IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 10 May 2024, accepted 9 June 2024, date of publication 12 June 2024, date of current version 19 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3413201

RESEARCH ARTICLE

A Novel Dynamic Model for Ranking Cryptocurrencies in Different Time Horizons Based on Deep Learning and Sentiment Analysis

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ABSTRACT This paper addresses the imperative task of assessing and ranking cryptocurrencies, particularly pertinent in the context of the burgeoning popularity of public blockchains. The proliferation of available options necessitates a rigorous evaluation, prompting the formulation of a novel model grounded in both objective and subjective criteria. To contend with the challenge posed by the expanding landscape of public blockchains, ten discerning criteria are delineated, encompassing facets such as Technology, TPS, Market capitalization, GitHub fork, GitHub stars, Twitter followers, Twitter hashtags, trading volume, sentiment score, and the price range differential. Leveraging expert opinions, the pairwise impact of these criteria is ascertained, and the DEMATEL method is judiciously employed to derive their respective weights. Subsequently, the PROMETHEE method is harnessed to effectuate the ranking of 20 cryptocurrencies predicated on the identified criteria. Furthermore, the integration of LSTM enables the prediction of values for four predictable criteria, seamlessly incorporated into the PROMETHEE model to furnish rankings across diverse temporal intervals. The proposed model, thus, presents a holistic and pragmatic approach to inform investment decision-making within the dynamic cryptocurrency market. By embracing a comprehensive set of criteria and integrating predictive analytics, this model stands as a valuable contribution to the field, offering nuanced insights to stakeholders navigating the complexities of cryptocurrency investment.

INDEX TERMS Cryptocurrency, LSTM, PROMETHEE, ranking, sentimental analysis.

I. INTRODUCTION

The cryptocurrency industry has gained media attention, widespread investor interest, and regulatory and analyst attention due to its innovative products and intense price activity during its short lifespan [1]. Additionally, since the launch of the first cryptocurrency, it has grown exponentially. Today, as a result of this growing interest, there are over 4,000 cryptocurrencies [2]. Our main effort is to determine which of the categorized factors are more crucial in the decision-making process of investors and analyze which factors are prioritized by investors. This study aims to evaluate cryptocurrencies and their future path from various dimensions. Over time, ranking these currencies based on a single index must provide complete information about their future and current status. For example, considering the technology index for evaluating cryptocurrencies, Bitcoin is ranked seventeenth in the CCID ranking [3]. In terms of popularity, Bitcoin is among the most popular cryptocurrencies.

Choosing the appropriate criteria for ranking is the first step in research, and we need to consider which criteria to examine for ranking cryptocurrencies. In the study by Sobhanifar [4], a consumer perspective model was used with 31 indicators for evaluating and ranking cryptocurrencies.

After selecting the criteria for evaluating cryptocurrencies, the next step is to predict their future. Extensive studies

The associate editor coordinating the review of this manuscript and approving it for publication was Giacomo Fiumara.

have been conducted to predict the prices of different cryptocurrencies. However, more research needs to be done on other criteria, such as the progress of blockchain technology. As activity on GitHub for a particular blockchain increases, it can attract more developers' attention, which can be a factor in the technology's advancement. Therefore, in this stage, we identify the factors affecting these indices and use them to predict their future behavior.

Finally, we choose a suitable multi-criteria decision-making method for ranking cryptocurrencies and perform the ranking using it. In summary, a model is described that selects selected cryptocurrencies for prediction using the information on currency index factors and predicts these criteria using prediction models. For evaluating the currencies, we determine the ranking of cryptocurrencies chosen using the multi-criteria decision-making (MCDM) technique, which helps to determine the priority of investment for investors in the future.

The remaining sections are structured as follows: Section Two studies on cryptocurrencies are conducted to identify decision-making criteria in the cryptocurrency market. The reasons for the growth of cryptocurrencies and the factors affecting their growth are examined. The impact of social networks on cryptocurrencies is also studied, and an overview of the market and financial indicators that affect decision-making is presented. Then, ranking articles related to the prediction and fluctuations of cryptocurrencies are reviewed. In section three, the method of data collection and quantification is explained. Next, the selected model of the DEMATEL weighting method and PROMETHEE ranking method is described, and the Recurrent Neural Network (RNN) prediction method is explained. Section four presents the relevant results of sentiment analysis and rankings, leading to future rankings for 5, 10, and 20 days. Finally, the conclusion is explained in section five, and a summary is provided.

II. LITERATURE REVIEW

In conducting a literature review on cryptocurrency ranking, the process unfolds in several key phases. Initially, previous studies addressing the characterization of cryptocurrencies are delved into, seeking to uncover the factors that render them important. This exploration then extends into comprehending the influencers compelling individuals to invest in cryptocurrencies, there is a meticulous examination of how these influencing criteria are categorized, unraveling insights from existing reviews.

The focus then shifts towards studies dedicated to cryptocurrency ranking. The synthesis of the wealth of information gathered aims to identify the key criteria and characteristics contributing to the ranking process. The culmination of this analysis leads to an exploration of forecasting endeavors within the cryptocurrency realm. This phase involves scrutiny of various forecasting models applied to cryptocurrencies, ultimately guiding the selection of a robust model for predicting specific criteria of interest.

Lastly, a meticulous exploration of works specifically centered on the ranking of cryptocurrencies is encompassed in this literature review. A comprehensive understanding of the approaches adopted to assess and rank cryptocurrencies is gained by analyzing diverse models and methodologies employed in these studies. This structured approach ensures that the literature review not only identifies existing knowledge but also aids in discerning gaps and potential avenues for research in the domain of cryptocurrency ranking.

To assess the performance and standing of different cryptocurrencies, various metrics, algorithms, and analytical tools have been employed. These include machine learning algorithms, statistical measures, and predictive models. For instance, Li [5] utilized the logistic regression (LR) algorithm to analyze determinants from a dataset collected from major cryptocurrency communities, while Erdinc et al. [6] employed machine learning classification algorithms such as support vector machines, logistic regression, artificial neural networks, and random forests to predict cryptocurrency returns using past price information and technical indicators. Additionally, Aljadani [7] utilized machine and deep learning algorithms such as Neural Networks (NN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Bidirectional LSTM (BiLSTM) to analyze factors influencing cryptocurrency prices and predict them.

Furthermore, Allen [8] applied entropy-based metrics to assess the relative stability of cryptocurrencies compared with equity markets during the COVID-19 pandemic, highlighting the higher levels of risk associated with cryptocurrencies. Lahmiri and Bekiros [9] used measures of the Largest Lyapunov Exponent (LLE) and Approximate Entropy (ApEn) to estimate degrees of stability and irregularity in cryptocurrency and international stock markets. Moreover, Alexiadou et al. [10] focused on forecasting cryptocurrency prices, returns, and risk, using statistical and machine learning tools.

In addition to machine learning and statistical measures, Xu and Sun [11] proposed an application to evaluate cryptocurrencies based on social metrics by establishing scores and models with machine learning and other tools. Furthermore, Sakas et al. [12] emphasized the importance of examining cryptocurrency data, such as website visitor analytic metrics and financial and strategic trading metrics, to refine marketing strategies for cryptocurrency trade websites.

Cryptocurrencies, increasingly rivaling cash due to lifestyle shifts and tech progress, expand their reach. This study analyzes Bitcoin prices from 2010 to 2023, aiming to understand price behavior and forecast future trends using triple exponential smoothing. Factors influencing prices, like herd behavior and news impact, are explored within behavioral finance. However, pinpointing reasons for all fluctuations may be challenging due to the personal nature of cryptocurrencies [13].

Vincent Gurgul's study explores the application of ML and NLP techniques in forecasting cryptocurrency prices, particularly Bitcoin and Ethereum. Analyzing sentiment from Twitter and Reddit, they find that integrating NLP data significantly enhances forecasting accuracy. Pre-trained models like Twitter-RoBERTa and BART MNLI prove effective in capturing market sentiment, with consistent profitability observed across different scenarios. This research underscores the potential of text analysis in refining financial forecasts and demonstrates the efficacy of various NLP techniques in capturing nuanced market sentiment [14]

Kochliaridis proposes a trading framework called UNSURE to address challenges in cryptocurrency trading, including extreme price fluctuations and market noise. This framework integrates technical analysis with Machine Learning (ML) components, including an Unsupervised component for improving feature quality, a Deep Reinforcement Learning (DRL) component for opening Buy or Short positions, and a Supervised component for efficient position opening and closing. By leveraging these components, UNSURE aims to increase profits and minimize risks in cryptocurrency trading. The author demonstrates the effectiveness of the framework across nine cryptocurrency markets using various risk-adjusted performance metrics [15].

Brini and Lenz [16] propose using machine learning, specifically regression-tree methods, to address challenges in pricing cryptocurrency options. Unlike classical models such as Black–Scholes and Heston, which struggle with cryptocurrency dynamics, machine learning models incorporate high-frequency volatility estimators for improved accuracy. Comparative analysis reveals inefficiencies in cryptocurrency option pricing compared to equity options, emphasizing the need for more data-oriented approaches. The prediction of market efficiency and performance has been analyzed in various studies. Duan et al. [17] examine the relationship between clean and dirty cryptocurrencies and traditional and green assets. Their study explores market inefficiencies across these assets using a quantile-on-quantile method and an international dataset. They find evidence of market inefficiency varying over time, with generally positive linkage between the different asset types, but fluctuations during extreme market conditions driven by cross-border arbitrage.

Mansurov et al. [18] apply advanced machine learning algorithms to simulate the cryptocurrency market. They introduce a self-learning agent using deep reinforcement learning techniques alongside traditional trading strategies. Their model shows improved approximation to real market behavior compared to models with classical agents, indicating the significance of incorporating self-learning agents for comprehensive market simulation. Verma et al. [19] investigates the market efficiency of cryptocurrencies, specifically examining their adherence to the random walk hypothesis. Analyzing daily data from January 1, 2016, to March 31, 2021, for Bitcoin, Ethereum, Litecoin, Tether, and Ripple, the study employs various statistical tests. Results strongly reject the random walk hypothesis, indicating market inefficiency in cryptocurrencies. This implies predictability in cryptocurrency returns, providing investors with opportunities for abnormal gains through trading strategies.

Stejskalova and Dominik [20] examines conditional volatility in cryptocurrency markets and how uncertainty spreads among different cryptocurrencies. Using GARCH family models, the study analyzes high-frequency 15-minute data for Bitcoin, Ethereum, Ripple, Cardano, and Litecoin from April 23, 2021, to December 20, 2023. Results show that uncertainty spreads most significantly between Bitcoin and Ethereum, with Ripple and Cardano less affected. The study also explores optimal cryptocurrency weight combinations in portfolio formation strategies, highlighting the DCC-GJR-GARCH(1,1) strategy for its low risk. Alvarez-Ramirez et al [21] study the topic at high frequencies and conclude that the market can be identified by changing periods of efficiency and inefficiency. Kristoufek [22] examines the evolution of the efficiency of two Bitcoin markets (the US Dollar and Chinese Yuan) and considers the markets largely inefficient. Al-Yahyaee et al. [23] compare the efficiency of Bitcoin with gold, stocks, and foreign exchange rates and find that Bitcoin has the lowest efficiency in this set. Zargar and Kumar [24] studied the efficiency of Bitcoin returns with high frequency using various variance ratio tests, which mainly indicate market inefficiency. And Begušić et al. [25] show that Bitcoin returns have limited second moments for different scales, making the efficiency discussion logical.

