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THE VALIDITY OF TECHNICAL ANALYSIS IN THE CRYPTOCURRENCY MARKET: EVIDENCE FROM MACHINE LEARNING METHODS

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ABSTRACT

Purpose- This study aims to assess the effectiveness of technical analysis indicators used by investors in the cryptocurrency market for making informed decisions. Emphasizing the importance of accurate decision-making methods in financial markets, this research particularly focuses on the cryptocurrency market, which has gained significant attention among investors in recent years.
Methodology- The study specifically examines technical analysis, a widely employed method in various financial markets, with a focus on its predictive capabilities concerning Bitcoin price forecasts. Leveraging advanced technologies, such as big data analysis and machine learning, the research utilizes daily trading data from January 1, 2017, to June 30, 2022, presenting technical indicators and their associated error margins.
Findings- The study highlights the significance of using Weighted Moving Average (WMA) and Stochastic Oscillator (STO) indicators in combination, demonstrating that multiple indicators outperform individual ones. This research underscores the effectiveness of technical analysis methods in the cryptocurrency market, aiding the development of enhanced investment strategies.
Conclusion- In conclusion, this study delves into the potency of technical analysis techniques employed by investors in cryptocurrency markets. The insights indicate that combining indicators and technical analysis methods holds promise for future investment strategies. It is essential to note that even the best method can lead to losses, as evidenced by the presence of error margins, and absolute profitability cannot be guaranteed through technical analysis methods.

Keywords: Cryptocurrency, technical analysis, machine-learning, classification algorithms, investment.
JEL Codes: C38, C55, G17

1. INTRODUCTION

Investing in a market creates the need to have a strong predictive power. One of the most important features that distinguishes investments from games of chance is that they involve rational and predictable decisions. When trading with any investment instrument, taking a position with a random decision is not much different from playing games of chance. Undoubtedly, the motivation that drives people to invest is their desire to increase their money and keep it safe. For this reason, when everyone wants to trade, they want to get important information about important elements such as the market, products and demands, today and the future. This has led to constant research for forecasting methods. As a result of these research, various methods have emerged and have been applied in financial forecasts.

Analysis methods have been developed on many issues such as foreign exchange, stock market and commodity prices. These methods are classified as fundamental and technical analysis and have been the subject of many studies (Abuselidze & Slobodianyk, 2021; Lee, 2020; Pu & Zulauf, 2021; Venkatesh et al., 2021). Studies on fundamental analysis have been examined with a large number of macroeconomic, global, country-specific and political developments (Stevenson, 2001; Spilioti, 2022; Lam, 2004). Similarly, studies on technical analysis have focused on many calculations using historical data (Maknickienė, Stankevičienė, & Maknickas, 2020; Chou & Lin, 2019). Whether technical analysis is really useful or not has been a subject that has been constantly wondered and researched. In the past, some researchers have argued that technical analysis cannot be useful, and that past data cannot affect future prices (Fama, 1970). However, there are important studies showing that technical analysis is an important tool for price predictions. Especially with the development of behavioral finance, some calculations in technical analysis can be put forward logically.

The proliferation of investment products over time has led to the necessity of testing analysis methods on more instruments. One of these products is cryptocurrencies. In recent years, a lot of research has also been carried out on cryptocurrencies (Patel et al., 2020: 2). In addition, many cryptocurrency traders also benefit from technical indicators. However, in relation to cryptocurrencies, it is not easy to put forward a clear conclusion regarding the performance of technical indicators. Measuring the performance of past technical indicators separately and together becomes easier with big data analysis. Today, thanks to the development of computer systems, it is possible to conduct clearer research on the subject. Calculations can be applied to larger data, statistical analyses can be performed on big data, and various inferences and rules can be obtained. Although machine learning is considered as a competitor to technical analysis in some studies (Anghel, 2021), they can also be used to reveal relationships from past knowledge such as regression methods. In this study, the reliability of technical analysis methods, which are most accepted and used by investors and researchers, is tried to be revealed by machine learning methods. Thus, it is aimed to ensure that investors and fund managers follow the right strategies in their buying-selling decisions. In addition, academically it is tried to determine whether technical analysis works in crypto markets or how effective it is. It is thought that this research will provide significant concrete evidence on the opinions in the literature and will contribute to the literature.

