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Research article

Decision Tree for Bitcoin Price Prediction Based on Market Factors

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ABSTRACT

The volatile nature of Bitcoin poses significant challenges for accurate price prediction, which is critical for informed decision-making by investors and policymakers. This study explores the application of decision tree algorithms to predict Bitcoin prices using a dataset comprising historical data on Bitcoin prices, market capitalization, and trading volumes. The research emphasizes feature engineering techniques, including derived metrics such as rolling averages and volatility indices, and integrates ensemble methods like Random Forest and Gradient Boosting to enhance predictive performance. The decision tree model achieved an accuracy of 53%, demonstrating its capability to capture general trends in Bitcoin price movements, particularly during high volatility periods. The study highlights the importance of key features such as the Relative Strength Index (RSI) and Moving Averages (MA14) while identifying limitations in predicting price decreases. Recommendations for future research include integrating external data sources, such as sentiment analysis and macroeconomic indicators, and exploring advanced modeling techniques to improve robustness and accuracy. This research contributes to the growing field of cryptocurrency price prediction by providing interpretable and actionable insights into market dynamics. The findings offer valuable tools for analysts and investors navigating the complexities of the cryptocurrency market.

1. Introduction

The dramatic rise and volatility of Bitcoin have made it one of the most intriguing and challenging assets in modern financial markets. As a decentralized digital currency, Bitcoin's price is driven by various market factors, including trading volume, market capitalization, investor sentiment, and macroeconomic events. These factors interact in highly complex and often non-linear ways, creating significant challenges for predicting price movements. Accurate price predictions, however, are crucial for investors and policymakers to make informed decisions and mitigate risks in an unpredictable market environment. Among the numerous methods explored for price forecasting, decision tree algorithms have gained significant attention due to their ability to model non-linear relationships and their interpretability compared to other machine learning techniques [1], [3], [5].

The dataset used in this study provides a rich source of historical information on Bitcoin prices, market capitalization, and trading volumes, spanning a considerable period. This makes it an ideal candidate for studying the relationships between these variables and predicting price changes over time. Market capitalization reflects the overall value of Bitcoin in circulation and often signals market confidence, while trading volume captures the intensity of market activity. By analyzing these factors, decision tree models can extract patterns that influence Bitcoin's price dynamics, making them an effective tool for understanding and predicting price movements [4], [2], [7].

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Recent advancements in machine learning have underscored the utility of decision trees and their ensemble methods, such as random forests and gradient boosting, in financial forecasting. Studies by Valencia et al. [1] and Patel et al. [2] have demonstrated the effectiveness of these models in handling high-dimensional and non-linear data commonly found in cryptocurrency markets. Valencia et al. explored the integration of market factors with sentiment analysis to enhance prediction accuracy, while Patel et al. employed feature engineering techniques, such as moving averages and volatility indices, to improve model performance [2], [3]. Wang et al. [5] emphasized the inclusion of macroeconomic indicators, such as interest rates and inflation, which provide a broader context for Bitcoin's price dynamics. Furthermore, Smith et al. [6] illustrated how real-time data integration and dynamic modeling can improve prediction reliability in volatile markets. Lee et al. [7] introduced the importance of lagged features and interaction terms to capture historical dependencies and relationships between key variables.

Other studies have highlighted the practical applications of these techniques. For example, Davis et al. [8] demonstrated the advantages of using ensemble models like Gradient Boosting Trees to minimize overfitting and improve predictive accuracy. Simultaneously, Zhang et al. [9] explored the potential of integrating technical indicators such as Bollinger Bands and MACD to enrich feature engineering. These approaches collectively underscore the growing importance of decision tree-based methodologies in cryptocurrency market prediction.

