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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. In this study, 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. By providing more reliable and attractive models for predicting the price of Bitcoin, these approaches are expected to provide a more robust understanding of the factors driving Bitcoin prices. 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.

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

JEL Classifications: B27, C61, C82, G12.

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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 (Jang & Lee, 2017). Blockchain, the decentralized ledger technology that underlies Bitcoin and other cryptocurrencies, has the potential to revolutionize various industries (Antonopoulos & Wood, 2018). 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 (Antonopoulos & Wood, 2018). 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 (Antonopoulos, 2014).

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 (Guo et al. 2021; Liu et al. 2021). 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 (Jang & Lee, 2017; Saad et al. 2020).

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.

1. 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.

1.1 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 (Auer et al., 2022; Koutmos, 2018). For example, a study by Kristoufek (2015) 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 (Meegan et al., 2021). On the other hand, the legalization and recognition of Bitcoin as a legitimate form of currency can lead to an increase in its price (Gandal et al. 2018; Sokic, 2021). 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 (Cheung et al., 2015) and positively correlated with inflation (Narayan et al., 2019). The relationship between interest rates and the price of Bitcoin is more complex, with some studies showing a positive correlation (Zhang et al., 2021) and others showing a negative one (Havidz et al., 2021). A study by Ciaian et al. (2016) do not support previous findings that macro-financial developments are driving Bitcoin price in the long run. Another study by Choi and Shin (2022) 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 Poyser (2019) 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 (Qin et al., 2021; Aysan et al., 2019). 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 Kristoufek (2015) found that the number of tweets containing the term "Bitcoin" is positively correlated with the Bitcoin. A study by Albrecht et al. (2019) 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 Phan et al. (2021) 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, Hajek et al. (2023) suggest that the addition of the investor sentiment based on Bitcoin Misery Index (BMI) enhances the predictive performance of their model significantly.

1.2 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 (Franco, 2015). Several studies have examined the use of Blockchain information in predicting Bitcoin prices. One of the earliest studies was conducted by Kristoufek (2015) who found a positive long-term correlation between the security of the network, measured by the network hashrate, and the price of Bitcoin. This was further explored by Kubal and Kristoufek (2022), who studied the relationship between the cost of mining Bitcoin and its price. The cost of mining was calculated based on the total hashrate, 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 Jang and Lee (2017) 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 Saad and Mohaisen (2018) who found that incorporating Blockchain factors, such as the number of Bitcoin wallets andunique 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. Kim et al. (2021) 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 Mallqui and Fernandes (2019) predicted the price of Bitcoin using Blockchain-based features, macro-economic factors, Google popularity index, and Wikipedia searches. Guo et al. (2021) 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. Chen et al. (2021) 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, Kubal and Kristoufek (2022) conducted a study to determine the underlying factors affecting the price of Bitcoin and its total hashrate. Their findings revealed that the hashrate generated by miners, positively impacts the Bitcoin price. However, the rising price does not result in a corresponding increase in hashrate, 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. Ahmed (2022) 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.

