EdinBurg Peer Reviewed Journals and Books Publishers
Journal of Information and Technology
Vol. 5||Issue 3||pp 11-19||June||2025
Email: info@edinburgjournals.org||ISSN: 3080-9576

Leveraging Machine Learning to Forecast Trends in Cryptocurrency Exchange Markets

Fils Munyawera[1*] & Enan N. Muhire[2]
[1,2]School of Computing and Information Sciences, University of Lay Adventists of Kigali
***Corresponding author E-mail: munfils96@outlook.com**

Accepted: 19 April 2025 || Published: 05 June 2025

Abstract

This research investigates the application of machine learning (ML) algorithms to enhance the predictability of movements in the cryptocurrency market, specifically examining changes in Bitcoin prices. Four ML models, Linear Regression (LR), Random Forest (RF), Gradient Boosting Machines (GBM), and Long Short-Term Memory (LSTM), were analyzed using historical data. The performance of these models was evaluated based on their accuracy, precision, and recall. The findings indicated that Random Forest surpassed the others with nearly perfect results in accuracy (0.99), precision (0.99), and recall (0.99). GBM demonstrated strong recall (0.99) but had lower accuracy (0.83) and precision (0.75), while Linear Regression showed commendable performance with accuracy (0.93) and precision (0.97). LSTM yielded the least favorable results. The study concludes that Random Forest is the most dependable model for predicting cryptocurrency prices, providing useful insights for traders and researchers navigating this highly volatile market.

Keywords: *Cryptocurrency Volatility, Machine Learning Algorithms, Price Prediction, Random Forest, Decision-Making Framework*

How to Cite Munyawera, F., & Muhire, E. N. (2025). Leveraging Machine Learning to Forecast Trends in Cryptocurrency Exchange Markets. *Journal of Information and Technology, 5*(3), 11-19.

1. Introduction

Within a distributed network, a consensus algorithm serves as a protocol or mechanism for achieving agreement among nodes (Hussein, May, & Sahar , 2023). Their worth is based on the trust of the underlying algorithm, rather than any actual item, allowing cryptocurrencies to be independent of any higher authority (Bouteska, Mohammad, Petr, & Kunpeng, 2024). The blockchain is a decentralized system, and the mechanism mathematically permits hundreds of nodes spread around the world to agree on the generation of blocks (Qianwen, et al., 2019). However, it may be susceptible to privacy breaches through big data analytics when combined with machine learning (Wu, Zehua, Yuxiang, & Leung, 2021). The high-level review focuses on improving blockchain performance, while the detailed analysis introduces a modular

EdinBurg Peer Reviewed Journals and Books Publishers
Journal of Information and Technology
Vol. 5||Issue 3||pp 11-19||June||2025
Email: info@edinburgjournals.org||ISSN: 3080-9576

blockchain framework that breaks down a blockchain system into interacting modules, emphasizing essential components such as the network, consensus, and distributed ledger. This framework serves as a basis for creating blockchains that are scalable, flexible, and adaptable (Minghui , et al., 2024). Additionally, the system is designed for the consortium blockchain, which is maintained by a group of members from various organizations to enhance efficiency (Sanghami, John, & Qin, 2023). The robustness of machine learning techniques in combating malicious behavior increases confidence in AI systems, strengthening their dependability and authenticity (Flare Team, 2024). The effectiveness of these technologies in real-world bitcoin market settings, particularly in addressing rapid price fluctuations, remains largely unexplored (Katsiampa, 2019). Moreover, there is a lack of a defined framework for applying AI technologies to aid decision-making in Bitcoin trading. Previous studies, such as those conducted by Zhang, Chen, & Zhang (2021), indicate that while various ML methods can improve predictive performance, the integration of these tools into a coherent decision-making framework is still in its infancy. This study aims to close these gaps by evaluating the efficacy of several ML strategies in bitcoin price prediction and creating a framework that enhances traders' decision-making processes using AI tools. Therefore, this paper aims to answer the question: "*How can Machine Learning algorithms be leveraged to improve the predictability of cryptocurrency exchange market trends, and what framework can be developed to support effective decision-making in this volatile environment?*"