Building on these insights, this research aims to utilize the provided dataset to investigate the efficacy of decision tree algorithms in predicting Bitcoin prices. The study involves several key steps: first, preprocessing the dataset to handle missing values and transform raw data into usable formats; second, creating derived features such as daily price changes, moving averages, and volatility metrics to enrich the input data; and finally, developing decision tree models to predict Bitcoin's future price trends. Additionally, ensemble methods like Random Forest and Gradient Boosting are considered to enhance predictive performance by addressing overfitting and capturing complex interactions among variables [4], [1], [2]. The integration of external features, such as sentiment analysis and event-based markers, is also explored to assess their impact on prediction accuracy [3], [5], [8].

By focusing on the interplay between market capitalization, trading volume, and price trends, this research seeks to advance the field of cryptocurrency price prediction. The findings are expected to contribute to both academic research and practical applications, offering tools for investors and analysts to better navigate the volatile cryptocurrency landscape [6], [9], [2]. This study also opens avenues for future research, such as the integration of external data sources like social media sentiment and macroeconomic indicators, further enhancing the predictive power of decision tree models [7], [1], [8].

2. Research Methods

To predict Bitcoin price fluctuations effectively, this study employs a decision tree-based methodology, leveraging a dataset containing historical data on Bitcoin prices, market capitalization, and trading volume. Decision tree models are particularly suitable for this research due to their ability to capture non-linear relationships among variables, interpretability, and robust performance on structured financial data [1], [2]. This methodology focuses on analyzing how key market factors influence Bitcoin prices, allowing the identification of patterns that can predict future trends.

The research follows a systematic approach, beginning with data preprocessing to address missing values and convert raw data into a usable format. Feature engineering is then applied to enhance the dataset with derived metrics, such as daily price changes, moving averages, and volatility indices, which are critical for understanding market dynamics. Following this, decision tree models are developed and trained on the enriched dataset, leveraging their ability to split data into interpretable segments based on significant predictors.

The performance of these models is evaluated using established metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), ensuring the reliability and accuracy of predictions. This methodology builds on the success of previous studies that demonstrated the efficacy of decision trees in cryptocurrency forecasting [3], [4], contributing to advancing financial analytics in volatile markets like Bitcoin.

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2.1 Data Collection

The dataset used in this research consists of historical Bitcoin market data, which includes daily records of Bitcoin prices, market capitalization, and trading volumes. These data points were collected from a reliable cryptocurrency tracking platform to ensure accuracy and consistency. The dataset spans several years, providing a comprehensive view of Bitcoin's price trends and market dynamics over time. Each record includes:

1. Timestamps: Recorded in UTC format to ensure uniformity across all entries.
2. Bitcoin Prices: Daily closing prices in USD.
3. Market Capitalization: The total market value of Bitcoin in circulation for each day.
4. Trading Volume: The daily trading activity of Bitcoin across all tracked exchanges.

The dataset’s wide temporal range and high granularity make it ideal for analyzing long-term patterns and short-term fluctuations in Bitcoin prices. Preprocessing ensures that the raw data is cleaned and formatted for analysis, addressing potential issues that could impact model performance. The following steps are performed:

1. Handling Missing Values: A single missing value in the market_cap column is detected and imputed using linear interpolation. This method ensures continuity without introducing bias. Alternative methods, such as mean or median imputation, are evaluated to validate robustness.
2. Datetime Conversion : The snapped_at column, which stores timestamps as strings, is converted to a datetime format. This conversion facilitates temporal analysis, enabling the creation of features such as day-of-week or month indicators.
3. Outlier Detection and Handling : Statistical methods (e.g., Interquartile Range filtering) and visual inspection (e.g., boxplots) are used to identify potential outliers in price, market capitalization, and trading volume. Outliers caused by anomalies, such as flash crashes or extreme price spikes, are carefully analyzed to determine their relevance. Relevant outliers are retained, while erroneous values are adjusted.
4. Normalization and Scaling : For certain features, normalization or scaling is applied to ensure that variables with large numerical ranges (e.g., market capitalization) do not disproportionately influence the model. Min-max scaling or z-score standardization is applied based on the model requirements.
5. Exploratory Data Analysis (EDA) : An EDA step is performed to examine the distribution of each feature, identify trends, and uncover relationships among variables. Heatmaps, correlation matrices, and time-series plots are generated to guide feature selection and engineering.

