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Predicting Bitcoin Price Using Random Forest Regression: A Non-Linear Machine Learning Approach to Cryptocurrency Forecasting

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Abstract

This paper examines the predictability of Bitcoin price changes through a Random Forest Regression model that is used to predict the future price using past daily OHLCV (Open, High, Low, Close, Volume) data between 2011 and 2025. Since the cryptocurrency markets are non-linear and heteroskedastic, as well-documented, the customary linear models are not sufficient to understand the intricate dynamics of Bitcoin prices. The approach of the present paper consists of an ensemble machine learning strategy, with engineered features, including lagged prices, moving averages, log returns, and volatility measures, to increase the predictive accuracy. The non-parametric model is justified as linearity diagnostics such as QQ plots, OLS residual analysis, rolling variance, and Pearson-Spearman correlation comparisons demonstrated that data have a non-linear form. On the test set, the Random Forest model has reached an R 2 value of 0.9878 and a mean absolute percentage error (MAPE) of 3.29% which is an outstanding predictive performance. The results are relevant in the emerging body of research on machine learning applications in financial forecasting and emphasize the need to use non-linear modelling in volatile asset markets. Feature importance analysis further identified lagged prices and moving averages as the dominant predictors, confirming that short-term price momentum is the primary driver of Bitcoin price behaviour.

Keywords: *Predicting Bitcoin; Forest Regression; Machine Learning; Cryptocurrency Forecasting*

Introduction

Bitcoin has had a cumulative price increase of 155.51 percent since January 1, 2022, to October 4, 2025, and its price is at $121,845.52 (Bitcoin (BTC) 2022 2025 Price Analysis: Trends, Volatility, and Risk Adjusted Outlook, 202 Relative Strength Index (RSI) was identified as 64.11, which indicates a neutral market situation instead of an overbought or oversold market situation (In-Depth Analysis of BTC Price Volatility (2022-2025), 2022–2025). The institutional adoption, the next 2024 halving, and macroeconomic factors should drive the further increase of Bitcoin, even though the risks related to regulatory crackdowns and changes in market sentiment may affect the Bitcoin price. The analysis shows that there is no statistically significant correlation between the price and volume of Bitcoin before 2019. There is a positive correlation after 2019, according to which in the short term, the volume influences the price, and in the long term, the price change influences the volume (Moyo and Phiri, 2023). The empirical findings suggest that the relationship between returns and volume of the Bitcoin market has non-linear dependencies and power-law cross-correlations. All the identified cross-correlations are multifractal and they have antipersistent behaviours (Zhang et al., 2018). The cross-correlation between the price and volume of bitcoin is anti-persistent, multifractal, and asymmetric, with higher anti-persistencies observed in the uphill market trends than the downhill market trends, which suggests that the relationship between bitcoin market price and trading volume is complex (Yan et al., 2022). Unexpected trading volume is a strong predictor of the Bitcoin spot volatility as it captures 20 percent of the changes in the price volatility in the exchange level. But the CME Bitcoin future volumes have less effect on systemic volatility (Conlon et al., 2023) and both the return and trading volume have a statistically significant leverage effect. The relationships between the return and the trading volume are diversified and both positive and negative tail dependence structures are found. The positive tail dependence is more common than the negative tail dependence, which implies that co-movements are greater in increasing rather than decreasing directions. The study reveals that there is a spillover effect between the Bitcoin return and trading volume and both positive and negative tail dependence structure exists. The positive tail dependence is more dominant, implying that the market prices tend to co-move more in the increasing market prices as compared to the trading volume (Chang, 2022). Volume of trading is highly volatile, which is a remarkable aspect of the Bitcoin market (Navarro et al., n.d.). It concludes that in the quantile range of 0.25 to 0.75, volume forecasts Bitcoin returns, which provide predictability in some market situations, not in extreme bear and bull regime. According to the study, nonlinearity in the volume-returns relationship should be detected and modelled because the conventional linear Granger causality tests can be misspecified (Balcilar et al., 2016).The researchers observed a causality effect between the Bitcoin price and trading volume that negative shocks in prices cause negative shocks in volume and the reverse is also true which is a cointegrated relationship (Gemici and Polat, 2019). There is a positive short-term correlation between the trading volume and the market price of Bitcoin. The relationship is in the long run described as a corrective and mean-reverting behaviour, which shows a dynamic interaction between price and volume changes (Gbadebo, 2023). There isn't any strong correlation between the market price and trading volume of Bitcoin. Nevertheless, it also observes that Bitcoin returns positively correlate with the trading volume, meaning that the greater returns are, the greater the trading volume (Figà-Talamanca and Patacca, 2020). The volume of trade can forecast the returns of Bitcoin within the quantile of 0.25-0.75, which is not in the case of extreme bear and bull market periods. The importance of nonlinearity modeling and tail behaviour in the investigation of the causal relationship in the Bitcoin (Balcilar et al., 2017). The linear causality test implies that the returns cannot be predicted by the bitcoin trading volume (TV), whereas there is a significant reverse causality. The non-linear causality indicates that TV is a cause of price changes, which implies that the relationship between them is complex but not a simple correlation (Sahoo et al., n.d.).

