Enhancing Stock Price Predictions by Integrating Cryptocurrency Dynamics and Macroeconomic Indicators

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***Abstract*—Integrating cryptocurrency dynamics with macroeconomic indicators presents a cutting-edge approach to improving the accuracy of stock price predictions. This research examines the interactions between key U.S. stock indices (NASDAQ, S&P 500, DJI) and major cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin) alongside critical macroeconomic indicators (GDP, Unemployment Rate, Consumer Price Index, Federal Funds Rate, and the 10-Year Treasury Rate). Utilizing advanced econometric models such as Multivariate Vector Autoregression (VAR) and Dynamic Conditional Correlation GARCH (DCC-GARCH), the study identifies significant correlations, with particularly strong predictive relationships observed between Bitcoin and the S&P 500, and Ethereum and the NASDAQ. The optimized Long Short-Term Memory (LSTM) model demonstrated exceptional performance, achieving over 97% directional accuracy and a Root Mean Square Error (RMSE) as low as 0.0968 for the Bitcoin-S&P 500 pair. These findings underscore the potential of integrating diverse financial data sources to significantly enhance stock price predictions, offering valuable insights for developing more effective investment strategies in the evolving financial landscape.**

Keywords— Cryptocurrency Dynamics, Macroeconomic Indicators, Stock Price Prediction, Econometric Models

I. Introduction

The financial world is experiencing a paradigm shift, driven by the emergence and proliferation of cryptocurrencies as a formidable asset class. Unlike traditional financial instruments such as stocks and bonds, cryptocurrencies are decentralized, highly volatile, and influenced by a myriad of factors, ranging from technological advancements to regulatory changes. As these digital currencies, including Bitcoin, Ethereum, Ripple, and Litecoin, continue to gain mainstream acceptance, their potential to influence traditional financial markets has garnered significant academic and professional interest. The intersection of these two domains—cryptocurrencies and traditional financial markets—presents a compelling area of study, particularly in the context of stock price prediction, a critical component of modern investment strategies.

Historically, stock price prediction models have relied heavily on macroeconomic indicators such as Gross Domestic Product (GDP), Unemployment Rate, Consumer Price Index (CPI), and interest rates. These indicators have long been considered reliable barometers of economic health, providing insights into market trends and investor behavior. However, the rise of cryptocurrencies introduces a new set of dynamics that these traditional models may not fully capture. Cryptocurrencies operate under different principles, often exhibiting high volatility and unique responses to market stimuli, which could either complement or complicate existing predictive models.

The correlation between cryptocurrencies and traditional stock indices is increasingly evident, as demonstrated in Fig. 1. The correlation heatmap reveals significant positive correlations between major cryptocurrencies like Bitcoin (BTC) and Ethereum (ETH) and key U.S. stock indices such as NASDAQ, S&P 500, and DJI. These findings suggest that cryptocurrency markets and traditional financial markets are not as isolated as previously thought. For instance, BTC shows a particularly strong correlation with NASDAQ, indicating that movements in the cryptocurrency market could have substantial implications for stock market performance. This interconnectedness highlights the need for more comprehensive predictive models that integrate both cryptocurrency dynamics and macroeconomic indicators to enhance the accuracy of stock price predictions.

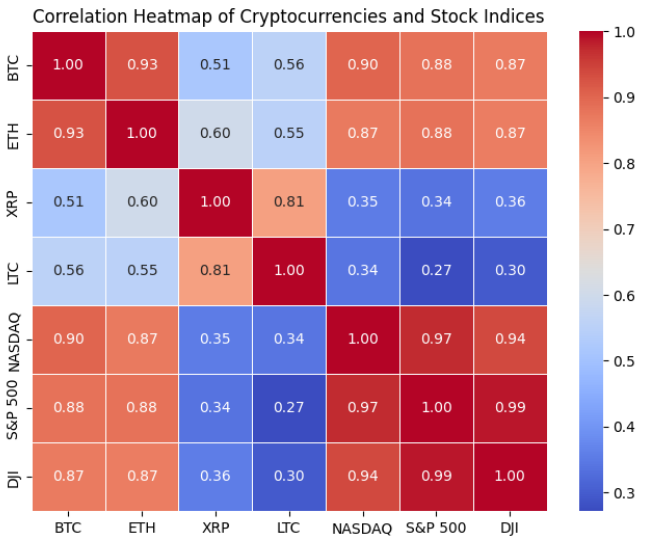

Fig. 1. Correlation heatmap illustrating the relationships between major cryptocurrencies (BTC, ETH, XRP, LTC) and U.S. stock indices (NASDAQ, S&P 500, DJI).

This research seeks to address the limitations of existing financial models by integrating cryptocurrency dynamics with traditional macroeconomic indicators to improve stock price predictions. By examining the interplay between major U.S. stock indices and leading cryptocurrencies, this study aims to provide a deeper understanding of how these markets influence each other. The outcomes of this research are expected to contribute to the development of more accurate and reliable predictive models, which are crucial for investors, financial analysts, and policymakers in navigating the increasingly complex and interconnected global financial landscape. As the influence of digital assets continues to grow, this study offers a timely and essential expansion of the tools available for stock price forecasting, ensuring they remain relevant in the face of evolving market conditions.