Overall, assessing cryptocurrency performance and standing involves a wide array of metrics, algorithms, and analytical tools, including machine learning algorithms, statistical measures, and predictive models, to predict returns, assess stability, and evaluate social metrics.

A. RANKING OF CRYPTOCURRENCIES

The ranking of cryptocurrencies is an important aspect of the field due to several key factors. Firstly, the performance expectancy of a cryptocurrency has been identified as a crucial factor for its success [26] This suggests that the perceived performance and utility of a cryptocurrency play a significant role in its ranking and adoption. Additionally, factors such as age, gender, education, occupation, and previous investment experience have been found to influence investment behaviors in cryptocurrencies, indicating that these demographic and experiential variables contribute to the ranking of cryptocurrencies [27]. Moreover, the intention to use cryptocurrencies is influenced by factors such as optimism, innovativeness, discomfort, insecurity, and other behavioral aspects, which are essential in determining the ranking of cryptocurrencies [28].

Furthermore, the ranking of the top cryptocurrencies, such as Bitcoin, Ethereum, Litecoin, and Ripple, based on their market performance and capitalization, is crucial in understanding the dynamics of the cryptocurrency market [29]. Additionally, the ease of use, social impact, convenience, trust, price volatility, individual beliefs, privacy, risk, and decision-making have been identified as factors influencing investors' behavioral intention toward cryptocurrency adoption, further emphasizing the significance of these aspects in the ranking of cryptocurrencies [30]. Moreover, technical factors, risk-taking, societal attitudes, and transaction-related challenges have been highlighted as important criteria affecting the adoption of cryptocurrencies in international trading, underscoring their relevance in the ranking of cryptocurrencies [31].

The motivations behind cryptocurrency investments have also been studied, indicating that understanding the main intentions or motivation factors that persuade people to invest in cryptocurrencies is essential for ranking and assessing the significance of different cryptocurrencies in the market [32]. Additionally, Jain [33] explores cryptocurrency market dominance, analyzing factors like technology, regulation, sentiment, and network effects. Using statistical models, the study correlates dominance with fundamental and technical indicators, offering insights for stakeholders and policymakers navigating the cryptocurrency landscape.

Moreover, the stability of the ranking, market share distribution, and birth and death rates of new cryptocurrencies have been identified as stable statistical properties of the cryptocurrency market, highlighting the importance of these factors in determining the ranking and evolution of cryptocurrencies [34]. Furthermore, the attractiveness and risk assessment of cryptocurrency exchanges, as well as the predictability of cryptocurrency price dynamics, are crucial in ranking and classifying cryptocurrencies based on their market efficiency and performance [35].

With the increasing number of public blockchains, China's Information Industry Development Center released the world's first public blockchain technology evaluation index in May 2018. The evaluation index shows that Ethereum is ranked first and Bitcoin is ranked thirteenth. The second global public blockchain technology evaluation index shows that EOS is ranked first, while Bitcoin is ranked seventeenth. However, although Bitcoin's technology is inferior, it is still one of the most popular blockchains.

Tang et al. [35] have designed three first-level indicators and eleven second-level indicators for evaluating public blockchains, using the technique of preference order similarity to the ideal solution (TOPSIS) method for ranking blockchains. The entropy method was used to calculate the weights of various indicators quantitatively. The three first-level indicators are technology, recognition, and activity. The results place Bitcoin, Ethereum, and EOS in the top three public blockchains.

Kristoufek and Vosvrda [36] investigated cryptocurrencies based on the efficient market hypothesis. They also compare efficiency levels in the cryptocurrency market using indicators including Hurst exponent, fractal dimensions, and entropy components. Ethereum and Litecoin are found to be the least efficient coins, while Dash is found to be the most efficient.

Sobhanifard and Sadatfarizani [4] have developed a combined model for the factors promoting the use of cryptocurrencies. This study used saturation theory, exploratory factor analysis, and the Friedman test. Thirty-one factors that affect cryptocurrencies have been identified. This research confirms the positive influence of technological skills, technological ambiguity, and technological benefits on cryptocurrency use.

1) COIN MARKET CAP METHODOLOGY

The Coin Market Cap ranking methodology scores based on exchange liquidity. It helps users find and understand the best exchanges for digital currencies. The liquidity score is based on exchange order book depth. For example, high slippage means that a buy or sell order has been processed at a price significantly different from what was expected, indicating high exchange volatility. Slippage is calculated based on the buy or sell order size and the percentage difference between the final order price and the average price of other buyers and sellers. Different order sizes are aggregated in time intervals between \$100 and \$200,000 to prevent bias among specific traders. Finally, slippage is summed across each bucket and normalized into a score ranging from 0 to 1000, where 1000 represents low slippage for maximum limit orders, and 0 indicates high slippage [22], [35].

2) COINGECKO METHODOLOGY

The CoinGecko ranking system is divided into several components that represent a relative proportion of the final score: liquidity (50%), the scale of operations (30%), and the application programming interface (API) interface of middleware software that allows multiple software to communicate with each other. Technical coverage (20%). In addition, estimated reserves of digital currencies and compliance with exchange regulations have been calculated but are still ongoing and are not used directly in calculating the score.

In conclusion, the ranking of cryptocurrencies is an important aspect of the field due to various factors such as performance expectancy, investment behaviors, adoption intentions, market stability, and risk assessment, which collectively contribute to the understanding and assessment of the significance of different cryptocurrencies in the market.

B. CRYPTOCURRENCY FORECASTING

Price movements and trading volume determine each digital currency's value. In addition, each digital currency has unique features (such as value fluctuations, transaction speed, usability, ecosystem, and unpredictability). Due to the independence of digital currencies, predicting their prices is challenging. For instance, Bitcoin, the most renowned cryptocurrency, witnessed a remarkable ascent in value, surging from virtually nothing to \$20,000 between 2009 and 2017, capturing the interest of both investors and policymakers. The ongoing expansion of the Bitcoin market parallelled this substantial price appreciation. As reported by CoinMarketCap, by December 2019, the market boasted an average daily trading volume of around \$19.45 billion. Bitcoin has various qualities, such as decentralized transactions, audibility, and anonymity when used as a currency. While Bitcoin has often been labeled a bubble and viewed as a potential threat to the stability of the financial system, it continues to be an enticing investment option offering significant potential for returns. Conversely, investing in Bitcoin carries substantial risks. The price of Bitcoin is far more volatile when compared to conventional financial assets like stocks and bonds. Financial market prediction is a valid field of economic research. Regression analysis of probabilistic signals to explain asset returns is a well-established method for analyzing predictive signals and has been used for years. Various features may be included in linear regression, but they are inflexible when combined, and precise assumptions are imposed on the functional movements of signals proposed to the market. On the other hand, ML approaches are increasingly used for financial market prediction because they do not impose these constraints. Among various methods, neural network-based systems have been widely acknowledged as advanced tools for forecasting financial market dynamics, making them particularly well-suited for this purpose.

Making well-timed and informed decisions to mitigate risks associated with critical investment processes is of paramount importance, and such precision can be attained through careful planning. Miura et al. [37], focusing on two cryptocurrencies, Litecoin and Monero, introduced a hybrid digital currency prediction system that leveraged Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) techniques. Additionally, in a study conducted by Huang et al. [38] a comprehensive range of high-dimensional technical indicators was harnessed for forecasting Bitcoin's daily returns, employing tree-based prediction models over the period from January 2012 to December 2017. In their research, Chen et al. explored a range of machine learning methods to forecast changes in Bitcoin prices. Surprisingly, their findings revealed that relatively straightforward techniques, like logistic regression, outperformed more intricate algorithms, including Recurrent Neural Networks (RNNs). When data was collected between February 2017 and February 2019, classification methods were used to determine price direction. However, the presence of an imbalanced training dataset could introduce a challenging learning environment, potentially leading to erroneous conclusions. Unbalanced training sets have the potential to misguide classifiers, particularly in the context of volatile financial time series, where they might consistently predict the majority class.

Pang et al. [39] adopted Support Vector Regression (SVR) for the prediction of digital currency price fluctuations. More recently, several studies have embraced deep learning models for price estimation, given their demonstrated superiority over shallow learning approaches [40]. For instance, Altan et al. [41] employed an LSTM neural network to unveil previously undiscovered non-linear features within the Bitcoin price time series. Although predicting stock prices is a crucial step toward optimizing portfolios and risk hedging, only a limited number of studies have focused on this topic, especially for the cryptocurrency market. For instance, Nakamoto and Takahashi used a set of technical indicators as inputs to a seven-layer deep learning architecture for predicting the future price trend of Bitcoin [42].

Efstathios Polyzos suggests using social media as a proxy for financial data. Analyzing a vast dataset of 53,580,759 tweets, the study employs text analysis tools to determine daily exchanged information. Machine-learning classifiers are trained to forecast price movements for over 8000 cryptocurrencies, assessing market efficiency. Results indicate higher efficiency during the first 6 months after the Initial Coin Offering, with individual currency efficiency behavior examined during crisis periods [43]. In another work, a deep learning-based system was proposed for predicting the price fluctuation and transactions of Bitcoin based on the opinions and sentiments of users obtained from online forums [44].

Zhongbao Zhou and Zhengyang used historical trading data, daily Google Trends, and sentiment indicators to forecast cryptocurrency price movements using Support Vector Machine (SVM). They then proposed a portfolio optimization model by considering the forecasting information and the global minimum variance model and derived the corresponding portfolio strategy. Finally, they compared the out-of-sample performance of the proposed method with classic portfolio strategies and the Cryptocurrency Index. The results showed that the proposed multi-source data could effectively help forecast cryptocurrency price movements. The proposed portfolio strategy outperforms traditional strategies regarding the out-of-sample Sharpe ratio, Sortino ratio, and certainty equivalent return. The above conclusions were well-verified in robustness tests [45].

Azeez A. Oyedele and Anuoluwapo O. Ajayi conducted a study comparing genetic algorithm-tuned Deep Learning (DL) models. They boosted tree-based techniques for predicting the closing prices of multiple cryptocurrencies. The DL models evaluated were Convolutional Neural Networks (CNN), Deep Forward Neural Networks, and Gated Recurrent Units. The study utilized six cryptocurrency datasets from various sources and assessed the performance using relevant metrics. The findings highlight CNN's reliability with limited training data and its ability to generalize well in predicting daily closing prices of different cryptocurrencies. The results offer valuable insights for practitioners, aiding their understanding of crypto market challenges and providing practical risk mitigation strategies [46].

Table 1 presents studies conducted on the ranking of cryptocurrencies. However, these rankings have weaknesses as some studies only consider financial criteria, while others focus solely on technology or risk assessment criteria. Moreover, some studies only rely on the information gathered from questionnaires without utilizing actual market data such as market value, trading volume, and other relevant factors. Thus, this study aims to propose a model that considers all these criteria for a more comprehensive and accurate ranking of cryptocurrencies.

TABLE 1. Literature review.

