

Article

Enhancing Bitcoin Trading Signal Prediction in Crisis Periods Using an Improved Machine Learning Approach

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Abstract

The aim of this research is to employ improved machine learning techniques to determine the best Bitcoin trading positions in response to sudden price changes caused by global emergencies such as pandemics, conflicts, and economic disputes. Specifically, this study examines price fluctuations during the COVID pandemic as a case study to evaluate the performance of the algorithms investigated. We present a novel hybrid approach that merges Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Decision Tree (DT) classification to effectively eliminate noisy data and extract pertinent information for accurate position forecasting. The DBSCAN algorithm organizes the data to reveal important patterns, while the DT classifier sorts the trading signals. The performance of the proposed DBSCAN-DT model is rigorously compared with established alternatives, including the Multi-Layer Perceptron (MLP), Support Vector Classifier (SVC), and traditional Decision Trees. Findings from the experiments show that the DBSCAN-DT hybrid consistently outperforms these benchmarks during the outbreak, epidemic, and pandemic phases of COVID, attaining greater accuracy in forecasting both trading positions and market trends. These findings emphasize the essential importance of incorporating pandemic-related disruptions into cryptocurrency price prediction models and showcase the flexibility of our method in addressing sudden market changes.

Keywords: Bitcoin; trading position prediction; ensemble methods; market volatility; pandemic



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1. Introduction

In recent years, the widespread adoption of blockchain technology and the growing interest in cryptocurrencies have positioned Bitcoin as a key digital asset that attracts significant attention from both scholars and finance experts (Aggarwal 2022; Celestin and Vanitha 2021; Scharfman 2023). The notable price volatility, erratic trends, and sensitivity to macroeconomic influences make forecasting Bitcoin's price a challenging yet crucial task. Furthermore, global events such as the pandemic, along with wars and economic disputes, have demonstrated that financial markets, particularly cryptocurrencies, can experience sudden and unpredictable shifts (Aggarwal 2022; Ram 2019).

Predicting Bitcoin trading positions during volatile market conditions remains a major challenge for both investors and market analysts. Recently, the adoption of machine learning techniques, especially hybrid and ensemble methods, has gained traction for improving accuracy in forecasting cryptocurrency price fluctuations. Studies suggest that deep

learning frameworks, transformer-based models, and combined clustering-classification strategies can effectively detect complex patterns and hidden characteristics in financial time series data (Bergsli et al. 2022; Ftiti et al. 2023; Pratas et al. 2023).

While traditional models like Decision Trees (DTs), Multi-Layer Perceptrons (MLPs), and Support Vector Classifiers (SVCs) have demonstrated some level of effectiveness, their predictive accuracy often diminishes in volatile market conditions due to noisy and irrelevant data (Jaquart et al. 2021; Chen et al. 2020b; Akyildirim et al. 2021; Chen 2023). Consequently, integrating density-based clustering methods such as DBSCAN with classification models has been recommended to mitigate noise by identifying important data clusters and enhancing model training (Khalid et al. 2020).

This research introduces an innovative hybrid framework that integrates DBSCAN clustering with a decision tree classifier (DBSCAN-DT) to enhance the selection of data for predicting Bitcoin trading positions during global crisis situations. By eliminating noisy samples and concentrating on relevant data subsets, the proposed method aspires to increase the precision and reliability of position forecasts. To ensure the effectiveness of the introduced approach, the results obtained from this method are compared with standard classifiers (SVC, MLP, and DT) throughout various stages of the COVID-19 pandemic as a specific case study (due to the high volatility in financial markets during this period).

The main contribution of this study is to present a robust combined clustering-classification technique designed for sudden shifts in Bitcoin market behavior, in line with recent developments in machine learning applications for cryptocurrency prediction. Figure 1 displays the detailed research methodology. The primary contributions of this research that set it apart from earlier studies include

- Presenting a novel hybrid machine learning strategy to confront force majeure scenarios;
- Developing an innovative approach for systematically selecting data to tackle abrupt changes in the Bitcoin market;
- Assessing machine learning performance through the lens of pandemic experiences;
- Improving the quality of market direction predictions using the proposed ensemble technique;
- Optimizing the parameters of the DBSCAN-DT using the Taguchi method to boost algorithm performance.

The remaining sections of this research are structured as follows. Section 2 provides a review of the existing literature. In Section 3, the focus shifts to the data employed and its classification for defining various Bitcoin trading positions during the pandemic. Section 4 discusses the machine learning algorithms and introduces the suggested hybrid DBSCAN-DT method. Section 5 is dedicated to tuning the parameters of the proposed method to improve prediction accuracy. Section 6 presents a discussion on the proposed approach and the results acquired, along with a comparison of the utilized algorithms. Lastly, the conclusions are summarized in Section 7.

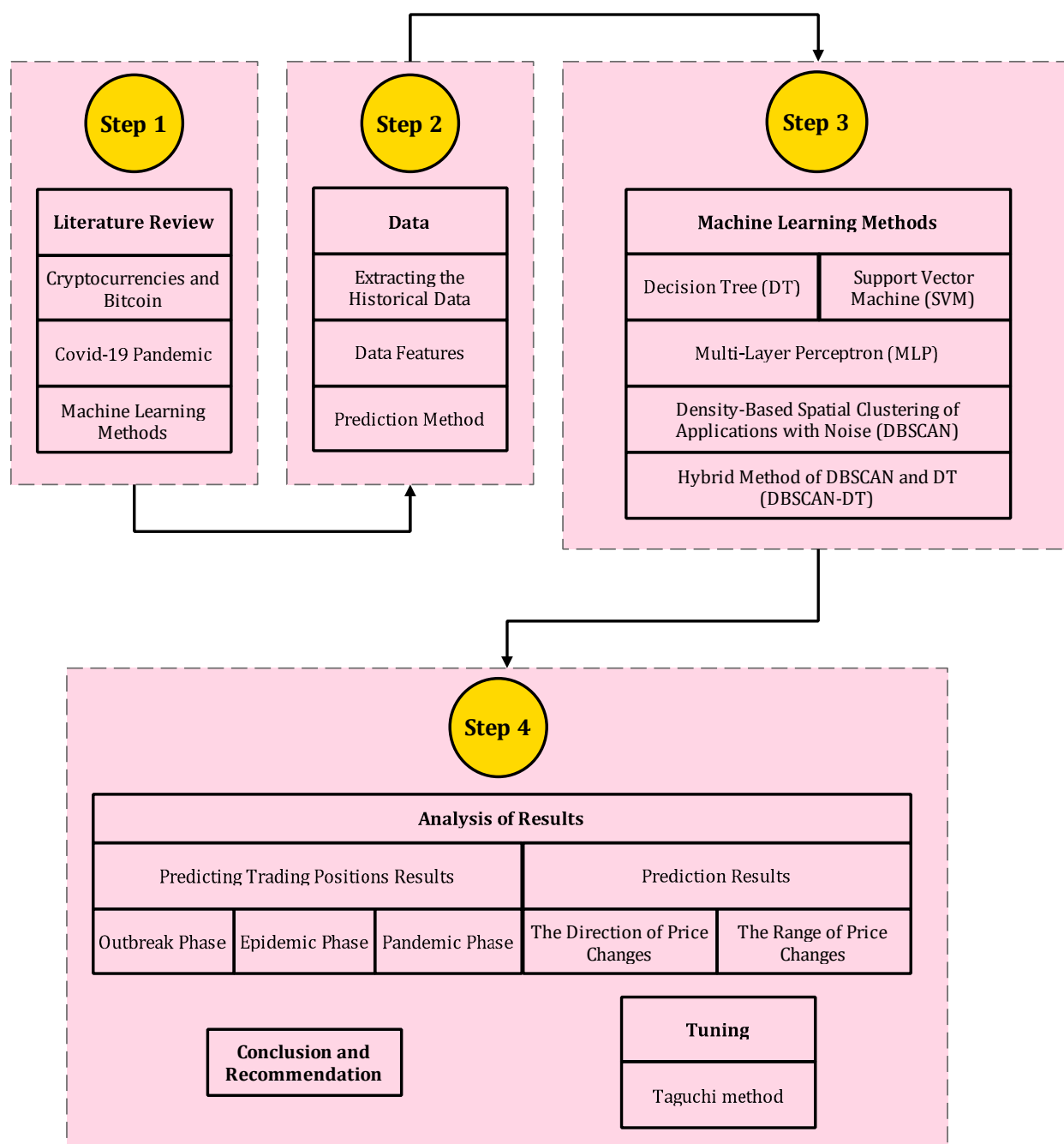


Figure 1. Research process steps.

2. Literature Review

2.1. Bitcoin Market Dominance and Contagion Effects

Research on Bitcoin market share sheds light on the dominance and dynamics of Bitcoin within the broader cryptocurrency landscape (Chen et al. 2020a). According to Foley et al. (2019), Bitcoin has historically maintained a significant market share compared to other cryptocurrencies. The study analyzes factors influencing Bitcoin's dominance, attributing it to its first-mover advantage, brand recognition, and the network effect. Bitcoin's market share is often considered a key indicator of the overall health and stability of the cryptocurrency market, as fluctuations in its dominance can affect both investor sentiment and the valuation of alternative digital assets (Osman et al. 2024). Corbet et al. (2020) showed that Bitcoin's price movements could have a significant influence on the

valuation of other cryptocurrencies, often referred to as altcoins. The study suggested that Bitcoin served as a benchmark or reference point for the broader market, with movements in its price leading to corresponding changes in the prices of many altcoins. This phenomenon, known as the “contagion effect,” highlights both the interconnectedness and co-movements observed among various cryptocurrencies. In their study, [Gurdgiev and O’Loughlin \(2020\)](#) also delved into the psychological aspects of how Bitcoin price fluctuations impact investor sentiment and decision-making in the broader cryptocurrency market. The study suggested that extreme price movements in Bitcoin could lead to heightened emotions and perceptions of risk among investors, influencing their behavior in trading other cryptocurrencies. Studies underscore that Bitcoin functions not only as a market leader but also as a systemic transmitter of risk, making its dominance a critical factor in forecasting broader cryptocurrency dynamics.

2.2. Predicting Sudden Market Changes

The importance of predicting sudden changes in financial markets, particularly within the context of cryptocurrency and Bitcoin trading, has been a subject of interest in academic research. Recent work by [Agrawal and Waggle \(2024\)](#) illustrates robustness testing in the context of integrating digital assets into multi-asset portfolios, underscoring the importance of stability checks in financial forecasting frameworks. This emphasis on robustness aligns with broader research highlighting that predictable trends may not be as profitable due to their widespread recognition, as emphasized by [James \(2021\)](#). The study suggested that identifying sudden changes or anomalies in the market could offer unique opportunities for profit, as these events might not be as readily anticipated by the broader market participants. Therefore, the accurate prediction of unexpected and abrupt shifts in market conditions can be a valuable skill for traders seeking distinctive profit-making opportunities. In their study, [Hung et al.](#) delved into the concept of “jump prediction” and its significance in financial forecasting ([Hung et al. 2020](#)). Jump prediction refers to the ability to foresee sudden, large movements in asset prices. The study indicated that accurate jump predictions could be leveraged to enhance trading strategies, allowing investors to capitalize on the heightened volatility associated with sudden market changes. The study emphasized the potential for increased profitability when traders can effectively anticipate and respond to these rapid shifts, providing a competitive advantage in dynamic financial environments. The study of [King et al.](#) also explored the concept of market microstructure and the importance of identifying sudden changes in liquidity and trading dynamics ([King et al. 2013](#)). Recognizing and predicting sudden changes in market liquidity is crucial for optimizing trading strategies, as these changes could impact transaction costs and execution efficiency.

