Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 222 (2023) 539–548

Procedia Computer Science

www.elsevier.com/locate/procedia

International Neural Network Society Workshop on Deep Learning Innovations and Applications (INNS DLIA 2023)

Maximizing portfolio profitability during a cryptocurrency downtrend: A Bitcoin Blockchain transaction-based approach

Esteban Wilfredo Vilca Zuniga[a], Caetano Mazzoni Ranieri[a,*], Liang Zhao[b], Jó Ueyama[a], Yu-tao Zhu[d], Donghong Ji[c]

[a] Institute of Mathematical and Computer Sciences, University of São Paulo, São Carlos, SP, Brazil
[b] Faculty of Philosophy, Sciences and Letters at Ribeirão Preto, University of São Paulo, Ribeirão Preto, SP Brazil
[c] School of Cyber Science and Engineering, Wuhan University, Wuhan, Hubei, China
[d] China Branch of the BRICS Institute of Future Networks, China

Abstract

The volatile and unpredictable nature of the cryptocurrency market makes it particularly challenging to make profitable investment decisions. Different machine learning-based techniques have been employed for forecasting cryptocurrency value. However, although some works have addressed incorporating the Blockchain transactions' data into the analysis, none of them has provided a hybrid solution, including features obtained through complex network modeling. In this paper, we investigated the use of machine learning and complex network techniques to improve the profitability of a cryptocurrency portfolio during a downtrend period. We extracted features through a complex network-building methodology based on the Bitcoin blockchain transactions, merged them with the historical cryptocurrency values, and generated the predictions using different machine-learning models. The results indicated that incorporating complex network features improved the performance in retaining the initial capital at the end of the experiment, leading to an increment of 7.09% and 4.33% for the CNN and LSTM models, respectively. Our findings suggest that the proposed method enhanced the performance of cryptocurrency investment strategies during downtrend periods.

Keywords: Blockchain; Complex networks; Cryptocurrency forecasting; Deep learning

1. Introduction

In recent years, the expansion of cryptocurrency markets has drawn the attention of investors and financial institutions alike [6]. Among the most well-known and widely traded cryptocurrencies is Bitcoin [17], which has exhibited significant fluctuations in value and adoption since its advent in 2009. As with any financial market, maximizing

* Corresponding author. Tel.: +55-16-3373-9997.
E-mail address: cmranieri@usp.br

1877-0509
10.1016/j.procs.2023.08.192

profitability during times of downturn can be a challenge for investors. In this context, machine learning techniques, such as neural networks, for analyzing and forecasting market trends have gained popularity in identifying profitable investment opportunities [23].

One area of particular interest is the analysis of Bitcoin blockchain transactions to understand market behavior and identify profitable investment strategies. The Bitcoin blockchain can be viewed as a complex network [12], with the nodes representing individual transactions and the edges representing their interactions. By analyzing the structure and evolution of this network using tools such as network metrics and machine learning techniques, it may be possible to gain insights into market trends and inform investment decisions.

Due to market volatility and complexity, cryptocurrency prediction using machine learning has gained interest. Previous studies have evaluated DL models, including CNN, Deep Forward Neural Networks, and Gated Recurrent Units, and boosted tree-based techniques. Also, they proposed a new approach to reveal Bitcoin's price changes by analyzing blockchain transaction patterns. In contrast, others proposed a crypto asset futures market price prediction model using Random Forest and incorporating candlestick patterns. The prior research has shown potential for machine learning in cryptocurrency prediction, but there is room for improvement and future research should focus on developing more advanced models.

In this study, we present a novel method for improving the profitability of cryptocurrency investment portfolios during market downturns. By combining the analysis of Bitcoin blockchain transactions and the use of machine learning techniques, specifically neural networks, we aim to contribute to the growing body of research on the application of these methods in the cryptocurrency market. Our method provides practical guidance for investors seeking to maximize their returns in challenging market conditions.

The blockchain transaction analysis allows us to gain insight into the relationships between transactions and investment profitability. Our focus on maximizing profitability allows for effective risk management strategies, while using deep neural networks enhances the accuracy of market predictions, providing increased reliability. Furthermore, our evaluation of profitability during market downturns provides valuable information for investors during times of instability.

