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A Research: Investigation of Financial Applications with Blockchain Technology

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ABSTRACT

Cryptocurrencies have revolutionized the financial landscape by providing decentralized and anonymous payment systems, making them an intriguing subject for investors and researchers. This article delves into applying machine learning techniques for predicting cryptocurrency prices, mainly focusing on Bitcoin, Ethereum, and Binance Coin. Employing a range of machine learning models, including XGBoost, Linear Regression, and Gaussian Processes, the study aims to evaluate their predictive performance comprehensively. The results are promising; our models outperform existing studies, achieving impressively low RMSE values of 0.0040 for Bitcoin, 0.028 for Ethereum, and 0.027 for Binance Coin. These findings contribute valuable insights into the volatility and dynamics of cryptocurrency prices and underscore the potential of machine learning in shaping financial decision-making. Future directions include integrating advanced deep learning models, additional data sources, and ensemble methods to enhance prediction accuracy and robustness.

Keywords:
Cryptocurrencies; Machine learning; Price prediction; Bitcoin; Ethereum; Binance coin

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INTRODUCTION

Over the last ten years, the swift rise of cryptocurrencies has triggered sweeping shifts in the worldwide economy, reshaping financial landscapes and remoulding transactional systems [1]. These seismic shifts owe much to rapid advancements in Information Technology (IT), enabling the emergence of blockchain and the birth of Bitcoin in 2009 by the enigmatic entity known as Satoshi Nakamoto [2]. The soaring popularity of digital currencies like Bitcoin and Ethereum is fuelled by an expanding community of users and the allure of substantial financial returns. These currencies use a decentralized architecture anchored by blockchain technology for the secure verification and logging of transactions. However, this decentralization poses complex challenges for regulatory bodies and traditional financial institutions [3].

As fascination with cryptocurrencies grows, so does academic interest in blockchain and its foundational technology. Digital currencies come into the blockchain each time a new block is formed, and they can be traded for various goods and services [4]. Mainstream cryptocurrencies like Bitcoin and Ethereum have attained widespread acknowledgement, notably for their hefty trading volumes and market capitalizations. For instance, in April 2021, Bitcoin displayed a market value of USDT 1,304 billion alongside a trading volume of USDT 64 billion. Ethereum posted a USDT 38 billion trading volume and a USDT 265 billion market cap [5]. This burgeoning value and interest have led researchers to dig deeper into the predictive analysis of cryptocurrencies to understand market trends and minimize investor risks.

While there are intrinsic challenges, recent years have seen remarkable progress in machine learning (ML) and blockchain technologies [6]. These technological leaps have culminated in new or enhanced products now used by billions worldwide. Numerous studies have honed in on applying these innovative technologies to financial markets, exploring areas like stock market prediction and fraud detection since ML research took off [7]. The insights from such research are especially crucial for cryptocurrencies, which are increasingly considered financial assets by a growing audience.

Blockchain and ML are relatively nascent, marked by a limited research corpus. Most existing studies in this domain have mainly concentrated on the non-technical facets of blockchain. Nonetheless, there lies

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a vast, untapped reservoir of research potential due to the frontier nature of blockchain and the rapid advancements in ML. In this thesis, we aim to delve into the complex interplay between cryptocurrencies, blockchain, and ML, examining their interconnected challenges and untangling the prospects for future innovations. The primary objective of this article is to enhance the understanding of cryptocurrency price movements by employing various ML techniques. Through a detailed analysis focusing on the daily closing prices of three significant cryptocurrencies, we aim to develop predictive models that can accurately forecast the next day's closing price. The research seeks to identify the most influential computational methods for predicting cryptocurrency prices by comparing a range of ML algorithms and their performance metrics. Ultimately, this study aims to contribute to both academic literature and practical applications by highlighting the potential of ML and blockchain technologies in influencing and transforming financial decision-making processes.

