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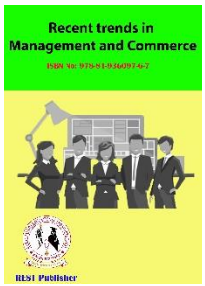

AI Applications in Analysing and Predicting Cryptocurrency Market

***Sruthi P J, M. Shahithabanu**

VLB Janaki Ammal College of Arts and Science, Kovaipudur, Coimbatore, Tamil Nadu, India.

Corresponding Author Email: sruthi.p.janardanan@gmail.com

Abstract: *The study explores diverse AI methodologies employed in the cryptocurrency domain, focusing on their applications in key areas such as price prediction, sentiment analysis, market trend analysis, volatility prediction, trading strategy optimization, fraud detection, and portfolio management. Various machine learning models, including regression, neural networks, and reinforcement learning, are investigated for their effectiveness in predicting cryptocurrency prices and optimizing trading strategies. The integration of Natural Language Processing (NLP) techniques is discussed in the context of sentiment analysis, where AI algorithms analyze vast amounts of textual data from social media, news articles, and online forums to gauge market sentiment and its potential impact on cryptocurrency prices. Additionally, the paper examines the role of AI in identifying patterns, trends, and anomalies in market data, facilitating effective decision-making for traders and investors. However, the paper emphasizes the need for caution, acknowledging the inherent uncertainties and risks associated with cryptocurrency investments. It concludes by highlighting the potential for continued advancements in AI applications, contributing to a deeper understanding of cryptocurrency market dynamics and aiding in more informed decision-making in this rapidly evolving financial landscape.*

Keywords: *Cryptocurrency markets, AI Applications, Natural Language Processing, and Sentiment Analysis.*

1. INTRODUCTION

Cryptocurrency markets have recently undergone a tremendous transition, both in terms of statistical data and public recognition. Cryptocurrency markets have been a popular topic for investors. Many investors have acquired a little fortune by speculating on cryptocurrency. They keep up with hot news on social media or surges of interest in cryptocurrency. However, there is a danger, as investors are prone to lose money due to the unpredictable nature of cryptocurrency markets. As a result, this produced a trading mechanism for predicting market trends, and ultimately, minimizing investment risks remains an open subject in cryptocurrency markets. To that purpose, there are an expanding number of potential ways for dealing with cryptocurrency analysis and predicting underlying patterns. However, because of their extreme volatility and the fact that cryptocurrencies do not behave like fiat currencies, investors (Abraham, J., et. al. 2018) must develop their trading techniques. The unpredictability in forecasting shows that various aspects of cryptocurrency price development have yet to be extensively investigated. As a result of these problems, more research into cryptocurrency marketplaces is required (Mittal, R, et. al. 2018). Asset trading has seen significant changes as computing and telecommunication infrastructures have advanced rapidly, allowing for a highly productive improvement in quantitative trading (Wu, X. et. al. 2020). Furthermore, the expanding number of investors and transactions, together with many sources of alternative data such as social media hashtags, tweets, and feeds, resulted in large blocks of big data surrounding cryptocurrency markets. As a result, market participants are looking beyond traditional ways to develop automated, profitable trading models that cope with this data. In contrast to the quantitative trading methodologies used for decades, financial technology (FinTech) companies have dramatically altered their trading strategies to properly handle big data. FinTechs are primarily concerned with combining artificial intelligence (AI) with finance (Dai, S. et. al., 2017).

2. OBJECTIVES OF THE STUDY

- ✓ To find out the problems in the crypto currency domain that has been approached with artificial intelligence techniques.
- ✓ To analyze the AI techniques investigated and applied to cryptocurrencies.

3. LITERATURE REVIEW

The term "artificial intelligence" was first used in a summer research project at Dartmouth College in 1956 (McCarthy, J. et. al. 2006). It was originally founded as a research discipline for building a machine to simulate every aspect of learning or any other feature of intelligence that can be described in principle (Dick, S.2022). Although there is still not a universally accepted definition for AI, as a general definition, AI leverages computers to solve problems and make decisions by mimicking the human brain's thinking ability and intelligence. AI empowers machines to exhibit human-like behaviors, such as driving a car autonomously, improving corporate productivity, or completing dangerous tasks (**https://apo.org.au/node/210501**). Despite having several winters as a seasonal metaphor, when technology, business, and the media paid less attention to AI, and recent predictions about another possible winter (Floridi, L, 2020), major tech companies still prioritize AI over other IT initiatives. As a consequence, the implementation of AI systems is expanding rapidly in a wide spectrum of domains, from health, criminal justice, welfare, and stream history-influenced video viewing suggestions to real-time evaluation of enormous data sets (big data) and fraud detection (Whittaker, M. et. al.2018). Artificial intelligence (AI) systems may learn from this vast volume of data by analysing and detecting patterns, making trading and mining more efficient and secure. Discovering trends in money-laundering transactions, as well as other fraudulent activities and trading schemes, can assist restrict cryptocurrency-related crimes due to the privacy and security risks they pose? AI techniques encompass not just machine learning (ML) techniques (supervised, unsupervised, semi-supervised, and reinforcement), but also evolutionary-based and knowledge-based strategies (S. Russell. Et. al.,2010). (H. Hassani et al., 2010) examined the relationship between Big Data and cryptocurrencies from two perspectives: security and privacy enhancement, and prediction and analysis. The term "cryptocurrencies" refers to the underlying blockchain technology and its applications, rather than digital currency as we define them. (K. Salah. Et. al. 2019) conducted surveys on blockchain applications in AI and robotics. No polls have examined how AI can address the difficulties of cryptocurrency.