2. Background

Cryptocurrencies, such as Bitcoin and Ethereum, are digital assets that use cryptography to secure financial transactions in a distributed ledger using Blockchain technology [7]. These currencies operate on a peer-to-peer network, making them a unique asset class with volatile prices that can be difficult to predict. Traditionally, financial analysts have used fundamental and technical analysis to predict the price of cryptocurrencies [29]. However, these methods can be limited in accurately predicting the highly volatile and complex cryptocurrency market.

Machine learning (ML) techniques have led to state-of-the-art performance on several tasks involving time series forecasting due to their ability to model long-term dependencies [14]. This ability makes them learn and adapt to changing market conditions. In this context, deep neural networks have been applied as a powerful tool for predicting the price of cryptocurrencies [4].

Along with other traditional ML techniques, the Multilayer Perceptron (MLP) can be modeled for analyzing time series data [8], which can be done by stacking a sequence of timesteps as independent input variables. However, recent work has focused on deep learning architectures such as Convolutional Neural Networks (CNN) [15, 24] and Long Sort-Term Memory (LSTM) [5, 30, 10]. Researchers have built deep learning models to gather, analyze and make predictions on raw data of digital currencies, such as Bitcoin, digital cash, and ripple [11], with excellent results.

In this work, we are concerned with complex networks' role in modeling cryptocurrencies' transaction data to generate helpful representations for building deep learning models aimed at profit maximization in a buy-and-sell strategy. Complex networks are characterized by their intricate connections and patterns, which can emerge from the interactions of their constituent elements [3]. In the field of cryptocurrency, the Bitcoin blockchain can be viewed as a complex network, with the nodes representing individual transactions and the edges representing the interactions between them [2]. A variety of complex network metrics can be used to analyze the structure and evolution of the Bitcoin blockchain and its interactions with other complex networks, such as assortativity and the Wiener index [27].

The analysis of complex networks can also be helpful in understanding the price and volatility of cryptocurrencies. By examining these systems' underlying network structures and dynamics, researchers can gain insights into factors that may affect the demand for and value of different cryptocurrencies. These insights can help to inform investment strategies and risk management techniques for dealing with the often volatile nature of these markets [18].

3. Related Work

The Bitcoin blockchain analysis has received considerable attention from the research community to understand the underlying transactions and patterns within the cryptocurrency. Researchers have employed various techniques, including network analysis, to gain insights from the Bitcoin blockchain [9, 28].

There has been a surge of interest in using machine learning techniques to predict the cryptocurrency market's behavior. This is due to the volatility and complexity of the market, which makes conventional techniques insufficient. Progress has been achieved using techniques for financial time series forecasting [22, 21]. Nonetheless, deep learning architectures have been predominant in recent research [26].

Oyedele *et al.* [20] evaluated the performance of deep learning models, including Convolutional Neural Networks (CNN), Deep Forward Neural Networks (DNN), and Gated Recurrent Units (GRU). The authors boosted tree-based techniques in predicting the closing prices of several cryptocurrencies. The study used six datasets from multiple sources and evaluated the models with relevant performance metrics. The results showed that the CNN model had the lowest mean average percentage error and a consistently high explained variance score, making it a more reliable option for predicting daily closing prices with limited training data.

An approach based on recurrent neural networks was presented by Liu *et al.* [16]. The authors proposed a deep learning structural time series model that considers dependencies among multiple correlated time series and extracts weighted differencing features for better trend learning. A spatial attention mechanism was also considered.

Li *et al.* [13] focused on predicting the changes in Bitcoin's price by analyzing its blockchain transaction patterns. The authors proposed a new approach that involves k-order transaction subgraphs to capture the patterns and a Multi-Window Prediction Framework based on machine learning models to learn the relationship between the patterns and Bitcoin prices. The results showed that the transaction patterns effectively capture price changes and the Multi-Window Prediction Framework outperforms other methods in integrating submodels trained on different historical periods.

Orte *et al.* [19] proposed a crypto asset futures market price prediction model using Random Forest. The authors evaluated three scenarios based on input variables: technical indicators, candlestick patterns, and a combination of both. The results showed that incorporating candlestick patterns improved the model's efficiency. The authors also conducted a one-year out-of-sample prediction and analyzed the simulation as a real-life operation, with the model being retrained after each new data collection.

Regarding complex networks' analysis, Serena *et al.* [25] utilized them to identify patterns in the transaction data of the Bitcoin blockchain. The authors demonstrated the potential for using such techniques to understand the underlying structure and behavior of the Bitcoin network. Overall, the analysis of the Bitcoin blockchain using techniques such as complex network analysis and machine learning has the potential to provide valuable insights into the functioning and behavior of the cryptocurrency.

