

AI-Powered Comparative Analysis of the Top Five Cryptocurrency Assets Using Real-Time Market Data

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<https://doi.org/10.68414/YKTK2543>

Abstract

The rapid expansion of blockchain technology and digital asset markets has increased the demand for intelligent tools capable of evaluating cryptocurrency performance using real-time financial data. As cryptocurrency markets become more dynamic and interconnected, investors, researchers, and financial technology practitioners require timely, data-driven insights to support informed investment decisions (Lazea et al., 2026). While numerous market platforms provide real-time price information, relatively few integrate live market data, technical analysis, artificial intelligence (AI), and comparative analytics within a unified decision-support environment.

The study demonstrates how integrating live market data, technical analysis, and AI-driven analytics within a browser-based platform enables transparent and efficient comparative evaluation of leading cryptocurrency assets. The proposed framework provides a practical approach for assessing digital asset performance and supports investment decision-making while offering a scalable foundation for future research involving alternative cryptocurrencies, sector-specific digital assets, and extended market periods.

I. Introduction

This research presents an AI-powered browser-based decision support approach for the comparative evaluation of the five largest cryptocurrency assets by market capitalization

(Coinbase, 2026): Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC), during the first half of 2026 (January 28 to June 24, 2026). The proposed platform is implemented using HTML, CSS, and JavaScript and integrates live cryptocurrency market data through application programming interfaces (APIs) to support real-time analysis within a web browser. The evaluation framework combines financial market indicators, including price performance, market capitalization, and trading volume, using four primary metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). These metrics quantify forecast accuracy and directional prediction capability for each cryptocurrency, enabling objective comparison of model performance across the selected assets. Technical indicators, including SMA, EMA, RSI, ROC, volatility, high-low spread, and open/close percentage change, serve as explanatory variables within the model rather than as the primary evaluation outcomes.

Figure 1

Top 5 Digital Assets by Market Capitalization as of June 2026 (Coinbase, 2026).

Asset	Market price	Chart	Change	Mkt cap	Volume
 Bitcoin BTC	\$59,966.83		↘ 2.81%	\$1.2T	\$44.5B
 Ethereum ETH	\$1,559.19		↘ 5.39%	\$187.6B	\$16.8B
 Tether USDT	\$0.9985		↗ 0.01%	\$186.1B	\$85.3B
 BNB BNB	\$560.80		↘ 1.88%	\$75.7B	\$1.5B
 USDC USDC • Earns unlimited 3.50% APY with 	\$1.00		0.00%	\$73.7B	\$15.8B

1.1 Background

The rapid evolution of blockchain technology has transformed the global financial landscape by enabling decentralized digital assets, peer-to-peer transactions, and innovative financial services. Since the introduction of Bitcoin in 2009, the cryptocurrency market has expanded into a diverse ecosystem that includes thousands of digital assets supporting

decentralized finance (DeFi), smart contracts, tokenized assets, and blockchain-based payment systems (Global Financial Market Association, 2026). As institutional adoption and retail participation continue to increase, cryptocurrencies have become an important asset class within modern financial markets, attracting growing attention from investors, researchers, and financial technology (FinTech) practitioners (Emmert, 2024).

The increasing size and complexity of cryptocurrency markets have created new challenges for evaluating digital asset performance. Unlike traditional financial markets, cryptocurrency prices are highly volatile and influenced by a combination of market sentiment, blockchain network activity, trading volume, macroeconomic conditions, and technological developments (Aivaz et al., 2023). Consequently, investors require more than real-time price information to make informed decisions. Comprehensive evaluation of digital assets often involves integrating financial market indicators with technical analysis to better understand market behavior and identify investment opportunities (Nie et al., 2024).

Artificial intelligence (AI) and data-driven analytics have emerged as valuable tools for enhancing financial decision-making (Oreoluwa Onabowale, 2025). AI-based techniques can process large volumes of real-time market data, identify trends, evaluate investment risks, and support comparative analysis across multiple assets. At the same time, advances in web technologies have enabled browser-based analytical platforms capable of performing sophisticated financial analyses without requiring specialized software or local installations. These technologies provide accessible decision-support environments that can assist both professional analysts and individual investors.

Despite the availability of numerous cryptocurrency information platforms, many existing solutions focus primarily on presenting individual market statistics rather than providing an integrated comparative evaluation of leading digital assets. Furthermore, comparative analyses are often performed using static datasets, limiting their applicability to rapidly changing market conditions (Mohammed Abdul et al., 2025). This study addresses this gap by presenting an AI-powered browser-based decision support approach that utilizes live market data to compare the performance of the five largest cryptocurrency assets by market capitalization during the first half of 2026. By combining real-time financial data, technical indicators, and AI-assisted analytics within a unified framework, the study provides a practical approach for evaluating digital asset performance and supporting informed investment decisions.

1.2 Research Objectives

The objective of this study is to develop and apply an AI-powered browser-based decision support approach for evaluating the comparative performance of the five largest cryptocurrency assets by market capitalization during the first half of 2026. By integrating live market data with technical analysis and AI-assisted analytics, the proposed framework aims to provide investors, researchers, and financial technology (FinTech) practitioners with an efficient and accessible tool for assessing cryptocurrency market behavior and supporting investment decisions.

The specific objectives of this study are to:

1. Develop a browser-based decision support platform that integrates live cryptocurrency market data through application programming interfaces (APIs) for real-time financial analysis.
2. Compare the market performance of Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC) during the study period from January 28, 2026, to June 24, 2026.
3. Evaluate each cryptocurrency using financial market indicators, feature-engineered technical indicators, and AI model performance metrics. Financial market indicators include price performance, market capitalization, and trading volume, while the feature-engineered technical indicators include the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change (ROC), Open/Close percentage change, High-Low spread, and historical volatility. The predictive performance of the AI model is assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA).
4. Demonstrate how AI-assisted analytics can enhance comparative evaluation and support informed decision-making within dynamic cryptocurrency markets.

1.3 Contributions

This study contributes to the fields of financial technology (FinTech), blockchain analytics, and artificial intelligence by presenting an AI-powered approach for the comparative evaluation of leading cryptocurrency assets using real-time market data. Unlike studies that focus on forecasting or analyzing a single cryptocurrency, this research provides a unified framework

for comparing multiple digital assets through live market information, technical analysis, and AI-assisted decision support within a browser-based environment.

The primary contributions of this study are as follows:

5. **A browser-based AI decision-support framework** that integrates live cryptocurrency market data through application programming interfaces (APIs) to support real-time comparative analysis without requiring specialized software.
6. **A comparative evaluation of the five largest cryptocurrency assets by market capitalization:** Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC), during the period from January 28, 2026, to June 24, 2026.
7. **An integrated evaluation methodology** that combines financial market indicators, technical analysis metrics, and AI-assisted analytics to assess cryptocurrency performance, market behavior, and investment characteristics.
8. **A practical decision-support approach** that enables investors, researchers, and FinTech practitioners to compare leading digital assets using a unified analytical framework that is scalable to additional cryptocurrencies and future market periods.

II. Literature Review

The rapid growth of cryptocurrency markets has stimulated extensive research on digital asset forecasting and financial decision support. Due to the high volatility, decentralized structure, and continuous trading nature of cryptocurrencies, traditional statistical models have increasingly been supplemented or replaced by artificial intelligence (AI) and machine learning techniques. Recent review studies indicate that deep learning models, particularly Long Short-Term Memory (LSTM) networks and their variants, have become dominant approaches for cryptocurrency price forecasting because of their ability to capture nonlinear relationships and temporal dependencies in financial time series (Zhang et al., 2023). Comparative studies have similarly demonstrated that recurrent neural networks, bidirectional LSTM models, and hybrid deep learning architectures often outperform conventional forecasting methods under highly volatile market conditions (Seabe et al., 2023).