Title	Method	The considered criteria	Advantages and disadvantages	Authors
China Information Industry Development Center	Review of blockchain experts' opinions	Technology (fundamental technology, application, creativity)	Considering the criterion of technology Not considering other influential criteria. No model has been defined for predicting rankings in the future	CCID[3]
Public blockchain evaluation using entropy and TOPSIS	*Using entropy and TOPSIS to determine weights and rankings*	*Technology, GitHub indicators, financial turnover*	Considering criteria Technology, GitHub indicators, financial turnover Not considering other influential criteria like social media influence. No model has been defined for predicting rankings in the future.	Huimin Tang , Yong Shi , Peiwu Dong[35]
Ranking of digital currency market performance	*Obtaining performance indicators*	*Performance including long-range dependency, fractal dimensions, and entropy components*	Not considering other influential criteria like social media influence. No model has been defined for predicting rankings in the future.	Kristoufek, L., & Vosvrda, M.[36]
Consumer-based modeling and ranking of digital currency consumption factors	*From theoretical saturation, exploratory factor analysis, and Friedman test*	*30 indicators obtained by questionnaire*	31 indicators obtained by questionnaire No model has been defined for predicting.	Yaser Sobhanifard, Seyedjavad Sadatfarizani[4]
Ranking of Coin Market Cap and CoinGecko for cryptocurrencies	*Highest market value*	*Maximum market value*	Maximum market value Not considering other influential criteria. No model has been defined for predicting	CMC, [47]
Ranking of exchanges by Coin Market Cap	Score based on exchange liquidity	Liquidity score based on order slippage	Liquidity score Not considering other influential criteria. No model has been defined for predicting	CMC, [48]
Ranking of exchanges by CoinGecko	Score based on assigned score.	Liquidity (50%), operations scale (30%), technical coverage (20%)	Liquidity, operations scale, technical coverage Not considering other influential criteria. No model has been defined for predicting	CoinGecko

Another limitation of the existing studies is their retrospective nature, as they must provide a model for predicting future rankings. Therefore, this study aims to overcome these limitations by proposing a model that incorporates various criteria and considers past and future perspectives. By doing so, this study seeks to provide a more holistic and practical approach to ranking cryptocurrencies that can be useful for investors and market analysts.

III. PROPOSED METHOD

The four main components of multi-criteria decision-making are alternatives, criteria, determination of criteria weights, and Methods for evaluating options based on criteria. The structure of our proposed model is presented in figure 1.

Based on the proposed structure, this section consists of four sub-sections: determining alternatives, identifying criteria, ranking alternatives using the PROMETHEE method, and finally, predicting ranking using deep learning.

A. ALTERNATIVES DETERMINATION

With technological advancement, digital currencies are recognized as an alternative to traditional investment methods. The popularity of this class of assets is increasing due to features such as their international nature, 24-hour trading capability, low transaction costs, and the impossibility of manipulating their transactions. The global nature of cryptocurrency has attracted the attention of many investors from countries. Our proposed model uses the data of the 10 most popular cryptocurrencies.

B. DETERMINING CRITERIA

Based on previous studies, ten influential criteria have been considered for determining the decision-making factors for investors in investment. In the following, we will explain these criteria.

1) TECHNOLOGY

Basic technology and applicability, and creativity are indicators of technology. These indicators are quantified by the expert scoring method. Since CCID has established a technology assessment index for blockchains, this paper will reference its scoring results for these criteria. The basic technology mainly examines the realization function, basic performance, safety, and degree of centralization of

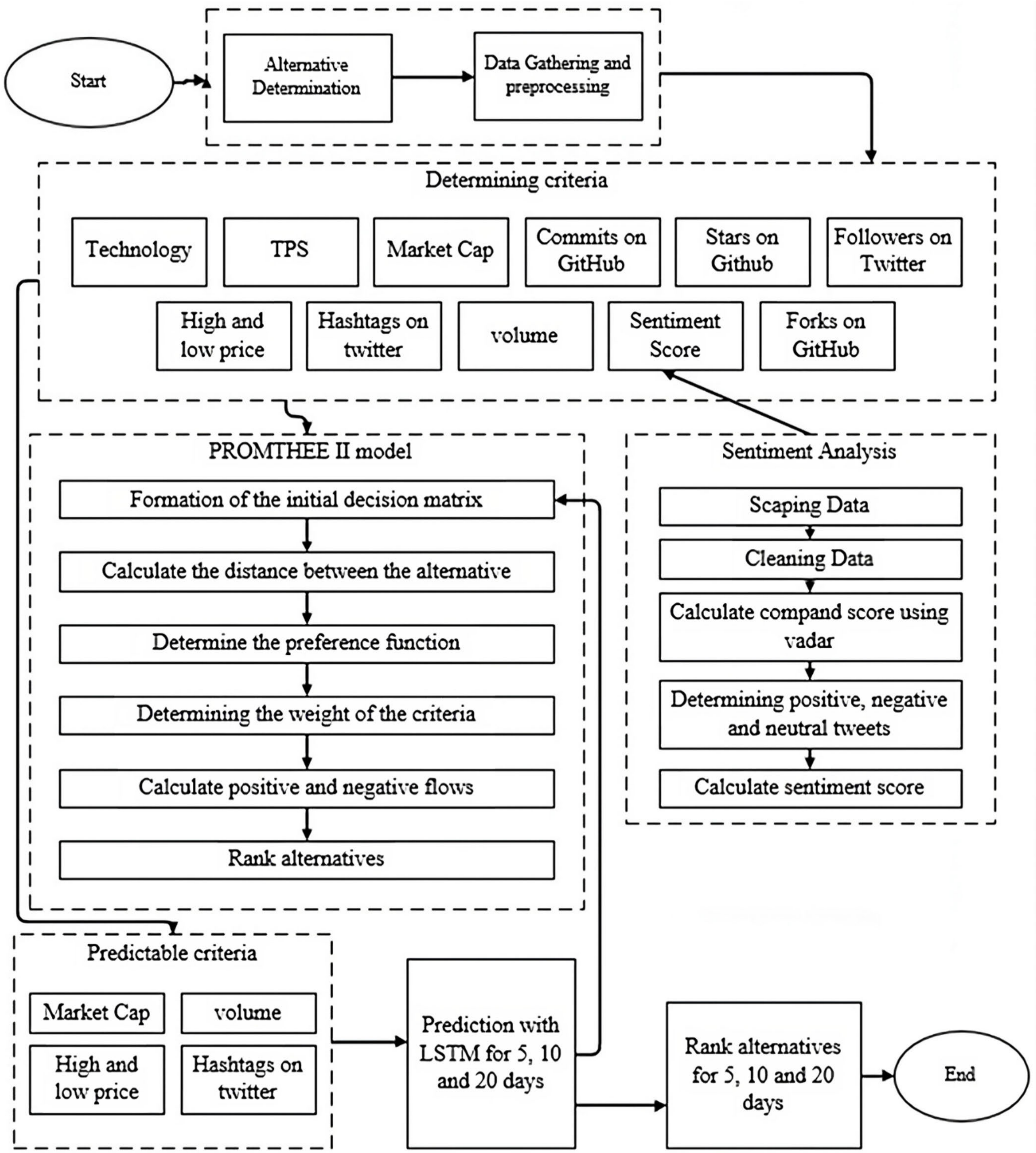

FIGURE 1. Flowchart for our proposed methods.

blockchain. The applicability focuses on the application scenarios, the number of wallets, the ease of use, and the development support on the chain.

2) TPS

In cryptocurrency, TPS refers to the maximum number of transactions that a blockchain can handle in one second. It is used to measure the speed and scalability of a network. Centralized systems like PayPal and Visa typically have higher TPS than most decentralized networks. PayPal has a TPS of 193, while Visa has a TPS of 1700. On the other hand, Bitcoin has a TPS of 7. To calculate the TPS of a blockchain, you need three pieces of data: the block time, block size, and average transaction size.

3) GITHUB

Forks and commits and stars are our reviewed indicators on GtHub. One of the main technical features of a blockchain is the need for multi-party participation and collaboration. Due to the open-source and transparent nature of blockchains, participants quickly recognize and trust them. Additionally, GitHub allows for the rapid collection of talented individuals for continuous progress. Forks indicate the number of people familiar with or wishing to participate in the blockchain. Commits on GitHub show the improvement of the blockchain. And stars on GitHub indicate the number of developers who like blockchain.

4) TWITTER

Twitter is one of the most famous online news services and social networks. Blockchain projects often have Twitter accounts to share the news with the public. The followers of these accounts for a public blockchain are individuals who recognize and value the importance of public blockchains. With the decentralized nature of blockchains, Twitter can also serve as a platform for community engagement and discussion among blockchain enthusiasts. Additionally, the transparency of Twitter and the traceability of information on the blockchain can increase accountability and trust in the blockchain ecosystem. Overall, Twitter can play a vital role in the success and growth of blockchain projects.

5) HASHTAGS

Hashtags are an essential tool for the crypto community on Twitter. They allow users to stay informed about the latest news and trends, increase visibility for their content and businesses, and promote events and initiatives. By using relevant hashtags in their tweets, individuals and companies in the crypto space can reach a wider audience and attract new followers. Hashtags also help build community and connect with other users with a common interest in cryptocurrencies. Overall, hashtags play a crucial role in facilitating conversations and engagement in the dynamic and constantly evolving crypto industry on Twitter.

6) VOLUME

The volume of exchange of cryptocurrencies refers to the total amount of cryptocurrencies bought and sold on a given exchange platform over a specific period. This volume is a critical metric for investors as it provides insight into the cryptocurrency's liquidity level and its demand in the market.

A higher trading volume can indicate a higher level of interest and demand for the cryptocurrency, which can result in a bullish trend and potentially increase the cryptocurrency's value. Conversely, a lower trading volume can indicate a lower direction and a bearish trend, decreasing the cryptocurrency's value. Investors often use trading volume data to make informed investment decisions. Higher trading volume typically provides more liquidity and can result in faster and easier transactions, making it a more attractive option for investors. However, investors should also be mindful of the potential risks of high-volume trading, such as increased volatility and possible price manipulation. As such, a comprehensive analysis of various metrics is essential when making investment decisions in the cryptocurrency market.

7) HIGH AND LOW PRICES

The difference between the high and low prices of a cryptocurrency can significantly affect the decisions of investors. A significant difference between the two prices indicates high volatility, which can attract some investors seeking high-risk, high-reward opportunities. However, it can also make the cryptocurrency unpredictable and unstable, leading to hesitation or caution among other investors. Additionally, a significant difference between the high and low prices may indicate a need for more liquidity in the market, making it difficult for investors to enter or exit positions at desirable prices. Therefore, investors must carefully consider the price difference of a cryptocurrency before making any investment decisions.

According to the explanations given, the ranking criteria are listed in Table 2, which are summarized in 10 metrics: Technology, TPS, market cap, Forks on Github, sentiment score of Twitter data, stars on Github, followers on Github, hashtags on Twitter, volume, and the difference between high and low prices. These 10 metrics are the criteria derived from studies and are influential factors in an investor's decision-making on investment in the cryptocurrency market. In determining these criteria, various aspects that impact investment decision-making have been considered, and it is not limited to just one aspect.

