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Predicting Bitcoin Prices using Machine Learning: A Comparative Analysis of Algorithms and Feature Engineering Techniques

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ABSTRACT: A lot of attention has been paid to cryptocurrency price prediction as digital assets become more and more important in the financial system. This paper provides a thorough analysis of the use of machine learning algorithms in bit coin price prediction. Historical open-source data from multiple bit coin exchanges is used. To deal with missing data, interpolation techniques are used, guaranteeing the dataset's trustworthiness and completeness. Four technical indicators have been chosen as prediction features. The study looks at how five machine learning algorithms might be used to identify intricate patterns in the wildly unstable bit coin market. The results show the benefits and drawbacks of the various strategies, emphasizing the role that feature engineering and algorithm selection play in producing reliable predictions of bit coin prices. As digital assets like cryptocurrencies become increasingly integrated into the financial system, predicting their prices has garnered significant attention from traders, investors, and researchers. This paper focuses on the application of machine learning algorithms to predict Bitcoin prices, a highly volatile and unpredictable market. By leveraging historical data from various Bitcoin exchanges, the study ensures data integrity by employing interpolation techniques to handle missing values, resulting in a trustworthy and complete dataset for analysis. The research explores the use of four key technical indicators as predictive features, carefully selected based on their relevance to cryptocurrency markets. These features serve as inputs to five different machine learning algorithms, which are employed to uncover complex patterns and relationships within the Bitcoin market. The paper offers a comparative analysis of these algorithms, examining their strengths and weaknesses in predicting Bitcoin prices under volatile market conditions. A key focus of the study is on the importance of feature engineering and algorithm selection in achieving accurate and reliable predictions. The results demonstrate that certain algorithms outperform others in terms of prediction accuracy, while highlighting the critical role that feature engineering plays in enhancing model performance. The insights from this study provide valuable guidance for traders and investors navigating the rapidly evolving world of cryptocurrency markets, offering a practical framework for using machine learning to improve prediction accuracy in financial decision-making.

KEYWORDS: Cryptocurrency Price Prediction, Machine Learning Algorithms, Feature Engineering, Performance Metrics globally

I. INTRODUCTION

The financial system is seeing a shift due to cryptocurrencies, which are bringing decentralized digital assets based on block chain technology. The original cryptocurrency, Bitcoin, is driving a global wave of digital currencies that are giving rise to a plethora of substitute cryptocurrencies, or altcoins. The increasing prevalence of cryptocurrencies is garnering substantial interest from traders, investors, and financial establishments. In the meantime, cryptocurrencies are becoming a more attractive and fascinating asset class due to its decentralized structure, possibility for large profits, and distinct market dynamics. The bit coin sector is becoming more and more legitimate as a result of mainstream organizations and businesses adopting cryptocurrencies. Furthermore, as governments are looking at digital alternatives to their fiat currencies, the development of digital currencies issued by central banks is a big step forward. Sustainability issues, interoperability across many block chain networks, and industry's progress is also being shaped by regulatory frameworks, but investors looking to take advantage of market opportunities face significant obstacles due to the tremendous volatility and unpredictability of bit coin values. Therefore, there is a strong need for reliable and accurate predictive models to help investors make wise decisions in this quickly changing financial environment.

The investigation of novel techniques to predict future price movements is driven by the intrinsic complexity and volatility of cryptocurrency markets. The distinctive qualities of cryptocurrencies are frequently difficult for traditional financial models to represent, which leads researchers to consider machine learning algorithms as a possible remedy.

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Machine learning methods are a good fit for predicting cryptocurrency prices because they have the ability to handle nonlinear relationships and identify patterns in large, complicated datasets. This research attempts to create predictive models that can identify significant trends and patterns by utilizing past price data and advanced machine learning techniques. In addition to helping regulators and policymakers develop suitable guidelines and safeguards for the cryptocurrency market, this research has practical significance as it can help traders and investors make well-informed decisions, manage risks, and potentially increase their returns in a highly volatile market. This promotes stability and protects consumers. Furthermore, companies stand to gain from integrating precise pricing projections into their financial strategy and planning. Our knowledge of the underlying market dynamics can be improved by this research, which also advances the discipline of financial analysis and encourages creativity and adaptation in the rapidly changing digital economy.