Although deep learning has received considerable attention, traditional machine learning and statistical methods remain valuable due to their interpretability, computational efficiency, and suitability for real-time financial applications. Multiple Linear Regression (MLR) continues

to serve as an effective baseline forecasting model, particularly when combined with feature engineering techniques that incorporate technical indicators such as moving averages, momentum indicators, and volatility measures. Previous studies have also emphasized the importance of evaluating forecasting performance using standardized metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA), which collectively provide comprehensive measures of numerical accuracy and directional prediction capability (Uras et al., 2020; Seabe et al., 2023).

Recent research has also explored the integration of additional information sources, including blockchain activity, trading volume, macroeconomic variables, and market sentiment derived from news and social media. These studies demonstrate that incorporating heterogeneous data sources can improve forecasting performance and provide richer decision-support information for investors (Dikovitsky, 2025). However, many existing forecasting systems remain offline implementations that rely on static historical datasets and are primarily designed to evaluate a single cryptocurrency or compare forecasting algorithms rather than support real-time comparative analysis.

Although several recent studies have examined multiple cryptocurrencies simultaneously, most primarily compare forecasting algorithms or evaluate prediction accuracy using static historical datasets. Few studies integrate live market data acquisition, browser-based analytics, feature engineering, standardized forecasting evaluation, and interactive decision-support visualization into a unified framework. Furthermore, existing comparative studies rarely provide an accessible web-based environment that allows users to conduct real-time cross-asset analysis using continuously updated market information. The proposed framework addresses these limitations by combining live API integration, browser-based AI analytics, standardized forecasting metrics, and comparative visualization within a single decision-support platform.

Despite the substantial progress in cryptocurrency forecasting, several research gaps remain. First, most existing studies focus on forecasting individual cryptocurrencies rather than conducting comparative evaluations across multiple leading digital assets. Second, relatively few studies integrate live market data with browser-based decision support to enable real-time comparative analysis. Third, while numerous investigations compare forecasting algorithms, fewer provide a unified framework that combines feature engineering, Multiple Linear

Regression, standardized AI performance evaluation using MAE, RMSE, MAPE, and Directional Accuracy, and interactive visualization within a browser-based environment. This study addresses these gaps by presenting an AI-powered browser-based decision support framework for the comparative analysis of the five largest cryptocurrency assets using live market data and standardized forecasting evaluation metrics.

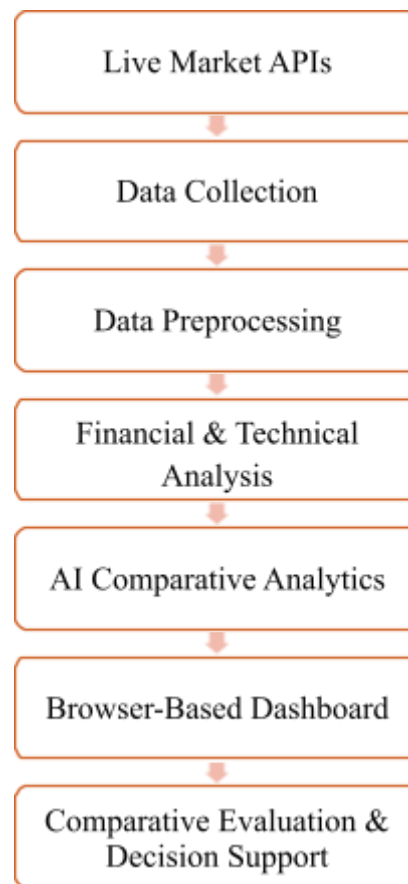
III. Methodology

3.1 Research Framework

This study adopts an AI-powered comparative analysis framework to evaluate the performance of the five largest cryptocurrency assets by market capitalization during the first half of 2026. The framework integrates live cryptocurrency market data, financial analytics, technical analysis, and browser-based decision support to provide a unified approach for comparing digital asset performance. The entire analytical process is implemented within a web-based platform, enabling real-time data acquisition, processing, visualization, and comparative evaluation without requiring specialized software.

Figure 2

Conceptual Research Framework for AI-Powered Comparative Cryptocurrency Analysis.



The proposed research framework consists of five sequential stages. First, live cryptocurrency market data are collected through publicly available Application Programming Interfaces (APIs), including historical and real-time information for Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC). The study period spans from January 28, 2026, to June 24, 2026.

Second, the collected data are preprocessed to ensure consistency and reliability before analysis. Market variables such as price, market capitalization, and trading volume are organized chronologically and prepared for subsequent financial and technical analysis.

Third, the browser-based analytics engine processes live cryptocurrency market data and computes a set of feature-engineered technical indicators, including the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change

(ROC), Open/Close percentage change, High-Low spread, and historical volatility. These indicators, together with market variables such as price, market capitalization, and trading volume, serve as input features for the Multiple Linear Regression (MLR) model. The predictive performance of the model is subsequently evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA), providing quantitative measures of forecast accuracy and trend prediction.

Fourth, an AI-assisted analytics module synthesizes the calculated indicators to perform comparative evaluations across the selected cryptocurrency assets. The framework generates visualizations, comparative metrics, and analytical insights that support assessment of each asset's relative market performance during the study period.

Finally, the comparative results are presented through an interactive browser-based decision support platform, enabling users to examine market behavior, compare cryptocurrency assets, and support investment decision-making using real-time financial market data.

3.2 Data Collection

This study evaluates the five largest cryptocurrency assets by market capitalization during the first half of 2026. The selected assets include Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance (BNB), and USD Coin (USDC). These cryptocurrencies were chosen because they collectively represent the largest share of the global cryptocurrency market and encompass diverse categories of digital assets, including decentralized payment networks, smart contract platforms, exchange-based utility tokens, and stablecoins.

Table 1*Top 5 Digital Assets Codes.*

Digital Asset (Code)	Description
Bitcoin (BTC)	“Bitcoin is an innovative payment network and a new kind of money.” (Bitcoin, 2009)
Ethereum (ETH)	“Ethereum is a global, decentralized platform for money and new kinds of applications.” (Ethereum, 2015)
Tether (USDT)	“Tether is a blockchain-enabled platform designed to facilitate the use of fiat currencies in a digital manner” (Tether, 2014)
Binance (BNB)	“BNB is the native token of the decentralized BNB Chain, where it powers transactions, pays for fees, and allows for participation in governance.” (Binance, 2017)
USD Coin (USDC)	“The world’s largest regulated digital dollar” (USDC, 2018)

The five selected assets collectively represent the majority of global cryptocurrency market capitalization and encompass different categories of digital assets, including decentralized payment systems (BTC), smart contract platforms (ETH), exchange utility tokens (BNB), and fiat-backed stablecoins (USDT and USDC). This diversity enables evaluation of the proposed framework across cryptocurrencies exhibiting substantially different volatility characteristics and market behavior.

The study analyzes market activity over the period from January 28, 2026, to June 24, 2026. This timeframe was selected to capture market dynamics during the first half of 2026 and to enable a consistent comparative evaluation of the selected cryptocurrency assets under the same market conditions.

Live cryptocurrency market data are collected through the CoinGecko Application Programming Interface (API) (CoinGecko, 2024), which provides publicly accessible and

continuously updated market information. The collected data include historical and real-time values for market price, market capitalization, trading volume, and other market statistics required for comparative financial analysis. Data retrieval and processing are performed automatically within the browser-based decision support platform using JavaScript, eliminating the need for local databases or external analytical software.

