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Crypto Price Analysis: An AI Perspective

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Abstract

Accurate prediction of Bitcoin market prices is challenging because of extreme volatility, nonlinear dynamics and rapid sentiment-driven fluctuations observed in the cryptocurrency market, especially Bitcoin. In this research, the authors investigate the use of machine learning and deep learning methods for forecasting Bitcoin prices using historical market data, technical indicators, and sentiment analysis from social media. A comprehensive dataset was used to develop and test three experimental setups from 2015 to 2024. The first configuration, an LSTM model was trained on historical OHLCV (Open, High, Low, Close, Volume) data only. In the second setup, the model was improved with the inclusion of technical indicators based on market behavior, including momentum indicators and trend indicators. The third configuration used social media sentiment features (extracted from over 2.5 million tweets related to Bitcoin, employing polarity and subjectivity scoring via TextBlob), added to the previous configuration. The results show that the LSTM model with technical indicators gave the best prediction performance with R2 of 0.9084 and Mean Absolute Error (MAE) of 0.0387, which is 8.5% better than the historical data-only model. By comparison, the accuracy of prediction did not significantly improve with the addition of Twitter sentiment features. The feature importance analysis also revealed that Relative Strength Index (RSI) and MACD histogram were the most significant features in predicting the price movements of Bitcoin. The study brings three significant findings: (1) a methodological framework based on LSTM neural networks for comparing the performance of various sets of features in predicting Bitcoin prices; (2) the discovery of the most relevant features in cryptocurrency markets; and (3) proof that technical indicators have a significant impact on the predictive accuracy of this model, while social media sentiment has a minor impact under the circumstances. The results offer valuable implications for researchers and practitioners building data-driven models for predicting cryptocurrencies.

Keywords: bitcoin price prediction, LSTM, technical indicators, sentiment analysis, cryptocurrency, machine learning, time series forecasting.

1 Introduction

Digital finance has been transformed over the last decade due to the rapid progression of cryptocurrency markets. Bitcoin is the first and most popular cryptocurrency, which is extremely volatile, decentralized and sensitive to the events of the world, and this is what has drawn the attention of researchers, investors and financial institutions. Not only is Bitcoin not regulated in the conventional sense, it does not even follow the same economic principles of price action as a traditional financial asset, making the price action more complex, less predictable, and highly non-linear [1]. Accurately forecasting Bitcoin prices is a critical yet challenging task. Accurate predictive models can aid in investment decisions, risk management, algorithmic trading strategies, and portfolio optimization. But, the nature of cryptocurrency markets is volatile, and forecasting is inadequate due to inherent randomness. This has encouraged the use of cutting-edge data-driven approaches, such as machine learning and deep learning models, which can identify the underlying patterns in vast amounts of historical data [2].

Research in recent years has moved away from the use of simple statistical forecasting models and towards more complex hybrid approaches that combine several data sources. Historical price

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information is the primary source of information for the majority of predictive systems - but it is also being combined with generated technical indicators and external behavioural data. Technical indicators are used to convert the raw information of the market into meaningful trend and momentum signals, while sentiment indicators are used to reflect the collective investor sentiment from social networks like Twitter [3]. Although there has been an increasing interest in multi-source predictive models, there are still some important research gaps. First, it's unclear whether deep learning models are always superior to ensemble models in cryptocurrency forecasting. First, it is not certain that deep learning models are always better than ensemble learning models in cryptocurrency forecasting. Second, there is a controversy over the actual predictive power of sentiment analysis, with many of the studies finding weak or inconsistent predictive power. Thirdly, there is no systematic and comparative study that has fully explored the interaction between technical indicators and deep learning architectures [4].

The prediction of Bitcoin's price has been extensively analyzed in various fields such as econometrics, computational finance, and artificial intelligence. The initial research focused on classical time series models including ARIMA, exponential smoothing, and models that involve volatility that are based on GARCH. These methods offered a mathematical framework for prediction, but were constrained by assumptions that markets are linear and stationary, and that market behavior is relatively stable, which are not valid in volatile and fast-changing cryptocurrency markets. In recent years, computational intelligence and machine learning techniques were growing in popularity, especially in the field of financial prediction [5]. The algorithms that outpaced the others were able to model complex, nonlinear patterns in past financial data, like Support Vector Machines, Random Forests or gradient boosting frameworks like XGBoost or LightGBM. Feature engineering is a major advantage of these models, including the incorporation of technical indicators that encapsulate various trends and volatility patterns in the market [6].

With the advent of deep learning, financial forecasting research took a new turn. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been found to be very powerful in tackling time series data with sequential dependencies. Bitcoin data is ideally suited for LSTM models due to its time-dependent nature, which enables the model to capture long-term trends and patterns in the market. Alongside model development, researchers have investigated the use of alternate data sources. Moving Average, RSI, MACD, Bollinger Bands, and others are some of the most popular technical indicators used in trading systems to identify momentum, strength, and volatility. These indicators offer a way to transform the raw price data in a structured way to facilitate the machine learning models to learn meaningful patterns [7].

Sentiment analysis is a recent and controversial data source for financial prediction because of its promise. Public opinion and investor sentiment is a wealth of information and can be found on social media platforms particularly Twitter. While there are some studies that suggest sentiment signals can have an impact on short-term price movements, the strength of this signal is inconsistent as it is subject to noise, misinformation and reactive sentiment on the web. While much research has been done, there are still some fundamental issues that have not been addressed. These encompass the best mix of data sources, the actual impact of sentiment features and which modeling methods work best under various market conditions. Further, there are numerous studies available, but few of them are thorough comparisons of the various models and feature sets, conducted in the same experimental conditions [8].

To address these limitations, this study develops a comprehensive experimental setup to systematically compare the performance of LSTM, XGBoost, and LightGBM models, given historical Bitcoin data, technical indicators, and large-scale sentiment data. The research focuses not just on predictive accuracy, but also on statistical validation, important features and the stability of the model performance in different market conditions. The aim of the study is to present a more detailed picture of cryptocurrency forecasting systems and to look for viable methods of increasing the accuracy of forecasts in highly dynamic financial markets. Prediction of Bitcoin prices continues to be a difficult task due to high volatility and nonlinearity of the market along with its sensitivity to various external events. Various research works provide conflicting evidence about the performance of the different models as well as the use of sentiment of social media as one of the data sources to predict Bitcoin prices. At the same time, no definitive conclusions have been made concerning the superiority of deep

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learning models such as LSTM compared to ensemble algorithms like XGBoost and LightGBM under identical conditions.

2 Related Works

In [9], Zhu et al. present a behavioral-volatility approach to the understanding of Bitcoin markets based on market attention and volatility dynamics, which provide an explanation for extreme volatility movements. Based on their findings, the authors prove that extreme volatility increases are highly linked to elevated investor attention levels and uncertainty shocks in stressed periods. Their findings clearly reveal that traditional finance cannot fully explain Bitcoin's volatility but rather behavioral and network information plays an important role in this case. Nevertheless, the paper is constrained by the use of aggregated attention measures that do not sufficiently reflect the multi-sourced nature of behavioral variables or sentiments polarization. Moreover, deep learning models are not applied by the author to analyze the relationship between attention and volatility dynamics. Our study intends to fill these gaps by using high-frequency sentiment measures generated from social media and applying both machine learning and deep learning algorithms.

In [10], Dudek et al. propose comparative analyses of Bitcoin's return characteristics relative to traditional financial assets using statistical and econometric models. The results demonstrate that Bitcoin exhibits heavy-tailed distributions, strong skewness, and pronounced jump behaviour, making classical Gaussian-based volatility models inadequate. The studies also highlight the inverse leverage effect, where volatility increases following positive price shocks, unlike traditional equity markets. However, these works are limited by their reliance on static econometric frameworks such as GARCH-type models, which struggle to capture nonlinear dependencies and evolving market structures. Moreover, they do not incorporate alternative data sources such as sentiment or blockchain activity. The present study addresses these limitations by employing machine learning and deep learning models, including LSTM and gradient boosting methods, which can learn nonlinear temporal dependencies. Additionally, it integrates sentiment and technical indicators to better capture the complex structure of Bitcoin returns and improve predictive robustness under high volatility conditions.

In [11], Ahmed et al. put forth a model for endogenous volatility, which treats volatility as an emergent characteristic of market processes instead of a function of external shock-driven events. The results obtained imply that volatility is highly sensitive to feedbacks created within trading volume, investor sentiments, and speculative tendencies in the market. This indicates the presence of self-reinforcing volatility clusters in the case of Bitcoins and implies that they can hardly be predicted through isolated predictors. The drawback with this research work is that it considers a limited set of factors in understanding interaction effects and lacks any connection with live sentiment streams or deep learning methods for sequence modeling. In addition, it fails to harness high frequency and voluminous social media data. On the other hand, our current research addresses these drawbacks and develops a multi-source integration model that utilizes live market data and sentiment signals alongside a sequence-based deep learning architecture.