The most commonly used and pioneering cryptocurrency, Bitcoin, constitutes a substantial portion of the overall cryptocurrency market (BlockChain 2022). Bitcoin boasts a Market Cap of approximately 402.84 billion dollars, underscoring its significant dominance within the market (Yahoo Finance 2022). Consequently, this study employs machine learning algorithms, with the assistance of Bitcoin, to investigate the validity of technical analysis in cryptocurrency markets.

2. LITERATURE REVIEW

Technical analysis is frequently used in price predictions of all kinds of financial instruments. For this reason, different technical analysis methods have been developed for many markets. However, it is known that not all of these methods are common. In addition, behavioral finance can explain the logic behind some methods, but some methods cannot reveal any logic. For these reasons, in this research, the most used methods in previous academic studies and the most preferred by investors in the markets were used.

Agrawal et al. (2019) conducted a study employing various technical indicators, including Moving Averages (MA), Exponential Moving Averages (EMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Stochastic Oscillator (STO), and Regression Analysis (R). Researchers conducted a study to predict stock prices. The research was conducted on the National Stock Exchange of India. As a result of the study, an accuracy of over 60% was observed.

Bustos et al. (2018) explored the effectiveness of Simple Moving Averages (SMA), Weighted Moving Averages (WMA), Momentum (MOM), MACD, RSI, Commodity Channel Index (CCI), STO, and Regression Analysis (R). The study focuses on the Colombian Stock Exchange. In this research, in which machine learning was used, the mentioned technical indicators were used as input. Up and down movements are used as output. Their study uncovered that the performance of support vector machines is better than artificial neural networks.

In Wang et al.'s (2018) investigation, they considered SMA, WMA, MOM, MACD, RSI, CCI, Regression Analysis (R), and STO. In their study examining the relationship between public sentiment and stock price movements and demonstrating the influence of public opinions on investment decisions, a new framework for financial market prediction was designed. This framework combines the wisdom of crowds and technical analysis. Based on real-world data collected, experimental results have shown that the proposed method outperforms baseline models by at least 14.2% in terms of the AUC value, indicating the effectiveness of DRSE as a viable mechanism for financial market prediction. This study emphasizes the importance of effectively integrating information sources in predicting financial markets and utilizing deep learning and ensemble learning techniques.

Labiad et al. (2016) focused on SMA, WMA, RSI, Rate of Change (ROC), and STO. Accurate prediction of very short-term fluctuations (up to 10 minutes ahead) in the Moroccan stock market has been the focus of this study, employing three distinct machine learning techniques: Random Forest (RF), Gradient Boosted Trees (GBT), and Support Vector Machine (SVM). In this investigation, a curated set of technical indicators served as input variables, with the objective of enhancing prediction accuracy and reducing training time through feature selection and sample selection processes. The experimental dataset encompassed an eight-year span of intraday tick-by-tick data from Maroc Telecom (IAM) stocks. The experimental results have unequivocally demonstrated the superior performance of RF and GBT over SVM. Furthermore, the computational simplicity and reduced training time of RF and

GBT have proven to be particularly suitable for short-term forecasting. This study aims to contribute to the ongoing efforts to predict nonlinear and non-stationary price movements in financial markets using machine learning techniques.

Ghanavati et al. (2016) analyzed SMA, WMA, MOM, RSI, CCI, STO, and Regression Analysis (R). Researchers have gone beyond the proposed forecasting approaches with this study, offering a framework that enables users to engage in stock market prediction using a broader array of tools.

Patel et al. (2015) examined SMA, WMA, MOM, MACD, RSI, CCI, STO, and Regression Analysis (R). This study deals with the problem of predicting the direction of stock price indexes and stock prices in the Indian stock markets. Using two distinct methods for data entry, four prediction models were examined. One of the strategies focuses on portraying these technical factors as trend-determining data, while the other data input approach employs stock trading data to calculate 10 technical parameters. For each of the two data input procedures, the accuracy of each prediction model was assessed. Reliance Industries and Infosys Ltd. stock history data from 2003 to 2012, as well as stock price indices CNX Nifty and S&P Bombay Stock Exchange (BSE) Sensex, were used to conduct the evaluation. The experimental results show that Random Forest beat the other three prediction models in terms of overall performance for the first data input technique, where the ten technical parameters are represented as continuous values. The experimental findings also show that when these technical factors are represented as trend-determining data, the performance of all prediction models increases.