The collected market data serves as the foundation for calculating financial performance metrics, technical indicators, and AI-assisted comparative analytics presented in the subsequent sections of this study.

3.3 Performance Evaluation Framework

The proposed evaluation framework assesses the comparative performance of the selected cryptocurrency assets using four complementary categories of metrics: market performance, technical indicators, AI-assisted analytics, and comparative evaluation. Together, these metrics provide a comprehensive assessment of each asset's market behavior, investment characteristics, and relative performance during the study period.

Table 2
Performance Evaluation Metrics.

Category	Evaluation Metrics
Market Performance	Price, Daily Return, Cumulative Return, Market Capitalization, Trading Volume
Feature Engineering	SMA (7-day), EMA (7-day), SMA (30-day), RSI (14), ROC (7-day), Open/Close % Change, High-Low Spread, Rolling Volatility (30-day)
AI Model Performance	MAE, RMSE, MAPE, Directional Accuracy (DA).
Comparative Evaluation	Cross-Asset Ranking, Performance Comparison, Relative Risk Analysis

Market Performance

Market performance is evaluated using fundamental financial indicators obtained from the live market data API. These indicators include market price, daily return, cumulative return,

market capitalization, and trading volume. Collectively, these measures provide insight into asset growth, market size, liquidity, and overall market activity throughout the observation period.

Feature Engineering

Feature engineering is performed to transform raw cryptocurrency market data into informative variables that enhance the predictive capability of the AI model. The browser-based analytics platform computes a set of technical indicators, including the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change (ROC), Open/Close percentage change, High-Low spread, and 30-day rolling volatility. These engineered features capture market trends, momentum, and price variability, providing meaningful inputs for the Multiple Linear Regression (MLR) model rather than serving as the primary evaluation outcomes.

AI Model Performance

The AI-assisted analytics module employs a feature-engineered Multiple Linear Regression (MLR) model to analyze and forecast cryptocurrency market behavior. The engineered features derived from market and technical data are integrated to estimate future price movements and support comparative analysis across the selected cryptocurrency assets. Model performance is evaluated using four primary metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). These metrics quantify forecast accuracy and directional prediction capability, enabling objective comparison of AI model performance for each cryptocurrency. Rather than functioning as an autonomous trading system, the AI module serves as a transparent decision-support tool that assists users in interpreting market behavior and comparing the predictive performance of the selected digital assets.

Mean Absolute Error (MAE): The Mean Absolute Error measures the average magnitude of prediction errors without considering their direction (Rajawat et al., 2022). It provides an intuitive assessment of how close predicted prices are to actual values:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Where y_i represents the actual values and $\hat{y}_i$ represents the predicted values, and n the total number of predictions.

A lower MAE indicates better model accuracy and consistency in approximating real

market values.

Root Mean Squared Error (RMSE): The Root Mean Squared Error penalizes larger deviations more heavily than MAE, providing a sensitive measure of forecast precision (Setiadi et al., 2023):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Because RMSE is expressed in the same units as the dependent variable (e.g., U.S. dollars), it is directly interpretable and useful for comparing forecasting methods across different assets or time horizons.

Mean Absolute Percentage Error (MAPE): The Mean Absolute Percentage Error expresses forecasting accuracy as a relative percentage (Kim & Kim, 2016), allowing for cross-scale comparison between different cryptocurrencies:

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

A lower MAPE indicates higher predictive efficiency. However, because division by y_i can inflate errors near zero, the application automatically omits or smooths zero-value records to prevent distortion.

Directional Accuracy (DA): Directional Accuracy measures the percentage of instances where the predicted direction of price movement (upward or downward) matches the actual observed direction (Moosa & Vaz, 2015):

$$DA = \frac{1}{n-1} \sum_{i=2}^n \delta \left[\text{sign}(y_i - y_{i-1}) = \text{sign}(\hat{y}_i - \hat{y}_{i-1}) \right] \times 100$$

Where $\delta[.]$ is an indicator function that equals 1 when the condition is true and 0 otherwise.

DA reflects the model's effectiveness in capturing trend behavior, which is critical for decision-making in trading and risk management.

Comparative Evaluation

The final stage of the evaluation framework compares the five cryptocurrency assets using the calculated financial metrics, technical indicators, and AI-assisted analytics. Comparative visualizations and summary statistics enable users to identify similarities and

differences in market performance, evaluate relative strengths and weaknesses, and support informed investment decision-making during the study period.

IV. Browser-Based Decision Support Platform

4.1 System Architecture

The proposed browser-based decision support platform was developed to provide an interactive environment for collecting, analyzing, and comparing cryptocurrency market data in real time. The platform adopts a lightweight client-side architecture implemented using HTML, CSS, and JavaScript, enabling users to perform comparative financial analyses directly within a standard web browser without installing specialized software or maintaining a local database.

The system architecture consists of four primary components: (1) a live data acquisition module, (2) a data processing and analytics module, (3) an AI-assisted analysis module, and (4) a visualization and decision-support interface.

The live data acquisition module retrieves cryptocurrency market information through the CoinGecko Application Programming Interface (API), including asset prices, market capitalization, trading volume, and other financial market variables. The retrieved data are processed within the browser to generate a set of feature-engineered variables, including the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change (ROC), Open/Close percentage change, High-Low spread, and 30-day rolling volatility. These engineered features are subsequently integrated into the Multiple Linear Regression (MLR) model to support cryptocurrency price forecasting and comparative performance analysis. The predictive performance of the model is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA), providing quantitative measures of forecast accuracy and trend prediction.

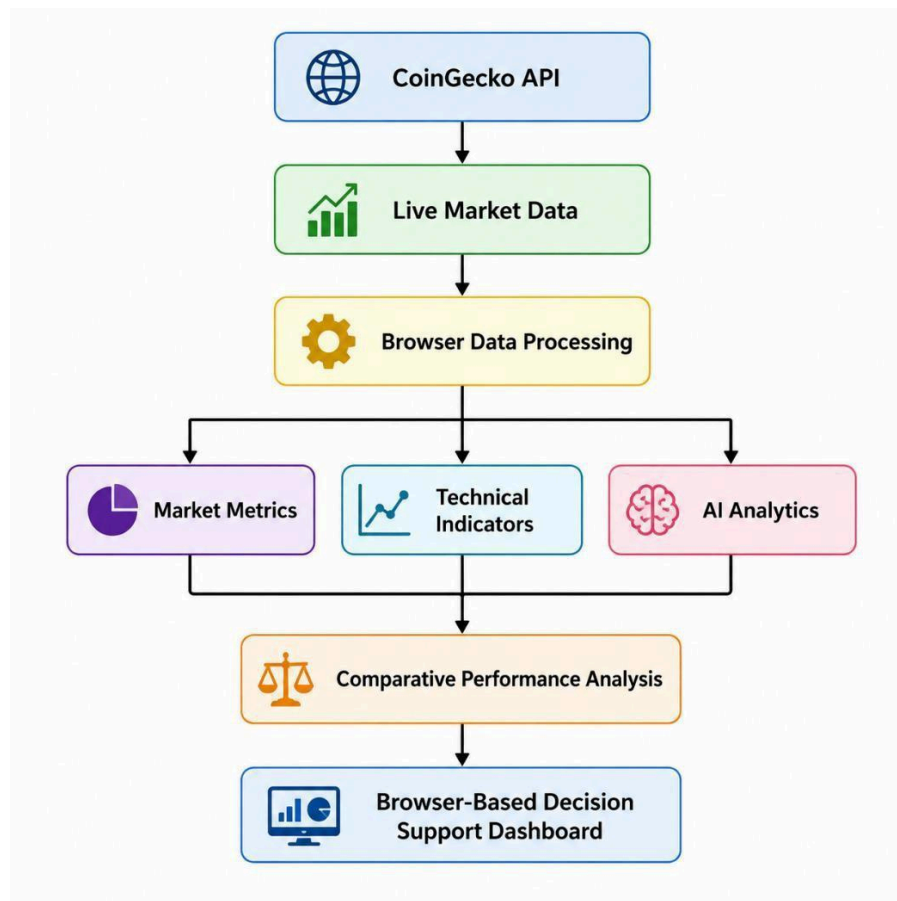
The AI-assisted analytics module integrates the calculated financial and technical indicators to generate comparative assessments of the selected cryptocurrency assets. The resulting analytics are presented through an interactive dashboard that enables users to compare asset performance, visualize historical market trends, evaluate technical indicators, and support investment decision-making using real-time market information.

