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# Prediction of Bitcoin Prices Based on Blockchain Information: A Deep Reinforcement Learning Approach

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## Abstract

Bitcoin, the first decentralized cryptocurrency, has attracted significant attention from investors and researchers alike due to its volatile and unpredictable price movements. However, predicting the price of Bitcoin remains a challenging task. This paper presents a detailed literature review on previous studies that have attempted to predict the price of Bitcoin. It discusses the main drivers of Bitcoin prices, including its attractiveness, macroeconomic and financial factors with a particular focus on the use of Blockchain information. We apply time series to daily data for the period from 28/04/2013 to 28/01/2023. We used Python and TensorFlow library version 2.11.0 and propose a deep multimodal reinforcement learning policy combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) neural network for cryptocurrencies' prices prediction. Also, this study attempts to predict the price of Bitcoin using a special type of deep neural networks, a Deep Autoencoders. Two results are worth noting: Autoencoders turns out to be the best method of predicting Bitcoin prices, and Bitcoin-specific Blockchain information is the most important variable in predicting Bitcoin prices. This study highlights the potential utility of incorporating Blockchain factors in price prediction models. Also, our findings show that sentiment indicator, Ethereum, XRP and Doge Coin prices, global currency ratio, macroeconomic factors, and Blockchain information of Ethereum did not contribute significantly toward predicting Bitcoin prices. These conclusions provide decision support for investors and a reference for the governments to design better regulatory policies.

**Keywords:** Bitcoin price prediction, Blockchain information, Deep Reinforcement Learning, CNN-LSTM, Deep Autoencoders.



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## 1. INTRODUCTION

Bitcoin, the first decentralized digital currency, has gained significant attention in recent years due to its high price volatility and potential as an alternative to traditional financial assets. Understanding the factors that determine the price of Bitcoin is crucial for investors and traders, as well as for policymakers and regulators. However, the complex nature of Bitcoin and the Blockchain technology that underpins it, as well as the lack of historical data, make this task challenging [1]. Blockchain, the decentralized ledger technology that underlies Bitcoin and other cryptocurrencies, has the potential to revolutionize various industries [2]. However, understanding and utilizing the information contained within the Blockchain for forecasting purposes is still in its infancy.

Blockchain technology has attracted substantial attention for its ability to resolve the trust problem among business participants by facilitating the sharing and verification of a decentralized ledger among network participants [2]. The Blockchain operates using a specialized component known as cryptocurrency to maintain the stability of its systems. Cryptocurrency has generated a new economic value that extends beyond its function of supporting Blockchain systems. They have been commonly utilized for purchasing goods and services as well as exchanging fiat currencies with coins. As interest in cryptocurrencies has increased, its underlying algorithm (i.e. the Blockchain) has gained recognition from academic researchers. Cryptocurrency is a compensation that is awarded when a new block is created and recorded officially in the Blockchain systems [3].

The motivation for this study arises from the increasing use of Bitcoin and other cryptocurrencies as a form of digital currency and investment. As the market for cryptocurrencies continues to grow, it is important to understand the factors that drive the price of these assets. This is especially important for investors, traders, and regulators who need to make informed decisions about the future of the cryptocurrency market. The problematic is that the traditional financial models are not well suited to predict the prices of Bitcoin as it operates 24/7 without closing, and any offline information and events could influence the price immediately, unlike traditional financial markets.

The research objectives are to identify the key factors that influence the price of Bitcoin and to develop a forecasting model that can accurately predict the future price movements of the cryptocurrency. Despite the large number of studies on the drivers of Bitcoin prices, there is still a lot of uncertainty about which factors are the most important. This is due in part to the fact that the cryptocurrency market is relatively new and has yet to be fully understood. Furthermore, given the complex nature of Bitcoin prices and the various factors that may influence them, there is a need for a comprehensive study that utilizes advanced techniques to investigate the determinants of Bitcoin prices and improve forecasting accuracy. This study aims to fill this gap by utilizing a deep reinforcement learning approach to investigate the factors that drive Bitcoin prices and improve the accuracy of price predictions. This methodology has been demonstrated to be effective in other fields, such as image and speech recognition, and it has the potential to capture complex and dynamic nature of the cryptocurrency market, by combining the strengths of deep learning and reinforcement learning. It is a powerful method that has revolutionized various industries, including the financial sectors ([4, 5]). Also, this study attempts to predict the price of Bitcoin using a special type of deep neural networks, a Deep Autoencoders. Briefly, combining Blockchain information with advanced deep learning techniques can improve the accuracy of predicting Bitcoin prices and fluctuations ([1, 6]).

The research objectives of this study are: 1) To identify the key factors that determine the price of Bitcoin, including macroeconomic factors, technical indicators, and Blockchain-specific factors, 2) To develop a deep reinforcement learning model and a deep Autoencoders one, that can accurately predict the future price of Bitcoin; and 3) To evaluate the performance of the proposed model and compare it with other existing models. Indeed, the contributions of this study are three-fold. First, we will provide a comprehensive review of the literature on the factors that determine the price of Bitcoin. Second, we will develop a deep reinforcement learning model and a deep Autoencoders one to predict the price of Bitcoin. Third, we will provide insights into the complex and dynamic nature of the cryptocurrency market that can be used by investors, traders, and regulators to make informed decisions about the future of the market.

The structure of this paper is as follows: the first section will provide a literature review of the main drivers of Bitcoin prices and the main methodologies used to forecast Bitcoin prices. In the second section, we will describe our methodology, including the data sources and the deep reinforcement learning model used in this study. The third section will present our results, including the factors found to have the most significant impact on Bitcoin prices and the performance of our deep reinforcement learning model in comparison to other forecasting models. Finally, the fourth section will present the discussion and provide implications for future research. The conclusion will summarize the main findings and contributions of the study.

## 2. LITERATURE REVIEW

Bitcoin, the world's first decentralized digital currency, has attracted a significant amount of attention from both academia and industry. Its decentralized nature and the lack of a central authority controlling its supply have made it an attractive asset to trade and invest in. However, the high volatility of its price, which can fluctuate significantly in a short period, has also made it a challenging asset to predict. Understanding the factors that drive the price of Bitcoin is crucial for traders, investors, and policymakers.

