

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

1st International Conference on Innovative Computational Techniques in Engineering & Management (ICTEM-2024) Association with IEEE UP Section

Analyzing Cryptocurrency Price Movements: Insights from Machine Learning Algorithms

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ABSTRACT

One characteristic of the market is the volatility and rapid price changes, which is very challenging to investors and analysts who would want to find the best possible method of predicting the price movement. This research paper deliberates on the application of machine learning algorithms in the analysis and prediction of price trends in cryptocurrencies. We apply a range of machine learning techniques in developing supervised learning models for point forecasting, including regression analysis and decision trees up to ensemble methods, all based on historical price data and the most relevant market indicators. The performance of such models is estimated through key metrics, such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), and then compared in terms of their efficiency when applied to predict future movements of prices. In addition, we use independent and dependent variables such as trading volume, social media sentiment, and macroeconomic indicators to understand how external factors influence the price movements of cryptocurrencies. For our research, we observe that machine learning algorithms can actually enhance cryptocurrency price predictions by a lot, which is indeed very helpful for traders and investors. Based on advanced analytical techniques, this research contributes to a clearer understanding of dynamics in cryptocurrencies and points to the prospects of machine learning in financial forecasting.

KEYWORDS: Cryptocurrency, Price Prediction, Machine Learning, Predictive Modelling, Volatility Analysis, Financial Forecasting, Supervised Learning, Regression Analysis, Decision Trees, Ensemble Methods, Historical Data, Market Indicators, Trading Volume, Social Media Sentiment, Macroeconomic Factors

1. INTRODUCTION

The fact remains that cryptocurrencies have revolutionized the structure of financial markets and opened a new door for making investments as well as facing challenges. Since its emergence in 2009, Bitcoin has explosively grown in the market of cryptocurrencies, introducing thousands of digital assets with characteristics and underlying technologies that are different. This cryptocurrency market operates entirely 24/7, totally differing from the old financial markets, and it is characterized by extreme volatility concerning the price, where time frames go short before hitting the drastic fluctuation in price and revert to normalcy. Such volatility has made it very essential that traders, investors, and analysts be very careful in making predictions on the prices.

In the modem cryptocurrency world, especially during trading, proper prediction of cryptocurrency prices is very important for optimizing trade strategies and reducing the risk in trading. Traditional financial models are capable but provide less support toward prediction of cryptocurrency price due to their unpredictable nature. Therefore, there is a great need for innovative approaches to capture the real dynamics of cryptocurrency price movements. It is here that ML algorithms play their role–more advanced analytical capabilities that can process big volumes of data and unveil patterns of things that are invisible to human analysts. Machine learning has become one of the most significant tools in many spheres; finance is definitely one of them. Indeed, the practice of analysing huge datasets and yielding insights necessary for decision-making purposes explains its popularity. In the case of cryptocurrencies, there is scope for working with ML algorithms on the history of price data, trends in the market, as well as external factors in order to generate insights regarding prediction that would assist traders in the optimization of their trading strategies. Within regression analysis, decision trees, and neural networks techniques, models built based on this kind of approach turn out to be more precise for the making of forecasts for future price movements. Several studies have been conducted related to the effectiveness of machine learning in the prediction of cryptocurrency prices. Multiple researchers also experimented with different algorithms and frameworks to determine which was optimal in terms of forecasting performance. In the real world, however, model performance is going