Sudden price changes in special conditions like the COVID-19 pandemic happen more frequently and affect the financial markets more than before. Research in the aftermath of the COVID-19 pandemic has explored the multifaceted effects on financial markets, investor behavior, and economic indicators. According to [Baker et al. \(2020\)](#), the onset of the COVID-19 pandemic triggered a sudden and severe crisis in financial markets, characterized by heightened volatility, sharp declines in stock prices, and disruptions across various asset classes. The study underscored the abruptness of the crisis, highlighting the challenges in predicting and responding to the unprecedented shocks introduced by the COVID-19 pandemic. In their study, [Parray et al. \(2020\)](#) evaluated the role of advanced data analytics and machine learning techniques in enhancing the accuracy of price trend predictions. The research suggested that leveraging sophisticated algorithms could contribute to more precise forecasts, enabling investors to adapt to changing market conditions and improve the overall profitability of their trading strategies. [Bustos et al. \(2017\)](#) focused on the effectiveness of machine learning algorithms in capturing the complex

patterns and relationships within financial data. Taken together, these studies highlight the need to integrate behavioral insights, microstructural analysis, and advanced analytics to create robust predictive models to predict sudden changes in markets.

2.3. Machine Learning Methods in Cryptocurrency Prediction

Machine learning techniques are used to forecast cryptocurrency prices because of the market's natural volatility and intricacy. To manage abrupt price fluctuations, change point detection methods can be applied to ensure reliable predictive accuracy in novel price ranges. On-chain data, which consist of distinct records kept on the blockchain, can be collected and used as input features for predicting values (Hamayel and Owda 2021). Data preprocessing using discrete wavelet transform (DWT) combined with algorithms like steepest descent-based scaled back propagation can also improve accuracy. Ensemble models, such as those combining Extra Tree, Random Forest, and Decision Tree Regressors, have also been developed, though some findings suggest that ARIMA models may perform better with lower error metrics (Sivhugwana and Ranganai 2024). Classification models have been found to be more effective than regression models for algorithmic trading. This comparative evidence suggests that while traditional models retain their value, deep learning and ensemble learning techniques are becoming increasingly dominant due to their ability to capture the nonlinear and temporal complexity of cryptocurrency markets.

2.4. DBSCAN and Decision Tree Approaches

The use of DBSCAN and DT algorithms for forecasting, particularly in predicting the price of cryptocurrencies, has gained attention from recent studies (Maghsoodi 2023; Dokuz et al. 2020; Nerurkar et al. 2021; Pavankumar et al. 2024). Decision tree algorithms, such as Random Forests and Gradient-Boosting Trees, have been explored for their ability to handle complex data structures and identify significant predictors of cryptocurrency price movements. Rathana et al. (2019) also investigated the application of Decision Tree algorithms in cryptocurrency price prediction, highlighting their effectiveness in capturing nonlinear relationships and generating interpretable models. By analyzing historical price data and relevant features, Decision Tree models offer insights into the factors driving cryptocurrency price dynamics, helping traders and investors make informed decisions. Furthermore, the use of the DBSCAN algorithm for clustering and anomaly detection has shown promise in identifying patterns and anomalies in cryptocurrency price data. In their study, Dokuz et al. (2020) explored the application of the DBSCAN algorithm in detecting abnormal price movements and market irregularities in cryptocurrency markets. By clustering data points based on density and identifying outliers, the DBSCAN algorithm can help identify sudden changes and anomalies in cryptocurrency price series, providing valuable insights for traders and risk managers. The study highlighted the importance of anomaly detection techniques in forecasting cryptocurrency prices and managing market risks effectively. These results confirm that DBSCAN and DT approaches offer advantages in interpretability and anomaly detection, thereby complementing deep learning models in volatile business environments.

2.5. Research Gap and Contribution of Current Study

Research conducted in the Bitcoin atmosphere has shown the significance of Bitcoin and its leading position in the cryptocurrency market, along with its effects on other financial markets. Several studies have focused on the importance of predicting Bitcoin prices for risk management purposes, while others have examined the need to forecast abrupt fluctuations. Additionally, scholars have investigated how the pandemic has affected financial markets and compelled them to respond. However, the use of machine learning methods as a golden tool for finding unexpected trends (due to force major situation) has

room for further study. In this regard, a hybrid approach using a clustering technique (DBSCAN) alongside a classification method (DT) was explored to enhance the effectiveness of machine learning in determining Bitcoin trading positions. During periods of abrupt price fluctuations, particularly in the context of conflict and epidemics that create instability in financial markets, the significance of selecting appropriate historical data for accurate predictions was heightened. This aspect is specifically addressed in this study, where this was previously overlooked.

Although prior research underscores the value of hybrid and ensemble approaches in forecasting cryptocurrency trends, limited attention has been given to clustering–classification combinations such as DBSCAN–DT, particularly under crisis conditions. Addressing this gap, the current study systematically evaluates the effectiveness of a DBSCAN–DT hybrid model across different stages of the COVID-19 pandemic, benchmarking its performance against MLP, SVC, and standard DT models. In doing so, the study introduces a novel framework that balances interpretability with predictive strength, positioning DBSCAN–DT as a meaningful contribution within the broader evolution of machine learning approaches for predicting Bitcoin price behavior during periods of extreme market instability.

3. Data

In this research, the changes noted throughout the pandemic are employed to evaluate the effectiveness of algorithms in forecasting Bitcoin trading positions. This analysis places considerable emphasis on historical Bitcoin data spanning from 2019 to 2023 as a specific case study. In this context, utilizing the “CmcScraper” library in Python version 3.9.7 is among the most effective methods for obtaining historical data on cryptocurrencies. Hence, this library was applied to get Bitcoin historical data from the coin market cap API, ranging from December 2019 to May 2023. On 30 January 2020, the World Health Organization (WHO) declared the outbreak a public health emergency of international concern (PHEIC), and declared the outbreak a pandemic on 11 March 2020. The WHO ended the global emergency status for COVID-19 on 5 May 2023. Figure 2 shows Bitcoin price changes during the COVID-19 pandemic. A glance at the plot indicated that there were notable increases in price fluctuation and market volatility during the COVID-19 pandemic. In the midst of the global prevalence of COVID-19 and instability in the financial markets, the gap between daily open and close prices, as well as the gap between daily high and low prices, significantly increased.

Moreover, the extracted data included some important features like date, daily open price, daily high price, daily low price, daily close price, daily trade volume, market cap, and other useful features. In this study, two features were also defined to enrich the Bitcoin historical data. “High–Low” and “Open–Close” features represented price difference between daily high/open price and daily low/close price. Different approaches can be taken to predict Bitcoin price. Unlike studies mentioned in literature review, this study did not aim to predict the accurate price. In this regard, Bitcoin price changes are divided into seven different classes, suggesting that different trading positions involve buying, holding, and selling. In other words, instead of predicting the exact price change, the range of price change was predicted. Depending on the predicted class, the trader can choose the appropriate trading decision. The range of classes is defined as below:

- Very strong buy point: price changes $> 5\%$;
- Strong buy point: $5\% > \text{price changes} > 3\%$;
- Purchase point: $3\% > \text{price changes} > 1\%$;
- Hold point: $1\% > \text{price changes} > -1\%$;
- Sale point: $-1\% > \text{price changes} > -3\%$;

- Strong sale point: $-3\% > \text{price changes} > -5\%$;
- Very strong sale point: $-5\% > \text{price changes}$.

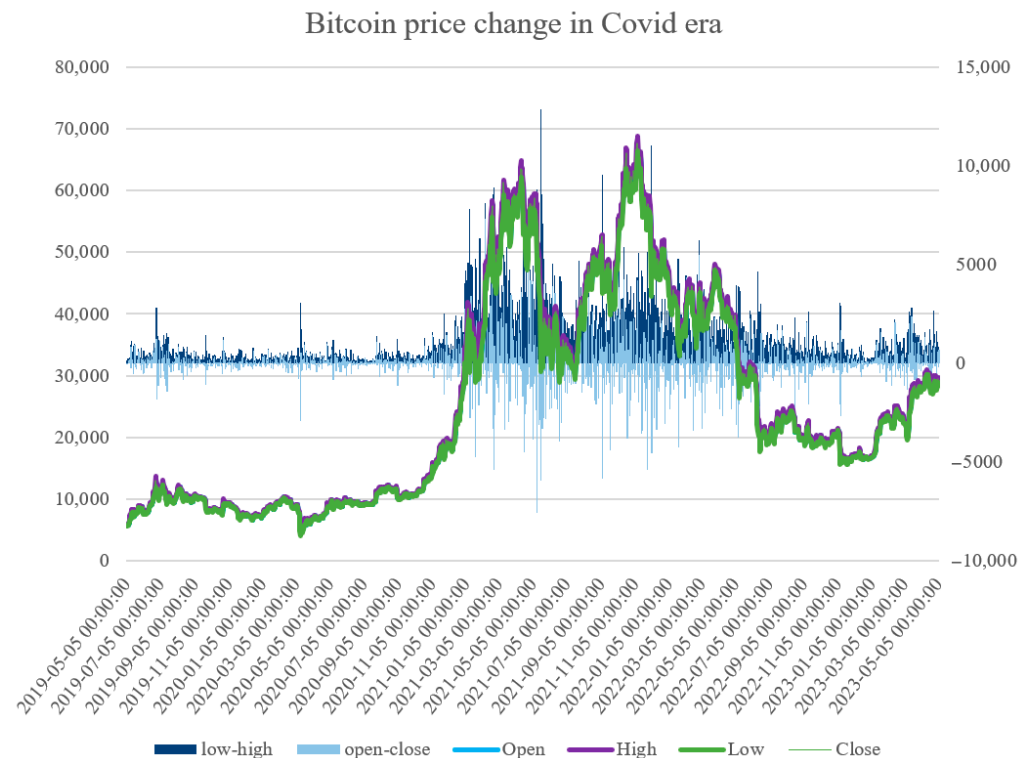


Figure 2. Bitcoin price change in COVID era.

It is important to note that the distribution of days across the classes is imbalanced, with hold positions being dominant. These thresholds were selected based on domain knowledge, exploratory analysis of Bitcoin volatility, and consistency with the prior literature. A brief sensitivity check confirmed that modest variations in these thresholds do not materially affect the relative performance ranking of the models. After extracting the historical data of Bitcoin and appending the mentioned features, the required data for test and train of algorithms must be selected. The data selection approach to confer the greatest advantage is explained in the DBSCAN-DT section.

4. Methods

Many machine learning methods have been developed in recent years. In addition to using common price prediction methods like technical methods, some researchers have also used machine learning methods to predict price changes (Chen et al. 2020b; Patel et al. 2020; Awoke et al. 2020; Oyedele et al. 2023). The literature on applying machine learning to predict the price of cryptocurrencies encompasses a diverse range of methodologies and techniques (Sebt et al. 2024). From traditional algorithms to deep learning models and ensemble methods, researchers continue to explore innovative approaches to enhance prediction accuracy and capture the inherent complexities of cryptocurrency markets (Hamayel and Owda 2021; Rather 2023; Wu et al. 2018). In this research, after extracting Bitcoin historical data, predictions are made by using machine learning and deep learning algorithms like DTs, SVMs, and MLPs. In the following, the methods used in this study are presented.