### 2.1 Overview of Main Drivers of Bitcoin Prices

One of the main drivers of Bitcoin prices is the level of adoption and acceptance of the currency. As more people and businesses start to use Bitcoin, the demand for the currency increases, leading to an increase in its price. Studies have shown that the number of merchants accepting Bitcoin as a form of payment and the number of Bitcoin transactions are positively correlated with the price of Bitcoin ([7, 8]). For example, a study by [9], found that the number of Bitcoin transactions per capital is positively correlated with the Bitcoin price. Another important driver of Bitcoin prices is the level of regulation and government intervention in the market. Governments and regulatory bodies have the power to influence the price of Bitcoin through laws and regulations that either support or restrict its use. Studies have shown that the announcement of regulatory measures and the imposition of restrictions on Bitcoin transactions can lead to a decrease in the price of Bitcoin [10]. On the other hand, the legalization and recognition of Bitcoin as a legitimate form of currency can lead to an increase in its price ([11, 12]). Macroeconomic factors, such as economic growth, inflation, and interest rates, also play a role in determining the price of Bitcoin. Studies have shown that the price of Bitcoin is positively correlated with economic growth [13], and positively correlated with inflation [14]. The relationship between interest rates and the price of Bitcoin is more complex, with some studies showing a positive correlation [15], and others showing a negative one [16]. A study by [17], does not support previous findings that macro-financial developments are driving Bitcoin price in the long run. Another study by [18], found that that Bitcoin appreciated against inflation shocks, supporting its reputation as an inflation hedge. However, it was found that Bitcoin prices declined in response to financial uncertainty shocks, contradicting its perceived role as a 'safe haven'. Interestingly, the results did not show a decline in Bitcoin prices after policy uncertainty shocks, suggesting a level of independence from government authorities. A study by [19], found that the price of Bitcoin is positively correlated with stock market index, USD to Euro exchange rate and negatively correlated with the price of gold as well as the exchange rate between Yuan and US Dollar.

The level of uncertainty and investor sentiment also plays a role in determining the price of Bitcoin. Studies have shown that period of high uncertainty, such as during the Eurozone crisis and the US presidential election, are associated with increased volatility in the price of Bitcoin ([20, 21]). Additionally, investor sentiment, as measured by the number of Google searches for the term "Bitcoin", is positively correlated with the Bitcoin price. For example, a study by Urquhart (2018) found that the number of Google searches for the term "Bitcoin" is positively correlated with the Bitcoin price. Another study by [9], found that the number of tweets containing the term "Bitcoin" is positively correlated with the Bitcoin. A study by [22], found that social media sentiment has a significant effect on the price of Bitcoin, suggesting that positive sentiment can lead to an increase in the demand for Bitcoin while negative sentiment can lead to a decrease in demand. Similarly, a study by [23], found that news sentiment has a significant effect on the price of Bitcoin, suggesting that positive news can lead to an increase in the demand for Bitcoin while negative news can lead to a decrease in demand. In addition, [24] suggest that the addition of the investor sentiment based on Bitcoin Misery Index (BMI) enhances the predictive performance of their model significantly.

### 2.2 Blockchain-Specific Factors

One area that has received particular attention is the use of Blockchain information in predicting Bitcoin prices. This technology has been widely adopted in various industries, and its potential applications are still being explored [25]. Several studies have examined the use of Blockchain information in predicting Bitcoin prices. One of the earliest studies was conducted by [9], who found a positive long-term correlation between the security of the network, measured by the network Hash Rate, and the price of Bitcoin. This was further explored by [26], who studied the relationship between the cost of mining Bitcoin and its price. The cost of mining was calculated based on the total Hash Rate, an electricity price index, and the best available miner efficiency. The study found that the impact of mining cost on Bitcoin price was weak and only temporary. A study by [1], aimed to explain the recent high volatility in Bitcoin prices and studied the fluctuation of Bitcoin prices over time by incorporating Blockchain data and macroeconomic factors. Another study in this area was conducted by [27], who found that incorporating Blockchain factors, such as the number of Bitcoin wallets and unique addresses, block mining difficulty, hash rate, etc., improved the accuracy of the machine learning models compared to traditional time series models. This study highlights the potential utility of incorporating Blockchain factors in cryptocurrency price prediction models. [28], used a combination of technical indicators and Blockchain-based features to predict Ethereum prices. They found that incorporating Blockchain-based features improved the accuracy of the predictions compared to using technical indicators alone. Another study by [29], predicted the price of Bitcoin using Blockchain-based features, macro-economic factors, Google popularity index, and Wikipedia searches. [4], aim to examine the factors affecting Bitcoin price forecasting based on the underlying Blockchain transactions. To that end, they incorporate factors such as the transaction volume of inter-exchange transactions, the market prices of inner-exchange, and the Google Trend search data that reflect social interest. [30], investigated the prediction of Bitcoin exchange rate by utilizing 24 economic and technological factors such as macroeconomic indicators, currency exchange rates, Blockchain elements, and public attention proxies. The findings indicate that these determinants provide enhanced forecasting performance, though the level of performance changes over time. Also, [26], conducted a study to determine the underlying factors affecting the price of Bitcoin and its total Hash Rate. Their findings revealed that the Hash Rate generated by miners, positively impacts the Bitcoin price. However, the rising price does not result in a corresponding increase in Hash Rate, indicating that profit is not a significant motivator in this scenario. They suggest that this may be due to increased investor confidence in the security and stability of the network, which can drive up demand for Bitcoin and, in turn, its price. [31] studied the strength of various internal factors such as number of transactions, mined Bitcoins, hash rates, trading volume, and realized volatility of Bitcoin prices, as well as external factors such as public interest indicated by Wikipedia views and global macroeconomic and financial factors including stock markets, energy markets, gold markets, investors' fear gauge, economic policy uncertainty, effective federal funds rate, and the trade-weighted US dollar index as determinants of Bitcoin price. The findings suggest that cryptocurrency-specific determinants have a greater impact on the fluctuation of Bitcoin prices compared to global macroeconomic and financial factors.

### 2.3 Main Methodologies Used to Forecast Bitcoin Prices

This section will review the literature on various methods that have been used to predict the price of Bitcoin, including traditional statistical and econometric methods, as well as more recent machine learning and artificial intelligence techniques.

Traditional statistical methods, such as time series analysis, have been widely used to predict the price of Bitcoin. One of the early studies on predicting the price of Bitcoin was conducted by [32], who used a time series analysis approach to predict the daily price of Bitcoin. They found that the price of Bitcoin is positively affected by several factors such as Twitter sentiment as well as Wikipedia search queries, and hash rate. However, USD to Euro exchange rate has a negative impact on Bitcoin price. Another study by [33], used ARIMA and GARCH models to predict the volatility of Bitcoin prices and found that these models performed well in capturing the volatility of Bitcoin prices. However, these traditional statistical methods have limitations in terms of their ability to capture non-linear and complex relationships in the data. A study by [34], used a Support Vector Regression (SVR) model to predict the price of Bitcoin and found that it was able to capture the dynamic and non-linear nature of the Bitcoin market. Furthermore, [1] employed Bayesian Neural Networks (BNN) to anticipate the price of Bitcoin using characteristics obtained from the Blockchain. They discovered an issue of collinearity between Blockchain features and macroeconomic variables. Their research demonstrated that BNN outperforms Linear Regression (LR) and Support Vector Regression (SVR) in predicting both fluctuations and volatility. Similarly, [1] used BNN to predict the price of Bitcoin. They found that it outperformed SVR and traditional time series models. A study by [4], presented models that use a combination of time-series and probability to predict short-term volatility, using both Bitcoin prices and order book data. The order book data contains information on buy orders, which are the highest prices at which someone is willing to purchase, and sell orders, the lowest prices someone is willing to sell at, which are stored in the exchange database. Their models were found to produce fewer errors compared to statistical models. Another study by [35], proposes a new dynamical modeling approach called the State-Space Model. The proposed method maintains the probabilistic aspect of the State-Space Model, which provides point estimates along with uncertainty about the estimate, as well as the deep neural network's capability of approximating functions. It has been compared to both advanced and traditional dynamic modeling techniques and has been found to have the highest accuracy in terms of overall results.