The modular architecture allows additional cryptocurrencies, evaluation metrics, and analytical models to be incorporated with minimal modification, providing a scalable framework

for future digital asset research.

Figure 3

System Architecture Workflow.



4.2 Live Data Integration

The proposed decision support platform integrates live cryptocurrency market data through the CoinGecko Application Programming Interface (API), enabling real-time acquisition of financial market information directly within a web browser. The API provides publicly accessible market data for the selected cryptocurrency assets, including Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC).

The platform retrieves historical and current market information required for comparative analysis, including asset price, market capitalization, trading volume, and price history. Data requests are executed dynamically using JavaScript, and the returned JSON data are processed entirely on the client side without requiring a dedicated application server or local database.

Figure 4

System Integration Process.



Following data retrieval, the browser-based analytics engine automatically calculates the financial metrics and technical indicators used throughout this study. The processed data are subsequently displayed through interactive charts, performance summaries, and comparative tables that update as new market information becomes available. This real-time integration enables users to monitor cryptocurrency market behavior and compare multiple assets within a unified analytical environment.

The use of a browser-based architecture provides several practical advantages, including platform independence, simplified deployment, reduced infrastructure requirements, and immediate access to current market conditions. Consequently, the proposed platform serves as an efficient decision-support tool for comparative cryptocurrency analysis using continuously updated financial market data.

4.3 AI Analytics and Visualization

The browser-based decision support platform incorporates an AI-assisted analytics module to transform live cryptocurrency market data into meaningful comparative insights. The analytics engine combines financial market metrics with technical indicators to evaluate the market behavior of the selected cryptocurrency assets and support comparative decision-making. A feature-engineered Multiple Linear Regression (MLR) model is employed to identify relationships among selected variables and generate predictive insights that complement traditional financial analysis.

The platform performs feature engineering by computing a set of technical indicators, including the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change (ROC), Open/Close percentage change, High-Low spread, and 30-day rolling volatility. These engineered features are combined with market variables such

as asset price, trading volume, and market capitalization as inputs to a Multiple Linear Regression (MLR) model for cryptocurrency price forecasting. The AI-assisted analytics module evaluates the predictive performance of the model using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). The resulting forecasts and performance metrics are then synthesized to provide comparative assessments of the selected cryptocurrency assets, supporting objective performance evaluation and investment decision-making.

Analytical results are presented through an interactive browser-based dashboard designed to support efficient interpretation of market conditions. The visualization interface includes comparative price charts, technical indicator graphs, performance summaries, and ranking tables that enable users to examine asset performance over the study period. Interactive controls allow users to select individual cryptocurrencies or compare multiple assets simultaneously while maintaining a consistent analytical framework.

Table 3
Technology Components.

Component	Technology
User Interface	HTML5, CSS3
Programming Language	JavaScript (ES6)
Data Source	CoinGecko API
Data Format	JSON
Charts	Chart.js
AI Analytics	Client-side JavaScript

By integrating AI-assisted analytics with real-time visualization, the proposed platform provides a transparent and accessible environment for comparative cryptocurrency evaluation. The browser-based implementation enables users to perform financial analysis and interpret

market trends using continuously updated data without requiring specialized analytical software.

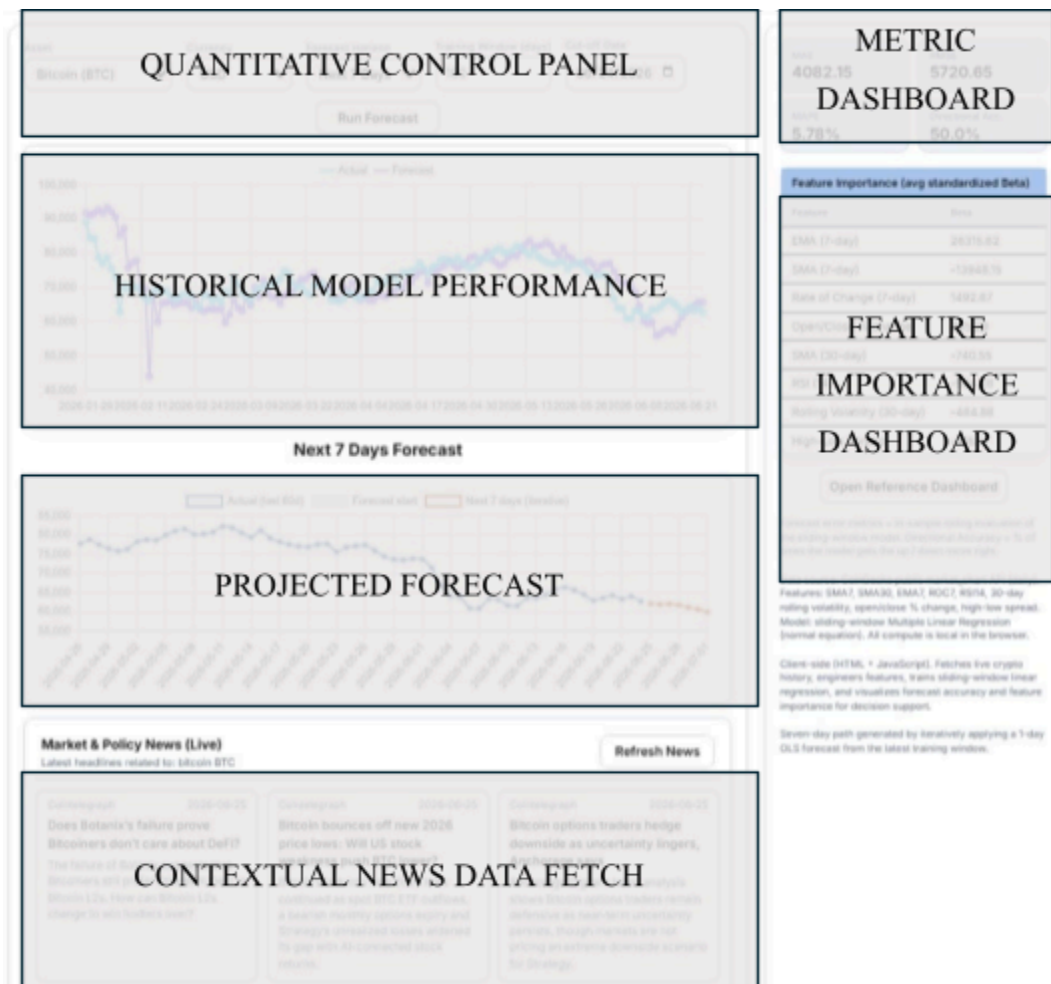
To demonstrate the proposed methodology, an interactive browser-based decision support platform was developed and deployed as a web application. The platform enables users to perform real-time comparative analysis of the selected cryptocurrency assets by retrieving live market data from the CoinGecko API, generating feature-engineered variables, executing the Multiple Linear Regression (MLR) forecasting model, and presenting analytical results through an interactive dashboard. Users can select a cryptocurrency asset, specify the forecast horizon and training window, define the cut-off date, and generate AI-assisted forecasting and comparative analytics directly within a standard web browser.