II. BACKGROUND AND RELATED WORK

A. *Cryptocurrency Dynamics and Financial Markets*

The advent of cryptocurrencies has reshaped global financial markets, with Bitcoin leading numerous studies on its impact on traditional financial assets. Reference [1] examined the effect of geopolitical risks on Bitcoin's returns and volatility, showing that cryptocurrencies often react differently to external shocks compared to traditional assets. This distinct behavior presents both challenges and opportunities for analysts aiming to improve market predictions. Additionally, [4] explored the relationship between cryptocurrencies and traditional financial assets, finding increased interconnectedness, especially during volatile periods. This suggests that cryptocurrencies could serve as useful indicators in forecasting stock prices.

Reference [2] studied Bitcoin's role as a hedge or safe haven during financial instability, concluding that it functions better as a diversifier rather than a reliable hedge in times of market stress. This distinction is important when considering the integration of cryptocurrency data into stock prediction models, highlighting the non-linear and unpredictable nature of digital currencies. These studies collectively suggest that while cryptocurrencies offer new analytical dimensions, their integration into traditional market models requires careful consideration of their unique behaviors.

B. *Macroeconomic Indicators and Stock Prices*

Macroeconomic indicators have long been recognized as key determinants of stock market performance. Classical economic theories, such as the Efficient Market Hypothesis (EMH), suggest that stock prices reflect all available information, including macroeconomic variables like GDP, inflation, and interest rates. Seminal works by [6] and [3] established a strong link between these macroeconomic factors and stock returns, using models like Vector Autoregression (VAR) to quantify these relationships. Recent studies have further explored the impact of macroeconomic indicators on stock prices, focusing on both long-term and short-term predictions. Reference [12], for instance, used VAR and GARCH models to analyze volatility spillovers between Bitcoin and traditional stock markets, incorporating macroeconomic indicators as control variables. Their findings underscore the importance of considering both emerging and traditional financial data in stock price forecasting.

Interest rates, particularly the Federal Funds Rate and the 10-Year Treasury Rate, have also been extensively studied in relation to stock market performance. These indicators are seen as economic health barometers, significantly influencing investor behavior and, consequently, stock prices. Research by [8] demonstrated that fluctuations in interest rates can have substantial implications for asset prices, including stocks, as they directly affect the cost of capital and future earnings potential. These studies collectively highlight the critical role of macroeconomic variables in shaping stock market dynamics and emphasize the need for their careful integration into predictive models.

C. *Integrating Cryptocurrency Dynamics with Macroeconomic Indicators*

While much of the existing literature has focused on either cryptocurrency dynamics or macroeconomic indicators in isolation, a growing body of research seeks to integrate these two domains. Reference [5] explored whether Bitcoin could enhance portfolio diversification, finding that its integration with traditional assets could improve portfolio performance under specific market conditions. This study provides a foundation for further exploration of how cryptocurrencies might interact with macroeconomic indicators to influence stock prices.

Reference [7] conducted a tail risk analysis to assess whether cryptocurrencies can serve as a safe haven during periods of extreme market volatility. Their research suggests that while cryptocurrencies can offer protection during market downturns, their effectiveness is highly context-dependent. This finding emphasizes the potential for integrating cryptocurrency data with macroeconomic indicators to develop more robust predictive models, capable of adapting to various market conditions.

Reference [14] examined the volatility connectedness within the cryptocurrency market, with a particular focus on Bitcoin's dominance. Their study found that Bitcoin often leads market movements, suggesting that it could be a valuable predictor of stock price changes when integrated with macroeconomic data. This integration could enhance the predictive accuracy of models used for both short-term and long-term stock price forecasting.

The conceptual framework for integrating cryptocurrency dynamics with macroeconomic indicators is illustrated in Fig. 2. This framework outlines the analytical techniques and processes involved in selecting relevant assets and models, culminating in an optimized prediction process that incorporates both traditional and emerging financial variables.

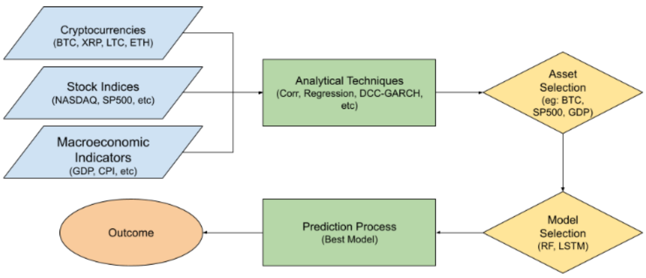

Fig. 2. Conceptual framework for integrating cryptocurrency dynamics with macroeconomic indicators in stock price prediction models.