Advanced artificial intelligence and machine learning algorithms have also been used to predict the price of Bitcoin ([29, 36–41]). Therefore, the artificial intelligence/machine learning community has thoroughly investigated machine learning techniques to automatically create lucrative trading indicators for the cryptocurrency market [42]. [42] combined Generalized Auto-regressive Conditional Heteroskedasticity (GARCH) and Artificial Neural Network (ANN) with Principal Component Analysis (PCA) to forecast the volatility of Bitcoin's price. They found that their proposed model was effective in capturing price volatility, thus reducing financial risk exposure. In their study, [43] evaluated the performance of several machine learning models including machine learning models including Random Forest (RF), XGBoost, Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM) and Long Short-term Memory (LSTM). The highest accuracy of 67.2% was achieved by the LSTM model. A study by [44], used various machine learning approaches. The study found that gradient boosting (GB) and recurrent neural networks (RNN) had the highest accuracy in predicting the price of Bitcoin. Another study by [45], used a real-time machine learning models to predict the price of Bitcoin and found that it performed better than traditional time series analysis and other machine learning methods. However, these machine learning methods also have limitations in terms of their ability to capture the complex and dynamic nature of Bitcoin prices. Deep reinforcement learning, which combines the strengths of both traditional statistical methods and machine learning methods, has emerged as a promising approach for predicting the price of Bitcoin. A study by [46], used deep reinforcement learning to predict the price of Bitcoin and found that long short-term memory (LSTM) outperformed other advanced machine learning methods such as support vector machine (SVM), multi-layer perceptron (MLP), temporal convolutional network (TCN), and Transformer in terms of accuracy. Similarly, [38] used a combination of a long short-term memory (LSTM) network and a Generalized Regression Neural Networks (GRNN) model to predict the price of Bitcoin. The study found that the LSTM performed better than GRNN.

Another recent study by [36], used a combination of a deep neural network and a recurrent neural network (RNN) to predict the price of Bitcoin. The study found that the deep neural network was able to capture the non-linear relationships in the data, while the RNN was able to capture the temporal dependencies in the data. [47] explored various neural network architectures and found that Convolutional Neural Networks (CNNs) can be applied in predicting Bitcoin prices. However, the methods that rely solely on past price data were not found to perform well in forecasting Bitcoin price. [4] proposed the WT-CATCN price-forecasting model, which uses the Wavelet Transform (WT) and Casual Multi-Head Attention (CA) Temporal Convolutional Network (TCN), to predict cryptocurrency prices. Their model can capture the significant positions of the input sequences and model the correlations between different data features. By utilizing actual Bitcoin trading data, they assess and compare the WT-CATCN with other advanced price forecasting models. The experiment results indicate that their model enhances the price forecasting accuracy by 25%. [48] assessed the performance of deep learning models and reinforced tree models on six cryptocurrency datasets using relevant performance measures. The results reveal that the CNN model is more reliable with limited training data and easily generalizable for predicting the daily closing prices of multiple cryptocurrencies.

Overall, studies using artificial intelligence/machine learning techniques in the past aimed to model the cryptocurrency market for better investment decision-making with high returns and low risks [49]. The drive for this is due to the increasing efforts by researchers and financial institutions to minimize financial risks. Despite this, the predictive accuracy of current models still requires improvement, as shown by various studies on cryptocurrency price modeling that aim to improve forecasting methods for profitable investment decisions ([1, 50–52]). Then, there is a need for more robust evaluation methods that consider the volatility of the Bitcoin market and the importance of real-time predictions.

**TABLE 1** summarizes the main studies that have been conducted, using different methods, to identify potential factors affecting cryptocurrency prices, as documented in the literature.

## 3. METHODOLOGY

**TABLE 2** shows and describes the full set of variables used in the empirical analysis. The different sources of data are reported in the last column. We gathered data regarding Bitcoin from various sources in the period of April 28, 2013, to January 28, 2023. We used Kaggle for the data pre-processing and for the experiments (60% training set and 40% test set). We applied four algorithms of deep learning. These latter consist of the Convolutional Neural Network algorithm (CNN), the Long Short-Term Memory algorithm (LSTM), the CNN-LSTM algorithm, and a Deep Autoencoders. An Autoencoder, introduced by [53], is a kind of ANN trained to learn the smaller number of latent features which can reconstruct the input data itself as much as possible [54]. We employed three evaluation criteria: mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE) to evaluate the used algorithms with cryptocurrency datasets. We also apply 50 epochs that correspond to the total number of iterations used with our datasets to follow the evolution of the evaluation criteria all over the time.

## 4. RESULTS

The descriptive statistics of macro-economic factors and global currency ratio are shown in **TABLE 3**. We report the mean and standard deviation values for the Blockchain information variables in **TABLE 4** and for attractiveness variable in **TABLE 5**. **FIGURE 1** illustrates the volatility of Bitcoin daily price (USD), from April-28, 2013, to January-28, 2023.

Based on the first evaluation criterion i.e., MSE, we find that Autoencoders performs better results than LSTM and CNN-LSTM methods, which perform better results than CNN algorithm. In fact, it provides a small MSE value and a stable model with all over the different iterations. It is obvious

Table 1: Previous studies using various approaches and main determinants for cryptocurrency price prediction.