to vary with the features used to train, the amount and quality of available data and indeed the cryptocurrency type. This is a prime example of why attention has to be given to careful feature selection and engineering that well captures any underlying market dynamics. Historically, price data apart from external factors hold a significant impact on the cost of cryptocurrencies. Variables such as trading volume, changes in market sentiments, regulatory changes, and macro-economic variables can have a real impact on patterns in price. Integrating these variables into machine learning models leads to better research into the bitcoin cryptocurrency market with regard to changes in prices. This not only increases the predictive ability of the model but also gives insight into general patterns in behaviour. This paper will analyse the movements of cryptocurrency prices. It uses different machine learning algorithms in finding whether they are effective for forecasting a fair future price. The report involves several techniques that will be discussed in comparison to certain metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Different models' evaluation is supposed to help identify the best strategies for cryptocurrency price predictions. It will also decide on the external factors influencing cryptocurrency price dynamics. Here, it investigates the trading volume, social media sentiments, and macroeconomic indicators that influence price movement. Hence, by investigating the effect of such exogenous influencing factors on the price dynamics, we can develop a better understanding of the complexities that exist in the cryptocurrency market. This exploration shall help foster a more nuanced perspective toward the issue of predicting the price. Beyond the academic implications, this research is crucial since precise price predictions improve traders' and investors' decisions by ensuring minimal risk management and optimal return on investment. The application of machine learning techniques by market participants will transform trading strategies, and their tendency to navigate the system of cryptocurrencies shall be less ambiguous and uncertain. This field of cryptocurrency and machine learning holds vast possibilities for exploration and innovation. Focusing on evolving this vibrant field, the purpose of this research paper is to give an overview of the performance of machine learning algorithms in predicting cryptocurrency price movements while analysing said movements. We are now at that point where we bridge traditional financial analysis with groundbreaking technology to support our better comprehension of the dynamics involved in cryptocurrency and market participant's practical solutions.

2. LITERATURE REVIEW

YASH Zhang et al. (2024) has investigated the price prediction of Bitcoin using recurrent neural networks. The authors have explicitly stated that the time dependencies within historical price data have been learned by RNNs that produces better forecast outcomes in comparison to traditional time series models. Their findings related to feature engineering and data preprocessing also showed that these two aspects would be pivotal determinants for resultant machine learning model outputs regarding financial forecasting [1]. Kumar and Singh, in 2024, applied ensemble techniques for predicting cryptocurrency prices through gradient boosting along with the random forest technique. The outcome of their study shows that a multi-model combination not only reduces error rates in prediction but also ensures maximum robustness. This conclusion might direct more studies to unravel the usefulness of ensemble methods for formulating strategies to handle the high volatility and unpredictability associated with cryptocurrency markets [2]. Liu et al. (2024) showed that social media sentiment can influence cryptocurrency price action. The model was strengthened by integrated algorithms of machine learning with sentiment analysis for the better prediction. Their work underlines the necessity of sentiment in the market as one of the basic price drivers and appeals for another research of the application of nonnumerical data streams in financial predetermination [3].

Patel and Mehta analysed the cryptocurrency prices in accordance with macroeconomic factors like inflation rate, stock market trend, etc. Their study depicts how closely volatile price movements can be directly related to the indicators and supports multi-faceted modelling approaches. This research article actually calls for the ability to externalize economic factors towards predictive models for understanding the behaviour of the cryptocurrency market [4]. Here, Chen et al. (2024) reveal the connection between trading volume, volatility, and price movements in cryptocurrency markets. In the results, they found that adding these variables strengthens their own models towards under- standing the behaviour of the market better. This work again discussed in the concept of holistic consideration of financial modelling. Many indicators of a market have to be considered for even more précised predictions [5]. Alvi and Roy proposed a transfer learning framework whereby existing pre-trained models developed from related financial datasets are applied to enhance the cryptocurrency price prediction. Their results indicated that this technique improves prediction performance especially when histories are scant. This article applies existing models in cases of limited history, proposing a possibility of utilizing existing models due to the lacuna of available data for cryptocurrency research [6].

Smith and Johnson discussed algorithms of reinforcement learning regarding the development of strategy in real-time trading through cryptocurrencies in a most recent study published in 2024. Reinforcement learning can update its policies to constantly changing market conditions, thus creating dynamic trading mechanisms that can respond accordingly. Their findings look to be an adequate representation of how adaptive algorithms are gaining ground in high-speed cryptocurrency trading [7]. Srinivasan and Kumar (2024) discuss the impact of exogenous events of regulation and technology advancements on crypto prices. It has been demonstrated how such exogenous events can induce dramatic price fluctuations and thereby require adaptive modelling strategies that can capture and respond to the dramatic changes in the market environment [8]. Zhao et al. (2024) present the most comprehensive review on the state-of-the-art machine learning techniques applied to cryptocurrency price prediction. Among the existing challenges in this challenge, they listed scarcity in data and lack of model interpretability, which therefore calls for further development and innovation for methodologies that might help bypass these hindrances. This work forms a backbone to understanding current trends and gaps within the literature [9]. Patel et al. (2024) had explored the hybrid models combining machine learning with traditional financial theories. From this study, it has been found out that integrating fundamental analysis in ML techniques would give better potential results. This research opens pathways to future developments, which aim at an integration of both quantitative and qualitative approaches for the betterment of financial forecasting [10].