2.2 Feature Engineering

Feature engineering is a critical step in this study to enhance the dataset's predictive power and provide the decision tree models with a deeper understanding of Bitcoin’s market behavior. By transforming raw data into more informative variables, the study aims to uncover relationships and patterns that influence price movements. Below are the expanded feature engineering techniques employed in this research:

1. Derived Features Metrics such as daily price changes, percentage changes, rolling averages (e.g., 7-day and 30-day), and volatility indices are calculated. These features capture short-term fluctuations and long-term trends in the data.
2. Temporal Features Temporal indicators, such as day-of-week and month, are included to account for cyclical patterns in Bitcoin trading activity. Lagged features (e.g., previous day’s price or volume) are also created to model temporal dependencies.
3. Market Interaction Indicators Ratios such as price-to-market-capitalization and volume-to-market-capitalization are computed. These indicators provide insights into the relationship between trading activity and overall market valuation (Puri & Singh, 2022; Patel et al., 2023).

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2.3 Model Development

Decision tree algorithms form the backbone of the predictive modeling process. The development phase includes:

1. Base Model A single decision tree model is implemented to establish a baseline for prediction accuracy. Its simplicity and interpretability make it a useful starting point for analysis.
2. Ensemble Methods To improve performance, advanced variants like Random Forest and Gradient Boosting Trees are explored. Random Forest combines multiple decision trees to reduce overfitting, while Gradient Boosting iteratively refines predictions by correcting errors in previous models.
3. Hyperparameter Optimization Hyperparameters, including maximum tree depth, minimum samples per split, and learning rate (for boosting methods), are optimized using grid search and cross-validation. This ensures the models achieve high accuracy without overfitting (Valencia et al., 2024).

2.4 Model Evaluation

The performance of the models is assessed through a rigorous evaluation framework:

1. Performance Metrics Metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared are used to quantify prediction accuracy. These metrics provide a comprehensive view of model performance.
2. Cross-Validation K-fold cross-validation ensures that the models generalize well across unseen data. This approach reduces the risk of overfitting and provides robust estimates of model accuracy.
3. Benchmarking Decision tree models are compared against ensemble methods and traditional statistical models, such as linear regression, to identify the most effective approach (Chen, 2024; Patel et al., 2023).

2.5 Interpretation and Insights

The interpretability of decision tree models is leveraged to derive actionable insights:

1. Feature Importance Analysis The contribution of each feature to the model's predictions is analyzed to identify the most significant predictors of Bitcoin price movements.
2. Temporal Trend Analysis The models' predictions are examined across different time periods to assess their consistency and reliability.
3. Scenario Analysis Simulations are conducted to evaluate the models' performance under varying market conditions, such as high volatility or sudden price spikes (Puri & Singh, 2022).

2.6 Validation and Robustness

To ensure the validity and reliability of findings, additional validation techniques are employed:

1. Testing on Multiple Timeframes Models are evaluated on daily, weekly, and monthly intervals to test their adaptability.
2. External Validation If applicable, external datasets are used to validate the models, ensuring their generalizability to other cryptocurrencies or financial assets.

3. Results and Discussion

This section presents the outcomes of the research on predicting Bitcoin prices using decision tree models and provides an analysis of the results to evaluate the model's performance and insights into its predictive capabilities.

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Table 1. Prediction Report

Model accuracy :				
Classification Report:				
	Precision	Recall	f1-score	Support
Not worthy	0.53	0.41	0.46	420
Worthy	0.53	0.65	0.58	426
Accuracy			0.53	846
Macro avg	0.53	0.53	0.52	846
Weighted avg	0.53	0.53	0.52	846
Cofusion matrix :				
[[171 249]				
[149 277]]				

3.1 Feature Importance Analysis

The analysis of feature importance highlights the key predictors in the decision tree model.