In [12], Leushuis & Petkov suggest a forecast model of volatility that guarantees strict temporal order among the features and target variables of time t+1. As seen from the experimental findings, maintaining causality when generating time-series plays an important role for improving prediction performance and minimizing information leaks in forecasting systems. Their research proves that temporal restrictions have a positive influence on achieving better accuracy compared with randomized or incorrectly ordered data sets used for training. Nonetheless, the drawback of the paper is that it considers only classic statistical and shallow neural networks as modeling techniques and lacks nonlinearities, since it is unable to account for them using the chosen methods. Moreover, the paper does not involve any additional behavioral or blockchain indicators into the analysis. In this respect, our study seeks to overcome these shortcomings by utilizing deep learning and boosting techniques for building forecasting models with sentiment and technical analysis involved.

In [13], Li et al. introduce an approach to predict volatility in the stock market through a transmission architecture of multiple layers where the intermediate market states like uncertainty serve as important factors linking external predictors with volatility effects. Their findings show that including uncertainty in the prediction model improves predictions as opposed to excluding the uncertainty component as a mediator variable between behavioral and market-based variables. The research shows the significance of having structural paths in financial prediction models. One of the limitations in the research is due to their conceptual approach which has not been empirically validated with extensive cryptocurrency data sets and sophisticated machine learning methods to account for the non-linear interactions between the predictor variables. Furthermore, the mediation model was conducted through regression analysis. The current study addresses these shortcomings by designing a data-driven neural network architecture which implicitly captures the representation of uncertainty within hidden layers.

In [14] Slim et al. introduce comparison of measurement systems has been provided based on realized volatility, historical volatility, and other proxies for measuring risks in the finance and cryptocurrency domains. In this case, the findings indicate that the various volatility measurements yield dissimilar risk estimates, where realized volatility measures short-run dynamics whereas historical volatility can estimate trends of the underlying asset's value over long periods. Additionally, it should be noted that low-frequency volatilities are more reliable when the market is incomplete or noisily observed, as is the case in cryptocurrency trading. On the other hand, the weakness of these studies is their inability to define volatility uniformly irrespective of the temporal resolution involved. Moreover, they overlook the integration of predictive modelling into their analysis. The current study addresses the identified gap by providing a uniform definition of "historical volatility," which has been set at eight weeks in this case.

Alternative risk measurement approaches such as Value-at-Risk (VaR) and implied volatility were suggested in [15] as ways of measuring uncertainty and downside risks in financial markets. The findings reveal that VaR can be seen as a measure based on quantiles, and implied volatility is market expectations estimated from options prices. Both approaches have been successfully applied to traditional financial markets with strong liquidity conditions and advanced derivatives infrastructure. However, one major drawback of these methods is their unsuitability for Bitcoin markets, as there is still an insufficient number of Bitcoin options contracts traded in the market, and VaR estimation is very distribution-dependent. Moreover, both alternatives fail to serve as direct measurements for time series forecast modeling compared to volatility-based measures. In contrast, this research project attempts to overcome these shortcomings by focusing on the prediction of historical volatility as the main forecasting target.

In [16], Cai et al. describe a theoretical model that defines blockchain fundamentals as a multidimensional construct consisting of such factors as decentralization, immutability, transparency, consensus, and blockchain network security features. According to their research findings, it turns out that all of these architectural characteristics have a significant impact on the level of trust and dependability associated with blockchain technology as an infrastructure for financial transactions. It is important to note, though, that this research suffers from the lack of operationalization and measurement tools for assessing the blockchain fundamentals concept as it is rather theoretical. Besides, the paper does not offer any quantitative measures that can be used to predict future dynamics within a certain timeframe. Therefore, the current study attempts to fill in this gap by transforming the abstract definition of the variable into concrete on-chain indicators

According to the study conducted in [17], congestion and block space usage could be useful for predicting the presence of network stress and users' demand. It was found that there was a positive correlation between the higher levels of congestion and transaction fees with a negative impact on user efficiency and consequently on the market perception of the usability of the technology. Therefore, according to their results, network pressure measurements could have an indirect effect on the value and volatility of cryptocurrencies. But the drawback of this paper was that congestion measures were studied separately from other predictors of sentiment and security. Besides, it should be noted that the results presented here are mainly descriptive but not predictive. This limitation is overcome by the current study that incorporates indicators related to network throughput into a structured blockchain fundamentals set along with sentiment and market indicators.

In [18] Omole & Enke suggest to consider active addresses as a measure of participation intensity in blockchains and its adoption. It was found that changes in active addresses have strong correlations with market dynamics, price trends, and volatility dynamics in Bitcoin networks. Thus, their work shows that address-level statistics are able to reflect significant differences in users' activity. But one should take into account the fact that the number of active addresses does not reflect

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real numbers of users, since every person has more than one address and might even use custodian's wallet with aggregation. Moreover, the use of off-chain technologies, such as the Lightning Network, influences estimates at the base layer. In our paper, we take these factors into consideration by considering active addresses as a measure of participation breadth and applying other fundamental indicators.

In [19], there is a theoretical link between blockchain fundamentals and market uncertainty, which implies that better network conditions will contribute to lower risks of trading cryptocurrencies. According to their findings, more activity and security in the blockchain network lead to less market volatility and uncertainty perception from traders. This means that blockchain fundamentals are able to become signals for stability in financial modeling. Nevertheless, the drawback of this research is that it does not apply any machine learning algorithms but rather has a strong theoretical component. Moreover, in both studies, uncertainty is not considered as an intermediary variable for estimating volatility. The current paper addresses these weaknesses as the empirical approach with the use of blockchain fundamentals as well as the role of uncertainty are implied.

3 Methodology

This part provides an overview of the methodology used in order to predict the prices of Bitcoin by employing machine learning and deep learning algorithms. This methodology was developed to analyze the effects of market history, technical analysis, and sentiment in the social media on the accuracy of forecasting of Bitcoin prices. Given the complexity of cryptocurrency markets, it is hard to identify temporal dependency between observations using traditional statistical methodologies. Thus, the current study adopts the use of contemporary artificial intelligence methods that can identify sequential relationships within massive datasets. Methodology comprises multiple stages combined together starting with the collection of cryptocurrency exchanges and social media data. Bitcoin historical market data consisting of OHLCV values were collected within the period ranging from 2015 to 2024. Moreover, big data associated with tweets on Bitcoin were obtained to explore how the sentiment expressed in social media impacts Bitcoin price changes. Following the data acquisition stage, a series of extensive data preprocessing activities were carried out, namely missing values handling, normalization, de-noising, and timestamp alignment. Then, feature engineering was performed through which different technical indicators, such as RSI, MACD, Bollinger Bands, Moving Averages, and ATR, were calculated to improve the prediction capability.

A set of several forecasting algorithms, such as LSTM, XGBoost, and LightGBM, were constructed and their performance was assessed via multiple experiments using several configurations. Statistical measures for performance assessment included R^2, MAE, RMSE, and MAPE. The process flow diagram presented in Figure (1) represents the process flow chart implemented in this study for the prediction of Bitcoin prices. The flow diagram consists of six phases where each phase accomplishes a specific function within the forecasting framework. The first phase is Data Collection, where the collection of past data related to Bitcoin markets and sentiment is accomplished from various sources.

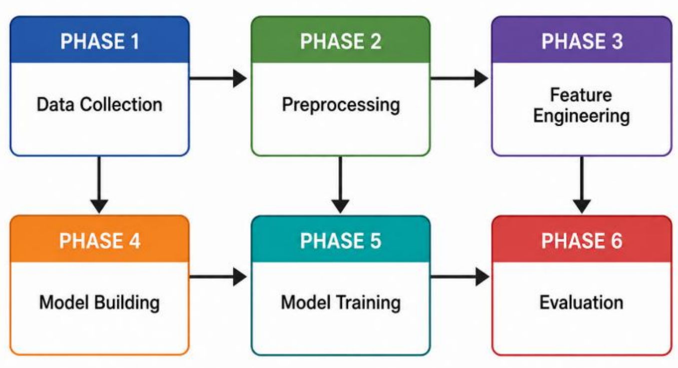

Figure 1 Methodology workflow

The second phase is Preprocessing, which deals with data cleaning and processing. This phase includes handling missing values and normalizing the data, among others. Phase three entails feature

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engineering; whereby informative features are created through technical indicators. These include Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Band (BB), Average True Range (ATR), and Moving Averages (MA). The fourth step is known as Model Building, where one has to design and configure different machine learning models, such as LSTM, XGBoost, and LightGBM. The fifth step is Model Training, which entails applying certain training processes using past data sets in order to enable the machine to learn complex patterns of behavior. Finally, the sixth step involves evaluating the performance of the models through metrics like R^2, MAE, RMSE, and MAPE.

3.1 Data Collection

Data gathering is among the key steps in the described prediction model, as the quality, variety, and reliability of gathered information significantly impact the accuracy of predictions made using different methods and approaches. To develop predictive models based on machine and deep learning techniques, two major types of data were collected during the course of this research. The first type includes market data associated with trading operations involving Bitcoins and gathered from financial platforms, while the second type comprises sentiments collected from social media sites. This type of data helps evaluate how people feel about Bitcoin, thus making it possible to take into account not only quantitative data related to market but also qualitative sentiments expressed by people. Historical data about market behavior gives information needed for developing technical indicators that will allow observing temporal dependencies and correlations within cryptocurrency market. Meanwhile, data collected from social media sites helped to explore whether public opinions or sentiments can affect Bitcoin prices. As it is obvious that cryptocurrencies depend on public perceptions and fears of investors to a great extent, this information can be obtained from various social media sites, especially Twitter. The gathered data sets include various years to make sure that the market has enough diversification in bullish, bearish, and neutral environments. Extensive data pre-processing and synchronization steps have been employed to synchronize data sets to extract features and train models.