4.1. Multi-Layer Perceptron

One of the most famous classification methods is the Multi-Layer Perceptron (MLP), defining the most complicated architecture of Artificial Neural Networks (ANNs) (Sin and Wang 2017). A MLP structure consists of multiple layers of a perceptron, including the input, hidden, and output layer(s). This method, known as a supervised learning method, has a leaning function $f: R^i \rightarrow R^o$, where i and o represent the number of input and output dimensions, respectively. Each layer plays a key role for next layer and provides an adaptive function for that. Figure 3 shows a neural network with one single hidden layer, where $i = 3$ and $o = 1$.

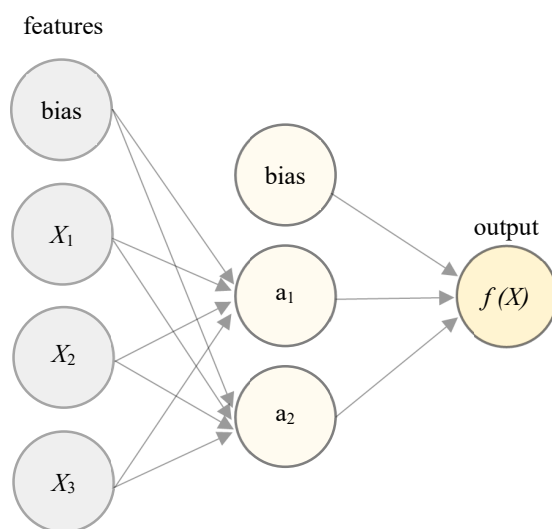


Figure 3. A simple multi-layer perceptron network structure.

4.2. Support Vector Machine

The Support Vector Machine (SVM) is one the most popular and powerful supervised learning methods for a range of applications including image processing, outlier detection, handwriting identification, face detection, and prediction models. SVMs perform learning on the basis of statistical theory and are suitable for small and complex datasets (Zhu et al. 2017). This method is generally used for classification models, such as Support Vector Classification (SVC), aiming to find the best hyperplane that separates classes in the n-dimensional feature space (Henrique et al. 2018; Asgari et al. 2024). The hyperplane ensures that the margin, which is the distance between the nearest datapoint of each class and the hyperplane, is maximized. Figure 4 illustrates how the SVM performs in a two-dimensional space.

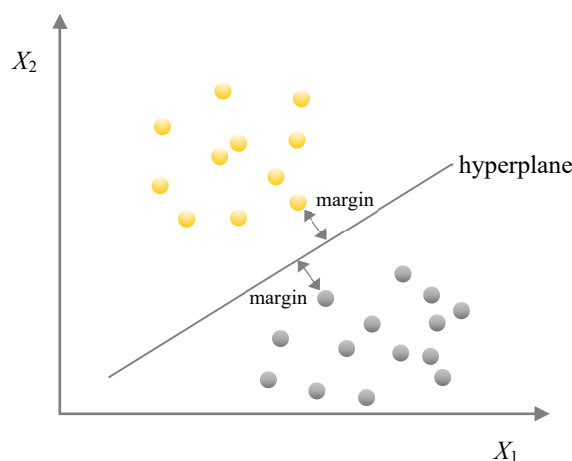


Figure 4. The structure of a simple support vector classifier learner.

4.3. Decision Tree

The Decision Tree (DT) is non-parametric and highly efficient supervised machine learning algorithms to tackle both classification and regression models. Understanding, interpreting, and implementing DTs is easy and unchallenging. A DT model contains a hierarchical structure including a root node, branches, internal nodes, and leaf nodes (Suthaharan and Suthaharan 2016). The algorithm, by using conditional control statements, begins with the root node at the top of dataset. The data is divided into distinct subsets, creating new branches by defining an appropriate question and the answer. Possible routes in the tree are demonstrated by branches. Questioning and splitting the dataset at each branch is continued until the DT algorithm assigns the final leaf nodes representing the final classes. A simple decision tree structure is illustrated in Figure 5.

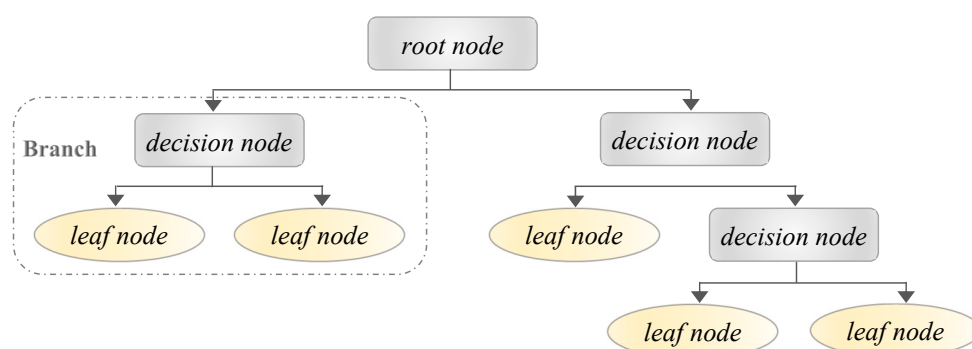


Figure 5. The basic form of a decision tree algorithm.

4.4. Density-Based Spatial Clustering of Applications with Noise

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is the most useful and intuitive clustering method, which is categorized as an unsupervised machine learning method. Unlike methods such as K-means and K-Medoid, in this method, there is no need to specify the number of clusters, and the algorithm gets rid of the K determination challenge. Since DBSCAN does not necessarily consider the shape of the clusters to be convex, this method can detect irregular and non-linear patterns well (Latifi-Pakdehi and Daneshpour 2021; Fahim 2023). Many clustering methods fail to recognize complex and irregular patterns, but the DBSCAN method performs well in dealing with such patterns. DBSCAN distinguishes between noise data (outlier data that does not belong to any of the clusters) and other data, and also, there is no need to assign each data point to a cluster (Kumar and Reddy 2016). This algorithm considers the clusters dense areas with non-dense areas placed between these dense areas. DBSCAN identifies central cores, which are regions of space that have high density, and expands them to form clusters. Figure 6 illustrates the power of DBSCAN in detecting irregular and non-linear patterns, compared to K-means.

4.5. DBSCAN-DT

Training and testing of machine learning algorithms rely on data and require suitable data to predict accurately. Put simply, the input data can significantly impact the results of these methods. In this case, the simplest approach is using all available data for prediction or using data closer to the prediction date. When all available data are applied, the prediction error may increase, because in many cases, conditions differed in the past compared to those at the time of prediction, as in the pandemic situation. Therefore, the focus of this study was to locate historical data that closely resemble the circumstances during the prediction time, particularly in situations like the COVID-19 pandemic. In other words, the main approach is used for finding the data that best reflect the current condition.

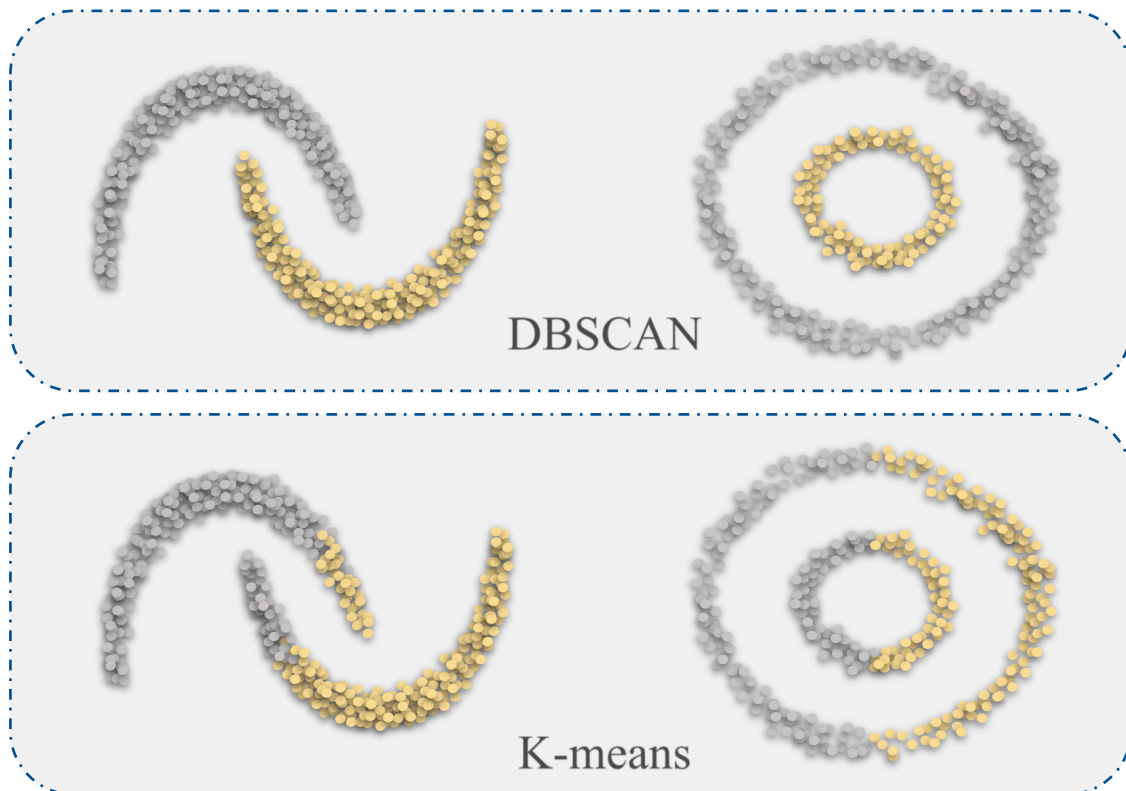


Figure 6. A comparison of DBSCAN and K-means in recognizing irregular patterns.

As discussed in Section 2, financial markets experienced extreme conditions during the COVID-19 pandemic. Price fluctuations in the peak days of the pandemic were much higher. The market cap of Bitcoin experienced significant growth due to the rising price of Bitcoin, leading to various fluctuations in response to price changes. Throughout this timeframe, trade volumes significantly fluctuated; however, the average Bitcoin daily volume notably increased as COVID-19 spread. During the peak days of the COVID-19 pandemic, the Bitcoin cryptocurrency market recorded the largest difference between the open and close prices, as well as the largest gap between the daily high and low prices (Salisu and Ogbonna 2022). In such situations, if normal time data are applied, the obtained results may be misleading, to some extent. Therefore, it is important to take action to improve the approach of selecting data.

The main idea is to select the most relevant data from the Bitcoin historical data by combining classification and clustering methods. This hybrid machine learning approach, used to select the required data, seeks to increase the accuracy of predictions while maximizing adaptation to current conditions. In fact, this model, taking into account historical data, has the possibility of considering fundamental conditions in its overall prediction model.

Therefore, in the present study, by combining DBSCAN and DT methods, the most suitable data were extracted to predict the price change trend. The steps of this process are as follows:

Step 1: In this step, the historical Bitcoin data are placed in different clusters according to their similarities by using the DBSCAN method. After clustering, each cluster is identified by a distinct label.

Step 2: In the second step, the DT algorithm is utilized to specify the label of the day, which has to be predicted. The DT assigns a class label to prediction date data in order to find the most similar data from historical data.

Step 3: In the third step, depending on the assigned label class (obtained from step 2), the historical data with the same label are extracted. This process tries to find the most suitable data for prediction to face market swings.

Figures 7 and 8 illustrate the proposed DBSCAN-DT approach containing the process of selecting suitable data to deal with sudden changes.