| References | Methodology | Data source | Predictors (category/determinants) | Results |
|---|---|---|---|---|
| [48] | Deep Learning (DL) models (Convolutional Neural Networks (CNN), Deep Forward Neural Networks, and Gated Recurrent Units)<br>Booted tree-based models | Yahoo Finance<br>UK Investing<br>Bitfinex | The closing price (Close), highest price (High), lowest price (Low), opening price (Open), the daily cryptocurrency volume (Volume) for the six cryptocurrencies (BTC-USD, ETH-USD, BNB-USD, LTC-USD, XLM-USD, and DOGE-USD) | The use of CNN has proven to be effective in predicting the daily closing prices of several cryptocurrencies, even with limited training data, and is highly adaptable for generalization purposes. |
| [24] | Bagged support vector regression (BSVR) | Refinitiv.com<br>Reuters.com | Investor sentiment based on Bitcoin Misery Index (BMI), cryptocurrency market, oil prices, and technical indicators | The addition of the sentiment index enhances the predictive performance of BSVR significantly. |
| [55] | Quantile cross-spectral analysis | Google Trends Data | Public sentiment toward the Russia-Ukraine conflict (Google Trend Russia-Ukraine war index) | Russia-Ukraine war public attention has a strong negative causal effect on the four cryptocurrencies (BTC, XRP, ETC, LTC) and G7 stock market returns. |
| [26] | Two-stage least squares estimation | CoinMetrics.io<br>Bitcoinblockhalf.com<br>Yahoo Finance<br>Google Trends | Network's hash rate<br>The network congestion (measured by the total transaction fees paid in BTC)<br>Interest and attention directed towards Bitcoin | Both directions of causal effect between the Bitcoin price and hash rate. |
| [35] | Time series analysis<br>Deep state space models | Yahoo Finance | Cryptocurrency dataset | The deep state-space model yields the best overall results than classical dynamical modeling techniques in predicting day-ahead crypto-currency prices. |
| [56] | Four different deep learning Algorithms: MLP, Convolutional Neural Network (CNN), Long Short-Term Memory, (LSTM) neural network and Attention Long Short-Term Memory (ALSTM) | https://www.cryptodata download.com/data/ bitfinex/.<br>https://www.bitfinex.com.<br>GitHub and users' comments on Reddit | Cryptocurrency dataset<br>Users' sentiment | Incorporating both trading and social media indicators leads to a substantial enhancement in the prediction accuracy and consistency across all algorithms. |
| [31] | Extreme bounds analysis (EBA) | https://Bitcoincharts.com/<br>https://data.nasdaq.com/ | Blockchain information<br>Realized volatility of Bitcoin prices<br>Wikipedia views<br>Macro-financial factors | Factors specific to cryptocurrencies, rather than global macroeconomic and financial factors, play a larger role in determining the movements of Bitcoin prices. |
| [28] | Time-series analyses<br>Advanced machine-learning techniques | Data Stream<br>Etherscan | Development Index<br>Global Currency Ratio<br>Generic Blockchain Information (Ethereum, Bitcoin, Litecoin, Dashcoin)<br>Ethereum-Specific Blockchain Information | Macroeconomic factors, information specific to Ethereum's Blockchain and information from the Blockchain of other cryptocurrencies, play a significant role in forecasting Ethereum prices. |
| [5] | Deep learning method named Stacked Denoising Autoencoders (SDAE) | www.BTC.com<br>Baidu and Google<br>Wind financial database<br>Choice financial database<br>Data Stream | Cryptocurrency market<br>Public attention<br>Macroeconomic environment | The SDAE model performs better in both directional and level prediction, measured. |

**Source**: Authors' Contribution.

Table 2: Data for empirical study.

| Data category | Research Variables | Definition | Data Source |
|---|---|---|---|
| Dependent variable | Bitcoin price | The daily US dollar price of one unit of Bitcoin on the Bitstamp exchange. | https://coinmarketcap.com/ |
| Independent variables | | | |
| Macro-economic Development Index | Standard & Poor's 500 index (S&P 500)<br>Stock Index of Eurozone (Euro Stoxx 50)<br>National Association of Securities Dealers Automated Quotations (NASDAQ)<br>Crude Oil<br>Gold<br>CBOE volatility index (VIX)<br>Nikkei Stock Average for the Tokyo Stock Exchange (Nikkei225)<br>Financial Times Stock Exchange 100 Index (FTSE100) | | Factset database |
| Global Currency Ratio | British Currency Sterling (GBP)/ US Dollar (USD)<br>Japanese Yen (JPY)/ US Dollar (USD)<br>Swiss Franc (CHF)/ US Dollar (USD)<br>Euro (EUR)/ US Dollar (USD) | | Factset database |
| Bitcoin-specific Blockchain information | Number of transactions (Demand for Bitcoin) | The daily total volume of Bitcoin transactions validated and recorded by a Blockchain ledger. | https://www.blockchain.com/ |
| | Number of Bitcoins mined (Supply for Bitcoin) | The daily total amount of Bitcoin units currently in circulation. | https://www.blockchain.com/ |
| | Total Hash Rate (TH/s) | This is an indicator of the processing capability of high-powered mining hardware that individual miners use to unlock new Bitcoin units. | https://www.blockchain.com/ |
| | Total number of transactions on the Blockchain (Transaction Volume (in USD))<br>Estimated Transaction Value (USD)<br>Miners Revenue (USD) | This variable is employed as a measure of the Bitcoin market activity. | https://www.blockchain.com/ |
| | Total Transaction Fees (USD)<br>Average Payments Per Block | Transaction fees are the difference between the amount of Bitcoin sent and the amount received. Fees are employed as an incentive for miners to add transactions to blocks. | https://www.blockchain.com/ |
| | Active Address (Unique Addresses Used) | The number of addresses which fulfills the defined activity parameter on a given Blockchain. This variable is employed to measure how active a given Blockchain is and can be more representative compared to tracking number of transactions. | https://www.blockchain.com/ |
| | Block Size<br>Average Block Size | The size of a block equals the amount of data it stores. And just like any other container, a block can only hold so much information. | https://www.blockchain.com/ |
| | Difficulty (Network Difficulty) | The difficulty is a measure of how difficult it is to mine a Bitcoin block, or in more technical terms, to find a hash below a given target. | https://www.blockchain.com/ |
| Generic Blockchain Information (Ethereum, Doge Coin, XRP) | Price | The daily US dollar price of one unit of cryptocurrency on the Bitstamp exchange. | https://coinmarketcap.com/ |
| | Number of transactions | The daily total volume of cryptocurrency transactions validated and recorded by a Blockchain ledger. | https://coinmarketcap.com/ |
| | Number of cryptocurrencies mined | The daily total amount of cryptocurrency units currently in circulation. | https://coinmarketcap.com/ |
| Investor sentiment and attention | Attractiveness | Searches Volumes of Bitcoin | Google Trend |

**Source**: Authors' Contribution.

Table 3: Descriptive Statistics of Macro-economic Factors and Global Currency Ratio.

| **Macro-Economy Factors** | | **Global Currency Ratio** | |
|---|---|---|---|
| **Index** | **Mean** | **Currency** | **Mean** |
| S&P 500 | 1.218544e+11 | GBP/USD | 1.597974 |
| Euro Stoxx 50 | 2887.838634 | JPY/USD | 0.010450 |
| NASDAQ | 3757.846408 | CHF/USD | 1.201803 |
| Crude Oil | 78.261296 | EUR/USD | 1.343046 |
| Gold | 29.550958 | | |
| CBOE volatility index (VIX) | 1.508611 | | |
| Nikkei225 | 16.937712 | | |
| FTSE100 | 22659.686614 | | |

Table 4: Descriptive Statistics of Bitcoin and Cryptocurrencies-Specific Blockchain Information.

