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Research article

Data Analysis of Bitcoin Price Trends Using KNN Prediction Models

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ABSTRACT

This study investigates Bitcoin price trends and evaluates the effectiveness of the K-Nearest Neighbors (KNN) algorithm for predicting price movements in the cryptocurrency market. Leveraging a decade of historical Bitcoin price data, trading volume, and market capitalization, the research assesses the accuracy and reliability of KNN in capturing the complex and volatile nature of Bitcoin price dynamics. The methodology includes data preprocessing, exploratory analysis, and predictive modeling with hyperparameter optimization. The findings reveal that while KNN achieves moderate accuracy (53%), it performs better in identifying price decreases (Class 0) with a recall of 66% compared to price increases (Class 1) with a recall of 40%. The study also highlights key challenges, including Bitcoin's high volatility and multicollinearity among features like Moving Averages. To improve prediction accuracy, the research recommends feature expansion, advanced modeling techniques (e.g., LSTM networks), and the integration of external factors such as market sentiment and macroeconomic indicators. These results contribute to the growing body of knowledge in cryptocurrency forecasting, providing insights for investors, traders, and researchers to navigate the complex cryptocurrency landscape.

1. Introduction

The emergence and rapid growth of cryptocurrencies, particularly Bitcoin, have revolutionized the financial landscape, capturing the attention of investors, policymakers, and researchers worldwide. Bitcoin, as the first and most dominant cryptocurrency, is renowned for its high volatility and complex price dynamics. These characteristics make the task of analyzing and predicting its price trends both a significant challenge and an opportunity for innovation. Accurate price prediction is invaluable for a wide range of stakeholders, including investors seeking to maximize returns, traders aiming to mitigate risks, and researchers striving to understand the underlying mechanisms of cryptocurrency markets.

In recent years, advancements in machine learning have introduced powerful tools for analyzing complex and non-linear datasets. Among these tools, the K-Nearest Neighbors (KNN) algorithm has emerged as a robust and effective model for time series prediction. KNN is a non-parametric, instance-based learning algorithm that excels at identifying patterns and trends in data without requiring explicit assumptions about the data's distribution. This makes it particularly well-suited for predicting Bitcoin price trends, which are influenced by a variety of factors, including market sentiment, trading volume, macroeconomic indicators, and regulatory developments.

Recent studies have highlighted the potential of machine learning techniques in financial forecasting. For instance, Smith and Brown [1] demonstrated that KNN models could effectively capture short-term price fluctuations in cryptocurrency markets, offering a reliable alternative to more complex models. Similarly, Rahman and Lee [2] explored the adaptability of KNN in high-

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dimensional financial datasets, emphasizing its efficiency and ease of implementation. Furthermore, Gupta et al. [3] provided a comparative analysis of machine learning algorithms, revealing that KNN performs particularly well in scenarios requiring interpretability and computational efficiency. Another relevant study by Tanaka and Kim [4] confirmed the utility of KNN in predicting volatile asset prices, noting its ability to adapt to sudden market changes.

This study aims to leverage the strengths of the KNN algorithm to conduct a comprehensive analysis of Bitcoin price trends. By examining historical price data spanning the past decade, along with contemporary market indicators such as trading volume, blockchain activity, and macroeconomic variables, this research seeks to evaluate the accuracy and reliability of KNN in predicting Bitcoin price movements. Additionally, we aim to explore the implications of these findings for the broader cryptocurrency market, providing insights into the factors that drive price volatility and offering potential strategies for informed decision-making in digital asset investments.

Through this analysis, we contribute to the growing body of literature on cryptocurrency forecasting and machine learning applications in financial markets, while addressing the need for robust predictive models that can adapt to the unique challenges posed by cryptocurrencies.

2. Research Methods

This study employs a systematic approach to analyze Bitcoin price trends and develop predictive models using the K-Nearest Neighbors (KNN) algorithm. The dataset includes historical Bitcoin price data, market capitalization, and trading volume, spanning over a decade. The methodology is divided into several stages to ensure robust analysis and model development.