Shynkevich et al. (2014) used SMA, WMA, MOM, MACD, RSI, CCI, STO, and Regression Analysis (R)in their research. This study has looked into the connection between one-step-ahead (varying steps) forecasting accuracy and the size of the window utilized to calculate technical indicators. With the help of machine learning algorithms and technical analysis, future price movements have been forecasted in their general directions. For the Support Vector Machines approach, the results have shown a correlation between the window size and forecasting step size, but other approaches have not shown such a correlation. In conclusion, the study investigates the use of technical analysis, machine learning, and the optimization of technical indicator parameters in financial forecasting.

Examining earlier studies reveals that in recent years, research on the topic has regularly incorporated a variety of artificial intelligence and machine learning algorithms and techniques. Support Vector Machines, Deep Learning, Artificial Neural Networks, Fuzzy logic, Genetic Algorithms, and Decision Trees are a few examples of these techniques (Chakraborty et al., 2018, Coyne et al., 2018, Di Persio & Honchar, 2018, Fischer & Krauss, 2018, Kia et al., 2018, Dingli & Fournier, 2017, Dang & Duong, 2016, Chai et al. The ability to draw conclusions about financial matters has increased with the growth of computer technologies. This gives researchers the chance to use huge data to generate more accurate observations. Particularly when applied to historical data, classification algorithms produce precise results. In particular, classification algorithms provide clear findings based on past data. For these reasons, in order to measure the validity of technical analysis in crypto markets, SMA, WMA, MACD, MOM, RSI, STO and CCI indicators have been tested with CHAID, C5.0 and CART algorithms, which are machine learning algorithms.

3. DATA AND METHODOLOGY

In the study, the most used methods in the literature were preferred to test the technical analysis indicators. Daily data of Bitcoin covering the dates 01/01/2017 – 06/30/2022 were used. The prices used in the study were obtained from the Yahoo Finance web page. In addition, the effectiveness of the methods was analyzed with three different classification algorithms. Through these methods, not only the individual efficiency of technical indicators, but also their best-matched uses together were observed for the historical process. While examining past observations, daily trading transactions were applied for profit and loss situations. Inferences were made, considering that every day purchase is made according to the results of the indicator at the opening price, and the sale is made according to the closing prices. In this section, brief information about all these methods and their uses is given.

3.1. Technical Indicators

Input variables used in the research were SMA, WMA, MACD, MOM, RSI, STO and CCI indicators, respectively. Buy, Sell and Hold signal results were used as output. Technical indicators were calculated as shown in Table 1.

Table 1: Mathematical Equations of Technical Indicators

Indicators	Equation
SMA	$\frac{\sum_{i=1}^{12} P_i}{n}$
WMA	$\frac{P_t \ x \ n + P_{t-1} \ x \ (n-1) + \cdots + P_{t-11}}{[n \ x \ (n+1)]/2}$
MACD	$EMA12_t - EMA26_t$
MOM	$\left(\frac{P_t}{P_{t-9}}\right) x100$
RSI	$RS = \frac{APH_n}{APL_n}$ $100 - (\frac{100}{1+RS})$
STO	$\%K = \ 100 \ x \ \frac{P_t - L_x}{H_x - L_x}$ $\%D = MA_n \ of \ \%K$
CCI	$\frac{TP_t - STP_t}{0{,}015 \ x \ D_t}$

In Table 1; P represents the price of Bitcoin. Also in equations, APH is the average of the prices on the bullish days, APL is the average of the prices on the days of the decline, L_x is lowest price in x days, H_x is the highest price in x days, TP typical price, STP average of typical price, and D deviation. The 12 and 26-day EMAs are preferred for the MACD. STO 9 and RSI, CCI 14 days calculated. The SMA gives the average of prices for a given period. Thus, it is possible to have an idea about the direction of the trend. WMA is also a trend indicator. However, the weight of the last days in the period determined in WMA is more. The MACD provides buy-sell signals from the relationship of two moving averages. After the MACD is found, the signal (trigger) line must be found. In the study, the 9-day exponential moving average of the obtained MACD was calculated. If the MACD rises above this trigger line, a buy signal is obtained, if it falls below the trigger line, a sell signal is obtained. On the other hand, Momentum, examines past price movements and provides information about the rate of decline and rise in prices. The RSI takes a value between 0 and 100. This indicator helps to understand whether a financial product is overvalued or undervalued. The STO indicator measures prices over a period of time by their highest and lowest levels and indicates the turning points of prices. The basic assumption of this indicator is that during periods when prices are in an upward trend, the Price will tend to move towards the highest price within the selected period. Likewise, if prices are falling, prices are expected to tend to go to the lowest price within the selected period. Finally, CCI, like many indicators, indicates whether prices are overvalued or undervalued. It shows how much equity prices deviate from the average.