2. Related Works

Previous research has explored the application of blockchain technology across various industries. In the context of financial technology (FinTech), blockchain has demonstrated its potential to alter traditional financial services by providing digital solutions and increasing trust through consensus-based methods. Studies have also examined the fundamental aspects of blockchain systems and their core elements, providing frameworks for creating scalable and adaptable blockchains. The rise of blockchain, which was initiated by the emergence of Bitcoin, has attracted considerable attention due to its potential to address trust issues in various industries (Tingting & Kui, 2020). The automotive industry, known for its advanced technology, has the potential to greatly benefit from blockchain technology by enhancing security, privacy, integrity, and traceability (Yazeed, Mohammad, Orieb, & Almaiah, 2023). It has the potential to alter traditional financial services by providing digital financial solutions around the world, particularly during the pandemic, which has increased the use of these services (Renduchintala, Alfauri, Yang, Pietro, & Jain, 2022). While these works highlight the broader applications of blockchain, this research focuses specifically on leveraging machine learning techniques for cryptocurrency market forecasting, building upon the growing interest in applying advanced computational tools to this volatile domain.

3. Methodology

3.1 Research Approach

This paper employs a quantitative methodology, involving an experiment to gather empirical data on cryptocurrency price forecasts based on historical data. The process includes creating

EdinBurg Peer Reviewed Journals and Books Publishers
Journal of Information and Technology
Vol. 5||Issue 3||pp 11-19||June||2025
Email: info@edinburgjournals.org||ISSN: 3080-9576

models using selected machine learning algorithms, followed by training, testing, and assessing these models using an appropriate dataset and performance metrics.

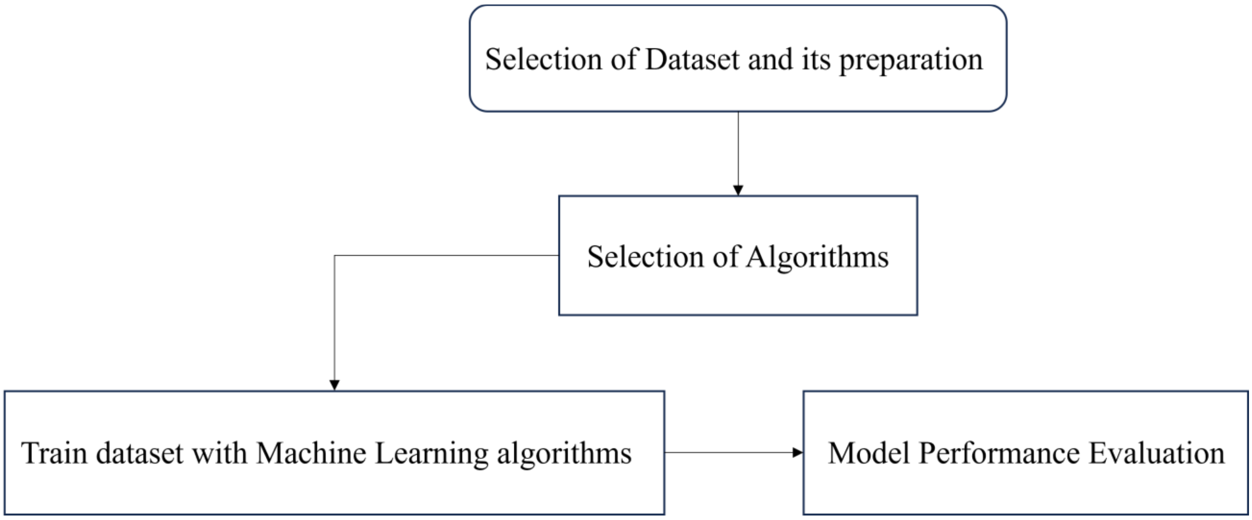

Figure 1 - Conceptual framework

3.1.1 Selecting Dataset

The dataset for this study consists of the prices of ten well-known cryptocurrencies: Tether, Bitcoin, Ethereum, TRON, BNB, XRP, Cardano, Dogecoin, Litecoin, and Polkadot. The data was acquired from finance.yahoo.com, considering features such as Date, Open, High, Low, Close, Adjusted Close prices, and Volume, for the period between January 1, 2018, and December 30, 2022.

3.1.2 Dataset Preparation

The analysis focuses on daily price data in USD. The pre-processed dataset, comprising 19,772 rows and 7 columns, was partitioned into training (70%), validation (10%), and testing (20%) sets, maintaining the temporal order of the data. These sets were used for developing and evaluating the performance of the chosen machine learning algorithms.