4. CRYPTOCURRENCY MARKET CHALLENGES

Some challenges are related to the trading process like price and trend prediction, volatility prediction, portfolio construction, fraud detection, and other analysis tasks to get insights and indicators about different cryptocurrencies. Trading bots do all of these tasks for trading cryptocurrencies. These challenges involve using machine learning techniques to learn from historical data on prices, other market indicators, and social media interests to make profitable trading decisions. Additionally, natural language processing (NLP) -which involves using many AI techniques- is needed for sentiment analysis and processing of news, and social media posts (e.g. Twitter, Facebook, Telegram, LinkedIn, Reddit, etc) (N. Smuts., 2019).

Price Prediction/Forecasting: Data analysis reveals correlations between variables and cryptocurrency prices. Supervised machine learning creates a model from data that can predict outcomes. Using variable history transforms price prediction into a time-series prediction task. The closing price can be predicted using a regression model based on specific indicators. A classification problem can be used to forecast whether a coin's price will climb, decline, or remain constant by encoding the cryptocurrency price time series output variable as rise and fall. Simple linear time series models may not fully describe economic and financial data (E. Zivot et. al. 2006). The results of research efforts in price prediction depended on different datasets with features at different periods. Therefore, the results cannot be fairly compared to conclude recommending or favoring one price prediction model over another. Tree-based models and probabilistic-based models were the least models to be tested. Probabilistic-based models are better to be investigated in more depth to model the uncertainty in the domain of cryptocurrencies. The introduction of some sort of trust or confidence score measure for the prediction accuracy or performance of the model to account for the uncertainty and missing factors or explanatory variables is recommended. Tree-based models and probabilistic-based models were the least models to be tested. Probabilistic-based models are better to be investigated in more depth to model the uncertainty in the domain of cryptocurrencies. The introduction of some sort of trust or confidence score measure for the prediction accuracy or performance of the model to account for the uncertainty and missing factors or explanatory variables is recommended. Nonlinear tests and techniques listed in (R. S. Tay and R. Chen, Nonlinear Time Series Analysis.

Hoboken, NJ, USA: Wiley, Aug. 2018.) have not yet been thoroughly explored for application on cryptocurrencies time series and need further investigation to capture the non-linear dependencies on the explanatory variables.

Volatility Prediction: Volatility refers to the degree of variation in a trading price series across time. This term refers to the uncertainty or risk associated with currency value fluctuations. Bitcoin and other cryptocurrencies are known to be volatile. Bitcoin investors view extreme volatility as a risky investment. Volatility refers to price change away from its average value. Cryptocurrency price ranges can be estimated by forecasting volatility for a day or week using past data. The GARCH statistical model, a time-series approach, is used to model volatility (A. Ngunyi, S. et. al. 2019). (Peng et al.2018) merged the classic GARCH model with Support Vector Regression (SVR), resulting in a strong coverage of multivariate and dynamic financial series. It was used to forecast the volatility of three cryptocurrencies (Bitcoin, Ethereum, and Dash), as well as three fiat currencies (Euro, British Pound, and Japanese Yen), in order to assess alternative hazardous assets and guide investment decisions. They provided compelling evidence that the SVR models outperform classic GARCH models.

Automated trading: Cryptocurrency trading bots provide customised strategies for customers. Trading bots are software products or websites that offer "algorithmic trading" by automatically analysing market movements and indicators and providing methods to maximise gains and improve trader happiness. These tools can analyse previous market data, create indicators, simulate orders, and even execute plans while the consumer sleeps. Bots can utilise natural language processing to communicate with customers in a more natural and friendly manner (Q. Xie. Et. al. 2019). Classifying investors can provide valuable insights into the cryptocurrency market and price dynamics, allowing for more effective trading techniques. In a recent study (A. Keller et. al. 2019), scientists employed unsupervised clustering to categorise distinct investor types. They clustered based on similarities in trading behaviour, such as trade volume, average bid volume, average relative pricing, and average time to complete a trade from the moment the offer is published on a popular exchange website. They were able to divide investors into ten groupings. The ARDL model was used to uncover factors influencing the trading behaviour of several investor categories, including speculators, cryptocurrency miners, knowledgeable traders, major professional investors, USD-oriented investors, and worldwide traders. The study found that Bitcoin's exchange rate is heavily influenced by a small group of investors.