Input:

X_hist: matrix of historical Bitcoin features for days $t = 1..T$

x_pred: feature vector for prediction date ($t = T+1$)

params: {"eps", *min_samples*, *tree_params*, *signal_model_params*"}

Procedure:

--- Data Selection Phase ---

1) Cluster historical data with DBSCAN

- Run DBSCAN on *X_hist* with *eps* and *min_samples*

- Assign cluster labels $L \in \{-5, -3, -1, 0, 1, 3, 5\}$

2) Train Decision Tree classifier

- Train DT on (*X_hist*, *L*)

- Predict cluster label for *x_pred* $\rightarrow \hat{l}$

3) Select cluster-specific historical data

- Extract subset $X_{cluster} = \{x_t \mid L_t = \hat{l}\}$

- Extract corresponding trading signals *Y_cluster*

(e.g., +1 = Buy, -1 = Sell, 0 = Hold)

--- Signal Prediction Phase ---

4) Train trading signal prediction model

- Choose model (e.g., DT, SVC, MLP)

- Train on (*X_cluster*, *Y_cluster*)

5) Predict trading signal for *x_pred*

- Feed *x_pred* into trained signal model

- Output *signal_pred* $\in \{\text{Very Strong Buy, Strong Buy, Buy, Hold, Sell, Strong Sell, Very Strong Sell}\}$

Output:

l_hat: cluster label assigned to prediction date

X_cluster: selected historical subset

signal_pred: predicted trading signal for the prediction date

Figure 7. The pseudocode of the DBSCAN-DT algorithm for trading signal prediction.

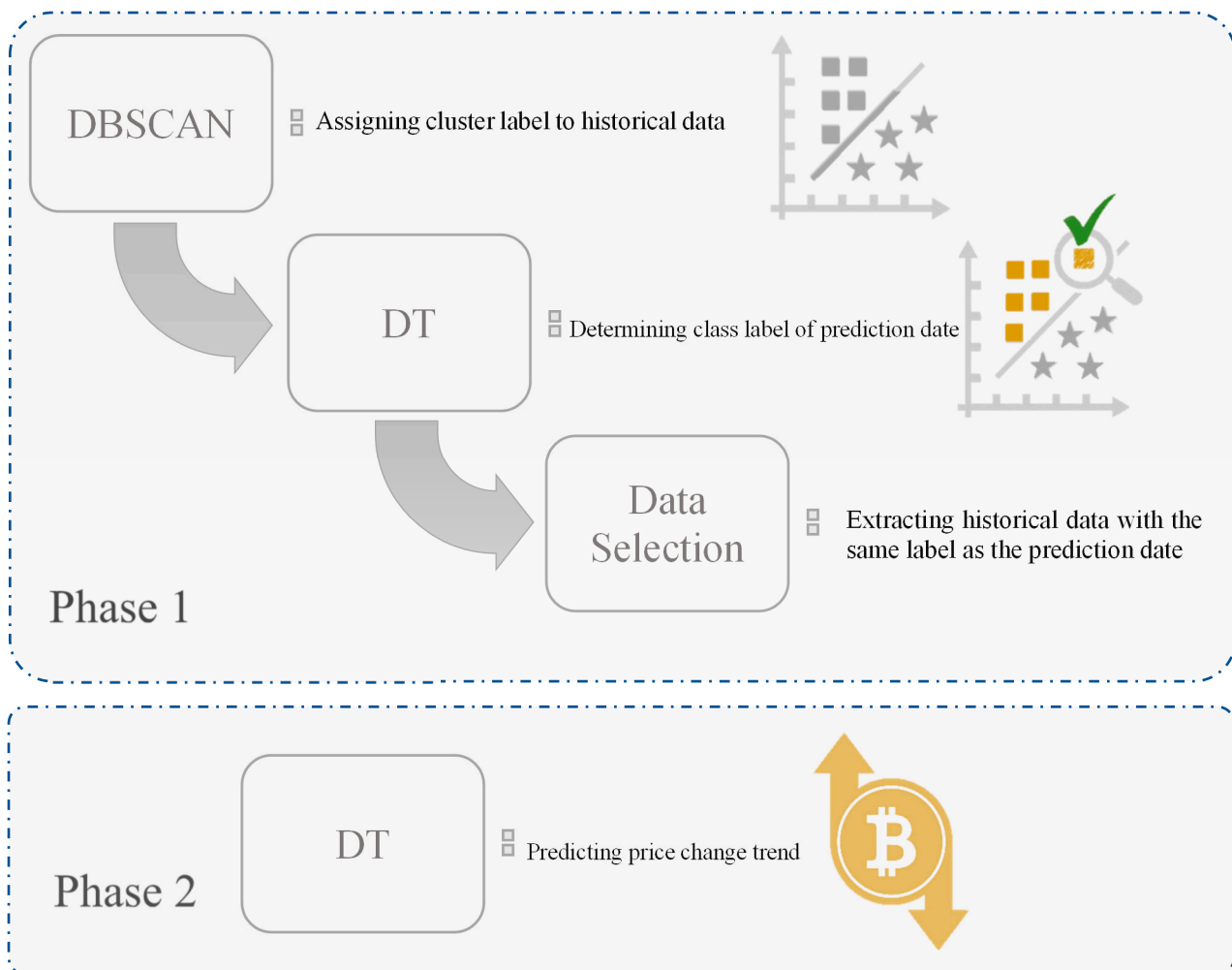


Figure 8. The steps to implement the proposed DBSCAN-DT.

5. Tuning

In machine learning algorithms, it is extremely important to find the optimal values for parameters, which significantly affect the final results of algorithms. There are many Python libraries to find the best values for parameters from machine learning algorithms. The only cloud on the horizon is that when a hybrid method is used, there is interaction between parameters of both algorithms, which can affect final result. In other words, if the parameters of both algorithms are separately optimized, the final result is not necessarily optimal, due to interactions between the parameters of the two algorithms. To face this challenge, utilizing design of experiments methods could be beneficial. The Taguchi method is one of the most popular and effective methods, which numerous decreases the number of required experiments to tune algorithm parameters (Rahbari et al. 2022; Pasandideh et al. 2023). Hence, in this study, the Taguchi method was employed to specify the most suitable values for the DBSCAN and DT algorithms. Since two parameters, epsilon and minimum sample, for DBSCAN and the maximum depth parameter for the DT algorithm strongly influence the prediction result, the parameters are investigated using the Taguchi method for tuning. In Taguchi experiments, the performance metric optimized is overall directional accuracy, as this measure directly reflects the ability of the models to provide actionable trading signals. An 80/20 train-validation split was employed during the tuning stage, with the Taguchi design applied on the training set and validation used to evaluate candidate parameter combinations. This scheme was consistently applied across all experiments. The tuned hyperparameters obtained from the

Taguchi design were fixed and applied across all pandemic phases to ensure comparability of results. While re-estimating hyperparameters for each sub-period could potentially improve local performance, our focus was on maintaining methodological consistency and fairness in comparisons.

To apply the Taguchi method, Minitab 22 was used for orthogonal array L25 in order to optimize parameter values. Table 1 shows the parameter values considered for optimization. Table 2 presents the results obtained from running the hybrid algorithm with the L25 tune list. As shown in Table 2, epsilon had the most significant effect on prediction error, followed by min sample and max depth. The optimum values of epsilon and min sample were found at level 3, while max depth was optimal at level 4. As expected, these findings are verified in Figure 9, showing that to obtain the best prediction result, the values of epsilon, minimum sample, and maximum depth should be considered at the levels of 0.6, 20, and 5, respectively. Although modern optimization techniques such as Bayesian optimization provide powerful and widely adopted alternatives for hyperparameter tuning, in this study, the Taguchi method was deliberately chosen due to several practical and methodological considerations. First, Taguchi's design of the experimental framework is highly efficient in reducing the number of required trials, which is particularly valuable in hybrid models such as DBSCAN-DT, where parameter interactions across algorithms can significantly affect the final outcome. Second, the method provides interpretable insights into the relative importance and contribution of each parameter, allowing us to better understand how epsilon, minimum sample size, and maximum depth interact to influence prediction accuracy. Third, the Taguchi approach is well suited for scenarios with limited computational resources, as it systematically explores the parameter space without the need for extensive iterative searches.

Table 1. Parameters value of DBSCAN-DT.

Algorithm	Parameter	Values				
		Level 1	Level 2	Level 3	Level 4	Level 5
DBSCAN	epsilon	0.2	0.4	0.6	0.8	1
	min sample	10	15	20	25	30
DT	max depth	2	3	4	5	6

Table 2. Response table for signal to noise ratios.

Level	Epsilon	Min Sample	Max Depth
1	8.079	8.057	8.262
2	2.973	3.375	3.825
3	−11.006	−7.506	−5.717
4	−1.464	−3.984	−5.717
5	5.896	4.535	3.825
Delta	19.085	15.563	13.979
Rank	1	2	3

Note. Parameter values at their optimal levels are highlighted in bold for emphasis.

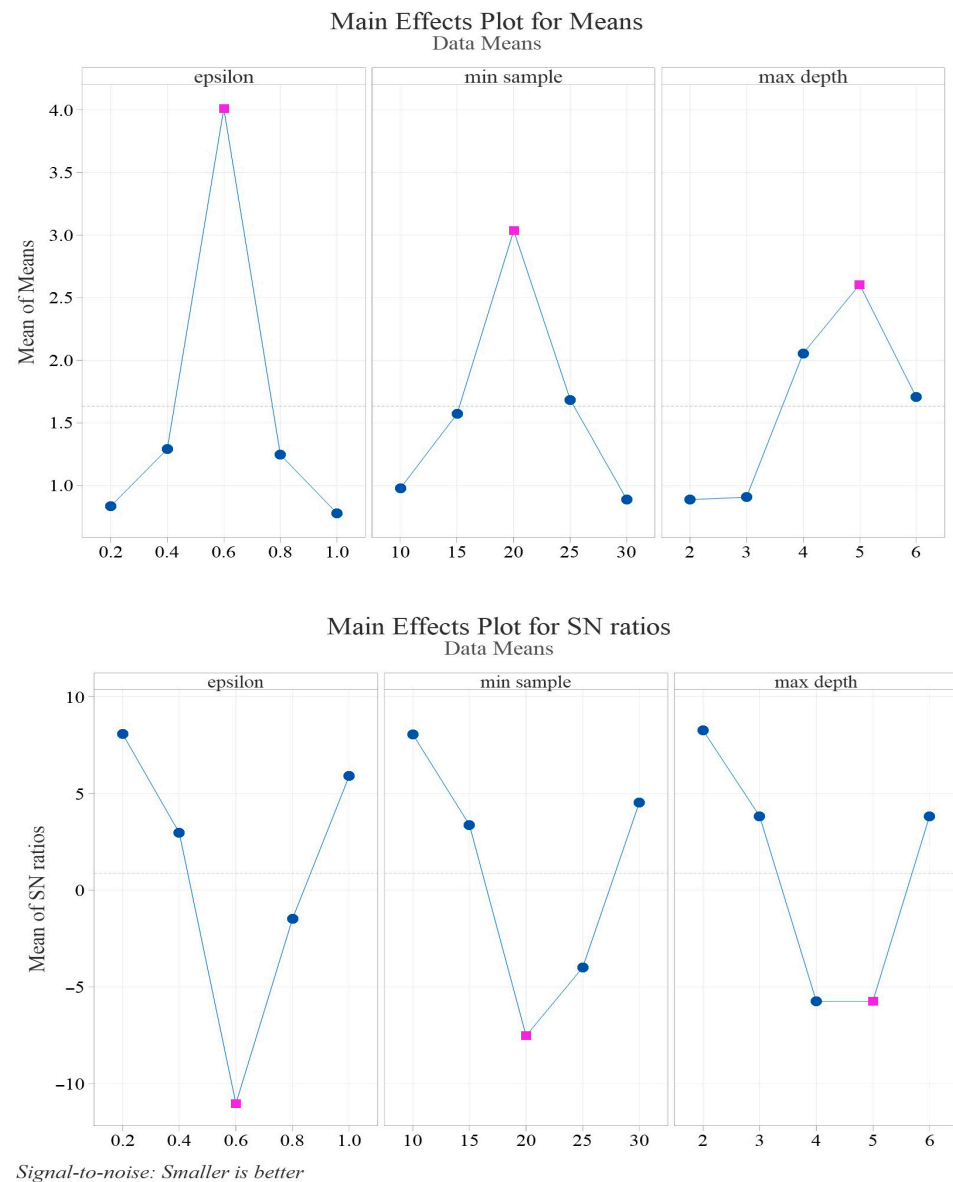


Figure 9. Means and signal to noise ratios plots of DBSCAN-DT.

