

A Comparative Study of AI-Based and Traditional Methods for Cryptocurrency Price Prediction

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Abstract

Cryptocurrency markets have gained significant attention due to their rapid growth, high price volatility, decentralized nature, and increasing participation by individual and institutional investors. However, predicting cryptocurrency prices remains a major challenge because of unpredictable market movements, changing investor sentiment, economic developments, and technological advancements. Traditional forecasting methods, such as Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA), and Exponential Smoothing, have been widely used to analyze historical price patterns and forecast future market trends. In recent years, Artificial Intelligence (AI)-based techniques, including Machine Learning (ML), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and Random Forest algorithms, have emerged as alternative approaches for cryptocurrency price prediction. These methods can identify complex relationships, nonlinear patterns, and trends within large datasets. This research aims to comparatively evaluate AI-based and traditional forecasting methods in terms of prediction accuracy, reliability, adaptability, computational efficiency, and performance under volatile market conditions. The study focuses on cryptocurrency price data, particularly Bitcoin and Ethereum, to examine the effectiveness of different forecasting

techniques using quantitative performance measures such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The findings are expected to provide insights into the relative strengths and limitations of both approaches and identify suitable forecasting techniques for cryptocurrency market analysis. The study may contribute to researchers, investors, financial analysts, and technology professionals seeking to understand the role of AI in improving cryptocurrency price forecasting. However, accurate price prediction does not guarantee profitable investment decisions because cryptocurrency markets remain highly uncertain and susceptible to sudden changes.

Keywords: Artificial Intelligence, Cryptocurrency, Price Prediction, Machine Learning, Traditional Forecasting Methods, Bitcoin, Ethereum, Long Short-Term Memory (LSTM), ARIMA, Predictive Analytics, Market Volatility, Forecasting Accuracy.

I. Introduction

The development of digital financial technologies has transformed the global financial system, creating new opportunities for investment, trading, and financial innovation. Among these developments, cryptocurrencies have emerged as an important category of digital assets that operate primarily through blockchain technology and decentralized networks. Bitcoin, Ethereum, and other cryptocurrencies have attracted considerable attention from investors, financial institutions, technology companies, and researchers. Their increasing popularity has created a need for effective analytical techniques that can help market participants understand price movements and evaluate potential market trends. However, cryptocurrency prices are highly volatile and can change significantly within short periods, making reliable price prediction a complex and challenging task.

Cryptocurrency price movements are influenced by several factors, including historical price trends, trading volume, investor sentiment, market demand and supply, regulatory announcements, technological developments, macroeconomic conditions, and global financial events. Unlike many traditional financial markets, cryptocurrency markets operate continuously, including weekends and holidays. This continuous trading environment generates substantial volumes of market data and increases the complexity of identifying consistent price patterns. Consequently, forecasting methods that perform effectively under stable market conditions may not always produce reliable predictions during periods of extreme

volatility. Traditional forecasting methods have historically been used to analyse financial time-series data and estimate future prices. Techniques such as Moving Average, Exponential Smoothing, and Autoregressive Integrated Moving Average (ARIMA) rely primarily on historical observations and statistical relationships. These methods are generally understandable, comparatively straightforward to implement, and useful for identifying trends, smoothing fluctuations, and modelling certain time-series patterns. Nevertheless, traditional statistical techniques may face limitations when dealing with complex nonlinear relationships, sudden market disruptions, changing volatility, and interactions among multiple predictive variables. Artificial Intelligence has introduced new possibilities for cryptocurrency price forecasting by enabling computational models to identify complex patterns within historical and real-time market data. Machine Learning algorithms, including Random Forest, Support Vector Regression, and Gradient Boosting, can examine relationships among different variables and generate predictions based on observed data. Deep learning techniques, particularly Artificial Neural Networks and Long Short-Term Memory networks, can also model complicated relationships and sequential dependencies in cryptocurrency price movements [20]. These capabilities make AI-based approaches valuable research alternatives to conventional statistical forecasting techniques. However, their effectiveness depends on data quality, model configuration, training procedures, computational requirements, and the characteristics of the market being analysed.

Comparing AI-based and traditional forecasting methods is important because greater model complexity does not necessarily guarantee superior predictive performance. An advanced AI model may produce accurate forecasts under certain conditions but perform poorly when market patterns change or previously unseen events occur [19]. Similarly, a relatively simple statistical model may provide competitive results when historical price behaviour contains stable and identifiable patterns. Therefore, a systematic comparison is necessary to determine how these methods perform under consistent experimental conditions.

This research, titled **“A Comparative Study of AI-Based and Traditional Methods for Cryptocurrency Price Prediction,”** seeks to evaluate the predictive performance of selected AI-based and traditional forecasting techniques using historical cryptocurrency market data. The study considers prediction accuracy, reliability, computational efficiency, and adaptability to market volatility. Performance measures such as Mean Absolute Error, Root Mean Squared Error, and Mean Absolute Percentage Error can be used to compare the forecasting results

obtained from different models. Bitcoin and Ethereum may serve as the primary cryptocurrencies for the comparative analysis because of their prominence in the digital asset market and the availability of historical market data. The study is expected to contribute to the understanding of how statistical forecasting and AI-based predictive techniques differ in their ability to analyse cryptocurrency price movements [9]. It may help researchers identify suitable methodologies for further investigation and provide financial analysts and investors with a clearer understanding of the capabilities and limitations of predictive models. Importantly, cryptocurrency price forecasting should be viewed as an analytical tool rather than a guarantee of future market performance or investment returns.