D. *Gaps in the Literature*

Despite the increasing interest in the integration of cryptocurrency dynamics with macroeconomic indicators, several gaps persist in the literature. Most studies have concentrated on long-term relationships, with relatively few examining the implications for intraday or short-term trading strategies. Additionally, while some research has explored the spillover effects between cryptocurrencies and traditional assets, there is a need for more comprehensive models that incorporate a wider range of macroeconomic indicators.

Furthermore, the majority of existing studies rely on traditional econometric models, such as VAR and GARCH, which may not fully capture the complex and nonlinear relationships inherent in financial markets. The application of advanced machine learning techniques, such as Long Short-Term Memory (LSTM) networks, presents an opportunity to address these limitations and enhance the accuracy of stock price predictions.

The integration of cryptocurrency dynamics with macroeconomic indicators offers a promising avenue for improving stock price predictions. By building on the existing literature and addressing its gaps, this research aims to develop more comprehensive and accurate predictive models. These models have the potential to provide valuable insights for both traders and investors, particularly in an increasingly interconnected and volatile financial landscape.

III. Methodology

A. Data Collection

a) Data Sources: Data was sourced from multiple reliable financial databases to ensure accuracy and comprehensiveness. Cryptocurrency data, including Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), and Litecoin (LTC), was obtained from Yahoo Finance. These cryptocurrencies were selected due to their significant market capitalization and influence on the overall cryptocurrency market, as highlighted by studies such as [2] and [4].

For stock market indices, data was collected for the NASDAQ Composite (^IXIC), S&P 500 (^GSPC), and Dow Jones Industrial Average (^DJI). These indices represent the broader U.S. equity market and have been widely used in financial studies to gauge market performance.

Macroeconomic indicators, including GDP, Unemployment Rate, Consumer Price Index (CPI), Federal Funds Rate, and the 10-Year Treasury Constant Maturity Rate, were obtained from the Federal Reserve Economic Data (FRED) database. These indicators were selected based on their established impact on stock markets, as discussed in the works of [6] and [3].

The financial market data was sourced from Yahoo Finance, and the macroeconomic data was obtained from the Federal Reserve Economic Data (FRED). The datasets were saved in a structured format (CSV) for further processing.

b) Timeframe: The data spans from January 1, 2018, to May 5, 2024. This period was chosen to capture significant economic events and trends, including the increasing integration of cryptocurrencies into global financial markets. The timeframe also ensures that the analysis includes periods of high volatility and market stress, which are critical for evaluating the robustness of predictive models as discussed by [1].

c) Data Characteristics: The cryptocurrency data includes daily closing prices, trading volumes, and market capitalization for each selected cryptocurrency. For stock market indices, the data includes daily closing prices and volumes. The macroeconomic indicators are available at different frequencies (e.g., monthly for CPI, quarterly for GDP), which necessitates careful alignment and interpolation during the preprocessing phase.

d) Tools and Libraries: Data collection was conducted using Python programming language, leveraging libraries such as yfinance for cryptocurrency and stock data, and pandas_datareader for macroeconomic indicators. These tools provide efficient access to historical financial data and are widely used in academic and industry research, for instance [13].

B. Data Preprocessing

a) Data Cleaning and Transformation: The first step in preprocessing was data cleaning, which involved removing irrelevant columns, handling missing values, and correcting any inconsistencies. For instance, columns such as 'Open', 'High', and 'Low' were removed to focus the analysis on 'Close' prices, which are most relevant for modeling price movements.

To align the datasets with different frequencies, the macroeconomic indicators, which are reported monthly or quarterly, were interpolated to match the daily frequency of the cryptocurrency and stock market data. This interpolation was necessary to ensure that all datasets could be integrated into a unified framework for analysis [10].

b) Data Standardization: Given the different scales and units of measurement across the datasets, it was essential to standardize the data to a common scale. This was achieved using the Z-score normalization technique, which transforms each feature to have a mean of zero and a standard deviation of one:

$$X_{scaled} = \frac{X - \mu}{\sigma} \quad (1)$$

where X is the original value, μ is the mean, and σ is the standard deviation of the feature.

Standardization is particularly important in machine learning models like LSTM and Random Forest, which can be sensitive to the scale of input features [13]. By ensuring all features are on the same scale, the models can learn more effectively, leading to more accurate predictions.

c) Handling Missing Data: The Missing data is a common issue in financial datasets, particularly in macroeconomic indicators and cryptocurrency data. In this research, forward and backward filling techniques were employed to handle missing data points. These methods involve replacing missing values with the most recent non-missing value or the next available non-missing value, respectively. This approach preserves the temporal structure of the data, which is crucial for time-series analysis [14].

In cases where missing data was extensive, affected features were either removed from the analysis or imputed using advanced techniques such as regression-based imputation, depending on the importance of the feature to the overall model [7].