3.1.1 Historical Price Data

Historical market data of Bitcoin was acquired from Yahoo Finance API via the yfinance package in Python. It is chosen due to its high reliability and continuous updates, making it an ideal source of information for cryptocurrency forecasting models. The dataset covers daily trades of Bitcoin from 01/01/2015 till 01/06/2024, allowing the models to learn long-term market behavior at various economic circumstances and degrees of volatility. The dataset comprises several key OHLCV features: open, high, low, close, adjusted closing, and volume. These parameters are essential as they allow obtaining comprehensive market activity information, which is often utilized in financial research. Open and Close prices show the overall direction of market movement, and High & Low describe intraday volatility. Meanwhile, the Trading Volume demonstrates market activity. These features will be used to compute technical indicators like RSI, MACD, Bollinger bands, ATR, and moving averages. Table 1 displays Historical Price Data Parameters.

Table 1. Historical price data parameters

Parameter	Value
Ticker	BTC-USD
Start Date	1/1/2015
End Date	6/1/2024
Frequency	Daily

3.1.2 Sentiment Data

For understanding the impact of the sentiment of people on the fluctuations in the price of Bitcoin, it was necessary to gather extensive data sets from Kaggle databases about Twitter discussions concerning cryptocurrencies. For that purpose, two prominent data sets on the tweets about Bitcoin covering the time frames of 2021-2022 and 2022-2024 were gathered to form an overall

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dataset on the sentiment analysis of over 2.5 million tweets. Such sets can help understand the opinion of investors and their emotions as well as attitude towards Bitcoin and cryptocurrency market as a whole. It is important to note that the tweets contain multiple attributes including text of the tweets, date of posting, verification statuses of users, number of followers, retweets information, and many others. Among these characteristics, tweet text serves as the main input for the sentiment analysis processes. With tweets being collected for various years, the study can analyze the behavior of sentiments in different market conditions, such as during times of explosive growth, stock market crashes, and recovery. The large collection of sentiments will enable the analysis of whether social media sentiments have an impact on the accuracy of Bitcoin price prediction. Figure 1: Tweets Dataset Summary.

Table 2. Tweets dataset summary

Attribute	Description
Total Tweets	~2.5M+
Date Range	2021 – 2024
Features	text, date, user_verified, user_followers, etc.
Format	CSV

3.1.3 Data Availability Visualization

The tweet availability plot visualizes the distribution of cryptocurrency tweets collected from 2021 to 2024. It is evident from the graph that there was sufficient tweet availability during the entire observation period. This will ensure adequate coverage during sentiment extraction and time-series synchronizing. Sufficient tweet availability makes sentiment analysis more reliable since it eliminates temporal gaps.

3.2 Data Preprocessing

The stage of data preprocessing is important in Bitcoin price prediction models since the data extracted may have errors in the form of inconsistency, missing values, noise, and other problems which can adversely affect the model accuracy. Preprocessing is necessary to make sure that the collected data sets are fit for the machine learning and deep learning techniques employed in building the forecast models. In the current research, preprocessing of the datasets was conducted on the market historical data and the sentiment data separately before the integration process of these sets in the models. In case of market data from historical Bitcoin price, there were several steps involved in preprocessing data which included treating missing values, construction of technical indicators, scaling of numerical attributes, and creation of sequential examples for deep learning models. Considering the sensitivity of financial series to temporal order, chronological preprocessing was carried out in all steps of processing. Also, normalization of features was performed. The dataset was partitioned into training, validation, and test sets through a chronological partitioning scheme as opposed to randomization. This is because the problem at hand mimics actual prediction scenarios where future predictions have to be made based on previous instances alone. Windows were created after which the datasets were transformed into supervised learning examples suitable for use in LSTM and other predictive models.

3.2.1 Historical Data Preprocessing Pipeline

Figure 2 provides a graphical representation of the sequence of procedures undertaken on the historical cryptocurrency market data for training and testing purposes. In this regard, the initial step involves obtaining the raw historical data that includes data fields with attributes such as Open, High, Low, Close, and Volume information about the Bitcoin market. To begin with, the first data preprocessing technique entails dealing with missing values, where any instance of missing value is filtered out to ensure completeness. Once the data has been cleaned, the next step entails conducting feature engineering in order to create new features or technical indicators. Examples of technical indicators generated include Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, moving averages, and Average True Range (ATR). Lastly, once feature extraction is done, the data set is split into train, validation, and test sets according to a

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chronological splitting scheme. Then comes the step where we use feature scaling by applying the method called MinMaxScaler in order to normalize all variables between -1 and 1. Normalizing helps achieve stability while training, and ensures that no one variable having high numeric value gets an edge in the learning algorithm. Finally, sliding windows with sequence lengths ranging from 10 to 30 are used to generate sequential data. The purpose of this is to convert our dataset into a supervised learning problem that can be fed into models like LSTM.

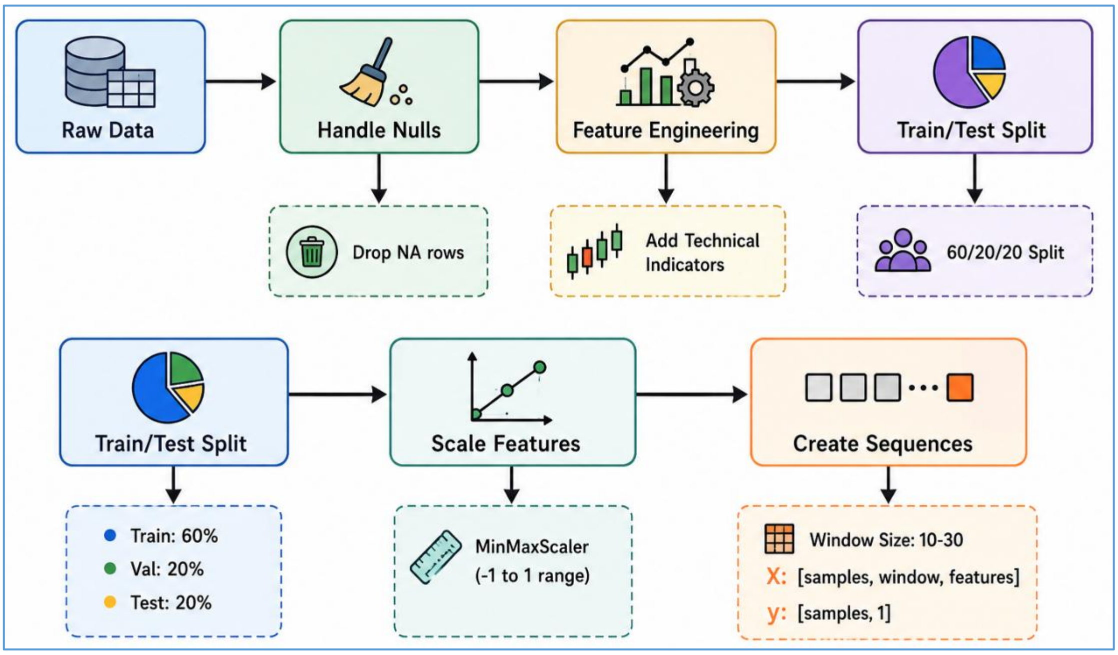

Figure 2 Historical data preprocessing pipeline

3.2.2 Text Preprocessing for Sentiment Analysis

The first stage in analyzing any social media content is text preprocessing. Tweets are very unstructured and usually consist of noisy data like URLs, hashtags, emojis, special characters, repeating letters, and informal language. The presence of this kind of data may lead to incorrect sentiment extraction from texts. Thus, it is required to apply a well-structured process of preprocessing tweets in order to obtain meaningful and useful text for further analysis. First, one should eliminate unnecessary data such as URLs, hyperlinks, and other types of noise. Next, all the letters in tweets should be turned to lowercase in order to have uniformity. Special characters and punctuation marks are then stripped from the text in order to minimize noise and have clear text. Then, the text is tokenized to split the tweet into several tokens or words which will be analyzed separately. Unimportant stopwords should be eliminated after that because they don't provide sentiment-related information. As a result, the text undergoes lemmatization which helps to transform words into their basic form.

The text preprocessing pipeline in Figure (3) provides a clear depiction of how raw tweets data are transformed step by step into the required data format to perform sentiment analysis and apply

machine learning algorithms. The input of the pipeline is raw tweets data containing unstructured and uncleaned text. To start the preprocessing process, URL links are filtered out using regular expressions such as http\S+. Subsequently, the text is converted to lowercase letters to ensure that all words have the same format. Special characters and symbols, except alphanumeric characters, are filtered out using expressions such as [^a-zA-Z0-9] to replace them with spaces. The result after filtering is then tokenized by splitting it into words. Words referred to as stop words are filtered out using the Natural Language Toolkit library to get only useful words for sentiment analysis. Lemmatization is performed using the WordNetLemmatizer to extract the roots of words, resulting in clean data.