High trading volumes tend to precede extreme positive returns in Bitcoin, suggesting a directional predictability. However, low trading activity generally lacks information about future returns, highlighting a complex relationship between Bitcoin's market price and trading volume (Fousekis & Grigoriadis, 2021).

Literature review

Bitcoin's volatility is significantly influenced by world events, particularly during the 2016 and 2020 U.S. elections, where political uncertainty and market sentiment led to dramatic price movements and heightened volatility, reflecting its evolving role as a financial asset (Medha & Tamizharasi, 2025).

Bitcoin volatility is significantly influenced by global events, particularly COVID-19, inflation, and the Russia-Ukraine conflict. Investors require about 45 minutes to process such news, impacting price movements and indicating increasing integration with traditional financial markets (Blasco et al., 2025). Bitcoin's average daily volatility is 2.73%, influenced by macro-economic tailwinds and institutional adoption. Price movements are affected by regulatory actions, macro-economic tightening, and network-level threats, with significant events like the 2024 halving likely to catalyze future price changes (*Bitcoin (BTC) 2022-2025 Price Analysis: Trends, Volatility, and Risk-Adjusted Outlook*, 2025). Bitcoin's average daily volatility is 2.73%, influenced by world events such as regulatory crackdowns, macroeconomic shocks, and market sentiment shifts. These factors can lead to significant price movements, creating both trading opportunities and heightened risks for investors (*Bitcoin (BTC) 2022-2025 Price Analysis: Trends, Volatility, and Risk-Adjusted Returns*, 2025).Heightened geopolitical risks are associated with decreased Bitcoin volatility in lower price levels, while in higher price levels, such risks initially spike volatility before decreasing. This indicates distinct reactions of Bitcoin prices and volatility to world events across different regimes (Buthelezi, 2024). Bitcoin's average daily volatility is 2.73%, influenced by macroeconomic shocks and geopolitical tensions. Regulatory uncertainty and network dynamics can trigger price corrections, while institutional adoption and halving cycles may sustain demand, impacting overall price movements (*Bitcoin (BTC) 2022-2025 Comprehensive Technical Analysis: Trends, Volatility, and Future Outlook*, 2025). The study indicates that news sentiment significantly influences Bitcoin's realized volatility, suggesting that world events reflected in news can drive price movements in the cryptocurrency market, providing valuable insights for traders and investors regarding market unpredictability (Miller, 2025).Bitcoin price volatility is significantly influenced by global factors, particularly the VIX. This relationship suggests that world events impacting market volatility can lead to notable price movements in Bitcoin, emphasizing the inherent risks of investing in it (Köse et al., 2024). The introduction of Bitcoin futures contributed to greater price stability as the market matured. Empirical evidence on the impact of macro-financial indicators on Bitcoin's price was mixed, with some models suggesting limited effects relative to internal market dynamics and investor sentiment ("Bitcoin: Price Formation, Economic Impact, and Volatility Dynamics," 2025). S&P 500 volatility negatively affects long-term Bitcoin volatility. Baltic dry index positively correlates with long-term Bitcoin volatility (Conrad et al., 2018). Bitcoin (BTC) achieved a 96% gain over the past year. The daily volatility of Bitcoin was recorded at 2.31%. Bitcoin's Sharpe ratio was noted to be 1.75, indicating strong risk-adjusted performance (*In-Depth Market Analysis of BTC (BTC-USD) for Investors*, 2025). Cryptocurrency volatility rises significantly during extreme geopolitical risk events. Cryptocurrencies are negatively correlated with safe-haven asset volatility (Fang et al., 2024). Major corporations' cryptocurrency adoption positively influences prices. Economic policy uncertainty and inflation negatively affect cryptocurrency prices (Mohammed et al., 2024). Cryptocurrency returns correlate positively with stock market and oil volatility. Weak volatility spillovers to cryptocurrency markets, intensify during turbulent periods (Będowska-Sójka et al., 2024). Geopolitical risk and economic policy uncertainty command a risk premium. Bitcoin investors can hedge their portfolio with gold during unfavorable economic conditions (Al Mamun et al., 2020)