In recent years, many studies have been undertaken to scrutinize different facets of cryptocurrency, most notably Bitcoin, by applying ML and deep learning (DL) methodologies. [8] employed a Stochastic Fluid Queueing Process to mathematically model Bitcoin transaction times, particularly in high-traffic scenarios, thereby shedding light on the probability distribution of confirmation times. Their work added crucial insights into understanding transaction times in congested network conditions. [9], on the other hand, it utilized Support Vector Machines (SVM) on time-series cryptocurrency data to compare the performance of ML systems in Bitcoin price forecasting. Their research concluded that there is significant scope for enhancing model accuracy, as evidenced by an accuracy rate of 95.50%.

Building upon similar themes, [10] proposed using generic machine learning algorithms to compare performance systems for Bitcoin forecasting, focusing on time series data but not quantifying the results regarding Root Mean Squared Error (RMSE). [11] devised an innovative approach using Random Forest (RF) Regressor, Multilayer Perceptron (MLP), and statistical regression models to predict the time needed for a mining node to validate and confirm a transaction. Their comparison indicated that the RF Regressor had an RMSE of 0.36, outperforming MLP and a previously introduced statistical model.

[12] tackled Bitcoin's notorious price volatility by employing DL models like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). They achieved a notable level of precision in predicting Bitcoin's price movements, with RMSE values of 0.045 and 0.051 for LSTM and GRU, respectively. Similarly, [13] engaged multiple machine learning techniques like SVM, Artificial Neural Networks (ANN), Naive Bayes (NB), RF, and Logistic Regression (LR) to forecast Bitcoin prices. Their results underscored that ANN, with an RMSE of 0.341, performed relatively better under certain conditions.

Researchers in [14] used ML to study the distribution of Bitcoin transaction times based on memory pool size, discovering an inverse Gaussian distribution. Tanwar et al. presented a hybrid deep learning model that combines LSTM and GRU to forecast Litecoin and Zcash prices, achieving an MAE of 0.02038 and 0.02103, respectively. In a parallel line of inquiry, [5] used ANN and SVM to study the relationship between Ethereum prices and blockchain data, finding ANN to be the superior model with an RMSE of 0.068. In [15], Ho et al. used LSTM and Linear Regression (LR) models to predict Bitcoin values, impressively achieving an accuracy rate of 99.87%.

Furthermore, [16] introduced novel on-chain metrics and developed a deep learning model for Bitcoin, reporting an RMSE of 0.045 for LSTM and 0.293 for Random Forest. Finally, in the most recent study [17] by Aziz et al. (2022), a Light Gradient Boosting Machine (LGBM) was used to identify fraudulent Ethereum transactions. Although they didn't provide RMSE values, they claimed that the LGBM model outperformed other machine learning and soft computing models like RF, MLP, and XGBoost.

These studies highlight the burgeoning potential of machine learning and deep learning techniques in various aspects of cryptocurrency, such as transaction time analysis, security vulnerability identification, and price prediction, thereby laying the groundwork for developing automated trading systems.

MATERIAL AND METHODS

Proposed model

Our proposed framework is a multi-faceted machine-learning model tailored for cryptocurrency price prediction. Utilizing three curated datasets, the model undergoes an initial data preprocessing phase where normalization ensures compatibility across various ML algorithms. This step streamlines the data and optimizes computational efficiency. Subsequently, a diverse suite of algorithms, including LSTM, CNN, KNN, XGBoost, Astro ML, and several regression techniques, are applied to construct the predictive model, as shown in Fig. 1. Aimed at providing reliable and precise price forecasts, our model equips traders, investors, and other market participants with actionable insights, offering a scalable and flexible tool responsive to the ever-changing cryptocurrency landscape.

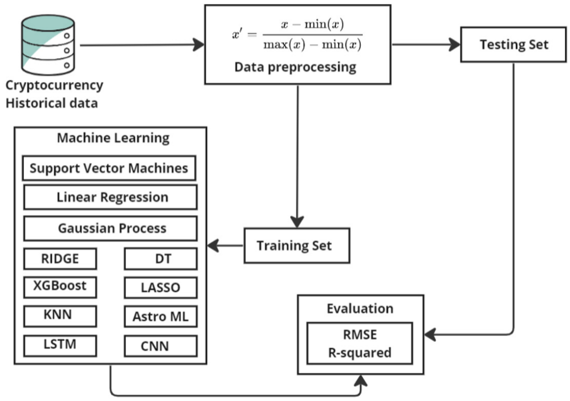

Figure 1. Cryptocurrency proposed model.