Our proposed method combines these prior works by analyzing pre-processed blockchain transactions to provide insight into the patterns and relationships between transactions and the profitability of cryptocurrency investments. Utilizing deep neural networks, our study will prioritize profitability as the primary objective and evaluate the results during a strong downtrend.

4. Methodology

Our methodology is presented in Figure 1 and described in the next subsections.

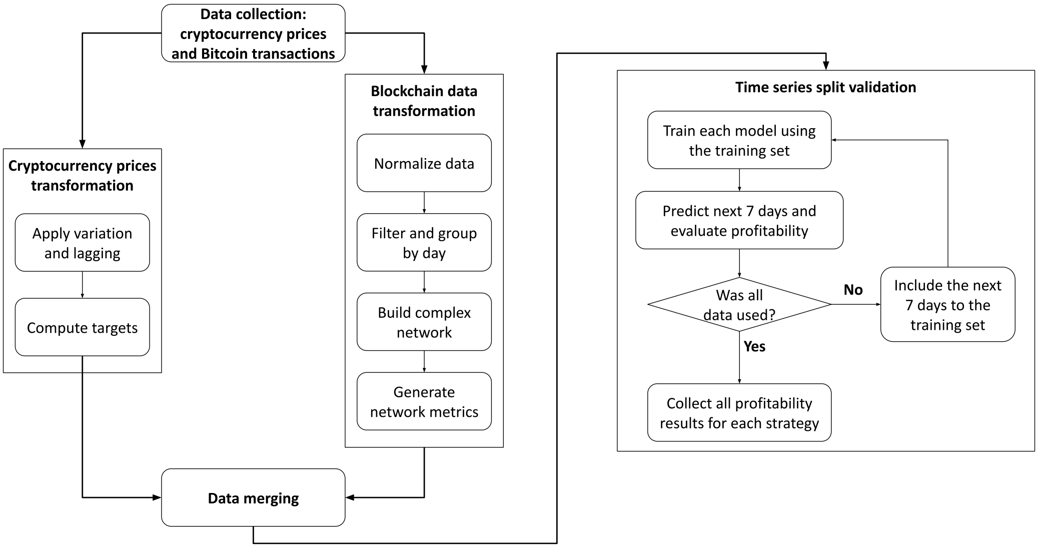


Fig. 1: Pipeline of our methodology. Historical data from the cryptocurrency value is preprocessed in parallel with the blockchain transaction data. The resulting features are then synchronized and merged so that the machine-learning models can be trained and evaluated.

4.1. Data Collection

In this study, we utilized daily closing price data for three cryptocurrencies (i.e., BTC, ETH, and MATIC) obtained from the Binance exchange [1]. In addition, we sourced information on sales transactions from the Bitcoin blockchain to provide additional input for our algorithms.

4.1.1. Cryptocurrency prices

We utilized cryptocurrency data from Binance covering the time frame of the 1st of January 2022 to the 1st of January 2023. The selection of this time frame was motivated by the notable decrease in prices observed during this period, which posed a significant challenge for maintaining or increasing value. The attributes registered were the final prices of BTC, ETH and MATIC at the end of each day, which we called “Close BTC”, “Close ETH”, and “Close MATIC”.

4.1.2. Blockchain data analysis

We collected transaction data from the Bitcoin blockchain involving transactions. Given its high capitalization, Bitcoin was the primary focus of this data collection. Specifically, we aimed to capture the interactions between wallets, the quantity of BTC transferred, and the number of transactions recorded per day. By examining these factors, we sought insights into the behavior and dynamics of the cryptocurrency price variation.

4.2. Cryptocurrency Prices Transformation

We applied the following strategies for preparing the data related to cryptocurrency values over time before merging such data with the blockchain data (transformed according to the steps devised in Section 4.3).

4.2.1. Variation and Lagging Application

Since this research aimed to optimize staking rewards’ profitability, we examined price variations instead of the raw cryptocurrency value at each timestep. The objective was to predict potential gains and compare the profitability of different assets. The price variation between timesteps t and $t-1$ were normalized by the price at $t-1$.