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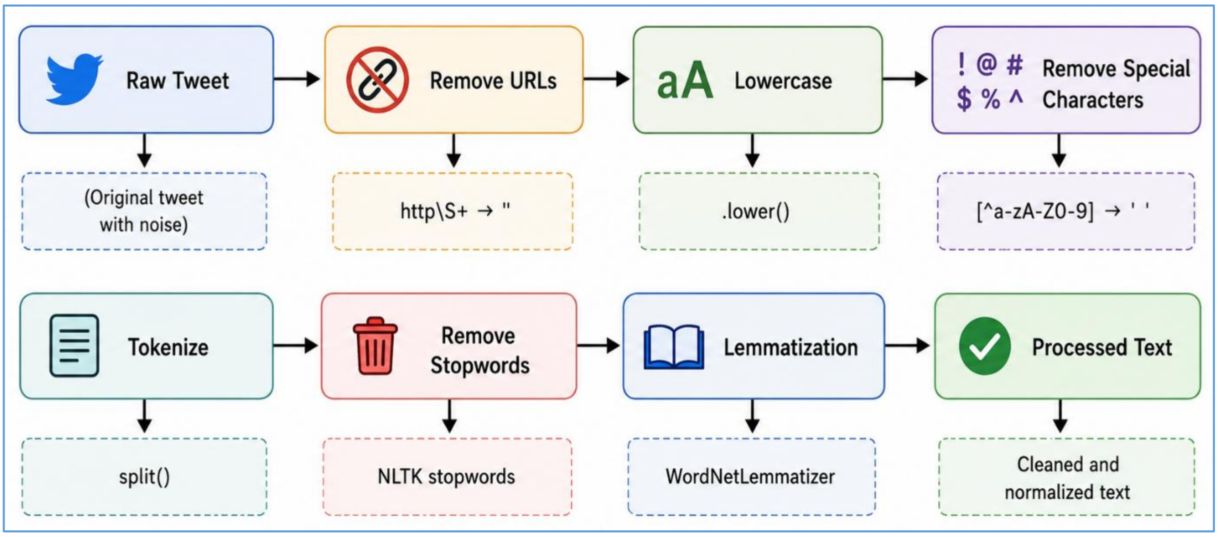

Figure 3 Text preprocessing pipeline

3.2.3 Sentiment Analysis Pipeline

Sentiment Analysis Pipeline forms an integral part of the proposed framework for mining emotionally driven data from social media networks related to Bitcoin. Once the pre-processing stage of the tweet data is completed, the sentiment analysis process kicks in and helps determine the public sentiment on the subject matter of Bitcoin. Sentiment analysis is important as it enables one to understand the possible impact of market sentiment on price changes. In this research, we use TextBlob to conduct the sentiment analysis task. The sentiment polarity of the text is determined by analyzing the text to determine the nature of the expressed opinion, which is positive, negative, or neutral. Further, the text is also subjected to the determination of subjectivity, which quantitatively determines the personal nature of the opinions contained in the text. The resulting values are then employed to categorize the sentiments, with values being assigned to these sentiments for incorporation into the forecasting models. The classification process uses the following rule mapping: a positive polarity implies a positive sentiment, a negative polarity implies a negative sentiment, while a zero polarity implies a neutral sentiment.

The sentiment analysis pipeline described in Figure (4) shows the process involved in transforming processed textual data to structured sentiment features that are useful in predictive analysis. In the pipeline, the text is first obtained after preprocessing such as cleansing, tokenizing, and normalization. The text then goes into the sentiment analysis engine, which in our case will be the TextBlob engine. The text blob sentiment analyzer will measure two major factors in the text, polarity, and subjectivity. While polarity indicates the emotional direction of the text in terms of negativity or positivity, subjectivity indicates the extent to which the text is opinionated or based on facts.

In cases where polarity scores are computed, the next step is rule-based classification of the sentiments. A sentiment whose polarity score is greater than zero is classified as positive, while if it equals zero, then it is classified as neutral, and if less than zero, it will be classified as negative. This classification method is not only simple but also interpretable. Sentiment classes are then encoded as numbers (-1 for negative, 0 for neutral, and 1 for positive), after which the scores are incorporated into the machine learning dataset.

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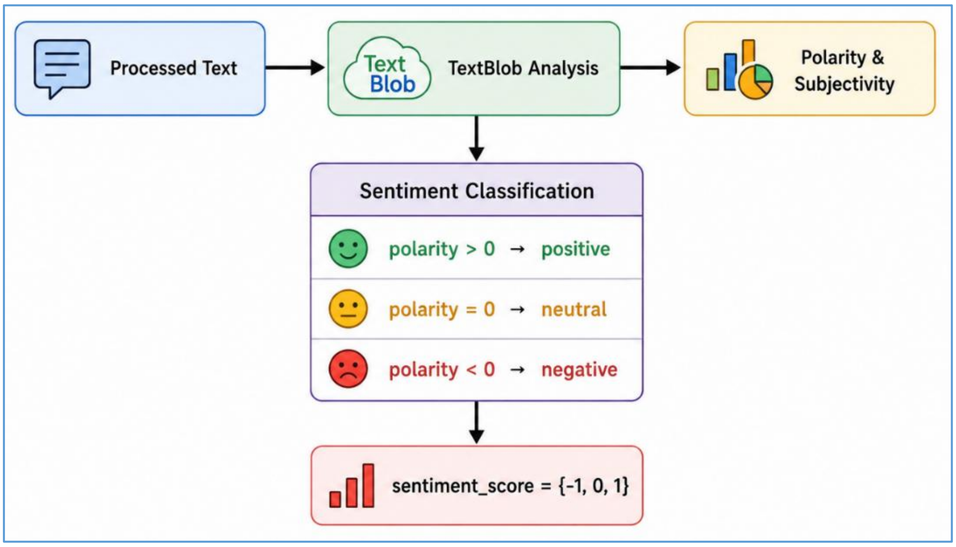

Figure 4 Sentiment analysis pipeline

3.2.4 Data Integration

Data Integration plays an important role in the suggested framework for the prediction of Bitcoin prices, as it involves combining the collected data of different types into a unified format. In this case, the proposed data integration process involves joining the data related to historical Bitcoin prices with the aggregated data about sentiments, which was obtained through mining the social networks' data. Given the fact that both sets of data are of a different nature and are characterized by different frequencies, special attention should be paid to their proper integration. First, the data about sentiments is aggregated in such a way that the final dataset would contain two values, including the average polarity value of all tweets made during a specific day and the number of tweets as an indicator of the level of activity in relation to the analyzed topic. As a result of such data aggregation, the final dataset is integrated into the OHLCV dataset by using the Date feature as an indexing criterion. The missing values result from days where no tweets have been collected or where there is an absence of sentiments collected on those days. These missing values are addressed by filling the data with zero values for the polarity feature and the tweet count feature. The output of the integration step will be the complete merged datasets that contain all the required information about market dynamics and sentiments.

3.3 Technical Indicators

Technical indicators are vital parts of any financial forecast system because they convert market prices into numeric signals which can be used for revealing market trends, momentum, and volatility. As for the application of technical analysis to the task of Bitcoin price forecast, using only the OHLCV data may prove ineffective in case of strong nonlinearity and high level of noise in cryptocurrency markets. Consequently, in this research, I use several technical indicators to expand the range of input features and make the model more effective. Technical indicators provide various types of market information, including trends, power, fluctuations, and possible reversals in market dynamics. Using the combination of several complementary indicators makes it possible for the model to have a deeper insight into market processes.

3.3.1 Moving Averages

Moving averages are some of the most extensively applied techniques in technical analysis used in determining trends and smoothing price movements in financial time series data. They enable noise filtering to allow for clear identification of the directionality of price movements. In this research, two kinds of moving averages – simple moving averages and exponential moving averages are adopted to determine the extent of the sensitiveness of the trend being determined. The simple moving average gives equal weighting to all the previous values, hence can be effectively used for finding stable trends whereas the exponential moving average emphasizes current values hence is more sensitive to market movements. Table 3 below gives the Moving Averages Features.

Table 3 Moving averages features

Indicator	Period	Purpose
SMA_20	20 days	Short-term trend
SMA_50	50 days	Intermediate trend
EMA_20	20 days	Short-term weighted trend
EMA_50	50 days	Intermediate weighted trend

3.3.2 MACD (Moving Average Convergence Divergence)

The Moving Average Convergence Divergence (MACD) is a powerful momentum oscillator that is used for determining trend changes, direction, and strength. The MACD indicator is especially useful in detecting bulls and bears signals in volatile markets such as the crypto market. The MACD line is obtained from the difference between two EMAs, usually a 12-day and a 26-day EMA. On the other hand, the signal line is calculated by computing the 9-day EMA of the MACD line. The MACD histogram measures the difference between the MACD line and the signal line. Table (4) below shows the MACD Indicator Components and Calculations.

Table 4 MACD indicator components and calculations

Component	Calculation
MACD Line	12-day EMA - 26-day EMA
Signal Line	9-day EMA of MACD Line
MACD Histogram	MACD Line - Signal Line

3.3.3 RSI (Relative Strength Index)

The Relative Strength Index (RSI) is an extensively popular momentum oscillator that determines the speed and change of price movement within a given period. This momentum indicator is mainly used to identify when the asset becomes overbought and oversold in the market, indicating a significant price reversal possibility. In this research, RSI is estimated over 14 days, ensuring an appropriate analysis of short-term momentum. The relative strength index takes values between 0 and 100, with any value over 70 signifying overbought status, while anything under 30 shows oversold status. This data proves highly useful when predicting Bitcoin’s turning points and thus enhances the prediction model. Table (5) RSI Indicator Settings and Interpretation.