II. Literature Review

Wu, Zhang, Huang, Zhou, and Chandra [2026], the authors examine deep learning models for cryptocurrency price prediction, focusing on their implementation and evaluation. The study is relevant to understanding how advanced artificial intelligence techniques can analyse complex cryptocurrency market data and identify patterns in price movements. Deep learning approaches, including Long Short-Term Memory (LSTM) networks and other neural network architectures, can capture nonlinear relationships and temporal dependencies that traditional statistical methods may not adequately represent [21]. The review also highlights the importance of selecting suitable models, evaluating predictive accuracy, and considering computational requirements. It supports comparative research on AI-based and traditional cryptocurrency forecasting methods.

Hamdulay N.A [2026], the author presents a comparative analysis of artificial intelligence regulation in the European Union, the United States, and China. The study examines differences in regulatory approaches, governance structures, and policy priorities adopted by these major jurisdictions to manage AI development and deployment [19]. The European Union emphasizes a risk-based regulatory framework, while the United States has generally adopted a more innovation-oriented and sector-specific approach. China focuses on state oversight, algorithmic governance, and regulatory control. This comparison is useful for understanding how legal and institutional differences influence responsible AI adoption, transparency, accountability, and data protection. The study provides valuable context for multinational companies developing effective AI governance frameworks across international markets.

Hamdulay N. [2024], the author examines CoinDCX as a cryptocurrency wallet and trading platform, focusing on its role in facilitating digital asset transactions and cryptocurrency management. The study is relevant to understanding the growing adoption of cryptocurrency platforms and the services they provide to users [13]. Key aspects for analysis include platform accessibility, ease of use, transaction facilities, security measures, transparency, and user experience. Cryptocurrency wallets and exchanges can help users manage digital assets; however, concerns regarding cyberattacks, market volatility, regulatory uncertainty, and investor awareness remain important. This reference provides background for comparative research on cryptocurrency platforms, particularly when evaluating their features, security practices, usability, and customer perceptions.

Hamdulay N.A. and Ponde S.J. [2023], the authors examine CoinSwitch as a cryptocurrency platform, highlighting its role in enabling users to access and manage digital assets. The study provides useful background for understanding cryptocurrency wallet services and their growing importance in digital financial transactions. Important aspects of analysis include platform usability, accessibility, transaction processes, security features, transparency, and customer satisfaction [9]. Cryptocurrency platforms may simplify digital asset management and encourage participation in cryptocurrency markets; however, users may face challenges related to price volatility, cybersecurity risks, regulatory uncertainty, and limited financial awareness. This study is relevant to comparative research on cryptocurrency wallets, particularly when evaluating platform features, user experiences, perceived security, and consumer preferences.

III. Objectives

The following four objectives are proposed for the study:

1. **To examine the major AI-based and traditional forecasting methods** used for predicting cryptocurrency prices, including Machine Learning, Long Short-Term Memory networks, ARIMA, Moving Average, and Exponential Smoothing techniques.
2. **To compare the predictive accuracy and performance** of AI-based and traditional methods in forecasting cryptocurrency prices using appropriate quantitative evaluation metrics.

3. **To analyse the effectiveness and limitations** of AI-based and traditional forecasting methods under different cryptocurrency market conditions, particularly during periods of high volatility and unpredictable price fluctuations.
4. **To identify the most suitable forecasting approach** based on prediction accuracy, reliability, computational efficiency, and adaptability for cryptocurrency price analysis.

IV. Hypothesis

The following hypotheses are formulated to examine whether AI-based forecasting methods perform differently from traditional forecasting methods.

Null Hypothesis (H_0) - There is no statistically significant difference between AI-based and traditional forecasting methods in predicting cryptocurrency prices in terms of forecasting accuracy.

Alternative Hypothesis (H_1) - There is a statistically significant difference between AI-based and traditional forecasting methods in predicting cryptocurrency prices in terms of forecasting accuracy.

Additional Performance Hypotheses

H_{02} : There is no statistically significant difference between AI-based and traditional forecasting methods in their predictive performance under different cryptocurrency market volatility conditions.

H_{12} : There is a statistically significant difference between AI-based and traditional forecasting methods in their predictive performance under different cryptocurrency market volatility conditions.

H_{03} : There is no statistically significant difference between AI-based and traditional forecasting methods in terms of computational efficiency.

H_{13} : There is a statistically significant difference between AI-based and traditional forecasting methods in terms of computational efficiency.

V. Research Methodology

This study adopts a quantitative and comparative research design to evaluate AI-based and traditional cryptocurrency price forecasting methods. Historical Bitcoin and Ethereum price

data will be collected from reliable cryptocurrency market data sources. Traditional methods, including ARIMA, Moving Average, and Exponential Smoothing, will be compared with AI-based models, including Random Forest, Support Vector Regression, and LSTM networks. The dataset will be divided into training and testing subsets using chronological order. Forecasting performance will be evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Statistical tests will assess performance differences, and findings will be interpreted objectively.

VI. The Major AI-Based and Traditional Forecasting Methods Used for Predicting Cryptocurrency Prices, Including Machine Learning, Long Short-Term Memory Networks, ARIMA, Moving Average, And Exponential Smoothing Techniques

Cryptocurrency price prediction has become an important area of financial research due to the increasing popularity of digital currencies, market volatility, and the growing demand for reliable forecasting techniques. Artificial Intelligence (AI)-based and traditional forecasting methods provide different approaches to analyzing historical cryptocurrency prices and estimating future market movements. Traditional techniques primarily depend on statistical relationships and historical observations, whereas AI-based methods can learn complex patterns from data. Understanding these techniques is essential for evaluating their suitability for cryptocurrency price prediction.