[1] https://www.binance.com/, accessed on the 24 of January 2023

We employed a lagged approach to utilize historical data for forecasting future outcomes. The approach involves introducing information from a specified number of previous days as inputs for the algorithm. In exploratory experiments, we considered using different numbers of days of historical data as inputs. We investigated the effect of varying the number of lagged days, with values ranging from 2 to 10. The results indicate that incorporating more than five lagged days did not improve performance.

4.2.2. Target Computation

To obtain the maximum profitability among the cryptocurrencies BTC, ETH, MATIC at the end of each day, we identified the cryptocurrency with the highest price variation at the end of the day. We used it as the target for the next day. For example, if on the 2 of February 2022, the price variations were 0.1% for BTC, -0.1% for ETH, and 0.01% for MATIC, the target for the 1st of February 2022 would be BTC. The resulting dataset included a column with the daily target, representing the cryptocurrency with the highest price variation. This procedure is illustrated in Figure 2.

BTC	ETH	MATIC	Target
0.1%	0.3%	0.1%	BTC
0.1%	-0.3%	-0.8%	MATIC
0.3%	0.8%	2.0%	

Fig. 2: Example for the target computation.

4.3. Blockchain Data Transformation

Daily a high number of transactions are made using the Bitcoin blockchain. Usually, the Bitcoin blockchain registers about 230,000 transactions daily [1]. In each transaction, there are wallets, a unique identifier for a sender or receiver of Bitcoin. Different types of transactions may be performed, such as one wallet sending values to another wallet, many wallets sending values to a unique wallet, or a wallet sending values to many others.

Before being merged with the cryptocurrency prices, the transactions' data needed to be prepared, modeled as a complex network, and had its metrics computed before (see Secion 4.2. The steps employed are described as follows.

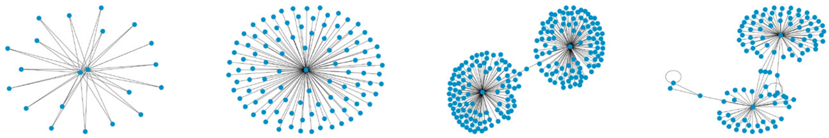
Data Normalization: to ensure compatibility with the neural networks utilized in this experiment, it was necessary to normalize the data. In this study, we employed min-max normalization, which performed best in exploratory experiments.

Transactions' Filtering: we collected all the transaction information in the defined date range. Then, we filtered all the transactions with less than 1,000 BTC movement. We employed this approach because small quantities of BTC usually do not affect the prices of cryptocurrencies. We created a dataset by collecting all the transactions that occurred during each day. An array containing all the transaction information for each day was constructed for this aim. The transactions were grouped by day, but other time intervals, such as 4 hours, one hour, or a week, could also be used for grouping.

Complex Network Building: we constructed the transaction graphs for each day by (i) creating a node for each wallet present in the transactions of that day; (ii) linking these nodes based on the movement of funds by connecting wallets that send money to other wallets; and (iii) detecting sub-graphs within the larger graph to identify instances of a wallet collecting BTC from other wallets and then sending it to another wallet to evade tracking.

The price of cryptocurrencies changes in response to the engagement of individuals in buying or selling activities, which affects the market price. The interconnectedness of these wallets, or their topology, can provide insight into the intentions and actions of investors. For example, there were several transactions with intricate structures on the 18 of October 2022, as demonstrated in Figure 3.

Network Metrics Generation: the network generated from the previous steps is disconnected due to transactions that do not have a relationship between the wallets. Therefore, we calculated the metrics for each subgraph separately and then obtained the average of these metrics. From the graph generated for each day's previous step, we obtained the assortativity, the Wiener index, the Average Shortest Path Length (ASPL), the number of graphs generated and the quantity of BTC moved in all transactions.



(a) A small number of wallets sends money to two wallets.

(b) Many wallets send money to one wallet.

(c) A large group of wallets sends money to another large group.

(d) A large group of wallets sends money to a smaller group.

Fig. 3: Graph of the transactions with more than 1000 BTC in the Bitcoin blockchain network on the 18 of October 2022.

Data Merging: after organizing the cryptocurrency prices and the blockchain metrics datasets by day and converting them, we merged them using the date as the key. The resulting feature vector was composed of the following attributes, both at the most recent timestamp and lagged i times: the close prices of each cryptocurrency (BTC, ETH, and MATIC), the average assortativity, the Wiener index, the ASPL, the numbers of graphs, and the amount of BTC moved.