| **Cryptocurrency** | **Attribute** | **Mean** | **Standard Deviation** | **Min** | **Max** |
|---|---|---|---|---|---|
| Bitcoin | Number of transactions (Demand) | 6762.858956 | 11349.306859 | 68.430000 | 63503.460000 |
| | Number of Bitcoins mined (Supply) | 1.093455e+10 | 1.887666e+10 | 2.857830e+06 | 3.509679e+11 |
| | Total Hash Rate (TH/s) | 5.175336e+07 | 6.444836e+07 | 7.388575e+01 | 2.277424e+08 |
| | Total number of transactions on the Blockchain | 3.073204e+08 | 2.318350e+08 | 1.690352e+07 | 7.449548e+08 |
| | Total Transaction Fees (USD) | 72.323858 | 112.678985 | 5.727917 | 1495.946477 |
| | Unique Addresses Used | 9.999203e+06 | 1.231284e+07 | 3.386393e+05 | 7.063725e+07 |
| | Block Size | 163897.357660 | 125554.19740 | 7651.0260330 | 413947.56476 |
| | Network Difficulty | 6.150910e+11 | 3.221152e+12 | .000000e+000 | 3.070586e+13 |
| | Average Payments Per Block | 1871.925877 | 2021.873015 | .000000 | 7236.203883 |
| | Miners Revenue (USD) | 4.683506e+11 | 2.586674e+12 | 0.000000e+00 | 2.321756e+13 |
| | Estimated Transaction Value (USD) | 416622.002001 | 207966.98300 | 0.000000 | 978252.00000 |
| | Average Block Size | 0.821488 | 0.384045 | 0.076149 | 1.530436 |
| Ethereum | Price | 573.057823 | 1035.287361 | 0.000000 | 4812.090000 |
| | Number of transactions | 6.514626e+09 | 1.013997e+10 | 0.000000e+00 | 8.448291e+10 |
| | Number of Ethereum mined | 6.557936e+10 | 1.225196e+11 | 0.000000e+00 | 5.690943e+11 |
| Doge Coin | Price | 9.398118e+09 | 1.375239e+10 | 0.000000e+00 | 1.308535e+11 |
| | Number of transactions | 0.013100 | 0.060813 | 0.000000 | 0.684800 |
| | Number of Doge Coin mined | 4.012605e+08 | 2.696688e+09 | 0.000000e+00 | 6.941068e+10 |
| XRP | Price | 1.015281e+09 | 1.671122e+09 | 1.153832e+07 | 1.464262e+10 |
| | Number of transactions | 0.227842 | 0.335793 | 0.000000 | 3.380000 |
| | Number of XRP mined | 1.220152e+09 | 3.090950e+09 | 0.000000e+00 | 3.695518e+10 |

Table 5: Descriptive Statistics of Attractiveness.

| | **Mean** | **Standard Deviation** | **Min** | **Max** |
|---|---|---|---|---|
| Attractiveness | 58.153436 | 22.7223 | 0.000000 | 95.00000 |

that CNN algorithm present non-stable results compared to the other methods. We conducted further analyses by applying the MAE criterion on our cryptocurrency datasets. Results highlight that Autoencoders, then both LSTM and CNN-LSTM, provide small MAE values. Moreover, it is obvious that the CNN does not perform accurately in the evaluation set which means that over-fitting occurs. To evaluate our used datasets, we apply the RMSE evaluation criterion on the cryptocurrency datasets. Results prove that the Autoencoders provides bigger RMSE value than


Figure 1: Bitcoin daily price (USD), from April-28, 2013, to January-28, 2023.

the other algorithms. In fact, Autoencoders proves again its stability and gives good results. The results of this third criterion confirm again that Autoencoders can minimize the RMSE value and hence to give accurate prediction of the tested datasets. We can confirm that Autoencoders method performs the best results compared to the LSTM, CNN-LSTM, and CNN methods using the MSE, MAE, and RMSE criterion. The novelty of this study is the ability of our tested method namely Autoencoders, to predict, with a very small error on both train and validation phases, the price of Bitcoin when using several cryptocurrency datasets.

To investigate the relationship between the predictor variables and the dependent variable, we refer to the study of [28], and we conduct a stepwise analysis from Models 1 to 8 (**TABLE 6**). Our analyses show that Autoencoders method works better than the other methods across all models. Among them, Model 3 with iteration of Bitcoin-specific Blockchain information presented the best performance, as shown in TABLE 6 (MSE = 0.0125610, MAE = 0.8600000, RMSE = 1.1200000). These results reveal that Bitcoin-specific Blockchain information includes information that is directly related to Bitcoin prices. **FIGURE 2** illustrates the MSE, MAE, and RMSE for Autoencoders of Models 1 and 3. Model 1 includes all variables. Model 2 includes variables with iteration of only macro-economic factors, and we found that MSE, MAE, and RMSE were stable. Also, Model 8 with iteration of Global Currency Ratio did not significantly improve the results of the analysis. However, we found that MSE, MAE, and RMSE were slightly improved in Model 4, with iteration of Ethereum-specific Blockchain information (MSE = 0.0285550, MAE = 0.9600000, RMSE = 1.6900000). Further, this study shows that Model 5, with iteration of Doge Coin-specific Blockchain information did not improve the analysis result. We also found that Model 6, without XRP-specific Blockchain information, had not improve the performance. However, Blockchain information of

Doge Coin did not contribute significantly to the prediction of Bitcoin price. Finally, Model 7, without Attractiveness variable, did not improve the analysis result.

Table 6: The Results of Data Analysis.