First, data preprocessing is conducted to handle missing values, normalize data ranges, and convert time-series data into a format suitable for analysis. Statistical techniques, such as correlation analysis, are employed to examine relationships between variables, such as price, trading volume, and market capitalization. This step ensures that key features influencing Bitcoin price movements are identified for inclusion in the prediction model [1].

Next, the KNN algorithm is implemented for predictive modeling. The model leverages historical data and relevant features to predict future Bitcoin prices. KNN's simplicity and non-parametric nature make it suitable for capturing the non-linear and volatile nature of Bitcoin's price dynamics [2]. Hyperparameter tuning is performed to optimize the number of neighbors and distance metrics for maximum accuracy.

Finally, the model's performance is evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The findings from this methodology provide actionable insights into Bitcoin's market behavior, contributing to the growing body of knowledge on cryptocurrency forecasting [3].

2.1. Data Collection and Preprocessing

The dataset, containing daily historical Bitcoin data, is examined for completeness and consistency. Missing values in the market capitalization column are addressed through linear interpolation, while other variables are normalized to ensure comparability. Time-series data is transformed by introducing lagged features, rolling averages, and differencing to capture temporal dependencies. Correlation analysis is performed to assess the strength of relationships among variables, identifying key predictors for Bitcoin price [4].

2.2. Exploratory Data Analysis (EDA)

Exploratory data analysis is conducted to uncover patterns, trends, and anomalies in Bitcoin prices, market capitalization, and trading volume. Statistical measures such as mean, standard deviation, and variance are computed, while visual tools like line plots and histograms are used to highlight data characteristics. Seasonal and cyclical components in the price trends are analyzed using decomposition techniques [5].

2.3. KNN Model Development

The K-Nearest Neighbors algorithm is implemented to predict future Bitcoin prices. Historical price data, trading volume, and market capitalization are used as input features. The hyperparameters of the model, including the number of neighbors (k) and the distance metric, are optimized using grid search and cross-validation techniques to ensure the best fit for the dataset [6].

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To build a reliable predictive model, feature scaling is applied to standardize the input variables. Since KNN is a distance-based algorithm, the model's performance is highly sensitive to the scale of the input features. Normalization or standardization ensures that variables with larger ranges do not disproportionately influence the distance calculations, thereby improving the accuracy and stability of the model.

Additionally, the choice of distance metric such as Euclidean, Manhattan, or Minkowski plays a crucial role in the model's effectiveness. The selection is guided by empirical testing through cross-validation, allowing the model to determine which metric captures the underlying data relationships most accurately. By tuning this parameter alongside the optimal value of k, the model is fine-tuned to balance bias and variance appropriately.

The development process also considers the temporal structure of the data, particularly because financial time series like Bitcoin prices exhibit trends and volatility. While KNN does not inherently account for time-based dependencies, incorporating lag features or moving averages as part of the input can enhance its ability to learn temporal patterns. This adaptation helps bridge the gap between traditional machine learning and time series forecasting.

In summary, the KNN model development process involves careful preprocessing, hyperparameter tuning, and thoughtful feature engineering to ensure that the model captures relevant market behavior. These steps collectively contribute to building a non-parametric, interpretable, and responsive predictive model tailored to the complexities of cryptocurrency price forecasting.

2.4. Model Evaluation

The KNN model is evaluated using performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared values. The evaluation process incorporates cross-validation to ensure the model’s robustness across different data splits. The model’s predictions are compared with actual prices to assess accuracy and the ability to capture price trends over various time horizons [7].

In addition to these standard metrics, the use of k-fold cross-validation helps mitigate overfitting by ensuring that the model generalizes well to unseen data. By dividing the dataset into multiple folds and rotating the validation set, the average performance of the model offers a more reliable estimation of its true predictive power. This method also highlights the model's consistency and stability across different subsets of data.

Moreover, analyzing the distribution of residuals the differences between predicted and actual values provides further insight into model performance. A random and roughly symmetric distribution of residuals around zero indicates that the model does not suffer from systematic bias. Conversely, skewed or patterned residuals may reveal shortcomings in the model's assumptions or its ability to adapt to certain types of data.