3.1.3 Machine Learning Algorithms

Prediction models were developed using the selected algorithms. The Random Forest model was implemented using the RandomForestRegressor() function from the scikit-learn library. Similarly, the Gradient Boosting Machines (GBM) model was generated using the GradientBoostingRegressor() function. The LSTM model was created using the Keras package with Sequential layers and LSTM units. Finally, the Linear Regression model was implemented using the LinearRegression() function from scikit-learn.

3.1.4 Model Performance Evaluation

The performance of the trained models was evaluated using accuracy, precision, and recall metrics, calculated using the sklearn library. These metrics were chosen to assess the models' predictive effectiveness in the context of cryptocurrency price forecasting

EdinBurg Peer Reviewed Journals and Books Publishers
Journal of Information and Technology
Vol. 5||Issue 3||pp 11-19||June||2025
Email: info@edinburgjournals.org||ISSN: 3080-9576

4. Results and Discussion

4.1 Presentation of the Dataset

The dataset utilized in this research includes the historical prices and trading volume of ten prominent cryptocurrencies from January 2018 to December 2022. The features considered for each cryptocurrency include the date, opening price, highest price, lowest price, closing price, adjusted closing price, and trading volume.

4.2 Data Visualization

Data visualization techniques were employed to gain insights into the cryptocurrency market dynamics.

4.3 Results for Objective 1

The predictive results of the four machine learning models on the cryptocurrency dataset are visualized in Figures 2, 3, 4, and 5.

Figure 2 - Linear Regression predictive results

Linear Regression: Showed a strong correlation between predicted and actual prices, indicating its ability to capture linear trends.

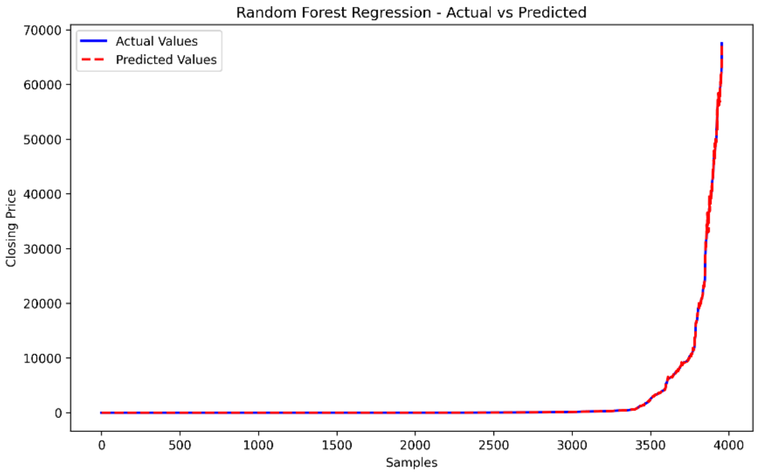

Figure 3- Random Forest predictive results

Random Forest: Exhibited a nearly perfect overlap between predicted and actual closing prices, demonstrating high accuracy in tracking price trends, even at elevated levels.

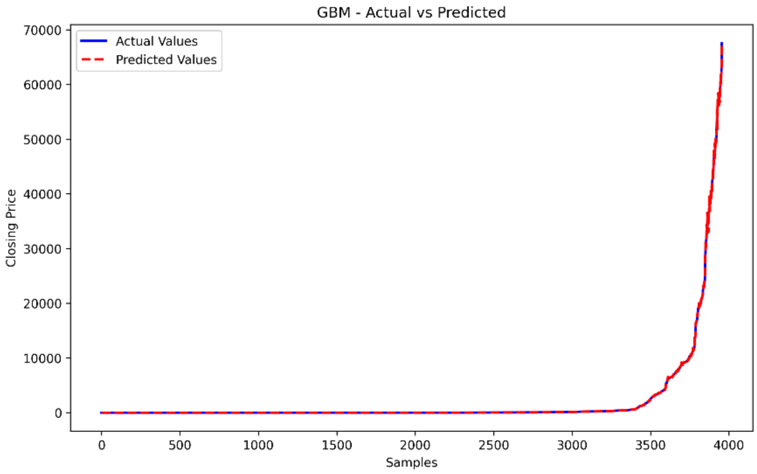

Figure 4 - GBM predictive results

Gradient Boosting Machine (GBM): Also showcased outstanding performance with predicted values closely aligning with actual values across the entire sample range, indicating its effectiveness in capturing both linear and nonlinear trends.