Figure 5

AI-Powered Analysis System.

System Application: <https://www.ariesbank.com/trietphan/fintech2026.html>

Reference Dashboard: <https://www.ariesbank.com/trietphan/reference-fintech2026.html>



V. Comparative Result and Discussion

For experimental consistency, identical forecasting parameters were used throughout the comparative analysis. Each cryptocurrency was evaluated using USD-denominated market data, a seven-day forecasting horizon, a 180-day rolling training window, and a common cut-off date of June 24, 2026. Standardizing these parameters ensures that differences observed among the selected assets are attributable to their underlying market characteristics rather than variations in the forecasting configuration.

Figure 6

Forecasting Parameters Selection.

Asset

Bitcoin (BTC)

Bitcoin (BTC)

Ethereum (ETH)

Tether (USDT)

BNB (BNB)

USD Coin (USDC)

Currency

USD

Forecast Horizon

Next 7 Days

Training Window (days)

180

Cut-off Date

06/24/2026

Run Forecast

Actual

Forecast

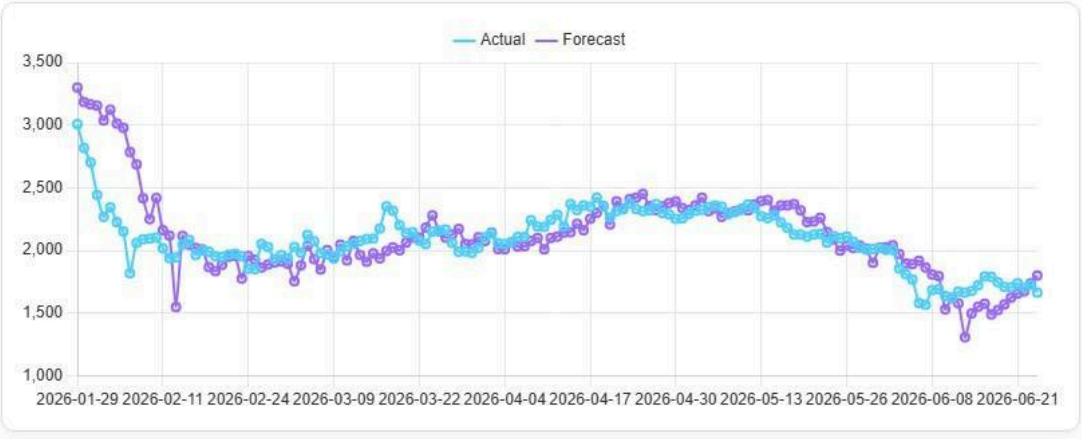
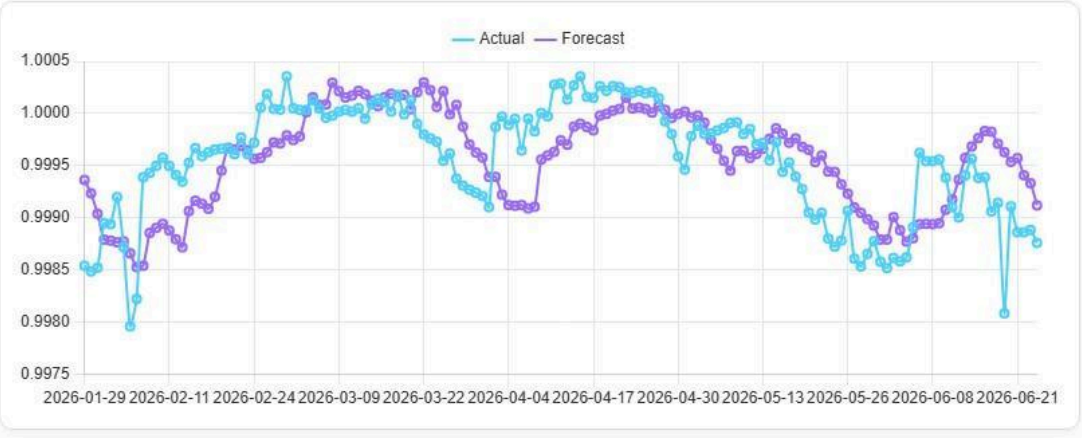
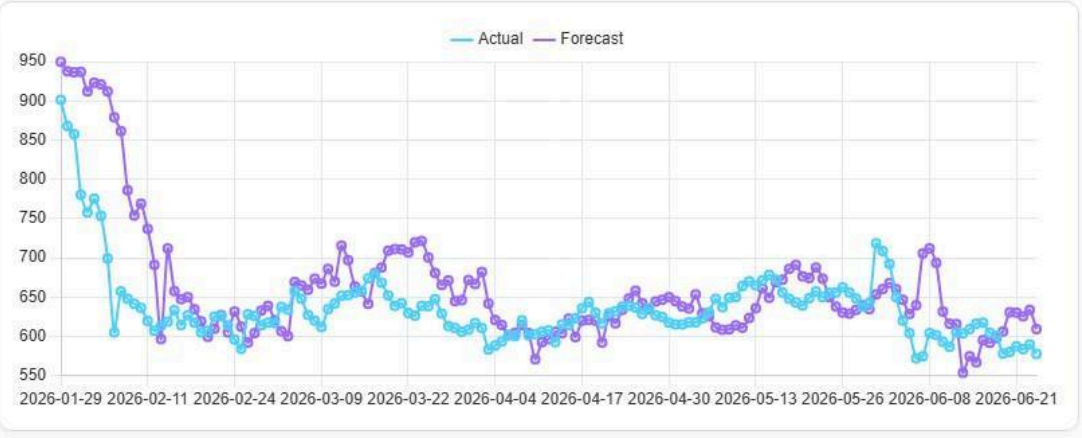
5.1 Market Performance Comparison

This study applies the proposed browser-based decision support platform to compare the market performance of the five largest cryptocurrency assets by market capitalization, Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC), during the study period from January 28, 2026, to June 24, 2026. Live market data collected through the CoinGecko API were used to examine price movements, market capitalization, and trading volume, providing a comprehensive overview of each asset's market behavior.

Table 4

Comparative Market Performance.