Our research utilizes a dataset comprising the historical prices and trading volumes of four cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and Tether (USDT). This dataset spans from November 9, 2017, to August 27, 2022, and includes data points collected for each cryptocurrency in terms of their adjusted closing prices and trading volumes. The datasets were sourced from Kaggle and processed using Python's Pandas library. Conversion to a data frame structure allows for robust data handling and efficient computational operations. We extracted this dataset for our analysis, focusing particularly on BTC, ETH, and BNB, due to their significant impact on the cryptocurrency market dynamics. This valuable dataset, uploaded to Kaggle two years ago, encompasses detailed records of each cryptocurrency's adjusted closing prices and trading volumes, enabling an in-depth analysis of market trends. Notably, this dataset has also been utilized in a study by Baviskar, V. S., Radha, D., & Sankari, S. U. in their 2023 publication on cryptocurrency price prediction and analysis, presented at the 14th International Conference on Computing Communication and Networking Technologies (ICCCNT) [29].

Our dataset includes seven critical features to facilitate a comprehensive market analysis:

1. Date: This column records the specific date for each data entry, formatted to capture the day, month, and year. It serves as the temporal reference for all other data points, providing the context in which the price and volume observations were made.
2. Close (BTC): This column contains the adjusted closing price of Bitcoin (BTC) on each respective date, expressed in USD. The adjusted close price reflects the final trading price of Bitcoin for the day and is adjusted for any corporate actions that might affect the price, such as stock splits.
3. Volume (BTC): This column reports the total trading volume of Bitcoin transactions on the corresponding date. It measures the number of Bitcoins that were traded during the day, offering insights into the trading activity and liquidity of Bitcoin in the market.
4. Close (ETH): Similar to the BTC close column, this column provides the adjusted closing price of Ethereum (ETH) for each date, in USD. It represents the final price at which Ethereum was traded at the end of the trading day, after adjustments for any applicable market events.
5. Volume (ETH): This column indicates the daily trading volume of Ethereum, capturing the total quantity of Ethereum traded on each day. The volume data helps assess Ethereum's market activity and investor interest over time.
6. Close (BNB): This column records the adjusted closing price of Binance Coin (BNB) on each date, expressed in USD. The price reflects the final market valuation of Binance Coin at the end of each trading day, adjusted for any significant events affecting stock prices.
7. Volume (BNB): Finally, this column measures the daily trading volume of Binance Coin, indicating the total amount of BNB traded on each date. It provides a gauge of Binance Coin's market activity and liquidity.

Data Preprocessing

Data preprocessing forms the backbone of our study, focusing on cleaning and transforming raw data to ensure its compatibility with machine learning algorithms. We deal with missing values and outliers during the data cleaning and employ Pandas' Dropna function to refine the dataset.

After cleaning, we retain only essential features like' date' and' close' to maintain data integrity. On the transformation front, we tackle feature scaling issues through Min/Max normalization. This approach harmonizes variable scales, enhancing the predictive accuracy of our machine-learning models in cryptocurrency price forecasting. Both data cleaning and transformation steps are instrumental in fortifying our dataset's quality and our predictive model's robustness.

Predictive Methods

In our study, we allocated 70% of the dataset for training and 30% for testing, adhering to a widely accepted practice in machine learning to balance robust training and unbiased evaluation. We employed eleven distinct predictive models, each tailor-made for a specific cryptocurrency. We used identical model parameters across the various cryptocurrencies to maintain consistency in our comparisons. Detailed analyses of each model will follow in subsequent sections of the article.