Table 3: VAR Lag Length Result

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	-2548.646	NA	6.69e+13	37.50950	37.55233	37.52690
1	-2363.036	363.0312	4.63e+12	34.83876	34.96726*	34.89098*
2	-2357.930	9.835301	4.55e+12	34.82251	35.03667	34.90954
3	-2352.959	9.430811	4.49e+12*	34.80822*	35.10805	34.93007
4	-2351.778	2.206269	4.68e+12	34.84967	35.23517	35.00633
5	-2348.858	5.366714	4.76e+12	34.86556	35.33673	35.05703
6	-2345.379	6.292966	4.80e+12	34.87322	35.43006	35.09951
7	-2341.005	7.782772	4.77e+12	34.86773	35.51023	35.12882
8	-2338.504	4.378226	4.88e+12	34.88976	35.61792	35.18567
9	-2334.361	7.127720	4.88e+12	34.88766	35.70149	35.21838
10	-2333.444	1.550396	5.11e+12	34.93300	35.83250	35.29854
11	-2331.456	3.303459	5.27e+12	34.96259	35.94776	35.36294
12	-2324.716	11.00270*	5.07e+12	34.92229	35.99312	35.35745

Note: LR: Likelihood Rate Test Statistics; FPE: Final Prediction-Error Criteria; AIC: Akaike Information Criteria; SIC: Schwarz Information Criteria; HQ: Hannan-Quinn Information Criteria.

3.2. Classification Algorithms

Classification methods are basically the process of estimating the class value and level according to certain characteristics. In this sense, it resembles classical statistical methods. However, there are a lot of assumptions in statistical methods. In classification methods, most assumptions such as constant variance or independence between variables are not required. In this study, Chaid, Cart and C5.0 algorithms, which are widely used classification methods, were used. R programming language was used for the implementation of classification methods.

The Chaid algorithm was developed by Kass (1980). It is preferred for situations where features are categorical. Branching operations are performed based on the chi-square statistic. It tries to reveal other variables and related data that explain the dependent variable as sparingly as possible. In order to best calculate the branching, it investigates whether the predictor variables have a statistically significant relationship with the target variables. In short, CHAID analysis uses chi-square statistics, Bonferronni approach, and category merging algorithm to enable the researcher to obtain the most important explanatory variables and interactions with the dependent variable. The method, which can work with both categorical and continuous variables, can branch more than 2 subgroups.

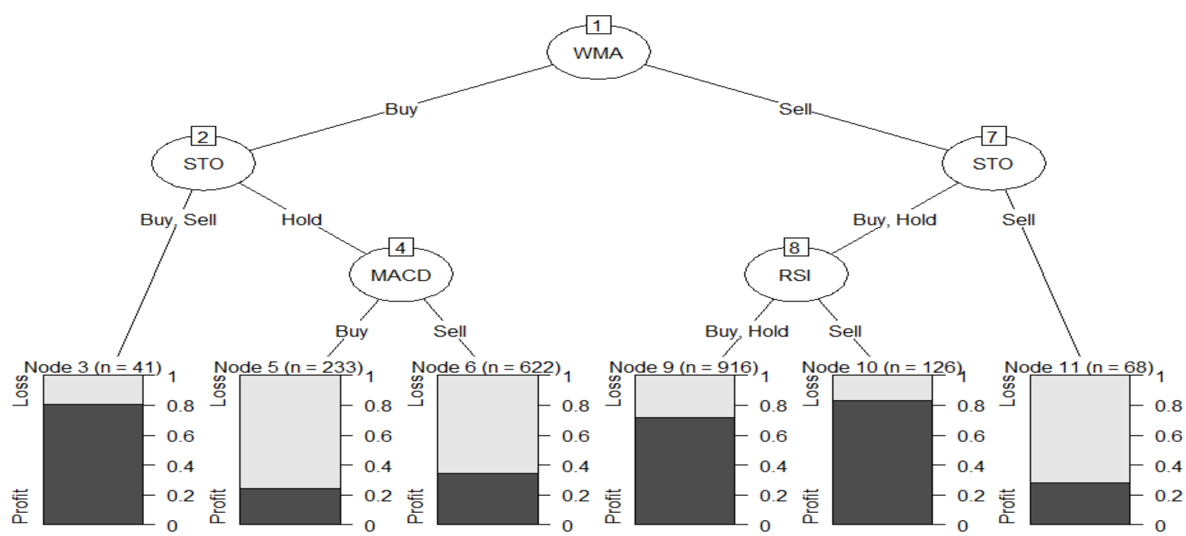
The Cart algorithm was developed by Breiman, Friedman, Olshen, and Stone (1984). It can only do double branching. In other words, it makes a branching process with yes or no answers on each question. The CART algorithm is based on entropy and uses Twoing and Gini techniques to calculate the branching criterion.