Table 5. RSI indicator settings and interpretation

Parameter	Value
Period	14 days
Range	0–100
Overbought	> 70
Oversold	< 30

3.3.4 Volatility Measures

The following volatility indicators are used in measuring the level of fluctuations of bitcoin prices with a lot of significance. Volatility indicators play a significant role in influencing price movements and accurate predictions in high volatility markets like cryptocurrencies. The following are the two main volatility indicators used in this research: Average True Range and standard deviation of closing prices. Average True Range measures the average range of price fluctuation over a period of time irrespective of its direction. This makes the indicator useful in measuring the level of market instability. Standard deviation measures the range between the closing price and the mean closing price. Table (6) shows Volatility Indicators Overview.

Table 6 Volatility indicators overview

Indicator	Period	Description
ATR	14 days	Average True Range
Std_Dev	14 days	Standard deviation of Close price

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3.3.5 Bollinger Bands

Bollinger Bands refer to an extensively applied technical volatility tool that provides dynamic upper and lower price channels around a moving average. This is especially useful when identifying periods of increased or decreased volatility, as well as breakout price levels. In this research, Bollinger Bands have been generated based on 14 days Simple Moving Average as the middle band, while the upper and lower bands represent two standard deviations above and below the mean, respectively. This flexible approach ensures that the indicators adjust to market volatility and signal either a trend reversal or continuance in Bitcoin prices. Table (7) represents the Bollinger Bands configuration.

Table 7 Bollinger bands configuration

Component	Period	Multiplier
Upper Band	14 days	+2σ
Middle Band	14 days	SMA
Lower Band	14 days	-2σ

3.4 Models Architecture

The entire process of pre-processing historical data is illustrated in figure (5). The preprocessing step is an essential part of the data modeling process since it involves making sure that the data quality and reliability have been improved by getting rid of noise and formatting the data to be compatible with deep learning. Initially, the raw historical data are acquired and checked for any inconsistencies or presence of missing values. The rows of any missing value are dropped since having them in the dataset would affect its accuracy. After data cleaning, the next step involves applying feature engineering techniques on the dataset to create more technical indicators.

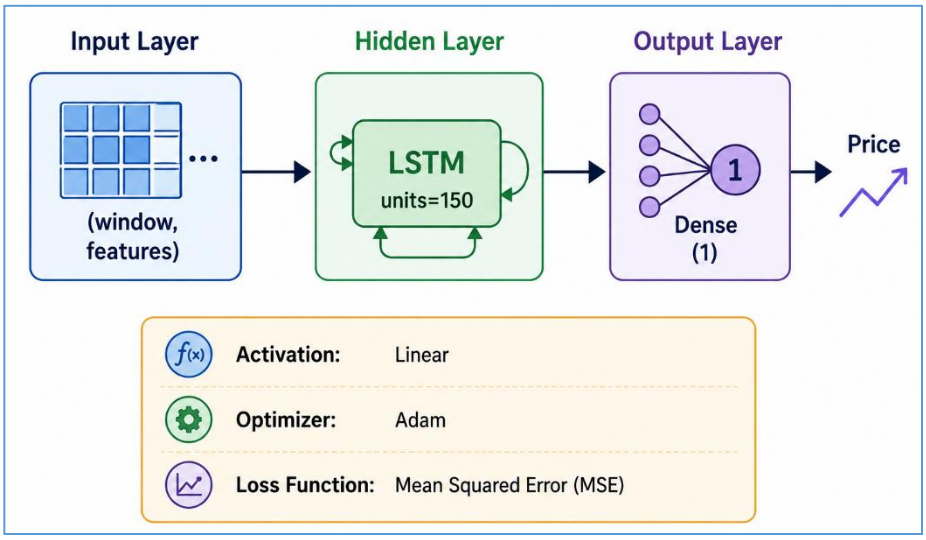

Figure 5 Workflow of historical data preparation for LSTM modeling

After feature engineering, the dataset is split into three data groups: training, validation, and testing data using the ratios of 60% training data, 20% validation data, and 20% testing data. Splitting the dataset in this way gives an opportunity for the model to learn from past data patterns and validate its prediction accuracy by using new samples to avoid overfitting and increase generalizability. Then the feature scaling procedure is applied using the MinMaxScaler method that will scale all features to lie in the interval $[-1,1]$. Feature scaling is necessary for LSTM neural network training since it ensures stable convergence and excludes some features from domination due to large numerical ranges. In conclusion, after feature scaling, data are reshaped to create sequences for making predictions. For that, the sliding window approach with a defined window size from 10 to 30 samples was utilized. The created input tensor takes the following form ([samples, window, features]), while the output target takes the form ([samples, 1]).

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For this study, both XGBoost and LightGBM algorithms have been used in order to predict the price of Bitcoin using the advanced gradient boosting approach. These models have been highly appreciated because of their capability of dealing with the non-linearity in the data, understanding feature interaction, and predicting the outcomes with higher precision. XGBoost has been designed in such a way that it has a robust regularizing parameter and the trees used in the process have a deeper structure in order to understand the complexities associated with Bitcoin prices. Moreover, the learning rate used is quite low and this would help in stabilizing convergence. Along with it, more number of estimators can be used to learn efficiently from the data. On the other hand, LightGBM is designed for efficiency and scalability, and it adopts a leaf-wise tree growth policy. The model parameters are set with a low maximum depth and few leaves in order to strike a compromise between performance and avoidance of overfitting. Higher learning rates than those of XGBoost are employed for faster convergence, but early stopping guarantees optimum training times. All in all, these tuning techniques make it possible for the two models to complement one another. Table (8) shows XGBoost and LightGBM Model Hyperparameter Configurations.

Table 8. XGBoost and light GBM model hyperparameter configurations

Parameter	XGBoost Value	LightGBM Value	Description
learning_rate	0.01	0.1	Controls step size for weight updates
max_depth	30	5	Maximum depth of trees
n_estimators	1000	2000	Number of boosting iterations
subsample	0.8	—	Fraction of samples per tree (XGBoost only)
colsample_bytree	0.8	—	Feature sampling ratio (XGBoost only)
gamma	1	—	Minimum loss reduction for split (XGBoost only)
num_leaves	—	31	Maximum leaves per tree (LightGBM only)
boosting_type	—	gbdt	Gradient boosting decision tree method
early_stopping_rounds	50	50	Stops training if no improvement

3.5 Training Process

The training stage represents one of the critical aspects of the Bitcoin price forecast methodology, as it directly influences the ability of machine learning and deep learning approaches to learn from historical data. Considering the highly temporal character of cryptocurrency markets, the training process is developed accordingly, which allows ensuring that all models are trained in an environment that mimics their potential operation in practice. The data preparation stage along with configuration parameters related to particular models is included in the training pipeline with the goal of achieving the best performance of approaches. In case of LSTM models, the training process begins with data transformation from the time-series format to the supervised learning one by applying the sliding window technique. By means of the latter approach, input-output sequences are formed such that the inputs contain a specific number of observations, while outputs represent the target values of the subsequent observation. This way, the model receives the opportunity to learn the relationships between various elements in the dataset. Thus, as a result of the process, a new 3D dataset is formed.

The training setup is specified by the essential hyperparameters responsible for efficient training and generalization. In particular, the batch size is set to 10 to provide an optimal trade-off between training costs and stabilization of gradients, while 100 epochs are performed to allow enough iterations of the model's learning process. Time series should be kept intact during the training process, so shuffling is turned off during the process. A 20% portion of the dataset is allocated for validation purposes during the learning process to observe the performance of the algorithm and avoid overfitting. Early stopping with 10 epochs of patience can also be performed to save resources on unnecessary iterations.

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3.6 Evaluation Metrics

Evaluation criteria will be critical to determining the quality of our forecasting models. Given that this research applies regression analysis techniques for prediction, we will use several statistical metrics for estimating the accuracy and the spread of prediction errors. Such criteria enable us to have a multi-faceted picture of how accurate our forecasts were and how close the predictions are to the actual Bitcoin prices. Using a combination of different measures of prediction errors, absolute errors, and goodness of fit will allow us to have a balanced evaluation of prediction quality and model performance. The first criterion we will apply is the mean absolute error (MAE). This statistic does not depend on whether the errors are positive or negative; rather, it estimates the average magnitude of the prediction error. The second statistical indicator we can use is the mean squared error (MSE). This criterion will be more sensitive to large differences between the predicted and the actual price since MSE tends to punish big mistakes by a bigger factor. The root-mean squared error (RMSE) represents an easier to understand error estimate expressed in the original units. We will also use the coefficient of determination (R^2).