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

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

Source: Authors' Contribution

References	Methodology	Data source	Predictors (category/determinants)	Results
Oyedele et al. (2023)	Deep Learning (DL) models (Convolutional Neural Networks (CNN), Deep Forward Neural Networks, and Gated Recurrent Units) Boosted tree-based models	Yahoo Finance UK Investing 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.
Hajek et al. (2023)	Bagged support vector regression (BSVR)	Refinitiv.com 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.
Khalfaoui et al. (2022)	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.
Kubal and Kristoufek (2022)	Two-stage least squares estimation	CoinMetrics.io Bitcoinblockhalf.com Yahoo Finance Google Trends	Network's hash rate The network congestion (measured by the total transaction fees paid in BTC) Interest and attention directed towards Bitcoin	Both directions of causal effect between the Bitcoin price and hash rate.
Sharma and Majumdar (2022)	Time series analysis 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.
Ortu et al. (2022)	Four different deep learning algorithms (Multi Layers Perceptron (MLP), Convolutional Neural Network (CNN), Long Short Term Memory (LSTM) neural network and Attention Long Short Term Memory (ALSTM)	https://www.cryptodatadownload.com/data/bitfinex/. https://www.bitfinex.com. GitHub and users' comments on Reddit	Cryptocurrency dataset Users' sentiment	Incorporating both trading and social media indicators leads to a substantial enhancement in the prediction accuracy and consistency across all algorithms.
Ahmed (2022)	Extreme bounds analysis (EBA)	https://Bitcoincharts.com/ https://data.nasdaq.com/	Blockchain information	Factors specific to cryptocurrencies, rather than global macroeconomic and financial factors, play a larger role in determining the movements of Bitcoin prices.
			Realized volatility of Bitcoin prices Wikipedia views Macro-financial factors	
Kim et al. (2021)	Time-series analyses Advanced machine-learning techniques	Data Stream Etherscan	Development Index Global Currency Ratio Generic Blockchain Information (Ethereum, Bitcoin, Litecoin, Dashcoin) 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.
Liu et al. (2021)	Deep learning method named Stacked Denoising Autoencoders (SDAE)	www.coindesk.com www.BTC.com Baidu and Google Wind financial database Choice financial database Data Stream	Cryptocurrency market Public attention Macroeconomic environment	Compared with the most popular machine learning methods, such as back propagation neural network (BPNN) and support vector regression (SVR) methods, the SDAE model performs better in both directional and level prediction, measured.
Guo et al. (2021)	Deep Learning (DL) mode (WT-CATCN)	WalletExplorer CoinMarketCap Google Trends Data	Market prices data Social interest data Inter-exchange transaction data	The results of a comparison between the WT-CATCN model and other advanced price forecasting models indicate that WT-CATCN enhances the accuracy of price prediction by 25%.
Mallqui and Fernandes (2019)	Artificial Neural Networks (ANN), Support Vector Machines (SVM), Ensemble algorithms (based on Recurrent Neural Networks and the *k*-Means clustering method)	Bitcoincharts Quandl	Bitcoin's Blockchain information: Volume of trades, total transaction fees, cost per transaction, number of transactions, hash rate Macro-economic factors: Crude oil, Gold, S&P 500, NASDAQ 100, DAX index Google popularity index - Wikipedia search volume	The combination of Recurrent Neural Networks and a Tree classifier obtained the best results to predict the Bitcoin price direction.
Poyser (2019)	Bayesian Structural Time Series Approach (BSTS).	www.Blockchain.info	Blockchain information	The price of Bitcoin has a negative correlation with the price of gold and the exchange rate between the Yuan and the US Dollar, but a positive

2. Methodology

2.1 Dataset and Experiments

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. Other cryptocurrencies having Blockchain information were chosen based on the following two criteria: (1) the coins had high transaction volumes in the market and (2) the Blockchain information of other coins overlapped temporally with that of Bitcoin. Hence, we selected the Blockchain information of Ethereum, Doge Coin, and XRP. 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 Hinton and Salakhutdinov (2006), 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 (Nakano & Takahashi, 2020).

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) Stock Index of Eurozone (Euro Stoxx 50) National Association of Securities Dealers Automated Quotations (NASDAQ) Crude Oil Gold CBOE volatility index (VIX) Nikkei Stock Average for the Tokyo Stock Exchange (Nikkei225) Financial Times Stock Exchange 100 Index (FTSE100)		Factset database
Global Currency Ratio	British Currency Sterling (GBP)/ US Dollar (USD) Japanese Yen (JPY)/ US Dollar (USD) Swiss Franc (CHF)/ US Dollar (USD) 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. This variable is used as a proxy for the demand side of the Bitcoin market.	https://www.Blockchain.com/
	Number of Bitcoins mined (Supply for Bitcoin)	The daily total amount of Bitcoin units currently in circulation. This variable is introduced as a proxy for the supply side of the Bitcoin market.	https://www.Blockchain.com/
	Total Hash Rate (TH/s)	The daily average exa-hashes per second (1 EH/s = 1018 hashes) is an indicator of the processing capability of high-powered mining hardware that individual miners use to unlock new Bitcoin units. The higher the hash rate is, the more resilient the network is to malicious cyber-attacks. We utilize this variable to represent the security aspect of the Bitcoin network.	https://www.Blockchain.com/
	Total number of transactions on the Blockchain (Transaction Volume (in USD)) Estimated Transaction Value (USD) Miners Revenue (USD)	The daily value of units traded on the Bitstamp platform, expressed in US dollars. This variable is employed as a measure of the Bitcoin market activity.	https://www.Blockchain.com/
	Total Transaction Fees (USD) 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 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 cryptocurrency mined	The daily total amount of cryptocurrency units currently in circulation.	https://coinmarketcap.com/
Investor sentiment and attention [e.g., expert media articles, StockTwits, Reddit, and other social media metrics such as Google trends, Twitter, Wikipedia searches]	Attractiveness	Searches Volumes of Bitcoin	Google Trend