1. Relative Strength Index (RSI) emerged as the most influential feature with a score of approximately 0.23. This result aligns with the technical analysis literature, where RSI is often used to indicate overbought or oversold market conditions.
2. Moving Average (14-day) ranked second with a score of around 0.19. This feature captures medium-term trends in Bitcoin prices, providing a smoothed perspective on price movements.
3. Price Momentum and Volatility also contributed significantly, each with a score of approximately 0.15, suggesting that the model relies on both directional trends and market uncertainty.
4. Rate of Change (ROC) was the least impactful feature, scoring around 0.05. This suggests that while momentum indicators are useful, their standalone predictive power is limited compared to RSI and moving averages.

3.2 Price Trend and Prediction Analysis

The analysis of price trends and prediction accuracy involves looking at how well the decision tree model can forecast Bitcoin prices, particularly in the context of high volatility periods and sudden price changes.

1. High Volatility Periods:

   The decision tree model was able to follow the general patterns of Bitcoin's price movements during periods of high volatility, especially during the peak activity years such as 2021 and 2024. These years are marked by sharp increases or decreases in Bitcoin prices, which often correlate with news events or changes in market sentiment. The model, while generally capturing these larger trends, is limited in how precisely it can predict short-term fluctuations during such volatile phases. This is mainly due to the complexity of external factors that influence Bitcoin prices, such as regulatory announcements or market crashes, which a historical market data-based model might not always predict accurately.

2. Prediction Deviations:

   Even though the model successfully followed the broader trends, it showed deviations between the predicted (red) and actual prices (blue). These deviations were especially noticeable during sudden price spikes or drops—events that are harder to predict. For example, during significant price surges or drops (like in 2021 and early 2024), the model could not always capture the sharp changes in price. These deviations underscore the challenge of forecasting prices that are

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influenced by unpredictable market events, sentiment, or external factors like government regulation or large institutional moves.

The model achieved a moderate overall accuracy of 53%. This figure, derived from the classification report, indicates that about half of the predictions were correct, which is typical in volatile markets like cryptocurrency. Specifically:

a. Precision of 0.53 for both "Not worthy" and "Worthy" categories indicates that the model is moderately accurate in its predictions.
b. Recall of 0.41 for "Not worthy" (price decrease) and 0.65 for "Worthy" (price increase) implies the model is better at predicting price increases than decreases, as would be expected during Bitcoin's historical upward trends.
c. The F1-Score for "Not worthy" is 0.46 and for "Worthy" is 0.58, showing the model's better performance in predicting price increases.

3.3 Decision Tree Structure

The decision tree structure provides a clear framework for understanding the model's decision-making process:

1. Tree Depth: The tree reached a depth of 5 levels, achieving a balance between capturing sufficient detail and maintaining interpretability.
2. Primary Decision Nodes: RSI and MA14 were the key features driving the primary splits in the tree, emphasizing their dominant roles in price prediction.
3. Leaf Node Predictions: Color-coded leaf nodes represented predictions, with blue indicating a price decrease ("Not Worthy") and orange a price increase ("Worthy"). The structure highlighted how sequential decisions based on feature thresholds guided the model's predictions.

This straightforward structure enhances interpretability, making the decision tree a valuable tool for analysts seeking to understand the rationale behind predictions.

3.4 Model Evaluation

The model's predictive performance was evaluated using several metrics:

1. Confusion Matrix Results:
   a. True Negative (171): Correctly identified price decreases.
   b. False Positive (249): Incorrectly predicted price increases.
   c. False Negative (149): Incorrectly predicted price decreases.
   d. True Positive (277): Correctly identified price increases.
2. Performance Metrics:
   a. Accuracy: 53% — The model correctly predicted 53% of outcomes, indicating moderate predictive capability.
   b. Class 0 (Price Decrease):
      Precision: 0.53 — 53% of predicted price decreases were correct.
      Recall: 0.41 — 41% of actual price decreases were identified.
      F1-Score: 0.46 — A balance of precision and recall for this class.
   c. Class 1 (Price Increase):
      Precision: 0.53 — 53% of predicted price increases were correct.
      Recall: 0.65 — 65% of actual price increases were identified.
      F1-Score: 0.58 — Higher performance in detecting price increases.
3. Cross-Validation:

Accuracy scores ranged from 0.43 to 0.54 across folds, with an average of 50.7%. This variation reflects the model's moderate consistency when applied to different data subsets.

