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Research article

Decision Tree Model for Predicting Ethereum Price Movements Based on Trends

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ABSTRACT

This research investigates the application of a Decision Tree model for predicting Ethereum price movements using historical trend data. The dataset includes key attributes such as open, high, low, close prices, and trading volume, offering insights into market dynamics. The research emphasizes preprocessing and feature engineering techniques, including normalization and the introduction of derived metrics like moving averages and Relative Strength Index (RSI). Despite the model's simplicity and interpretability, it achieved an accuracy of 49.10%, indicating limited effectiveness in capturing non-linear relationships in volatile cryptocurrency markets. Analysis reveals challenges in distinguishing price trends and handling data imbalances, leading to suboptimal performance. These findings highlight the complexities of financial prediction and underscore the need for advanced machine learning methods. Future work should explore ensemble models, richer datasets incorporating sentiment analysis, and resampling techniques to improve robustness and predictive accuracy. This research contributes to the growing literature on machine learning applications in cryptocurrency analytics.

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1. Introduction

The cryptocurrency market, characterized by its high volatility and dynamic trends, has become a focal point for traders and researchers seeking to understand price movements. Among these cryptocurrencies, Ethereum (ETH) stands out due to its dual role as both a digital currency and a blockchain platform enabling smart contracts. Predicting Ethereum's price movements has significant implications for investors and market participants aiming to optimize trading strategies and manage risks effectively. To address this challenge, this study explores the application of a Decision Tree model, a machine learning technique known for its interpretability and effectiveness in analyzing structured data[1],[2].

Decision Trees are particularly suited for financial market prediction due to their ability to capture non-linear relationships and provide clear decision-making paths. Recent studies have highlighted their utility in forecasting stock and cryptocurrency price movements, showing promising results in accuracy and computational efficiency. This paper builds upon these findings by utilizing historical Ethereum price data to train a Decision Tree model. The dataset encompasses key metrics such as open, high, low, close prices, and trading volume, offering a comprehensive view of market dynamics.

Ethereum's price behavior is influenced by a myriad of factors, including market sentiment, macroeconomic events, and technological developments. Unlike traditional financial assets, Ethereum's value is closely tied to its ecosystem's growth, including decentralized applications (DApps) and non-fungible tokens (NFTs). By incorporating historical price trends and trading volume, the Decision Tree model aims to identify patterns that indicate potential price movements.

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This approach provides a data-driven framework to support traders in making informed decisions. Machine learning models have gained traction in financial analytics due to their scalability and ability to adapt to evolving data patterns[3]. However, one of the challenges in cryptocurrency analysis is the noisy and sparse nature of the data. This study employs preprocessing techniques to handle data irregularities, ensuring the model's robustness and reliability. Furthermore, the interpretability of Decision Trees offers an advantage over more complex models like neural networks, enabling traders and analysts to understand the reasoning behind predictions..

In conclusion, this research contributes to the growing body of knowledge on cryptocurrency price prediction by demonstrating the application of a Decision Tree model for Ethereum price movements. By analyzing historical trends and identifying actionable insights, the study highlights the potential of machine learning to enhance trading strategies in volatile markets. Future work can extend this approach by integrating additional features, such as social media sentiment and blockchain activity metrics, to further improve prediction accuracy[4].

2. Research Methods

The methodology of this study focuses on constructing and evaluating a Decision Tree model to predict Ethereum's price movements based on historical trend data. Cryptocurrency markets, including Ethereum, are inherently volatile, requiring a systematic approach to develop accurate and reliable predictive models[5]. This research leverages a dataset containing hourly Ethereum price data, including open, high, low, and close prices, as well as trading volume. These attributes offer a detailed and comprehensive view of market behavior, making them suitable for identifying trends and patterns. The Decision Tree model is selected for its interpretability, allowing for transparent predictions—a key factor in financial applications.

The first step in the methodology is data preprocessing, which ensures the dataset's quality and consistency. Missing values, common in financial datasets, are addressed using imputation techniques such as interpolation or deletion. Data normalization is applied to scale numerical features into a uniform range, preventing any single attribute from disproportionately influencing the model. Temporal features, such as day-of-week or hour-of-day, are extracted to capture cyclical market behavior. This stage ensures that the data is clean, structured, and ready for analysis. Feature engineering follows data preprocessing, aimed at enhancing the dataset's predictive power. Derived features, including moving averages, price momentum, and relative strength index (RSI), are introduced to represent market dynamics more effectively[6]. Lagged variables are also incorporated to model the influence of historical prices and volume on current movements. These engineered features provide additional context and improve the model's ability to detect meaningful patterns that influence price trends.