2.2 Evaluation Criteria

We employed three evaluation criteria. The 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 in order to follow the evolution of the evaluation criteria all over the time.

The formulas of the evaluation criteria are as follows:

$$\boldsymbol{MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i{}^{real} - y_i{}^{pred})^2}$$

$$\boldsymbol{RMSE = \sqrt{MSE}}$$

$$= \sqrt{\boldsymbol{\frac{1}{N}\sum_{i=1}^{n}(y_i{}^{real} - y_i{}^{pred})^2}} \boldsymbol{MAE}$$

$$= \boldsymbol{\frac{1}{N}\sum_{i=1}^{n}\left|y_i{}^{real} - y_i{}^{pred}\right|}$$

Where $\boldsymbol{N}$ is the number of samples, $\boldsymbol{y_i{}^{real}}$ is the actual value, and $\boldsymbol{y_i{}^{pred}}$ is the estimated value. MSE measures the average of the squares of the errors between the forecasting result and the true price. MAE represents the average of the absolute errors between the forecasting result and the true price. RMSE measures the deviation of forecasting prices.

3. 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**.

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	7651.0260330.0	413947.564763.
	Network Difficulty	6.150910e+11	3.221152e+1220	00000e+000.00	070586e+13
	Average Payments Per Block	1871.925877	21.873015	0000	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

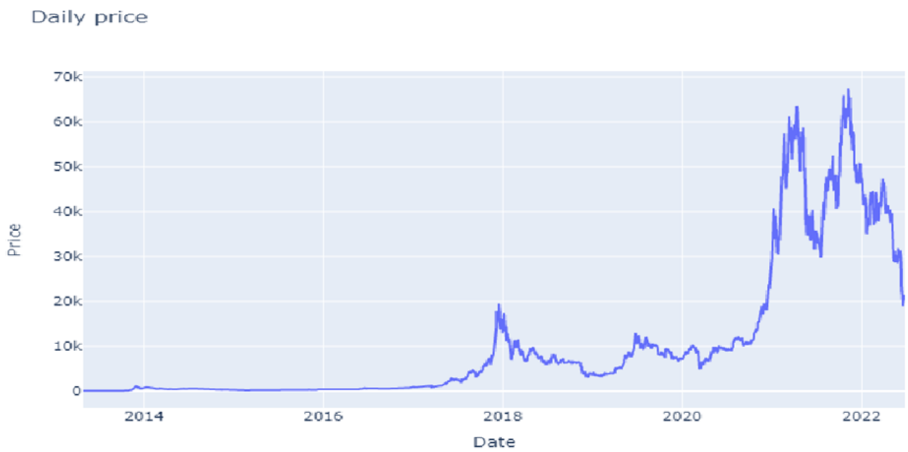


Figure 1 illustrates the volatility of Bitcoin daily price (USD), from April-28, 2013 to January-28, 2023. This high volatility explains why Bitcoin is not currently used as a unit of account, because merchants would have to be forced to constantly calculate prices, which would involve significant updating costs (Lo & Wang, 2014). The permanent variability of prices would also induce uncertainty for consumers who are used to relatively fixed prices (Figuet, 2016).

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 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 the other algorithms. In fact, Autoencoders proves again its stability and gives good results. The results of this third criterion confirm again that Autoencoders is able to 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.

