

Next step for bitcoin: Confluence of technical indicators and machine learning

Domicián Máté

Department of Engineering Management and Enterprise, Faculty of Engineering, University of Debrecen, Debrecen, Hungary
mate.domician@eng.unideb.hu
ORCID 0000-0002-4995-7650

Hassan Raza

Department of Management Sciences, Shaheed Zulfikar Ali Bhutto Institute of Science & Technology University, Islamabad, Pakistan
hassanrazaa@live.com
ORCID 0000-0002-9394-4961

Ishtiaq Ahmad

Department of Management Sciences, National University of Modern Languages University, Islamabad, Pakistan
iahmed@numl.edu.pk
ORCID 0000-0001-6038-4470

Sándor Kovács

Coordination and Research Centre for Social Sciences, Faculty of Economics and Business, University of Debrecen, Debrecen, Hungary
kovacs.sandor@econ.unideb.hu
ORCID 0000-0002-1216-346X

Abstract. Cryptocurrencies are quickly becoming a key tool in investment decisions. The volatile nature of bitcoin prices has spurred the demand for robust predictive models. The primary objective of this study is to evaluate and compare the effectiveness of different machine learning models with the combination of technical indicators in predicting bitcoin prices. The study used 27 critical technical indicators to evaluate four machine learning techniques, namely Artificial Neural Network (ANN), a Hybrid Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM), Support Vector Machine (SVM), and

Received:
September, 2023
1st Revision:
June, 2024
Accepted:
September, 2024

DOI:
10.14254/2071-
8330.2024/17-3/4

Random Forest. The results showed that ANN and SVM achieve a significant prediction accuracy of 81% and 82%, respectively, which is higher than the results of traditional models such as standard ARIMA. In practical applications, these methods often improve prediction accuracy by 20-30% over traditional models. The novelty of the analysis lies in the use of temporal and spatial trends via momentum, ROC, and %K features, making for a holistic approach to cryptocurrency market forecasting. This study underscores the critical importance of specific technical indicators and the imperative role of data mining in revolutionizing cryptocurrency market navigation. The research results highlight opportunities to improve investment strategies and risk management policies in the bitcoin market using machine learning models, making the latter valuable to investors and financial experts.

Keywords: bitcoin forecasting, comparative analysis, cryptocurrency market trends, machine learning algorithms, predictive model evaluation

JEL Classification: C53, C81, G17

1. INTRODUCTION

Since their emergence in 2009 with the introduction of bitcoin, cryptocurrencies have been the subject of intrigue, speculation, and intense economic interest. The decentralized and digital nature of cryptocurrencies has changed the conventional financial paradigm, attracting institutional investors and individual traders alike (Henrique et al., 2019; Kozlovskiy et al., 2021; Bagh et al., 2023). Several attempts have been made to identify the changeable behavior of bitcoin as the pioneering and most valuable digital currency, as it is often considered a benchmark for the entire cryptocurrency market (Böhme et al., 2015). Bitcoin price advances offer lucrative opportunities, especially for daily speculators who want to take advantage of short-term market fluctuations (Kyriazis, 2020).

In recent years, cryptocurrency trading has garnered considerable interest, as several traders engage in day trading efforts to capitalize on the fluctuating bitcoin market (Hudson & Urquhart, 2021). In addition, Jung et al. (2023) emphasized the importance of predicting bitcoin exchange rate patterns as they are indicative of larger trends in the cryptocurrency industry. In their research, the authors focused on integrating machine learning and sentiment analysis with technical indicators to predict bitcoin exchange rate fluctuations. In addition, Gyamerah (2021) proposed a two-stage hybrid machine learning system to predict high-frequency intraday bitcoin prices. This approach highlighted the importance of using technical indicators to predict short-term fluctuations in the bitcoin price.

Numerous studies suggest that machine learning models, such as Long Short-Term Memory (LSTM) networks, are better at predicting bitcoin prices than traditional regression-based techniques. Research by various authors has consistently shown that LSTM outperforms traditional time series models such as ARIMA and ARMA (Chen et al., 2020; Włodarczyk, 2017). In addition, incorporating bitcoin-specific variables like difficulty and hash rate further improves the predictive power of LSTM (McNally et al., 2018). Deep learning algorithms such as Convolutional Neural Networks (CNN), LSTM, and Gated Recurrent Units (GRU) provide superior predictive accuracy, with LSTM being particularly effective (Jain et al., 2019). Furthermore, machine learning models such as Recurrent Neural Networks (RNN) and LSTM have been found to outperform traditional time series models in predicting cryptocurrency prices (Yu & Liu, 2021).

The instability of the dynamic bitcoin market, driven by various internal and external factors, has driven the need for predictive tools (Li et al., 2022). These tools serve to determine the potential price direction

and assist traders in making informed decisions, thereby mitigating risks while maximizing returns. Therefore, as the nexus between financial markets and technology continues to expand, there has been a surge in the use of machine learning techniques to predict cryptocurrency price movements (Koker & Koutmos, 2020).

However, despite the growing body of literature on the topic, there is still a research gap. While many studies have examined individual machine learning models for predicting bitcoin prices, few have conducted a comprehensive, side-by-side comparison of these advanced methods within the bitcoin ecosystem. The goal of this study was to develop a predictive model capable of predicting the directional movement of the bitcoin price within a one-day time frame. This study aimed to bridge this gap by juxtaposing models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Convolutional Neural Networks and Long Short-Term Memory (CNN-LSTM), and Random Forest (RF). The comparative lens employed here seeks to uncover the nuances of each model's predictive power, thereby providing a holistic understanding of their effectiveness (Song & Choi, 2023).

To enrich this comparative exploration, the study focused on 27 specific technical indicators, mainly %R, %K, Momentum and Disparity. Several researchers have relied on technical indicators derived from the historical price and volume data to predict market movements (Schabacker & Mack, 1997). There has been little quantitative analysis of the integration with machine learning models, especially in the unpredictable realm of cryptocurrencies, which can lead to breakthrough insights. Preliminary findings suggested the pivotal role of these indicators in refining predictive models (Khan et al., 2023). The unique contribution of the current work was the use of temporal and spatial trends via momentum, ROC, and %K features, which demonstrated a holistic approach to cryptocurrency market forecasting.

As the global landscape of cryptocurrency trading continues to evolve, and with the confluence of technology and finance becomes more intertwined than ever, this research stands at the forefront. This investigation focused on the development of hybrid models that integrate the ANN, SVM, CNN-LSTM, and Random Forest, aiming to create a more robust and accurate forecasting approach. In addition, it explored the integration of real-time data and bitcoin market analysis to ensure the accuracy and timeliness of cryptocurrency price forecasts can fill an existing research gap and provide practical value to investors and traders in this area. The study not only highlighted the state of the art, but also set the stage for future investigations into the global cryptocurrency trading. The results of this empirical research extended to a wide range of stakeholders. The findings can enable investors to refine day trading strategies and improve decision-making processes. The study highlighted the importance of technical indicators and introduced a data-driven framework for navigating the complex landscape of the bitcoin market.

The following sections of the paper provided a comprehensive insight into the research process. The article was structured as follows. Section 2 reviewed the relevant literature, Section 3 detailed the data preparation techniques and the formulation of critical technical indicators, Section 4 presented the results, and Section 5 concluded with key findings and potential avenues for future research.

2. LITERATURE REVIEW

Predicting bitcoin prices has received immense attention due to the unpredictable and volatile nature of the cryptocurrency. Historically, traditional statistical methods served as the primary tools for price prediction. However, much of the focus has turned to machine learning techniques, which have proven to be better suited to handle the complex data flows associated with bitcoin (Sebastião & Godinho, 2021).

A large and growing body of literature has investigated the predictability of bitcoin prices, delving into various machine learning algorithms ranging from support vector machines and logistic regression to artificial neural networks (Dutta et al., 2020; Kim et al., 2016). Chowdhury et al. (2020) also discussed the

challenge of predicting component prices and cryptocurrency trends using machine learning models. Jaquart et al. (2021) examined the predictability of bitcoin over short-term horizons and found that predictability increases over longer horizons.

The comparison between traditional methods such as ARIMA and machine learning models in predicting bitcoin prices consistently favors machine learning models, especially LSTM, due to their ability to better capture the complex dynamics of bitcoin prices (Akyildirim et al., 2021; Civelek et al., 2021). Several other studies have examined the accuracy of bitcoin price prediction using traditional methods and machine learning models. Ula et al. (2024) compared the accuracy of LSTM and Random Forest (RF) methods for bitcoin price forecasting, highlighting the effectiveness of different machine learning approaches. In contrast to traditional methods, (Zhu, 2023) compared Neural Network Autoregression (NNAR) and ARIMA with linear regression for bitcoin price prediction, demonstrating the superiority of machine learning models.