This research's main goal is to use machine learning algorithms to forecast cryptocurrency prices in the future. This study aims to train models that can provide precise price predictions and insightful information about possible trends in cryptocurrency prices by generating pertinent features unique to cryptocurrency price data, such as simple moving average, relative strength index, moving average convergence divergence, and on-balance volume in the selected dataset. This research is significant since it can improve the way that decisions are made for assisting traders and investors in the bitcoin space with trade planning, risk management, and the identification of profitable opportunities. About 60% accuracy is seen sufficient in the realm of cryptocurrencies, however this research seeks to obtain over 90% accuracy on specific models. This study also advances the field of bitcoin price prediction by providing insightful information about the advantages and disadvantages of various machine learning methods. Overall, this research aims to close the knowledge gap in this quickly expanding field by bridging the gap between conventional financial models and the particular difficulties presented by the bit coin market.

II. LITERATURE REVIEW

In the field of predicting cryptocurrency prices, experts are presently investigating several approaches and methods. Support vector machines, random forests, and neural networks are just a few examples of the machine learning techniques, statistical models, and traditional time series analysis that are often used to estimate cryptocurrency values. As predictive elements, these analyses frequently include historical price data, trading volumes, technical indications, and market sentiment. Furthermore, the use of sentiment analysis derived from news and social media data aids in evaluating the influence of public opinion on price changes. Although there have been some encouraging results, the complex and unstable nature of bit coin marketplaces presents difficulties for precise forecasting. As the subject develops, scientists look for new ways to improve forecast accuracy and take into consideration the volatile nature of the bit coin market. They also incorporate additional data sources. A range of machine learning methods are used in the field of cryptocurrency price prediction to take use of the predictive power of data. When attempting to anticipate whether prices will rise or fall, traditional statistical methods such as logistic regression and quadratic discriminant analysis (QDA) are frequently used for binary classification tasks. Decision trees are used as maps to comprehend the influence of these interactions on cryptocurrency prices, capturing intricate relationships between predictors and anticipate price changes. Additionally, K-nearest neighbourhood (KNN) is used to find comparable patterns in utilizing past data to infer future price movements. Furthermore, a lot of research has been done on neural networks [8], especially deep learning architectures like long short-term memory (LSTM) networks, to identify sequential patterns in time-series bit coin data. While all algorithms show potential for predicting cryptocurrency prices, their effectiveness frequently depends on how effectively features are chosen and maintained, as well as how well they can handle noise and inherent market volatility.

There are clear advantages and disadvantages to the bit coin price prediction methods now in use. One important benefit is the use of technical analysis, which is looking at past price charts to find trends, patterns, and levels of support and resistance. This method produces insightful market data. attitude and the actions of investors. It does, however, have limitations because technical analysis may fail to take into account outside influences like changes in market mood or regulatory changes (which is also a shortcoming of the methodology adopted for this research). Furthermore, fundamental analysis provides a long-term view on price changes by evaluating the intrinsic worth of cryptocurrencies based on factors like adoption, technology, and utility. However, fundamental analysis is still arbitrary and difficult to measure, leading to a variety of interpretations and forecasts. Combining several strategies that take into account both technical and fundamental elements may result in a more thorough understanding of cryptocurrency price fluctuations.

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III. DATA COLLECTION AND PRE-PROCESSING

The dataset utilized in this study is created by gathering historical data from open sources. It includes information on Bit coin prices throughout a seven-month period in 2018.

Managing missing values in the historical pricing dataset is a problem during the data pre-processing stage. Interpolation techniques are used to estimate and fill in the missing data points in order to overcome this problem. In order to create a continuous and comprehensive dataset, missing values in the time series data are approximated using linear interpolation. The performance of the machine learning models is less affected by missing data when interpolation is used, resulting in a more reliable and insightful dataset for cryptocurrency price prediction. The gathered bit coin price data is put through a number of pre-processing stages before the machine learning algorithms are trained, to ensure data quality and improve the models' functionality. To facilitate working with and managing the dataset, all numerical data is transformed to a single data type (float64). It also facilitates the analytical process' streamlining.

Furthermore, feature selection which is typically used to stock markets as well as cryptocurrency markets is carried out to determine which features are most pertinent for price prediction. Based on prior research and domain expertise, the most significant indicators among the many possible ones are the moving average convergence divergence (MACD), on-balance volume (OBV), relative strength index (RSI), simple moving average (SMA) , and moving average convergence divergence (MACD). As SMA smoothed historical data, it highlights underlying trends and reduces noise, making it a useful characteristic for prediction. Because of this, it is useful for determining and comprehending the course of price changes over time, providing a basis for enabling more consistent and comprehensible trend forecasting in the future. By measuring price movement momentum, RSI can be used to determine when an asset is overbought or oversold. It helps forecast price movements by providing information about probable trend reversals and when an asset is most likely to have a correction or resume its current trend. Short- and long-term moving averages are combined by MACD to identify possible trend shifts and the degree of price momentum. It is useful for forecasting price fluctuations and determining entry and exit positions in the market because it gives timely indications. Possible avenues for trading. OBV aids in determining how much trading activity occurs in tandem with price changes. It displays buying and selling pressure and can give early warning signs of impending trend continuations or reversals. It provides useful insights for forecasting price direction and market trends by integrating volume data. Following feature selection, all infinite values are removed from the dataset using outlier removal to avoid disrupting computations and to improve the depiction of underlying patterns by lessening the impact of extreme values. Your methodology and model evaluation are well-structured, presenting a clear picture of your approach to feature engineering and the performance of different machine learning models.