C. DEMATEL METHOD

The DEMATEL (Decision Making Trial and Evaluation Laboratory) method analyzes cause-and-effect relationships among factors impacting a problem. It quantifies the strength of influence between objects using a normalized direct-influence matrix (B), which is then used to compute the total influence matrix (T). From T, importance (t+) and relation (t−) indicators are derived, facilitating criteria weight determination:

$$B = \left[0 b_{1,2} \ldots b_{1,n} b_{2,1} 0 \ldots b_{2,n} \ldots\ldots\ldots\ldots b_{n,1} b_{n.2} \ldots 0\right] \tag{1}$$

$$\hat{B} = \frac{1}{\max(\sum_{j=1}^{n} b_{ij})} B \tag{2}$$

$$T = \hat{B}(I - \hat{B})^{-1} \tag{3}$$

$$t_i^{+} = \sum_{j=1}^{n} t_{ij} + \sum_{j=1}^{n} t_{ji} \tag{4}$$

$$t_i^{-} = \sum_{j=1}^{n} t_{ij} - \sum_{j=1}^{n} t_{ji} \tag{5}$$

$$w_i = ((t_i^{+})^2 + (t_i^{-})^2)^{0.5} \tag{6}$$

$$W_i = \frac{w_i}{\sum_i^n w_i} \tag{7}$$

TABLE 2. Explanation of criterion.

Criteria	Explanation of criterion
Technology	technology mainly examines the realization function, basic performance, safety, and degree of centralization of blockchain. The applicability focuses on the application scenarios, the number of wallets, the ease of use, and the development support on the chain.
TPS	maximum number of transactions that a blockchain can handle in one second.
Forks on GitHub	Forks indicate the number of people familiar with or wishing to participate in the blockchain.
Market cap	The market capitalization of a public blockchain is the total value of its coin in circulation, calculated by multiplying the coin's price in the cryptocurrency market by the total number of coins.
sentiment score	Twitter data provides valuable insights into customer attitudes and opinions,
stars on GitHub	stars on GitHub indicate the number of developers who like the blockchain.
followers on Twitter	The followers of these accounts for a public blockchain are individuals who recognize and value the importance of public blockchains.
Hashtags on Twitter	number of posts that have hashtags of the name of cryptocurrency
Volume	The volume of cryptocurrency exchange refers to the total amount of cryptocurrencies bought and sold on a given exchange platform over a specific period.
High and low prices	A significant difference between the two prices indicates high volatility, which can attract some investors seeking high-risk, high-reward opportunities.

where Wi represents the ultimate criteria weights that will be utilized in the decision-making process.

D. VADAR

VADER is a rule-based sentiment analysis tool for social media. It employs a sentiment intensity analyzer and polarity scores to categorize tweets as positive, negative, or neutral based on compound values. Typical threshold values used in this study are Refer to:

positive sentiment: compound value > 0.001,

neutral sentiment: (compound value > -0.001) and (compound value < 0.001),

Negative sentiment: compound value < -0.001,

E. PROMETHEE METHOD

The PROMETHEE method relies on pairwise comparisons between alternatives to generate the Preference Global Index (PGI), representing alternative performance relative to others. It involves defining preference functions for criteria evaluation, establishing preference and indifference thresholds, normalizing alternative performance, and determining criteria weights to compute PGI using formulas like.

$$\varphi^{+} = \frac{1}{n-1}\sum\nolimits_{x\epsilon A}^{n} \pi\ (a, x) \tag{8}$$

$$\varphi^{-} = \frac{1}{n-1}\sum\nolimits_{x\epsilon A}^{n} \pi\ (x, a) \tag{9}$$

$$\varphi\ (a) = \varphi^{+}\ (a) - \varphi^{-}\ (a) \tag{10}$$

F. LONG-SHORT-TERM MEMORY DEEP LEARNING NEURAL NETWORKS

As discussed in [36] and [37], LSTM neural networks offer a substantial enhancement over the conventional recurrent neural network (RNN) topology in terms of non-linear modeling and, notably, forecasting. Deep learning LSTM neural network systems excel in retaining adjacent temporal information while effectively managing long-term (LT) data. In simpler terms, LSTM can retain past data, greatly enhancing its capacity to grasp signal sequences and innate non-linear patterns.

The primary innovation in LSTM is the introduction of a "controlling gate." In this context, the LSTM memory cell can selectively retain or discard specific cell states, depending on the input conditions. Three essential gates govern the behavior of the cell: the input gate, the forget gate, and the output gate.

The input gate determines how much of the current information should be incorporated as input to compute the current state.

The forget gate decides how much information from the previous state should be retained or forgotten.

The output gate filters and selects the information deemed most relevant, ultimately producing the output – which, in our context, typically represents a forecast.

This sophisticated gating mechanism empowers LSTM to effectively manage and manipulate information flow, making it a potent tool for modeling and predicting sequences and patterns. Let's denote the input to all cells as x_t and the previous time-step output as h_{t-1} Then, the forget gate f_t computes the input for the cell state c_{t-1} using a sigmoid function, given by:

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{11}$$

The input gate i_t calculates the values to be updated to c_t As follows:

$$i_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_i\right) \tag{12}$$

Following that, the output gate, denoted as o_t, regulates the output values:

$$o_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_o\right) \tag{13}$$

Ultimately, the output value of the LSTM memory cell is determined as follows:

$$h_t = o_t \odot C_t \tag{14}$$

where,

$$C_t = f_i \odot C_{t-1} \oplus i_t \odot \underline{C}_{t-1} \tag{15}$$

the $\underline{C}_{t-1}$ This output is represented by the result of the non-linear hyperbolic tangent (tanh) function. In our paper, we employ historical sequences as inputs to the LSTM to uncover concealed information, with the predicted digital currency price serving as the desired output.

The application of the tanh function within the deep learning LSTM architecture transforms the raw (input) vector into the range of [−1,1]. Given the limited number of available sample observations, this scaling is particularly advantageous for accommodating deep learning LSTM networks. We allocate the majority for training purposes and reserve the remaining 10%, which represents the most recent data, for testing and out-of-sample forecasting.

To assess the forecasting performance, we employ the mean squared error (RMSE) metric, a widely used measure in the fields of signal processing and prediction. The RMSE is calculated as follows:

$$\mathrm{RMSE} = \sqrt{N^{-1} \sum_{i=1}^{N} (x_i - \hat{x}_i)^2} \tag{16}$$

G. WEIGHTED SPEARMAN'S RANK CORRELATION COEFFICIENT

The calculation of the distance between two ranks in Spearman's coefficient is typically represented as $\boldsymbol{D_i^2} = (\boldsymbol{R_i} - \boldsymbol{Q_i})^2$, which does not consider the relative importance of ranks. Another formula, $(\frac{R_i - Q_i}{R_i})^2$, is also used but has several drawbacks. First, it does not produce the expected inverted ranking. $\boldsymbol{Q_i = n - R_i + 1}$, that yields the largest distance from R. Second, this function is asymmetric, meaning that the distance between series R and series Q can be different from the distance between Q and R. In this context, an alternative distance measure is proposed:

$$\begin{aligned} W_i^2 &= (R_i - Q_i)^2\,((n - R_i + 1) + (n - Q_i + 1)) \\ &= D_i^2\,((n - R_i + 1) + (n - Q_i + 1)) \end{aligned} \tag{17}$$

The first term of this product, $\boldsymbol{D_i^2}$, mirrors Spearman's method by quantifying the distance between $\boldsymbol{R_i}$ and $\boldsymbol{Q_i}$. The second term goes beyond, accounting for not only the significance of $\boldsymbol{R_i}$ but also the significance of $\boldsymbol{Q_i}$.

An expression of the form $\boldsymbol{A + B \sum_i^n W_i^2}$, which typically falls within the range of [−1, 1], adheres to the convention for correlation coefficients. It assumes the value of −1 when the rankings are completely inverted and 1 when they are identical. This expression characterizes the weighted rank measure of correlation, taking into account the maximum value of the weighted distance between two rankings.

$$r_w = 1 - \frac{6 \sum_{i=1}^{N} (x_i - y_i)^2\,((N - x_i + 1) + (N - y_i + 1))}{N^4 + N^3 - N^2 - N} \tag{18}$$

In this study, we first determine the decision-making criteria, and then, as shown in Fig.1, after identifying the decision options, we gather data for the decision-making criteria. For some, we can use data available on websites, such as market cap, while for others, we gather the data ourselves. To obtain the sentiment score, we scrape Twitter data and analyze it. For the number of hashtags, we use a script to monitor the number of hashtags per day. After obtaining the data, we seek the help of experts to determine the weights of the data, and we convert this data into weights for each criterion using the DEMATEL method. For ranking, we use the PROMETHEE method and follow the steps outlined in Fig.1. Then, to predict the rankings in the future, we forecast the predictable criteria using the LSTM method for different time intervals and obtain the rankings for these intervals.

TABLE 3. Datasets.

datasets	Timestamps	explanation
historical data of volume and prices	starts of March 2022 to the end of January 2023	These data were obtained from the Investing.com site.
Hashtags in day	monitoring data for 30 days of December 2022	This data was obtained using a Python script to count the number of hashtags per day.
twitter data	tweets of December 2022	These tweets were obtained from Twitter using the Twitter API.

IV. DATA AND RESULT

A. DATA

In this study, we assessed ten criteria to rank cryptocurrencies: Technology, TPS (Transactions Per Second), Market Capitalization, GitHub activity (including forks and stars), Twitter engagement (followers and hashtags), trading volume, sentiment score, and price volatility (represented by the difference between high and low prices).

The datasets utilized in this study are depicted and summarized in Table 3, demonstrating their relevance to each segment of the study. Detailed explanations for each dataset are provided within their respective sections. Here, we provide a concise overview of these datasets in Table 3.

The hybrid dataset utilized in this study combines historical cryptocurrency price and volume data with Twitter-related metrics, including daily hashtag counts and tweet data. This integrated dataset provides a comprehensive view of cryptocurrency market activity and sentiment, allowing for a more thorough analysis and ranking of cryptocurrencies based on various criteria.

B. EXPERIMENTS

Data collection from Twitter was automated using Python and Selenium, focusing on tweets mentioning or related to cryptocurrencies. A sample tweet is provided in Figure 2, showcasing the type of data analyzed. However, to ensure data cleanliness, we implemented preprocessing steps such

TABLE 4. Weights for ten criteria.

	w_i
I_1	0.069
I_2	0.067
I_3	0.11
I_4	0.071
I_5	0.116
I_6	0.115
I_7	0.122
I_8	0.111
I_9	0.111
I_{10}	0.104

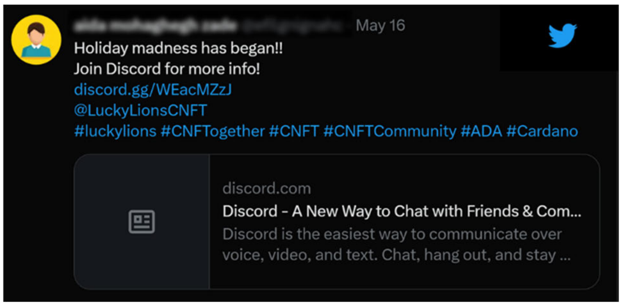

FIGURE 2. Sample of a tweet.