In summary, recent research have shown a growing interest in the use of machine learning techniques, deep learning models, and technical indicators. These studies have highlighted the importance of integrating diverse data sources, advanced algorithms, and domain knowledge to improve predictive capabilities in the cryptocurrency market.

Bariviera (2017) used Artificial Neural Networks (ANNs) to explore inefficiencies, anomalous profits, and complex patterns in the bitcoin market. In the context of bitcoin forecasting, the effectiveness of ANNs has been highlighted for the complex patterns of bitcoin flows that the deep learning methods can capture (Akyildirim et al., 2021). In addition, there is a growing literature on stock market forecasting, where neural networks have shown better performance in extracting information from residuals (Chong et al., 2017). ANNs have also been applied to shape memory alloys and spiking neural networks, demonstrating their versatility in various scientific domains (Hmede et al., 2022).

Deep learning models, such as Convolutional Neural Networks (CNNs), have received considerable attention and application in various fields, including finance and cryptocurrency analysis (Fang et al., 2022). Scholars have explored the application of deep learning models to predict price movements in financial markets, with a particular focus on the cryptocurrency market. Yamashita et al. (2018) used the copula-quantile causality method to investigate the correlation between trading volume and return and volatility variables in the cryptocurrency market. The research results indicate a causal relationship between trading volume and the occurrence of highly negative and positive returns in cryptocurrencies such as bitcoin, ripple, ethereum, litecoin, nem, dash, and stellar. In addition to evaluating trading volume, several other aspects were considered to predict cryptocurrency prices. Sirignano and Cont (2019) proposed a deep learning model that integrates price history and order flow data to predict the direction of price movements in financial markets. The researchers conducted experiments on different sets and time intervals to evaluate the predictive accuracy of their model in situations beyond the data used to develop it.

While deep learning models have demonstrated the potential to predict the price of cryptocurrencies, it is important to recognize that the predictability of bitcoin may vary. Hudson & Urquhart (2021) found that bitcoin did not exhibit predictability over the out-of-sample time. However, predictability has been shown in other cryptocurrency markets. Several attempts have been made to use of alternative machine learning methods to improve the predictive accuracy of deep learning models. Qin et al. (2022) investigated the use of advanced machine learning methods, including decision trees, to predict cryptocurrency prices. Zhang & Wu (2009) emphasized the importance of accurate price predictions for investors and traders. In addition, scholars conducted research on other data sources to improve the accuracy of bitcoin price forecasts. Kim et al. (2016) introduced a methodology that uses user comments and responses in online forums to forecast fluctuations in cryptocurrency transactions. By accounting for the limited resources present in online communities, the researchers are able to achieve prediction rates that are equivalent to bitcoin and other cryptocurrencies (Lahmiri & Bekiros, 2020).

Long Short-Term Memory (LSTM) networks are also at the forefront of bitcoin prediction. Ji et al. (2019) showed how LSTM models can detect temporal dependencies, which are crucial for predicting the price of bitcoin. In addition, Zhang et al. (2022) merged the deep neural network models with denoising autoencoders to predict Bitcoin prices. Jay et al. (2020) also developed a prediction model that included CNN-LSTM and applied stochastic neural networks to predict the price of various cryptocurrencies using deep learning models.

While neural network architectures have been widely researched, ensemble learning models such as Random Forest (RF) have also come under the spotlight. Alessandretti et al. (2018) pointed out the effectiveness of RF models in exploiting market inefficiencies for profit. In a comparative study, Pabuçcu et al. (2020) found that RF models outperformed several other machine learning models in predicting bitcoin prices. Basher and Sadorsky (2022) provided insights into the application of Random Forests in bitcoin forecasting, emphasizing the need for a holistic approach that considers various factors (interest rates, inflation, and market volatility) and models to improve forecasting accuracy. Chen (2023) compared RF regression with LSTM and determined significantly better prediction accuracy for RF regression.

Support Vector Machines (SVM) have been recognised for their usefulness in predicting bitcoin prices (Brereton & Lloyd, 2010). Munim et al. (2019) conducted a study that highlights the effectiveness of SVMs in this regard. Shu and Zhu (2020) highlighted the ability of the SVM method to predict significant price changes, such as the collapse of the bitcoin bubble. The use of SVM in time series forecasting, for non-linear and non-stationary data, is well-documented. Khedmati (2020) discussed the motivation for using SVMs in time series forecasting, noting their ability to accurately forecast data with complex underlying processes. Valencia et al. (2019) discussed that the widespread use of SVMs to predict cryptocurrency price movements, along with other techniques such as Neural Networks and Random Forests. Hitam et al. (2019) introduced an optimized SVM based on Particle Swarm Optimization (PSO) for cryptocurrency prediction. It is worth noting that SVMs are not limited to cryptocurrency research. Bashkin (2018) provided a comprehensive overview of SVMs for classification and regression tasks, and discussed the SVMs in the context of computational toxicology.

Wang and Yan (2023) proposed a comprehensive approach by combining multiple machine learning models, including Artificial Neural Networks (ANNs), support vector machines (SVM), long short-term memory (LSTM), and Random Forest (RF) to demonstrate their collective effectiveness in quantitative bitcoin trading. This approach aligned with the growing interest in machine learning and AI-assisted trading in the cryptocurrency market (Alessandretti et al., 2018). The combination of ANNs, SVM, LSTM, and RF models allowed for a thorough analysis of bitcoin price forecasting and trading strategies (Chen et al., 2020). These models have been proven successful in predicting time series data, including cryptocurrency prices (Torres et al., 2021). In addition, the proposed approach incorporated feature engineering techniques, such as sentiment analysis using social media data, to assess investor sentiment and integrated it into the predictive models. The integration of sentiment analysis with machine learning models has been proposed as a powerful tool for predicting bitcoin prices (Frohmann et al., 2023). Wang & Yan's approach also considered hybrid models that combine different machine learning techniques, which were shown to improve prediction accuracy. Overall, the holistic approach suggested the potential of combining multiple machine learning models to improve quantitative bitcoin trading strategies.

Recent studies have moved towards integrating unconventional data sources to increase predictive accuracy. Kraaijeveld and Smedt (2020) used Twitter sentiment analysis, suggesting a correlation between Twitter and bitcoin price movements. Li et al. (2020) integrated deep learning models with gated recurrent units and attentive LSTM, incorporating social media data streams to predict bitcoin prices. Collectively, these studies highlighted the need for a contemporary literature that underscores the dominance of machine learning in predicting bitcoin prices. Techniques such as ANN, SVM, CNN-LSTM, and RF have captured

complex patterns in bitcoin price data. The integration of various data sources, primarily technical indicators, has emerged as a key strategy for improving predictive accuracy. This development reflects the dynamic nature of the cryptocurrency market and the continuous search for optimal prediction techniques.

Xiang (2024) highlighted the potential of hybrid deep learning models in improving cryptocurrency valuation accuracy and risk management strategies. Manjunath et al. (2023) demonstrated the effectiveness of combining technical factors with machine learning models to predict stock market trends. Otabek and Choi (2024) discussed the significant role of bitcoin in the global financial landscape and its implications for financial technology innovation. Erfanian et al. (2022) apply machine learning approaches, including support vector regression and multilayer perceptron, to predict bitcoin prices based on economic theories.

Overall, the literature suggested that machine learning models, particularly deep learning approaches, tend to provide higher accuracy in predicting bitcoin prices than traditional methods (Lu et al., 2023). These models leverage the complexity of cryptocurrency data and market dynamics to provide more accurate predictions, making them valuable tools for investors and policymakers.

3. DATA DESIGN AND METHODOLOGIES

3.1. Data and selected features

The study embarked on an extensive research endeavor from September 17, 2014, to October 1, 2023 to conduct an exhaustive and meticulous analysis of historical bitcoin stock data. The primary objective was to explore the complex dynamics of the crypto markets. The research extensively examined numerous data variables from the Yahoo Finance API, including opening and closing prices, daily highs and lows, and trading volumes. To maintain the integrity and reliability of the analytical framework, a rigorous data cleansing procedure was applied, carefully eliminating missing data. Python was used for data analysis, and the corresponding code has been updated in the supplemental document.