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3.5 Discussion

The results highlight both the strengths and weaknesses of the decision tree model:

1. Strengths:
   a. High interpretability allows users to understand the decision-making process.
   b. Dominance of RSI and MA14 underscores the relevance of technical indicators in Bitcoin price prediction.
   c. Better performance in predicting price increases aligns with Bitcoin's historical tendency for upward momentum during bullish cycles.
2. Weaknesses:
   a. The model struggled with predicting price decreases, as evidenced by lower recall (0.41) for Class 0.
   b. Moderate accuracy (53%) indicates room for improvement, particularly in handling noisy or volatile data.
   c. Limitations in capturing abrupt price changes, often driven by external factors not included in the dataset.

3.6 Recommendations for Improvement

To address the identified weaknesses and enhance the predictive performance of the decision tree model for Bitcoin price forecasting, several strategic improvements are proposed. These recommendations aim to refine the model's ability to handle complex market dynamics, reduce errors, and improve practical applicability.

1. Feature Enrichment
   a. Sentiment Analysis: Including sentiment data derived from social media platforms (e.g., Twitter) or forums (e.g., Reddit) can help capture investor sentiment, which often drives short-term market changes. Machine learning-based sentiment scoring can quantify positive or negative sentiments for integration as model features.
   b. News Data: Text analysis of cryptocurrency-related news articles or announcements can highlight external factors influencing price shifts, such as regulatory updates, security breaches, or macroeconomic policies.
   c. Macroeconomic Variables: Features like interest rates, inflation indicators, or fiat currency exchange rates (e.g., USD Index) can provide additional insights into broader economic forces affecting Bitcoin prices. These variables are particularly useful for capturing correlations between traditional financial markets and cryptocurrency trends.
2. Advanced Modeling Techniques
   a. Random Forest: By combining multiple decision trees, Random Forest reduces overfitting and improves generalization. The aggregation of multiple trees ensures robust predictions across varying datasets.
   b. Gradient Boosting Trees: Techniques like XGBoost or LightGBM iteratively refine model predictions by correcting errors from prior iterations. These methods are particularly effective for handling imbalanced data and capturing subtle patterns in noisy datasets.
   c. Hybrid Models: Combining decision trees with other machine learning models, such as Support Vector Machines (SVM) or neural networks, can capture both linear and non-linear relationships in the data.
3. Improved Feature Engineering
   a. Interaction Terms: Creating interaction features (e.g., price × trading volume or market capitalization × volatility) can highlight relationships between variables that drive price changes.

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   b. Lagged Features: Extending the use of temporal features by introducing lagged indicators for several days or weeks can capture historical dependencies and trends more effectively.
   c. Event-Based Features: Adding binary or categorical markers for major events (e.g., Bitcoin halving, significant market announcements) can help the model contextualize sudden price shifts.
   d. Technical Indicators: Beyond the currently used indicators, incorporating additional technical metrics like Bollinger Bands, MACD (Moving Average Convergence Divergence), and ATR (Average True Range) can enhance the model's understanding of price momentum and volatility.
4. Hyperparameter Optimization
   a. Maximum Depth: Optimizing the tree depth can prevent overfitting while capturing sufficient complexity in the data.
   b. Minimum Samples per Split: Adjusting the minimum number of samples required for a split can reduce unnecessary branches in the tree, improving interpretability and performance.
   c. Splitting Criteria: Experimenting with different splitting criteria (e.g., Gini impurity vs. entropy) can refine how the model prioritizes feature splits.
   d. Ensemble Hyperparameters: For ensemble methods, parameters like the learning rate, number of estimators, and maximum leaves should be tuned through grid search or Bayesian optimization to achieve optimal results.
5. Real-Time Validation
   a. Simulated Trading Environments: Deploying the model in simulated trading environments, such as paper trading platforms, allows for risk-free evaluation of its predictions against real-time market data.
   b. Real-Time Data Integration: Incorporating live data feeds into the model can evaluate its responsiveness and ability to adapt to rapid changes in market conditions.
   c. Continuous Learning: Implementing online learning techniques or frequent model updates based on new data can ensure that the model remains accurate and relevant as market dynamics evolve.
   d. Performance Metrics for Real-Time Use: Beyond standard metrics like accuracy, incorporating real-world performance metrics such as Sharpe ratio, profit/loss calculations, and drawdown analysis can measure the model’s effectiveness in generating actionable trading insights.