4 Results and Discussions

In this part, a detailed analysis of the experimental results will be provided regarding the three proposed architectures for predicting the price of Bitcoin. The experiment will be carried out on various machine learning and deep learning algorithms, including LSTM, XGBoost, and LightGBM, as well as with various sets of input features, including historical information, technical indicators, and social media sentiment analysis. The results will be carefully analyzed based on metrics like MAE, MSE, RMSE, and R2 score. Discussion is designed in such a way that would emphasize both quantitative and qualitative aspects obtained through the use of the experiments. First of all, a general overview of the performance of models is provided to determine the best performing model among the set considered. Detailed analyses of each experiment are performed considering their learning process, predictions, and error distribution pattern. Additionally, feature importance is calculated to analyze the value of using technical indicators and sentiment for the forecasting process. Finally, the evaluation section provides conclusions about the effectiveness of particular modeling strategies and discusses results obtained during this study.

4.1 Overall Performance Comparison

The performance comparison assesses all created models under various experiment conditions to find out which one will produce the highest accuracy for predicting Bitcoin price. To test the effectiveness of our forecasting approaches, we employ typical regression performance indicators, such as MAE, MSE, RMSE, and R^2. Thus, we can clearly see how each set of features influences the forecasting accuracy of our algorithm. According to the results presented in Table (9), the usage of technical indicators leads to better accuracy for all models, especially LSTM, which shows the highest values of all indicators. At the same time, tree-based algorithms, such as XGBoost and LightGBM, have demonstrated good performance in our research as well, thus proving their ability to analyze structured features efficiently. Finally, sentiment data adds just marginal changes to forecasting accuracy, demonstrating its poor potential as a predictor of future prices compared to other features used in our research.

Table 9 Overall performance comparison of All models

Model	Data Type	MAE	MSE	RMSE	R^2
LSTM	Historical Only	0.0423	0.0038	0.0616	0.8912
LSTM	Historical + Technical	0.0387	0.0032	0.0566	0.9084
XGBoost	Historical + Technical	0.0412	0.0035	0.0592	0.8996
LightGBM	Historical + Technical	0.0405	0.0034	0.0583	0.9021
LSTM	Historical + Sentiment	0.0418	0.0037	0.0608	0.8945

4.2 LSTM with Historical Data Only

The LSTM architecture adopted for this study has been designed to recognize the temporal dependencies in the price dynamics of the Bitcoin through sequential learning. The architecture

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settings have been chosen carefully in order to achieve maximum learning capability with minimal computation. In this regard, a time step size of 10 is considered while building the input sequences for learning short term temporal dependencies based on the historical behavior of the market. On the other hand, there are 150 LSTM units which make the model sufficiently expressive to capture any non-linear dependencies in the data. The model learns from the data over 100 epochs using batches of 10 each for optimal training process. Finally, the input features include the Open, High, Low, and Volume parameters, which are the essential features of price dynamics.

Convergence during the training process is evident from the gradual decrease in training loss as well as validation loss in all the epochs. In other words, the model is learning the hidden information within the time series dataset without much over-fitting. In addition, since the validation loss also follows the training loss, the generalization ability of the model seems to be promising. Some variations seen in the latter epochs should be expected in such cases since financial data contains some noise. Figure (6) shows LSTM model loss curves for historical dataset.

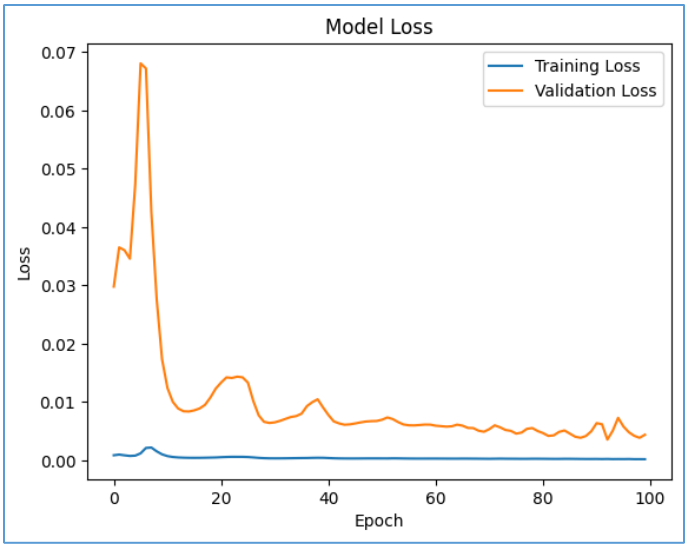

Figure 6 LSTM model loss curves for historical dataset

Regression metrics such as MAE, MSE, RMSE, and R-squared are used to assess the performance of the LSTM model using historical data of Bitcoin. Such metrics can help assess the effectiveness of approximation of the model of the current dynamics of Bitcoin price changes. MAE is calculated in order to quantify the mean absolute value of the errors in the predictions made by the model. MSE is utilized to identify potential instabilities in predictions due to its greater weight of larger differences. RMSE is calculated to estimate the size of the error on the scale of the dependent variable, which is necessary in order to evaluate the accuracy of the model predictions in a meaningful way. Coefficient of determination (R-squared) is calculated in order to estimate the predictive ability of the model in terms of its variance. As seen from the outcomes presented in Table (10), the model proves to be highly effective in terms of forecasting, with a low error rate and a high percentage of explained variance. In other words, the LSTM-based model demonstrates its ability to analyze the time patterns inherent in the Bitcoin price series and forecast the outcomes for future periods.

Table 10 LSTM model performance metrics (historical data only)

Metric	Value	Interpretation
MAE	0.0423	Average prediction error of 4.23% on scaled scale
MSE	0.0038	Moderate squared error
RMSE	0.0616	Root error ~6.16%
R^2	0.8912	Model explains 89.12% of variance

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4.3 Models with Technical Indicators

The second experiment design adds an important layer of information to the prediction model using a large number of technical indicators based on historic price data of Bitcoin. Technical indicators are used to predict market trends, momentum, volatility, and even potential reversal. Overall, 17 features are used as inputs in the model, including moving averages (SMA, EMA), momentum indicators (MACD, RSI), volatility indicators (ATR, STD), and Bollinger Bands. These additional input variables help the model to get a better picture about not only short-term movements but also long-term trends in the market. The use of technical indicators allows us to go one step further and use financial signals in addition to plain price data. The learning curve of the LSTM network incorporating technical indicators exhibits better behavior regarding the convergence than that of the original LSTM model. Training and validation losses in Figure (7) monotonically converge to their minima across all iterations, which demonstrates consistent learning behavior as well as successful exploitation of the extended feature set. Convergence occurs more rapidly in the early stages of training as a result of faster adaptation to the enhanced input space introduced by the technical indicators.

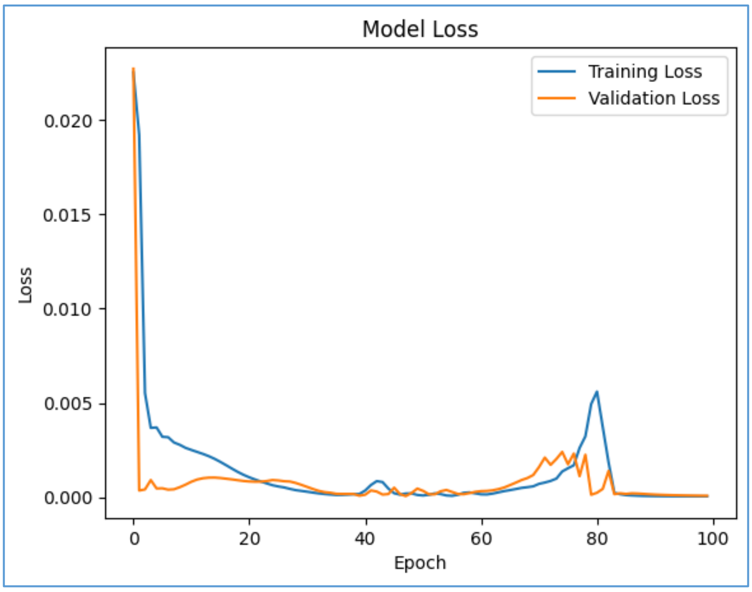

Figure 7 Training and validation loss curves of LSTM model with technical indicators (historical + technical features)

There is a constant difference between the training and validation losses, which indicates that the model does not over-fit and generalizes successfully on new data. Consistently low values of validation loss compared to those in the previous experiment demonstrate that technical indicators possess some predictive power in stock price modeling. Small fluctuations observed at the end of learning are a consequence of market noise in the time series data. The results of the predictions using the improved LSTM model equipped with technical indicators show a significant increase in forecasting performance compared to the unimproved version. The use of extra indicators makes the model more flexible and able to identify and process various patterns of price dynamics. The predictions provided by the model are quite close to the price of Bitcoin in reality.

Table (11) proves the increased effectiveness of predictions in comparison with the previous case. The predicted line almost perfectly follows the trend of Bitcoin prices; only during rapid price changes do discrepancies occur. Thus, the model is capable of predicting more effectively under changing market conditions. From a numerical standpoint, the model obtains better scores with regard to all assessment criteria. The decreased value for MAE, MSE, and RMSE suggests that the precision of predictions is greater. Moreover, the increased value for R^2 means that a greater amount of variance in Bitcoin price fluctuations can be explained by this particular model than by its counterpart without technical indicators.