TABLE 5. Sample tweets for Cardano.

tweet	date	username
It's great to see so many people discovering the fantastic potential of Cardano! I can't wait to see what the future of DeFi holds for us!	12/16/2022	biggereg
Can't wait for you guys to become one of the most successful projects soon! Welcome to Cardano	12/16/2022	$mikotonft | BEAST

as removing links, mentions, emojis, single-letter mistakes, and hashtags from the tweets.

Table 5 is an example of Cardano cryptocurrency tweets. The above tweet is transformed into the following tweet:

Holiday madness has begun.
Join discord for more info
luckylions CNFTogether CNFT CNFTCommunity ADA Cardano

Sentiment analysis was conducted using the VADER tool, categorizing tweets as positive, negative, or neutral based on compound scores. This sentiment analysis, as shown in Table 6, provided valuable insights into the community's opinions and sentiments regarding various cryptocurrencies. To obtain the sentiment score for each cryptocurrency, we use the following formula:

$$\text{Sentiment Score} = \frac{\text{P} - \text{N}}{\text{P} + \text{N}} \tag{19}$$

Technology-related insights were obtained from CCID ranking points, evaluating blockchain projects based on criteria such as scalability, security, and innovation. Additionally, transaction rate data was sourced from reputable websites, and market capitalization data from investing.com.

We have got the transaction rate on reputable websites for each cryptocurrency. We have used data from investing.com to obtain market capitalization, and we have referred to the page of each cryptocurrency on GitHub for information. As explained in detail in the previous section, we have used sentiment analysis to obtain sentiment analysis. Finally, we monitored the number of hashtags per hour for one week using a Python script to get information related to hashtags per day. Using the PROMETHEE method, we ranked cryptocurrencies based on the explained criteria and their scores. For instance, Table 7 presents the ranking for 2018, showcasing the relative positions of cryptocurrencies like Bitcoin, Ethereum, and XRP. To evaluate the accuracy of our model, we compared its rankings to those from a previous study by Huimin Tong. This comparison, presented in Table 8, demonstrated the superiority of our proposed model in predicting price changes in cryptocurrencies.

Based on Table 8, as we can see, the proposed model has shown a higher similarity in terms of ranking based on price percentage changes in cryptocurrencies. Therefore, it can be said that the proposed model has performed better. Then we have done the ranking based on the data of 2023, the results of which are given in Table 8.

In this study, we have access to historical data for four criteria that can be considered predictable. These criteria are crossings, which refer to specific events or conditions that can be measured or observed. While the characteristics of these crossings may have changed over time, we do not have access to the data that would allow us to predict their future occurrence or quantity. Furthermore, leveraging the LSTM method, we generated predictions for key criteria such as market capitalization, trading volume, and hashtags over different time intervals (5 days, 10 days, and 20 days). These predictions, organized in Tables 9 and 10, facilitated the ranking of cryptocurrencies over various time horizons. Handling NaN data involves removing any rows or columns from the dataset that contain missing values (NaN). In our case, because there were only one or two NaN values in three of the datasets, we opted to drop them entirely from the dataset. This ensures that the dataset remains clean and accurate for analysis without significantly affecting the overall data

TABLE 6. **Sample tweet and sentiment analysis result for Bitcoin.**

tweet	Negative Score	Positive Score	Neutral Score	Compound Score	Overall Sentiment
Cyril should have asked his corruptors to send him the illegal money as Bitcoin no one would have found out	0.244	0	0.756	0.7003-	Negative
new post check bitcoin Ethereum xrp Solana fees read it at	0	0	1	0	Neutral
once reaches stability, it will be the most sound money in the world the only next step is the bitcoin standard if there is to be prosperous future it through btc it is the world best hope by far	0	0.251	0.749	0.886	Positive

TABLE 7. **Ranking for 2018.**

cryptocurrency	rank	phi
BTC	1	0.47866
ETH	2	0.29888
XRP	3	0.04957
EOS	4	0.4437
ADA	5	-0.0633
NEO	6	-0.0638
BTS	7	-0.127
QTUM	8	-0.1766
KMD	9	-0.1984
NAS	10	-0.2424

TABLE 8. **Similarity of ranking.**

cryptocurrency	Ranking based on price changes	Huimin Tong ranking[38]	proposed ranking
BTC	1	1	1
XRP	2	5	3
ETH	3	2	2
EOS	4	3	4
KMD	5	7	9
ADA	6	9	5
NEO	7	4	6
QTUM	8	6	8
NAS	9	10	10
BTS	10	8	7
	r_w	0.768595	0.8732782

integrity. In addition, it's important to note that 80 percent of the data was used for training the model, while the remaining 20 percent was reserved for testing purposes. The predictions are structured over three distinct intervals: 5 days, 10 days, and 20 days. This information is meticulously organized and presented in Table 9 and Table 10. Using the predicted data in Table 9, the ranking is determined using the same method that has been fully explained for the next 5, 10, and 20 days. There is no difference in the method except that the predicted data is placed in the position of the previous data.

TABLE 9. **Ranking for 2023.**

cryptocurrency	rank	phi
BTC	1	0.616
ETH	2	0.2578
EOS	3	0.03391
NEO	4	-0.0534
ADA	5	-0.0724
XRP	6	-0.0733
BTS	7	-0.1205
QTUM	8	-0.1652
KMD	9	-0.1913
NAS	10	-0.2315

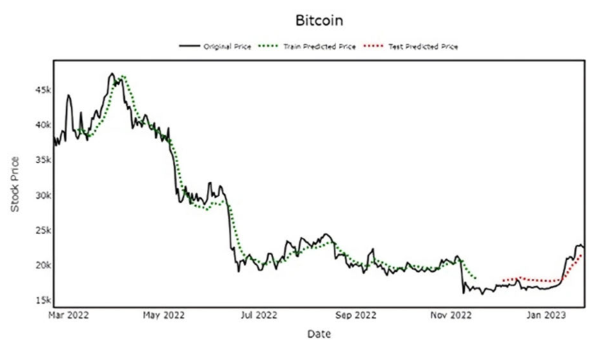

FIGURE 3. **Bitcoin close price model.**

Figure 3 to Figure 41 serve as visual representations showcasing the performance of LSTM models in fitting historical data alongside their division into training and testing

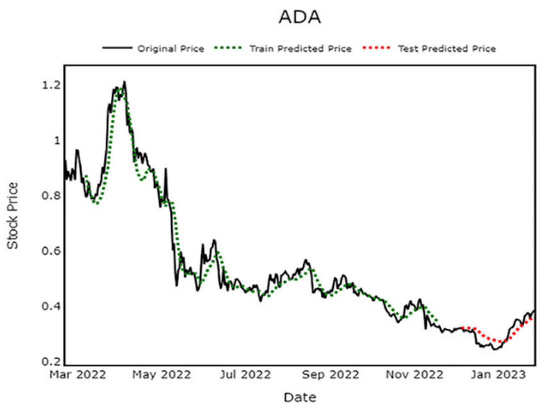

FIGURE 4. ADA close price model.

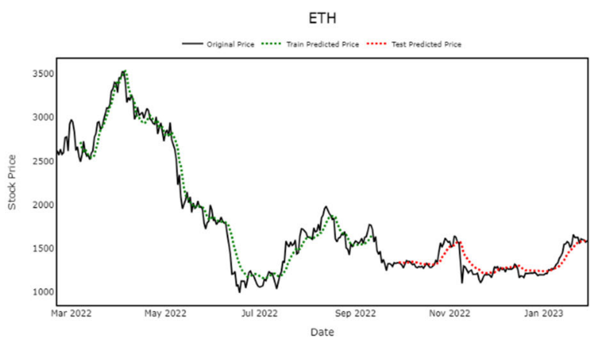

FIGURE 5. ETH close price model.

FIGURE 6. XRP close price model.

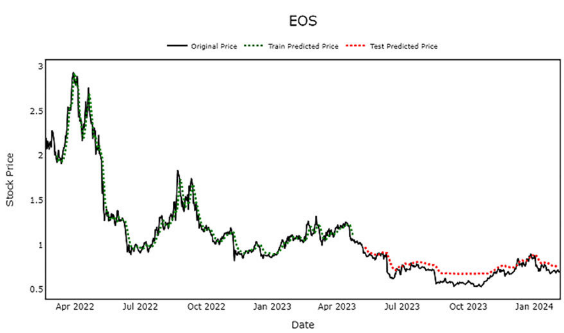

FIGURE 7. EOS close price model.

datasets. These figures are instrumental in illustrating the accuracy and predictive capabilities of LSTM models across

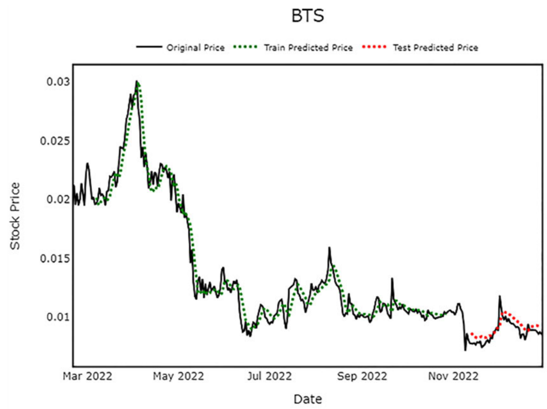

FIGURE 8. BTS close price model.

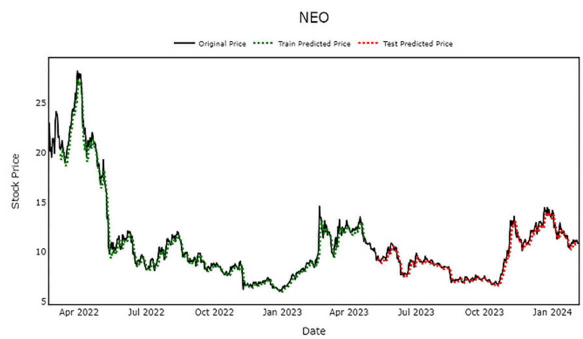

FIGURE 9. NEO close price model.

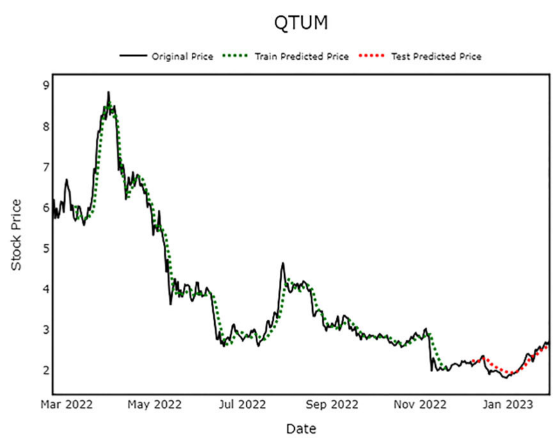

FIGURE 10. QTUM close price model.

various criteria, including market capitalization, HL (High-Low prices), volume, and the number of hashtags associated with specific assets or entities within the dataset.