Assets	Market Performance
BTC	

Assets	Market Performance
ETH	
USDT	
BNB	

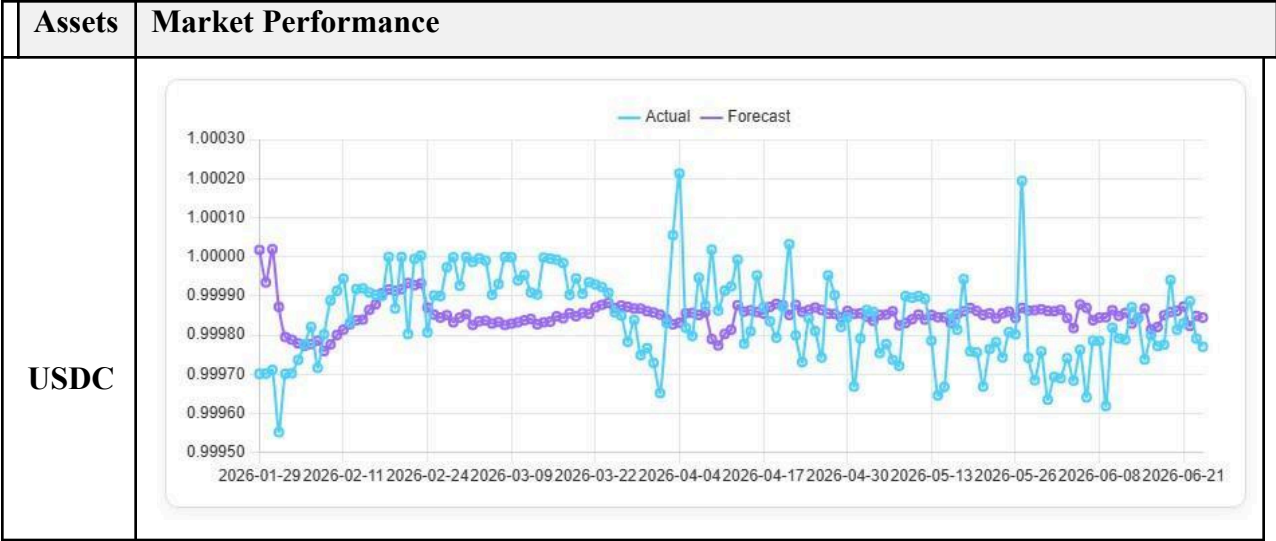


Table 4 presents the comparative forecasting results generated by the proposed platform. The blue line represents the actual market prices obtained from the CoinGecko API, while the purple line represents the prices forecasted by the feature-engineered Multiple Linear Regression (MLR) model.

Among the five assets, Bitcoin (BTC), Ethereum (ETH), and BNB exhibited substantially greater price variability throughout the study period, reflecting the higher volatility typically associated with growth-oriented cryptocurrencies. Despite these fluctuations, the forecasted values generally followed the overall market trends, indicating that the proposed forecasting framework effectively captured medium-term price movements while smoothing short-term market noise.

In contrast, Tether (USDT) and USD Coin (USDC) demonstrated relatively stable price behavior, remaining close to their one-dollar peg during the entire observation period. The limited price variation of these stablecoins resulted in comparatively smoother forecast curves, with only minor deviations from the observed market prices. This behavior is consistent with the primary objective of fiat-backed stablecoins, which is to maintain price stability rather than generate capital appreciation.

Overall, the browser-based decision support platform successfully produced real-time forecasts for all five cryptocurrency assets using a unified analytical framework. Although the market characteristics differed considerably between growth-oriented cryptocurrencies and stablecoins, the platform consistently generated forecasted price series that closely followed the

corresponding market trends.

5.2 Feature Engineering Analysis

Table 5 summarizes the average standardized beta coefficients generated by the Multiple Linear Regression (MLR) model for each cryptocurrency asset. These coefficients provide insight into the relative influence of the engineered features on the forecasting model and demonstrate how different market characteristics contribute to price prediction. The feature set consists of the 7-day Exponential Moving Average (EMA), 7-day Simple Moving Average (SMA), 7-day Rate of Change (ROC), Open/Close percentage change, 30-day SMA, 14-day Relative Strength Index (RSI), 30-day rolling volatility, and High-Low spread.

Table 5
Average Standardized Beta Coefficients of Feature-Engineered Variables for the Multiple Linear Regression Model.

Feature	BTC	ETH	USDT	BNB	USDC
EMA (7-day)	26315.62	733.21	0.0007	252.09	3.95e-5
SMA (7-day)	-13948.15	-104.54	-0.0006	-125.79	-2.76e-5
Rate of Change (7-day)	1492.87	-69.52	0.0003	19.31	-2.69e-5
Open/Close % change	865.29	43.25	0.0002	-10.10	1.63e-5
SMA (30-day)	-740.55	30.66	-5.21e-5	7.03	9.82e-6
RSI (14)	-584.28	-26.06	4.06e-5	5.46	-8.92e-6

Feature	BTC	ETH	USDT	BNB	USDC
Rolling Volatility (30-day)	-484.88	12.22	1.22e-5	-4.28	8.38e-6
High-Low Spread	-316.57	7.11	-8.12e-6	2.33	6.05e-7

Across the five cryptocurrency assets, the 7-day EMA consistently exhibited the strongest positive influence on the forecasting model, indicating that recent price trends contribute substantially to short-term price prediction. Conversely, the 7-day SMA generally produced negative coefficients, suggesting that longer smoothing effects provide complementary information to the EMA and help balance the regression model. The ROC and Open/Close percentage change also contributed to the prediction process by capturing short-term market momentum and daily price movements.

The influence of the remaining engineered features varied among the selected assets. The 30-day SMA, RSI, rolling volatility, and High-Low spread generally exhibited smaller beta coefficients, indicating that these variables played supporting roles within the forecasting model. While these indicators contributed additional market information, their influence was generally less pronounced than the short-term trend indicators represented by the 7-day EMA and SMA.

It should be noted that the magnitude of the beta coefficients should not be directly compared across different cryptocurrency assets because each asset operates on a different price scale. Bitcoin, Ethereum, BNB, Tether, and USD Coin differ substantially in market price and volatility, resulting in corresponding differences in coefficient magnitude. Therefore, the primary purpose is to identify the relative importance of engineered features within each forecasting model rather than to compare coefficient values between assets.

Overall, the feature engineering process successfully transformed raw market data into informative explanatory variables for the MLR model. The combination of trend, momentum, and volatility indicators provided a comprehensive representation of cryptocurrency market behavior and established the foundation for the AI-assisted forecasting evaluation presented in

the following section.

5.3 AI-Based Comparative Evaluation

This section summarizes the forecasting performance of the proposed Multiple Linear Regression (MLR) model for the five selected cryptocurrency assets. Model performance was evaluated using four complementary metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). Together, these metrics assess both numerical forecasting accuracy and the model's ability to correctly predict market direction.

Table 6
Forecasting Performance Analysis.

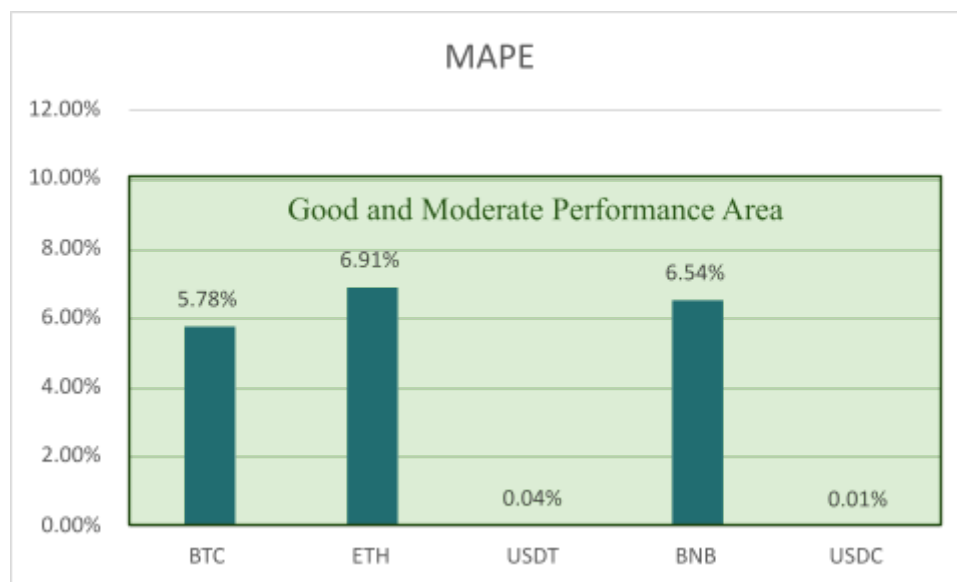
Performance Metric	BTC	ETH	USDT	BNB	USDC
MAE	4082.15	143.84	0.0004	42.18	9.76e-5
RMSE	5720.65	222.96	0.0004	60.93	0.0001
MAPE	5.78%	6.91%	0.04%	6.54%	0.01%
Directional Accuracy	50.0%	51.4%	56.2%	52.1%	48.6%