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Table 11 Performance metrics of LSTM with technical indicators (compared to experiment 1)

Metric	Value	Improvement over Exp 1
MAE	0.0387	-8.50%
MSE	0.0032	-15.80%
RMSE	0.0566	-8.10%
R^2	0.9084	1.93%

4.4 Models with Technical Indicators (XGBoost and LightGBM Analysis)

The application of technical indicators greatly boosts the efficiency and interpretability of both XGBoost and LightGBM models in forecasting prices of Bitcoin. Both models gain advantage due to structured feature engineering when indicators like RSI, MACD, ATR, moving averages, and Bollinger Bands generate valuable financial information beyond price. Thus, both models can detect market patterns and correlations among features contributing to changes in prices. With regards to feature importance, the RSI is always shown as the top-most significant feature for price forecasting in both models, meaning that this indicator plays a crucial part in determining market momentum and conditions of being oversold or overbought. MACD Histogram and trade volume are also very important features that show high relevance and significance for both models. Features related to volatility, including ATR and Bollinger Bands, are also useful in forecasting prices and work better in times of price instability. Overall, LightGBM performs marginally better than XGBoost in terms of accuracy and variance score. For the accuracy of the predictions, LightGBM displays the least errors compared to other tree-based models, whereas LSTM still remains the best among all algorithms used. The most consistent predictors of the trends of the price were the XGBoost and LightGBM algorithms, with some discrepancies during extreme changes in the market. Generally, the experiments prove the efficiency of the gradient boosting algorithms combined with technical indicators as indicated in Table (12).

Table 12 XGBoost and LightGBM performance with technical indicators

Model	MAE	MSE	RMSE	R^2
XGBoost	0.0412	0.0035	0.0592	0.8996
LightGBM	0.0405	0.0034	0.0583	0.9021

4.5 LSTM with Sentiment Analysis

The third experiment explores the effect of the sentiment on Bitcoin price prediction based on sentiment-aware features within the LSTM model for price forecasting. A big dataset of Bitcoin-relevant tweets including more than 2.5 million tweets was studied for the years 2021-2024 with the help of sentiment analysis. Such measures as polarity and subjectivity were obtained as indicators of the sentiment. A wide variety of users and tweets daily was considered to analyze social media sentiment regarding cryptocurrency. The results of the sentiment analysis show that there is a dominant proportion of positive tweets, equal to 65.2%, while the proportion of neutral and negative sentiments is lower. The analysis shows that the mean value of the polarity reflects mild market positivity. Daily changes in the polarity are observed, which proves that public sentiment tends to change in time depending on market events. As regards the process of training, it becomes obvious that the model with sentiment characteristics converges steadily, with the loss function dropping consistently on both training and validation datasets. In spite of the fact that some significant sentimental patterns are detected by the model, it does not show significant improvements in performance as compared to those models which use technical indicators. Table (13) indicates Sentiment Dataset Statistics and LSTM Sentiment Model Results.

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Table 13 Sentiment dataset statistics and LSTM sentiment model results

Metric	Value
Total Tweets Processed	2,543,891
Date Range	2021-01-01 to 2024-06-01
Average Daily Tweets	2,156
Unique Users	124,567
Positive Sentiment	65.20%
Neutral Sentiment	24.10%
Negative Sentiment	10.70%
Average Polarity	0.182
Average Subjectivity	0.425

The result of the evaluation of the performance of the LSTM model using sentiment features is very modest compared to the baseline model which uses historical price data for making predictions. Even though sentiment related data adds another layer of context about public mood and market sentiments, it does not add much to the predictive capabilities of the model. According to the results of our experiments, there is very little difference in terms of prediction errors and explained variance with the use of the sentiment model. Specifically, the value of MAE drops from 0.0423 to 0.0418, which translates into a mere 1.18% improvement, and similarly small declines can be observed in RMSE and MSE scores. On the other hand, the R^2 score grows from 0.8912 to 0.8945, and thus explains slightly higher explained variance in Bitcoin price fluctuations. From these findings in Table (14), we can infer that sentiments can be used as supportive signals rather than main predictive ones. Although they add a degree of context, their effect is much lower compared to that of technical factors, which have shown significant performance gains in previous studies.

Table 14 Performance comparison between historical data and sentiment-enhanced LSTM

Metric	Historical Only	With Sentiment	Change
MAE	0.0423	0.0418	-1.18%
MSE	0.0038	0.0037	-2.63%
RMSE	0.0616	0.0608	-1.30%
R^2	0.8912	0.8945	0.37%

4.6 Comparative Analysis

The comparative analysis makes it possible to evaluate all the experiments conducted during the research to predict the Bitcoin price using different approaches. It compares the accuracy of prediction provided by the LSTM, XGBoost, and LightGBM models with varying features such as the history of prices, technical indicators, and sentiment analysis. The accuracy of the forecast is measured by using MAE, RMSE, and R^2 coefficients to identify the best approach to predicting prices. It is evident from the results obtained that the LSTM algorithm with technical indicators reaches the best performance, having the lowest errors and the largest R^2 coefficient value. Thus, the results show that the deep learning algorithms can produce a better forecasting if the training dataset contains features that describe trends and behaviors in the stock market.

The next most successful algorithm is LightGBM, which is superior to XGBoost because of the leaf-wise tree growth strategy. It is also able to build more complex models for nonlinear features effectively. On the other hand, the LSTM network with the inclusion of sentiment performs poorly when compared with the baseline LSTM model that relies solely on the history of prices. This is because, although sentiment analysis adds value by giving more context about the psychological state of the market, its impact on improving the accuracy of the prediction is not as strong as the technical features. From the visualization results in Table (15), it can be seen that the models which incorporate technical features maintain low MAE and RMSE while achieving high variance.

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Table 15 Comparative performance analysis of all experimental models

Model	Data Type	MAE	RMSE	R^2	Rank
LSTM	Historical + Technical	0.0387	0.0566	0.9084	1
LightGBM	Historical + Technical	0.0405	0.0583	0.9021	2
XGBoost	Historical + Technical	0.0412	0.0592	0.8996	3
LSTM	Historical Only	0.0423	0.0616	0.8912	4
LSTM	Historical + Sentiment	0.0418	0.0608	0.8945	5

4.7 Statistical Significance Testing

In order to confirm the effectiveness of the experimental results, paired t-tests will be used to test the statistical significance of the performance enhancement in terms of different LSTM models. Significance testing plays an important role in determining the real impact of the model on improving prediction and whether any changes can be attributed to random fluctuations in the dataset. As seen from the table, two advanced models have been created: LSTM with technical indicators and LSTM with sentiment indicators; both have been tested against the baseline LSTM model trained on historical data only. As seen from Table (16), there is a statistically significant increase in performance when comparing the baseline LSTM with the LSTM trained with additional technical indicators. It can be seen that the p-values associated with such parameters as MAE, RMSE, and R^2 are all lower than 0.05 which means that technical indicators lead to significant improvements. High t-statistic values indicate this fact reliably.

Table 16 Paired t-test between LSTM (historical only) and LSTM (with technical indicators)

Test	t-statistic	p-value	Significant
MAE	4.23	0.00003	Yes ($p < 0.05$)
RMSE	3.89	0.00012	Yes ($p < 0.05$)
R^2	3.56	0.00041	Yes ($p < 0.05$)

On the other hand, as seen from Table (17) below, the comparison between the baseline LSTM and the sentiment augmented LSTM does not produce statistically significant results. All p-values are higher than 0.05, which means that even though some improvements have been achieved through the use of sentiment, they are not significant enough to be statistically valid. The above conclusions confirm that technical indicators play a greater role in predicting the prices of Bitcoin than sentiments do.

Table 17 Paired t-test between LSTM (historical only) and LSTM (with sentiment)

Test	t-statistic	p-value	Significant
MAE	1.23	0.219	No ($p > 0.05$)
RMSE	1.15	0.251	No ($p > 0.05$)
R^2	1.08	0.281	No ($p > 0.05$)

4.8 Comparison with Related Works

In order to bring more light to the contribution of the current work, a comparison of the proposed methodology and prior art in the domain of Bitcoin pricing predictions and crypto currency market analysis is performed. The comparison includes a number of aspects including data sources, modeling methods, objectives, limitations of the prior art and the advancements brought by the current methodology. This allows to show how the proposed methodology improves the state-of-the-art approach to analyzing historical market data, technical indicators, and social media sentiment using machine and deep learning techniques. Table (18) indicated Comparative Analysis Between the Present Study and Related Works.