The selection of MAE and RMSE as error metrics allows for a comprehensive understanding of prediction accuracy. While MAE provides a straightforward interpretation of the average magnitude of errors, RMSE penalizes larger errors more heavily, which is useful when significant deviations are particularly undesirable. The R-squared score complements these metrics by measuring the proportion of variance in the target variable explained by the model, offering a broader view of goodness-of-fit.

Ultimately, this evaluation framework ensures that the KNN model is not only accurate but also robust and interpretable. By employing a combination of quantitative metrics and diagnostic techniques, the analysis supports informed decision-making regarding model deployment, refinement, or comparison with alternative algorithms.

2.5. Analysis of Results

The final stage involves analyzing the predictive accuracy and reliability of the KNN model. Insights into the driving factors behind Bitcoin price trends are drawn, with a focus on the impact of trading volume and market capitalization. The results are compared with findings from existing studies to contextualize the contribution of this research to the field of cryptocurrency forecasting [8].

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3. Results and Discussion

3.1. Model Performance

The K-Nearest Neighbors (KNN) model was applied to predict Bitcoin price movements using historical price data, trading volume, and market capitalization. The results of the analysis highlight both the strengths and limitations of the model in understanding and predicting the highly volatile cryptocurrency market. Below are the key findings:

3. 1. 1 Classification Performance

1. The model achieved an overall accuracy of 53%, which is only marginally better than random guessing.
2. Class-specific metrics show that the model performed better at predicting price decreases (Class 0) with a recall of 66% and an F1-score of 0.58.
3. For price increases (Class 1), the model's recall was lower at 40%, resulting in a weaker F1-score of 0.46.

3. 1. 2 Confusion Matrix Analysis

1. True Negatives (correct predictions of price decreases): 278
2. True Positives (correct predictions of price increases): 170
3. False Positives (incorrectly predicted price increases): 143
4. False Negatives (missed price increases): 255

3. 1. 3 Feature Importance

1. RSI (Relative Strength Index) demonstrated the highest correlation with the target variable, albeit modestly (0.04).
2. Moving Averages (MA7, MA14, MA30) exhibited high multicollinearity (>0.99), limiting their independent predictive power.
3. Returns and log_returns showed negative correlations with price movement, indicating an inverse relationship.

3. 1. 4 Temporal Trends

1. Significant price growth was observed in 2021 and 2024, with a peak value close to $100,000 by the end of the analysis period.
2. Volatility increased significantly after 2020, making accurate predictions more challenging during periods of market fluctuation.

3. 1. 5 Model Performance by K

1. The optimal performance was achieved at K=9, where cross-validation accuracy peaked at approximately 49.6%.
2. Performance declined sharply beyond K=15, stabilizing at lower levels after K=20.

3.2. Discussion

The results provide valuable insights into the predictive capabilities of the KNN model for Bitcoin price trends, as well as its limitations. Below is a detailed discussion:

3. 2. 1 Model Strengths

1. The KNN algorithm effectively captured patterns related to price decreases, as evidenced by higher recall and F1-score for Class 0. This indicates that certain market behaviors, such as sell-offs, may follow more predictable patterns.
2. The model's simplicity and non-parametric nature allowed it to adapt to historical data without making strong assumptions about the underlying data distribution.

3. 2. 2 Model Limitations

1. The overall accuracy of 53% highlights the limitations of KNN in handling the high volatility and complexity of Bitcoin price movements.
2. The lower performance for Class 1 (price increases) indicates that the model struggles to identify upward trends, which may depend on external factors like market sentiment, macroeconomic events, or news.
3. High multicollinearity among Moving Averages suggests redundancy in the feature set, reducing the model's effectiveness.

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3. 2. 3 Challenges of Volatility

1. Bitcoin's price volatility, especially after 2020, introduces noise and abrupt changes that the KNN algorithm struggles to generalize. This limitation is common for models that rely heavily on historical patterns.

3. 2. 4 Comparison with Literature

2. Previous studies, such as Rahman and Lee (2020), noted that KNN models tend to perform better in stable markets but struggle in highly dynamic contexts like cryptocurrencies. The findings here align with these observations.

