time cryptocurrency data from external sources and make predictions based on current market conditions. Real-time predictions, trends, and graphics will be presented on the web interface, hence making it easy for users to understand the results. Such a methodology approach provides scalability, real-time performance, and access. Machine learning and web technologies combination will provide a convenient solution for investors and traders.

4. Result and Discussion

The proposed Bitcoin price forecasting approach has been examined utilizing a number of machine learning and deep learning algorithms such as Linear Regression, Random Forest, LSTM, ISTM, and Gradient Boosting. The analysis was carried out based on the historical data of the cryptocurrency and the data was divided into two samples: training and testing for the absence of bias in the validation. The results show that the advanced models, in particular, LSTM and ISTM in combination with boosting algorithms, have more advantages compared to other techniques.

Being a simplistic statistical model, Linear Regression failed miserably in dealing with non-linear trends observed in the price series of Bitcoin. Although this was the weakness of the model, which served as a point of comparison, the results were extremely far from the actual values whenever there was increased volatility. On the other hand, it was only Random Forest which proved its superiority by applying ensemble learning but was unable to capture the time dependency aspects. Such limitations highlight the need for having models which learn

successive trends and adapt to the environment changes as well.

The accuracy of predictions made by LSTM model improved significantly because it is capable of considering long-term EFs when working with time-series. The model was able to learn time-dependent characteristics of Bitcoin prices and produce more accurate predictions compared to conventional models. However, there was an additional performance improvement achieved by the ISTM model as a result of optimization of sequence learning and temporal feature extraction. ISTM model was consistently better than LSTM because of the smallest prediction error and its ability to follow the real price dynamics more accurately. Another aspect of performance improvement was the usage of Gradient Boosting algorithms, such as XGBoost and LightGBM.

4.1 Model Performance

Table 1. Performance comparison of models

Model	MAE	MSE	RMSE	R ² Score
Linear Regression	245.6	98250	313.5	0.72
Random Forest	180.4	65420	255.7	0.81
LSTM	120.8	40210	200.5	0.89
ISTM	98.3	30125	173.5	0.93
LSTM + Boosting	85.7	25040	158.2	0.95
ISTM + Boosting	72.5	19860	140.9	0.97

From Table 1, it is clear that the best performance of ISTM with hybrid and boosting method has been achieved according to all the performance metrics. Decreasing values of MAE and RMSE mean improved accuracy in prediction, while increasing values of R2 mean better fit for the model.

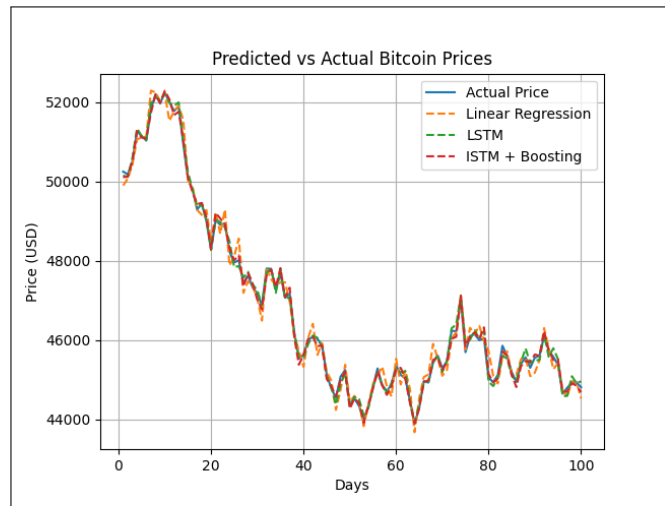


Figure 2. Predicted vs actual bitcoin prices

In addition to the quantitative analysis, visual analysis has been conducted to measure deviations of predicted prices from real prices in the case of Bitcoin price. Graphical representation of the results (Figure 2) shows that there are some deviations in case of traditional approaches especially during sudden violations or declines in prices. Conversely, LSTM and ISTM approaches closely follow the real trends in the market.