The sample was divided into 80% for training and 20% for testing. The results and classification matrix demonstrated the predictive ability of the training algorithm during the testing phase, with the remaining 20% of actual data used for evaluation purposes. The classification matrix showed a prediction accuracy of 85%, underscoring the reliability of these features and algorithms. Classification matrices were constructed using the test data to compare actual and predicted data. This comparison effectively demonstrated the predictive capabilities of the modeling techniques.

The graph of bitcoin price data over time was plotted on the vertical axis (See Figure 1). The slope of this line served as a visual indicator of bitcoin's performance and indicated positive or negative trends. An uptrend indicated an improved market performance, while a downtrend suggested a decline. The line chart of bitcoin showed fluctuations in the form of intermittent spikes and dips, providing insights into the transient dynamics of the bitcoin market. These fluctuations can be attributed to numerous factors, including domestic and global economic conditions, political stability, and other determinants. Meanwhile, the long-term trend of the line provided a holistic perspective on the market's cumulative performance over time.

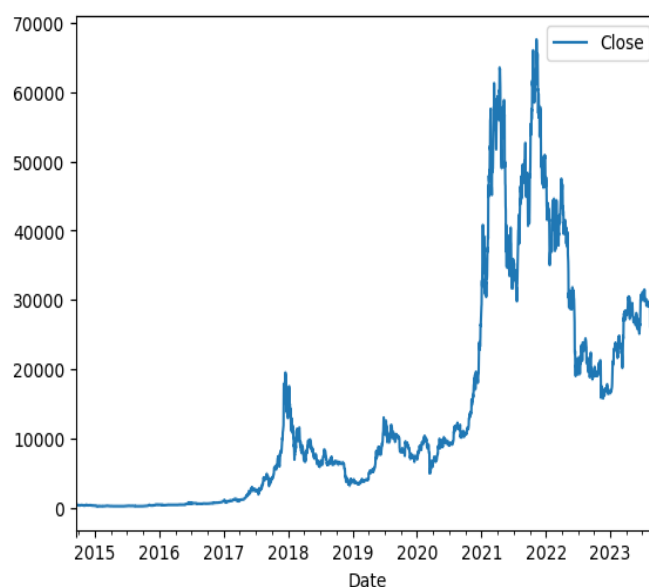


Figure 1. Line graphs of the close price of bitcoin

Source: own evaluation

A comprehensive and rigorous technical analysis of the pre-processed dataset was performed, using carefully selected technical indicators to gain a deeper insight into the behavior of cryptocurrencies. The analysis included various aspects, such as price trends, Momentum, and potential trade signals, facilitated by the following technical indicators: %K (Stochastic Oscillator's %K), %D (Stochastic Oscillator's %D), ROC (Price Rate of Change), %R (Williams Percent Range), Momentum, Disparity Indices (5 and 14), OSCP (Price Oscillator), CCI (Commodity Channel Index), RSI (Relative Strength Index), PP (Pivot Points), S1 (Support Level 1), S2 (Support Level 2), R1 (Resistance Level 1), R2 (Resistance Level 2), EMA (Exponential Moving Average), WMA (Weighted Moving Average), Upper Band (Upper Bollinger Band), Lower Band (Lower Bollinger Band), MACD (Moving Average Convergence Divergence), Signal Line (Signal Line of MACD), ATR (Average True Range), OBV (On-Balance Volume), Chaikin Oscillator (Money Flow Indicator), MFI (Money Flow Index), Day-of-the-Week Anomaly, and Week-of-the-Month Anomaly.

This comprehensive analysis looked at pivot points and their associated support and resistance levels, with the goal of identifying potential pivot points and critical price levels within bitcoin's trajectory. In addition, the application of exponential and weighted moving averages played a pivotal role in uncovering valuable insights into potential trends and crossover points, facilitating crucial buy and sell signals. To understand the interplay between trading volume and price fluctuations, additional indicators such as On-Balance Volume (OBV) and the Chaikin Oscillator were integrated. These indicators allowed to delve into the dynamics of liquidity, money flow indices, and calendar anomalies, further enhancing the depth of analysis. Full details of the characteristics, including specific characteristics, concise descriptions, and corresponding mathematical formulas, were provided in Table 1.

Table 1

Technical indicators and mathematical expressions

Feature Name	Description	Formula
%K	Stochastic Oscillator comparing close price to price range	$\%K = \frac{(close_Price - lowest_low)}{(highest_high - lowest_low)} * 100$
%D	Moving average of %K	$\%D = (1/n) \sum_{i=0}^{n-1} \%K_{i-1}$
ROC	Percentage change in current price from a certain period ago	$ROC = \frac{(cp - cp_n)}{cp_n} * 100$
%R	Momentum indicator measuring overbought and oversold levels	$\%R = \frac{(highest_high - close)}{(highest_high - low)} * 100$
Momentum	Measures the rate of rise or fall in stock prices	$Momentum = close - close_4$
Disparity_5	Measures the ratio of the current price and the 5-day moving average	$Disparity_5 = \frac{close}{MA5} * 100$
Disparity_14	Measures the ratio of the current price and the 14-day moving average	$Disparity_14 = close / MA14 * 100$
OSCP	Price Oscillator based on moving averages	$OSCP = MA5 - MA10$
CCI	Momentum-based oscillator used to determine overbought or oversold conditions	$CCI = \frac{(typical_price - MA)}{(0.015 \times mean_deviation)}$
RSI	Momentum indicator measuring the magnitude of recent price change	$RSI = 100 - \left[\frac{100}{(1 + relative_strength)} \right]$
PP	Pivot point for determining overall market trend	$PP = \frac{(high + low + close)}{3}$
S1	First support level	$S1 = (PP * 2) - high$
S2	Second support level	$S2 = PP - (high - low)$
R1	First resistance level	$R1 = (PP * 2) - low$
R2	Second resistance level	$R2 = PP + (high - low)$
EMA	Exponential moving average	$EMA_t = EMA_{t-1} + \alpha * (Price_t - EMA_{t-1})$
WMA	Weighted moving average	$WMA = \frac{\omega_1 P_t + \omega_2 P_{t-1} + \dots + \omega_n P_{t-n} + 1}{\omega_1 + \omega_2 + \dots + \omega_n}$
Upper_Band	Upper Bollinger Band	$Upper_Band = SMA + (std_multiplier * STD)$
Lower_Band	Lower Bollinger Band	$LB = SMA - (std_multiplier * STD)$
MACD	Moving Average Convergence Divergence	$MACD = Short_EMA - Long_EMA$
Signal_Line	Signal line for MACD	$Signal_Line = EMA(MACD_Histogram, Signal_Window)$
ATR	Average True Range	$ATR = \frac{ATR_{prev}(n-1) + TR}{n}$

OBV	On-Balance Volume	$OBV = OBV_{prev} + \begin{cases} volume, & \text{if } close > close_{prev} \\ 0, & \text{if } close = close_{prev} \\ -volume, & \text{if } close < close_{prev} \end{cases}$
Chaikin_Oscillator	Chaikin Oscillator	$CO = (3 - day\ EMA\ of\ ADL) - (10 - day\ EMA\ of\ ADL)$
MFI	Money Flow Index	$100 - \frac{100}{(1 + Money_Flow_Ratio)}$
Day-of-the-Week Anomaly	Anomaly detection based on the day of the week	$close.groupby(Day_{of_Week}).trans(mean)$
Week-of-the-Month Anomaly	Anomaly detection based on the week of the month	$close.groupby(Week_{of_month}).trans(mean)$

A pivotal facet of the research involved the integration of a “direction” column into the dataset, an indispensable element within the analytical framework. This meticulously designed column served as the linchpin of the categorization task, providing binary delineations of bitcoin’s daily price fluctuations and, more importantly, distinguishing whether bitcoin is on an upward or downward trend relative to a predetermined threshold. The study categorized the movement of bitcoin price as upward or downward, assigning a value of 1 for upward movement and 0 for downward movement. As a result, our study utilized a binary dependent variable to represent the price movement of bitcoin.

The deliberate partitioning of the dataset into training and test subsets was done with utmost precision, with 80% of the data allocated for extensive training and the remaining 20% meticulously reserved for rigorous testing. To enhance the robustness and adaptability of the predictive model when confronted with divergent data scales, Min-Max scaling was judiciously implemented. This normalization method, known for its ability to rescale feature values to a uniform range between 0 and 1, played a critical role, especially in the context of highly optimized machine learning models. The judicious application of this scaling technique significantly enhanced the convergence of the model and overall performance, representing a comprehensive and progressive approach to unraveling the intricacies of stock market dynamics.