Long Short-Term Memory (LSTM) Model

In cryptocurrency price prediction, LSTM networks [18] have garnered attention for their capability to model time series data effectively. These networks can capture long-term dependencies in historical price data and other

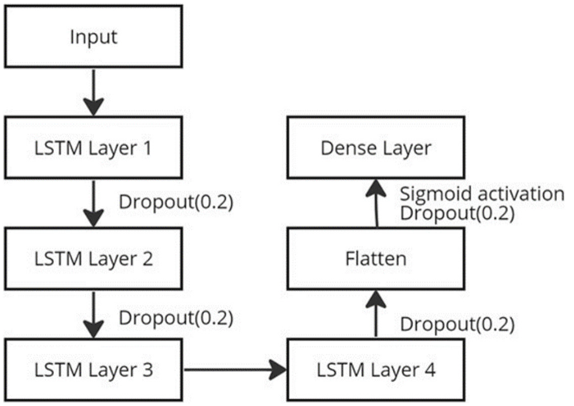

Figure 2. Our LSTM architecture.

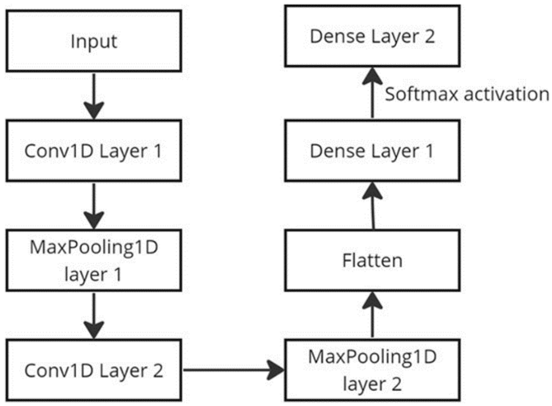

Figure 3. Our CNN architecture

market variables like trading volume and trends. After training on this historical data, LSTMs can generate future price predictions with considerable accuracy. Their performance is competitive compared to other predictive models, making them a popular choice for this application. Specific architecture and training steps for LSTM models in cryptocurrency prediction are detailed in Fig. 2.

Convolutional Neural Network Model

CNNs [19] are increasingly used for cryptocurrency price prediction, offering valuable insights into market trends and trading opportunities. Designed to excel at handling image and time-series data, CNNs are particularly apt for analyzing complex cryptocurrency data structures. A typical CNN architecture for this use case consists of multiple layers: An input layer that accepts preprocessed historical price data, convolutional layers that identify patterns and features, pooling layers that simplify the model's complexity, and fully connected layers that finally make price predictions. The output layer then delivers these predicted future cryptocurrency prices. This structured approach makes CNNs a reliable tool for making informed cryptocurrency trading decisions.

Support Vector Regression (SVR) Model

The SVR model [20] uses historical price data to forecast future cryptocurrency prices. Through mathematical optimization, SVR identifies an optimal function that minimizes error between actual and predicted values. The data is transformed into a high-dimensional feature space, where a hyperplane represents the prediction function. The goal is to find a hyperplane that minimizes errors and maximizes the margin between itself and the nearest data points, enhancing the model's robustness and preventing overfitting. Once established, this prediction function can forecast future cryptocurrency prices by projecting new data points into this high-dimensional space.

K-Nearest Neighbors (KNN) Model

The KNN model [21] predicts future cryptocurrency prices by storing historical data points and their target values. When a new data point emerges, the model identifies its K nearest neighbours from the stored data based on a selected distance metric. The forecast is then calculated as the average of these neighbours' target values. While KNN is a quick and straightforward algorithm, its accuracy depends on the careful choice of distance metric and the number of neighbours. Additionally, KNN may struggle with high-dimensional data, as the distance metrics might not effectively capture relationships between data points.

XGBoost Model

XGBoost [22] operates by combining the forecasts of multiple weak decision tree (DT) optimized using gradient descent. The process starts by initializing residuals representing the differences between actual target values and current predictions. Trees are built by iteratively finding the split that minimizes loss, subject to stopping criteria like maximum tree depth or minimum samples per node. Tree pruning further refines the model by eliminating less essential branches. Through a boosting technique, the model iteratively adds trees and updates the forecast based on these residuals. Each tree's accuracy contributes to its weighting, and the final prediction is an aggregated, weighted sum of all trees. This boosting approach allows XGBoost to correct individual tree biases and produce more accurate predictions.