C. Statistical Analysis

a) Correlation Analysis: The first step in statistical analysis was to examine the pairwise correlations between the variables. This analysis helped identify the strength and direction of linear relationships between cryptocurrencies, macroeconomic indicators, and stock indices. The Pearson correlation coefficient was used, which is defined as:

$$r = \frac{Cov(X,Y)}{(\sigma_X * \sigma_Y)} \quad (2)$$

where *Cov(X,Y)* represents the covariance between variables X and Y, and σ_X and σ_Y are their standard deviations.

Correlation analysis revealed significant relationships between certain cryptocurrencies and stock indices, as well as between macroeconomic indicators and stock prices. For instance, Bitcoin showed a strong positive correlation with the S&P 500, while GDP and CPI had significant correlations with major stock indices. These findings are consistent with studies by [5] and [2], which highlighted the interconnectedness of cryptocurrency markets with traditional financial assets.

b) Regression Analysis: To further quantify the impact of cryptocurrencies and macroeconomic indicators on stock indices, multiple linear regression models were employed. The general form of the regression model used is:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \epsilon \tag{3}$$

where Y is the dependent variable (e.g., stock index), X_i represents the independent variables (e.g., cryptocurrency prices and macroeconomic indicators), β_i are the coefficients, and ϵ is the error term.

Regression analysis allowed us to identify which variables had the most significant impact on stock prices. For example, it was observed that Bitcoin and Ethereum had strong predictive power for the NASDAQ and S&P 500 indices. Additionally, macroeconomic indicators like the Federal Funds Rate and GDP were found to be significant predictors, aligning with findings by [6] and [3] regarding the influence of macroeconomic factors on stock markets.

c) Dynamic Conditional Correlation (DCC)-GARCH Model: The DCC-GARCH model was employed to analyze the time-varying correlations between cryptocurrencies and stock indices, as well as between cryptocurrencies and macroeconomic indicators. The DCC-GARCH model extends the traditional GARCH model by allowing correlations to evolve over time, which is crucial for capturing the dynamic nature of financial markets. The model is specified as:

$$r_t = \mu + \epsilon_t \tag{4}$$

$$\epsilon_t = H_t^{\{\frac{1}{2}\}} z\_t \tag{5}$$

$$H_t = D_t R_t D_t \tag{6}$$

where r_t is the vector of asset returns, μ is the mean return, H_t is the conditional covariance matrix, D_t is the diagonal matrix of time-varying standard deviations from univariate GARCH models, and R_t is the time-varying correlation matrix.

Correlation analysis revealed significant relationships between certain cryptocurrencies and stock indices, as well as between macroeconomic indicators and stock prices. For instance, Bitcoin showed a strong positive correlation with the S&P 500, while GDP and CPI had significant correlations with major stock indices. These findings are consistent with studies by [5] and [2], which highlighted the interconnectedness of cryptocurrency markets with traditional financial assets.

d) Vector Autoregression (VAR) Model: To examine the interdependencies and potential causality between the variables, a VAR model was applied. The VAR model is particularly useful for capturing the dynamic relationships between multiple time-series variables, where each variable is modeled as a function of its own past values and the past values of all other variables in the system. The model is specified as:

$$Y_t = c + A_1 Y_{\{t-1\}} + \dots + A_p Y_{\{t-p\}} + \epsilon_t \tag{7}$$

where Y_t is a vector of the variables being analyzed (e.g., cryptocurrencies, stock indices, macroeconomic indicators), A_i are the coefficient matrices, c is the intercept vector, and ϵ_t is the error term.

VAR model provided insights into the short-term dynamics and potential feedback loops between the variables. For example, the model indicated that changes in Bitcoin prices could predict future movements in the S&P 500, while macroeconomic shocks, such as a change in the Federal Funds Rate, had significant effects on both cryptocurrency prices and stock indices. These findings are supported by the work of [10], who highlighted the importance of capturing lagged effects in financial models.

D. Feature Selection

The selection of features for predicting stock prices in this research was guided by the insights gained from the statistical analyses performed earlier. Specifically, correlation analysis, regression analysis, and advanced econometric models like DCC-GARCH and Multivariate VAR were used to identify significant relationships between cryptocurrencies, macroeconomic indicators, and stock indices. For example, the analysis revealed that Bitcoin (BTC) and macroeconomic indicators such as Gross Domestic Product (GDP), Consumer Price Index (CPI), and the Federal Funds Rate exhibited strong correlations with the S&P 500 index, suggesting their potential as key predictive features for modeling the S&P 500.

E. Feature Engineering

Feature engineering involved creating additional variables that could enhance the predictive power of the models. This included generating lagged features, moving averages, and volatility measures for the selected cryptocurrencies. For example, lagged features for BTC were created to capture the delayed effects of Bitcoin price movements on stock prices. The lagged features are defined as:

$$BTC_{lag_{k(t)}} = BTC(t-k) \tag{8}$$

where k is the lag period, and *BTC(t)* is the Bitcoin price at time t. Similarly, moving averages (MA) were calculated to smooth out short-term fluctuations and highlight longer-term trends. The 7-day and 21-day moving averages were calculated as follows:

$$MA_{k(t)} = \frac{1}{k} \sum_{i=0}^{k-1} BTC(t-i) \tag{9}$$

where k is the window size (7 or 21 days).