| | | **Train** | | | **Validation** | | |
|---|---|---|---|---|---|---|---|
| | **Model** | **MSE** | **RMSE** | **MAE** | **MSE** | **RMSE** | **MAE** |
| | LSTM | 0,04751411 | 0,8472200 | 1,4183775 | 0,0402829 | 0,5646000 | 1,2650960 |
| Model 1: | CNN | 0,05039000 | 0,5839000 | 1,4371000 | 0,0439062 | 0,3063000 | 1,2902530 |
| All Inputs | CNN-LSTM | 0,04787500 | 0,8620720 | 1,4268200 | 0,0408800 | 0,5892800 | 1,2747800 |
| | Autoencoders | **0,03685700** | **1,9200000** | **1,1500000** | **0,0293870** | **1,7100000** | **1,0300000** |
| Model 2: | LSTM | 0,04881000 | 0,8184220 | 1,4449500 | 0,0414600 | 0,5292400 | 1,2858310 |
| Iteration of | CNN | 0,05094300 | 0,6075100 | 1,4492231 | 0,0438000 | 0,3204200 | 1,2941318 |
| Macro-economic | CNN-LSTM | 0,05032600 | 0,8370850 | 1,4714300 | 0,0427636 | 0,5500300 | 1,3084490 |
| Development Index | Autoencoders | **0,03684000** | 1,9200000 | **1,1100000** | **0,0290380** | 1,7000000 | **0,9700000** |
| Model 3: | LSTM | 0,01948000 | 0,1899591 | 1,0607050 | 0,0184420 | 0,1796391 | 1,0337500 |
| Iteration of | CNN | 0,02024600 | 0,0640858 | 1,0729750 | 0,0191550 | 0,0712940 | 1,0481038 |
| Blockchain information | CNN-LSTM | 0,01952330 | 0,1788110 | 1,0633804 | 0,0185340 | 0,1705050 | 1,0376490 |
| of Bitcoin | Autoencoders | **0,01408100** | 1,1900000 | **0,9100000** | **0,0125610** | 1,1200000 | **0,8600000** |
| Model 4: | LSTM | 0,04718500 | 0,8660600 | 1,4179490 | 0,0401520 | 0,5894450 | 1,2659500 |
| Iteration of | CNN | 0,05179280 | 0,6437880 | 1,4654950 | 0,0445400 | 0,4147731 | 1,3116193 |
| Blockchain information | CNN-LSTM | 0,04649500 | 0,8706400 | 1,4096280 | 0,0395960 | 0,5985900 | 1,2595570 |
| of Ethereum | Autoencoders | **0,03624400** | 1,9000000 | **1,0900000** | **0,0285550** | 1,6900000 | **0,9600000** |
| Model 5: | LSTM | 0,04750260 | 0,9210654 | 1,4804370 | 0,0405540 | 0,6701460 | 1,3434700 |
| Iteration of | CNN | 0,05091900 | 0,5673340 | 1,4427276 | 0,0442930 | 0,3207423 | 1,2944690 |
| Blockchain information | CNN-LSTM | 0,04879699 | 0,8502358 | 1,4576265 | 0,0416459 | 0,5839299 | 1,3036750 |
| of Doge Coin | Autoencoders | **0,03670500** | 1,9200000 | **1,1500000** | **0,0292690** | 1,7100000 | **1,0300000** |
| Model 6: | LSTM | 0,04780900 | 0,8526759 | 1,4237351 | 0,0408956 | 0,5722654 | 1,2746058 |
| Iteration | CNN | 0,05206790 | 0,5772272 | 1,4525970 | 0,0458222 | 0,3346786 | 1,3028590 |
| of Blockchain | CNN-LSTM | 0,04902878 | 0,8507892 | 1,4513571 | 0,0418278 | 0,5613451 | 1,2974208 |
| information of XRP | Autoencoders | **0,03664300** | 1,9100000 | **1,1500000** | **0,0292230** | 1,7100000 | **1,0200000** |
| Model 7: | LSTM | 0,04753820 | 0,8488625 | 1,4311196 | 0,0404904 | 0,5718507 | 1,2792518 |
| Iteration of | CNN | 0,05092435 | 0,5807415 | 1,4427263 | 0,0440317 | 0,3143629 | 1,2908217 |
| Attractiveness | CNN-LSTM | 0,04778260 | 0,8406861 | 1,4128419 | 0,0406806 | 0,5545860 | 1,2588790 |
| | Autoencoders | **0,03637300** | 1,9100000 | **1,1300000** | **0,0288890** | 1,7000000 | **1,0000000** |
| Model 8: | LSTM | 0,04790828 | 0,8443941 | 1,4339188 | 0,0407739 | 0,5677671 | 1,2807266 |
| Iteration of | CNN | 0,05032755 | 0,5720812 | 1,4320440 | 0,0438208 | 0,3021521 | 1,2850731 |
| Global | CNN-LSTM | 0,04913750 | 0,8332948 | 1,4515045 | 0,0416855 | 0,5433593 | 1,2923743 |
| Currency Ratio | Autoencoders | **0,03743100** | 1,9300000 | **1,1500000** | **0,0297770** | 1,7300000 | **1,0200000** |

## 5. DISCUSSION

Several studies have examined the use of Blockchain information in predicting Bitcoin prices and have found a positive long-term correlation between Bitcoin Blockchain information and Bitcoin prices ([1, 6, 9, 26]). Our research confirms these findings and suggests that Blockchain informa-

| **Model 1**: All Inputs | **Model 3**: Iteration of Bitcoin-specific Blockchain information |
|---|---|

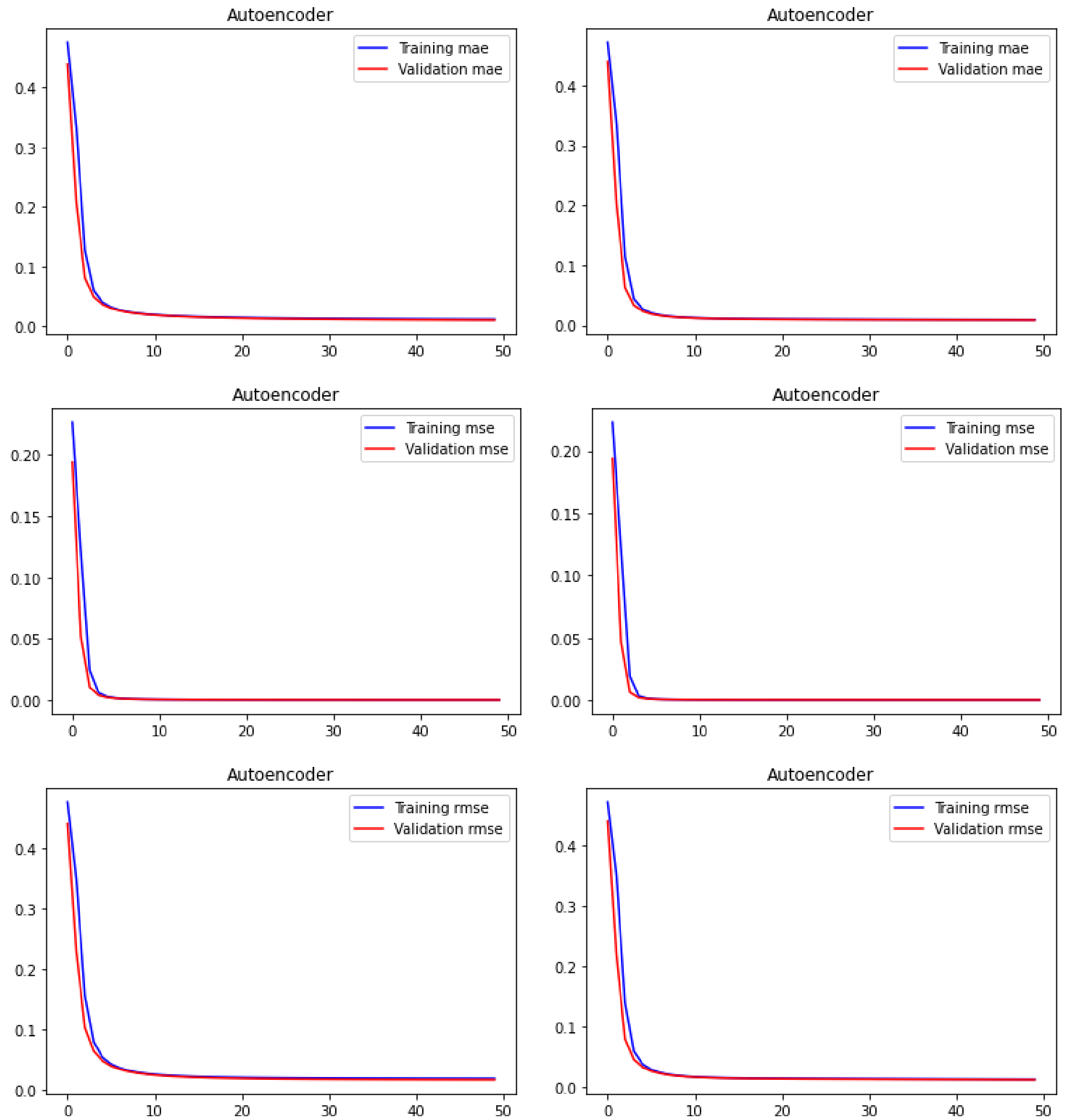


Figure 2: MSE, MAE and RMSE for Autoencoders.

tion should be employed for predicting future Bitcoin prices. Second, we found that Blockchain information of Ethereum did not contribute significantly to predicting Bitcoin prices. This result did not corroborate the findings of [28], who found that Ethereum-specific Blockchain information contributed to the best performance. Third, Ethereum, XRP and Doge Coin prices did not contribute significantly toward predicting Bitcoin prices. One of the main goals of this paper is to prove if

Bitcoin is a speculative asset, in such case its behavior must be related to other assets or market indexes.