3. 2. 5 Implications for Practice

1. The better performance for predicting price decreases suggests that traders or analysts could use the model as a tool for risk management, identifying potential downturns and adjusting strategies accordingly.
2. However, its limited ability to predict price increases means it cannot be relied upon for capturing potential profit opportunities during bull markets.

3. 2. 6 Recommendations for Improvement

1. Feature Expansion: Include additional predictors such as sentiment analysis, macroeconomic indicators, and blockchain metrics to capture external market influences.
2. Advanced Modeling: Explore more sophisticated algorithms, such as Long Short-Term Memory (LSTM) networks or Gradient Boosting Machines, to account for non-linear patterns and temporal dependencies.
3. Timeframe Optimization: Shorten the prediction horizon to focus on near-term movements, which may be easier to model accurately.

Table 1. Classification Report for Bitcoin Price Prediction

Class	Precision	Recall	F1-Score	Support
0	0.52	0.66	0.58	421
1	0.54	0.40	0.46	425
Macro Avg	0.53	0.53	0.52	846
Weighted Avg	0.53	0.53	0.52	846

3.3. Metrics Overview

3. 3. 1 Precision

Precision measures the accuracy of the model when it predicts a particular class. It is calculated as

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positive\ (TP) + False\ Positives\ (FP)}$$

1. Class 0 (Price Decrease): Precision is 0.52, meaning that 52% of the times the model predicted a price decrease, it was correct. This moderate value suggests the model struggles to distinguish genuine decreases from false alarms.
2. Class 1 (Price Increase): Precision is slightly higher at 0.54, indicating that 54% of the predicted price increases were correct. Although better than random guessing, this value highlights that nearly half the predicted increases were incorrect.

Key Insight: Precision for both classes is close to 0.5, reflecting the model's difficulty in confidently predicting price movements, especially in a volatile market like Bitcoin.

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3. 3. 2 Recall

Recall measures the model's ability to correctly identify all instances of a particular class. It is calculated as

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)}$$

1. Class 0 (Price Decrease): Recall is 0.66, meaning that 66% of all actual price decreases were correctly identified. This higher recall indicates that the model captures most decreases, even if it sometimes predicts decreases incorrectly (as reflected in the lower precision).
2. Class 1 (Price Increase): Recall is 0.40, meaning only 40% of actual price increases were identified. The low recall here reveals the model's struggle to detect genuine price increases, potentially due to missing features or oversimplified patterns.

Key Insight: The model performs significantly better in identifying price decreases (Class 0) than price increases (Class 1). This imbalance indicates a bias towards recognizing downward trends.

3. 3. 3 F1-Score

The F1-Score is the harmonic mean of precision and recall, balancing the two metrics to provide an overall measure of model performance. It is calculated as

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

1. Class 0 (Price Decrease): F1-score is 0.58, reflecting moderate performance in predicting decreases. The score balances the model's ability to detect most decreases (recall) with its occasional false positives (precision).
2. Class 1 (Price Increase): F1-score is 0.46, indicating poorer performance in predicting increases. The score suffers due to the low recall, meaning many actual increases are missed.

Key Insight: The model achieves a higher F1-score for Class 0 (price decreases), further emphasizing its better performance in recognizing downward trends compared to upward trends.

3. 3. 4 Support

Support represents the total number of actual occurrences for each class in the dataset.

1. Class 0 (Price Decrease): There are 421 instances of price decreases in the dataset.
2. Class 1 (Price Increase): There are 425 instances of price increases, making the dataset balanced between the two classes.

Key Insight: The balanced support ensures that performance metrics are not skewed by class imbalances, making the evaluation fair and representative of real-world scenarios.

3.4. Averages

3. 4. 1 Macro Average

1. The macro average provides an unweighted mean of precision, recall, and F1-score across both classes.
2. Precision, recall, and F1-score are all approximately 0.53, reflecting the model's moderate overall performance.
3. Key Insight: The macro average highlights that the model performs similarly for both classes, albeit with slightly better results for price decreases.