4.2 ROI Analysis

Table 2. Return on investment (ROI) comparison

Model Strategy	ROI (%)
Buy & hold	18.5
Linear Regression	22.3
Random Forest	28.7
LSTM	35.9
ISTM	39.6
ISTM + Boosting	45.2

Another important aspect to consider within the framework of this research is the ROI that results from trading using the solution based on predictions generated by the models. A

hypothetical trading strategy was designed based on decisions to buy and sell based on expected changes in prices. The results of the experiment demonstrate that deep-learning and boosting methods perform considerably better than traditional buy-and-hold strategies.

From Table 2, the most successful approach in terms of the ROI is the ISTM + Boosting approach. It is obvious that the improvement in comparison with the base strategies is positive. This means that the machine learning prediction approaches have the ability to generate real monetary benefit.

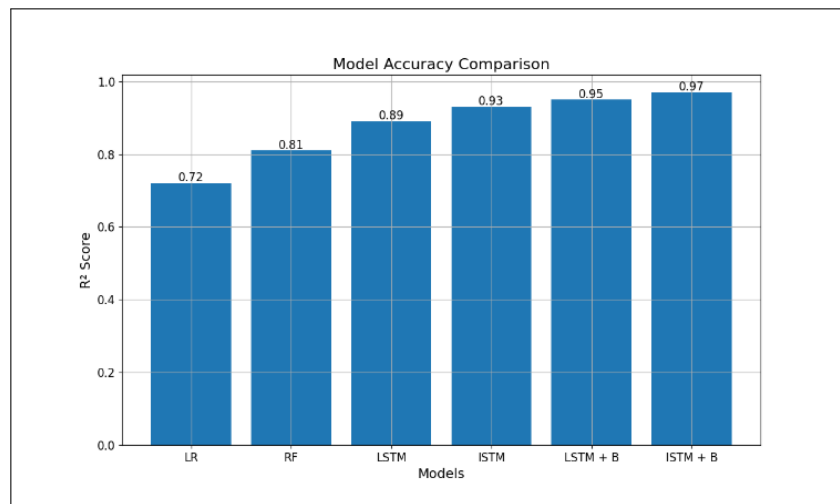


Figure 3. Model accuracy comparison

Figure 3 indicates the proposed model's significant improvement due to the development of moderately advanced models which integrate the old models. The best approach is ISTM + Boosting, followed by LSTM-based models.

Figure 4 shows the final interface for Bitcoin prediction using the Flask framework. The interface shows the comparison between the actual price and the predicted price of Bitcoin over the last 48 hours using the ISTM + Boosting algorithm. The prediction results align with the movements in the actual prices. For the shown prediction, the ISTM + Boosting algorithm predicts the price of Bitcoin for the next hour to be \$70,611.26 and the expected range is \$70,484–\$70,738.