Our findings show that macro-economic factors did not significantly improve the performance of predicting Bitcoin prices. This is not in line with previous studies that have shown a significant positive link between macroeconomic factors and Bitcoin price ([13–15]). Therefore, we do not recommend considering the macro-economic factors for the prediction of prices. However, it was found that global currency ratio did not contribute significantly toward predicting Bitcoin prices. This suggests that Bitcoin can be seen as a 'safe haven' asset during times of economic uncertainty. Based on the MSE, MAE and RMSE values, our findings show that our sentiment indicator (Attractiveness) did not improve the efficiency of our forecasting model. First, this result is not in line with the work of [9, 57] and [22] who found a correlation between sentiment and Bitcoin prices. So, Bitcoin price may not be affected by its attractiveness as an investment opportunity. We support the idea that the alteration of positive or negative news doesn't cause variations in the price of Bitcoin. The theoretical implication of this result is interesting. Because this sentiment factor is not an important determinant of Bitcoin's price. Also, considering all inputs in our model, the findings show that Deep Autoencoders performs very well, and it is better than the traditional popular deep learning methods. CNN-LSTM performs the second best, and the CNN performs the worst. The major conclusions and implications are two-fold. Firstly, the deep learning method, particularly Autoencoders method, is an effective tool for forecasting the price of Bitcoin. This conclusion provides decision support for investors and a reference for the governments to design better regulatory policies. Secondly, researchers can easily replicate the methods and results of this study. Finally, one last point worth noting is that our study has incorporated most of variables that may influence the price of Bitcoin, something that has not been considered in previous studies. However, our research does not aim to predict the volatility of future Bitcoin prices, which is necessary for investors.

## 6. CONCLUSIONS

The goal of this paper is to solve the problem focusing on Bitcoin, the most popular cryptocurrency. It explores which variables affect Bitcoin price level. To achieve this objective, we follow [28] method conducting a stepwise analysis. Two results are worth noting: Autoencoders turns out to be the best method of predicting Bitcoin prices, and Bitcoin specific Blockchain information is the most important variable in predicting Bitcoin prices. Then, our study highlights the potential utility of incorporating Blockchain factors into cryptocurrency price prediction models. Given that Blockchain and cryptocurrency are important information technologies that can affect various academic domains, information system researchers need to focus more attention on Blockchain. The use of Blockchain factors as drivers of cryptocurrency prices is an important and growing area of research. The studies reviewed in our literature review and the empirical results highlight the potential of incorporating Blockchain information in cryptocurrency price prediction models and suggest that this information can improve the accuracy of these models. However, there is still much room for further research to fully exploit the potential of this unique data source and to develop more effective methods for incorporating Blockchain information in cryptocurrency price prediction models.

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## References

[1] Jang H, Lee J. An Empirical Study on Modeling and Prediction of Bitcoin Prices With Bayesian Neural Networks Based on Blockchain Information. IEEE Access. 2017;6:5427-5437.

[2] Antonopoulos AM, Wood G. Mastering Ethereum: Building Smart Contracts and DApps. 2018:384.

[3] https://scirp.org/reference/referencespapers.aspx?referenceid=3098381

[4] Guo H, Zhang D, Liu S, Wang L, Ding Y. Bitcoin Price Forecasting: A Perspective of Underlying Blockchain Transactions. Decis Support Syst. 2021;151:113650.

[5] Liu F, Li Y, Li B, Li J, Xie H. Bitcoin Transaction Strategy Construction Based on Deep Reinforcement Learning. Appl Soft Comput. 2021;113:107952.

[6] Saad M, Choi J, Nyang D, Kim J, Mohaisen A. Toward Characterizing Blockchain-Based Cryptocurrencies for Highly Accurate Predictions. IEEE Syst J. 2020;14:321-332.

[7] Auer R, Cornelli G, Doerr S, Frost J, Gambacorta L, et al. Crypto Trading and Bitcoin Prices: Evidence From a New Database of Retail Adoption. SSRN Journal. 2022;1049.

[8] Koutmos D. Bitcoin Returns and Transaction Activity. Econ Lett. 2018;167:81-85.

[9] Kristoufek L. What Are the Main Drivers of the Bitcoin Price? Evidence From Wavelet Coherence Analysis. PLOS ONE. 2015;10:e0123923.

[10] Meegan A, Corbet S, Larkin C, Lucey B. Does Cryptocurrency Pricing Response to Regulatory Intervention Depend on Underlying Blockchain Architecture? J Int Financ Markets Inst Money. 2021;70:101280.

[11] Gandal N, Hamrick JT, Moore T, Oberman T. Price Manipulation in the Bitcoin Ecosystem. J Monet Econ. 2018;95:86-96.

[12] Sokic A. Bitcoin Price Dynamics and Hyperdeflation: A Monetary Theory Approach. Rev Econ. 2021;72:135-146.

[13] Cheung A, Roca E, Su JJ. Crypto-Currency Bubbles: An Application of the Phillips–Shi–Yu (2013) Methodology on MT. Gox Bitcoin Prices. Applied Economics. 2015;47:2348-2358.

[14] Narayan PK, Narayan S, Eki Rahman R, Setiawan I. Bitcoin Price Growth and Indonesia's Monetary System. Emerg Markets Rev. 2019;38:364-376.

[15] Zhang S, Hou X, Ba S. What Determines Interest Rates for Bitcoin Lending?Res Int Bus Fin. 2021;58:101443.

[16] Havidz SAH, Karman VE, Mambea IY. Is Bitcoin Price Driven by Macro-Financial Factors and Liquidity? A Global Consumer Survey Empirical Study. Organ Markets Emerg Econ. 2021;12:399-414.

[17] Ciaian P, Rajcaniova M, Kancs. The Economics of Bitcoin Price Formation. Appl Econ. 2016;48:1799-1815.

[18] Choi S, Shin J. Bitcoin: An Inflation Hedge but Not a Safe Haven. Fin Res Lett. 2022;46:102379.

[19] Poyser O. Exploring the Dynamics of Bitcoin's Price: A Bayesian Structural Time Series Approach. Eurasian Economic Review. 2019;9:29-60.

[20] Qin M, Su CW, Tao R. Bitcoin: A New Basket for Eggs?Econ Modell. 2021;94:896-907.

[21] Aysan AF, Demir E, Gozgor G, Lau CKM. Effects of the Geopolitical Risks on Bitcoin Returns and Volatility. Res Int Bus Fin. 2019;47:511-518.