The Decision Tree model is then constructed and trained using the preprocessed and engineered dataset. The data is split into training and testing sets, typically with an 80-20 ratio, to validate the model's performance on unseen data. Hyperparameter tuning, such as adjusting tree depth and minimum samples per split, is carried out to optimize the model's performance. Finally, the model is evaluated using metrics such as accuracy, precision, recall, and F1 score, providing a comprehensive assessment of its predictive capabilities[7],[8]. Visualization of the decision-making paths further ensures transparency and interpretability, highlighting the rationale behind each prediction. This structured methodology aims to align with the study's objective of delivering a robust and practical solution for predicting Ethereum price movements.

The evaluation process also involves analyzing the Decision Tree model's performance in the context of different market conditions. Since the cryptocurrency market is highly volatile, the model's ability to adapt to sudden price fluctuations is tested through scenario-based simulations. For example, the model is exposed to datasets from high-volatility periods (e.g., market crashes or surges) to assess its resilience and accuracy in extreme conditions. This step provides insights into the model's reliability and robustness, ensuring its practical application in real-world trading scenarios. Additionally, comparisons are made with baseline models, such as linear regression, to benchmark the Decision Tree's performance and demonstrate its advantages in handling complex, non-linear relationships.

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Finally, the research incorporates visual tools to enhance the interpretability and usability of the predictions. Decision Tree visualizations allow traders and analysts to understand the logic behind each prediction, enabling informed decision-making. Furthermore, feature importance scores are calculated to identify the most influential factors driving Ethereum price movements, providing valuable insights into market dynamics[9],10]. These insights can be used to refine trading strategies or guide future research on cryptocurrency prediction. By combining rigorous evaluation, interpretability, and practical insights, this methodology not only builds a reliable prediction model but also contributes to the broader understanding of the factors influencing Ethereum price trends.

2.1. Data Collection

The data used in this study consists of hourly Ethereum price records, including attributes such as open, high, low, close prices, and trading volume. These attributes were chosen because they offer granular insights into the dynamics of the Ethereum market, capturing fluctuations that occur within short timeframes. By incorporating hourly data, the model gains a detailed perspective on intra-day price movements, allowing it to recognize not only rapid price reversals but also subtle shifts that may lead to emerging trends. This fine-grained resolution enables the detection of both short-term volatility and longer-term directional patterns, offering predictive power that would be less effective with lower-frequency data.

This granularity is particularly important in the volatile cryptocurrency market, where price movements can change significantly within hours, providing a rich dataset for training and testing predictive models. Volatility and rapid shifts are inherent characteristics of cryptocurrencies, and having access to high-frequency data allows for better anticipation of abrupt changes, which are often driven by investor sentiment, news events, or market speculation.

To ensure the data's accuracy and relevance, it is sourced from trusted cryptocurrency exchanges or financial data providers. These sources offer high-frequency data with minimal latency, ensuring that the dataset reflects real market conditions and is suitable for time-sensitive financial modeling. Moreover, the inclusion of trading volume alongside price data helps to capture market sentiment and liquidity, which are critical in predicting price movements. Trading volume serves as a proxy for market activity, often correlating with significant price changes and indicating the strength behind price trends. This combination of reliable sources and comprehensive attributes ensures the dataset is both robust and representative of Ethereum's market behavior, forming a strong foundation for the development of the Decision Tree model.

2.2. Data Preprocessing

This step ensures the dataset's consistency and quality, a critical prerequisite for building a reliable predictive model. Financial datasets, especially those with high-frequency data like hourly cryptocurrency prices, are prone to missing or incomplete entries due to network delays, API interruptions, or exchange maintenance. These missing values are addressed using techniques such as interpolation, which estimates the missing data points based on trends in the surrounding values, or through removal of records if interpolation is not feasible or appropriate. Addressing these gaps is essential to maintain data integrity, prevent the introduction of noise, and reduce potential biases that could skew the model's outcomes.

Furthermore, normalization is applied to scale numerical attributes, such as prices and volumes, into a uniform range. This is particularly important in decision tree models to ensure that the scale of input variables does not impact the feature selection process. While decision trees are generally robust to unscaled data, normalization can still enhance training efficiency and make comparisons between different attributes more meaningful. It ensures that no single feature—especially one with large numerical values like trading volume—dominates the learning algorithm simply due to its magnitude.