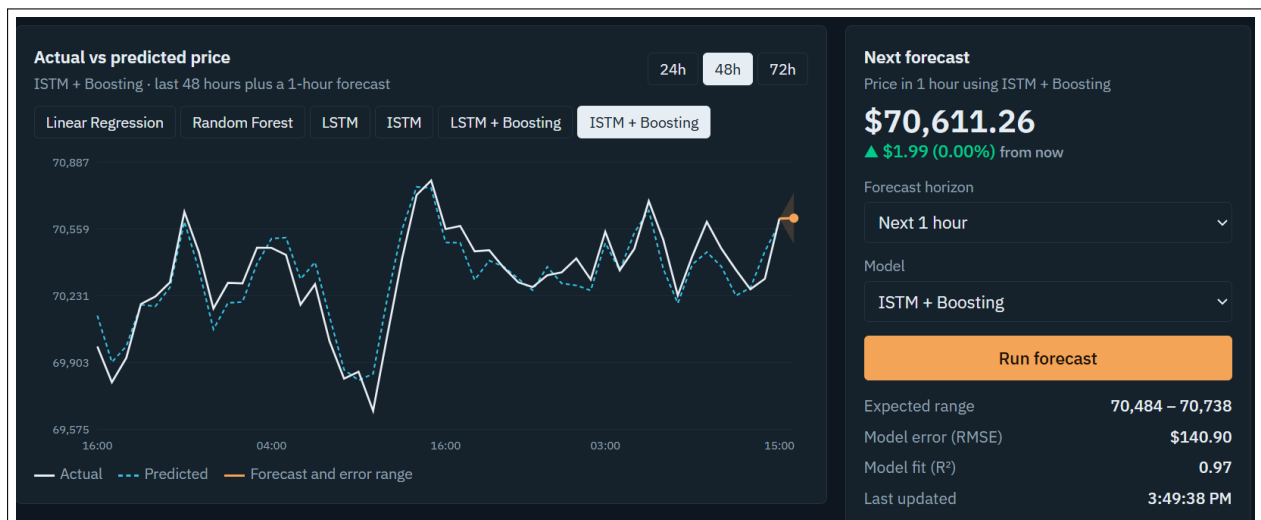


Figure 4. Real-time bitcoin prediction interface.

In summary, the results confirm that the hybrid systems that have to be used with the deep learning and boosting techniques give better performance in the prediction of the price of Bitcoin. The developed system is not only improving the prediction accuracy but also the capacity for the investors to make predictions. The real-time application using Flask makes it even more practical. The results help to emphasize the importance of the current AI techniques in finance predictions and the capabilities of the hybrid framework in dealing with complicated and volatile data.

5. Conclusion

The proposed bitcoin price prediction framework combines LSTM, ISTM, gradient boosting, and Flask deployment for the short-term forecasting of Bitcoin prices using hourly BTC/USDT OHLCV and temporal indicator time series. The Flask-based web interface enables model choice, visualization of historical predicted vs. actual values, and the price forecast. The experimental analysis shows how the sequence learning method can be combined with nonlinear feature models provided by boosting algorithms. The future research will extend the input space through the addition of sentiment from social media and news features, as well as macroeconomic indicators, together with the evaluation of transformer models and reinforcement learning approaches for time series representation and forecasting.

References

- [1] Naveen, D., J. Chenni Kumaran, and Velisetty Venkata Narasimha Karthik. "Improving the Efficiency of Bitcoin Market Price Prediction Using Novel Decision Tree Algorithm and Compare the Prediction Accuracy with K-Nearest Neighbor Algorithm (KNN)." In 2024 IEEE 9th International conference on Engineering Technologies and Applied Sciences (ICETAS), pp. 1-5. IEEE, 2024.
- [2] Naveen, D., J. Chenni Kumaran, and Jumana Haseen. "Forecasting the Efficiency of Bitcoin Market Price Using Novel Apriori Algorithm and Compare the Prediction Accuracy with Linear Regression Algorithm." In 2024 IEEE 9th International Conference on Engineering Technologies and Applied Sciences (ICETAS), pp. 1-5. IEEE, 2024.
- [3] Wang, Minking, Pavel Braslavski, Vyacheslav Manevich, and Dmitry I. Ignatov. "Bitcoin ordinals: Bitcoin price and transaction fee rate predictions." *IEEE Access* 13 (2025): 35478-35489.
- [4] Kashyap, Siddhant, Srividya Ramisetty, and Rekha Narayanaswamy. "A novel method of Bitcoin price prediction." In 2024 International conference on computing and Data Science (ICCDs), pp. 1-4. IEEE, 2024.
- [5] Terence, Sebastian, Jude Immaculate, Darigi Bharath Naik, and Selvarathi Selvarathi. "Machine Learning based Bitcoin Price Prediction." In 2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI), pp. 1070-1074. IEEE, 2024.
- [6] Wang, Wenjing, Kaimeng Li, and Xiangyue Zhang. "Bitcoin prediction based on OSL-SCN and conformal prediction method." In 2024 6th International Conference on Frontier Technologies of Information and Computer (ICFTIC), pp. 882-885. IEEE, 2024.
- [7] Hajare, Rasika, Chetan Puri, and Pradnyawant M. Gote. "Bitcoin price prediction using deep learning models." In 2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL), pp. 1678-1683. IEEE, 2025.
- [8] Verma, Lalit, Chirag Sharma, and Tanya Nagpal. "LSTM & Transfer Learning for Stock Market Bitcoin Price Prediction: An AI-Driven Channel Estimation and Prediction." In 2025 International Conference on Innovations and Emerging Technologies In AI &