The central goal was to determine the next day’s price movement of bitcoin, coded as binary values 1 and 0, representing upward and downward trends. Temporal alignment involved the shifting of data from previous days forward by one day, effectively assimilating historical data to inform predictive projections. This meticulous practice effectively mitigated the common error associated with using same-day data for predictive purposes. Ultimately, the curation of our training dataset culminated in the merging of this temporally adjusted data with the critical target variable, providing a comprehensive foundation for our predictive model.

3.2. Machine learning models

In this study, four different machine learning models were used to predict the daily closing bitcoin price. The following section provided a brief overview of these models.

3.2.1. Artificial neural network

After careful preparation and data processing, our focus shifted to the construction of an Artificial Neural Network (ANN) using TensorFlow library. The architecture of the ANN was tailored to adequately address the complex task of predicting the directional movements that characterize the daily closing bitcoin

price. The structural foundation of this neural network rested on three distinct layers: (1) the input layer, (2) the hidden layer, and (3) the output layer.

The input layer of our model was carefully constructed to incorporate the 27 unique technical features derived from historical bitcoin data. These features are critical to making informed predictions about the cryptocurrency market. The input layer computes a weighted sum of its inputs using the following equation for each neuron:

$$Z_i = \sum_j W_{i,j} x_j + b_i$$

where: Z_i is the weighted sum at neuron i in the input layer. $W_{i,j}$ is the weight of the connection between neuron i in the input layer and neuron j in the hidden layer. x_j is the input of neuron j . b_i denotes the bias associated with neuron i in the input layer.

The hidden layer, consisting of 32 neurons, is critical to the model's ability to capture complex patterns in the data. Each neuron used a Rectified Linear Unit (ReLU) activation function, which was defined as follows:

$$\alpha_i = \text{Max}(0, z_j)$$

where: α_i represents the activation of neuron i in the hidden layer. z_j is the weighted sum of inputs to neuron i in the hidden layer.

The use of rectified linear unit (ReLU) activation functions for each neuron allowed the model to effectively capture nonlinear associations within the dataset. The primary function is to skillfully process and transform information from the input layer. The next stage involved the careful implementation of the output layer, which was tasked with providing the final predictions. The output layer generated the final prediction, primarily whether the daily closing bitcoin price would rise or fall. This binary classification was achieved by using a sigmoid activation function, defined as:

$$h(x) = \frac{1}{1 + e^{-z}}$$

where: $h(x)$ denotes the predicted probability of an increase in the closing price of bitcoin, and z is the weighted sum of inputs to the output layer. Throughout the model building process, the Adam optimizer's role in guiding the training process and skillfully fine-tuning the model weights to minimize error was indispensable. The choice of the binary cross-entropy loss function was deliberate because of its compatibility with binary classification tasks. This loss function quantified the mismatch between predicted results and actual targets. In an extensive training program of 50 iterations, called "epochs," the model carefully adjusted its internal weights in each epoch to limit prediction errors. A batch size of 64 was judiciously chosen, meaning that 64 data points were analyzed simultaneously in each iteration. The use of batch-wise training accelerated convergence and ensured efficient learning within the model. Consistent evaluation of model performance underpinned the training process. The critical role of validation through the test set was emphasized throughout this phase. Real-time performance metrics allowed continuous monitoring of the model's ability to generalize to unfamiliar data and early detection of overfitting.

3.2.2. Support vector machines model

Support Vector Machines (SVM) are a class of supervised machine learning algorithms widely used in both classification and regression problems. When predicting bitcoin price movements, SVMs establish optimal decision boundaries, called hyperplanes, that effectively categorize the data into discrete classes, such as upward and downward price trends.

Historical bitcoin price data and relevant technical indicators were collected and preprocessed as the first step in forecasting bitcoin price trends. These features served as the primary input data for the SVM

model. The dataset was split into two central components, e.g., the features that act as predictors and the labels that convey the direction of bitcoin price movements.

Feature scaling techniques were applied to ensure the optimal performance of the model and to mitigate the disproportionate influence of different features with different scales on the predictions. A commonly used technique is min-max scaling, which standardizes all features within a uniform range of 0 to 1. The fundamental goal of SVMs is to identify an appropriate hyperplane that is thoughtfully positioned to maximize the margin or separation between different classes of bitcoin price movements, specifically „up” and „down” trends. SVM demonstrated versatility by utilizing different kernel functions, with the Radial Basis Function (RBF) being a preferred choice. Kernel functions allow SVMs to proficiently map data into higher-dimensional spaces, significantly enhancing their capacity to capture complex and nonlinear associations within bitcoin price data.

The SVM model relies on support vectors, which are data points located around the decision boundary. The vectors play a central role in the SVM technique and strongly influence the optimal placement of the hyperplane. The SVM model was trained on historical bitcoin price data with the primary goal of identifying the hyperplane that best classified bitcoin price movements based on the input variables. This process resulted in a proficiently trained SVM model that predicted bitcoin price trends.

The SVM model is an optimization problem, especially in the case of linearly separable data. It attempts to find the optimal hyperplane described by the equation:

$$w \cdot x + b = 0$$

where: w is the weight vector, x is the input feature vector, and b denotes the bias term, also known as the intercept. The margin, which is the distance between the hyperplane and the nearest data point, can be represented as:

$$\frac{1}{\|W\|}$$

The objective of SVM is to maximize this margin while correctly classifying data points. In cases where the data is not linearly separable, the kernel trick is used, and the decision boundary is mapped to a higher-dimensional space. The decision boundary equation then becomes:

$$w \cdot \Phi(x) + b = 0$$

where: $\Phi(x)$ represents the transformed feature vector. The training process involved optimizing the parameters w and b to find the hyperplane that maximized the margin while satisfying constraints to correctly classify data points. Overall, SVMs are an effective tool for predicting bitcoin price trends due to their ability to separate and categorize complex cryptocurrency market data.

3.2.3. CNN-LSTM model

The use of Convolutional Neural Network (CNN) in conjunction with the Long Short-Term Memory (LSTM) model in the field of bitcoin price movement prediction provided a powerful framework for improving prediction accuracy. LSTM, a specialized variant of the Recurrent Neural Network (RNN), has been instrumental in effectively handling sequential data, making it a robust choice for time series analysis in the dynamic world of cryptocurrency.

The process of bitcoin price prediction unfolded through a series of well-defined stages. First, the dataset was carefully prepared and restructured into a time series format, where each data point was associated with a distinct time interval. This dataset included critical components, in particular key technical indicators and the closing price of bitcoin.

The data was transformed into a 3-dimensional format to unleash the potential of LSTM, allowing the seamless processing of time series. The architectural design of the model included two LSTM layers. The

first LSTM layer consisted 50 LSTM units that were carefully designed to generate sequences that reveal intricate patterns and relationships within the input. The second LSTM layer mirrored the configuration of the first layer and contained 50 LSTM units. The model ended with a densely connected layer that accommodates a single unit using a sigmoid activation function. This strategic setup enabled the model to provide binary predictions that indicated the direction of bitcoin price movements (up or down).

The LSTM model was trained using the Adam optimizer, while binary cross-entropy was used as the loss function, which is a highly appropriate choice for binary classification tasks. Accuracy was used as the performance metric during training. The model was rigorously trained on the training dataset over a predefined number of epochs, typically 10 epochs with a batch size of 32. These hyperparameters remained adjustable, allowing for careful fine-tuning and performance optimization, an essential process in strengthening the model's predictive ability with respect to bitcoin price fluctuations.

As a central component of this method, the integration of CNN and LSTM was a robust strategy that capably handled the intricacies of sequential bitcoin price data and spatial features. This integrated approach demonstrated significant promise for cryptocurrency market forecasting and provided an indispensable tool for market analysts and investors.

In the context of the model design, the fundamental equation guiding the training process can be summarized as follows:

$$w \cdot x + b$$

where: w is the weight vector, x is the input feature vector, and b denotes the bias term or intercept.

This equation represents the decision boundary that the model seeks to optimize and fine-tune during the training process in order to accurately classify bitcoin price movements.

3.2.4. Random forest model

To further explain the Random Forest (RF) methodology, the entire process can be broken down into a series of equations. It should be noted that these equations are a simplified representation to provide a clearer understanding: in the first step of decision tree construction, each decision tree T_i in the RF model is built on a subset of data and features:

$$T_i = f(D_i, F_i)$$

where: T_i is the i -th decision tree, D_i is a random sample from the training data (using bootstrap sampling), and F_i denotes a random subset of features.