Volatility measures were computed using rolling standard deviations, which capture the degree of variation in BTC prices over a specified window. The volatility $\sigma_k(t)$ for a window size k is defined as:

$$\sigma_{k(t)} = \sqrt{\frac{1}{k}\sum_{i=0}^{k-1}\left(BTC(t-i) - MA_{k(t)}\right)^2} \quad (10)$$

Additionally, the Relative Strength Index (RSI) was calculated to measure the speed and change of price movements, which is particularly useful in identifying overbought or oversold conditions. The RSI is given by:

$$RSI(t) = 100 - \frac{100}{1 + \frac{Average\ Gain(t)}{Average\ Loss(t)}} \quad (11)$$

where the average gain and loss are computed over a specified period (e.g., 14 days).

F. Model Selection

The process of model selection in this research involved a comprehensive evaluation of several machine learning and statistical models to determine their suitability for predicting stock prices influenced by cryptocurrency dynamics and macroeconomic indicators. The models evaluated include Linear Regression, Random Forest, Long Short-Term Memory (LSTM) Networks, and a Feedforward Neural Network (FNN) using PyTorch. The choice of models was guided by their proven effectiveness in capturing complex patterns in financial data, as established in the literature.

a) Linear Regression: Linear Regression served as the baseline model due to its simplicity and interpretability. It is a fundamental tool in financial modeling, allowing for straightforward interpretation of how each macroeconomic indicator and cryptocurrency affects stock prices. Despite its simplicity, Linear Regression provides a valuable benchmark against more complex models.

b) Random Forest: Random Forest, an ensemble learning method, was selected for its ability to model complex, non-linear relationships. It constructs a multitude of decision trees and aggregates their predictions, reducing the risk of overfitting and enhancing predictive accuracy. The model's predictive power is derived from the diversity of the decision trees, each trained on random subsets of the data and features.

$$\hat{Y} = \frac{1}{T}\sum_{t=1}^{T}\hat{Y}_t \quad (12)$$

where T is the number of trees, and $\hat{Y}_t$ is the prediction from the t-th tree.

Hyperparameter tuning for Random Forest was conducted using GridSearchCV, optimizing parameters such as the number of trees ($n_{estimators}$), the maximum depth of the trees (*max_depth*), and the minimum number of samples required for a node split (*min_samples_split*).

The Random Forest model was chosen due to its robustness in handling the inherent non-linearity and high dimensionality of financial datasets, characteristics often observed in financial markets [2]. The model's effectiveness in capturing interactions between features, including macroeconomic indicators and cryptocurrencies, is well-documented in financial forecasting literature.

c) LSTM Networks: LSTM networks, a variant of Recurrent Neural Networks (RNNs), are particularly effective for time-series prediction, making them well-suited for financial data that involve sequential dependencies. LSTM networks address the vanishing gradient problem inherent in traditional RNNs by incorporating memory cells that retain information over long sequences. The LSTM model's ability to capture temporal patterns in stock prices influenced by cryptocurrency and macroeconomic data is a significant advantage.

$$h_t = \sigma(W_h \cdot [h_{t-1}, x_t] + b_h) \quad (13)$$

where h_t is the hidden state at time t, W_h is the weight matrix, x_t is the input at time t, and σ is the activation function

The LSTM model was optimized using the Adam optimizer, which is well-suited for non-stationary data, such as financial time series. LSTMs have been increasingly adopted in financial forecasting due to their superior performance in capturing non-linear and sequential patterns, as evidenced by [12].

LSTM networks were selected for their ability to model long-term dependencies in time-series data, which is critical in financial markets where historical price movements influence future trends. The model's architecture is particularly effective for datasets with complex temporal structures, making it ideal for integrating cryptocurrency and macroeconomic indicators into stock price prediction.

d) Feedfoward Neural Networks: The Feedforward Neural Network (FNN) was implemented using PyTorch, with multiple hidden layers and ReLU activation functions to introduce non-linearity. This model is particularly effective for capturing complex interactions between input features and the target variable, which are common in financial markets. The architecture of the FNN is represented as:

$$h = ReLU(W \cdot X + b) \quad (14)$$

where W and b are the weights and biases, and X is the input.

Hyperparameter tuning was conducted using Optuna, optimizing the number of hidden units, learning rate, and choice of optimizer (Adam, SGD, RMSprop). The FNN's flexibility in capturing non-linear relationships is particularly valuable in financial forecasting, where multiple factors simultaneously influence stock prices.

The FNN was chosen for its ability to model complex, non-linear relationships in financial data, an essential feature for accurately predicting stock prices. The flexibility offered by neural networks in handling diverse data types, including both macroeconomic indicators and cryptocurrency data, makes them a powerful tool for financial modeling, as suggested by studies such as those by [4].