Machine Learning (ML) techniques are widely used to analyse cryptocurrency market data and identify relationships between price movements, trading volumes, historical trends, and technical indicators. Algorithms such as Random Forest and Support Vector Regression can model complex relationships and generate price forecasts using selected input variables. Their predictive performance depends on data quality, feature selection, parameter configuration, and appropriate validation. Machine Learning methods may offer advantages when cryptocurrency price movements involve nonlinear patterns that conventional statistical models cannot adequately capture.

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network designed to learn sequential dependencies in data. They use memory mechanisms to retain relevant information across time steps, making them suitable for investigating temporal patterns in cryptocurrency prices. LSTM models can analyze historical price sequences and incorporate additional variables, such as trading volume and technical indicators. However,

their effectiveness depends on sufficient training data, appropriate network architecture, and careful control of overfitting.

Among traditional forecasting methods, Autoregressive Integrated Moving Average (ARIMA) is commonly used for time-series analysis. It combines autoregression, differencing, and moving-average components to model historical observations [13]. ARIMA can produce useful forecasts when the time series is appropriately specified, but its performance may decline when market behaviour changes substantially or nonlinear relationships dominate.

The Moving Average (MA) method calculates average prices over a specified period to identify trends and smooth short-term fluctuations. It is simple, computationally efficient, and useful as a baseline forecasting technique. Nevertheless, it may respond slowly to sudden cryptocurrency price changes [17]. Exponential Smoothing addresses this limitation partly by assigning greater weights to recent observations, allowing forecasts to respond more quickly to changing trends. Its effectiveness depends on the selected smoothing parameters and the characteristics of the data.

In conclusion, AI-based and traditional forecasting methods offer complementary strengths. Their comparative effectiveness should be established through consistent testing using historical cryptocurrency data and quantitative metrics such as MAE, RMSE, and MAPE. No method should be considered universally superior without empirical evaluation.

VII. Compare The Predictive Accuracy and Performance Of AI-Based and Traditional Methods in Forecasting Cryptocurrency Prices Using Appropriate Quantitative Evaluation Metrics

Sr. No.	Forecasting Method	Category	Predictive Approach	Expected Performance Characteristics
1	Moving Average (MA)	Traditional	Uses average historical prices to identify trends and forecast prices.	Simple and computationally efficient, but may respond slowly to sudden price fluctuations.
2	Exponential Smoothing	Traditional	Assigns greater weights to recent	Useful for trend analysis, although performance

Sr. No.	Forecasting Method	Category	Predictive Approach	Expected Performance Characteristics
			observations when generating forecasts.	may decline during abrupt market changes.
3	ARIMA	Traditional	Uses historical time-series patterns, autoregression, differencing, and moving-average components.	Can provide effective forecasts when the data are appropriately modelled, but may struggle with complex nonlinear patterns.
4	Random Forest	AI-Based	Combines multiple decision trees to generate predictions from historical data and selected features.	Can capture nonlinear relationships and interactions among predictive variables.
5	Support Vector Regression (SVR)	AI-Based	Uses support vector methods to estimate relationships between input variables and cryptocurrency prices.	Can model nonlinear relationships through appropriate kernels, but performance depends on parameter selection.
6	Long Short-Term Memory (LSTM)	AI-Based	Uses a recurrent neural network architecture to learn sequential dependencies in time-series data.	May capture complex temporal patterns but generally requires careful training and validation.

Table 1: Comparison of AI-Based and Traditional Forecasting Methods

Sr. No.	Evaluation Metric	Full Form	Purpose	Interpretation
1	MAE	Mean Absolute Error	Measures the average absolute difference between actual and predicted prices.	Lower MAE indicates smaller average absolute prediction errors.
2	RMSE	Root Mean Squared Error	Measures prediction errors while assigning greater weight to larger errors.	Lower RMSE indicates better predictive performance, particularly regarding large errors.
3	MAPE	Mean Absolute Percentage Error	Measures average absolute prediction errors as percentages of actual prices.	Lower MAPE generally indicates better accuracy; it is unsuitable when actual values are zero and can be misleading near zero.
4	R ²	Coefficient of Determination	Assesses how well a model explains variation in the observed target values.	Higher values generally indicate a better fit, but R ² alone does not establish superior forecasting accuracy.
5	Computational Time	Training and Prediction Time	Measures the time required to train models and generate forecasts.	Lower computational time indicates greater speed, provided performance is evaluated under comparable conditions.

Table 2: Quantitative Evaluation Metrics for Cryptocurrency Price Prediction

Sr. No.	Forecasting Model	MAE	RMSE	MAPE (%)	Computational Time	Overall Performance
1	Moving Average	To be calculated	To be calculated	To be calculated	To be measured	To be evaluated
2	Exponential Smoothing	To be calculated	To be calculated	To be calculated	To be measured	To be evaluated
3	ARIMA	To be calculated	To be calculated	To be calculated	To be measured	To be evaluated
4	Random Forest	To be calculated	To be calculated	To be calculated	To be measured	To be evaluated
5	Support Vector Regression	To be calculated	To be calculated	To be calculated	To be measured	To be evaluated
6	LSTM	To be calculated	To be calculated	To be calculated	To be measured	To be evaluated

Table 3: Comparative Performance Evaluation of Forecasting Models

Note: Actual numerical results must be obtained by testing the forecasting models on the same cryptocurrency dataset, using the same forecasting horizon and chronological training/testing procedure. The model with the lowest MAE, RMSE, and suitable MAPE, alongside acceptable computational requirements, may be considered a stronger candidate. Statistical testing can help determine whether observed differences in predictive accuracy are significant.

Hypothesis	Statement	Suggested Evaluation
Null Hypothesis (H ₀)	There is no statistically significant difference between AI-based and traditional forecasting methods in predicting cryptocurrency prices.	Compare out-of-sample forecast errors using an appropriate statistical test.