In the next step, the prediction by each tree was performed using the individual trees that gave a prediction based on the input data:

$$P_i(x) = T_i(x)$$

where: $P_i(x)$ is the prediction of the i -th decision tree for input x , and T_i denotes the function of the i -th decision tree. In the next step, in classification tasks (e.g., predicting whether the price of bitcoin will rise or fall), a majority voting mechanism can be used:

$$P(x) = \text{mode}\{P_1(x), P_2(x), \dots, P_n(x)\}$$

For regression tasks (e.g., predicting the actual bitcoin price), a weighted average or a simple average can be used:

$$P(x) = \frac{1}{n} \sum_{i=1}^n P_i(x)$$

where: $P(x)$ is the final prediction for input x , and n is the total number of decision trees.

RF performance was affected by hyperparameters such as n (the number of trees), d (the maximum depth of the tree), and m (the number of features considered for splitting at each node). These

hyperparameters are often chosen based on cross-validation performance:

$$\operatorname{argmin}_{n,d,m} CV_error(n,d,m)$$

Where: $CV_error(n,d,m)$ represents the cross-validation error using n trees, d is the maximum depth, and m is the number of features for splitting.

The model representation provided a high-level view of the process. The inner workings, especially the construction of the decision tree and the prediction functions, can be complex. However, it should provide a mathematical basis for predicting bitcoin price movements.

3.3. Model evaluation

The performance of the models was compared using several metrics including accuracy, precision, recall and F1-score. These metrics provide insight into whether the model can correctly distinguish the price movement of bitcoin as a rising or falling exchange rate. A confusion matrix and classification reports were generated. The inclusion of a confusion matrix allowed for an in-depth understanding of true positives, false positives, true negatives and false negatives, thus providing a more nuanced assessment of each model's strengths and areas for improvement. This visualization highlights the parallels and discrepancies between the model predictions and actual bitcoin price movements, providing a more accurate picture of the model effectiveness. In addition, visual representations were included to illustrate the performance indicators of each model. All calculations were performed in Python 3.10.4. using the numpy, pandas, tensorflow, and sklearn packages.

4. RESULTS AND INTERPRETATIONS

This section delved deeply into the results generated by the predictive models for bitcoin price trends. These models were developed using various approaches, such as the ANN, SVM, CNN-LSTM. First, the authors presented a detailed analysis of the statistics related to the technical indicators used in this paper, focusing on the prominent bitcoin market indices. Next, the classification reports of each model were discussed, shedding light on their effectiveness and ability to accurately classify bitcoin price fluctuations. Graphical representations of actual and predicted bitcoin flows were also provided for a better understanding, highlighting the predictive ability of the models. Finally, the authors delved into the feature importance graphs for each model, highlighting the critical influence certain features have in shaping predictions and improving the overall performance of the models.

4.1. Descriptive analysis of technical indicators

Table 2 provided a comprehensive look at historical bitcoin data from inception to the present day, as well as a number of fundamental technical indicators. The data showed significant changes in the bitcoin exchange rate over this long period, with the open, high, low, close and volume averages falling within the range of \$14847.48 to \$16085.41, indicating the volatility that characterized the cryptocurrency market. Despite these fluctuations, the Standard Deviations (SD) showed pronounced price fluctuations, underscoring the dynamic nature of the cryptocurrency market.

Table 2

Summary Statistics of bitcoin data and technical indicators

Variables	Mean	SD	Min	Max
Open	14847.48	16085.41	210.07	67549.73
High	15199.75	16480.01	223.83	68789.62
Low	14461.64	15634.05	199.57	66382.06
Close	14854.67	16081.54	210.49	67566.83
Volume	1.75E+10	1.94E+10	10600900	3.51E+11
%K	55.14	30	0	100
%D	55.13	28.2	1.37	99.2
ROC	2.73	13.83	-42.73	103.62
%R	-71.27	27.04	-100	0
Momentum	34.25	1592.57	-10446.1	9270.4
Disparity_5	100.33	4.04	67.49	133.4
Disparity_14	101.12	7.83	59.9	161.14
OSCP	21.14	748.88	-4499.34	4229.8
CCI	17.99	116.14	-498.77	498.83
RSI	53.82	18.54	4.7	99.77
PP	14838.69	16061.05	215.83	67294.74
S1	14477.63	15651.73	195.44	66059.15
S2	14100.59	15232.9	179.8	65146.47
R1	15215.73	16498.35	222.28	69045.69
R2	15576.79	16924.17	226.29	71245.83
EMA	14774.06	15981.05	229.88	63208.3
WMA	14800.74	16029.86	227.52	63953.42
Upper_Band	16604.02	18033.82	238.95	69260.21
Lower_Band	12943.64	14144.16	200.03	58932.84
MACD	59.32	975.62	-5053.27	5273.81
Signal_Line	59.34	927.47	-4439	4517.1
ATR	737.09	964.95	2.86	5794.52
OBV	7.14E+11	7.46E+11	-2.4E+08	2.69E+12
Chaikin_Oscillator	-1172783	1.04E+10	-6.5E+10	5.65E+10
MFI	93.4	2.25	68.69	98.52
Day-of-the-Week Anomaly	1.06	1.15	0.02	4.83
Week-of-the-Month Anomaly	1.06	1.15	0.02	4.78

Source: own evaluation

4.2. Results of the Models

The results (Table 3) presented in this analysis were derived from the evaluation of the ANN model applied to binary classification. Binary classification classified stock movements into two different outcomes, "0" and "1", corresponding to lower and higher stock prices. Model performance was carefully evaluated using comprehensive evaluation metrics, including confusion matrix, accuracy, recall and F1 score.

Table 3

Classification results of the ANN model

Class	Precision	Recall	F1-score	Confusion Matrix		Support
0	0.78	0.81	0.80	[237	54]	291
1	0.83	0.80	0.81	[67	263]	330
accuracy			0.81			621
macro avg	0.80	0.81	0.80			621
weighted avg	0.81	0.81	0.81			621

Source: own evaluation

In the context of the confusion matrix, the ANN model correctly classified 237 cases as "0" and 263 cases as "1". However, the model produced 54 incorrect "0" predictions and 67 incorrect "1" predictions. Despite these misclassifications, the model struck an optimal balance between the accuracy and recall of the two categories, accentuating its ability to produce accurate predictions for both positive and negative scenarios.

The classification report showed that the model achieves an accuracy score of 0.78 for class "0" and 0.83 for class "1". In terms of recall, the model scores 0.81 for class "0" and 0.80 for class "1", indicating that the model can correctly identify relevant instances from both classes. The F1 score for class "0" is 0.80, and for class "1" it is 0.81, highlighting the balanced performance that effectively balances precision and recall. Regarding overall model accuracy, the ANN model demonstrated an accuracy rate of 81%, which was consistently reflected by the macro and weighted averages for precision, recall, and F1 score, which all hovered around 0.80 to 0.81.

The results of this analysis conclusively demonstrated that the ANN model exhibits strong and reliable performance in accurately predicting stock price movements. The model's remarkable balance between accuracy and recall for both classes showed its ability to effectively minimize Type I and Type II errors, making it an effective tool for financial forecasting and decision making.

The results of the feature importance from the ANN model provide valuable insights into the aspects that influence the prediction of bitcoin price movements. The ANN model assigned average absolute weights to various technical indicators. The weight assigned to each indicator indicated the influence it has on the direction of bitcoin's price movement, with higher weights indicating greater influence.

The %R indicator was the most significant element, with an average absolute weight of 0.22014. The results suggested that the %R indicator has significant predictive power and should be considered when evaluating the dynamics of the bitcoin exchange rate. This was followed by %D, %K, and the Chaikin Oscillator, with significant average absolute weights of approximately 0.16778, 0.15491, and 0.14894, respectively. These indicators played a crucial role in contributing to the decision-making process of the model.

In addition, EMA, OBV, and ATR had average absolute weights ranging from 0.14236 to 0.13874. These measures were crucial in determining the predictions made by the ANN. Factors such as Disparity_5, Momentum and Disparity_14 also contributed significant and relevant information, with weights ranging from 0.13560 to 0.13551. While somewhat less influential, indicators such as CCI, Day-of-the-Week Anomaly, and PP, each with weights averaging around 0.13412 to 0.12967, were still valuable to the model's understanding of bitcoin price dynamics. On the other hand, the Upper Band, WMA, MACD, MFI, S2, and R2 indicators had relatively lower average absolute weights, ranging from 0.12807 to 0.11087. Although their influence was comparatively lower, they contributed to the model's comprehensive understanding of bitcoin price dynamics (Figure 2).