IV. METHODOLOGY

The methodology for feature engineering involves comparing the closing prices of consecutive rows at various time intervals to label the data for different look ahead periods. Labels are assigned based on whether the closing price at a given time is higher or lower than the price an hour later, with intervals of 1, 3, 7, and 14 hours, resulting in columns named ‘Label 1’, ‘Label 3’, ‘Label 7’, and ‘Label 14’. Feature engineering includes techniques like Simple Moving Average (SMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and On Balance Volume (OBV). SMA is calculated using a 30-hour rolling window, RSI is derived from average gains and losses over a 14-hour window, MACD involves exponential moving averages, and OBV updates are based on price changes relative to volume.

Machine learning algorithms such as Quadratic Discriminant Analysis (QDA), K-Nearest Neighbours (KNN), Logit Model (logistic regression), Decision Tree, and Neural Networks are trained on the dataset. QDA shows high accuracy for 1-hour predictions but lower performance for longer periods, while KNN performs poorly across all horizons. The Logit Model excels with high accuracy and low error across all time frames, particularly for long-term predictions, whereas the Decision Tree performs well for 1 and 14-hour predictions but poorly for intermediate periods. Neural Networks also show strong performance, particularly for long-term forecasts. Comparisons reveal that the Legit Model with interpolation and feature engineering performs well, but models without interpolation or feature engineering demonstrate better accuracy or lower MSE, indicating the importance of specific configurations in predictive performance.

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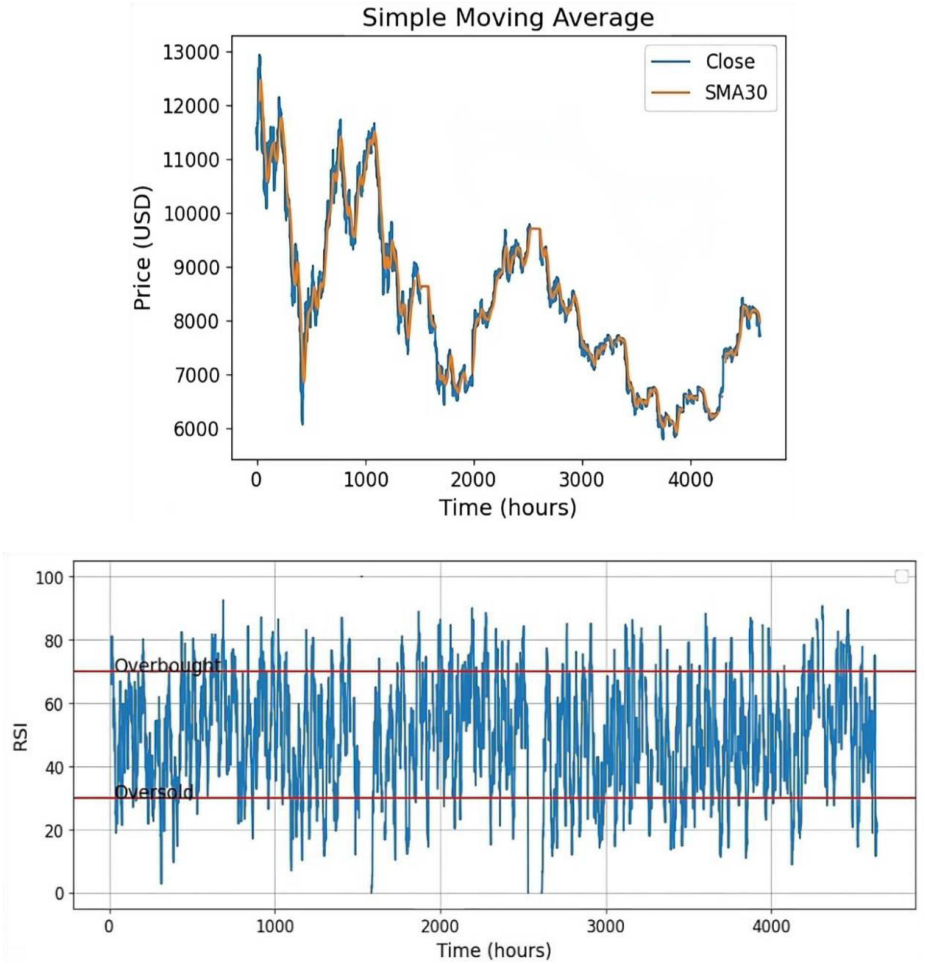
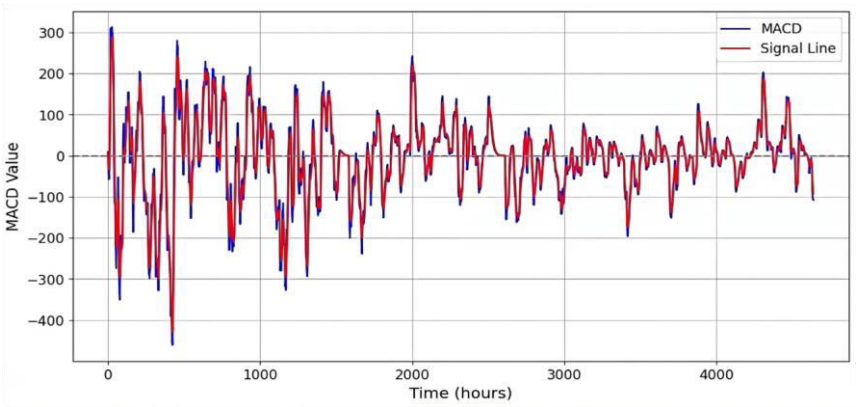