In addition to cleaning and scaling the data, temporal features such as the day of the week or hour of the day are extracted to account for periodic trends in the cryptocurrency market. These features allow the model to capture cyclical patterns that frequently occur in financial markets, such as increased volatility during certain hours or consistent trading behaviors linked to time zones and global market openings. For instance, certain weekdays might see more trading activity due to market

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sentiment or macroeconomic events. Incorporating these temporal attributes improves the model's ability to identify recurring price movements that may otherwise go unnoticed.

This combination of preprocessing steps—handling missing values, normalization, and feature extraction ensures the dataset is clean, structured, and enriched with relevant information. It lays a solid groundwork for the subsequent stages of model development by enhancing data quality and equipping the model with features that reflect both raw market data and derived temporal patterns.

2.3. Feature Engineering

Feature engineering is employed to enhance the dataset's predictive power by creating meaningful indicators that reflect market dynamics. In the context of financial time-series data, raw attributes such as price and volume can be transformed into more informative features that reveal deeper patterns and relationships. Derived features like moving averages are used to capture momentum by averaging price data over specified time periods. This technique helps highlight longer-term trends and smooth out short-term volatility, allowing the model to focus on sustained movements rather than random noise. By using various time windows for the moving averages—such as short-term (e.g., 5-hour) and long-term (e.g., 20-hour)—the model can differentiate between quick shifts and broader market direction.

The Relative Strength Index (RSI), a widely used technical indicator, is included to evaluate whether Ethereum is in overbought or oversold conditions. RSI provides a normalized score based on recent gains and losses, offering insight into potential price reversals and shifts in momentum. This indicator helps identify periods where price movements may deviate from typical behavior due to speculative activity or market corrections, which are common in cryptocurrency trading.

Additionally, the volume-weighted average price (VWAP) is introduced to represent the relationship between price and trading volume. VWAP is particularly valuable in understanding price levels that attract significant trading interest, as it integrates both the magnitude of trades and their corresponding prices. This feature helps the model identify equilibrium points in the market where buying and selling pressures may balance out or shift, providing context for decision-making.

Lagged features are another essential component of feature engineering, as they incorporate the historical influence of past prices and trading volumes on current price movements. These features, derived by shifting existing variables backward by one or more time steps, enable the model to consider how recent changes influence the present. For instance, the inclusion of lagged price data from one or several hours prior allows the model to recognize short-term trends or reversal patterns that evolve over time. This is particularly important in a volatile market like cryptocurrency, where price action is often autocorrelated, and recent movements serve as predictors for near-future changes.

By combining derived indicators and lagged features, the dataset is enriched with contextually relevant information that goes beyond raw data points. This comprehensive set of features enables the Decision Tree model to detect subtle patterns, interactions, and market signals, ultimately improving its ability to make accurate and timely predictions about Ethereum's price movements.

2.4. Model Construction

The Decision Tree algorithm is commonly utilized for constructing predictive models due to its simplicity, interpretability, and capability to handle both linear and non-linear relationships within the data. This algorithm operates by recursively splitting the dataset into subsets based on feature values that lead to the highest information gain or lowest impurity, depending on the chosen criterion such as Gini index or entropy. One of the key strengths of Decision Trees lies in their ability to provide clear and easily understandable decision rules, which are represented in a hierarchical structure. This transparency makes the model particularly valuable in domains where interpretability is essential, as users can trace the logic behind each prediction in a straightforward manner.

Moreover, Decision Trees are highly versatile, as they can handle both categorical and continuous variables without requiring extensive data transformation. This characteristic allows them to work effectively across diverse datasets, including those that involve a mix of numeric indicators and discrete classifications. In financial time-series data like cryptocurrency prices, where attributes such as price, volume, and technical indicators vary continuously, this flexibility is especially advantageous.

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To ensure the model is evaluated in an unbiased manner, the dataset is typically split into training and testing subsets. An 80-20 split is commonly used to provide the model with a substantial amount of data for learning patterns while reserving a separate portion for validation. This separation helps assess the model's ability to generalize to new, unseen data and prevents overly optimistic performance evaluations that may arise from testing on training data.

Hyperparameter optimization is then performed to fine-tune the model's performance and address the risks of overfitting or underfitting. Key parameters such as maximum tree depth, the minimum number of samples required to split a node, and the minimum number of samples per leaf are systematically adjusted. Deeper trees tend to capture more detail from the training data but may become overly complex and less generalizable. Conversely, shallower trees may overlook important relationships. Finding the optimal balance through techniques like grid search or cross-validation enhances the model's predictive capability while maintaining its robustness and efficiency.