AstroML Model

AstroML [23], initially designed for machine learning applications in astrophysics, offers valuable tools for cryptocurrency analysis. AstroML's regression capabilities within the crypto landscape can model the correlation between multiple variables and coin price. The optimal regression model depends on factors like data complexity and the desired level of accuracy. Methods such as linear regression, polynomial regression, DT, and RF can be deployed to forecast cryptocurrency prices based on historical data and other influencing factors.

Lasso Model

Lasso [24] is a machine learning approach often employed in cryptocurrency price prediction to enhance model interpretability and accuracy. It distinguishes itself by incorporating a penalty term into the loss function minimized during optimization. This term pushes the model towards sparsity in its coefficients, effectively downplaying less essential features. Consequently, Lasso often yields simpler, more interpretable models by focusing on a subset of relevant features for its predictions.

Ridge Model

Ridge Regression [25] is a regularization method commonly employed for predicting cryptocurrency prices to bolster the model's stability and interpretability. During optimization, ridge Regression nudges the model towards smaller coefficients across all features by introducing a penalty term to the loss function. This diminishes the model's sensitivity to minor data fluctuations, resulting in a more stable and robust predictive framework.

Linear Regression Model

Linear regression [26] is a foundational statistical method to model the relationship between a dependent variable and one or more independent variables. In the context of cryptocurrency, LR uses historical data to map the connection between various features and the cryptocurrency's price. It operates on the principle that these relationships can be linearly represented. The model aims to optimize coefficients for each feature to minimize the difference between predicted and actual values. Optimization techniques like gradient descent and ordinary least squares are commonly employed. Once the coefficients are optimized, the LR model can forecast future cryptocurrency prices through a weighted sum of the independent variables.

DT Model

DT [27] refers to machine learning algorithms that provide a structured, tree-like approach to decision-making by considering various possible outcomes and the factors influencing them. The tree starts from a root node, branching into different scenarios, each leading to subsequent child nodes and relevant probabilities. This allows for hierarchical mapping.

RESULTS AND DISCUSSION

Evaluation Models

We employ key performance metrics, RMSE and R-squared (R^2), to evaluate our model's effectiveness for forecasting cryptocurrency prices. A lower RMSE score and a higher R^2 value indicate superior predictive performance, providing a comparative measure to gauge the accuracy of the various predictors.

Evaluation metrics with Bitcoin dataset

In our study, we evaluated the performance of various machine learning methods for predicting Bitcoin prices using two key metrics: RMSE and R^2. As presented in Table 1, different models yield distinct results. The LR and GP models outperformed other techniques, achieving the lowest RMSE values of 0.022368 and 0.022381, respectively, and high R^2 values exceeding 0.98. These results suggest exceptional predictive accuracy. The Ridge model also exhibited strong performance, with an R^2 value of 0.980667.

On the other hand, the CNN model had the highest RMSE of 0.166565 and the lowest R^2 value of 0.308789, indicating suboptimal performance for this dataset. The XGB Regressor model demonstrated an impressively low RMSE of 0.004042, but its R^2 value was slightly lower than that of the Ridge and LR models. The ASTRO ML model, adapted from astrophysics, also performed well with an RMSE of 0.063575 and an R^2 value of 0.899303. These evaluations provide valuable insights into the most suitable ML methods for accurate and reliable Bitcoin price prediction, with LR and GP emerging as the leading candidates.

Table 1. Performance metrics of various models for Bitcoin dataset

Model Name	*RMSE*	*R^2*
LSTM	*0.088911*	*0.803051*
CNN	*0.166565*	*0.308789*
SVR	*0.066702*	*0.889154*
KNN	*0.085906*	*0.816138*
XGBRegressor	*0.004042*	*0.899303*
ASTRO ML	*0.063575*	*0.899303*
Ridge	*0.027857*	*0.980667*
LR	*0.022368*	*0.987535*
DT	*0.074230*	*0.862722*
GP	*0.022381*	*0.987520*

Evaluation metrics with Ethereum dataset

Our study includes an in-depth performance evaluation of multiple machine learning algorithms for predicting Ethereum prices, focusing on RMSE and R^2. As depicted in Table 2, the results vary significantly among different models. The LR and GP models showcase the lowest RMSE values of 0.028457 and 0.028346, respectively, while achieving exceptionally high R^2 values, just above 0.98. This suggests that these models provide remarkably accurate and reliable predictions for Ethereum prices. The Ridge model also performed notably well, with an R^2 value of 0.956592.