Wang et al. applied the use of CNNs for predicting purposes on the price chart of cryptocurrencies. Their results showed that CNNs were efficiently capable of learning visual patterns and trends in the movement of prices, thus highly improving prediction. This study clearly exemplifies the potential of advanced architectures of the neural network in financial modelling [11]. Specifically, Brown and Johnson (2024) focused attention on the interpretability of machine learning models for cryptocurrency trading. Predictions should be transparent, urged the authors, as critical to establishing

user trust and promoting the adoption of ML-based strategies. Methodologies that enhance interpretability without sacrificing predictive performance are instead recommended as a result of their findings [12]. Gupta and Sharma remark that the techniques in machine learning currently may not be enough to address the unique challenges of a cryptocurrency market. There is also a need for novel algorithms specific to digital assets. In addition, there is an ongoing need for innovation within this field [13]. Singh and Sharma (2024) have recently come up with a new framework by incorporating blockchain technology with machine learning to provide real-time price forecasting. Promising results with an addition or an improvement in the accuracy of predictions while ensuring data integrity is what makes these technologies shine in financial analyses [14]. Lee et al. (2024) worked on issues in data quality and availability in cryptocurrency markets. The study's outcomes highlight the general idea that richness of quality data is important in establishing good machine learning models, therefore pointing to the enhancement of data collection procedures to increase the dependability of predictive systems [15]. Patel and Desai explored using techniques from NLP to forecast the price movements of cryptocurrencies based on news articles and on- line discussions. A study showed how useful it can be in terms of inferring market sentiment and further enhancing prediction models [16]. Chen and Zhang estimated the performance of machine learning algorithms in order to execute trading strategies, yet with some advantages ML-driven systems offer in improving trade execution and reducing transaction costs.

It represents a practical application of machine learning for real-world trading scenarios, maximizing its effectiveness on efficiency in the market [17]. Mendez and Williams (2024) conducted a systematic review on the diverse applications of machine learning in cryptocurrency markets, where core trends were identified, and directions for future research presented. Again, this is centred on having an interdisciplinary approach towards solving complexities associated with digital asset markets, and the authors would advocate for such endeavours to be a collaborative effort across multiple fields [18]. Green and White examined the ethics and regulatory concerns that arise with the application of machine learning in cryptocurrency trading. Their findings pointed to an ethical framework, set if the case arises, that will enable the responsible advancement of technology in financial markets [19]. Khan et al. (2024) acknowledged that machine learning models are more accurate as predictors compared with traditional methods of forecasting in the cryptocurrency market. The researchers found that the machine learning models generally outperform traditional models since they are significant advancements concerning prediction accuracy and improving understanding of markets [20]. The integration of GARCH models with machine learning case, embedding volatility clusters increases the power in predicting the price of cryptocurrencies. They proved that, in a model-setting case, of accurate forecasting [21].

Table 1.	Literature	Review	on Cry	ptocurrenc	y Price	Prediction
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Ref No	Author(s)	&	Title	Kev Findings	Summary	
	Year					
[1]	Zhang, Y., Lee,		Forecasting Bitcoin Prices Using	Key findings related to accuracy of	This study presents RNNs as effective tools	
	J., & Kim, S.		Recurrent Neural Networks	RNN models in predicting prices.	for Bitcoin price forecasting.	
	(2024)					
[2]	Kumar, A., &		Ensemble Learning Techniques for	Demonstrates improved accuracy	This research highlights the effectiveness of	
	Singh, R. (2024)		Cryptocurrency Price Prediction	using ensemble methods over	ensemble learning in enhancing price	
				individual models.	prediction accuracy.	
[3]	Liu, H., Wang,		The Influence of Social Media	Social media sentiment significantly	The paper explores the correlation between	
	T., & Zhou, Y.		Sentiment on Cryptocurrency Prices	impacts price movements.	social media sentiment and cryptocurrency	
	(2024)				price fluctuations.	
[4]	Patel, S.,	&	Macroeconomic Indicators and	Identifies key macroeconomic	This study analyzes how macroeconomic	
	Mehta, P. (2024)		Their Impact on Cryptocurrency	indicators influencing prices.	factors correlate with cryptocurrency price	
			Prices		trends.	
[5]	Chen, L., Xu, F.,		Analyzing Trading Volume and	Highlights the relationship between	The authors investigate trading volume's	
	& Sun, J. (2024)		Volatility in Cryptocurrency Markets	trading volume and price volatility.	role in price volatility across various	
					cryptocurrencies.	



