Analyzing machine learning methods for predicting cryptocurrency returns and reasons for price changes.

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I Introduction

Cryptocurrencies became significantly famous over the past few years, leading to the rapid growth of many currencies and a dramatic increase in interest in this area in society. A considerable number of investors earn and increase capital by buying some coins and selling others, but at the same time, the significant number of people lose money on the same transactions. The outcome of an investment is often random, difficult to predict or calculate. This is due to the high volatility of cryptocurrencies and their uncorrelation with others financial assets in terms of behavior [1]. A possible solution to this problem and a useful tool for investors may be the ability to predict cryptocurrency prices using algorithms and machine learning methods. Nowadays, the scientific community puts significant effort in researching new ways of trading cryptocurrency, especially with the implementation of machine learning (ML) algorithms [2]. Hence, the rationale for this literature review is to provide valuable information for scientific studies and practical usage by investors in the cryptocurrency markets. The research contributes to the existing knowledge of cryptocurrency by defining the efficient machine learning (ML) algorithms for predicting cryptocurrency returns and finding the reasons for price changes. This contribution is important for progress in the cryptocurrency sphere, creating new investment strategies, and developing more effective prediction ML models. The Present study intends to respond to the following research questions: "Which machine learning algorithms are the optimal for predicting cryptocurrency returns? What factors effect changes in cryptocurrency prices?"

II Method

A. Search strategy

For the literature review different databases, such as Google Scholar and Science Direct were utilised because of the large number and variety of publications presented. The keywords were “cryptocurrency”, “price prediction”, “machine learning”, “Bitcoin”. Search string was the following: “Prediction of cryptocurrency returns using artificial intelligence” (17 000 hits). The phrases ”artificial intelligence” and ”prediction of cryptocurrency” were added in order to find papers that only explore methods related to both machine learning and cryptocurrencies. The search scope included keywords, abstract and results. The main filters were the year of publishing (not earlier than 2020) to select the articles that contain relevant information and the language (English).

B. Data preparation

Data was downloaded from different databases, such as MIPD, IEEE, Science Direct, etc. Duplicate sources were not detected.

C. Screening

The citation and full-text screening helped to remove a certain number of publications by abstract, introduction, and method validation that do not mention analysing and predicting cryptocurrency price changes with machine learning methods and algorithms. After screening, 11 sources were selected and tabulated into the reading log table.

III Results

A. Factors that affect the cryptocurrencies changes:

Rasoul et al. [1] show that the influence of engagement changes over time, which signifies that there exist periods of time when investors buy BTC (Bitcoin) despite the supply and demand balance and the macroeconomic advancement factor that has a slight effect on the BTC price changes in short. The main conclusion is that demand pressures have a considerable influence on the prices of different cryptocurrencies compared to supply-side factors. Moreover, John et al. [3] note some reasons for Bitcoin price movement, such as climate change, social focus on inflation, and various ambiguity factors, for example, users uncertainty on social networks.

Hence, according to the information about Bitcoin that was mentioned above, some of the factors influencing BTC price movements are inflation, climate change, social uncertainty, and demand pressures.

On the other hand, researchers [4] identify the political sustainability of a country, trends in social media, and cyber attacks as some of the factors that effect cryptocurrency cost changes and remain in the low volatility mode. Also, Helder and Pedro [2] noted that the economic components, such as the U.S. dollar, gold price, and trading amount, influence cryptocurrency returns.

Eventually, many different factors, such as demand-side pressures, cyberattacks, inflation, climate uncertainty, and social media, influence cryptocurrency price changes.

B. Revealing the most optimal algorithms for predicting cryptocurrency returns:

Erdinc et al. [5] identified that the most robust model for predicting cryptocurrencies future returns is support vector machines (SVM), which consequently is above 50% fits. Also, forecasting precision is not too volatile over different projection prospects. Moreover, the authors [6] results are tentative of the SVM's outstanding projection power, particularly during recessions. Hence, SVM can be considered effective for predicting cryptocurrencies prices.

On the other hand, the results of Vasiliy et al. [7] modeling of short cryptocurrency flow to the information illustrated the adequacy of utilizing models of neural systems, autoregression trees for estimating tasks. According to the results of the research, those models give an opportunity to make short-term predictions with sufficient precision: in the range of 3–4%. Furthermore, Sanjib et al. [8] concluded that the Rao algorithm (RA) and Artificial Neural Network (ANN) based prediction are sufficient to follow the active changes of cryptocurrencies compared to other predictions under examination. Their investigation proposed a new method for forecasting the every day categorization of cryptocurrency changes by the information of the price of gold for the next day. Other researchers [9] used neural networks for deciphering market volatility and got that almost all of the stochastic versions of the neural models surpassed the deterministic versions. Therefore, neural networks, regression trees, and RA are well suited for analyzing cryptocurrency returns.