Table 2. Performance metrics of various models for the Ethereum dataset

Model Name	RMSE	R^2
LSTM	0.144385	0.525188
CNN	0.208044	0.014207
SVR	0.191266	0.166793
KNN	0.100407	0.770383
XGBRegressor	0.124654	0.646093
ASTRO ML	0.161861	0.403296
Ridge	0.043656	0.956592
LR	0.028457	0.981556
DT	0.129323	0.619086
GP	0.028346	0.981700

On the contrary, the CNN model yielded the highest RMSE of 0.208044 and a deficient R^2 value of 0.014207, indicating its poor suitability for this particular task. Among ensemble models, the XGBRegressor exhibited a relatively low RMSE of 0.124654, although its R^2 was somewhat less impressive than the Ridge and LR models. Interestingly, the ASTRO ML model, adapted from astrophysics, had an RMSE of 0.161861 and an R^2 of 0.403296, placing it in the middle range of performance. The analysis reveals that LR and GP models are the most effective for predicting Ethereum prices regarding RMSE and R^2.

Evaluation metrics with Binance Coin dataset

Our analysis rigorously evaluates the performance of different ML algorithms for forecasting Binance Coin prices, emphasizing RMSE and R^2. As shown in Table 3, the metrics exhibit considerable variation across models. The LSTM and CNN models yielded unusually high R^2 values above R^2 and the highest RMSE of 0.265808, suggesting potential overfitting or other anomalies in their predictive performance. In stark contrast, the LR and GP models outperformed others with the lowest RMSE values, 0.027286 and 0.027298, respectively, and R^2 values around 0.968. This indicates exceptional accuracy and reliability for these methods in predicting Binance Coin prices. The Ridge model also showed high reliability with an R^2 of 0.924290, albeit with a slightly higher RMSE of 0.041881.

Interestingly, SVR and DT models presented moderate R^2 values of 0.636128 and 0.350212, respectively, but could not match the top-performing models in terms of RMSE. The ensemble model XGBRegressor exhibited minor effectiveness with an R^2 of 0.122999, raising questions about its suitability for this task. The data suggests that for Binance Coin price prediction, LR and GP models are the most reliable in terms of both RMSE and R^2.

Table 3. Performance metrics of various models for the Binance Coin dataset

Model Name	RMSE	R^2
LSTM	0.265808	2.049658
CNN	0.265808	2.049658
SVR	0.091816	0.636128
KNN	0.136745	0.192878
XGBRegressor	0.142542	0.122999
ASTRO ML	0.128486	0.287434
Ridge	0.041881	0.924290
LR	0.027286	0.967863
DT	0.176865	0.350212
GP	0.027298	0.967835

Comparison Results

In an endeavour to place our contributions within the broader scope of research in cryptocurrency price prediction, we present a comparative evaluation in Table 4. Our model significantly outperforms existing models across multiple cryptocurrencies in terms of RMSE. For Bitcoin, the XGBoost model generated an impressively low RMSE of 0.0040, which is considerably smaller than the values reported by Pabuc et al. (2020) for ANN, SVR, Naive Bayes, and RF, which ranged from 0.293 to 0.461. Similarly, our XGBoost model outshines the LSTM model by Jagannath et al. (2021), which recorded an RMSE as high as 1.9. In the Ethereum context, our LR and GP models delivered an RMSE of 0.028, again establishing superior performance when compared to the ANN and SVR models by Kim et al. (2021) that reported RMSEs of 0.068 and 0.048, respectively. Lastly, for Binance Coin, our LR and GP models achieved an RMSE of 0.027, though a direct comparison with previous works is not available for this specific cryptocurrency. These results corroborate our models' robustness and superior predictive accuracy, offering significant improvements over existing methods in the literature.