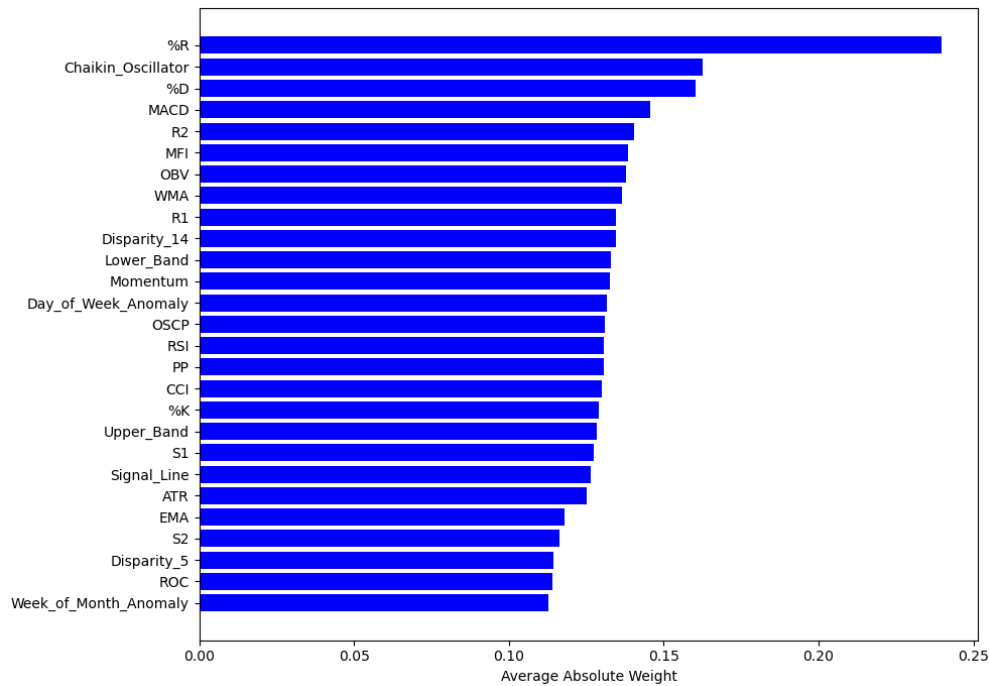


Figure 2. Feature importance of the ANN model

Source: own evaluation

These results implied that the Artificial Neural Network (ANN) model uses a variety of technical indicators to predict fluctuations in bitcoin prices. Investors and analysts can use this information to focus on the most important characteristics, including %R, %D, %K, and the Chaikin Oscillator. At the same time, they need to distinguish the more significant signals, as these indicators together contributed to a comprehensive forecasting framework. These insights provided a solid statistical basis for making well-informed investment decisions in the bitcoin market to effectively navigate the complex dynamics of bitcoin price movements.

The SVM was mainly used for binary classification and distinguishes between two distinct results, called 0s and 1s. The SVM model showed impressive accuracy, with a score of 0.78 for "0" and 0.86 for "1," indicating a high degree of accuracy in positive predictions. For recall, the SVM model showed remarkable performance, with a score of 0.85 for "0" and 0.79 for "1," confirming its ability to accurately identify cases from both classifications. The F1 score, a harmonious balance between precision and recall, was 0.82 for both categories. This resulted in an impressive overall accuracy of 82%, clearly establishing the SVM model as a reliable tool for predicting stock market movements (see Table 4).

Table 4

Classification results of the SVM model

Class	Precision	Recall	F1-score	Confusion matrix		Support
0	0.78	0.85	0.82	[248	43]	291
1	0.86	0.79	0.82	[69	261]	330
accuracy			0.82			621
macro average	0.82	0.82	0.82			621
weighted average	0.82	0.82	0.82			621

Source: own evaluation

In a comparative analysis with the previously used ANN model, it was evident that the SVM model achieved almost the same accuracy, recall and F1 score. Both models achieved the same overall accuracy of 85%, underscoring that they show significant parity in predictive performance. This comparative finding provided valuable insights for researchers and analysts, highlighting that both models can be reliable choices for financial forecasting and can serve a range of preferences and purposes. Importantly, the performance of the SVM model demonstrated its effectiveness and compatibility with the ANN model, further increasing the depth of predictive tools available for market analysis.

The feature importance analysis derived from the SVM model provided deep insights into the factors influencing bitcoin market predictions. In this context, the SVM assigned absolute weights to technical indicators, indicating their contribution to the prediction of market movements. The %D indicator was the most influential factor with a significant weight of 7.36412. This underscored the importance of %D in shaping the predictive capabilities of the SVM and highlighted its importance in understanding the dynamics of the bitcoin market. The %K and %R follow closely with significant absolute weights of 5.02149 and 5.04162, respectively.

Features such as "Disparity_5", "Chaikin Oscillator", and "RSI" had significant absolute weights ranging from 1.20 to 3.64, and thus played an important role in SVM decision making. Indicators such as "PP", "Signal Line" and "S2" showed their importance with absolute weights around 0.25. In addition, characteristics such as "Monthly Anomaly" and "PP" had smaller but still significant absolute weights, ranging from 0.05 to 0.10, and contributed to the SVM's overall understanding of bitcoin market dynamics.

The results (Figure 3) emphasized that the SVM model exploited a wide range of technical variables, highlighting the importance of "%D", "%K", "%R" and many other variables. Investors and analysts can use this information to prioritize the most influential features, while acknowledging the importance of other indicators, and together build a robust framework for forecasting the bitcoin market. These insights provided a data-driven foundation for making informed investment decisions in the bitcoin market and navigating the complex dynamics of bitcoin price movements.

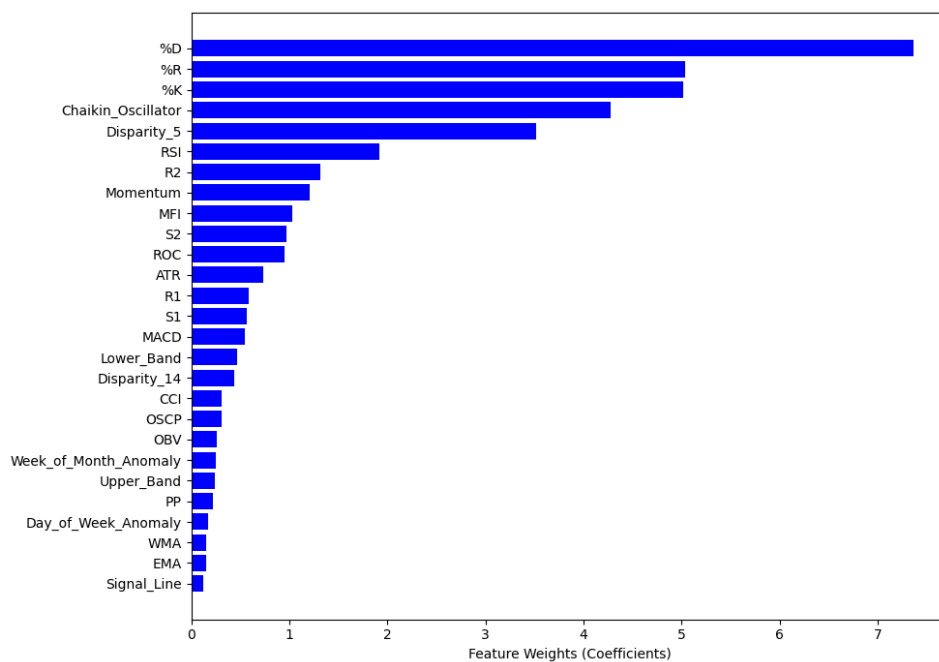


Figure 3. Feature importance of the SVM model

Source: own evaluation

The study used a long short-term memory (LSTM) model, an accepted tool for time series analysis to explore the complex dynamics of stock markets. The primary purpose of the LSTM model was to perform the challenging task of binary classification, efficiently distinguishing between "0" and "1", to represent different market scenarios. Table 4 summarized the comprehensive performance evaluation of the LSTM model and provides valuable insights into its effectiveness in stock market prediction.