Methodology

A random forest classifier was used to employ non-linear data and decrease over fitting through ensemble learning using variables like high low open, close percentage change and volume in order to test the the interactions among all the financial variables. Data was split between training and test data where the split was (80-20). Model performance was evaluated by checking Accuracy, R^2, RMSE, MAPE, MAE, F1, confusion matrix.

Research Design

The research design used in this study is based on a quantitative, data-driven research design founded on supervised machine learning. The study is based on a predictive modelling framework where the history of the Bitcoin market is used to train and test a Random Forest Regression model. It is an explanatory study that aims at not only predicting the prices of Bitcoin but also identifying the most important variables in the market that influence price behaviour. The entire structure is enforced to be cross-sectional in time-series and to ensure that time-order is enforced to avoid data leakage.

Data Collection and Sources.

The historical data on the prices of Bitcoin was obtained daily and spanning the years between 2011 and April 2026 and generated around 5,000 observations was collected from source. The data consisted of six main variables of the market, which are: Date, Price (Close), Open, High, Low, Volume, and percentage Change. The volume figures were documented in different units (K thousands, M millions, B billions) and had to be standardised before analysis as parsing was to be done. The data is one of the most extensive publicly accessible Bitcoin price histories, which allows the model to observe several market cycles such as bull runs, crashes, halvings, and consolidation periods.

Data Pre-processing

Raw data was extremely dirty before it could be modelled. Numbers with comma-formatted numbers were de-commafied and changed into float. Shorthand notation (K, M, B) volume entries were changed to absolute numeric values with a custom parsing function. The values of percentage change were cast to float and their symbol was removed. Day-first formatting was used to date the data and the data was chronologically ordered. After cleaning, list-wise deletion was used to eliminate missing values created by feature engineering to generate a final analytical data set of about 4,987 useful observations.

Feature Engineering

The fourteen features of the base variables were assembled to provide more predictive information to the model. The Lag features (Lag_1, Lag_2, Lag_3) have captured the prices of yesterday and the preceding days closing prices giving the model the short-term price memory. Rolling moving averages of 3 days (MA 3) and 7 days (MA 7) took short term trend momentum. The natural log of the ratio of successive closing prices was calculated to give a normalised measure of the change in price during a day, Log Return. Volatility was measured as intraday price range (High and Low). Price_Range_% gave this range in terms of a percent of the Low price. Volume Change recorded the daily percentage changes in trading volume. These characteristics combined to take a price momentum, trend direction, intraday volatility, and volume dynamics.