G. Evaluation

Following metrics were selected due to their effectiveness in assessing different aspects of model performance, especially within the context of financial stock prediction, where both the precision of predictions and the accuracy in capturing market trends are crucial. effectiveness in capturing complex patterns in financial data, as established in the literature:

a) Root Mean Squared Error (RMSE): It provides a single measure of how far the predicted values deviate from the actual observed values, calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (15)$$

where y_i represents the observed values, $\hat{y}_i$ represents the predicted values, and n is the number of observations.

RMSE is particularly important in financial markets because it penalizes larger errors more heavily than smaller ones due to the squaring of the residuals. Large prediction errors can lead to significant financial losses, making RMSE a critical metric for evaluating the precision of the model's predictions. A lower RMSE indicates more accurate predictions, which is essential for minimizing risk in financial decisions.

b) Mean Absolute Percentage Error (MAPE):

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right) \times 100 \quad (16)$$

MAPE is particularly useful for understanding the average prediction error in percentage terms. In financial stock prediction, this metric allows for a straightforward comparison of model performance across different stocks or time periods, providing insights into the model's reliability and consistency.

c) Directional Accuracy (DA): It is defined as:

$$DA = \left(\frac{1}{n}\sum_{i=1}^{n} I[(\hat{y}_i - y_{i-1}) \cdot (y_i - y_{i-1}) > 0]\right) \times 100 \quad (17)$$

where *I(.)* is an indicator function that equals 1 if the sign of the predicted change matches the sign of the actual change, and 0 otherwise.

In financial markets, accurately predicting the direction of price movement (whether prices will rise or fall) is often more valuable than predicting the exact magnitude of the change. High directional accuracy implies that the model effectively captures the underlying market trends, which is crucial for developing trading strategies that can capitalize on these predictions.

IV. Results and Discussions

A. Statistical Analysis

The statistical analysis conducted in this research provides a comprehensive understanding of the interrelationships between macroeconomic indicators, cryptocurrencies, and stock indices. The correlation heatmap Fig. 3, serves as a visual representation of these relationships, revealing several key insights into how these variables interact with one another in the financial ecosystem.

The analysis demonstrates that GDP exhibits positive correlations with traditional stock indices, such as the S&P 500 (0.84) and the DJI Average (0.88). These findings align with established economic theory, which posits that economic growth, as measured by GDP, typically leads to improved corporate earnings and, consequently, higher stock prices. This positive relationship underscores the importance of GDP as a primary driver of stock market performance, reflecting its role as a barometer of economic health.

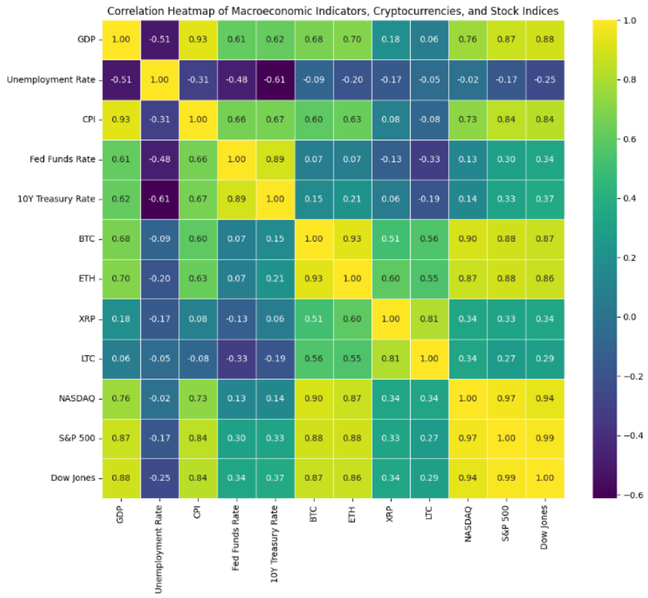

Fig. 3. Correlation Heatmap of Macroeconomic Indicators, Cryptocurrencies, and Stock Indices.

Conversely, the analysis indicates a negative correlation between the Unemployment Rate and cryptocurrencies, particularly Bitcoin (BTC, -0.51). This suggests that during periods of economic downturn, characterized by rising unemployment, there may be a reduction in speculative investments in cryptocurrencies. This finding is particularly significant as it challenges the notion of Bitcoin as a "safe haven" asset during economic crises, indicating that investor behavior in relation to cryptocurrencies may be more risk-averse during such periods.

Inflation, as measured by the CPI, shows correlation with cryptocurrencies, especially with BTC and ETH. This suggests that these digital assets may serve as potential hedges against inflation, a concept that has gained traction among investors amid rising global inflation concerns.