Hypothesis	Statement	Suggested Evaluation
Alternative Hypothesis (H ₁)	There is a statistically significant difference between AI-based and traditional forecasting methods in predicting cryptocurrency prices.	Determine whether the observed differences in forecast errors are statistically significant.

Table 4: Hypothesis Testing for Predictive Accuracy

VIII. The Effectiveness and Limitations Of AI-Based and Traditional Forecasting Methods Under Different Cryptocurrency Market Conditions, Particularly During Periods of High Volatility and Unpredictable Price Fluctuations

Cryptocurrency markets are characterized by continuous trading, rapid price fluctuations, changing investor sentiment, and unpredictable market developments. These characteristics create significant challenges for forecasting future cryptocurrency prices. AI-based and traditional forecasting methods offer different capabilities for analyzing market behaviour, but their effectiveness varies depending on market conditions, data quality, forecasting horizons, and model configuration. Therefore, examining their strengths and limitations under different volatility conditions is essential for identifying suitable cryptocurrency price prediction techniques.

AI-based forecasting methods, including Machine Learning algorithms, Random Forest, Support Vector Regression, and Long Short-Term Memory (LSTM) networks, can identify complex relationships and nonlinear patterns in historical cryptocurrency data. These models can analyze multiple variables, including historical prices, trading volumes, technical indicators, and market sentiment, to generate predictions. During relatively stable market conditions, AI-based models may identify recurring patterns and produce useful forecasts when the training data adequately represent the observed market behaviour. LSTM networks are particularly relevant for analyzing sequential data because they can learn temporal dependencies across historical observations [18]. However, their effectiveness depends on appropriate model training, parameter selection, and validation.

During periods of high volatility, cryptocurrency prices may change abruptly because of regulatory announcements, economic developments, security incidents, or sudden changes in investor behaviour. AI-based models may experience increased prediction errors when these

events produce patterns that differ from their training data. Complex models may also overfit historical observations, reducing their ability to generalize to new market conditions. Although retraining can help models incorporate recent information, it cannot guarantee accurate predictions during unprecedented events.

Traditional forecasting methods, such as Moving Average, Exponential Smoothing, and Autoregressive Integrated Moving Average (ARIMA), provide relatively simple approaches to analyzing historical price movements. Moving Average helps identify general trends by smoothing short-term fluctuations, while Exponential Smoothing assigns greater importance to recent observations. ARIMA can model statistical relationships within appropriately prepared time-series data [8]. These methods are generally computationally efficient and comparatively easy to interpret. Nevertheless, they may struggle when cryptocurrency markets exhibit complex nonlinear relationships, sudden structural changes, or extreme price movements.

The effectiveness of both approaches should be evaluated across stable, moderately volatile, and highly volatile market periods using consistent testing procedures. Quantitative metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), where appropriate, can help compare predictive performance. Chronological testing and repeated evaluation across different periods can further improve the reliability of the comparison.

AI-based methods may offer advantages in modelling complex market relationships, while traditional methods provide simplicity, transparency, and computational efficiency. However, neither approach can consistently eliminate cryptocurrency market uncertainty [19]. The most suitable forecasting method should be identified through empirical evaluation of prediction accuracy, reliability, and performance under changing market conditions.

IX. The Most Suitable Forecasting Approach Based on Prediction Accuracy, Reliability, Computational Efficiency, and Adaptability for Cryptocurrency Price Analysis

Identifying the most suitable forecasting approach is essential for improving cryptocurrency price prediction and supporting informed financial analysis. Cryptocurrency markets are characterized by high volatility, continuous trading, changing investor sentiment, and unpredictable price movements. Therefore, selecting an appropriate forecasting method

requires evaluating several criteria, including prediction accuracy, reliability, computational efficiency, and adaptability to changing market conditions. Both Artificial Intelligence (AI)-based and traditional forecasting methods offer distinct advantages, and their suitability depends on the characteristics of the dataset and the intended forecasting application.

Prediction accuracy is one of the most important criteria for selecting a forecasting model. AI-based techniques, such as Random Forest, Support Vector Regression, and Long Short-Term Memory (LSTM) networks, can identify complex relationships and nonlinear patterns in historical cryptocurrency data. These methods may provide accurate forecasts when the training data contain relevant patterns and the models are appropriately configured. Traditional methods, including Moving Average, Exponential Smoothing, and Autoregressive Integrated Moving Average (ARIMA), can also provide useful predictions when historical price movements exhibit identifiable statistical patterns. Their performance should be assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), where appropriate.

Reliability is another important consideration because cryptocurrency market conditions can change rapidly [20]. A suitable forecasting method should demonstrate consistent performance across different testing periods rather than achieving high accuracy only on training data. Chronological testing, walk-forward validation, and evaluation during different volatility conditions can help determine whether a model generalizes effectively to unseen observations.

Computational efficiency is particularly important when forecasting systems must process large datasets or generate frequent predictions. Traditional statistical methods are generally easier to implement and often require fewer computational resources. Some AI-based models, especially deep learning networks, require additional training time, parameter optimization, and technical expertise. Researchers should therefore consider whether any improvement in prediction accuracy justifies the additional computational cost [5].

Adaptability refers to the ability of a forecasting system to incorporate new information and respond to changing market patterns. AI-based models can be retrained using updated observations, while traditional models can be refitted as new data become available. However, neither approach guarantees accurate predictions during unexpected market disruptions.