Table 4. Comparison of RMSE values for various models and cryptocurrencies

AUTHORS	CRYPTOCURRENCY	TECHNIQUES	RMSE
Pabuc et al. (2023)	Bitcoin	ANN	0.341
Pabuc et al. (2023)	Bitcoin	SVR	0.438
Pabuc et al. (2023)	Bitcoin	Naive Bayes	0.461
Pabuc et al. (2023)	Bitcoin	RF	0.293
Jagannath et al. (2021)	Bitcoin	LSTM	1.9
Kim et al. (2021)	Ethereum	ANN	0.068
Kim et al. (2021)	Ethereum	SVR	0.048
Our model	Bitcoin	XGBoost	0.0040
Our model	Ethereum	LR, GP	0.028
Our model	Binance coin	LR, GP	0.027

CONCLUSION

This study ventured into the burgeoning field of ML and blockchain to predict cryptocurrency prices. These models were selected for their ability to handle the complex and nonlinear nature of cryptocurrency price movements, leading to our achieving remarkably low RMSE values of 0.0040 for Bitcoin, 0.028 for Ethereum, and 0.027 for Binance Coin. This performance significantly surpasses that of previous studies, such as those by Pabuc et al. (2023) and Kim et al. (2021), where the best RMSE

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values reported for Bitcoin and Ethereum were 0.293 and 0.048, respectively. Our models' superior accuracy can be attributed to the sophisticated data handling and learning capabilities of XGBoost, along with the robustness of LR and GP in capturing the underlying trends and volatility of cryptocurrency markets. These compelling results substantiate the potential of ML techniques in innovating and informing decision-making in the financial sector. In future work, we suggest exploring advanced deep-learning models for sentiment analysis and integrating additional data sources to refine prediction accuracy. Ensemble learning and model interpretability also offer promising avenues for further research.

CONFLICT OF INTEREST

Authors approve that to the best of their knowledge, there is not any conflict of interest or common interest with an institution/organization or a person that may affect the review process of the paper.

AUTHOR CONTRIBUTION

Mohammed Ali Mohammed: Conceptualization, Methodology, Software, Validation, Writing- original draft
Fuat Turk: Data curation, Visualization, Investigation, Writing- review and editing