4.4. Time series split validation

The following strategy was implemented for time series split validation:

1. The algorithms were trained using 150 days of data, and the profitability of the subsequent seven days was tested.
2. In the next iteration, the initial seven days with the best target were added to the training data, and the profitability of the subsequent seven days was tested.
3. If not all data was used, go back to step 1.
4. The average and standard deviation of profitability across all iterations were calculated.

Performance Evaluation Criteria: a common strategy for cryptocurrency investment is to hold assets for an extended period of time. However, this approach can lead to significant losses, as seen in our preliminary analysis, in which a holding strategy resulted in a 53% loss of initial value in USD. This performance is calculated using the price variation of BTC over the test period. Specifically, the weekly depreciation of the value of BTC in dollars is calculated, with a final decrease from 35868 to 16858, representing a loss of 53%. By implementing a buy-and-sell strategy between assets, we aim to increase the final value of our assets in USD.

To achieve this goal, we employed neural networks to predict the best assets for the next day based on their variation. The neural network was trained to identify assets with the highest variation and subsequently buy them. We used the Mean Absolute Error (MAE) as the loss function to optimize the neural network. Besides the MAE, we evaluated the average profitability of the model at the end of the experiment, according to Equation 1, where r_i is the rentability of the predicted best variation in the day i and N is the number of rows evaluated. The rentability can be expressed in Equation 2, where v_i is the variation of the cryptocurrency selected and r_{i-1} is the previous rentability. If the model can predict the target accurately, its profitability will increase as it can select digital assets with higher variations in price.

$$R = \frac{1}{N}\sum_{i=1}^{N}(r_i) \tag{1}$$

$$\begin{cases} r_i = r_{i-1} * (v_i + 1) & \text{if } i > 0 \\ r_i = 1.0 & \text{if } i = 0 \end{cases} \tag{2}$$

5. Results

As already mentioned, we compared three types of neural networks: Multi Layer Perceptron (MLP), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). The BTC hold strategy performance was considered as a baseline. We trained the neural networks using the Adam optimizer with learning rate of 0.001 and beta1 of 0.9 and beta2 of 0.999, and the MAE loss function. The architectures designed for each of them and are described as follows:

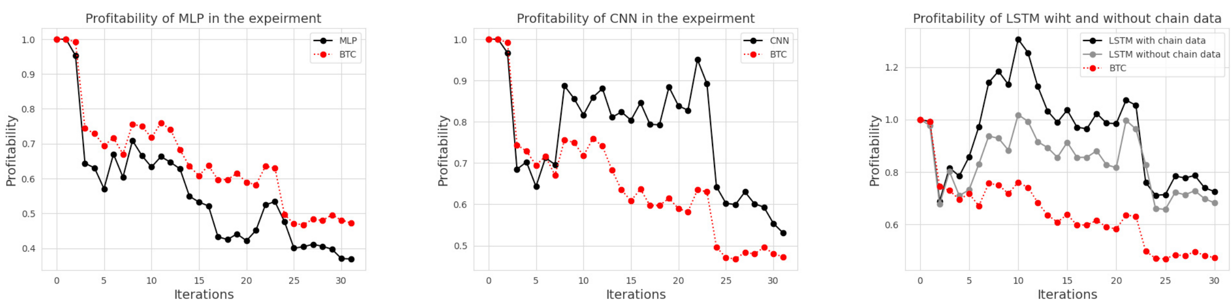
- **MLP**: we considered 1-6 hidden layers, each containing 2-32 neurons and using the hyperbolic tangent activation function, except for the last layer, which used a linear activation function. Although increasing the number of neurons decreased the MAE, it also reduced profitability. The best MLP model had 4 neurons and 1 hidden layer, running for 20 epochs.
- **CNN**: we considered 2-32 filter nodes and 1-4 fully connected layers containing 2-32 nodes. Again, increasing the complexity of the neural network decreased profitability. The best CNN model had 16 filter nodes and 1 hidden layer with 32 neurons, running for 20 epochs.
- **LSTM**: we considered 2-32 memory cells and 1-4 fully connected layers containing 2-32 nodes. As with the previous models, increasing complexity reduced profitability. The best LSTM model had 8 memory cells and 1 hidden layer with 8 neurons, running for 20 epochs.

Across all experiments, we found that increasing the complexity of the neural network structure led to overfitting, resulting in lower MAE but decreased profitability at the end of the experiment. The best results were obtained with smaller network structures.