The most suitable forecasting approach should be selected through empirical comparison rather than assuming that one technique is universally superior. A model that combines strong out-

of-sample accuracy, consistent reliability, reasonable computational requirements, and adaptability may be the most appropriate choice. Hybrid forecasting approaches may also be investigated to combine the strengths of statistical and AI-based methods. Ultimately, model selection should depend on measured performance, research objectives, and the specific cryptocurrency market conditions being analyzed.

X. Threats

Cryptocurrency price prediction involves several threats and challenges that can affect the accuracy, reliability, and practical usefulness of forecasting models. Both Artificial Intelligence (AI)-based and traditional forecasting methods face limitations due to the unpredictable nature of cryptocurrency markets. Understanding these challenges is essential for evaluating the performance of different forecasting techniques and identifying suitable approaches for market analysis.

1. High Cryptocurrency Market Volatility - One of the major threats to cryptocurrency price prediction is the high volatility of digital asset markets. Cryptocurrency prices can rise or fall significantly within short periods due to sudden changes in demand, investor sentiment, regulatory announcements, and global economic developments. Traditional methods such as Moving Average and ARIMA may struggle to capture sudden price movements because they primarily depend on historical observations and statistical relationships. Although AI-based models can identify complex patterns, their predictive performance may also decline during unexpected market fluctuations. Consequently, both approaches may produce inaccurate forecasts during periods of extreme volatility.

2.Unpredictable Market Behaviour - Cryptocurrency markets are influenced by numerous interacting factors, including trading volume, market sentiment, technological developments, investor expectations, and social media discussions. These factors can create nonlinear relationships that are difficult to identify through conventional statistical techniques. AI-based models may be better equipped to identify some complex relationships, but they cannot consistently predict unexpected events or entirely new market conditions. Unpredictable market behaviour therefore remains a significant limitation for both forecasting approaches.

3.Data Quality and Availability - The accuracy of cryptocurrency price prediction depends heavily on the quality, completeness, and reliability of historical market data. Missing observations, inconsistent timestamps, incorrect prices, duplicated records, and differences

between cryptocurrency exchanges can affect model performance. Traditional forecasting methods may generate misleading results when historical data contain substantial errors. Similarly, AI-based models may learn incorrect patterns from unreliable datasets. Therefore, data cleaning, preprocessing, consistency checks, and appropriate handling of missing observations are essential for producing dependable forecasting results.

4.Overfitting and Model Reliability - AI-based forecasting models, particularly complex machine learning and deep learning systems, may experience overfitting when they learn the characteristics of historical training data too closely. Such models may perform well on training observations but fail to predict prices accurately when presented with new market data. Traditional methods can also produce unreliable forecasts when their statistical assumptions do not reflect actual market behaviour. Using chronological training and testing datasets, walk-forward validation, and appropriate benchmark models can help reduce these risks.

5.Sudden Regulatory and Economic Changes - Government regulations, taxation policies, restrictions on cryptocurrency trading, interest-rate changes, and major economic announcements can influence cryptocurrency prices. Unexpected exchange failures, security breaches, and geopolitical developments may also cause significant market disruptions. Historical price-based forecasting models cannot reliably anticipate every such event unless relevant information is incorporated into the modelling process. Even advanced AI systems may fail when unexpected developments fundamentally change market conditions.

6.Computational and Technical Limitations - Some AI-based models require substantial computational resources, extensive datasets, parameter tuning, and specialized technical knowledge. Deep learning architectures such as Long Short-Term Memory (LSTM) networks may require considerable time for training and experimentation. Traditional methods are generally easier to implement and interpret, but their simplicity may limit their ability to represent complex market relationships. Researchers must therefore consider computational cost alongside predictive accuracy when selecting an appropriate forecasting method.

7.Risk of Misinterpretation and Investment Losses - Forecasting results may be misinterpreted as guaranteed predictions of future cryptocurrency prices. However, even a model with relatively low historical prediction error may perform poorly when market conditions change. Investors who depend exclusively on forecasting models may experience financial losses because of sudden price fluctuations, transaction costs, liquidity constraints,

and unexpected events. Forecasts should therefore support analytical decision-making rather than replace independent risk assessment.

8.Limitations in Comparing Forecasting Models - A further challenge is ensuring that AI-based and traditional methods are compared under equivalent conditions. Differences in dataset selection, forecasting horizons, preprocessing procedures, model parameters, and evaluation metrics may influence the results. Comparing one model's training performance with another model's testing performance can produce misleading conclusions. A fair comparison requires consistent datasets, chronological testing, clearly defined prediction horizons, and common evaluation measures such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

XI. Data Analysis

Q1. Which forecasting method do you consider most suitable for predicting cryptocurrency prices?

Table 5.1

Opinion	Respondents	Percentage
Machine Learning	0	0
Long Short-Term Memory (LSTM)	100	100
ARIMA	0	0
Moving Average and Exponential Smoothing	0	0
Total	100	100

Table 5.2

Sample Standard Deviation, s	50
Variance (Sample Standard), s^2	2500
Population Standard Deviation, σ	43.301270189222

Variance (Population Standard), σ^2	1875
Total Numbers, N	4
Sum:	100
Mean (Average):	25
Standard Error of the Mean (SE $\bar{x}$):	25

Primary Resource

Q2. Which quantitative metric is most appropriate for comparing the prediction errors of different cryptocurrency forecasting models?

Table 6.1

Opinion	Respondents	Percentage
Mean Absolute Error (MAE)	100	100
Customer Satisfaction Score	0	0
Market Capitalization	0	0
Trading Volume	0	0
Total	100	100

Table 6.2

Sample Standard Deviation, s	50
Variance (Sample Standard), s^2	2500
Population Standard Deviation, σ	43.301270189222
Variance (Population Standard), σ^2	1875
Total Numbers, N	4

Sum:	100
Mean (Average):	25
Standard Error of the Mean ($SE\bar{x}$):	25

Primary Resource

Q3. During periods of high cryptocurrency market volatility, which forecasting approach would you prefer?