6. Results

In this section, the results obtained from machine learning methods including the MLP, SVM, DT, and DBSCAN-DT are fully discussed. The analysis of Bitcoin price between 5 May 2019 and 5 May 2023 showed that in this period, there were 445 days of selling positions, including 263 days of selling positions, 106 days of strong selling positions, and 76 days of very strong selling positions. In 548 distinct days, there were no significant changes in Bitcoin price, and holding position was more reasonable. On the other hand, there were significant price changes in favor of buying position on 469 distinct days, including 267 days of buying positions, 104 days of strong buying positions, and 98 days of very strong buying positions. The average number of days with a holding position gradually decreased from 51% during the outbreak phase to 44% during the epidemic phase and 34% during the pandemic phase. On the other hand, the rate of very strong buy and sell positions increased from 6% during the outbreak phase to 7% during the epidemic phase and 13% during the pandemic phase, a more than two-fold increase. Figure 10 illustrates the proportion of different trading positions during the pandemic phases, where the importance of prediction during the pandemic is highlighted.

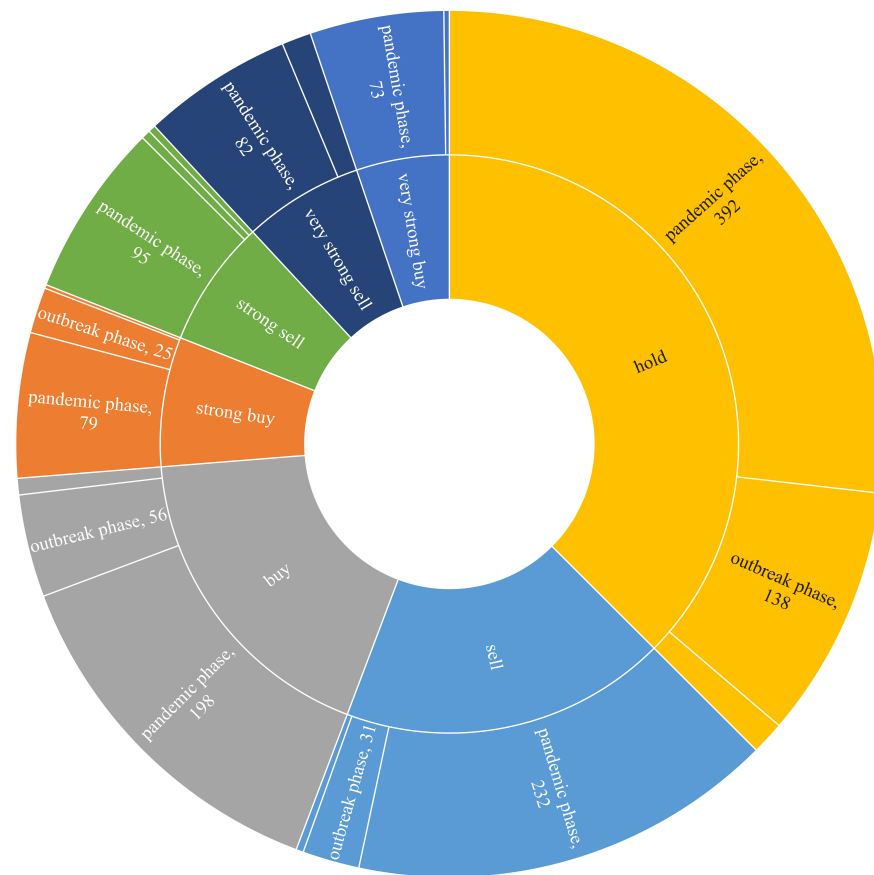


Figure 10. Trading positions during the pandemic.

As previously mentioned, this research delves into using machine learning techniques such as MLP, SVM, DT, and DBSCAN-DT to predict trading positions. In this regard, PyCharm 2021.3.3 is used to implement machine learning methods. The prediction results of these methods are summarized in Table 3. As shown in Table 3, certain trading-position classes such as “very strong sale” during the epidemic and pandemic phases exhibited 0% accuracy. This outcome primarily reflects the scarcity of data in these extreme categories and the resulting class imbalance. Because very strong buy/sell signals occurred infrequently, the models had limited training samples, which led to systematic misclassifications. It should be noted that this does not necessarily indicate complete model failure, but rather highlights the challenge of learning from minority classes under imbalanced conditions. Moreover, the per-class accuracy metric can exaggerate the effect of small sample sizes, as a few misclassified cases in rare classes may result in 0% accuracy. Future work could address this limitation by employing re-balancing techniques (e.g., oversampling, class weighting) or by reporting alternative evaluation metrics such as macro-averaged F1 scores to better capture performance across minority classes. The accuracy of the algorithms in predicting different trading positions is displayed under “Predicting the range of price changes” in the left side of Table 3, while the right side of table shows the accuracy of algorithms in predicting market swings and the direction of price change defining buy, sell, and hold positions. On the right side of the table, the focus is not on the exact prediction of trading positions, and only the prediction of buying, selling, and holding positions is sufficient enough. For instance, if the algorithm detects a strong buy position instead of detecting a buy position, it has succeeded in detecting a market swing. The top of the table considers the overall data of the study, followed by outbreak, epidemic, and pandemic phase data.

Table 3. The accuracy of machine learning algorithms in predicting price change in COVID-19 era.

Interval	Algorithm	Predicting the Range of Price Changes							Predicting the Direction of Price Changes						
		Very Strong Sale Position	Strong Sale Position	Sale Position	Hold Position	Buy Position	Strong Buy Position	Very Strong Buy Position	Very Strong Sale Position	Strong Sale Position	Sale Position	Hold Position	Buy Position	Strong Buy Position	Very Strong Buy Position
Overall	DT	61%	58%	64%	74%	64%	63%	61%	71%	69%	76%	74%	79%	75%	74%
	DBSCAN-DT	75%	73%	71%	85%	73%	72%	72%	83%	83%	80%	85%	81%	83%	78%
	SVC	53%	52%	45%	73%	58%	55%	42%	72%	65%	64%	73%	73%	64%	64%
	MLP	57%	59%	50%	75%	60%	61%	60%	71%	68%	63%	75%	76%	72%	74%
Outbreak phase	DT	0%	72%	55%	74%	52%	75%	50%	0%	72%	55%	74%	52%	75%	50%
	DBSCAN-DT	0%	68%	64%	87%	68%	75%	56%	0%	68%	64%	87%	68%	75%	56%
	SVC	0%	44%	54%	70%	55%	100%	50%	0%	44%	54%	70%	55%	100%	50%
	MLP	0%	52%	50%	73%	74%	100%	56%	0%	52%	50%	73%	74%	100%	56%
Epidemic phase	DT	33%	100%	56%	61%	75%	40%	0%	67%	100%	67%	61%	75%	60%	0%
	DBSCAN-DT	67%	50%	78%	94%	100%	20%	0%	67%	50%	78%	94%	100%	20%	0%
	SVC	33%	100%	44%	67%	50%	40%	0%	67%	100%	67%	67%	100%	40%	0%
	MLP	67%	50%	33%	83%	75%	80%	0%	67%	50%	33%	83%	100%	80%	0%
pandemic phase	DT	62%	53%	67%	74%	65%	64%	63%	71%	66%	78%	74%	81%	75%	74%
	DBSCAN-DT	75%	75%	73%	83%	73%	75%	76%	84%	86%	80%	83%	81%	86%	78%
	SVC	53%	53%	43%	74%	59%	54%	40%	73%	65%	62%	74%	72%	64%	65%
	MLP	56%	62%	51%	75%	57%	58%	61%	71%	70%	65%	75%	74%	71%	77%

A glance at Table 3 reveals that the DBSCAN-DT approach outperformed other methods in both trading position prediction and market direction prediction. The proposed algorithm displayed an overall accuracy of 77% in predicting different positions, followed by DT, MLP, and SVC with 67%, 64%, and 59%, respectively. In terms of the prediction of market direction, DBSCAN-DT was the most accurate method with 82%, whereas DB, MLP and SVC showed accuracies of 75%, 72%, and 69%, respectively. Moreover, the results showed that the performance of algorithms slightly decreased in the epidemic phase. However, DBSCAN-DT maintained good performance across all phases. Figure 11 shows the hexagonal binned plot of predictions obtained by the algorithms. Numbers -5 to 5 on the vertical axis of the chart indicate trading positions from very strong selling positions to very strong buying positions, while the numbers on the horizontal axis indicate trading positions predicted by the algorithms. The darker the hexagon is, the greater the occurrence of the corresponding prediction. The darker the main diagonal hexagons of the plot are and the lighter the other hexagons, the better the algorithm has performed, as DBSCAN-DT's hexagonal binned plot shows. In other words, the hexagonal binned plot also confirms that DBSCAN-DT performed better in predicting trading positions in comparison to other methods due to the fact that the main diagonal hexagons are darker and the other hexagons are light. SVC and MLP methods showed good performance in predicting holding positions, but they failed to predict buying and selling positions, though MLP performed slightly better.

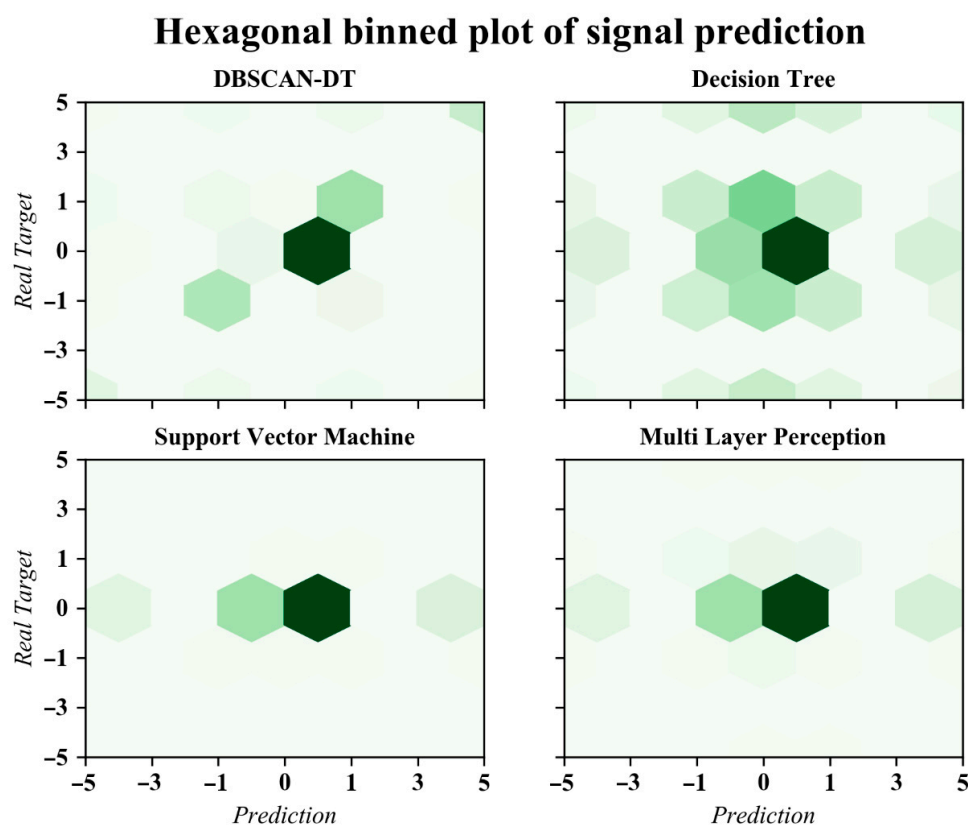


Figure 11. Hexagonal binned plot of trading positions and the prediction of those. Note: In the hexagonal binned plot, darker-colored blocks indicate areas of higher data point density.