Through the detailed analysis presented in Figure 3 to Figure 41, we thoroughly understand the LSTM model's capabilities in fitting historical data, segmenting it into training and testing sets, and predicting future trends across specified intervals. This visual journey not only underscores the model's accuracy and adaptability but also reinforces its

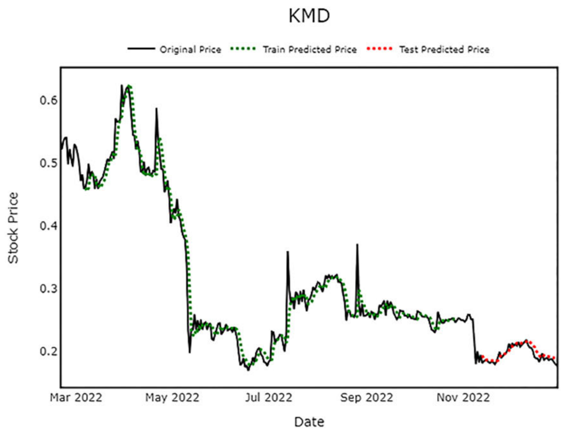

FIGURE 11. KMD close price model.

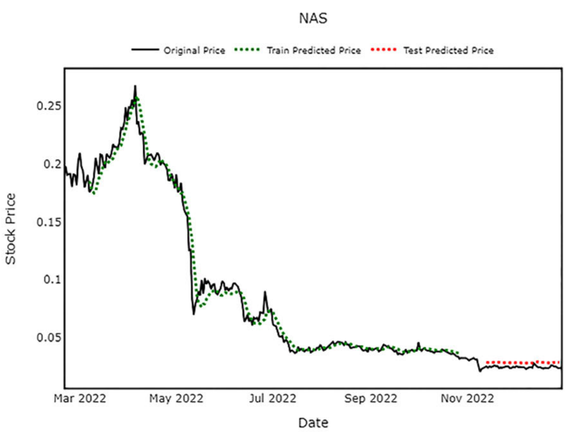

FIGURE 12. NAS close price model.

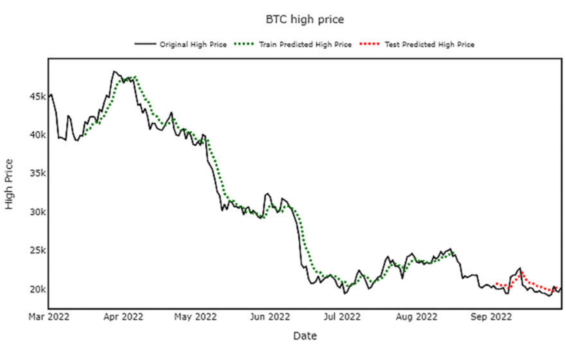

FIGURE 13. BTC high price model.

potential as a tool for data-driven decision-making in various domains, including finance and social media analytics.

Finally, Table 11 provides performance metrics for our predictive model, including R-squared values and RMSE (Root Mean Square Error) for cryptocurrencies like Bitcoin, Ripple, and Ethereum. These metrics offer insights into the model's accuracy in predicting cryptocurrency prices and volume.

R^2 (R-squared): This metric indicates the proportion of the variance in the dependent variable (cryptocurrency price) that is predictable from the independent variables in the model. Higher values of R-squared indicate a better fit of the model to the data. For instance, BTC has an R-squared value

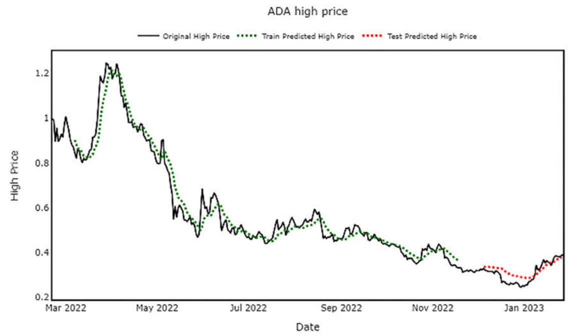

FIGURE 14. ADA high price model.

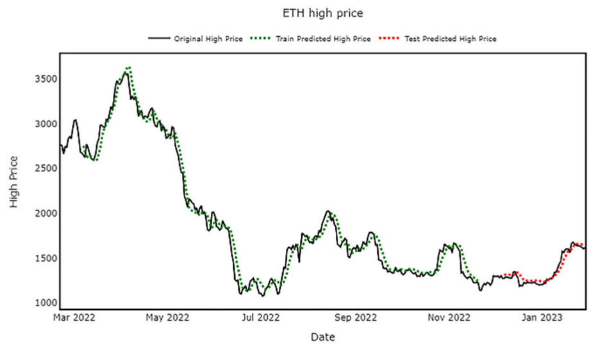

FIGURE 15. ETH high price model.

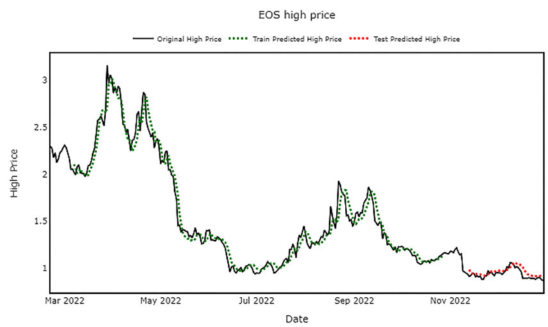

FIGURE 16. EOS high price model.

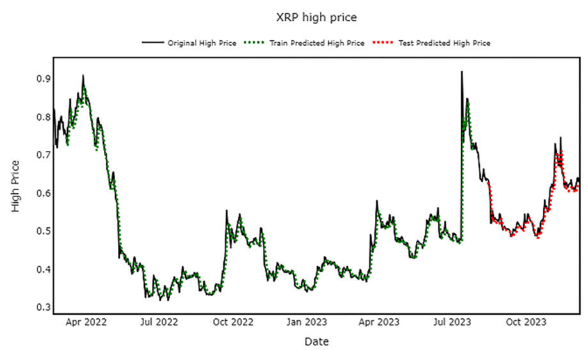

FIGURE 17. XRP high price model.

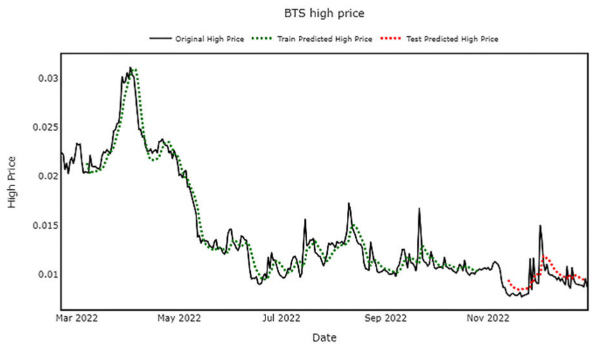

FIGURE 18. **BTS high price model.**

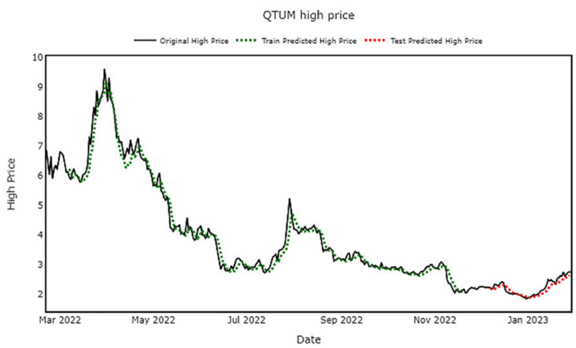

FIGURE 19. **QTUM high price model.**

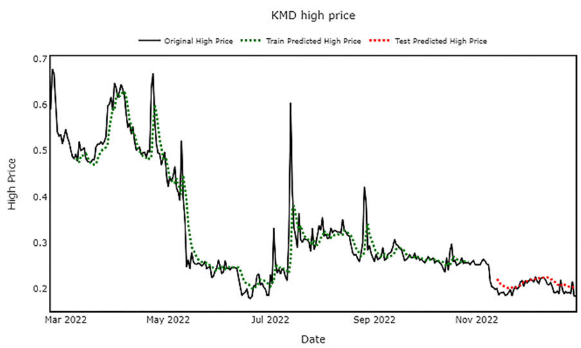

FIGURE 20. **KMD high price model.**

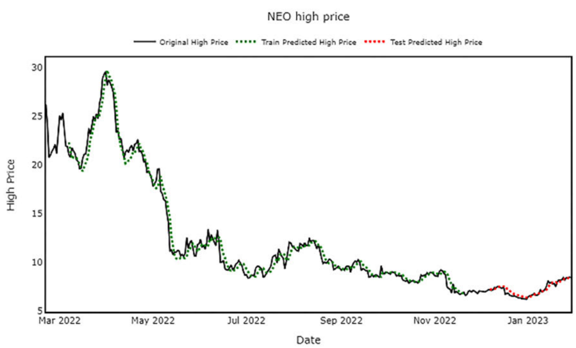

FIGURE 21. **NEO high price model.**

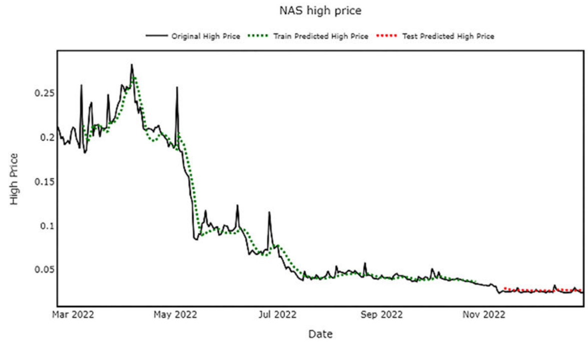

FIGURE 22. **NAS high price model.**

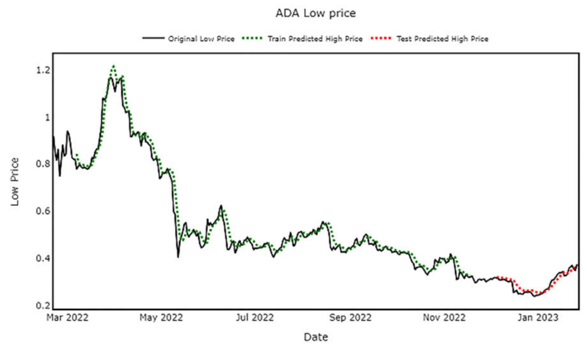

FIGURE 23. **ADA low price model.**

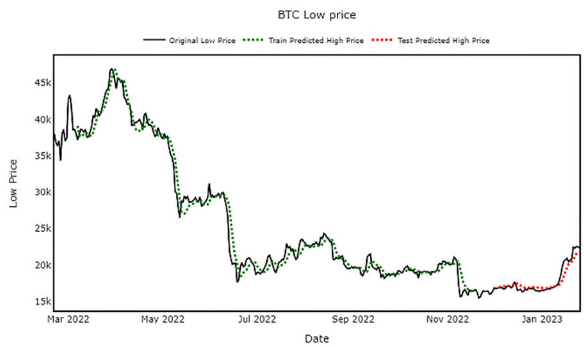

FIGURE 24. **BTC low price model.**

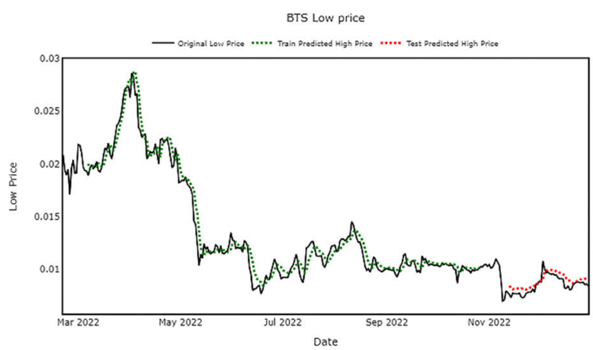

FIGURE 25. **BTS low price model.**

of approximately 0.98, indicating that the model explains about 98% of the variance in Bitcoin's price.