The results demonstrate that forecasting accuracy varies according to the market characteristics of each cryptocurrency. Bitcoin (BTC), Ethereum (ETH), and BNB exhibited larger MAE and RMSE values than Tether (USDT) and USD Coin (USDC), reflecting the substantially higher price levels and greater market volatility of these growth-oriented cryptocurrencies. In contrast, the stablecoins USDT and USDC produced extremely small forecasting errors because their prices remained close to their one-dollar peg throughout the study period. Consequently, direct comparisons of absolute error metrics across assets with different price scales should be interpreted with caution.

The Mean Absolute Percentage Error (MAPE) provides a normalized measure of forecasting accuracy. BTC, ETH, and BNB achieved MAPE values of 5.78%, 6.91%, and 6.54%, respectively, indicating satisfactory forecasting performance despite significant market fluctuations. USDT and USDC recorded substantially lower MAPE values of 0.04% and 0.01%, respectively, reflecting the limited price variability of stablecoins rather than a fundamentally different forecasting capability.

Figure 7

MAPE Results Confirm Good and Moderate Forecast Performance.

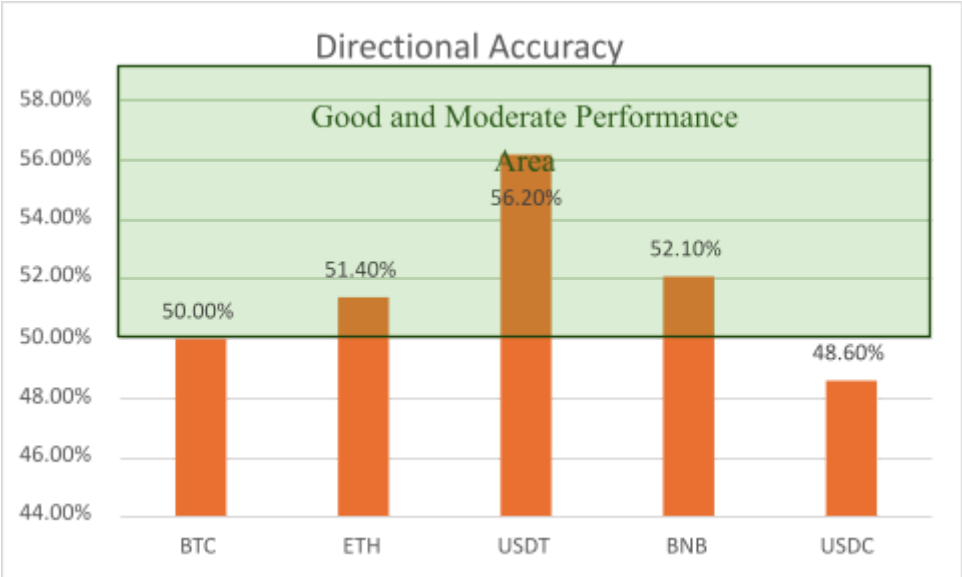


The Mean Absolute Percentage Error (MAPE) measures forecasting error as a percentage of the observed asset price, providing a scale-independent metric for evaluating predictive performance. By expressing prediction error relative to the actual price, MAPE enables meaningful comparisons across cryptocurrencies with substantially different price levels. Unlike absolute error measures, MAPE provides an intuitive interpretation of forecasting accuracy; for example, a MAPE value of 10% indicates that, on average, the predicted values differ from the actual market prices by approximately 10%. Consequently, MAPE is widely used in financial forecasting as a standard benchmark for assessing and communicating model performance to researchers, practitioners, and other stakeholders (Kaur et al., 2025).

Directional Accuracy (DA) evaluates the model's ability to correctly predict the direction of price movement and provides a scale-independent measure for cross-asset comparison. The model achieved Directional Accuracy values ranging from 48.6% to 56.2% across the five cryptocurrencies. USDT achieved the highest Directional Accuracy (56.2%), followed by BNB (52.1%), Ethereum (51.4%), Bitcoin (50.0%), and USDC (48.6%).

Figure 8

Directional Accuracy Results Confirm Good and Moderate Forecast Performance.



Directional Accuracy (DA) values slightly above 50% are commonly reported in short-term financial forecasting studies due to the inherently volatile and uncertain nature of financial markets. A DA of approximately 50% indicates that the model performs no better than random directional prediction, whereas values between 50% and 55% suggest that the model captures a modest yet statistically meaningful predictive signal beyond random chance. In highly competitive financial markets, consistently achieving a Directional Accuracy within this range is generally regarded as evidence that the forecasting model provides useful directional information and outperforms the random-guessing benchmark (Yao, 2025).

Overall, the proposed AI-assisted forecasting framework successfully generated consistent predictive results for all five cryptocurrency assets using a unified browser-based decision support platform. The combination of feature engineering, Multiple Linear Regression, and real-time market data provides an effective and transparent framework for comparative

cryptocurrency analysis while demonstrating the adaptability of the proposed system across both highly volatile cryptocurrencies and relatively stable digital assets.

5.4 Discussion

The findings demonstrate that the proposed AI-powered browser-based decision support platform provides an effective framework for comparative analysis of leading cryptocurrency assets using live market data. By integrating real-time data acquisition, feature engineering, Multiple Linear Regression (MLR), and interactive visualization within a single browser-based environment, the platform enables consistent evaluation of cryptocurrency market behavior and forecasting performance without requiring specialized analytical software.

The comparative analysis highlights the distinct market characteristics of growth-oriented cryptocurrencies and stablecoins. Bitcoin (BTC), Ethereum (ETH), and BNB exhibited greater price volatility and larger forecasting errors due to their dynamic market behavior, whereas Tether (USDT) and USD Coin (USDC) maintained relatively stable prices throughout the study period. Consequently, the substantially lower forecasting errors observed for the stablecoins should be interpreted within the context of their price stability rather than as evidence of superior model performance. Directional Accuracy provides a more appropriate metric for comparing forecasting capability across assets with different price scales.

From a practical perspective, the proposed platform offers investors, researchers, and FinTech practitioners an accessible decision-support environment for monitoring cryptocurrency markets and evaluating AI forecasting performance. The browser-based implementation simplifies deployment by eliminating the need for dedicated software installations while supporting real-time analysis through publicly available market data APIs. In addition, the unified analytical framework enables objective comparison across multiple cryptocurrency assets using standardized forecasting parameters and evaluation metrics.

Despite these contributions, several limitations should be acknowledged. The study employs a Multiple Linear Regression model and focuses on five cryptocurrency assets over a single observation period. Market conditions, macroeconomic events, and regulatory developments may influence forecasting performance and limit the generalizability of the results. Furthermore, the analysis relies primarily on market-based and technical features and does not incorporate alternative information sources such as blockchain network activity, on-chain metrics, news sentiment, or macroeconomic indicators.