Fraud Detection: The combination of bitcoin and artificial intelligence heralds a new era in market security. As blockchain technology promises openness and security, the integration of AI ensures that these promises withstand the scrutiny of potential fraudsters. While AI-based fraud detection systems are not without flaws, their capacity to constantly learn and adapt makes them vital assets in the crypto world's drive for security and legitimacy. In the future crypto scene, human-AI collaboration will be critical in creating a secure, transparent, and trustworthy cryptocurrency market. Navigating the world of cryptocurrencies is analogous to exploring uncharted territory; the challenges are numerous, but the rewards are significant. Monamo et al. 2016, employed semi-supervised trimmed k-means and k-means clustering with transaction graph features to detect fraudulent behaviour in the Bitcoin network. Both algorithms performed optimal clustering. The reduced algorithm detected 5 of 30 well-known abnormalities, including Mt Gox, Linode Hack, and 50 BTC Theft. Using k-d trees, they detected 2 further thefts. The authors used supervised classification models to analyse the relationship between outlier labels and predictor variables. Random forest achieved the highest precision.

Anonymity And Privacy: Privacy and anonymity are essential for online financial trade. Criminals often use anonymity to conceal their identity when dealing in illegal drugs, weapons, or money laundering transactions. However, privacy-conscious individuals prefer to keep their identities and transactions anonymous and hidden. Privacy refers to safeguarding transacting users' data, including the amount transacted, persons involved, balances, and transaction time. To identify Bitcoin users and their transactions, "deanonymization" involves leveraging publicly available data from social media or other sources. Data can be linked to blockchain transactions using heuristics or AI approaches (S. Meiklejohn et. al. 2013) Deanonymization has been approached using AI in two ways: clustering (D. Ermilov et. al. 2017) or classification (H. J. Singh and A. S. Hafid, 2020)

Cryptocurrency mining: Mining pools consume significant amounts of electricity during PoW computations, which is a downside of the technique. One miner successfully adds a block of transactions, while other mining pools incur high energy expenditures. This disadvantage undermines cryptocurrency's decentralisation and leaves it vulnerable to monopolisation, especially when block rewards diminish over time owing to Bitcoin's halving. Some researchers (A. Baldominos and Y. Saez, 2019) theoretically proposed using deep-learning tasks as a PoW to let the electricity be consumed in useful tasks. A coin is rewarded when a miner exceeds a minimum threshold for performance. They also proposed a proof-of-storage mechanism to store the deep learning models on distributed nodes called keepers which are also to be rewarded as per the proposed model for keeping secure storage for the models. While the idea of saving the electricity for useful operations seems beneficial, yet the proposed model ignored some important aspects. Among them is the required security and protection for the training and validation data.

Security: Despite the security and privacy properties of blockchain-based cryptocurrencies, as evaluated in (R. Zhang et al., 2019), the cryptocurrency ecosystem faces various security concerns (M. Conti et al., 2017). They are categorised into four types: distributed network attacks, mining process assaults, double spending attacks, and transaction malleability attacks. There are also client-side security attacks and privacy risks to wallet, exchange, and escrow services (F. Sabry et al., 2019). In this paper, we solely discuss security-related research papers that use AI approaches. Johnson et al. (2014) employed game-theoretical models of competition between two mining pools with variable sizes to determine the trade-off between mining techniques. They took into account disparities in investment and attack expenses, as well as the uncertainty of DDoS attack success. By examining the game's equilibria, they discovered that large pools had a higher incentive to attack than small ones. It was also determined that larger mining pools have a stronger motivation to attack than smaller ones

5. CONCLUSION

Artificial Intelligence (AI) has found various applications in the realm of cryptocurrencies, enhancing efficiency, security, and overall user experience. AI algorithms analyze market data, identify patterns, and execute trades at high speeds. Machine learning models can adapt and improve trading strategies based on historical data and real-time market conditions. It models use historical price data, market indicators, and social media sentiment analysis to predict future price movements. These predictions can assist traders in making more informed decisions and managing risks. It also helps to identify unusual patterns of transactions that may indicate fraudulent activities. Behavioural analysis and anomaly detection algorithms enhance security and protect against hacking attempts. AI-powered tools can analyze a user's investment portfolio, recommend adjustments, and provide personalized investment strategies. Automated portfolio rebalancing based on market conditions is also possible with AI. It facilitates the creation and management of tokenized assets, representing real-world assets on the blockchain. This allows for increased liquidity and accessibility to a wider range of investors. As the cryptocurrency space continues to evolve, AI is likely to play an increasingly significant role in enhancing various aspects of this dynamic and rapidly changing industry.

Discussion And Possible Future Research Directions

Technology has impacted the evolution of cryptocurrencies by enabling new techniques to generate coins, store blockchains on distributed nodes, safeguard the network and analyze massive trades and transactions beyond human capabilities. This report presents a survey of cutting-edge research using artificial intelligence to address cryptocurrency difficulties. Table 6 shows that there are significantly more AI research papers on Bitcoin than other altcoins. Further investigation is needed to identify potential price connections between cryptocurrencies. Further research is needed to explore the use of AI approaches to improve the security, anonymity, and privacy of other cryptocurrencies, as these are significant concerns. Traders might obtain more trust during trading.

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