5.1. Profitability

As previously mentioned, we used 150 days of data to train our model and iterated the process every seven days. The profitability of each model over the course of the experiment can be seen in Figure 4.

The MLP model (Figure 4a) led to inferior results for the whole series compared to the buy-and-hold strategy. On the other hand, the CNN (Figure 4b) and LSTM (Figure 4c) models were superior starting from around iteration 5. The LSTM model was the only one that eventually led to actual profit (see the graph around iteration 10).



(a) MLP predictions. (b) CNN predictions. (c) LSTM predictions.

Fig. 4: Profitability over time of each model compared to the BTC buy-and-hold strategy.

Although the overall profitability at the end of the experiment was negative for all cases, it is crucial to consider that a significant downward trend characterized the selected time frame. Therefore, any algorithm that can preserve the portfolio's value under these conditions is valuable. Nonetheless, the CNN and LSTM results were superior to the buy-and-hold strategy considered as the baseline and shown in the graphs.

Another essential metric to consider is the average profitability of the algorithms across the experiments. Table 1 shows that the LSTM algorithm has the highest average performance.

Table 1: The average capital maintained for each iteration, considering each model.

Model	Average capital maintained
MLP	97.49 %
CNN	98.49 %
LSTM	99.56 %

5.2. The chain analysis importance

Another objective of this study was to incorporate data from the Bitcoin blockchain into the analysis to enhance the algorithms' performance. The table below illustrates the performance of the algorithms with and without the inclusion of chain data.

Table 2: Capital maintained at the end of the experiment, considering each model with or without the chain data.

Model	With chain data	Without chain data
MLP	36.93 %	49.94 %
CNN	53.11 %	46.02 %
LSTM	72.50 %	68.17 %

Including the chain data improved the performance of the CNN and LSTM architectures by 7.09% and 4.33%, respectively. However, it reduced led to less accurate results for the MLP, with a 10.01% decrease in accuracy. Comparing the results with the chain data, the MLP model provided the less accurate performance, with only 36.93% of the initial capital remaining. In comparison, the BTC hold strategy, which maintained 47% of the initial capital, had better performance than the best MLP combination. However, the CNN model demonstrated better performance, retaining 53% of the initial capital. The LSTM model demonstrated the most accurate performance, with 72.50% of the initial capital remaining at the end of the experiment. This algorithm also exhibited a more extended period of positive profitability.

6. Discussion

During the time frame under examination, we observed a marked downward trend in the value of Bitcoin denominated in US dollars, which declined from $47,286$ to $16,858$, resulting in a decrease of 64.34%. This trend was consistent with broader market conditions in the cryptocurrency and technology sectors, including Facebook. Our algorithm, however, demonstrated its efficacy in mitigating the impact of such a trend on the USD value of cryptocurrencies by implementing a proposed buying and selling strategy. This outcome is a valuable resource for potential investors.

We leveraged transaction data from the Bitcoin blockchain to enhance profitability and incorporated complex network metrics in our analysis. This approach markedly improved the performance of the LSTM neural network utilized in our analysis. Furthermore, our observations indicate that following significant price movements, complex structures emerge within the Bitcoin blockchain, suggesting a tendency among large currency holders to consolidate their investments into long-term wallets. This strategy could reduce risk and maximize returns in the long run.

To optimize investment strategies for the subsequent day, we employed various neural network models that incorporated both blockchain and price data and a training strategy aimed at mitigating overfitting. This approach builds upon prior studies and highlights the importance of utilizing complex network metrics in informed investment decisions in the cryptocurrency market.

The LSTM model was the most successful, possibly because of its enhanced ability to model long-term dependencies. When the chain data was included, it even provided a peak in which a 20% profit could be observed around iterations 10 and 21, while the buy-and-hold strategy still yielded consistent loss. The CNN model provided a recovery period around iteration 22, where the loss could be almost neutralized. However, all strategies led to a loss at the end of the experiment. Both the CNN and LSTM models (with or without the chain data) improved performance compared to the buy-and-hold strategy.

7. Conclusion

In this research, we aimed to examine the feasibility of using machine learning to enhance the profitability of cryptocurrency investments during a downturn. Specifically, we focused on analyzing Bitcoin blockchain transactions to extract market information and identify profitable investment strategies. The complex network structure of the Bitcoin blockchain was taken into account, where transactions were represented as nodes and interactions as edges.