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

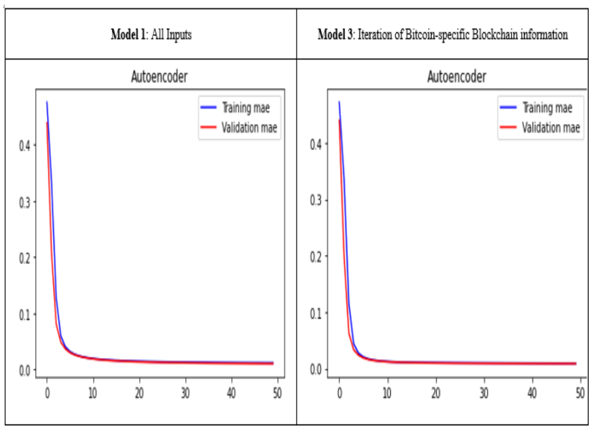
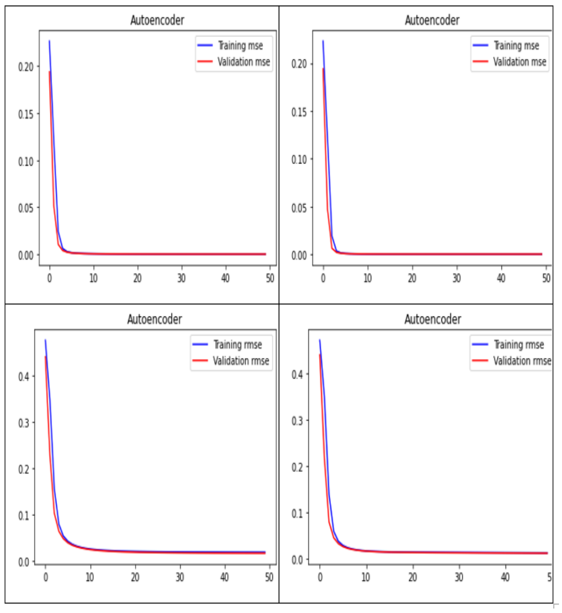


Figure 2. MSE, MAE and RMSE for Autoencoders



To investigate the relationship between the predictor variables and the dependent variable, we refer to the study of Kim et al. (2021) 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 (MSE = 0.0293870, MAE = 1.0300000, RMSE = 1.7100000). Model 2 includes variables with iteration of only macro-economic factors and we found that MSE, MAE and RMSE were stable (MSE = 0.0290380, MAE = 0.9700000, RMSE = 1.7000000). Also, Model 8 with iteration of Global Currency Ratio did not significantly improve the results of the analysis (MSE = 0.0297770, MAE = 1.0200000, RMSE = 1.7300000). 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 show that Model 5, with iteration of Doge Coin-specific Blockchain information did not improve the analysis result (MSE = 0.0292690, MAE = 1.0300000, RMSE = 1.7100000). We also found that Model 6, without XRP-specific Blockchain information, had not improve the performance (MSE = 0.0292230, MAE = 1.0200000, RMSE = 1.7100000). 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 (MSE = 0.0288890, MAE = 1.0000000, RMSE = 1.7000000).

Table 6.The Results of Data Analysis

		Train			**Validation**		
	Model	**MSE**	**RMSE**	**MAE**	**MSE**	**RMSE**	**MAE**
Model 1 : All Inputs	**LSTM**	0,04751411	0,8472200	1,4183775	0,0402829	0,5646000	1,2650960
	CNN	0,05039000	0,5839000	1,4371000	0,0439062	0,3063000	1,2902530
	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 : Iteration of Macro-economic Development Index	**LSTM**	0,04881000	0,8184220	1,4449500	0,0414600	0,5292400	1,2858310
	CNN	0,05094300	0,6075100	1,4492231	0,0438000	0,3204200	1,2941318
	CNN-LSTM	0,05032600	0,8370850	1,4714300	0,0427636	0,5500300	1,3084490
	Autoencoders	**0,03684000**	1,9200000	**1,1100000**	**0,0290380**	1,7000000	**0,9700000**
Model 3 : Iteration of Blockchain information of Bitcoin	**LSTM**	0,01948000	0,1899591	1,0607050	0,0184420	0,1796391	1,0337500
	CNN	0,02024600	0,0640858	1,0729750	0,0191550	0,0712940	1,0481038
	CNN-LSTM	0,01952330	0,1788110	1,0633804	0,0185340	0,1705050	1,0376490
	Autoencoders	**0,01408100**	1,1900000	**0,9100000**	**0,0125610**	1,1200000	**0,8600000**