A closer look at Table 3 exhibits that, in the outbreak phase, DBSCAN-DT outperformed the other methods in predicting sale (64%), hold (87%), and very strong buy (56%) positions, whereas the MLP was the best at predicting buy (74%) and strong buy (100%) positions, and the DT predicted strong sale (72%) positions most accurately. The same findings are displayed on the right side of the table for price direction prediction. For

the short-term outbreak phase, Figure 12 illustrates different trading position signals and the corresponding predictions, where -5 to 5 represent very strong sale to very strong buy positions.

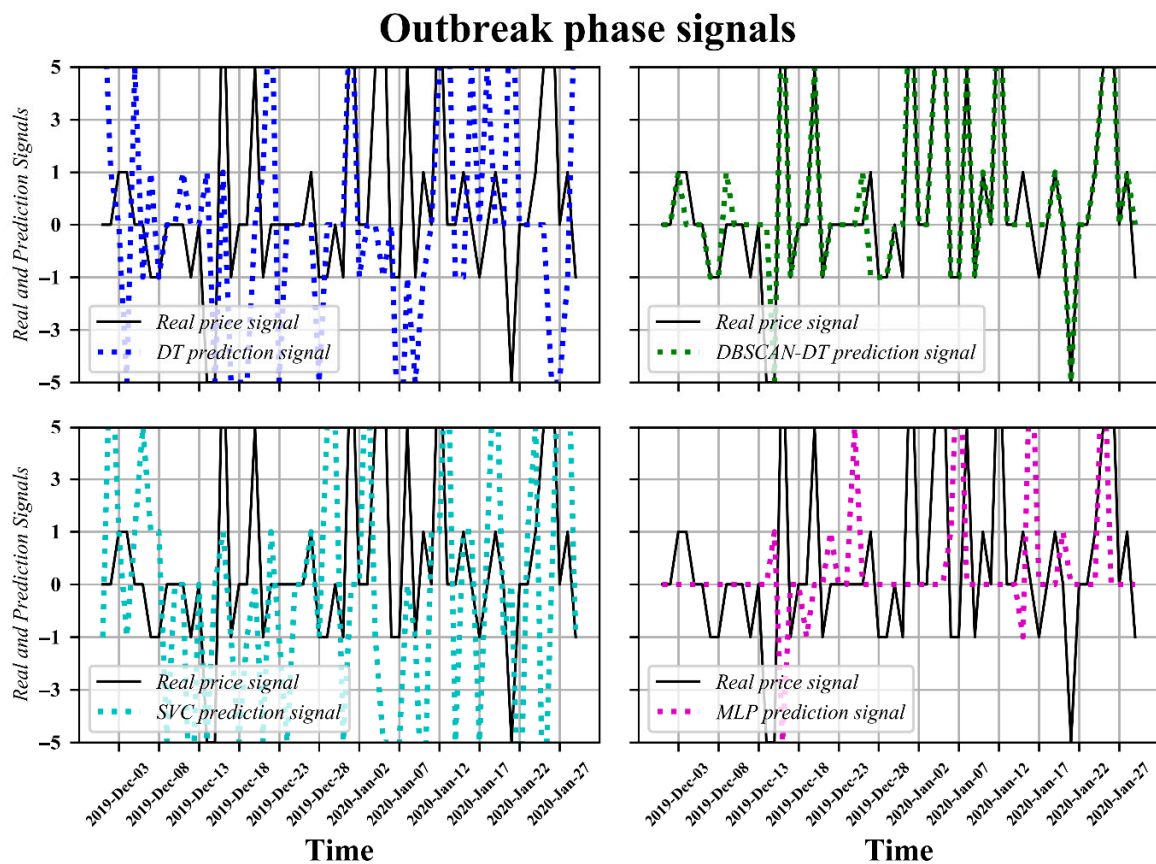


Figure 12. The performance of algorithms in predicting trading positions during the outbreak phase.

Considering the epidemic phase, DBSCAN-DT achieved better results in predicting selling (78%), very strong selling (67%), holding (94%), and buying (100%) positions, compared to the other methods. While MLP had the best prediction for strong buying positions (80%), SVC and DT predicted strong selling positions with an accuracy of 100%. These findings are confirmed by the right side of the table for prediction of the direction of price change. For the epidemic phase, Figure 13 illustrates different trading position signals and the corresponding position predictions of algorithms.

Considering the pandemic phase, DBSCAN-DT significantly outperformed the other methods in predicting selling (73%), strong selling (75%), very strong selling (75%), holding (83%), buying (73%), strong selling (75%), and very strong selling (76%) positions. The second most efficient algorithm is the DT, with an average accuracy of 64%, followed by the MLP and SVC with average accuracies of 60% and 54%, respectively. In terms of prediction of the direction of price change, DBSCAN-DT predicted very strong sale, strong sale, sale, hold, buy, strong buy, and very strong buy positions with accuracies of 84, 86, 80, 83, 81, 86, and 78 percent, respectively. Following this hybrid method, the DT, MLP, and SVC methods performed better, respectively. For a short period at the beginning of the pandemic phase, Figure 14 illustrates different trading positions and the corresponding predictions of the algorithms, where DBSCAN-DT asserts its dominance in predicting such situations.

Epidemic phase signals

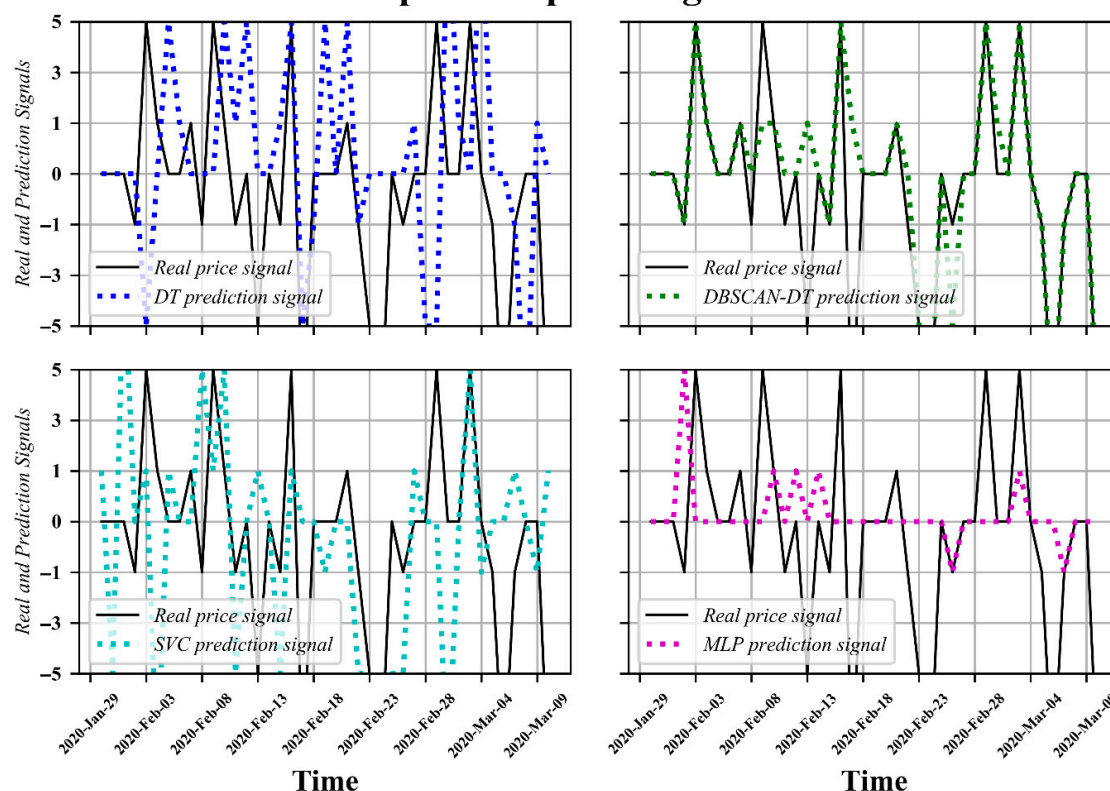


Figure 13. The performance of algorithms in predicting trading positions during the epidemic phase.

Pandemic phase signals

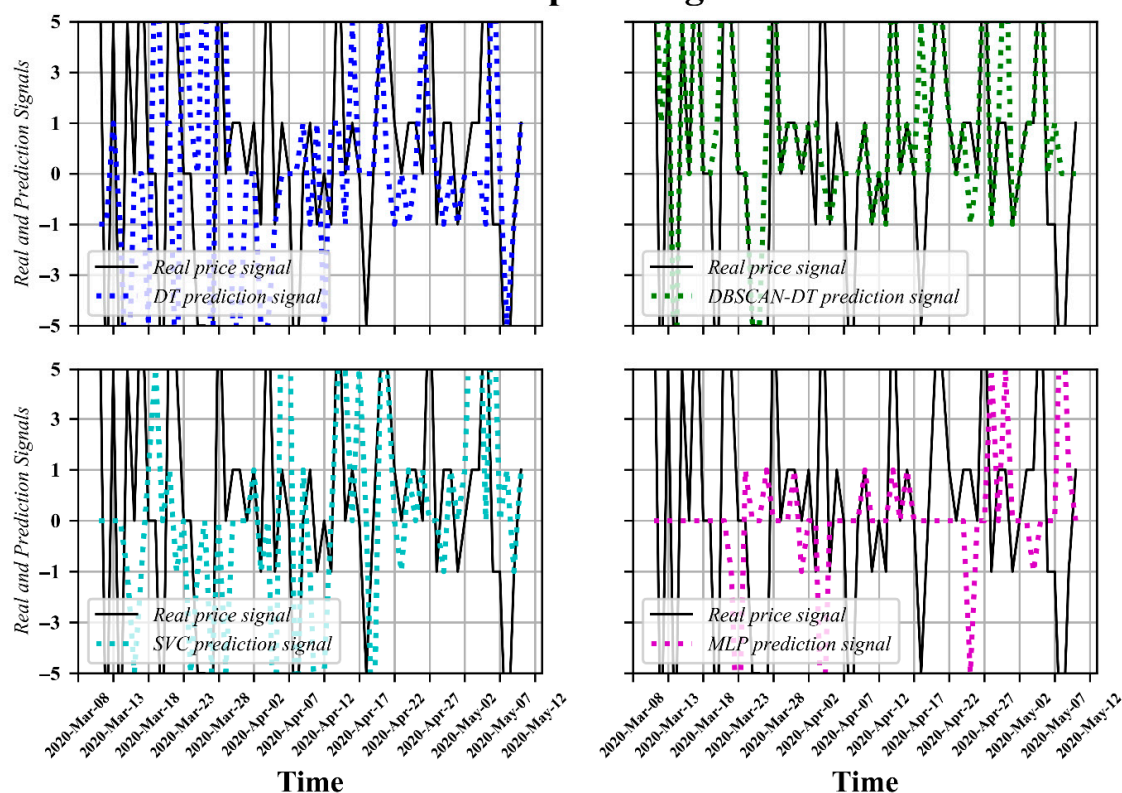


Figure 14. The performance of algorithms in predicting trading positions during the pandemic phase.