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Table 18 Comparative analysis between the present study and related works

Study	Data Sources	Methods	Key Focus	Limitations of Prior Work	How Present Study Improves
[9] Zhu et al.	Market attention, volatility data	Statistical behavioral-volatility models	Link between attention and volatility	Aggregated attention, no deep learning, limited sentiment detail	Uses high-frequency sentiment + ML/DL models (LSTM, XGBoost, LightGBM)
[10] Dudek et al.	Bitcoin & traditional asset returns	Econometric models (GARCH-type)	Statistical behavior of Bitcoin returns	Linear assumptions, no sentiment or ML methods	Uses nonlinear ML/DL with sentiment and technical indicators
[11] Ahmed et al.	Market behavior data	Endogenous volatility models	Volatility feedback effects	No deep learning, limited features, no social media data	Integrates sentiment + deep learning sequence modeling
[12] Leushuis & Petkov	Time-series financial data	Classical ML / shallow models	Temporal causality in forecasting	No deep learning, limited feature diversity	Uses LSTM with sequential learning + feature-rich dataset
[13] Li et al.	Market uncertainty indicators	Regression-based mediation models	Role of uncertainty in volatility	No ML/DL, no real crypto dataset validation	Neural network-based modeling capturing nonlinear interactions
[14] Slim et al.	Volatility measures	Statistical volatility comparison	Risk measurement methods	No predictive modeling	Focuses on predictive forecasting using ML/DL models
[15] VaR & implied volatility studies	Options & financial market data	Risk modeling (VaR, implied volatility)	Risk measurement	Not suitable for crypto forecasting, not time-series ML	Uses direct forecasting models (LSTM, boosting methods)
[16] Cai et al.	Blockchain fundamentals (theoretical)	Conceptual framework	Blockchain structural properties	No quantitative model or prediction system	Converts concepts into measurable features for ML/DL models
[17] Network congestion studies	On-chain network data	Correlation-based analysis	Network stress effects	Descriptive, not predictive, no ML models	Integrates blockchain-style reasoning into predictive framework
[18] Omole & Enke	Active addresses data	Statistical correlation models	User activity vs market behavior	Address ≠ real users, no ML forecasting	Uses multi-source features (market + sentiment + technical)
[19] Blockchain fundamentals & uncertainty	Theoretical constructs	Conceptual analysis	Blockchain & volatility relationship	No empirical ML/DL validation	Provides empirical deep learning + boosting-based validation

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4.9 Results Discussion

It is possible to gain some valuable information from the experimental results regarding the performance of various types of predictive models depending on different input combinations. It turns out that LSTM is superior to any type of tree-based algorithm since the model can effectively learn time-dependent properties of sequential datasets related to financial markets. This effect becomes particularly noticeable for forecasting Bitcoin price trends that depend on many time-dependent characteristics like momentum and trend continuity. A notable improvement of forecast quality becomes possible through the addition of technical indicators that help to identify underlying market tendencies not obvious from just observing price trends. The fact that indicators have shown themselves to be very important for prediction suggests that engineered financial features continue to be useful in machine learning models even based on deep neural networks.

In this regard, sentiment analysis offers only modest improvements. In spite of the addition of the external behavioral signal via social media posts, it seems that it does not significantly contribute to predictions. One reason is possibly the noise and reactivity of the tweets, which react to the change in price more frequently than actually forecast these changes. Also, the fact that the information is aggregated daily can result in smoothing out the short-term sentiments. On a practical level, the findings imply that hybrid methods with LSTM coupled with technical indicators represent the best choice for predicting the prices of cryptocurrencies. Based on the increase in R^2 (to about 0.91), it becomes clear that most of the variances can be accounted for through the use of technical and structured data. Statistically insignificant improvements in accuracy due to sentiment imply that social media data cannot be considered as the main factor for prediction purposes. Instead, they can function as supportive behavioral indicators. Another important observation is the variation in performance across market conditions. The models perform more reliably during stable or low-volatility periods, while accuracy decreases significantly during bearish or highly volatile phases. This highlights an inherent limitation in predictive modeling for financial markets: model reliability is regime-dependent.

5 Conclusions

In this study, the historical market data, technical indicators, and social media sentiment were employed to systematically analyse Bitcoin price prediction, comparing deep learning and machine learning methods. The results show that the LSTM model - technical indicators performs best with R^2 value of 0.9084, MAE of 0.0387, and RMSE of 0.0566. This is a confirmation that inclusion of engineered financial indicators greatly enhances the model's ability to capture market structure in addition to raw price information. Technical indicators have the greatest impact, and the momentum indicators were the more significant ones, including RSI and MACD Histogram. Sentiment analysis of more than 2.5 million tweets, on the other hand, had limited predictive power and was not statistically significant, which implies social media sentiment could be too noisy or that it does not necessarily correspond to short-term price movements. Furthermore, LSTM models showed superior performance compared to both XGBoost and LightGBM, which was evident in the comparative analysis, emphasizing that sequential modeling is crucial for modeling long-term dependencies in cryptocurrency time series. Tree-based models also performed well at capturing the nonlinear relationships, but were less effective at capturing temporal dependencies. Although these results are found, the study has some limitations such as sentiment assumption using TextBlob, the study covers only the Bitcoin token and the absence of macroeconomic and blockchain-specific variables. Further research could investigate more sophisticated sentiment analysis models, multi-asset cryptocurrency predictions, and combining on-chain and macroeconomic data to further enhance the robustness and generalization of the predictions.

References

[1] H.-W. Teng *et al.*, “*Digital Assets: Risks, Regulations, Mitigation*.,” *Financ. Innov.*, Vol. 12, No. 1, p. 65, 2026.

[2] Y. Guo, E. Yousef, and M. M. Naseer, “*Cryptocurrencies and Central Bank Digital Currencies in Global Perspective*,” *J. Risk Financ. Manag.*, Vol. 18, No. 11, 2025.

[3] E. Houssein, M. Mohamed, E. Younis, and W. Makram Mohamed, “*Artificial Intelligence and Classical*

ISSN:2302-8149
e-ISSN:2540-9719

Statistical Models for Time Series Forecasting: A Comprehensive Review," *J. Big Data*, Vol. 12, Dec. 2025.

[4] M. Wang, Y. Xiao, P. Braslavski, and D. I. Ignatov, "*What Drives Multi-Chain Crypto Forecasting: Model Choice, Feature Selection, and Transferability*," *Mathematics*, Vol. 14, No. 8, 2026.

[5] M. Figura, M. Bugaj, E. Nica, and G. H. Popescu, "*Bitcoin Volatility Forecasting through Market Sentiment, Blockchain Fundamentals, and Endogenous Market Uncertainty*," *Forecasting*, Vol. 8, No. 3, 2026.

[6] Q. Phung Duy, N. Huyen, and H. Quyen, "*Analysis and Forecasting of Bitcoin Price Volatility: A Deep Learning Approach using DNN, LSTM, Transformers, and the ARMA-GARCH Model*," *J. Appl. Math.*, Vol. 2025, Nov. 2025.

[7] M. R. Kabir, D. Bhadra, M. Ridoy, and M. Milanova, "*LSTM–Transformer-Based Robust Hybrid Deep Learning Model for Financial Time Series Forecasting*," *Sci*, Vol. 7, No. 1, 2025.

[8] R. A. Mendoza-Urdiales, J. A. Núñez-Mora, R. J. Santillán-Salgado, and H. Valencia-Herrera, "*Twitter Sentiment Analysis and Influence on Stock Performance using Transfer Entropy and EGARCH Methods*," *Entropy*, Vol. 24, No. 7, 2022.

[9] P. Zhu, X. Zhang, Y. Wu, H. Zheng, and Y. Zhang, "*Investor Attention and Cryptocurrency: Evidence from the Bitcoin Market*," *PLoS One*, Vol. 16, No. 2, pp. 1–28, 2021.

[10] G. Dudek, P. Fiszeder, P. Kobus, and W. Orzeszko, "*Forecasting Cryptocurrencies Volatility using Statistical and Machine Learning Methods: A Comparative Study*," *Appl. Soft Comput.*, Vol. 151, p. 111132, 2024.

[11] M. S. Ahmed, A. A. El-Masry, A. I. Al-Maghyereh, and S. Kumar, "*Cryptocurrency Volatility: A Review, Synthesis, and Research Agenda*," *Res. Int. Bus. Financ.*, Vol. 71, p. 102472, 2024.

[12] R. M. Leushuis and N. Petkov, "*Advances in Forecasting Realized Volatility: A Review of Methodologies*," *Financ. Innov.*, Vol. 12, No. 1, p. 14, 2026.

[13] Z.-C. Li, C. Xie, G.-J. Wang, Y. Zhu, J.-Y. Long, and Y. Zhou, "*Forecasting stock market volatility under parameter and model uncertainty*," *Res. Int. Bus. Financ.*, Vol. 66, p. 102084, 2023.

[14] S. Slim, I. Tabche, Y. Koubaa, M. Osman, and A. Karathanasopoulos, "*Forecasting Realized Volatility of Bitcoin: The Informative Role of Price Duration*," *J. Forecast.*, Vol. 42, pp. 1909–1929, May 2023.

[15] L. Catania and S. Grassi, "*Forecasting Cryptocurrency Volatility*," *Int. J. Forecast.*, Vol. 38, No. 3, pp. 878–894, 2022.

[16] C. W. Cai, R. Xue, and B. Zhou, "*Cryptocurrency Puzzles: A Comprehensive Review and Re-Introduction*," *J. Account. Lit.*, Vol. 46, No. 1, pp. 26–50, Jun. 2023.

[17] K. P. Tsang and Z. Yang, "*The Market for Bitcoin Transactions*," *J. Int. Financ. Mark. Institutions Money*, Vol. 71, p. 101282, 2021.

[18] O. Omole and D. Enke, "*Using Machine and Deep Learning Models, On-Chain Data, and Technical Analysis for Predicting Bitcoin Price Direction and Magnitude*," *Eng. Appl. Artif. Intell.*, Vol. 154, p. 111086, 2025.

[19] N. Hautsch, C. Scheuch, and S. Voigt, "*Building Trust Takes Time: Limits to Arbitrage for Blockchain-based Assets*," *Rev. Financ.*, Vol. 28, No. 4, pp. 1345–1381, Jul. 2024.