[22] Albrecht S, Lutz B, Neumann D. How Sentiment Impacts the Success of Blockchain Startups - An Analysis of Social Media Data and Initial Coin Offerings. Proceedings of the annual Hawaii international conference on system sciences 2019. 2019:4545-4554.

[23] Phan HT, Nguyen NT, Hwang D. Sentiment Analysis for Social Media: A Survey. J Comput Sci Cybern. 2021;37:403-428.

[24] Hajek P, Hikkerova L, Sahut JM. How Well Do Investor Sentiment and Ensemble Learning Predict Bitcoin Prices? Res Int Bus Fin. 2023;64:101836.

[25] Franco P. Understanding Bitcoin: Cryptography, Engineering and Economics. 2015;631.

[26] Kubal J, Kristoufek L. Exploring the Relationship Between Bitcoin Price and Network's Hash Rate Within Endogenous System. Int Rev Financ Anal. 2022;84:102375.

[27] Saad M, Mohaisen A. Towards Characterizing Blockchain-Based Cryptocurrencies for Highly-Accurate Predictions. IEEE Conference on Computer Communications Workshops. IEEE Publications Infocom; 2018.

[28] Kim HM, Bock GW, Lee G. Predicting Ethereum Prices With Machine Learning Based on Blockchain Information. Expert Syst Appl. 2021;184:115480.

[29] Mallqui DC, Denny's. C.A., and Ricardo A.S. Fernandes. "Predicting the Direction, Maximum, Minimum and Closing Prices of Daily Bitcoin Exchange Rate Using Machine Learning Techniques." Appl Soft Comput. 2019;75:596-606.

[30] Chen F, Wan H, Cai H, Cheng G. Machine Learning In/for Blockchain: Future and Challenges. Can J Statistics. 2021;49:1364-1382.

[31] Ahmed WMA. Robust Drivers of Bitcoin Price Movements: An Extreme Bounds Analysis. North Am J Econ Fin. 2022;62:101728.

[32] Georgoula I, Pournarakis D, Bilanakos C, Sotiropoulos DN, Giaglis GM. Using Time-Series and Sentiment Analysis to Detect the Determinants of Bitcoin Prices. SSRN Electron J. 2015: 2607167.

[33] Katsiampa P. Volatility Estimation for Bitcoin: A Comparison of Garch Models. Econ Lett. 2017;158:3-6.

[34] Chen Z, Li C, Sun W. Bitcoin Price Prediction Using Machine Learning: An Approach to Sample Dimension Engineering. J Comp Appl Math. 2020;365.

[35] Sharma S, Majumdar A. Deep State Space Model for Predicting Cryptocurrency Price. Inf Sci. 2022;618:417-433.

[36] Dutta A, Kumar S, Basu M. A Gated Recurrent Unit Approach to Bitcoin Price Prediction. J Risk Financ Manag. 2020;13:23.

[37] Kwon, Hyung D, Kim JB, Heo JS, Kim CM, et al . Time Series Classification of Cryptocurrency Price Trend Based on a Recurrent Lstm Neural Network. J Inf Process Syst. 2019;15:694-706.

[38] Lahmiri S, Bekiros S. Cryptocurrency Forecasting With Deep Learning Chaotic Neural Networks. Chaos Solitons Fract. 2019;118:35-40.

[39] Lahmiri S, Bekiros S. Intelligent Forecasting With Machine Learning Trading Systems in Chaotic Intraday Bitcoin Market. Chaos Solitons Fract. 2020;133:109641.

[40] Miura R, Pichl L, Kaizoji T. Artificial Neural Networks for Realized Volatility Prediction in Cryptocurrency Time Series. Lect Notes Comput Sci. 11554 LNCS:165–72. 2019:165-172.

[41] Zoumpekas T, Houstis E, Vavalis M. ETH Analysis and Predictions Utilizing Deep Learning. Expert Syst Appl. 2020;162:113866.

[42] Kristjanpoller W, Minutolo MC. A Hybrid Volatility Forecasting Framework Integrating Garch, Artificial Neural Network, Technical Analysis and Principal Components Analysis. Expert Syst Appl. 2018;109:1-11.

[43] Chen Z, Li C, Sun W. Bitcoin Price Prediction Using Machine Learning: An Approach to Sample Dimension Engineering. J Comp Appl Math. 2020;365:112395.

[44] Jaquart P, Dann D, Weinhardt C. Short-Term Bitcoin Market Prediction via Machine Learning. J Fin Data Sci. 2021;7:45-66.

[45] Amjad S, Abbas S, Abubaker Z, Alsharif MH, Jahid A, et al . Blockchain Based Authentication and Cluster Head Selection Using Ddr-Leach in Internet of Sensor Things. Sensors. 2022;22:1972.

[46] Liu M, Li G, Li J, Zhu X, Yao Y. Forecasting the Price of Bitcoin Using Deep Learning. Fin Res Lett. 2021;40:101755.

[47] Alonso-Monsalve S, Suárez-Cetrulo AL, Cervantes A, Quintana D. Convolution on Neural Networks for High-Frequency Trend Prediction of Cryptocurrency Exchange Rates Using Technical Indicators. Expert Syst Appl. 2020;149.

[48] Oyedele AA, Ajayi AO, Oyedele LO, Bello SA, Jimoh KO. Performance Evaluation of Deep Learning and Boosted Trees for Cryptocurrency Closing Price Prediction. Expert Syst Appl. 2023;213:119233.

[49] Borges TA, Neves RF. Ensemble of Machine Learning Algorithms for Cryptocurrency Investment With Different Data Resampling Methods. Appl Soft Comput. 2020;90:106187.

[50] Ibrahim A, Kashef R, Corrigan L. Predicting Market Movement Direction for Bitcoin: A Comparison of Time Series Modeling Mthods. Comput Electr Eng. 2021;89:106905.

[51] Huang Y, Duan K, Mishra T. Is Bitcoin Really More Than a Diversifier? A Pre- And Post-covid-19 Analysis. Fin Res Lett. 2021;43:102016.

[52] Wątorek M, Drożdż S, Kwapień J, Minati L, Oświęcimka P, et al. Multiscale Characteristics of the Emerging Global Cryptocurrency Market. Phys Rep. 2021;901:1-82.

[53] Hinton GE, Salakhutdinov RR. Reducing the Dimensionality of Data With Neural Networks. Science. 2006;313:504-507.

[54] Nakano M, Takahashi A. A New Investment Method With Autoencoder: Applications to Crypto Currencies. Expert Syst Appl. 2020;162:113730.

[55] Khalfaoui R, Rabeh, Gozgor G, Goodell JW. Impact of Russia-Ukraine War Attention on Cryptocurrency: Evidence From Quantile Dependence Analysis. Fin Res Lett. 2022:103365.

[56] Ortu M, Uras N, Conversano C, Bartolucci S, Destefanis G. On Technical Trading and Social Media Indicators for Cryptocurrency Price Classification Through Deep Learning. Expert Syst Appl. 2022;198.

[57] Urquhart A. What Causes the Attention of Bitcoin? Econ Lett. 2018;166:40-44.