The C5.0 algorithm was created by Quinlan with the development of the C4.5 algorithm and was released in 1994. Its advantages over the C4.5 algorithm are that it is faster, uses less memory, creates more precise rules, can weight variables and types of misclassifications, and can exclude variables that do not contribute to the formation of the tree. The C5.0 algorithm can create smaller decision trees and is more effective at parsing data and improving dirty data (Quinlan, 1993; Quinlan, 1996). Unlike other methods, it grows the tree with the criterion of information gain. C5.0 can provide fairly robust predictions in data sets with lost data and a large number of independent variables.

4. FINDINGS AND DISCUSSIONS

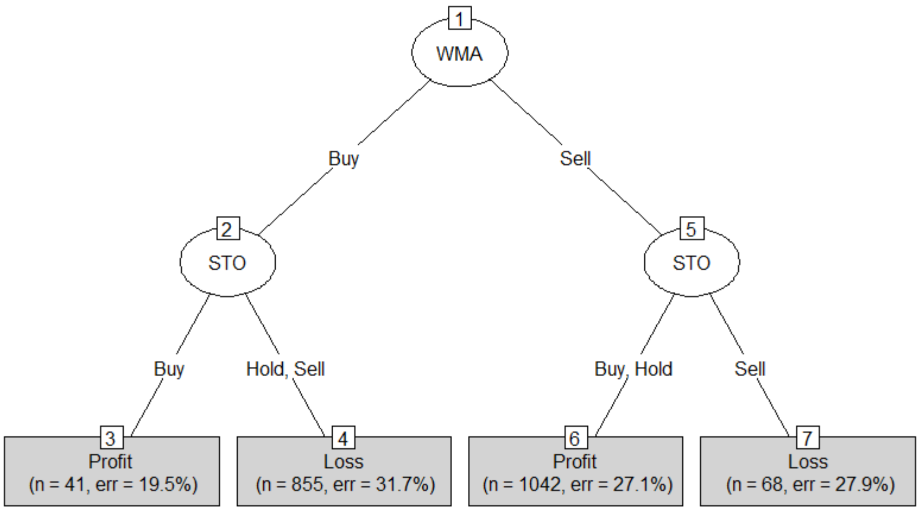
Each algorithm can produce different results for testing and classifying indicators together and alone to provide the best performance. Figure 1 shows the classification made by the Chaid algorithm. According to this algorithm, The WMA indicator signaling buy and the STO indicator signaling buy or sell occurred 41 times, which resulted in a significant profit. But after the WMA indicator, the wait signal in the STO generally indicated a loss. In addition, WMA's sell and STO's buy or wait signals often resulted in profit. This situation occurred 1042 times in total. It appeared with the buy or wait signal of the RSI 916 times and the sell signal of the RSI 126 times.