Model 4 : Iteration of Blockchain information of Ethereum	**LSTM**	0,04718500	0,8660600	1,4179490	0,0401520	0,5894450	1,2659500
	CNN	0,05179280	0,6437880	1,4654950	0,0445400	0,4147731	1,3116193
	CNN-LSTM	0,04649500	0,8706400	1,4096280	0,0395960	0,5985900	1,2595570
	Autoencoders	**0,03624400**	1,9000000	**1,0900000**	**0,0285550**	1,6900000	**0,9600000**
Model 5 : Iteration of Blockchain information of Doge Coin	**LSTM**	0,04750260	0,9210654	1,4804370	0,0405540	0,6701460	1,3434700
	CNN	0,05091900	0,5673340	1,4427276	0,0442930	0,3207423	1,2944690
	CNN-LSTM	0,04879699	0,8502358	1,4576265	0,0416459	0,5839299	1,3036750
	Autoencoders	**0,03670500**	1,9200000	**1,1500000**	**0,0292690**	1,7100000	**1,0300000**
Model 6 : Iteration of Blockchain information of XRP	**LSTM**	0,04780900	0,8526759	1,4237351	0,0408956	0,5722654	1,2746058
	CNN	0,05206790	0,5772272	1,4525970	0,0458222	0,3346786	1,3028590
	CNN-LSTM	0,04902878	0,8507892	1,4513571	0,0418278	0,5613451	1,2974208
	Autoencoders	**0,03664300**	1,9100000	**1,1500000**	**0,0292230**	1,7100000	**1,0200000**
Model 7 : Iteration of Attractiveness	**LSTM**	0,04753820	0,8488625	1,4311196	0,0404904	0,5718507	1,2792518
	CNN	0,05092435	0,5807415	1,4427263	0,0440317	0,3143629	1,2908217
	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 : Iteration of Global Currency Ratio	**LSTM**	0,04790828	0,8443941	1,4339188	0,0407739	0,5677671	1,2807266
	CNN	0,05032755	0,5720812	1,4320440	0,0438208	0,3021521	1,2850731
	CNN-LSTM	0,04913750	0,8332948	1,4515045	0,0416855	0,5433593	1,2923743
	Autoencoders	**0,03743100**	1,9300000	**1,1500000**	**0,0297770**	1,7300000	**1,0200000**

4. Discussion

The contribution of our research is to discover new variables that can explain Bitcoin prices. The results will enable researchers and practitioners to better understand Blockchain and crypto-currencies. In addition, our study has both theoretical and practical implications for related literature. Firstly, it has highlighted the relevance of Blockchain information in predicting Bitcoin prices. 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 (Kristoufek, 2015; Kubal & Kristoufek, 2022; Jang & Lee, 2017; Saad & Mohaisen, 2018). Our research confirms these findings and suggests that Blockchain information should be employed for predicting future Bitcoin prices. Indeed, we found that Bitcoin specific Blockchain information is the most important variable in predicting Bitcoin prices. Also, this study illustrates convincing evidence of the benefits of integrating Blockchain data into Bitcoin price forecasts. Second, we found that Blockchain information of Ethereum did not contribute significantly in predicting Bitcoin prices. This result did not corroborate the findings of Kim et al. (2021), who found that Ethereum-specific Blockchain information contributed to the best performance when it was considered within the model along with macro-economic factors, the generic Blockchain information of Ethereum, and Bitcoin's Blockchain information. Thirdly, as some authors have confirmed in their works the existence of direct relationships between Blockchain information and the price of crypto-currencies (Mallqui & Fernandes, 2019; Guo et al., 2021), it would be possible that there is a relationship between the Blockchain information of other crypto-currencies and the price of Bitcoin, thus playing an important and determining role in predicting Bitcoin prices. It would therefore be wise to study the impact of other coins' Blockchain information on future Bitcoin prices. In this study, Bitcoin's Blockchain information is not related to Ethereum prices, neither to the Blockchain information of XRP and Doge Coin. It appears that Ethereum, XRP and Doge Coin prices did not contribute significantly toward predicting Bitcoin prices. 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 (Cheung et al., 2015; Narayan et al., 2019; Zhang et al., 2021). Therefore, we not recommend considering the macro-economic factors for the prediction of prices. Also, it was found that global currency ratio did not contribute significantly toward predicting Bitcoin prices. These findings corroborate the result of Guizani and Nafti (2019) suggesting that global currency ratio, macroeconomic and financial development does not determine the price of the Bitcoin in the short term as well as in the long term. 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 of all, this result is not in line with the work of Urquhart (2018), Kristoufek (2015) and Albrecht et al. (2019) who found a correlation between sentiment and Bitcoin prices. So, Bitcoin price may not be affected by its attractiveness as an investment opportunity. Thus, we can see that variations in the Bitcoin price are in no way influenced by the alteration of positive or negative news. This result has an interesting theoretical implication. Researchers and financial analysts should not incorporate the sentiment factor into their valuation models, as it is not an important determinant of Bitcoin's price and therefore returns.