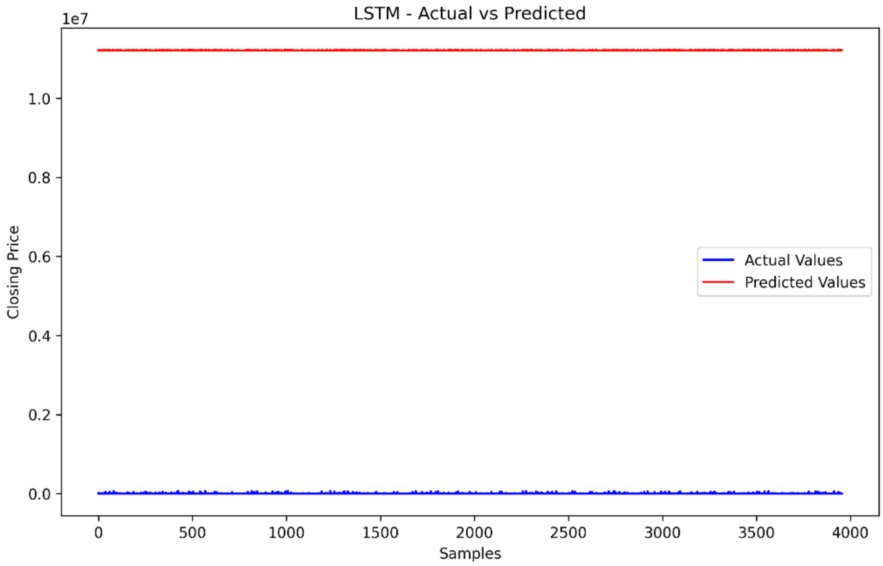

Figure 5 - LSTM predictive results

Long Short-Term Memory (LSTM): Displayed a considerable difference between actual and predicted closing prices, with the model significantly overestimating and producing constant predictions, suggesting an inability to effectively capture the data's underlying patterns.

The strong performance of Random Forest and GBM aligns with research indicating the effectiveness of ensemble learning methods in financial forecasting due to their ability to handle noisy and high-dimensional datasets.

4.4 Results for Objective 2

The performance of the machine learning algorithms was evaluated using accuracy, precision, and recall, as presented in Table 1.

Table 1: Comparative performance of built models

Model	Accuracy	Precision	Recall
Linear Regression	0.93	0.97	0.9
Random Forest	0.99	0.99	0.99
Gradient Boosting Machine	0.83	0.75	0.99
Long Short-Term Memory	0.5	0.5	1

Random Forest demonstrated the most balanced and highest performance across all metrics, achieving near-perfect scores. Linear Regression also performed well in accuracy and precision. GBM excelled in recall but had lower accuracy and precision, indicating a higher rate of false positives. LSTM underperformed significantly in accuracy and precision despite achieving perfect recall, suggesting challenges in generalization. The superior performance of

Random Forest is consistent with studies highlighting the robustness of ensemble methods in volatile markets.

5. Conclusion

Objective 1: To select the appropriate machine learning algorithms, determine the best effective one for predicting patterns in cryptocurrency exchange markets using historical data

The first objective of this research was to determine the most effective machine learning methods for predicting cryptocurrency exchange market prices using historical data. The analysis revealed that the Gradient Boosting Machine (GBM) and Random Forest models were the most dependable techniques for this purpose. Both models exhibited high predictive accuracy, with their forecasts closely matching the actual data. The GBM model demonstrated outstanding ability in capturing both linear and nonlinear trends, resulting in minimal prediction errors across various price ranges. Likewise, the Random Forest model performed exceptionally well in tracking price trends, showing nearly perfect alignment between actual and predicted values, which highlights its robustness and accuracy. On the other hand, while the Linear Regression model displayed strong correlations and low bias in its predictions, its performance was somewhat less adaptable compared to GBM and Random Forest. The Long Short-Term Memory (LSTM) model, in contrast, significantly underperformed, failing to identify the underlying patterns in the data and yielding constant, unrealistic predictions.