RMSE (Root Mean Square Error): This metric measures the average magnitude of the errors between the predicted values and the actual values. Lower values of RMSE indicate better model accuracy. For example, BTC has an RMSE of

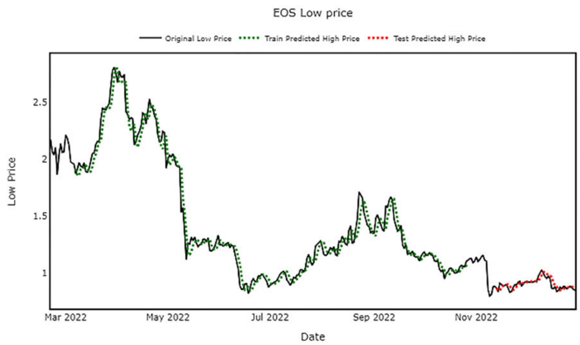

FIGURE 26. EOS low price model.

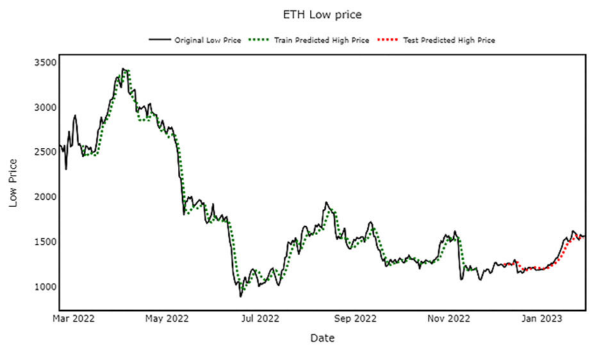

FIGURE 27. ETH low price model.

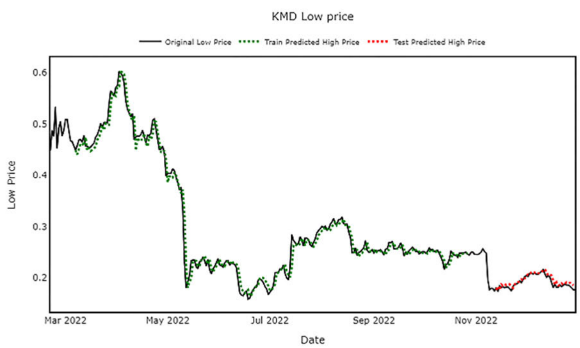

FIGURE 28. KMD low price model.

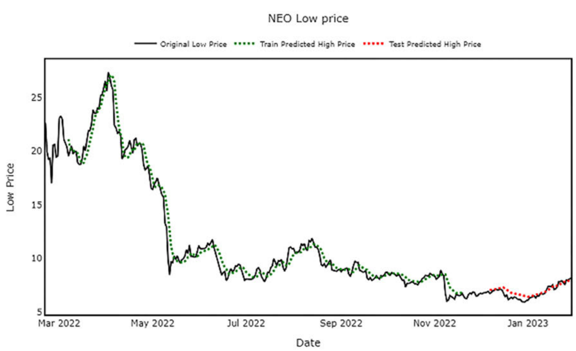

FIGURE 29. NEO low price model.

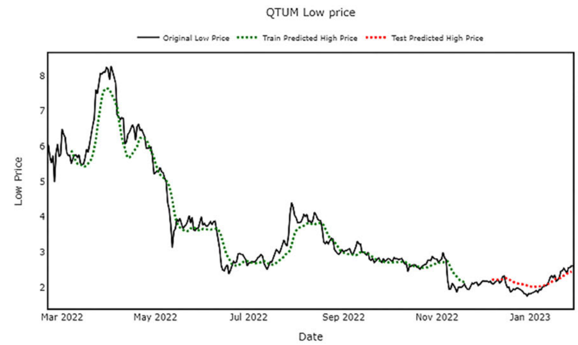

FIGURE 30. QTUM low price model.

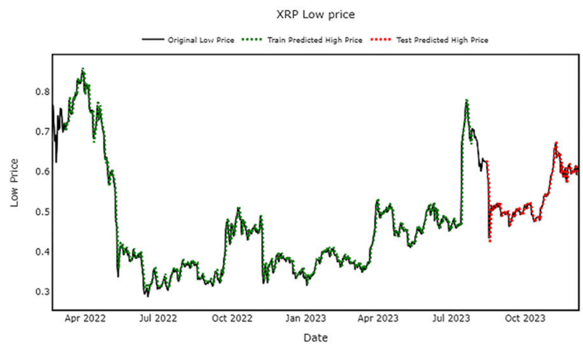

FIGURE 31. XRP low price model.

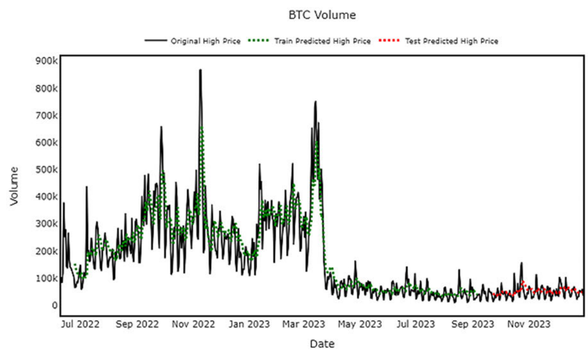

FIGURE 32. BTC volume model.

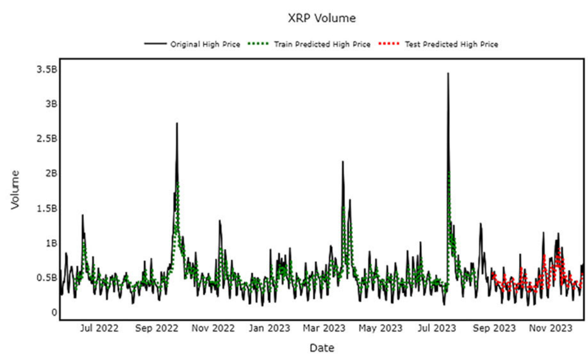

FIGURE 33. XRP volume model.

approximately 284, suggesting that, on average, the model's predictions for Bitcoin's price are off by about $284.

The R^2 and RMSE values for each cryptocurrency and each price metric (Close price, High price, Low price, and

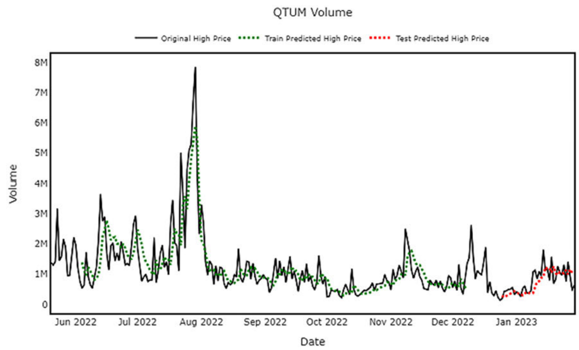

FIGURE 34. **QTUM volume model.**

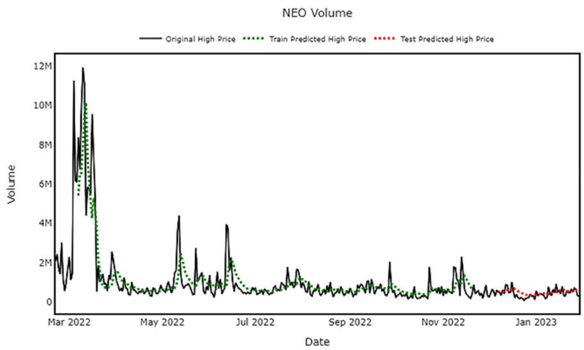

FIGURE 35. **NEO volume model.**

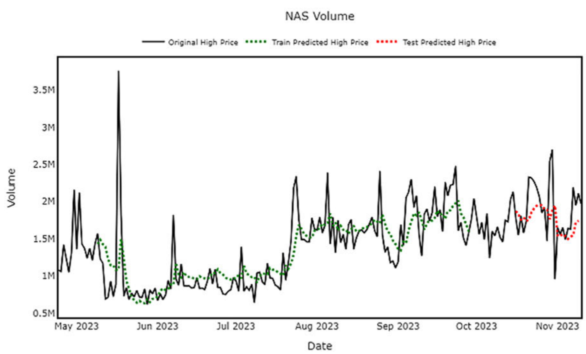

FIGURE 36. **NAS volume model.**

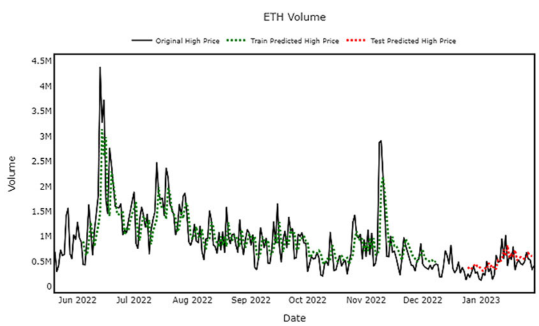

FIGURE 37. **ETH volume model.**

Volume) are provided in the table. These metrics allow for evaluating the model's performance in predicting cryptocurrency prices and volume.