REFERENCES

1. Marc Pilkington. 11 Blockchain technology: principles and applications. Research handbook on digital transformations, 225(2016), 2016.
2. Pinyaphat Tasatanattakool and Chian Techapanupreeda. Blockchain: Challenges and applications. In 2018 International Conference on Information Networking (ICOIN), pages 473–475. IEEE, 2018.
3. Thippa Reddy Gadekallu, Thien Huynh-The, Weizheng Wang, Gokul Yenduri, Pasika Ranaweera, Quoc-Viet Pham, Daniel Benevides da Costa, and Madhusanka Liyanage. Blockchain for the metaverse: A review. arXiv preprint arXiv:2203.09738, 2022.
4. Saveen A Abeyratne and Radmehr P Monfared. Blockchain-ready manufacturing supply chain using distributed ledger. International journal of research in engineering and technology, 5(9):1–10, 2016.
5. Han-Min Kim, Gee-Woo Bock, and Gunwoong Lee. Predicting ethereum prices with machine learning based on blockchain information. Expert Systems with Applications, 184:115480, 2021.
6. Evangeline Ducas and Alex Wilner. The security and financial implications of blockchain technologies: Regulating emerging technologies in canada. International Journal, 72(4):538–562, 2017.
7. Peter Gomber, Robert J Kauffman, Chris Parker, and Bruce W Weber. On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. Journal of management information systems, 35(1):220–265, 2018.
8. David Koops. Predicting the confirmation time of bitcoin transactions. arXiv preprint arXiv:1809.10596, 2018.
9. Azizah Hitam and Amelia Ritahani Ismail. Comparative performance of machine learning algorithms for cryptocurrency forecasting. Ind. J. Electr. Eng. Comput. Sci, 11(3):1121–1128, 2018.
10. S Yogeshwaran, Maninder Jeet Kaur, and Piyush Maheshwari. Project based learning: predicting bitcoin prices using deep learning. In 2019 IEEE global engineering education conference (EDUCON), pages 1449– 1454. IEEE, 2019.
11. Harsh Jot Singh and Abdelhakim Senhaji Hafid. Transaction confirmation time prediction in ethereum blockchain using machine learning. arXiv preprint arXiv:1911.11592, 2019.
12. Temesgen Awoke, Minakhi Rout, Lipika Mohanty, and Suresh Chandra Satapathy. Bitcoin price prediction and analysis using deep learning models. In Communication Software and Networks: Proceedings of INDIA 2019, pages 631–640. Springer, 2020.
13. Hakan Pabuc¸cu, Serdar Ongan, and Ayse Ongan. Forecasting the movements of bitcoin prices: an application of machine learning algorithms. arXiv preprint arXiv:2303.04642, 2023.
14. Rowel Gundlach, Martijn Gijsbers, David Koops, and Jacques Resing. Predicting confirmation times of bitcoin transactions. ACM SIGMET- RICS Performance Evaluation Review, 48(4):16–19, 2021.
15. Alvin Ho, Ramesh Vatambeti, and Sathish Kumar Ravichandran. Bitcoin price prediction using machine learning and artificial neural network model. Indian Journal of Science and Technology, 14(27):2300–2308, 2021.
16. Nishant Jagannath, Tudor Barbulescu, Karam M Sallam, Ibrahim Elgendi, Asuquo A Okon, Braden McGrath, Abbas Jamalipour, and Kumudu Munasinghe. A self-adaptive deep learning-based algorithm for predictive analysis of bitcoin price. IEEE Access, 9:34054–34066, 2021.
17. Rabia Musheer Aziz, Mohammed Farhan Baluch, Sarthak Patel, and Abdul Hamid Ganie. Lgbm: a machine learning approach for ethereum fraud detection. International Journal of Information Technology, 14(7):3321–3331, 2022.
18. Alex Graves and Alex Graves. Long short-term memory. Supervised sequence labelling with recurrent neural networks, pages 37–45, 2012.
19. Jiuxiang Gu, Zhenhua Wang, Jason Kuen, Lianyang Ma, Amir Shahroudy, Bing Shuai, 19. Ting Liu, Xingxing Wang, Gang Wang, Jianfei Cai, et al. Recent advances in convolutional neural networks. Pattern recognition, 77:354–377, 2018.
20. Alex J Smola and Bernhard Scho¨lkopf. A tutorial on support vector regression. Statistics and computing, 14:199–222, 2004.
21. Padraig Cunningham and Sarah Jane Delany. k-nearest neighbour classifiers-a tutorial. ACM computing surveys (CSUR), 54(6):1–25, 2021.
22. Syeda Sarah Azmi and Shwetha Baliga. An overview of boosting decision tree algorithms utilizing adaboost and xgboost boosting strategies. Int. Res. J. Eng. Technol, 7(5), 2020.
23. Snigdha Sen, Sonali Agarwal, Pavan Chakraborty, and Krishna Pratap Singh. Astronomical big data processing using machine learning: A comprehensive review. Experimental Astronomy, 53(1):1–43, 2022.
24. Lukas Meier, Sara Van De Geer, and Peter Bu¨hlmann. The group lasso for logistic regression. Journal of the Royal Statistical Society Series B: Statistical Methodology, 70(1):53–71, 2008.
25. Arthur E Hoerl and Robert W Kennard. Ridge regression: applications to nonorthogonal problems. Technometrics, 12(1):69–82, 1970.
26. Sanford Weisberg. Applied linear regression, volume 528. John

Wiley & Sons, 2005.
27. Sotiris B Kotsiantis. Decision trees: a recent overview. Artificial Intelligence Review, 39:261–283, 2013.
28. Christopher Williams and Carl Rasmussen. Gaussian processes for regression. Advances in neural information processing systems, 8, 1995.
29. Baviskar, V. S., Radha, D., & Sankari, S. U.. Cryptocurrency Price Prediction and Analysis. In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-7). July,2023.