Objective 2: To evaluate the performance of diverse ML algorithms using metrics such as accuracy, precision, and recall, in relation to market fluctuations and trends

To determine how well various machine learning algorithms handled market trends and swings, the second goal was to compare their performance using measures like accuracy, precision, and recall. The Random Forest model routinely beats alternative methods, as seen by the comparison study, which yields almost flawless accuracy (0.99), precision (0.99), and recall (0.99) scores. This strong performance demonstrates how consistently it can predict and classify market movements with accuracy while reducing false positives and negatives. Linear Regression shows impressive results, achieving an accuracy of 0.93 and a precision of 0.97. Nonetheless, its slightly lower recall of 0.9 indicates a small drawback in capturing all positive instances. On the other hand, the Gradient Boosting Machine (GBM) excels in recall with a score of 0.99 but struggles with accuracy at 0.83 and precision at 0.75, suggesting a greater chance of false positives, even though it effectively identifies positive cases. The Long Short-Term Memory (LSTM) model significantly underperforms, with both accuracy and precision at 0.5, despite attaining perfect recall of 1, which means it successfully identifies all positive cases but results in a considerable number of false-positive predictions. In summary, Random Forest is the best option for predictive analysis in this situation as it is the most dependable and well-rounded model according to all evaluation metrics.

6. Recommendation

Future researchers would work on this:

- Investigate sophisticated AI frameworks such as transformers or combined deep learning techniques to improve predictions of cryptocurrency prices.

- Integrate live news, social media sentiment analysis, and blockchain transaction information to enhance market evaluation.
- Create and implement real-time forecasting systems to assess their effectiveness and dependability in practice.
- Tackle ethical issues, avoid market manipulation, and improve transparency in AI-based financial advice.

References

Bouteska, A., Mohammad, A. Z., Petr, H., & Kunpeng, Y. (2024). Cryptocurrency price forecasting – A comparative analysis of ensemble learning and deep learning methods. *International Review of Financial Analysis*. doi:https://doi.org/10.1016/j.irfa.2023.103055

Flare Team. (2024, May 06). *Consensus learning: harnessing blockchain for better AI - Flare*. Retrieved from Flare Network: https://flare.network/consensus-learning-harnessing-blockchain-for-better-ai/

Hussein, Z., May, S. A., & Sahar , E.-R. A. (2023). Evolution of blockchain consensus algorithms: a review on the latest milestones of blockchain consensus algorithms. *Cybersecurity*, 127-138.

Katsiampa, P. (2019). Volatility Estimation for Bitcoin: A Comparison of GARCH Models. *Economics Letters*, 17-20.

Minghui , X., Yong , G., Liu, C., Hu, Q., Yu, D., Xiong, Z., . . . Xiuzhen, C. (2024). Exploring Blockchain Technology through a Modular Lens: A Survey. *ACM computing surveys*, 1-9.

Renduchintala, T., Alfauri, H., Yang, Z., Pietro, R., & Jain, R. (2022). A Survey of Blockchain Applications in the FinTech Sector. *Journal of Open Innovation: Technology, Market and Complexity*, 65-71.

Sanghami, V., John, L., & Qin, H. (2023). Machine-Learning-Enhanced Blockchain Consensus With Transaction Prioritization for Smart Cities. *IEEE Internet of Things Journal*, 6661 - 6672.

Tingting, H., & Kui, G. (2020). Review of Blockchain Consensus Algorithms. *Scientific Journal of Intelligent Systems Research*, 1-5.

Wu, Y., Zehua, W., Yuxiang, M., & Leung, V. C. (2021). Deep reinforcement learning for blockchain in industrial IoT: A survey. *Computer Networks*, 1-6.

Yazeed, A., Mohammad, Q., Orieb, A., & Almaiah, M. (2023). Using Blockchain in the Context of the Automotive Industry: A Survey. *2023 International Conference on Information Technology (ICIT)* (pp. 123-128). Amman, Jordan: Al Zaytoonah University of Jordan.

Zhang, L., Chen, Y., & Zhang, W. (2021). A Survey on Machine Learning in Cryptocurrency Trading. *IEEE Access*, 123456-123478.

Zhang, X., Zhang, Y., & Wang, S. (2020). A hybrid model for financial time series forecasting based on ensemble empirical mode decomposition and random forest. *Applied Soft Computing*, 105905.