Figure 1: Result of the Chaid Algorithm



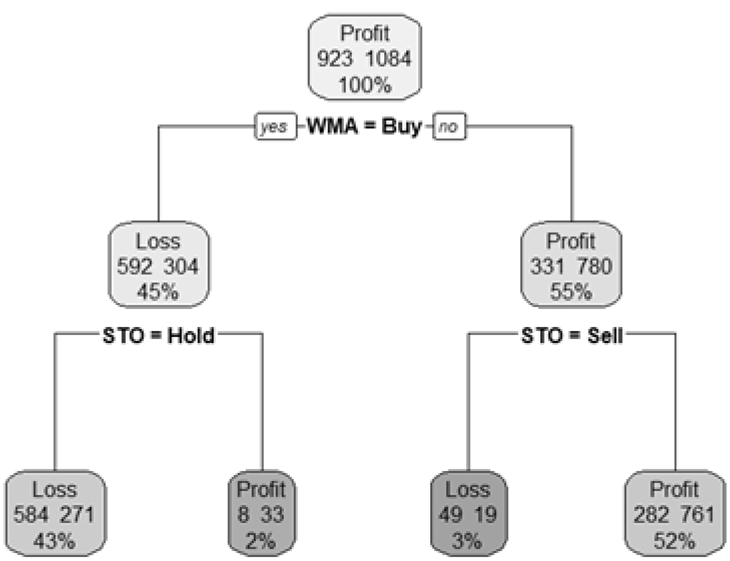
On the other hand, when Figure 2 is examined, the C5.0 algorithm also shows that a profit can be obtained with a 19.5% margin of error with the buy signal of WMA and the buy signal of STO. It states that, unlike the Chaid algorithm, both the wait and sell signals of the WMA cause losses with an error of approximately 31% after the buy signal. This state of the indicators has been observed 855 times. After WMA's sell signal, STO's signals also produced similar results to the Chaid algorithm.

Figure 2: Result of the C5.0 Algorithm



In also the Cart algorithm, WMA and STO indicators came to the prominence as important indicators. In this algorithm, it is understood that after WMA's buy signal, it is important whether only the STO has a wait signal or not. If there is a wai t signal, loss is possible, otherwise, there is the possibility of profit. It is stated that if the WMA does not give a buy signal, it is necessary to check whether the STO gives a sell signal.

Figure 3: Result of the Cart Algorithm



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In all these observations, margins of error can be perceived as high or low for the decision maker. In addition, no single indicator can be deduced that it will be significantly beneficial. However, it is understood from the observations obtained from the past data that the use of the indicators of the WMA and STO indicators together can significantly increase the predictive power.

5. CONCLUSION

In this study, it is aimed to obtain information about the importance and importance level of technical analysis indicators in the cryptocurrency market. However, instead of investigating the importance levels of technical indicators as singles, it was thought that it was more important to evaluate them both individually and multiple. Therefore, the daily data between 01/01/2017-06/30/2022 were tested with machine learning methods. Due to the fact that the cryptocurrency market is dominated by Bitcoin and the Bitcoin market cap has a very high share in the market, the research was carried out on Bitcoin prices. It is a very difficult process to apply the indicators in long data sets and to compare each observation by examining them with both single and multiple indicators, and then to evaluate these results. However, with machine learning methods, the implementation of these processes can be done much easier and more reliably. Chaid, C5.0 and Cart methods were used in the study.

Findings from the analyses showed that using two or more indicators together produces better results than using them individually. In addition, it can be said that the main indicator according to all three methods is the WMA indicator. All three methods showed that the WMA indicator should be evaluated with the STO indicator. Only the Chaid algorithm has shown that after WMA and STO, MACD and RSI can also be considered. However, to generalize according to three methods, it can be said that profits can be made after WMA and STO give a buy signal. In addition, after both indicators give a sell signal, it is necessary not to buy, otherwise, it is understood from the past data observations that the probability of loss is high. When the STO gives a buy or hold signal after the WMA gives a sell signal, it usually results in a profit.

The main motivation for the study is that investment advice, especially in media such as websites and social media, are usually given by using technical analysis. This situation has led to the necessity of investigating whether technical analysis will really be a reliable method in the cryptocurrency market. The results show that a single indicator cannot be highly reliable. In addition, it has been shown in the analyses that technical indicators used together have margins of error. Therefore, when past performances are analyzed, technical indicators can be used by considering the performance of the indicators and the margins of error obtained. This situation shows that other useful strategies can be found with the help of different indicators and analyses made at different periods. For this reason, it is very important to conduct new research on different crypto coins, different indicators, and different periods, and also to give the necessary importance to the subject by researchers.

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