Examining the accuracy ratings of the "0" and "1" classes, values of 0.76 and 0.84 were found, indicating a remarkable accuracy of the model's positive predictions. Recall, a critical metric, confirms the model's effectiveness in identifying relevant cases within the "0" and "1" classes, with values of 0.84 and 0.77. The strength of the CNN-LSTM model was in its ability to strike a balance between precision and recall, as evidenced by F1 values of 0.80 for class 0 and 0.81 for class 1, confirming its ability to make well-informed judgments about stock market trends. The model showed a commendable overall accuracy rate of 0.80, clearly demonstrating the model's robust predictive ability (Table 5).

Table 5

Classification results of the CNN-LSTM model

Class	Precision	Recall	F1-score	Confusion matrix		Support
0	0.76	0.84	0.80	[244	47]	291
1	0.84	0.77	0.81	[75	255]	330
accuracy			0.80			621
macro average	0.80	0.81	0.80			621
weighted average	0.81	0.80	0.80			621

Source: own evaluation

The CNN-LSTM model, with an accuracy rate of 0.80, revealed a level of proficiency similar to that of the SVM model. However, the ANN model had a slightly higher accuracy of 0.81, suggesting its superior ability to predict stock market movements. This comparison highlighted the nuanced differences between these models and provided valuable guidance for researchers and analysts. While the LSTM and SVM models showed comparable performance, the ANN model showed a slight advantage in predictive accuracy, catering to different preferences and research needs. Researchers and stakeholders now have a diverse arsenal of financial analysis tools at their disposal, each with unique strengths that allow for nuanced and comprehensive market assessment.

In our relentless pursuit to improve the predictability of bitcoin price movements, we have applied a robust CNN-LSTM model. This sophisticated approach seamlessly blends Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks, effectively deciphering intricate spatial and temporal patterns within time series data. The result has proven to be indispensable in predicting the volatility of cryptocurrencies. The in-depth exploration of the significance of the features provided insight into the elements that have a significant impact on predicting bitcoin's movements.

The model showed significant importance across several variables. In particular, the variables %K and ROC (0.3349) consistently significantly influenced the prediction results. The model exhibited notable significance in several variables, particularly %K and ROC (0.3349), which significantly influenced the predictions. Their continued presence at the top of the list confirms their importance in predicting bitcoin price movements. %D (0.1675), while slightly less critical than %K and ROC, still plays a pivotal role in contributing to the model's predictive ability. Momentum (0.3140) continues to strengthen its influence, while Disparity_5 (0.2641) is important and contributes significantly to the accuracy of bitcoin price forecasts. Even Disparity_14 (0.1449), although less prominent than the previously mentioned characteristics, still occupies a significant place in the model's predictive.

In contrast, some variables contributed moderately to the predictive ability of our CNN-LSTM model.

For example, OSCP (0.0709), although not as dominant as the fundamental determinants, was of moderate importance in influencing our predictions. Similarly, CCI (0.0193) contributed to the overall accuracy of the model, albeit to a lesser extent. Numerous features had minimal to negligible impact on predicting bitcoin movements. Variables such as the RSI, PP, S1, R1, R2, MACD, Signal Line, ATR, OBV, Chaikin Oscillator, Day-of-the-Week Anomaly and Week-of-the-Month Anomaly showed significant values that were close to zero, indicating that they had a limited impact on the model's ability to predict bitcoin price movements.

In summary, the in-depth analysis underscored the importance of key determinants such as %K, ROC, %D, Momentum, Disparity_5 and Disparity_14 in shaping the accuracy of bitcoin's future movements. Meanwhile, other characteristics played a moderate or limited role in the overall forecasting framework. The results of the dynamic perspective on the features importance (Figure 4) provided essential insights for refining cryptocurrency trading strategies and making informed decisions.

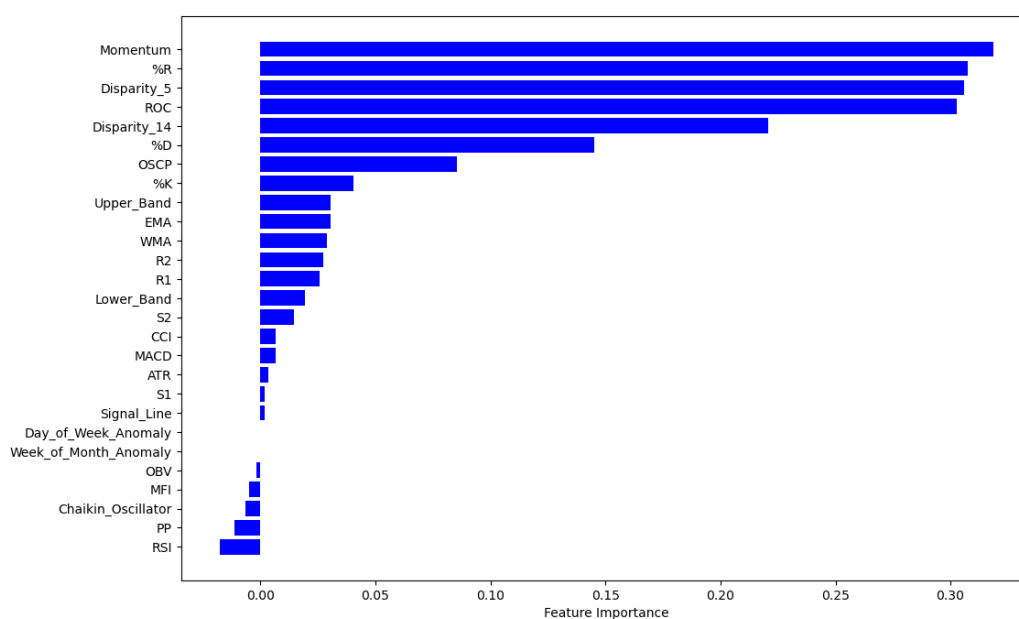


Figure 4. Feature importance of the CNN-LSTM model

Source: own evaluation

The Random Forest (RF) model has demonstrated strong classification performance (Table 6). The model had an impressive accuracy rate of 81%, indicating its ability to identify stock market trends. The accuracy values for Class 0 and Class 1 were commendable, with values of 0.80 and 0.83, respectively. This illustrated the RF model's ability to make accurate predictions in both categories. Similarly noteworthy were the model's recall scores, which were 0.80 for class 0 and 0.83 for class 1, highlighting the model's ability to accurately identify positive cases. The F1 score, a balanced measure of accuracy and recall, demonstrated strong performance, with a value of 0.80 for class 0 and 0.83 for class 1. This further confirmed the consistent and harmonious model performance.

Table 6

Classification results of the RF model

Class	Precision	Recall	F1-score	Confusion matrix		Support
0	0.80	0.80	0.80	[233	58]	291
1	0.82	0.83	0.83	[57	273]	330
accuracy			0.81			621
macro average	0.81	0.81	0.81			621
weighted average	0.81	0.81	0.81			621

Source: own evaluation

A closer look at the confusion matrix revealed that the model correctly classified 233 out of 291 instances in Class 0 and correctly identified 273 out of 330 instances in Class 1. These results, coupled with the application of macro-averaged and weighted-averaged measures, reinforce the resilience and robust classification capabilities of the RF model.

Comparatively, the performance of the RF model was robust, similar to the previously implemented models, including the ANN, SVM, and CNN-LSTM. The RF model had an accuracy of 81%, providing competitive performance alongside the ANN model. In terms of precision, recall, and F1 scores, the RF model maintained balanced values for both classes, with a macro average and weighted average of 0.81. This indicates that the RF model correctly identified both upward and downward stock movements. Furthermore, the model achieved a balanced F1 score of 0.80 for Class 0 and 0.83 for Class 1 for both classes, confirming its overall suitability. These comparative findings provided a valuable perspective for researchers and analysts and illustrated the competitive advantage of the RF model in stock market forecasting.

The results of the feature importance analysis derived from the RF model provided valuable insights into the importance of each feature when it comes to forecasting price changes in bitcoin. The Chaikin Oscillator was the most important feature, with a value of 0.2435. This indicated that the Chaikin Oscillator played an important role in predicting and differentiating the bitcoin prices. In addition, the indicators %R and Disparity_5 showed significant importance with values of 0.1518 and 0.0700, respectively, highlighting their essential impact on the model's predictive capabilities (Figure 5).