Linearity Testing

Before the model was selected, six formal and visual diagnostic tests were performed to determine the presence of a linear or non-linear behaviour of the Bitcoin price data. These were: (1) visual comparison of raw versus log-scaled price plots; (2) QQ plots of raw prices and log returns; (3) comparison of Pearson and Spearman correlation coefficients of feature pairs; (4) Shapiro-Wilk and Jarque-Bra normality tests on log returns; (5) OLS residual analysis looking at both residuals-versus-fitted and residuals- The combination of all six tests established the non-linear, non-normal and heteroskedastic character of data, which is statistically justified to use the non-linear model.

Model Training and Selection.

According to the linearity diagnostics, the main model chosen was a Random Forest Regressor since it was capable of dealing with non-linear relationships, it does not develop overfitting through ensemble averaging, and it generates interpretable feature importance scores. The model was set up based on 200 decision trees, a maximum depth of 5, a minimum of 3 samples per split, a minimum of 2 samples per leaf, and square root sampling of features per tree. To maintain the temporal order, which is important in time-series modelling, the dataset was divided 80/20 into training and test sets with no shuffling. This model was trained using about 3990 observations and tested using about 997 observations.

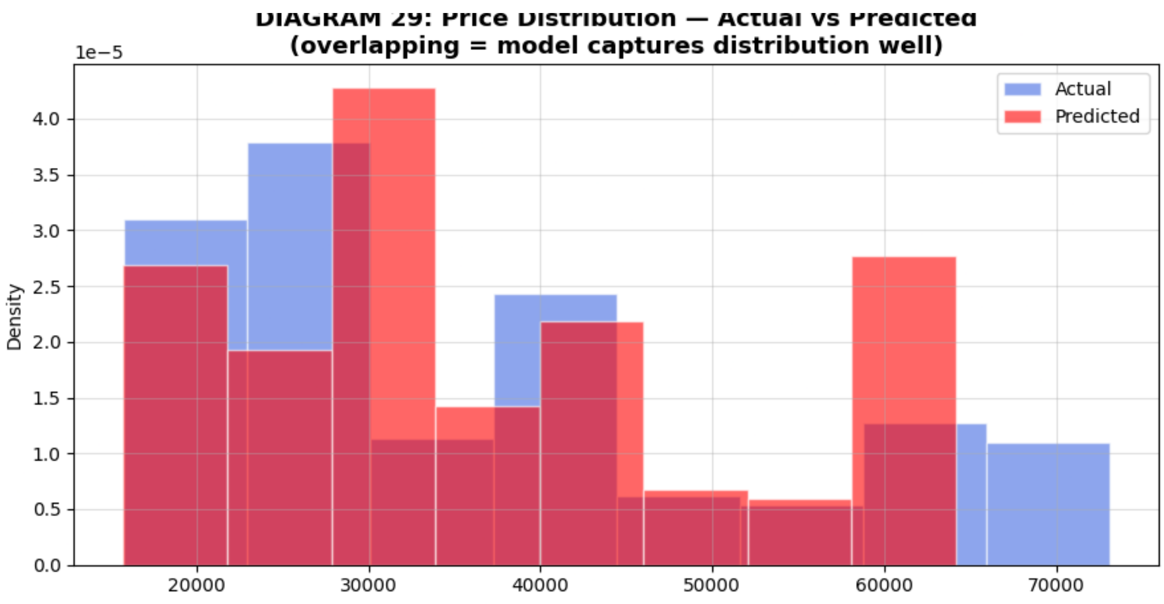
Model Evaluation

There were four regression measures of model performance, namely R 2 (coefficient of determination), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Moreover, cross-validation (5-fold) was performed to test the stability of the models using various data segments. Visual analysis involved actual-versus-predicted plots, residual analysis, a 95 percent confidence band calculated using individual tree predictions, partial dependence plots of the four best features, and rankings of feature importance using Gini impurity and permutation-based measures. The visualisation of decision trees of the first five trees were also created, which offered structural transparency into the decision-making process of the ensemble.