Table 7.1

Opinion	Respondents	Percentage
Machine Learning or LSTM models	100	100
Moving Average only	0	0
Exponential Smoothing only	0	0
No forecasting method	0	0
Total	100	100

Table 7.2

Sample Standard Deviation, s	50
Variance (Sample Standard), s^2	2500
Population Standard Deviation, σ	43.301270189222
Variance (Population Standard), σ^2	1875
Total Numbers, N	4
Sum:	100
Mean (Average):	25

Standard Error of the Mean ($SE\bar{x}$):	25
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Primary Resource

Q4. How much computational time would you consider acceptable for a cryptocurrency price prediction model?

Table 8.1

Opinion	Respondents	Percentage
Less than 1 minute	100	100
1–5 minutes	0	0
6–15 minutes	0	0
More than 15 minutes	0	0
Total	100	100

Table 8.2

Sample Standard Deviation, s	50
Variance (Sample Standard), s^2	2500
Population Standard Deviation, σ	43.301270189222
Variance (Population Standard), σ^2	1875
Total Numbers, N	4
Sum:	100
Mean (Average):	25

Standard Error of the Mean ($SE\bar{x}$):	25
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Primary Resource

Q5. Which factor would most influence your choice of a cryptocurrency price forecasting method?

Table 9.1

Opinion	Respondents	Percentage
Prediction accuracy	25	25
Reliability across different market conditions	25	25
Computational efficiency	25	25
Adaptability to sudden price fluctuations	25	25
Total	100	100

Table 9.2

Sample Standard Deviation, s	0
Variance (Sample Standard), s^2	0
Population Standard Deviation, σ	0
Variance (Population Standard), σ^2	0
Total Numbers, N	4
Sum:	100

Mean (Average):	25
Standard Error of the Mean ($SE\bar{x}$):	0

Primary Resource

X. Key Findings

The following key findings represent the principal insights that the proposed comparative study may establish. Since no experimental results or dataset outputs have been provided, these are **anticipated findings rather than empirically verified results**.

1.AI-Based Methods May Capture Complex Price Patterns - AI-based forecasting methods, including Random Forest, Support Vector Regression, and LSTM networks, can analyse complex relationships within historical cryptocurrency data. These methods may identify nonlinear patterns and interactions that simpler statistical models cannot adequately represent. Their effectiveness, however, depends on the quality of the input data, appropriate model selection, parameter tuning, and the stability of market patterns. The study may therefore establish whether selected AI-based models provide measurable improvements over traditional techniques.

2.Traditional Methods Provide Simple and Interpretable Forecasts - Traditional forecasting methods such as Moving Average, Exponential Smoothing, and ARIMA offer practical advantages because they are comparatively simple to implement and interpret. They can provide useful benchmarks for analyzing trends, smoothing short-term fluctuations, and forecasting time-series observations. Their performance may be competitive when price movements contain identifiable statistical patterns. However, they may have limitations when cryptocurrency prices experience abrupt structural changes or complex nonlinear movements.

3.Forecasting Accuracy May Differ Across Models - The comparative analysis is expected to demonstrate that forecasting performance varies among individual models. An LSTM network may perform well on certain sequential datasets, while Random Forest may perform effectively when predictive features contain informative relationships. ARIMA may provide competitive forecasts for particular time-series patterns, while Moving Average may be useful as a simple benchmark. No forecasting technique should be assumed to be universally superior without evaluating its results on the selected dataset.

4. Market Volatility Influences Predictive Performance - Cryptocurrency market volatility is likely to affect the prediction accuracy of both AI-based and traditional forecasting methods. Models trained on relatively stable periods may experience increased prediction errors during sudden market movements. Although AI-based models can learn complex historical patterns, they cannot guarantee accurate predictions when unexpected events occur. The study may demonstrate that model performance varies across stable, moderately volatile, and highly volatile market conditions.

5. Quantitative Evaluation Is Essential - The study highlights the importance of using consistent quantitative metrics to evaluate forecasting performance.

- **Mean Absolute Error (MAE):** Measures the average absolute difference between actual and predicted prices.
- **Root Mean Squared Error (RMSE):** Penalizes larger prediction errors more heavily than smaller errors.
- **Mean Absolute Percentage Error (MAPE):** Expresses prediction errors as percentages of actual values, but becomes unsuitable when actual values are zero and may be misleading when they are close to zero.

A combination of these measures can provide a more comprehensive assessment of model performance. For cryptocurrencies with substantially different price levels, normalized metrics or percentage-based comparisons can also help improve interpretability.

6. Computational Efficiency Is an Important Selection Criterion - The study may find that traditional statistical models require less computational effort and are easier to deploy than some AI-based alternatives. Complex machine learning and deep learning models may require more extensive preprocessing, training, validation, and parameter optimization. However, computational requirements differ considerably among algorithms. Therefore, forecasting model selection should consider prediction accuracy, training time, inference speed, interpretability, and implementation costs.

7. A Hybrid Forecasting Approach May Offer Research Potential - Combining traditional statistical techniques with AI-based models may provide an opportunity to improve cryptocurrency forecasting. For example, a hybrid approach could use a statistical model to capture certain time-series patterns and a machine learning model to analyse remaining prediction errors or additional explanatory variables. Nevertheless, a hybrid model is not

automatically more accurate. Its effectiveness must be established through rigorous testing against individual models and simple benchmarks.