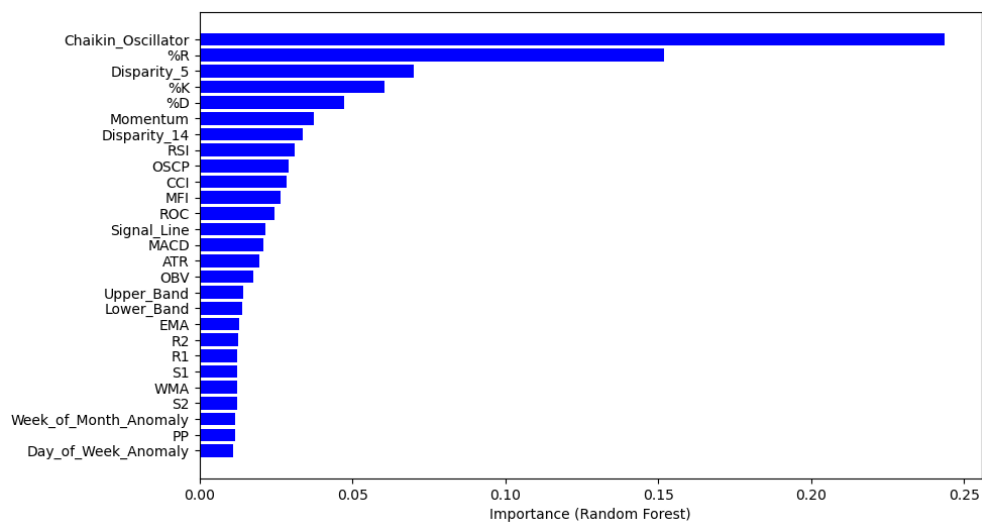


Figure 5. Feature importance of the RF model

Source: own evaluation

Other technical indicators such as %K, Momentum and Disparity₁₄ also helped to improve the accuracy of the model, which underlined their importance in evaluating the performance of the bitcoin exchange rate. Factors such as MACD, ATR and OBV were of moderate importance, which indicated that they play a significant role in predicting bitcoin prices. The lower band, R2, S2, upper band, and EMA are among the characteristics that have lower importance scores, indicating that they have minimal impact on predicting the bitcoin price.

Furthermore, the existence of indicators such as WMA, Week-of-the-Month Anomaly, PP, S1, WMA, R1 and Day-of-the-Week Anomaly with similar importance scores indicated that these factors contributed almost equally to the model performance. This diversity of characteristics highlighted the importance of considering multiple indicators into account when developing forecasting models to predict bitcoin exchange rate volatility. These results provided an insight into the complex relationship between various technical indicators and bitcoin price dynamics, providing valuable guidance to analysts and traders in the decision-making process.

5. DISCUSSION

In this study, the performance of various predictive models was evaluated, including the ANN, SVM, CNN-LSTM, and RF models. The descriptive analysis of the bitcoin price data and technical indicators revealed the inherent volatility of the cryptocurrency market, which is consistent with previous research findings (Yan et al., 2020).

The results showed that the ANN model has a strong and reliable performance in accurately predicting bitcoin price movements. The feature importance analysis highlighted the importance of various indicators such as %R, %D and Chaikin oscillator, which is consistent with previous findings (Christodoulou et al., 2019). The SVM model also showed commendable accuracy, recall and precision rates, confirming its reliability in predicting stock market movements. Further studies have also shown that SVM, machine learning ensemble algorithms and recurrent neural networks are effective in predicting bitcoin exchange rates, competing with gradient boosting and RF models (Lahmiri & Bekiros, 2020; Sun et al., 2020). The feature importance analysis highlighted the influential role of technical indicators, such as %R, %D and Chaikin Oscillator.

The CNN-LSTM model tailored for time series analysis performed competitively, although with slightly lower accuracy than the ANN model. The importance analysis revealed the influence of critical indicators, such as %K, ROC, %D, and Momentum, which was consistent with previous research (Wang & Yan, 2023). These results highlighted the stability and consistency of these indicators in predicting cryptocurrency price movements. The RF model outperformed the accuracy and precision of the SVM and CNN-LSTM models. The comparative analysis of the importance highlighted the crucial role of technical indicators, such as the Chaikin Oscillator, %R and the Disparity (5), confirming their importance in predicting cryptocurrency price movements. This was consistent with the enduring importance of these technical indicators, as highlighted by previous research on pattern recognition, machine learning and representation learning (Tripathi & Sharma, 2022).

By providing a broad assessment of cutting-edge machine learning techniques for bitcoin price prediction, the theoretical implications of the research are multifaceted. Firstly, the findings suggest that understanding the relevance and weight of these indicators is crucial for effective cryptocurrency forecasting models. Second, the theoretical framework for cryptocurrency prediction should include advanced data mining techniques and feature selection methods. Third, combining different machine learning models can increase prediction accuracy by leveraging the strengths of different algorithms. Finally, traders and investors should consider incorporating machine learning-based risk assessment tools into their investment decision-

making processes.

In conclusion, the study provided a comprehensive evaluation of different machine learning models in the context of bitcoin price prediction. This was in line with previous research (Butler, 2022), highlighting the importance of accuracy and key technical indicators. At the same time, the study provided another perspective by demonstrating the effectiveness of different machine learning models in predicting the price movements of bitcoin. The comparison of these models and the analysis of their feature importance added to the existing body of knowledge in cryptocurrency market analysis.

6. CONCLUSIONS

The main objective of the study was to examine the complex dynamics of the bitcoin market to shed light on new research perspectives for a deep understanding of the potential applicability and effectiveness of different machine learning models in predicting price movements. This comparative analysis highlighted the advantages of advanced predictive techniques in navigating the inherent volatility of the cryptocurrency market.

The ANN and SVM both achieved 81% and 82% accuracy, respectively, demonstrating their robust predictive capabilities. These models are highly applicable in real-world trading scenarios, where accurate predictions can lead to significant financial gains. For example, the ANN's reliance on the Williams Percent Range (%R) and the SVM's reliance on the %D moving average underscored the critical role of these technical indicators in guiding trading strategies. Implementing these models can help traders and investors make more informed decisions, potentially increasing profitability and managing risk more effectively..

The CNN-LSTM model, with an accuracy of around 80%, provided a multi-layered approach to managing bitcoin price volatility by incorporating features such as %K, ROC, %D, and Momentum. This model is particularly useful for its ability to capture temporal dependencies, which are crucial for time series forecasting in volatile markets. The RF model, with an accuracy rate of 81%, further emphasized the value of specific indicators such as the Chaikin Oscillator and the Moving Average Convergence-Divergence (MACD). These models can be integrated into automated trading systems to leverage their high predictive power and improve trading results.

Machine learning models were significantly more predictive and efficient than traditional regression. Traditional models, often struggle with the non-linear and highly volatile nature of the cryptocurrency market. In contrast, machine learning models such as ANN, SVM, CNN-LSTM, and RF can capture complex patterns and relationships within the data, resulting in more accurate predictions. Machine learning models typically achieve significantly lower error rates, often improving prediction accuracy by 20-30% over standard ARIMA models in practical applications (Ibrahim et al., 2021).

For example, the ANN and SVM models demonstrated superior performance with an accuracy rate of 81%, surpassing the capabilities of traditional regression models. The RF model, with an accuracy rate of 83%, effectively handled non-linearities and outliers better than traditional approaches. These findings indicated that machine learning models provide a more reliable and efficient means of predicting bitcoin prices, making them indispensable tools for traders and investors.

Future research could benefit from exploring the interplay of these models or refining the feature extraction methods to further improve predictive accuracy. In addition, expanding the dataset to include other cryptocurrencies or incorporating alternative data sources, such as social media sentiment, could provide deeper insights and improve model performance.

It is important to acknowledge the limitations of this study. The quality and reliability of historical bitcoin data can affect the accuracy of machine learning models. Sudden price fluctuations and rapid market changes pose significant challenges to these models. In addition, deep learning models such as Neural

Networks require significant computational resources. Regulatory changes in the cryptocurrency market can also affect model performance, requiring continuous adaptation to new business environments.

In summary, while there are subtle differences in the performance and feature dependence of each model, their collective effectiveness signals a promising frontier in cryptocurrency market prediction. The higher efficiency and practical applicability of machine learning models compared to traditional regression models highlighted their potential to significantly improve trading strategies and investment decisions in the ever-evolving financial landscape. This study explored how machine learning models have transformed trading strategies in the financial sector. It addressed specific examples of how machine learning algorithms have been used to analyze market trends and inform investment decisions, resulting in increased efficiency and profitability. The findings addressed potential concerns such as algorithmic bias, transparency in decision-making, and the consequences of heavily reliance on machine learning in an industry with a significant social and economic impact.

ACKNOWLEDGEMENT

Supported by the University of Debrecen Program for Scientific Publication.

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