Also, our study employed popular and well-accepted deep-learning techniques (i.e., CNN, LSTM, and CNN-LSTM) and used a special type of deep neural networks, a Deep Autoencoders for cryptocurrencies' prices prediction. 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. This method achieves the lowest MSE (0.0293870), RMSE (1.7100000) and MAE (1.0300000). This means that it performs the best in forecasting the price of Bitcoin. CNN-LSTM performs the second best and the CNN performs the worst. The main implications are threefold. Firstly, the autoencoder method proves to be a relevant Bitcoin price forecasting tool, compared to traditional deep learning methods. Indeed, autoencoders can extract several sophisticated and relevant pieces of information about Bitcoin's characteristics. This implication could serve as a reference for governments and a decision aid for investors to design better regulatory policies. Secondly, the results of this study can serve as a good reference for researchers and practitioners wishing to predict Bitcoin prices. As for the academic implications, this research has broadened theoretical perspectives by discovering significant new variables for predicting Bitcoin prices. A third and final point worth emphasizing is that our study incorporated the majority of variables likely to influence Bitcoin prices. Indeed, this study considered macro-economic factors, Bitcoin-specific Blockchain information, Global Currency Ratio, Blockchain information of other cryptocurrencies, and social variable for predicting Bitcoin prices, something that has not been considered in previous studies. However, it should be emphasized that, although our study has identified a set of influential factors related to Bitcoin price changes and future prices of this cryptocurrency, it does not precisely aim to predict the volatility of future Bitcoin prices. This is the fundamental limitation of our study, which presented results deemed insufficient in terms of the actual buying and selling of Bitcoin for traders. Thus, as a future research path, we advise researchers to continue research on Bitcoin price volatility prediction since we believe that Bitcoin volatility prediction can provide important information to companies using Bitcoin.

Conclusion

Although financial market practitioners and researchers have recognized the importance of cryptocurrency price forecasting, the question of how best to predict cryptocurrency prices, given their extremely volatile nature, remains a thorny issue. The goal of this paper is to solve this problem focusing on Bitcoin, the most popular cryptocurrency. It explores which variables affect Bitcoin price level. In order to achieve this objective, we follow Kim et al. (2021) 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. This study, and the studies reviewed in our literature review and the empirical results, highlight the importance of integrating Blockchain factors into cryptocurrency price prediction models. The use of Blockchain factors as drivers of cryptocurrency prices is an important and growing area of research. As such, information systems researchers need to pay more attention to Blockchain in their various academic works. However, we believe that the potential of this unique data source should be fully exploited and new methods should be effectively developed to integrate information from the Blockchain and predict cryptocurrency prices. We hope that our results have served to provide, not only a theoretical basis for future cryptocurrency researchers to uncover additional variables, but also to expand the knowledge in the field of cryptocurrency research.

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