Figure 1. Comparing the closing prices of consecutive rows at various time intervals

The initial On Balance Volume (OBV) value is set to 0 for all rows, with comparisons made between the closing price of each row and the row before it. The first row is excluded from this comparison. If the closing price of the current row is higher than that of the previous row, its OBV is updated by adding the current volume to the OBV of the previous row. Conversely, if the closing price is lower, the OBV is updated by subtracting the current volume from the OBV of the previous row. If the closing prices of two consecutive rows are the same, their OBV values remain unchanged. These calculated OBV values are assigned to a new column and plotted as a line plot



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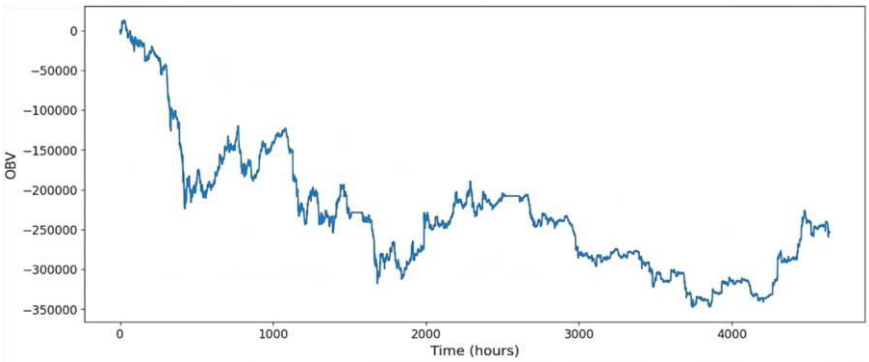

Figure 2. After training on the cryptocurrency price dataset, several machine learning algorithms are implemented.

Quadratic Discriminant Analysis (QDA), a statistical technique for classifying data into multiple classes using quadratic equations, captures complex relationships and non-linear interactions, which can be useful in modelling cryptocurrency price movements, though its effectiveness depends on data distribution aligning with its assumptions. K-Nearest Neighbours (KNN), a simple algorithm that classifies data points based on their nearest neighbours, excels in capturing local patterns and short-term trends but may struggle with market shifts and long-term trends due to its sensitivity to noise and lack of complex relationship modelling. The Logit Model (logistic regression), suitable for binary classification tasks, predicts the probability of price movements (increase or decrease) and can offer insights into price changes, though it may not capture all market nuances.

Decision Trees model decisions as a tree-like structure, handling non-linear relationships and volatility well, and are easy to interpret, though over fitting is a concern not addressed in this paper. Neural Networks, inspired by the human brain, excel in learning complex, non-linear relationships and adapting to new patterns, making them effective for capturing both short-term and long-term price dynamics in the volatile cryptocurrency market. The dataset is divided into five parts “X” (features), “y” (1-hour look ahead predictions), “y3” (3-hour), “y7” (7-hour), and “y14” (14-hour) and algorithms are tested on these combinations. Performance metrics include Accuracy (proportion of correct predictions), Mean Squared Error (MSE) (average squared difference between predicted and actual values), Area under the Curve (AUC) (evaluation of binary classifiers), and Cross-Validation Score (CV Score) (model generalizability). Results, including those for QDA with an accuracy of 0.998 for 1-hour look ahead predictions.