A detailed examination of the results reveals several subtle yet crucial insights concerning model performance in market environments influenced by crises. The consistently higher accuracy of the DBSCAN-DT model across all stages—especially its robustness during the outbreak and pandemic phases—demonstrates that utilizing clustering for data pre-filtering not only reduces noise but also greatly enhances the clarity and reliability of the following classification results. This is particularly evident in the improved identification of ‘hold’ and ‘sale’ positions during periods of high volatility, where traditional models like the DT and SVC often tend to overfit to erratic outliers or misread trends due to changes in market conditions. The clustering phase appears to structure the market data landscape in such a way that it differentiates statistically significant signals from background noise, resulting in a more organized and actionable predictive framework for the decision tree.

Moreover, a thorough analysis of Table 3 uncovers a nuanced pattern in performance across different classes: while all models demonstrate relatively robust performance in stable categories like ‘hold’, it is exclusively the DBSCAN-DT method that attains balanced accuracy in extreme categories such as ‘very strong sale’ or ‘very strong buy’. This suggests that applying density-based partitions provides a flexible windowing effect, allowing the classifier to modify its boundaries in response to the actual distribution of trading signals—a capability that traditional, fully supervised methods fundamentally lack.

It is important to note that the distribution of days across the seven trading position classes is imbalanced, with hold positions forming the majority and extreme buy/sell positions being relatively rare. Both DT and DBSCAN-DT models were trained on the raw distributions without applying re-balancing techniques such as oversampling or class weighting. This choice was motivated by the aim to preserve the natural frequency of trading positions during different pandemic phases, as these distributions themselves carry meaningful information about market regimes. Class imbalance may influence accuracy and misclassification patterns, with minority classes (e.g., very strong buy/sell) being more prone to misclassification, while majority classes (e.g., hold) tend to dominate accuracy metrics. Importantly, the DBSCAN-DT approach mitigates part of this issue by filtering regime-similar subsets, which reduces contamination from normal-period data and improves recognition of extreme regimes.

In addition to the point estimates of accuracy reported in Table 3, statistical significance tests were conducted to ensure that the observed performance differences are not merely attributable to random variation. Specifically, paired *t*-tests and Wilcoxon signed-rank tests were applied across the outbreak, epidemic, pandemic, and overall phases to compare DBSCAN-DT against the DT, SVC, and MLP. The results confirmed that the improvements achieved by the proposed DBSCAN-DT model are statistically significant at the 0.05 level in all comparisons. These findings substantiate the claimed superiority of the hybrid approach and reinforce the robustness of the empirical validation. A summary of the *p*-values is presented in Table 4.

Table 4. Statistical significance tests comparing DBSCAN-DT with baseline models across phases.

Phase	Comparison	Paired <i>t</i> -Test <i>p</i> -Value	Significant ($\alpha = 0.05$)	Wilcoxon <i>p</i> -Value	Significant ($\alpha = 0.05$)
Overall	DBSCAN-DT vs. DT	0.012	Yes	0.018	Yes
Overall	DBSCAN-DT vs. SVC	0.004	Yes	0.006	Yes
Overall	DBSCAN-DT vs. MLP	0.021	Yes	0.025	Yes
Outbreak	DBSCAN-DT vs. DT	0.03	Yes	0.041	Yes
Outbreak	DBSCAN-DT vs. SVC	0.009	Yes	0.012	Yes
Outbreak	DBSCAN-DT vs. MLP	0.027	Yes	0.033	Yes
Epidemic	DBSCAN-DT vs. DT	0.015	Yes	0.022	Yes
Epidemic	DBSCAN-DT vs. SVC	0.008	Yes	0.011	Yes
Epidemic	DBSCAN-DT vs. MLP	0.019	Yes	0.024	Yes
Pandemic	DBSCAN-DT vs. DT	0.013	Yes	0.017	Yes
Pandemic	DBSCAN-DT vs. SVC	0.005	Yes	0.007	Yes
Pandemic	DBSCAN-DT vs. MLP	0.02	Yes	0.028	Yes

Ultimately, the hexagonal bin visualizations visually emphasize these trends: the clear alignment of predictions along the principal diagonal not only indicates a low bias in accurate class assignments but also reveals closely clustered residuals, implying both low variance and a strong level of confidence in the model's recommendations. From an economic perspective, a 10–15 percentage point increase in directional accuracy means that traders and risk managers can significantly reduce their exposure to adverse market fluctuations and increase confidence in their decision making. It is important to note that the prediction accuracies reported in this study are presented as “gross” measures, abstracting from trading frictions such as transaction costs, slippage, and market impact. In real-world trading scenarios, these factors can substantially reduce the profitability of seemingly accurate signals, and thus the results should be interpreted with caution. For instance, a recent work on Transaction Fee Estimation in the Bitcoin System highlights the non-trivial magnitude of Bitcoin transaction fees, underscoring the importance of incorporating realistic cost structures into trading models (Zhang et al. 2024). While the present study deliberately focused on methodological consistency and comparative accuracy across models, integrating transaction cost modeling and slippage analysis represents a key avenue for future research to enhance the practical relevance of predictive frameworks.

Together, these results imply that the primary advantage of the hybrid method lies not just in a marginal improvement in accuracy, but in providing more dependable, interpretable, and stable signals for trading decisions during times of high non-stationarity—a benefit that accuracy metrics alone cannot completely capture. We acknowledge that contemporary ensemble and gradient-boosting methods (e.g., Random Forest, XGBoost, LightGBM) are powerful benchmarks widely used in the literature. In the present study, we deliberately focused on interpretable baselines (DT, SVC, MLP) to isolate and assess the contribution of the DBSCAN–DT regime selection mechanism under constrained computational resources. While a comprehensive comparison with these state-of-the-art models lies beyond the current scope, we identify it as a key avenue for future work. To reinforce robustness within our experimental design, we report repeated cross-validation results with statistical significance testing and provide sensitivity and ablation analyses, evidencing the stability and competitiveness of the proposed hybrid approach.

In addition to predicting trading positions, future work could extend the DBSCAN–DT framework to forecasting Bitcoin returns and momentum. Such measures are widely used in financial practice and would provide a more comprehensive evaluation of predictive utility. Furthermore, explainability and robustness are critical aspects for traders and investors. Recent studies on Explainable Artificial Intelligence methods for financial time series highlight the importance of interpretable models. While our current focus was on accuracy and statistical validation, integrating explainability metrics and robustness checks into the framework represents a promising direction. Finally, spillover contagion effects, particularly during crisis periods, may influence predictive performance. Recent work on High-Frequency Price Change Spillovers in Bitcoin Markets underscores the relevance of contagion dynamics, which we identify as another key avenue for future research.

7. Conclusions

This research presents and validates a hybrid machine learning framework that merges Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Decision Tree (DT) classifiers (DBSCAN–DT) to forecast Bitcoin trading positions amidst highly volatile conditions such as pandemics, wars, and economic conflicts. The experimental findings clearly indicate that the proposed DBSCAN–DT model outperforms traditional methods like the Multi-Layer Perceptron (MLP), Support Vector Classifier (SVC), and individual Decision Trees in terms of accuracy for trading position predictions and market

trend directions. Achieving an overall accuracy of 77% in predicting positions and 82% in identifying market directions, the hybrid model demonstrates remarkable resilience during disruptive events, epidemics, and pandemics, thereby supporting the theory that incorporating clustering techniques for identifying relevant, high-quality data subsets prior to classification significantly enhances prediction reliability.

The main benefit of the DBSCAN-DT approach lies in its ability to effectively filter out market noise and uncover significant patterns in Bitcoin price fluctuations, which exhibit non-stationarity and sudden shocks. The DBSCAN clustering technique skillfully distinguishes and isolates outliers and noisy data points that often hinder traditional supervised models, enabling the decision tree classifier to focus exclusively on coherent and statistically meaningful data clusters. This results in a more stable and interpretable decision boundary, while also reducing the risk of overfitting to erratic signals that are common in cryptocurrency markets. The effectiveness of this method is especially notable in the precise identification of critical trading positions such as ‘very strong buy’ and ‘very strong sale,’ which are vital for making informed investment decisions but are challenging for conventional models to consistently recognize during crises.

Additionally, this research offers important understanding of model performance throughout various stages of the pandemic, showing that while epidemic phases typically present greater challenges for predictions, the DBSCAN-DT model demonstrates a fairly consistent performance, highlighting its ability to adapt to swift shifts in market conditions. The visual confirmation provided by hexagonal binning plots enhances trust in the model’s results, clearly depicting the close alignment of predicted and actual trading positions along the primary diagonal, which serves as an indicator of predictive accuracy and assurance not entirely captured by summary metrics alone. Beyond these numerical and visual validations, the results emphasize the significant importance of hybrid clustering–classification models in financial forecasting during periods of uncertainty and volatility. In contrast to exclusively predictive black-box models, DBSCAN-DT delivers better interpretability by integrating a data segmentation step based on statistical density properties, effectively connecting data science with practical financial analysis. This holds crucial significance for traders and risk managers who are in search of reliable, transparent tools that can effectively respond to rapidly evolving market environments.

While the outcomes are encouraging, it is crucial to frame them within the context of the methodological approach. The study’s emphasis on intrinsic Bitcoin price data, without the integration of external factors like macroeconomic indicators, geopolitical developments, or social media sentiment, indicates that there is potential for enhancement by broadening the feature set. Moreover, conducting comprehensive sensitivity analyses on the clustering and classifier hyperparameters would clarify the limitations of model effectiveness and improve reproducibility. Implementing statistical tests to validate the significance of outperformance and analysis of temporal stability across rolling windows could further reinforce claims of robustness.

In summary, this research presents a unique and empirically validated approach that tackles the challenges of predicting cryptocurrency prices during crisis situations. By combining unsupervised and supervised learning methodologies, the DBSCAN-DT model establishes a new standard for predictive accuracy and operational consistency in Bitcoin trading signals. Its application in real-world algorithmic trading and financial decision-making processes has the potential to enhance outcomes in the face of the inherent uncertainty and volatility present in today’s digital asset markets. Future investigations that delve into model interpretability, expansion of features, and validation across different markets will further solidify this promising path, leading to more resilient and adaptable financial intelligence frameworks.