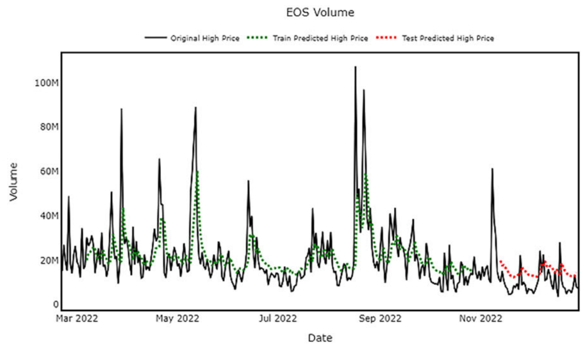

FIGURE 38. **EOS volume model.**

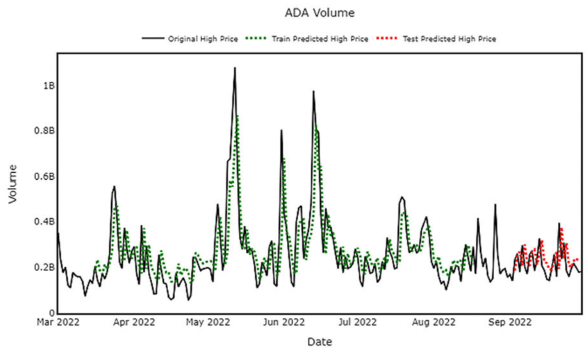

FIGURE 39. **ADA volume model.**

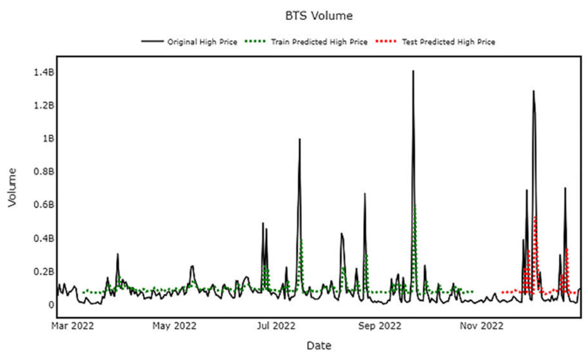

FIGURE 40. **BTS volume model.**

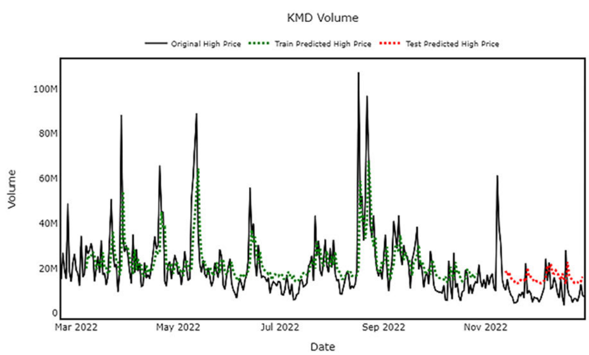

FIGURE 41. **KMD volume model.**

Overall, cryptocurrencies such as BTC, XRP, and ETH exhibit relatively high R-squared values and low RMSE

TABLE 10. The predicted amount for marketcap and volume(24h).

	MARKETCAP			volume(24h)		
	5 days	10 days	20 days	5 days	10 days	20 days
EOS	1,203,394,866	1,386,612,213	1,677,823,374	19,778,910	29,811,140	2,818,890
ETH	202,957,546,256	210,074,443,181	225,626,448,316	3,306,824,743	3,306,824,743	3,306,824,743
NEO	641,829,861	695,984,778	813,140,607	771,769	1,005,016	1,062,278
QTUM	304,860,106	329,762,386	394,018,793	1,118,387	1,207,223	1,286,745
BTC	475,403,229,560	517,849,147,970	596,960,754,985	314,113	311,734	310,970
BTS	34,499,010	43,617,561	63,421,215	111,138,400	113,560,200	127,159,700
XRP	21,700,210,842	25,423,946,321	37,950,157,388	712,589,700	983,938,000	1,613,713,000
KMD	27,151,756	28,739,806	32,158,837	205,926	205,926	205,926
ADA	15,224,469,510	17,640,341,170	21,899,469,501	271,051,000	334,937,200	548,100,400
NAS	1,529,281	1,512,336	1,477,244	1,105,050	1,469,860	2,473,572

TABLE 11. The predicted errors.

cryptocurrency	Close price		High price		Low price		Volume	
	R2	RMSE	R2	RMSE	R2	RMSE	R2	RMSE
BTC	0.983839866	284.4105821	0.982196975	305.576047	0.98263634	291.0358855	0.861721906	5.131626437
XRP	0.967173674	0.024660377	0.965364645	0.026448007	0.977892471	0.020359762	0.804679591	7.282567278
ETH	0.977414278	106.144699	0.970915084	119.4451852	0.965975064	126.0016767	0.857921003	1.094735895
EOS	0.953669323	0.118314948	0.97003195	0.099180753	0.963312235	0.101075632	0.81347814	1.478164781
KMD	0.963170846	0.022595312	0.895209965	0.03994443	0.857158279	0.067001934	0.818558737	1.554555892
ADA	0.963681649	0.042407195	0.966020638	0.04420182	0.956179591	0.205953972	0.886140068	1.091319006
NEO	0.978295425	0.817235959	0.972216075	0.959385935	0.986121799	0.632350177	0.736538254	0.839675872
QTUM	0.975234264	0.239615524	0.973390864	0.283844262	0.977676338	0.237864083	0.849998652	1.446785034
NAS	0.977726897	0.010593661	0.975281509	0.011682368	0.988810717	0.007313246	0.895338522	1.080306051
BTS	0.972064315	0.000898517	0.956064293	0.001173348	0.943267342	0.001236197	0.839362386	1.272605366

values, indicating that the model performs well in predicting their prices. However, cryptocurrencies like EOS, KMD, and BTS show slightly lower R-squared values and higher RMSE values, suggesting that the model may have more difficulty accurately predicting their prices. In Table 13, we showcase the ranking changes of cryptocurrencies over the past 5, 10, and 20 days. Notably, Bitcoin and Ethereum maintained their top positions, while other cryptocurrencies experienced fluctuating rankings based on various factors such as market capitalization, trading volume, and technology score.

The rankings also highlight the importance of market capitalization and trading volume in determining a cryptocurrency's position. Factors such as technology score, TPS, GitHub activity, and Twitter hashtags are crucial in determining a cryptocurrency's ranking.

EOS initially ranked third due to its high technology score, TPS, and Twitter hashtags, has dropped to fourth. Despite initially having a higher market capitalization than EOS, these factors were insufficient to maintain its ranking.

XRP, on the other hand, has experienced a significant surge in value over the past 20 days. This increase can be attributed to its rising trading volume and market capitalization.

It is noteworthy that while EOS had a higher technology score, it was not enough to maintain its ranking due to these factors' limitations. Similarly, market capitalization and trading volume play crucial roles in determining a cryptocurrency's ranking.

ADA maintained its position at rank 6 until the 10th day, but on the 20th day, despite an increase in four predicted criteria, this cryptocurrency was unable to keep up with BTS and ended up in 7th place.

Neo's increase in hashtags has helped to compensate for its lack of market cap. However, this cryptocurrency has scored high in some criteria, such as technology and TPS.

TABLE 12. The predicted amount for HL and hashtag in day.

	HL			hashtag in day		
	5 days	10 days	20 days	5 days	10 days	20 days
EOS	0.2731	0.4715	0.7831	10422	8444	7545
ETH	66.639	160.66	296.49	173200	148300	108800
NEO	1.767	3.8728	6.0309	47100	51600	62400
QTUM	0.5523	0.9127	1.5498	750	834	1208
BTC	284.4	177.09	1387.9	194900	237700	255300
BTS	0.0015	0.0034	0.0067	38	30	102
XRP	0.0211	0.0349	0.0737	15115	19200	21701
KMD	0.0284	0.0942	0.2355	404	740	500
ADA	0.04828	0.0664	0.1056	22527	24807	30787
NAS	0.0777	0.093	0.0874	87	55	174

TABLE 13. Ranking for 5, 10 and 20 days.

rank	5 days		10 days		20 days	
1	BTC	0.495678	BTC	0.490808	BTC	0.498328
2	ETH	0.371373	ETH	0.405829	ETH	0.302472
3	EOS	-0.01825	EOS	-0.02497	XRP	-0.00915
4	NEO	-0.04636	XRP	-0.0424	EOS	-0.01953
5	XRP	-0.0485	NEO	-0.05275	NEO	-0.04356
6	ADA	-0.06018	ADA	-0.06392	BTS	-0.046
7	BTS	-0.11378	QTUM	-0.11856	ADA	-0.11053
8	QTUM	-0.16253	BTS	-0.16706	QTUM	-0.15987
9	KMD	-0.18862	KMD	-0.19347	KMD	-0.18594
10	NAS	-0.22884	NAS	-0.23351	NAS	-0.22622

The number of hashtags and trading volume had the potential to push BTS higher than QTUM, but in the past 5 days, this trend did not continue and caused its downfall. However, in the next 20 days, BTS managed to surpass not only QTUM but also ADA, reaching a higher position in terms of market cap, hashtags, and trading volume. Overall, the table provides insight into the dynamic nature of the cryptocurrency market and highlights the importance of various factors in determining the ranking of cryptocurrencies.

This study comprehensively analyzes cryptocurrency ranking, considering multiple criteria such as technology, market capitalization, social media engagement, and sentiment analysis. By integrating various datasets and employing robust methodologies, including sentiment analysis using the VADER tool and LSTM models for prediction, the study offers valuable insights into the dynamic nature of the cryptocurrency market. However, it's important to acknowledge limitations such as data accuracy and subjectivity in sentiment analysis and rigorously evaluate model performance.

The findings of the study have implications for investors, cryptocurrency projects, and stakeholders in the market. Investors can use the insights to inform their investment strategies, adjusting their approaches based on factors influencing cryptocurrency value. Cryptocurrency projects can gain valuable market insights to guide their development and marketing strategies, while stakeholders can leverage the findings for risk management purposes, identifying and mitigating risks associated with market volatility and sentiment fluctuations.

V. CONCLUSION

This paper introduced a novel model to evaluate and rank cryptocurrencies based on ten criteria. We employed a rigorous methodology, utilizing the DEMATEL method for index weighting and the PROMETHEE method for ranking cryptocurrencies. Criterion weights were determined through a consultative process with industry experts, and impact intensity among indices was mitigated.

Furthermore, we utilized the PROMETHEE method not only to present current rankings but also to project future rankings based on historical data for four indices. Despite limitations stemming from a paucity of historical data for certain criteria and uncertainties regarding achieving targets for others, such as GitHub stars and transactions per second, we supplemented our approach with the Long Short-Term Memory (LSTM) model. This allowed us to furnish rankings for intervals spanning 5 days, 10 days, and 20 days.

Through comparative analysis with an extant model ranking ten cryptocurrencies using 2018 data, we demonstrated the superior performance of our proposed model in terms of percentage increases in cryptocurrency prices. While we acknowledge limitations, including the exclusion of variables such as government policies, influential individuals, and advertising impact, we maintain methodological rigor.

Moving forward, we advocate for the consideration of these influential factors in future research endeavors. By refining our model to incorporate government policies, influential individuals, and advertising impact, we aim to enhance its comprehensiveness and accuracy. This study lays a promising groundwork for future investigations in this burgeoning field.

In summary, our proposed model offers a systematic approach to cryptocurrency ranking, providing potential benefits to investors in making informed decisions. By meticulously weighing diverse indices and incorporating historical data, our model furnishes a holistic perspective on cryptocurrency performance. It's crucial for scholars and practitioners to recognize the dynamic and mutable nature of the cryptocurrency market, understanding that any ranking model is inherently subject to limitations and challenges. Nevertheless, this study paves the way for further research and advancements in this evolving field.

In deploying our cryptocurrency ranking method, we recognize the potential ethical implications inherent in influencing market sentiment and investor behavior. While our model aims to provide transparency and objectivity, it's essential to acknowledge the responsibility of researchers and practitioners in the cryptocurrency space. Cryptocurrency investments involve financial risks, and our ranking system, while designed to aid decision-making, should be used cautiously and in conjunction with other sources of information. Moreover, as the market is susceptible to manipulation and volatility, there's a need for ethical considerations regarding the dissemination of rankings and their potential impact on market dynamics. We advocate for responsible use of our model, transparency in research practices, and ongoing dialogue within the cryptocurrency community to address ethical concerns and promote integrity in investment decisions.

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