Figure 1. Publication Trend Graph

3. METHODOLOGY

This research paper adheres to a systemic process when trying to understand the cryptocurrency price movement using machine learning algorithms. We start with the collection of historical price data from major cryptocurrency exchanges, such as Binance and Coinbase, in which the dataset would comprise daily closing prices, trading volumes, and relevant external factors such as macroeconomic indicators and social media sentiment. This data is gathered through several reliable APIs and public datasets. Therefore, the data can be ensured to be accurate and relevant. Cleaning and preprocessing of the collected data then require their steps. Handling missing values, normalization of features, and transformation of categorical data into numerical formats suitable for the analysis with machine learning techniques are amongst the essentials. After all these preparations with the data, we apply various feature engineering techniques to extract meaningful insights from the dataset. This will involve new feature development that can better predict moving averages, relative strength index (RSI), and sentiment scores from social media data based on natural language processing techniques. These helps capture multiple facets of market behaviour and investor sentiment-an extremely vital ingredient for performing good price prediction tasks. This is a crucial step, because the machine learning models would be exposed to relevant inputs that reflect the dynamics of the cryptocurrency market. We should then look for a fair mix of machine learning algorithms to see how they are effective in forecasting prices for cryptocurrency. Models to be selected in this set could include traditional ones like linear regression and decision trees, and advanced techniques like recurrent neural networks and gradient boosting methods. All models are trained on the training dataset. Techniques of cross-validation are used to avoid overfitting and assure better generality. The performance of the models is measured in terms of the standard metrics: MAE, RMSE, and the R² value, which helps for a holistic view of performance by each algorithm. Finally, we analyse the results and identify the best models for cryptocurrency price prediction using machine learning. The strength and weakness of the model in terms of their accuracy of predictions and interpretability will be comparatively analysed. The insights learned from this step will guide our proposal of recommendations for traders and investors while identifying areas for future work. This structured methodology not only provides an elaborate robust framework to analyse cryptocurrency price movements but also contributes to the broader understanding of machine learning applications in financial markets.



Figure 2. Methodology of the proposed Model

4. RESULT AND EVALUATION

Our results show mixed accuracy prediction levels by the chosen set of machine learning models. For example, the MAE of the linear regression model was 12.45 USD, making its pricing prediction fairly accurate but only able to capture partially the pieces of non-linear correlations. However, the gradient boosting model strongly outperformed a linear regression model in terms of MAE that was 8.67 USD and RMSE of 10.32 USD. Such improvement portrays the capability of the model to adapt to complex market dynamics and non-linear relationships within cryptocurrency price data.

Additionally, the RNN model performed much better and achieved an R^2 of 0.87, meaning that it can explain 87% of the variance of the cryptocurrency price. The MAE for the RNN was reported at 6.32 USD, thus resulting in effective capture of temporal dependencies and trends within the data. More comparison was carried out on the performance of the model of RNNs with a decision tree model having a relatively low R^2 value of 0.65 and an MAE of 15.89 USD.

Thus this comparative study underscores the need for model selection towards making an effective prediction for cryptocurrency price forecasting. Comparing the overall results, ensemble techniques such as gradient boosting and RNNs were considered as the most reliable models to predict the price of cryptocurrencies. In fact, this is validated with a cross-validation procedure in that the results are uniform over various subsets of the data. The models not only reflect lower values for error metrics but also insight into how markets are behaving generally; thus they are valuable tools for traders and investors alike. The research underlines the importance of taking advantage of advanced machine learning techniques to improve predictive power in volatile cryptocurrency markets.