Analysis

Figure1

Price Distribution – actual vs predicted

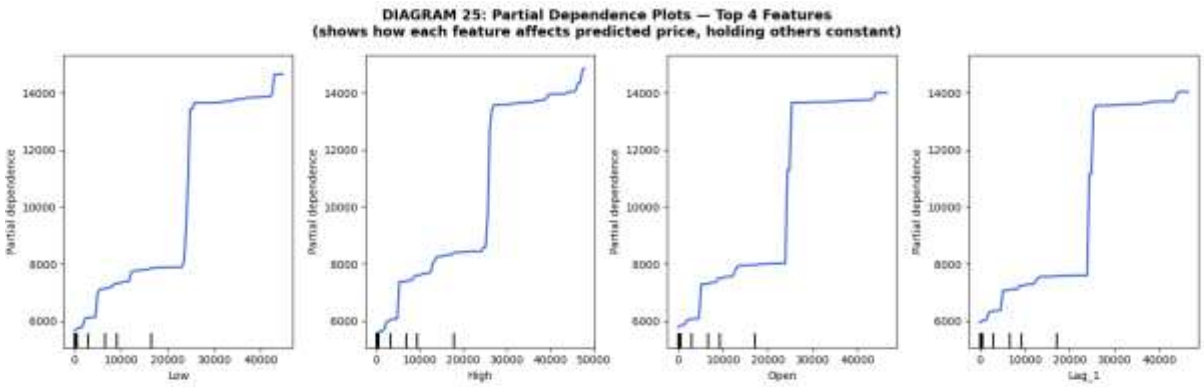


The figure is a comparative distribution of actual and projected prices using overlapping density histograms. Price in USD is plotted on the x-axis and probability density on the y-axis. The real price distribution is indicated in blue and the supposedly predicted distribution is indicated in red.

All in all, the model can describe the underlying price patterns fairly well, as the predicted distribution follows the overall pattern of the actual distribution closely. The distributions are both multimodal with apparent concentrations in the lower (around $20,00030,000), mid-range (around 35,00045,000), and high price ends (around 60,000 and above). The fact that the two histograms overlap in these areas indicates that the model is working well to give the approximations on the central tendencies.

Figure 2

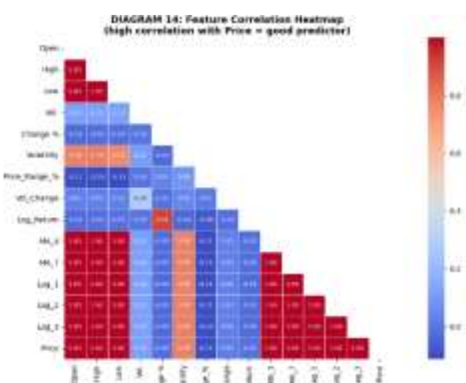
Partial dependence plot



In the figure, the partial dependence plots (PDPs) of the four most significant features, such as Low, High, Open and Lag 1, are used to show the marginal effects of the features on the predicted price, all other factors remaining unchanged. The x-axes denote the range of each feature and the y-axes denote the respective partial dependence values i.e. the price responsiveness as predicted by the model.