Future research will continue expanding the proposed browser-based decision support platform by incorporating additional digital assets, longer market observation periods, and broader comparative analysis across different cryptocurrency categories. Further improvements may include enhanced visualization capabilities, additional financial indicators, and expanded analytical modules to support more comprehensive digital asset evaluation. These extensions will preserve the platform's core design principles of real-time data integration, transparency, accessibility, and practical decision support.

VI. Conclusion

This study presented an AI-powered browser-based decision support approach for the comparative analysis of the five largest cryptocurrency assets by market capitalization using real-time market data. By integrating live cryptocurrency data from the CoinGecko API with feature engineering, Multiple Linear Regression (MLR), and interactive web-based visualization, the proposed platform provides a unified environment for analyzing cryptocurrency markets and supporting data-driven investment decisions. The browser-based implementation demonstrates that sophisticated financial analytics can be performed efficiently without requiring specialized software or dedicated computational infrastructure.

The proposed framework contributes to FinTech research by combining live market data acquisition, AI-assisted forecasting, and comparative cryptocurrency evaluation within a single browser-based platform. Unlike traditional cryptocurrency dashboards that primarily present descriptive market information, the proposed system integrates predictive analytics and standardized model evaluation using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). This integrated approach enables consistent comparison of multiple cryptocurrency assets using a common analytical framework and standardized forecasting methodology.

The browser-based architecture provides a scalable foundation for future research involving additional digital assets, extended observation periods, and more advanced machine learning techniques. Future enhancements may incorporate deep learning models, blockchain network metrics, on-chain analytics, sentiment analysis, macroeconomic indicators, and portfolio optimization strategies to further improve forecasting performance and decision-support capabilities. The proposed framework can also be adapted to evaluate other classes of digital assets, supporting broader applications in financial technology, blockchain analytics, and

artificial intelligence.

References

- Lazea, G.-I., Lungu, C., & Bunget, O.-C. (2026). The Role of AI in Revolutionising Cryptocurrency Trading. *Electronics*, 15(4), 742.
<https://doi.org/10.3390/electronics15040742>
- Cryptocurrency Prices, Charts, Daily Trends, Market Cap, and Highlights | Coinbase. (2026).
<https://www.coinbase.com/explore>
- Global Financial Market Association. (2026). The Impact of Distributed Ledger Technology in Capital Markets Ready for Adoption, Time to Act.
<https://www.gfma.org/wp-content/uploads/2025/08/1.-full-report-impact-of-dlt-in-cap-mkts-final-1.pdf>
- Emmert, F. (2024). The Regulation of Cryptocurrencies in the United States of America. *Social Science Research Network*.
<https://doi.org/10.2139/ssrn.4690980>
- Aivaz, K.-A., Munteanu, I. F., & Jakubowicz, F. V. (2023). Bitcoin in Conventional Markets: A Study on Blockchain-Induced Reliability, Investment Slopes, Financial and Accounting Aspects. *Mathematics*, 11(21), 4508.
<https://doi.org/10.3390/math11214508>
- Nie, Y., Kong, Y., Dong, X., Mulvey, J. M., Vincent, P. H., Wen, Q., & Zohren, S. (2024). A Survey of Large Language Models for Financial Applications: Progress, Prospects and Challenges. *ArXiv.org*. <https://arxiv.org/abs/2406.11903v1>
- Oreoluwa Onabowale. (2025). AI and Real-Time Financial Decision Support. *International Journal of Research Publication and Reviews*, 02(06), 329–350.
<https://doi.org/10.55248/gengpi.6.0625.2260>
- Mohammed Abdul, S. S., Shrestha, A., & Yong, J. (2025). Toward the Mass Adoption of Blockchain: Cross-Industry Insights from DeFi, Gaming, and Data Analytics. *Big Data and Cognitive Computing*, 9(7), 178. <https://doi.org/10.3390/bdcc9070178>
- Zhang, J., Cai, K., & Wen, J. (2024). A Survey of Deep Learning Applications in Cryptocurrency. *IScience*, 27(1), 108509–108509.

<https://doi.org/10.1016/j.isci.2023.108509>

Seabe, P. L., Moutsinga, C. R. B., & Pindza, E. (2023). Forecasting Cryptocurrency Prices Using LSTM, GRU, and Bi-Directional LSTM: A Deep Learning Approach. *Fractal and Fractional*, 7(2), 203.

<https://doi.org/10.3390/fractalfract7020203>

Uras, N., Marchesi, L., Marchesi, M., & Tonelli, R. (2020). Forecasting Bitcoin closing price series using linear regression and neural networks models. *ArXiv.org*.

<https://arxiv.org/abs/2001.01127>

Vladimir Dikovitsky. (2025). Short-term cryptocurrency price forecasting based on news headline analysis. *Frontiers in Blockchain*, 8.

<https://doi.org/10.3389/fbloc.2025.1627769>

Bitcoin. (2009). Bitcoin - Open source P2P money. *Bitcoin.org*. <https://bitcoin.org/en/>

What is Ethereum? | *Ethereum.org*. (2015). *Ethereum.org*.

<https://ethereum.org/what-is-ethereum/>

Why use Tether? (2014). *Tether.to*. <https://tether.to/en/why-tether>

Binance. (2017). BNB - What is BNB and What Is It Used For? *Binance*.

<https://www.binance.com/en/bnb>

What is USDC? Learn about Circle's stable digital dollar. (2018).

Usdc.com. <https://www.usdc.com/learn/what-is-usdc>

CoinGecko. (2024). Cryptocurrency Prices, Charts, and Crypto Market Cap. *CoinGecko*.

<https://www.coingecko.com/>

Rajawat, A. S., Mohammed, O., Shaw, R. N., & Ghosh, A. (2022, January 1). Chapter six - Renewable energy system for industrial internet of things model using fusion-AI (R. N. Shaw, A. Ghosh, S. Mekhilef, & V. E. Balas, Eds.). *ScienceDirect*; Academic Press.

<https://www.sciencedirect.com/science/article/abs/pii/B9780323916998000061>

Setiadi, D. R. I. M., Rustad, S., Andono, P. N., & Shidik, G. F. (2023). Digital image steganography survey and investigation (goal, assessment, method, development, and dataset). *Signal Processing*, 206, 108908.

<https://doi.org/10.1016/j.sigpro.2022.108908>

Kim, S., & Kim, H. (2016). A new metric of absolute percentage error for intermittent demand forecasts. *International Journal of Forecasting*, 32(3), 669–679.

<https://doi.org/10.1016/j.ijforecast.2015.12.003>

Moosa, I., & Vaz, J. (2015). Directional accuracy, forecasting error and the profitability of currency trading: model-based evidence. *Applied Economics*, 47(57), 6191–6199.

<https://doi.org/10.1080/00036846.2015.1068917>

Kaur, R., Uppal, M., Gupta, D., Juneja, S., Arafat, S. Y., Rashid, J., Kim, J., & RoobaeaAlroobaea. (2025). Development of a cryptocurrency price prediction model: leveraging GRU and LSTM for Bitcoin, Litecoin and Ethereum. *PeerJ Computer Science*, 11, e2675–e2675. <https://doi.org/10.7717/peerj-cs.2675>

Yao, C. (2025). Stock Trend Prediction with tuned Machine Learning Models. *Advances in Computer Science Research*, 725–733.

https://doi.org/10.2991/978-94-6463-823-3_71