2.5. Model Evaluation

To gain a deeper understanding of the model's decision-making process, a sensitivity analysis is The model's predictive performance is assessed using a variety of standard evaluation metrics to provide a comprehensive understanding of its capabilities. Accuracy, precision, recall, and F1 score are calculated to gauge the model's overall effectiveness and its ability to make correct predictions for both classes in a binary classification task. Accuracy measures the overall correctness, while precision and recall focus on the positive class's performance. The F1 score balances these two metrics, providing a single value that represents both precision and recall. A confusion matrix is also employed to visualize the model's performance, helping to highlight where the model might be making errors, such as false positives and false negatives, for a clearer assessment of its classification quality.

To enhance transparency and interpretability, the Decision Tree's decision paths are visualized. This allows users to follow the model's logic in making predictions, showcasing the specific features and thresholds that lead to certain outcomes. Such visualizations offer insights into how the model operates and aids in understanding its decision-making process. Furthermore, a comparative analysis is conducted with baseline models like linear regression to contextualize the Decision Tree's effectiveness. By comparing performance metrics across different algorithms, the strengths and weaknesses of the Decision Tree model are better understood, helping to justify its use or suggest possible improvements.

3. Results and Discussion

The Decision Tree model achieved an accuracy of 49.10%, which falls below the baseline of random guessing (50%). This indicates that the model is not performing well in predicting Ethereum price movements, as its predictions are less reliable than random chance. The confusion matrix reveals significant misclassifications between class -1 (price decrease) and class 1 (price increase), demonstrating the model's difficulty in distinguishing between opposing trends. This suggests that the decision boundaries formed by the model are insufficient to capture the underlying patterns in the data.

Additionally, the classification report highlights low precision, recall, and F1-scores across all classes, reflecting the model's inability to generalize effectively to unseen data. The low recall for class 1 (price increase) is particularly concerning, as it indicates the model often fails to detect instances of price increases. These results point to inherent challenges in modeling financial price movements, which are influenced by complex and noisy factors that a simple Decision Tree algorithm may struggle to capture.

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Table 1. Decision Tree Model for Predicting Ethereum Price Movements Based on Trends

Metric	Value	Explanation
Accuracy	49.10%	The model correctly predicted 49% of test instances. Slightly below the baseline (50%), showing poor performance.
Runtime	0.13 seconds	Indicates computational efficiency for predictions.
Confusion Matrix		Highlights misclassification across three classes (-1, 0, 1):
	[[1660, 268, 1188]	- Predicted Class: -1 (correct: 1660, misclassified as 0: 268, as 1: 1188)
	[118, 404, 118]	- Predicted Class: 0 (correct: 404, misclassified as -1: 118, as 1: 253)
	[1567, 253, 1324]]	- Predicted Class: 1 (correct: 1324, misclassified as -1: 1567, as 0: 253)
Classification Report		
Precision (-1, 0, 1)	0.50, 0.44, 0.50	Measures correct positive predictions. Precision is low across all classes.
Recall (-1, 0, 1)	0.53, 0.63, 0.42	Indicates how well the model identifies true instances of each class. Recall is particularly low for class 1.
F1-Score (-1, 0, 1)	0.51, 0.52, 0.46	Balance of precision and recall. Reflects underwhelming model performance.
Macro Avg (P/R/F1)	0.48/0.53/0.50	Equal weight to all classes; low averages reflect overall poor performance.
Weighted Avg (P/R/F1)	0.49/0.49/0.49	Weighted by the number of instances per class, similar to macro averages.

3.1. Complexity of Financial Data

Predicting price movements in volatile markets such as Ethereum is inherently challenging due to noise, rapid fluctuations, and external influences like market sentiment and macroeconomic factors. The cryptocurrency market operates 24/7 and is influenced by a wide range of unpredictable variables, including regulatory announcements, technological advancements, and even social media trends. This level of volatility creates a highly dynamic environment that traditional models often struggle to navigate.

Furthermore, the lack of standardized data and the potential presence of anomalies, such as sudden price spikes or drops, make it difficult for models to identify consistent patterns. Unlike traditional financial markets, where trends may follow more predictable cycles, cryptocurrency price movements often deviate from standard economic principles, adding an extra layer of complexity.

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This unpredictability challenges even advanced models to generalize effectively across different timeframes and market conditions.