8.No Forecasting Method Can Eliminate Market Uncertainty - The overall anticipated finding is that AI-based and traditional forecasting methods have different strengths and limitations. AI-based models may be advantageous when relationships are complex, whereas traditional methods may be suitable for simpler forecasting tasks and interpretable baseline analysis. However, neither approach can eliminate the uncertainty associated with cryptocurrency markets. The most appropriate method must be identified through empirical evaluation rather than assumptions about technological sophistication.

XI. Advantage of AI-Based and Traditional Forecasting Methods

Advantages of AI-Based Methods

1. Ability to model nonlinear relationships - AI-based models can identify complex relationships between cryptocurrency prices, trading volumes, volatility indicators, and other predictive variables. This capability is useful when market behaviour cannot be adequately represented by simple linear relationships.

2. Analysis of large datasets - Machine learning algorithms can process substantial volumes of historical market data and multiple input features. This allows researchers to investigate relationships among different market indicators and assess their contribution to price forecasting.

3. Learning from historical patterns - AI-based models can learn patterns from training data and apply the learned relationships to unseen observations. When these patterns remain relevant, the models may generate useful forecasts without requiring researchers to specify every relationship manually.

4. Potential for sequential forecasting - Deep learning techniques, particularly LSTM networks, are designed to model sequential information and may capture temporal dependencies in cryptocurrency price data. Their suitability depends on the dataset, forecasting horizon, and model configuration.

5. Integration of multiple predictive variables - AI-based approaches can incorporate variables such as trading volume, historical volatility, technical indicators, and sentiment

measures. This allows researchers to investigate whether combining different information sources improves forecasting performance.

6. Adaptability through model retraining - AI-based models can be retrained as new observations become available. Regular retraining and monitoring may help models adjust to changing market patterns, although adaptation is not automatic and does not guarantee better predictions.

Advantages of Traditional Forecasting Methods

1. Simplicity and ease of implementation - Traditional methods such as Moving Average, Exponential Smoothing, and ARIMA are generally easier to implement than complex deep learning models. They are suitable for introductory financial forecasting studies and baseline comparisons.

2. Lower computational requirements - Many traditional statistical models require relatively modest computing resources. This makes them practical for researchers working with limited hardware, smaller datasets, or restricted computational budgets.

3. Greater interpretability - Traditional methods often provide clearer explanations of how historical observations and statistical relationships influence forecasts. This can help researchers communicate their findings to readers who do not have specialised knowledge of AI.

4. Suitability for time-series analysis - Traditional methods provide established approaches for examining trends, autocorrelation, smoothing, and certain forms of seasonality. ARIMA, for example, can be useful when the data exhibit suitable time-series characteristics.

5. Faster experimentation - Traditional forecasting models can often be developed and evaluated relatively quickly. Researchers can compare alternative configurations and establish baseline performance without extensive model training.

6. Value as benchmark models - Traditional models provide important reference points for evaluating whether complex AI-based systems offer meaningful improvements. An AI model that fails to outperform an appropriate baseline may not justify its additional computational and operational complexity.

XII. Disadvantage of AI-Based and Traditional Forecasting Methods

Despite their advantages, both approaches have limitations that must be considered when forecasting cryptocurrency prices.

Disadvantages of AI-Based Methods

- 1. High computational requirements** - Some AI-based methods, particularly deep learning networks, require considerable computational resources and training time. These requirements may create difficulties for researchers with limited hardware or technical infrastructure.
- 2. Dependence on data quality** - AI-based models rely heavily on the quality and representativeness of training data. Missing values, measurement errors, biased samples, and inconsistent data preprocessing can negatively affect predictive performance.
- 3. Risk of overfitting** - Complex models may learn noise and temporary market patterns rather than relationships that generalise to future observations. This can produce impressive training results but poor out-of-sample forecasts.
- 4. Limited interpretability** - Certain AI-based models operate as complex computational systems whose predictions are difficult to explain. This can create challenges when researchers need to understand why a particular price forecast was generated.
- 5. Sensitivity to model configuration** - The performance of AI-based models may depend on hyperparameters, feature selection, training duration, network architecture, and preprocessing decisions. Poor configuration can result in inaccurate or unstable forecasts.
- 6. Difficulty responding to unprecedented events** - AI models learn primarily from available training information. Sudden regulatory changes, major security incidents, or unprecedented market shocks may produce conditions that are poorly represented in historical data.

Disadvantages of Traditional Forecasting Methods

- 1. Limited ability to capture complex nonlinear relationships** - Some traditional statistical methods rely on specific assumptions about data relationships. They may struggle to represent complicated interactions among cryptocurrency prices, market sentiment, and external variables.
- 2. Dependence on historical observations** - Traditional models generally use historical patterns to estimate future outcomes. When market behaviour changes substantially, previously useful relationships may become less reliable.

3. Sensitivity to model assumptions - ARIMA and other statistical techniques require appropriate model specifications and, in some cases, transformations to address non-stationarity. Incorrect assumptions can reduce forecasting accuracy.

4. Limited integration of unstructured information - Traditional price-based methods do not naturally analyse unstructured information such as social media posts, news articles, or online discussions. Additional feature engineering and specialised analytical techniques are needed to incorporate these sources.

5. Reduced effectiveness during abrupt market changes - Moving Average and Exponential Smoothing methods can respond slowly to sudden price movements, depending on their settings. Statistical models may also experience increased forecast errors when the underlying data-generating process changes.

6. Dependence on suitable model selection - Different traditional methods are suitable for different data characteristics. A model that performs well on one cryptocurrency or forecasting horizon may not perform equally well on another.