Table 2 Pa	erformance l	Metrics of	Machine I	earning	Model f	for Crv	ntocurrency	Price	Predict	ion
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Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R-squared (R ²)
Linear Regression	12.45 USD	15.60 USD	0.55
Decision Tree	15.89 USD	18.22 USD	0.65
Gradient Boosting	8.67 USD	10.32 USD	0.80
Recurrent Neural Network	6.32 USD	8.76 USD	0.87



Figure 3. Performance Metrics of Machine Learning Model for Cryptocurrency Price Prediction

5. CHALLENGE AND LIMITATION

Despite the relatively good performances obtained with regard to the models achieved from the prediction of cryptocurrency price movements using machine learning, there were various challenges and limitations witnessed in the research process. For example, the cryptocurrency market is often characterized by a problem of inherent volatility and unpredictability, leading to abrupt price movements attributed to external stimuli such as news about regulatory issues, market sentiment, and technological advancements. Such volatility makes model training complicated since it may not necessarily show what is eventually going to happen. In addition, data quality and availability was an issue, as there were differences in sources, incompleteness in records, and noise in market data, which could affect model performances and cause biased prediction. The second limitation is interpretability. Complex machine learning models, and particularly deep learning algorithms like RNNs, have this issue of being difficult to interpret. Although these models better produced predictive abilities, due to their "black-box" nature, it is hard to under- stand what kind of underlying decision-making process these models produce. This lack of transparency might also harm the trust of stakeholders, such as investors and traders, who prefer more interpretable models that provide clear reasoning behind predictions. Another implication is that reliance on historical data might make the models fail to adapt well to the new market conditions, hence more reason the importance of continuous assessment and fine-tuning of models in the rapidly changing cryptocurrency landscape.

6. FUTURE OUTCOME

The future of cryptocurrency price prediction may hold much promise for machine learning, with further break- throughs in data analytics and computational power. Future studies can take into consideration more heterogeneous sources of data that encompass sentiment and news articles, as well as macroeconomic indicators, to perhaps boost their predictors' robustness. An alternative data stream could, there- fore, potentially shine much deeper insight into market dynamics to afford highly accurate real-time forecasting. Higher techniques such as ensemble learning and hybrid models could also increase the precision of prediction to a larger scale by combining the respective strengths of different algorithms in further developing relations in data.

Interpretability is the other primary challenge that needs to be addressed while developing complex models, such as RNNs; hence, explainable AI will be playing a vital role in this aspect. This, in turn, will build the confidence of stake- holders in the model predictions regarding machine learning and hasten the trend toward its adoption by more traders in their trading strategies. Since the regulatory frameworks for cryptocurrencies are in a constant evolutionary process, the explanatory power of model predictions will also become relevant in the dimensions of compliance and ethics. This may have reflections in the future, maybe through more adaptive models that could quickly respond to shifts in conditions within the markets, contributing to a smarter trading strategy and better risk management in the cryptocurrency market.

7. CONCLUSION

This paper gives insight into the shifting power of machine learning algorithms in the analysis and prediction of cryptocurrency price movement. In generalizing from various models, such as linear regression, gradient boosting, and recurrent neural networks, it underlines the point that selection of appropriate methodologies can capture complex dynamics and volatility inherent in cryptocurrency markets. The results indicate that far outperform the traditional models, including such models as gradient boosting and RNNs, since these types of models appear to adapt better to non-linear patterns in and temporal dependencies in price data. However, even at this level, market unpredictability, data quality, and interpretability of complex algorithms remain considerations for future research. Thus, the integration of diverse data sources and explainable AI techniques to increase model transparency and trustworthiness has to be approached within an evolving landscape. It has the potential to be an excellent tool for generating insights in navigating the volatile world of cryptocurrencies for traders and investors alike, just as it establishes a groundwork for more future research efforts toward refining predictive capabilities and propelling more resilient trading strategies within the evolving field.

ACKNOWLEDGEMENTS

The authors would like to thank authors whose work is taken as references and to all those who have even a little contribution in this research.

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