Figure 3

Feature correlation heatmap

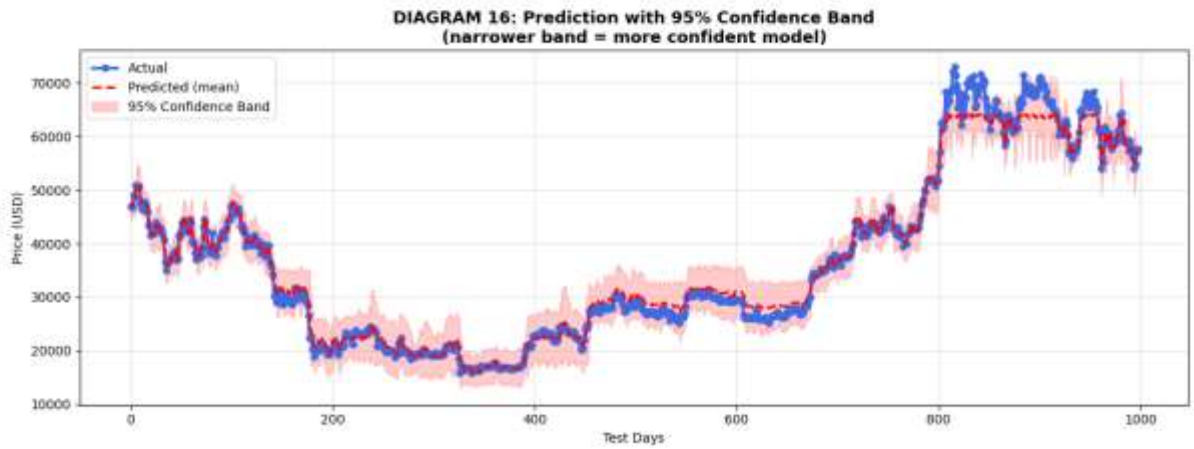


The figure shows a heatmap of the results of a correlation between the essential features employed in the model, such as price-related factors, technical indicators, and derived facets. The scale of the color goes between strong negative relationship (blue) and strong positive relationship (red) and the numerical coefficients are indicated in each cell. One of the most obvious findings in the heatmap is that the primary price variables (Open, High, Low, and Price) are positively correlated almost with each other, along with their derived lag features (Lag_1, Lag_2, Lag_3) and moving averages (MA_3, MA_7). The correlation coefficients of these variables are about 1.00 and this implies that multicollinearity is very high. This is expected in time-series financial data, where these variables interact with each other. The high correlations indicate that these variables are highly predictive of the target variable (Price) yet they can also cause redundancy to the model.

There is a moderate positive correlation of Volatility with the core price variables (around 0.76-0.79) which indicates that when prices are higher, market fluctuations are higher. Volume shows weak positive correlations i.e approximately 0.12 with price-related features, suggesting that trading activity has a small direct linear relationship with the price levels. The characteristics, including Change %, Price_Range_%, Vol_Change, and Log_Return, have a comparatively low or almost zero correlation with the majority of other variables, which suggests that they represent different facets of market behavior. It is worth noting that there is a strong positive correlation between Log_Return and Price_Range_% (around 0.91) because they are both dependent on the dynamics of price movements, and not on the absolute price levels.

In general, the heatmap reveals two important findings: first, the strong predictors are highly correlated price-based features, which can create a problem of multicollinearity; and second, there are a number of weakly correlated variables that can potentially be used to complement each other rather than to be redundant within the model. The results highlight the need to exercise caution in the selection of features and possible dimensionality reduction in the process of building predictive models.

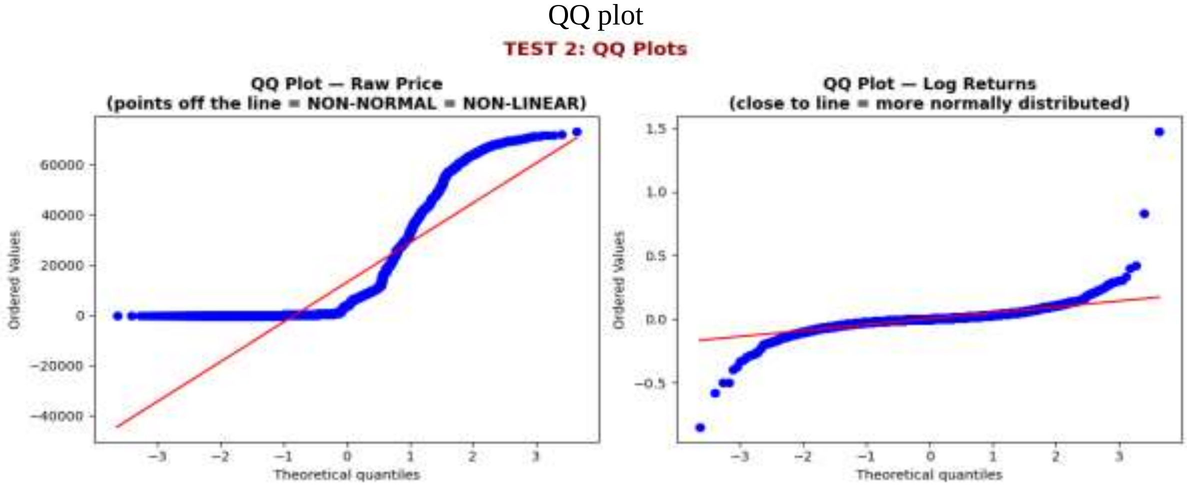
Figure 4
Prediction with 95% confidence band