Table 1. Analysis of Machine Learning Model (Quadratic Discriminant)

Performance Metric	Machine Learning Model			
	Quadratic Discriminant Analysis			
	1-Hour Lookahead Predictions	3-Hour Lookahead Predictions	7-Hour Lookahead Predictions	14-Hour Lookahead Predictions
Accuracy	0.998	0.711	0.768	0.941
MSE	0.005	0.289	0.232	0.059
AUC	0.317	0.421	0.447	0.529
CV Score	0.998	0.698	0.756	0.932

The performance of the machine learning models on cryptocurrency price predictions varies across different look ahead periods.

Quadratic Discriminant Analysis (QDA) shows exceptionally high performance for the 1-hour look ahead prediction with an accuracy of 0.998, a very low MSE of 0.005, and a high CV score of 0.998, reflecting excellent generalizability. However, its AUC of 0.317 suggests limited ability to distinguish between price rises and falls, worse than random chance. For the 3-hour look ahead, accuracy drops to 0.711, MSE increases to 0.289, and AUC improves slightly to 0.421. The CV score also decreases to 0.698. The 7-hour forecast sees a further decrease in accuracy to 0.768, though MSE improves to 0.232 and AUC rises to 0.447. The CV score is 0.756, indicating slightly less generalizability compared to the 3-hour forecast. For the 14-hour look ahead, accuracy is 0.941 with a low MSE of

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0.059 and a higher AUC of 0.529, showing improved but still modest binary classification performance. The CV score of 0.932 reflects good generalizability. Overall, QDA performs best for the 1-hour forecast but shows declining performance for longer periods, with binary classification performance needing improvement across all horizons.

K-Nearest Neighbours (KNN) results are detailed in Table 2. The accuracy for the 1-hour look ahead is 0.497, suggesting moderate performance. The MSE is 0.418, indicating significant prediction error, and the AUC of 0.5 suggests the model's performance is equivalent to random guessing. The cross-validation score is 0.489, reflecting moderate generalizability. As the look ahead period increases, KNN's accuracy improves slightly, though it still faces challenges in achieving higher performance and accurately capturing price movements. Further tuning and evaluation are needed to enhance its effectiveness in cryptocurrency price predictions.

Table 2. K-Nearest Neighbourhood Analysis

Performance Metric	Machine Learning Model			
	K-Nearest Neighbourhood			
	1-Hour Lookahead Predictions	3-Hour Lookahead Predictions	7-Hour Lookahead Predictions	14-Hour Lookahead Predictions
Accuracy	0.497	0.537	0.591	0.674
MSE	0.418	0.369	0.274	0.059
AUC	0.5	0.5	0.5	0.5
CV Score	0.489	0.502	0.501	0.507

Table 3. Logit Model Analysis

Performance Metric	Machine Learning Model			
	Logit Model			
	1-Hour Lookahead Predictions	3-Hour Lookahead Predictions	7-Hour Lookahead Predictions	14-Hour Lookahead Predictions
Accuracy	0.979	0.737	0.787	0.899
MSE	0.418	0.369	0.274	0.059
AUC	0.633	0.718	0.779	0.931
CV Score	0.987	0.735	0.779	0.878

V. CONCLUSIONS

This study aimed to predict future cryptocurrency prices using various machine learning algorithms, involving data preprocessing and feature engineering tailored to cryptocurrency data. Five different algorithms were implemented, and their performances were evaluated using multiple metrics. The research led to several key findings: Logistic regression exhibited exceptional performance across all prediction horizons, proving effective for binary classification tasks. Neural networks demonstrated strong predictive capabilities, particularly for the 14-hour lookahead forecasts, though their performance varied across different prediction periods. This underscores the need for tailored approaches when dealing with the diverse cryptocurrency market. The study offers valuable insights into the strengths and limitations of each algorithm, providing a comprehensive comparison. Accurate price predictions are crucial for investors to make informed decisions and manage risks more effectively. The research enriches the field of cryptocurrency price prediction, highlighting the potential of machine learning while acknowledging the limitations and biases in data selection, algorithm choice, and evaluation metrics. Future work should address these limitations and explore advanced techniques to enhance model accuracy and generalizability. Overall, this study lays a foundation for further advancements in predicting cryptocurrency prices in this rapidly evolving field.

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