Moreover, the regression models, which include interaction terms between cryptocurrencies and macroeconomic indicators, reveal an enhancement in predictive power, particularly for stock indices like the S&P 500 and NASDAQ. As depicted in Fig. 4, the R-squared values from these regression models indicate how well the model explains the variability of the stock indices based on the selected features. High R-squared values for models predicting S&P 500 and NASDAQ highlight the significant explanatory power of the selected macroeconomic indicators and their interactions with cryptocurrency prices. This underscores the importance of including interaction terms in financial models to capture the nuanced effects of combined economic variables.

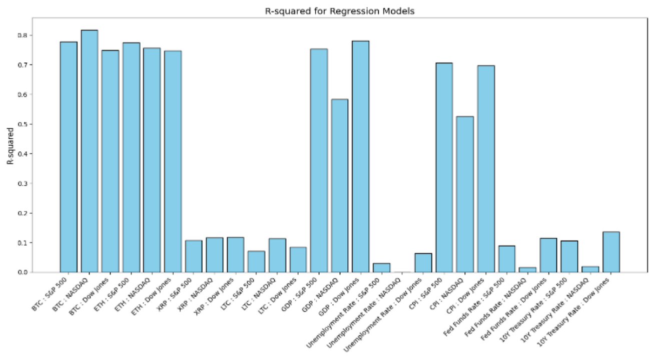

Fig. 4. R-Squared Values for Regression Models Across Various Financial Indicators.

The VAR results revealed significant autocorrelation within each cryptocurrency, particularly with BTC and ETH. For instance, BTC's past values strongly influenced its future prices (as evident from significant coefficients in the lagged terms), indicating a high degree of momentum in its price movements. This autocorrelation was also observed in ETH, albeit to a slightly lesser extent. Moreover, the VAR model showed that BTC's prices had a measurable, though less pronounced, effect on traditional stock indices, particularly the S&P 500 (as shown in Fig. 5). This suggests a potential spillover effect where movements in BTC prices may foreshadow or contribute to shifts in equity markets.

Fig. 5. Vector Autoregression (VAR) Model Results for Cryptocurrencies and Stock Indices.

The DCC-GARCH model further complemented these findings by capturing the time-varying correlations between the assets. The model revealed that correlations between cryptocurrencies and stock indices are not constant but fluctuate with market conditions. For example, during periods of market stress or high volatility, the correlations between BTC and S&P 500 tended to increase, suggesting that these assets might move more closely together during market downturns. This could be visualized in Fig. 6. This behavior aligns with the flight-to-safety phenomenon, where investors may move out of riskier assets, causing previously uncorrelated assets to behave more similarly.

Fig. 6. DCC-GARCH Time-Varying Correlations Between Cryptocurrencies and Stock Indices.

The DCC-GARCH model's ability to capture these dynamic correlations is crucial for understanding the evolving relationship between cryptocurrencies and traditional assets, especially in the context of portfolio diversification. The varying correlations indicate that the diversification benefits of holding both cryptocurrencies and traditional stocks may diminish during times of financial stress, a critical insight for portfolio management.

B. Model Performance and Analysis

The performance of various machine learning models was assessed to predict the price movements of cryptocurrencies and their relationships with traditional stock indices. The analysis included Linear Regression, Random Forest, Long Short-Term Memory (LSTM) networks, and Feedforward Neural Networks (FNN). The model evaluation metrics—Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA)—are summarized in Table 1 and depicted in the bar chart (Fig. 7).

The baseline Linear Regression model exhibited relatively high RMSE values of 0.223 and 0.221 for the training and validation datasets, respectively. This indicates that while the model captures the general trend of the data, it fails to account for the complexities inherent in the relationships between cryptocurrencies and stock indices. This is further evidenced by the MAPE values, which suggest considerable prediction errors, particularly in the validation phase (MAPE = 1.175). Despite its simplicity, the model achieved a reasonable Directional Accuracy (DA) of approximately 92%, indicating that it could correctly predict the direction of price changes more often than not.

The Random Forest model outperformed Linear Regression by a significant margin, particularly in terms of RMSE and MAPE. With RMSE values of 0.025 (train) and 0.063 (val), this model demonstrated a strong ability to fit the training data and generalize to unseen data. The low MAPE values, especially during training (0.056), indicate minimal errors in prediction, suggesting the model's robustness in capturing complex, non-linear relationships. However, the high accuracy during training (DA = 99.1%) compared to validation (DA = 98.6%) raises concerns about potential overfitting, where the model may be learning noise in the training data rather than the underlying data distribution.

LSTM models, known for their capability to model sequential data, provided a balanced performance with RMSE values of 0.076 and 0.081 for training and validation, respectively. The MAPE values, particularly in validation (0.185), were lower compared to the Linear Regression model but higher than those of Random Forest. The LSTM model's Directional Accuracy remained high (97.1%), indicating its strength in predicting the directional movement of asset prices. This suggests that while LSTM networks may not always outperform Random Forest in terms of raw error metrics, they provide robust directional predictions, crucial in financial forecasting.