Most of the real observations fall within the 95 percent confidence band, which shows that the uncertainty estimates in the model are well-calibrated and valid. The fact that the confidence interval is covered supports the strength of the model in measuring both the uncertainty of prediction and the point forecasts.

The figure demonstrates that the model delivers a good balance between the accuracy and the uncertainty estimate and thus successfully captures the price dynamics offering significant confidence boundaries that change with different degrees of market volatility.

Figure 5
QQ plot



The QQ plot of raw prices indicates that the data is not quite normal and skewed with a lot of deviation being above or below the reference. Conversely, the log returns are closer to the line indicating that it is more or less normally distributed with slight tail distortions. This shows that log transformation enhances normality and therefore log returns are more appropriate to model.

Figure 6
Train vs Test predictions

The actual observed values within the training area are represented by a continuous blue line, which reflects the historical development of the asset, including the time intervals of relative stability and steep increase, and high volatility in later years. The training set model predictions depicted in a blue dotted model line are close to the actual model predictions, which means that the model has been able to learn the underlying trends in the past data with reasonable accuracy.

Green markers indicate the real values in the testing region, whereas the red dashed ones depict the predicted ones. The forecasts tend to follow the trend of the real prices, and most of the significant trends, including an upwards and a downwards trend, are captured. Nonetheless, there are certain deviations that can be observed especially at times when there is a lot of fluctuation, whereby the model either underestimates the peaks or filters sharp changes. This implies that the model is a moderately generalized one to unseen data, but has weaknesses in extreme volatility. Generally, the figure shows that the model fits the training data reasonably well and retains a reasonable predictive accuracy on the test data although with lower precision in highly volatile periods. This action is also in line with much of the time-series forecasting literature that tends to be weak at capturing nonlinear, abrupt market processes.

Limitations

The limitation of this study is the use of technical price and volume data only without any consideration of potentially significant external factors like macroeconomic variables, investor sentiment, regulatory announcements, and social media activity that are cited in the literature as factors that affect Bitcoin volatility. Moreover, as the model has a high in-sample accuracy, the failure of the Random Forest to predict beyond the scope of training data could reduce its accuracy in unparalleled market conditions or extreme price movements that have not been studied in the historical data.

Conclusion

The paper has proven that Random Forest Regression is a robust and useful method to predict Bitcoin closing price, as it has an R 2 of 0.9878 and a MAPE of 3.29 percent when using unseen test data covering almost 1,000 days. The model has been able to capture key market cycles such as the bull runs in 2017 and 2021, the crash in 2022 and the recovery in 2024, though there was some minor underestimation in the most volatile periods of the market - which is unsurprising given the general literature on non-linear financial forecasting. The non-parametric ensemble model was selected because the linearity diagnostics revealed the non-linear structure of Bitcoin price data with unanimous support. The feature importance analysis showed that moving averages and lagged prices were the most significant predictors, which means that next-day Bitcoin prices are the strongest predictors by short-term price momentum, with the secondary but complementary roles of volume and percentage change. These results are consistent with the current literature that indicates the presence of complex and non-linear relationships between the price and the volume of trade in Bitcoin. The paper adds a reproducible, end-to-end machine learning pipeline forecasts cryptocurrency prices which combines data cleaning, linearity test, feature engineering, ensemble modelling, as well as overall visual diagnostics.

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