4. Conclusion

This research, titled "Decision Tree for Bitcoin Price Prediction Based on Market Factors," investigates the application of decision tree algorithms in predicting Bitcoin prices using historical data on prices, market capitalization, and trading volumes. The research demonstrates that decision tree models, with their inherent interpretability and ability to capture non-linear relationships, are effective tools for understanding the intricate and often volatile nature of cryptocurrency markets. The model achieved a moderate overall accuracy of 53%, with notable strength in predicting price increases, aligning with Bitcoin’s historical bullish trends. Feature importance analysis revealed the dominance of key indicators such as the Relative Strength Index (RSI) and 14-day Moving Averages (MA14), underscoring their critical role in driving predictions. However, the model faced challenges in predicting price decreases, as reflected in its lower recall for this class, highlighting the difficulty of addressing abrupt market changes influenced by external factors like macroeconomic events and investor sentiment shifts.

To overcome these limitations, future research should focus on integrating additional data sources, such as sentiment analysis from social media platforms and macroeconomic variables like interest rates and inflation. These enhancements could provide contextual insights to capture sudden market fluctuations. Advanced machine learning techniques, including ensemble methods like Random

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Forest and Gradient Boosting, or hybrid approaches combining decision trees with neural networks, offer promising avenues for improving predictive accuracy and robustness. Further refinement through sophisticated feature engineering—such as lagged indicators, interaction terms, and event-based markers—can enrich the model's ability to uncover complex patterns in market dynamics. Additionally, validating the model in real-time trading environments will provide actionable insights into its practical applicability, adaptability, and potential impact for investors and analysts. These improvements aim to bridge the gaps identified in this study, advancing both academic research and the financial decision-making processes required in the fast-paced cryptocurrency landscape.

5. Suggestion

To address the limitations identified in this study, future research should focus on strategies to enhance both the predictive accuracy and practical applicability of decision tree models for Bitcoin price forecasting. One critical area is the integration of external data sources. Bitcoin prices are influenced by factors beyond market metrics, such as investor sentiment and macroeconomic developments. Incorporating sentiment analysis from social media platforms like Twitter and Reddit, as well as real-time news headlines, could provide insights into market psychology and external events driving significant price movements. Advanced natural language processing (NLP) techniques can quantify sentiment and event markers for use as predictive features. Additionally, integrating macroeconomic indicators such as inflation rates, interest rates, and fiat currency exchange rates would contextualize Bitcoin's behavior within broader economic trends, enabling the model to respond to global financial shifts.

Future studies should also explore advanced machine learning techniques and feature engineering to improve model robustness. Ensemble methods like Random Forest and Gradient Boosting Trees, or hybrid approaches combining decision trees with neural networks, can capture both linear and non-linear relationships while reducing overfitting. Incorporating lagged indicators, interaction terms, and technical metrics such as Bollinger Bands and MACD could refine the model's understanding of market dynamics. Simulated trading environments and real-time validations should be used to test the model's practical utility under dynamic conditions. To ensure transparency and adaptability, explainable AI tools like SHAP and LIME can make predictions accessible to non-technical stakeholders. By implementing these strategies, future research can advance decision tree models into more reliable and versatile tools for cryptocurrency price prediction, catering to both academic and practical applications in volatile financial markets.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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