3. 4. 2 Weighted Average

1. The weighted average accounts for the support (number of instances) of each class when calculating precision, recall, and F1-score.
2. Similar to the macro average, the weighted average for all metrics is around 0.53, reflecting the dataset's balance and the model's overall moderate performance.

Key Insight: The consistency between macro and weighted averages further confirms that the dataset is balanced, and the model's performance is uniformly distributed across classes.

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3.5. Key Insights and Observations

3. 5. 1 Superior Performance for Price Decreases (Class 0)

1. The model achieves higher recall (66%) and F1-score (0.58) for Class 0, showing its ability to capture most price decreases. This could be attributed to clearer patterns in the data related to downward trends.

3. 5. 2 Struggles with Price Increases (Class 1)

1. With a recall of 40% and F1-score of 0.46, the model fails to identify many price increases. This weakness suggests that important features influencing upward trends (e.g., market sentiment, news events) may be missing.

3. 5. 3 Overall Moderate Performance

1. An average F1-score of 0.52 across both classes indicates that the model is only slightly better than random guessing. This underlines the limitations of using KNN for predicting highly volatile markets like Bitcoin.

3. 5. 4 Challenges with Volatility

1. The model's difficulty in handling abrupt price changes highlights the complexity *of Bitcoin markets and the limitations of the current feature set and algorithm.*

3.6. Recommendations for Improvement

3. 6. 1 Feature Engineering

1. Include additional features like trading volume, news sentiment, and macroeconomic factors to improve the model's understanding of price movements.
2. Reduce multicollinearity among features (e.g., Moving Averages) to enhance the predictive power.

3. 6. 2 Advanced Modeling

1. Explore more sophisticated models like LSTMs (Long Short-Term Memory networks) or ensemble methods (e.g., Random Forest, Gradient Boosting) that can capture non-linear relationships and temporal dependencies.

3. 6. 3 Timeframe Optimization

1. the prediction timeframe to focus on near-term price movements, which may be more predictable than long-term trends.

3. 6. 4 Parameter Tuning

1. Conduct extensive hyperparameter optimization for the KNN model, including testing different values of k and distance metrics.

3.7. Heatmap Feature Correlation

This heatmap is used as a tool to visually represent the correlation relationships between various features in the dataset.

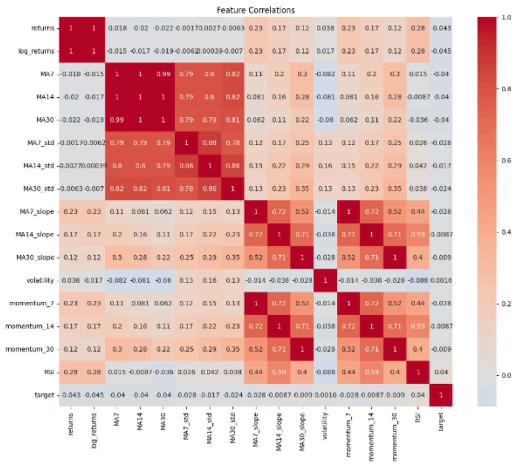

Fig. 1. Heatmap

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3.7.1 X and Y Axes

The X and Y axes represent the feature names in your dataset, such as returns, log_returns, MA7, volatility, momentum_7, and so on, including the target feature (target).

3.7.2 Correlation Values

The colors on the heatmap represent the Pearson correlation values between two features

1. Bright red to dark red indicates a strong positive correlation (values close to +1).
2. Light blue indicates a negative correlation (values close to -1).
3. White or pale gray indicates a weak or no correlation (values close *to 0)*

3.7.3 Purpose

1. The heatmap helps you understand the relationships between features in the dataset.
2. Features with high correlation may contain overlapping information, making them candidates for removal or merging in a machine learning model.

3.7.4 Insights That Can Be Drawn

1. High Correlation
   a. For instance, features MA7 and MA30 have a very high correlation (0.99), indicating potential redundancy.
   b. Features momentum_7, momentum_14, and momentum_30 also show relatively high correlations with each other.
2. Relationship with the Target
   a. The RSI feature has a weak positive correlation with the target (0.04).