Additionally, external factors such as geopolitical events or major shifts in global financial markets can indirectly influence cryptocurrency prices, further complicating prediction efforts. These external influences are often difficult to quantify and incorporate into predictive models. As a result, capturing the nuanced and interconnected nature of Ethereum's price movements requires more sophisticated modeling techniques and richer datasets that go beyond traditional technical indicators.

3.2. Data Limitations

The model may lack important features that are essential for accurately predicting price movements. Technical indicators such as the Relative Strength Index (RSI), Moving Averages (MA), Bollinger Bands, or even momentum oscillators are often critical for capturing trends and reversals in financial data. Without these features, the model might struggle to identify key patterns that are commonly used by traders and analysts to make decisions. Incorporating these indicators could provide the model with a more comprehensive view of the market dynamics, potentially improving its performance.

Another limitation lies in the absence of external contextual data, such as market sentiment or news sentiment analysis. Sentiment data derived from social media platforms, news outlets, or blockchain activity can provide insights into the psychological and behavioral factors influencing traders. For example, sudden spikes in social media discussions or news coverage about Ethereum could indicate market movements that are not reflected in historical price data alone. Including these types of features might help the model better understand the drivers behind sudden price changes.

Additionally, the dataset may suffer from class imbalance, with unequal representation of price increases, decreases, and stable trends. This imbalance can lead the model to become biased toward the majority class, reducing its ability to predict minority classes accurately. For instance, if stable trends dominate the dataset, the model might overpredict stability while neglecting instances of significant price changes. Addressing this issue through data resampling techniques, such as oversampling the minority classes or using synthetic data generation methods like SMOTE, could help balance the dataset and improve the model's learning process.

3.3. Model Simplicity

Decision Trees, while interpretable and easy to implement, are less effective for solving complex, non-linear problems such as financial predictions. Their structure relies heavily on splitting the data based on thresholds, which can oversimplify intricate relationships within the dataset. In the context of predicting Ethereum price movements, the Decision Tree's inability to capture non-linear interactions between variables may lead to suboptimal decision boundaries. This limitation makes it difficult for the model to adapt to the dynamic and chaotic nature of financial markets.

The confusion matrix highlights significant misclassifications, particularly between opposing classes like price increases (-1) and decreases (1). This suggests that the model struggles to differentiate between these trends, possibly due to overlapping features or insufficiently informative splits. As Decision Trees partition the feature space into discrete regions, they may fail to capture subtle but crucial nuances in the data. This challenge is exacerbated when the features lack predictive strength or when the dataset contains noise, both of which are common in financial data.

Another inherent weakness of Decision Trees is their susceptibility to overfitting, especially when dealing with noisy or unbalanced data. While pruning techniques can mitigate this issue, they may still fail to address the model's fundamental limitations in representing complex relationships. Alternative approaches, such as ensemble methods like Random Forests or Gradient Boosting, can combine multiple Decision Trees to create more robust and accurate predictions. These methods can help smooth out individual tree errors and better capture the non-linear patterns required for reliable financial predictions.

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3.4. Feature Engineering

Introducing additional features like trading volume, momentum indicators, or news sentiment analysis can provide richer context and significantly enhance the predictive capability of the model. Trading volume, for example, is a critical metric that reflects market activity and interest. High trading volumes often indicate strong investor confidence or significant price movement potential, while low volumes may signal indecisiveness or consolidation periods. Including this feature can help the model capture underlying market dynamics that are not immediately evident in price trends alone.

Momentum indicators, such as the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), or Stochastic Oscillator, can provide valuable insights into the strength and direction of price movements. These technical indicators are widely used in financial analysis to identify overbought or oversold conditions, potential trend reversals, or the momentum behind price changes. Incorporating these indicators as features can give the model a more nuanced understanding of market behavior, enabling it to better predict short-term and long-term price movements.

Additionally, news sentiment analysis can play a pivotal role in capturing external factors that influence Ethereum's price. By analyzing sentiment from news outlets, social media, and public forums, the model can incorporate qualitative data into its predictions. For instance, positive sentiment around Ethereum's technological advancements or regulatory developments might precede price increases, while negative sentiment related to security concerns or market uncertainty could signal potential downturns. Integrating sentiment analysis as a feature could allow the model to account for market psychology, providing a more holistic approach to predicting price movements.

3.5. Data Balancing

Using resampling techniques, such as oversampling the minority classes or undersampling the majority classes, can help address the issue of class imbalance in the dataset. Oversampling involves duplicating instances from underrepresented classes to increase their proportion in the dataset, ensuring that the model receives sufficient examples to learn from. Conversely, undersampling reduces the number of instances in overrepresented classes, creating a more balanced dataset. Both approaches can help mitigate the bias that occurs when the model overemphasizes the dominant class, improving its ability to generalize across all classes.