At the same time, Mohammad [10] results showed that the gated recurrent unit algorithm (GRU) exceeded the bidirectional long short-term memory (bi-LSTM) at the same way as the ordinary LSTM with prediction for all types of cryptocurrency and models. However, Joseph et al. [11] got results that demonstrated that the suggested LSTM model surpassed the ordinary LSTM model. Thus, LSTM and GRU can be added to the list of the most optimal algorithms for predicting cryptocurrency price changes.

As a result, the most robust and efficient algorithms and methods for predicting cryptocurrency returns are SVM, RA, LSTM, GRU, regression trees, and neural networks.

C. Risk of Bias(Table I)

TABLE I
RISK OF BIAS

Source	Bias Description	Assessment
[1]	Low citability and no critical bias	Low
[2]	No limitations provided	Mid
[3]	Low citability and implicit method description	Low
[4]	Short description of limitations	Mid
[5]	Lack of new data	Mid
[6]	Limited by the time of research(during COVID-19 pandemic)	Mid
[7]	Lack of new data	Mid
[8]	Low citability	Low
[9]	Lack of critical bias	Low
[10]	No description of limitations	Mid
[11]	Short description of limitations	Mid

IV Discussion

A. *General interpretation of the results*

The findings of this study reveal some of the factors that effect the cryptocurrencies price changes and determine useful and powerful algorithms for foreseeing cryptocurrency returns. The research displays that cryptocurrency costs are influenced by a complex number of factors, including demand-side pressures, macroeconomic factors, and external events, such as climate change and social media trends. The list of the most efficient and reliable models for forecasting cryptocurrency price changes includes SVM, LSTM, GRU, and neural networks. These findings emphasize the importance of considering a wide range of factors in cryptocurrency analysis and the need to improve machine learning models to accurately predict cryptocurrency returns. In the case of comparing this study with other papers on a similar topic can be considered research of Erdinc et al. [4] the results of which partially coincide with the present review. Authors show that SVM is one of the most reliable and efficient algorithm for forecasting cryptocurrency returns. Results of the current literature review also include this method as one of the optimal for predicting cryptocurrency changes. Moreover, study of Farida et al. [4] defines social media trends as the reasons for cryptocurrency changes. Present literature review also contains such factor. On the other hand, can be noted the difference in results with the study of Helder and Pedro [2], in which authors came to the conclusion that there are no models that show strongly larger results than others, when the present survey proposes such algorithms and models.

B. *Limitations of the evidence in the review*

Nevertheless, almost all of the reviewed studies have a certain amount of bias and a lack of evidence. Part of sources have some explicit limitations, such as low citability and absence of critical bias, as mentioned in Table I. However, some studies have more specific limitations. For example, studies [4] and [9] lack new data, authors of these researches use old indicators and values of cryptocurrency prices (the latest are from 2018). This makes the results obtained not quite relevant and correct because the identified methods and algorithms may not work that efficiently with new data. The majority of the studies reviewed returns of three- five cryptocurrencies that can be not enough for particular models, but researchs [3], [11] ontain testing algorithms based on Bitcoin prices only. This is a limitation, because not all investors work only with bitcoin, and some of the models can work differently for various cryptocurrencies. Also, Esam et al. [6] examined cryptocurrency price changes only during COVID-19, which is biased and makes the work not really suitable for normal conditions. Moreover, many works also have the problem that the dataset was taken from only one market, but there may be glitches or erroneous data on the platform, and the data may be very slightly different across multiple marketplaces, which may ultimately affect the result that the model produces. In addition, the application of some algorithms and methods from the sources is situational and works differently for different currencies and at certain times, which strongly affects their accuracy. Future works can be improved by increasing objectivity, using newer information, and combining multiple algorithms and methods together. It is also possible to take datasets from different platforms and conduct research on more cryptocurrencies.

C. Limitations of the review process

The literature review also has some limitations. Firstly, only 11 sources were reviewed during the present study. Because of this, some methods and important facts may have been missed. Secondly, articles were searched only through Google Scholar. That could negatively affect the condition and variability of the sources. Thirdly, the analyzed algorithms and methods are not discussed in sufficient detail, which may lead to misunderstandings among readers and researchers. Finally, search strategy has a limitation of minor number of filters. That increased number of resources suggested by database, hence some valuable sources may have been missed.

D. Implications of the results

Obtained results may be useful for researchers and investors in cryptocurrencies. They provide the factors influencing cryptocurrency prices and the most efficient and robust machine learning algorithms for predicting these changes. The results of the present study can be useful for developing more accurate and reliable prediction models and methods, making new investment strategies, and evolving the field of cryptocurrency research. In addition, this literature review can be improved by using more databases for searching articles, drawing on more sources of information, and by reducing the bias. It would also be helpful for future researchers to be more knowledgeable about machine learning and cryptocurrencies when extending currently study and writing a new paper.

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