The FNN model displayed moderate performance with RMSE values of 0.120 and 0.130 for training and validation. The MAPE values were notably higher than those for LSTM and Random Forest models, indicating that the FNN had more difficulty in accurately predicting the price levels. However, its DA was still strong, suggesting that while the FNN struggled with the magnitude of price changes, it was relatively effective in predicting the general trend.

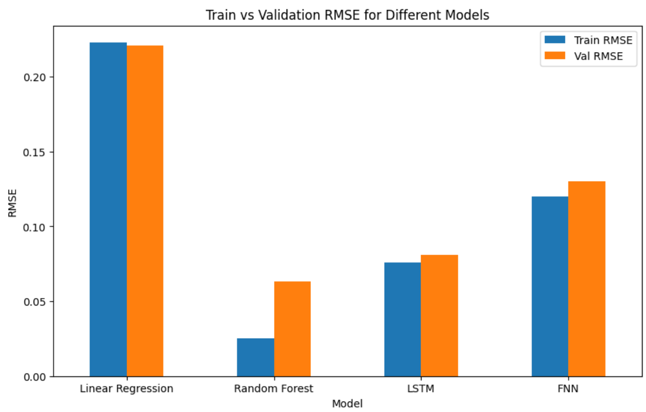

Fig. 7. Comparison of Train vs. Validation RMSE Across Different Models.

When comparing the models, as summarized in Table II and visualized in Fig. 7, the Random Forest model exhibits the lowest RMSE and MAPE, suggesting the best performance in terms of minimizing prediction errors. However, the risk of overfitting, as indicated by the significant difference between training and validation RMSE, necessitates caution in relying solely on this model for predictions. The LSTM model, with its balanced performance across all metrics, emerges as a strong candidate, particularly when considering its ability to handle sequential data effectively.

The detailed analysis for predicting specific asset-target pairs, as shown in Table I, highlights the practical utility of these models. For instance, the LSTM model applied to the BTC-SP500 pair resulted in an RMSE of 0.0968, a MAPE of 0.5336, and a Directional Accuracy of 94.92%. Similarly, for the ETH-NASDAQ pair, the LSTM model yielded even better results, with an RMSE of 0.0616, a MAPE of 0.1593, and a Directional Accuracy of 96.47%. These results underline the LSTM model's capability to capture the nuanced dynamics between specific cryptocurrencies and stock indices, making it a preferable choice for predictive modeling in these contexts.

TABLE I.

Asset-Target	**RMSE**	**MAPE**	**DA (%)**
BTC-SP500	0.0968	0.5336	94.92
ETH-NASDAQ	0.0616	0.1593	96.47

a. This table displays the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA) percentages for the predictions of cryptocurrency assets (BTC and ETH) against traditional market indices (SP500 and NASDAQ).

The findings suggest that Bitcoin (BTC) is a more suitable predictor for the S&P 500, while Ethereum (ETH) shows a stronger predictive relationship with the NASDAQ index. These conclusions are supported by the superior performance metrics observed in the LSTM models for these asset-target pairs. The comprehensive evaluation of these models demonstrates the critical importance of selecting the appropriate model type based on the specific financial context and prediction task at hand.

V. Conclusion

This study provides a framework for integrating cryptocurrencies with macroeconomic indicators to predict stock prices effectively. By first analyzing the relationship between a particular cryptocurrency, relevant macroeconomic indicators, and stock indices, as done in this research, one can determine whether proceeding with predictive modeling is justified. When such relationships are strong, the LSTM model, as shown in this study, can be employed to achieve reliable and robust predictions. These findings underscore the potential of cryptocurrencies as valuable predictors in the financial markets and pave the way for more informed and data-driven decision-making in investment strategies.

VI. Future Work

The findings of this study open several avenues for future research. One of the key areas for further exploration is the dynamic nature of the relationships between cryptocurrencies and traditional financial markets. Given the time-varying correlations observed in this study, future research could focus on developing and applying more advanced models that can better capture these dynamic interdependencies, particularly during periods of market stress or high volatility. This could include exploring other time-series models, such as regime-switching models or non-linear causality models, which may provide deeper insights into how these relationships evolve under different market conditions.

Future research could explore the practical application of these predictive models in real-time trading strategies and portfolio management. By testing the models in live market conditions, researchers could assess their effectiveness in generating returns and managing risks. Such studies would not only validate the theoretical findings but also contribute to the development of actionable tools for investors and financial professionals.

VII. References

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VIII. APPENDIX

TABLE II.

Model	RMSE		MAPE		DA (%)	
	Train	***Val***	***Train***	***Val***	***Train***	***Val***
Linear Regression	0.223	0.221	0.835	1.175	92.1	92.9
Random Forest	0.025	0.063	0.056	0.168	99.1	98.6
LSTM	0.076	0.081	0.139	0.185	98.0	97.1
FNN	0.120	0.130	0.271	0.341	96.4	96.0

b. This table compares the performance of different models (Linear Regression, Random Forest, LSTM, FNN) based on training and validation metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). The values indicate the models' effectiveness in predicting the target variable.