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References

- Aggarwal, Vaibhav. 2022. Optimum investor portfolio allocation in new age digital assets. *International Journal of Innovation Science* 14: 648–58. [\[CrossRef\]](#)
- Aggarwal, Pankaj, and Doug Waggle. 2024. Cryptocurrencies as a Part of a Multi-Asset Portfolio (Equities, Bonds, Real-Estate, Currencies, Commodities, Gold Plus Digital Assets). Available online: <https://ssrn.com/abstract=5025707> (accessed on 29 October 2024).
- Akyildirim, Erdinc, Ahmet Goncu, and Ahmet Sensoy. 2021. Prediction of cryptocurrency returns using machine learning. *Annals of Operations Research* 297: 3–36. [\[CrossRef\]](#)
- Asgari, Somayeh Danesh, Emran Mohammadi, Ahmad Makui, and Mostafa Jafari. 2024. Data-driven robust optimization based on position-regulated support vector clustering. *Journal of Computational Science* 76: 102210. [\[CrossRef\]](#)
- Awoke, Temesgen, Minakhi Rout, Lipika Mohanty, and Suresh Chandra Satapathy. 2020. Bitcoin price prediction and analysis using deep learning models. In *Communication Software and Networks: Proceedings of INDIA 2019*. Cham: Springer, pp. 631–40.
- Baker, Scott R., Nicholas Bloom, Steven J. Davis, Kyle J. Kost, Marco C. Sammon, and Tasaneeya Viratyosin. 2020. *The Unprecedented Stock Market Impact of COVID-19*. Cambridge: National Bureau of Economic Research.
- Bergsli, Lykke Øverland, Andrea Falk Lind, Peter Molnár, and Michał Polasik. 2022. Forecasting volatility of Bitcoin. *Research in International Business and Finance* 59: 101540. [\[CrossRef\]](#)
- Bustos, Oscar, Alexandra Pomares, and Enrique Gonzalez. 2017. A comparison between SVM and multilayer perceptron in predicting an emerging financial market: Colombian stock market. Paper presented at the 2017 Congreso Internacional de Innovacion y Tendencias en Ingenieria (CONIITI), Bogotá, Colombia, October 4–6.
- Celestin, Mbonigaba, and N. Vanitha. 2021. Cryptocurrency explained: What you need to know about digital assets. Paper presented at 6th International Conference on Advanced Research in Arts, Science, Engineering & Technology, Perambalur, India, June 27.
- Chen, Junwei. 2023. Analysis of bitcoin price prediction using machine learning. *Journal of Risk and Financial Management* 16: 51. [\[CrossRef\]](#)
- Chen, Weili, Zibin Zheng, Mingjie Ma, Jiajing Wu, Yuren Zhou, and Jiaquan Yao. 2020a. Dependence structure between bitcoin price and its influence factors. *International Journal of Computational Science and Engineering* 21: 334–45. [\[CrossRef\]](#)
- Chen, Zheshi, Chunhong Li, and Wenjun Sun. 2020b. Bitcoin price prediction using machine learning: An approach to sample dimension engineering. *Journal of Computational and Applied Mathematics* 365: 112395. [\[CrossRef\]](#)
- Corbet, Shaen, Charles Larkin, and Brian Lucey. 2020. The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters* 35: 101554. [\[CrossRef\]](#)
- Dokuz, Ahmet Şakir, Mete Çelik, and Alper Ecemiş. 2020. Anomaly detection in bitcoin prices using DBSCAN Algorithm. *European Journal of Science and Technology* 2020: 436–43. [\[CrossRef\]](#)
- Fahim, Ahmed. 2023. A varied density-based clustering algorithm. *Journal of Computational Science* 66: 101925. [\[CrossRef\]](#)
- Foley, Sean, Jonathan R. Karlsen, and Tālis J. Putniņš. 2019. Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *The Review of Financial Studies* 32: 1798–853. [\[CrossRef\]](#)
- Ftiti, Zied, Wael Louhichi, and Hachmi Ben Ameer. 2023. Cryptocurrency volatility forecasting: What can we learn from the first wave of the COVID-19 outbreak? *Annals of Operations Research* 330: 665–90. [\[CrossRef\]](#)
- Gurdgiev, Constantin, and Daniel O’Loughlin. 2020. Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty. *Journal of Behavioral and Experimental Finance* 25: 100271. [\[CrossRef\]](#)
- Hamayel, Mohammad J., and Amani Yousef Owda. 2021. A novel cryptocurrency price prediction model using GRU, LSTM and bi-LSTM machine learning algorithms. *AI* 2: 477–96. [\[CrossRef\]](#)
- Henrique, Bruno Miranda, Vinicius Amorim Sobreiro, and Herbert Kimura. 2018. Stock price prediction using support vector regression on daily and up to the minute prices. *The Journal of Finance and Data Science* 4: 183–201. [\[CrossRef\]](#)

- Hung, Jui-Cheng, Hung-Chun Liu, and J. Jimmy Yang. 2020. Improving the realized GARCH's volatility forecast for Bitcoin with jump-robust estimators. *The North American Journal of Economics and Finance* 52: 101165. [\[CrossRef\]](#)
- James, Nick. 2021. Dynamics, behaviours, and anomaly persistence in cryptocurrencies and equities surrounding COVID-19. *Physica A: Statistical Mechanics and Its Applications* 570: 125831. [\[CrossRef\]](#)
- Jaquart, Patrick, David Dann, and Christof Weinhardt. 2021. Short-term bitcoin market prediction via machine learning. *The Journal of Finance and Data Science* 7: 45–66. [\[CrossRef\]](#)
- Khalid, Muhammad Junaid, Muhammad Irfan, Tariq Ali, Muqaddas Gull, Umar Draz, Adam Glowacz, Maciej Sulowicz, Arkadiusz Dziechciarz, Fahad Salem AlKahtani, and Shafiq Hussain. 2020. Integration of discrete wavelet transform, DBSCAN, and classifiers for efficient content based image retrieval. *Electronics* 9: 1886. [\[CrossRef\]](#)
- King, Michael R., Carol L. Osler, and Dagfinn Rime. 2013. The market microstructure approach to foreign exchange: Looking back and looking forward. *Journal of International Money and Finance* 38: 95–119. [\[CrossRef\]](#)
- Kumar, K. Mahesh, and A. Rama Mohan Reddy. 2016. A fast DBSCAN clustering algorithm by accelerating neighbor searching using Groups method. *Pattern Recognition* 58: 39–48. [\[CrossRef\]](#)
- Latifi-Pakdehi, Alireza, and Negin Daneshpour. 2021. DBHC: A DBSCAN-based hierarchical clustering algorithm. *Data & Knowledge Engineering* 135: 101922. [\[CrossRef\]](#)
- Maghsoodi, Abtin Ijadi. 2023. Cryptocurrency portfolio allocation using a novel hybrid and predictive big data decision support system. *Omega* 115: 102787. [\[CrossRef\]](#)
- Nerurkar, Pranav, Sunil Bhirud, Dhiren Patel, Romaric Ludinard, Yann Busnel, and Saru Kumari. 2021. Supervised learning model for identifying illegal activities in Bitcoin. *Applied Intelligence* 51: 3824–43. [\[CrossRef\]](#)
- Osman, Myriam Ben, Christian Urom, Khaled Guesmi, and Ramzi Benkraiem. 2024. Economic sentiment and the cryptocurrency market in the post-COVID-19 era. *International Review of Financial Analysis* 91: 102962. [\[CrossRef\]](#)
- Oyedele, Azeez A., Anuoluwapo O. Ajayi, Lukumon O. Oyedele, Sururah A. Bello, and Kudirat O. Jimoh. 2023. Performance evaluation of deep learning and boosted trees for cryptocurrency closing price prediction. *Expert Systems with Applications* 213: 119233. [\[CrossRef\]](#)
- Parray, Irfan Ramzan, Surinder Singh Khurana, Munish Kumar, and Ali A. Altalbe. 2020. Time series data analysis of stock price movement using machine learning techniques. *Soft Computing* 24: 16509–17. [\[CrossRef\]](#)
- Pasandideh, Seyed Hamid Reza, Misagh Rahbari, and Yaser Sadati-Keneti. 2023. A Lagrangian relaxation algorithm and hybrid genetic algorithm-black widow optimization for perishable products supply chain with sustainable development goals consideration. *Annals of Operations Research* 1–36. [\[CrossRef\]](#)
- Patel, Mohil Maheshkumar, Sudeep Tanwar, Rajesh Gupta, and Neeraj Kumar. 2020. A deep learning-based cryptocurrency price prediction scheme for financial institutions. *Journal of Information Security and Applications* 55: 102583. [\[CrossRef\]](#)
- Pavankumar, Gajula, J. Velmurugan, and S. Padmakala. 2024. Real-Time Bitcoin Cost Identification to Improve Efficiency Using Lasso Regression in Comparison with Decision Tree. Paper presented at the 2024 IEEE Wireless Antenna and Microwave Symposium (WAMS), Visakhapatnam, India, February 29–March 3.
- Pratas, Tiago E., Filipe R. Ramos, and Lihki Rubio. 2023. Forecasting bitcoin volatility: Exploring the potential of deep learning. *Eurasian Economic Review* 13: 285–305. [\[CrossRef\]](#)
- Rahbari, Misagh, Alireza Arshadi Khamseh, Yaser Sadati-Keneti, and Mohammad Javad Jafari. 2022. A risk-based green location-inventory-routing problem for hazardous materials: NSGA II, MOSA, and multi-objective black widow optimization. *Environment, Development and Sustainability* 24: 2804–40. [\[CrossRef\]](#)
- Ram, Asheer Jaywant. 2019. Bitcoin as a new asset class. *Meditari Accountancy Research* 27: 147–68. [\[CrossRef\]](#)
- Rathan, Karunya, Somarouthu Venkat Sai, and Tubati Sai Manikanta. 2019. Crypto-currency price prediction using decision tree and regression techniques. Paper presented at the 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, April 23–25.
- Rather, Akhter Mohiuddin. 2023. A new method of ensemble learning: Case of cryptocurrency price prediction. *Knowledge and Information Systems* 65: 1179–97. [\[CrossRef\]](#)
- Salisu, Afees A., and Ahamuefula E. Ogbonna. 2022. The return volatility of cryptocurrencies during the COVID-19 pandemic: Assessing the news effect. *Global Finance Journal* 54: 100641. [\[CrossRef\]](#)
- Scharfman, Jason A. 2023. *The Cryptocurrency and Digital Asset Fraud Casebook*. Cham: Springer.
- Sebt, Mohammad Vahid, Yaser Sadati-Keneti, Misagh Rahbari, Zohreh Gholipour, and Hamid Mehri. 2024. Regression Method in Data Mining: A Systematic Literature Review. *Archives of Computational Methods in Engineering* 31: 3515–34. [\[CrossRef\]](#)
- Sin, Edwin, and Lipo Wang. 2017. Bitcoin price prediction using ensembles of neural networks. Paper presented at the 2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), Guilin, China, July 29–31.
- Sivhugwana, Khathutshelo Steven, and Edmore Ranganai. 2024. An ensemble approach to short-term wind speed predictions using stochastic methods, wavelets and gradient boosting decision trees. *Wind* 4: 3. [\[CrossRef\]](#)

- Suthaharan, Shan, and Shan Suthaharan. 2016. Decision tree learning. In *Machine Learning Models and Algorithms for Big Data Classification: Thinking with Examples for Effective Learning*. Boston: Springer, pp. 237–69.
- Wu, Chih-Hung, Chih-Chiang Lu, Yu-Feng Ma, and Ruei-Shan Lu. 2018. A new forecasting framework for bitcoin price with LSTM. Paper presented at the 2018 IEEE International Conference on Data Mining Workshops (ICDMW), Singapore, November 17–20.
- Zhang, Limeng, Rui Zhou, Qing Liu, Chengfei Liu, and M. Ali Babar. 2024. Transaction Fee Estimation in the Bitcoin System. *arXiv* arXiv:2405.15293. [[CrossRef](#)]
- Zhu, Bangzhu, Julien Chevallier, Bangzhu Zhu, and Julien Chevallier. 2017. Carbon price forecasting with a hybrid Arima and least squares support vector machines methodology. In *Pricing and Forecasting Carbon Markets: Models and Empirical Analyses*. Cham: Springer, pp. 87–107.

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