Synthetic methods like the Synthetic Minority Oversampling Technique (SMOTE) can further enhance the effectiveness of addressing class imbalance. Unlike simple duplication, SMOTE generates new synthetic data points for the minority class by interpolating between existing instances. This approach creates more diverse and representative data samples, reducing the risk of overfitting caused by repetitive patterns. By using SMOTE, the model can learn more robust decision boundaries, particularly in cases where the minority class is crucial for the problem at hand, such as predicting significant price movements.

Incorporating these resampling strategies can lead to a more balanced representation of price increases, decreases, and stable trends, ultimately improving the model's performance. However, careful consideration is needed to avoid introducing noise or distorting the original data distribution. Combining resampling techniques with cross-validation can ensure that the model is evaluated on unbiased subsets of the data, providing a clearer picture of its real-world applicability. These steps can collectively enhance the reliability and accuracy of predictions in volatile financial markets like Ethereum.

3.6. Model Optimization

Hyperparameter tuning is a technique used to improve a model’s performance by adjusting specific parameters that affect the training process. For decision tree models, some important hyperparameters to experiment with include tree depth, minimum samples per split, and minimum samples per leaf. By modifying these values, you can control the complexity of the model and prevent overfitting or underfitting. For instance, increasing the tree depth can make the model more flexible in capturing data patterns, but it also risks making the model too complex if not properly regulated.

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Additionally, experimenting with ensemble methods can significantly enhance predictive capability. Random Forests is a popular ensemble method that works by combining the results of multiple decision trees to improve accuracy and reduce variance. In Random Forests, each tree is built using a random subset of the data and features, which helps prevent the overfitting commonly associated with a single decision tree. Trying various numbers of trees or sample sizes for each tree can result in a more stable and accurate model.

Gradient Boosting is another popular method to improve predictive performance. Unlike Random Forests, which build trees in parallel, Gradient Boosting builds trees sequentially, with each new tree attempting to correct the errors made by the previous one. This technique is very powerful in handling complex data and can produce highly accurate models if hyperparameter tuning, such as adjusting the learning rate or tree depth, is done correctly. Combining Random Forests and Gradient Boosting in experiments can provide better insights into the strengths and weaknesses of each method for a particular dataset.

4. Conclusion

This research demonstrates the application of Decision Tree models for predicting Ethereum price movements based on historical trend data. The model, while simple and interpretable, achieved an accuracy of 49.10%, falling below the baseline of random guessing. This underperformance is attributed to its challenges in distinguishing between price increase and decrease trends, as evidenced by the confusion matrix and low F1-scores across all classes. These results underline the inherent complexity of financial data and the inadequacy of a basic Decision Tree model in capturing the intricate patterns of a volatile market like cryptocurrency.

The research also highlights external and technical limitations that constrained the model's performance. External factors, such as market sentiment and macroeconomic influences, were not included in the analysis, limiting the model’s ability to account for key drivers of price movements. Additionally, the dataset suffered from insufficient feature engineering and imbalances in class distribution, further impacting prediction accuracy. These limitations emphasize the need for more sophisticated modeling approaches and enriched datasets to address the dynamic and unpredictable nature of cryptocurrency markets.

5. Suggestion

To improve model performance, future research should explore advanced machine learning techniques such as Random Forests or Gradient Boosting. These methods are better equipped to handle the non-linear and complex relationships inherent in financial data, offering improved accuracy and robustness compared to basic Decision Trees. Incorporating additional features like technical indicators, sentiment analysis, and blockchain activity metrics can further enrich the dataset, enabling the model to capture a broader range of factors influencing Ethereum price movements. These enhancements will provide a more comprehensive understanding of market dynamics, improving the model’s ability to identify meaningful patterns.

Addressing data imbalances is another critical step, which can be achieved using resampling techniques like SMOTE to balance the representation of price increase, decrease, and stability classes. Optimizing hyperparameters, such as tree depth and minimum samples per split, will also enhance the model's robustness and adaptability. Additionally, integrating visual tools to explain prediction logic will improve model interpretability, empowering traders and analysts to make more informed decisions. Conducting scenario-based evaluations under varying market conditions will further ensure the model's reliability and alignment with real-world applications, making it a more practical tool for navigating the volatile cryptocurrency market.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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