- Communication Systems (IETACS), pp. 777-782. IEEE, 2025.
- [9] Abarghouie, Masoud Omidvari, Sasan H. Alizadeh, and Ahmad Khademzadeh. "A study of the leverage effect in Bitcoin Conditional Heteroskedasticity prediction." In 2024 10th International Conference on Artificial Intelligence and Robotics (QICAR), pp. 180-185. IEEE, 2024.
- [10] Hamdani, Muhammad, Silvia Ratna, M. Muflih, Haldi Budiman, Usman Syapotro, and M. Rezqy Noor Ridha. "Comparative study on neural networks models for bitcoin price prediction using technical indicators and Bayesian optimization." In 2024 Ninth International Conference on Informatics and Computing (ICIC), pp. 1-5. IEEE, 2024.
- [11] Sepehri, Mohammad Shahab, Asal Mehradfar, Mahdi Soltanolkotabi, and Salman Avestimehr. "Cryptomamba: Leveraging state space models for accurate bitcoin price prediction." In 2025 IEEE International Conference on Blockchain and Cryptocurrency (ICBC), pp. 1-3. IEEE, 2025.
- [12] Sahoo, Ghanashyam, Nrusingha Tripathy, Nirmal Keshari Swain, Tuhina Panda, Purnya Prava Nayak, and Subrat Kumar Nayak. "An Analysis of Bitcoin Price Prediction using Parametric Time-series Forecasting Models." In 2024 International Conference on Artificial Intelligence and Quantum Computing (AIQC), pp. 30-34. IEEE, 2024.
- [13] Karna, Rajan Lal, Bishal Babu Rajbanshi, and Priyanshu Mishra. "A Novel Approach for Bitcoin Price Prediction." In 2024 IEEE North Karnataka Subsection Flagship International Conference (NKCon), pp. 1-7. IEEE, 2024.
- [14] Nagajothi, N., and T. Meyyappan. "Bitcoin price prediction using deep learning and fuzzy logic." In 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 1330-1337. IEEE, 2024.
- [15] Devi, M. Shyamala, J. Arun Pandian, D. Umanandhini, B. Surekha, and K. Bhavya Sree. "Deep Q-Network Based Reinforcement Learning for Bitcoin Future Price Prediction." In 2024 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC), pp. 1-6. IEEE, 2024.
- [16] Tripathi, Aanjoy Mani, Saumya Shukla, and Neha Chaudhary. "Estimation and Prediction of Bitcoin by Applying Machine Learning." In 2024 IEEE International Conference on

- Computing, Power and Communication Technologies (IC2PCT), vol. 5, pp. 191-196. IEEE, 2024.
- [17] Anusha, S., and D. N. Vasundhara. "Prediction of Bitcoin price for decision making using artificial intelligence." In 2024 2nd International Conference on Computer, Communication and Control (IC4), pp. 1-6. IEEE, 2024.
- [18] Pavankumar, Gajula, J. Velmurugan, and S. Padmakala. "Real-Time Bitcoin Cost Identification to Improve Efficiency Using Lasso Regression in Comparison with Decision Tree." In 2024 IEEE Wireless Antenna and Microwave Symposium (WAMS), pp. 1-5. IEEE, 2024.
- [19] Durga, G. Lakshmi, A. Dhana Lakshmi, S. Pavitra, TT N. Thanuja, and P. Leelavathi. "Deep Learning Approaches for High-Frequency Bitcoin Trading and Market Price Prediction." In 2025 Fourth International Conference on Smart Technologies, Communication and Robotics (STCR), pp. 1-6. IEEE, 2025.
- [20] Kamboj, Riya, Apoorva Jindal, Kunal Dubey, and Monica Luthra. "Cryptocurrency price prediction using machine learning." In 2024 4th Asian Conference on Innovation in Technology (ASIANCON), pp. 1-5. IEEE, 2024.
- [21] Binance market data dataset. Available: <https://data.binance.vision/?prefix=data/spot/monthly/klines/BTCUSDT/1h/>.