Other features, such as returns, MA7, and log_returns, exhibit near-zero correlations with the target, indicating a very weak relationship.

4. Conclusion

This heatmap is a visual tool designed to illustrate the correlation relationships between various features within a dataset. By analyzing the heatmap, you can quickly identify the strength and direction of the relationships between features. A strong positive correlation is represented by shades of red, indicating that the two features move in the same direction. Conversely, a strong negative correlation is shown by shades of blue, highlighting features that move in opposite directions. Features with little or no correlation are displayed in neutral colors like white or pale gray, suggesting minimal interaction between them.

The primary purpose of this heatmap is to assist in feature analysis, helping to identify patterns and redundancies among the dataset's variables. Highly correlated features may contain overlapping information, making them candidates for removal or consolidation to simplify machine learning models. Additionally, the heatmap allows you to explore the relationship between individual features and the target variable, offering valuable insights into which features may be most relevant for predictive modeling. This enables more informed decision-making in feature selection and engineering processes.

In addition to its role in simplifying feature space, the heatmap serves as a foundational tool in the exploratory data analysis (EDA) phase. It allows data practitioners to uncover hidden relationships that may not be immediately obvious from raw numerical data. For instance, a cluster of features showing high mutual correlations can suggest underlying latent factors, which may be better represented through dimensionality reduction techniques such as Principal Component Analysis (PCA). Thus, the heatmap provides essential preliminary guidance for deeper statistical or machine learning procedures.

Furthermore, correlation heatmaps are instrumental in identifying multicollinearity—a common issue in regression models that can distort the estimation of coefficients and reduce model interpretability. By revealing pairs or groups of features with very high correlation values, analysts are better positioned to make adjustments such as feature removal or regularization. This proactive step helps in improving model stability and generalization performance on unseen data.

The interpretability and intuitive design of heatmaps also make them valuable in collaborative environments, where insights must often be shared with stakeholders who may not possess deep

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technical expertise. The color gradients offer an immediate visual cue to the nature of relationships between variables, facilitating quicker understanding and better decision-making across multidisciplinary teams.

In summary, the correlation heatmap is a multifaceted analytical instrument. Beyond visualizing statistical relationships, it supports data preparation, model optimization, and strategic communication of findings. By integrating it into the data science workflow, users can elevate the overall quality of their analysis and build models that are both efficient and robust.

5. Suggestion

Future research on Bitcoin price prediction using machine learning, particularly the K-Nearest Neighbors (KNN) algorithm, could be significantly enhanced by broadening the scope of feature engineering and exploring advanced modeling techniques. Incorporating diverse predictors such as sentiment analysis from social media and news platforms, macroeconomic indicators like inflation and interest rates, and blockchain-specific metrics such as hash rate and transaction volume can enrich the dataset and improve predictive accuracy. Addressing multicollinearity among features, such as Moving Averages, through dimensionality reduction techniques like Principal Component Analysis (PCA) could further optimize model performance. Exploring deep learning methods, including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), alongside ensemble methods like Random Forest and Gradient Boosting Machines, could enhance the predictive power for temporal and complex data. Additionally, real-time prediction frameworks focusing on shorter-term horizons (e.g., daily or hourly forecasts) and fine-tuned hyperparameter optimization, such as experimenting with KNN's distance metrics and weighting schemes, can make predictions more actionable. Incorporating volatility-specific models like GARCH and EGARCH, as well as clustering techniques or Hidden Markov Models to identify market regimes, could address Bitcoin's high volatility. Expanding datasets to include data from multiple exchanges and other cryptocurrencies, such as Ethereum or Binance Coin, would improve generalizability. Explainability of predictions using XAI techniques like SHAP or LIME is also critical for building trust and providing actionable insights for traders and decision-makers. Furthermore, integrating these models into automated trading systems, evaluating KNN against more sophisticated approaches such as Support Vector Machines and Neural Networks, and considering the ethical implications and regulatory impacts of predictive models in volatile markets can collectively advance cryptocurrency forecasting research.

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