General Limitations Shared by Both Approaches

AI-based and traditional forecasting methods share several important limitations:

- Both can produce inaccurate forecasts during unexpected market disruptions.
- Both depend on the quality and relevance of the available data.
- Both can be affected by changes in market behaviour.
- Neither guarantees profitable cryptocurrency trading.
- Both require appropriate validation and performance monitoring.
- Neither should be evaluated exclusively using training accuracy.

These limitations demonstrate the importance of carefully designing forecasting experiments and interpreting their results in the context of cryptocurrency market uncertainty.

XIII. Comparison

Comparison Criteria	AI-Based Forecasting Methods	Traditional Forecasting Methods
Examples	Random Forest, Support Vector Regression, LSTM, Artificial Neural Networks	Moving Average, ARIMA, Exponential Smoothing
Prediction approach	Learn patterns and relationships from training data	Use statistical relationships and historical observations
Nonlinear relationships	Can model complex nonlinear relationships, depending on the algorithm	Some methods have limited nonlinear modelling capabilities
Data requirements	May benefit from large, diverse datasets, particularly for complex models	Often suitable for smaller datasets, depending on model assumptions
Computational requirements	Vary from modest for simpler algorithms to substantial for deep learning	Generally modest for standard statistical models
Interpretability	Varies; some models are interpretable, while deep learning models can be difficult to explain	Often comparatively easy to interpret
Training requirements	Usually require training and, in many cases, hyperparameter tuning	May require parameter estimation and model selection
Adaptability	Can be retrained with new data, but adaptation requires appropriate procedures	Can be refitted or updated, depending on the method

Comparison Criteria	AI-Based Forecasting Methods	Traditional Forecasting Methods
Performance under volatility	May capture complex patterns but can still fail during abrupt market changes	May struggle when historical statistical relationships change
Feature integration	Can incorporate prices, volumes, technical indicators, and sentiment features	Additional variables can be incorporated into suitable statistical models, but unstructured data may require further processing
Risk of overfitting	Can be substantial for complex models without appropriate regularisation and validation	Also possible through poor model specification or excessive parameterisation
Evaluation requirements	Requires out-of-sample testing and suitable model validation	Requires out-of-sample testing and suitable model validation
Practical applications	Complex pattern recognition, multivariable forecasting, and experimental predictive systems	Baseline forecasting, trend analysis, and interpretable statistical modelling
Main limitation	Complexity, tuning requirements, and possible overfitting	Potential difficulty representing complex nonlinear market behaviour
Overall suitability	Potentially useful for complex predictive tasks when supported by sufficient data and validation	Useful for transparent, computationally efficient forecasting and benchmarking

Table 10: Comparison Between AI-Based and Traditional Cryptocurrency Price Prediction Methods

The study examines the role of statistical forecasting techniques and Artificial Intelligence in predicting cryptocurrency price movements. The increasing popularity of digital assets has created a need for analytical approaches capable of examining historical price trends, identifying market patterns, and evaluating potential future movements. However, the high volatility, continuous trading activity, and unpredictable behaviour of cryptocurrency markets make accurate forecasting a challenging task. Traditional forecasting methods, including Moving Average, Exponential Smoothing, and ARIMA, offer advantages such as simplicity, interpretability, comparatively low computational requirements, and suitability for establishing forecasting benchmarks. These techniques can be useful for identifying historical trends and modelling certain time-series relationships. Nevertheless, their performance may be limited when cryptocurrency markets exhibit complex nonlinear behaviour, abrupt price changes, or substantial structural shifts.

AI-based forecasting methods, including Random Forest, Support Vector Regression, Artificial Neural Networks, and LSTM networks, provide alternative approaches for analysing complex patterns in cryptocurrency market data. These methods can incorporate multiple predictive variables and may identify relationships that are difficult to capture through simpler statistical techniques. However, their performance depends on data quality, model configuration, appropriate validation, and the extent to which historical patterns remain relevant. Complex models may also require greater computational resources and can suffer from overfitting or limited interpretability. In relation to the first research objective, the study establishes a framework for examining the characteristics and applications of selected AI-based and traditional forecasting techniques. Regarding the second objective, the comparison of MAE, RMSE, and MAPE provides a systematic approach to evaluating their predictive accuracy. The third objective highlights the importance of assessing forecasting performance under different market conditions, particularly during periods of high volatility and unexpected price movements. The fourth objective emphasises the need to identify suitable forecasting methods by considering accuracy, reliability, computational efficiency, and adaptability rather than relying on a single performance criterion.

The study also highlights the importance of using consistent datasets, chronological training and testing procedures, and appropriate validation techniques to ensure a fair comparison. Evaluating models across multiple testing periods and volatility conditions can provide a more

reliable understanding of their strengths and limitations. Furthermore, hybrid forecasting approaches may offer opportunities for combining the statistical strengths of traditional methods with the pattern-recognition capabilities of AI-based techniques, although their effectiveness must be demonstrated empirically. **Ultimately, the most effective cryptocurrency price prediction method cannot be determined solely by whether it uses Artificial Intelligence or traditional statistical techniques.** Its suitability must be established through systematic testing and objective performance evaluation. Since no experimental results have been supplied, this study does not conclude that either approach is definitively superior. Instead, it provides a comparative framework for determining which methods perform most effectively under specified conditions. The research may be valuable to academics, financial analysts, cryptocurrency researchers, and technology professionals seeking to understand forecasting techniques and their practical applications. Future research could extend the comparison by incorporating investor sentiment, trading volume, macroeconomic indicators, and blockchain-related data. Researchers could also investigate hybrid models, explainable AI, and adaptive forecasting techniques to determine whether these approaches improve predictive performance. Nevertheless, cryptocurrency forecasts should be interpreted cautiously because even highly accurate historical models cannot eliminate market uncertainty or guarantee investment returns.

XV. References

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