Three machine learning algorithms were used and compared to a simple hold strategy for Bitcoin (BTC): Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), and Long Short-term Memory (LSTM). Our findings showed that the more complex the algorithm, the higher the likelihood of overfitting, resulting in decreased profitability. The best performance was achieved by the LSTM algorithm, which retained 72.50% of the initial capital and showed a period of positive profitability. The CNN algorithm also outperformed the hold strategy, retaining 53.11% of the initial capital. Meanwhile, the MLP algorithm had the worst performance, with only 36.93% of the initial capital remaining. The results also indicated that incorporating blockchain data into the analysis improved the performance of the CNN and LSTM algorithms.

Our research highlights the potential for using machine learning techniques, specifically the LSTM algorithm and considering the complex network structure of the blockchain, to optimize the profitability of cryptocurrency investments during market downturns. This information could be valuable for investors looking to maximize returns in challenging market conditions. Further research could consider other blockchains, such as Ethereum, and the use of leverage and short strategies for enhancing profitability. By expanding the analysis, it may be possible to identify even more profitable investment strategies for the cryptocurrency market.

Acknowledgements

The authors of this work would like to thank the Center for Artificial Intelligence (C4AI-USP) and the support from the São Paulo Research Foundation (FAPESP grant #2019/07665-4) and from the IBM Corporation. This work was also funded by FAPESP grants #2021/10921-2 and #2013/07375-0.

References

[1] , . Charts - confirmed transactions per day. URL: https://www.blockchain.com/explorer/charts/n-transactions.

[2] Barabási, A.L., Pósfai, M., 2016. Network science. Cambridge University Press, Cambridge. URL: http://barabasi.com/networksciencebook/.

[3] Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., Hwang, D.U., 2006. Complex networks: Structure and dynamics. Physics reports 424, 175–308.

[4] Christoforou, E., Emiris, I.Z., Florakis, A., 2020. Neural networks for cryptocurrency evaluation and price fluctuation forecasting, in: Mathematical research for blockchain economy. Springer, pp. 133–149.

[5] D'Amato, V., Levantesi, S., Piscopo, G., 2022. Deep learning in predicting cryptocurrency volatility. Physica A: Statistical Mechanics and its Applications 596, 127158. URL: https://www.sciencedirect.com/science/article/pii/S0378437122001704, doi:https://doi.org/10.1016/j.physa.2022.127158.

[6] Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., Li, L., 2022. Cryptocurrency trading: a comprehensive survey. Financial Innovation 8, 1–59. doi:https://doi.org/10.1186/s40854-021-00321-6.

[7] Härdle, W.K., Harvey, C.R., Reule, R.C., 2020. Understanding cryptocurrencies. Journal of Financial Econometrics 18, 181–208. doi:https://doi.org/10.1093/jjfinec/nbz033.

[8] Ibrahim, A., Kashef, R., Corrigan, L., 2021. Predicting market movement direction for bitcoin: A comparison of time series modeling methods. Computers & Electrical Engineering 89, 106905. URL: https://www.sciencedirect.com/science/article/pii/S0045790620307576, doi:https://doi.org/10.1016/j.compeleceng.2020.106905.

[9] Khan, A., 2022. Graph analysis of the ethereum blockchain data: A survey of datasets, methods, and future work, in: 2022 IEEE International Conference on Blockchain (Blockchain), pp. 250–257. doi:10.1109/Blockchain55522.2022.00042.

[10] Kwon, D.H., Kim, J.B., Heo, J.S., Kim, C.M., Han, Y.H., 2019. Time series classification of cryptocurrency price trend based on a recurrent lstm neural network. Journal of Information Processing Systems 15, 694–706.

[11] Lahmiri, S., Bekiros, S., 2019. Cryptocurrency forecasting with deep learning chaotic neural networks. Chaos, Solitons, Fractals 118, 35–40. URL: https://www.sciencedirect.com/science/article/pii/S0960077918310233, doi:https://doi.org/10.1016/j.chaos.2018.11.014.

[12] Li, P., Li, K., Wang, Y., Zheng, Y., Wang, D., Yang, G., Yu, X., 2022. A systematic mapping study for blockchain based on complex network. Concurrency and Computation: Practice and Experience 34, e5712. doi:https://doi.org/10.1002/cpe.5712.

[13] Li, X., Du, L., 2022. Bitcoin daily price prediction through understanding blockchain transaction pattern with machine learning methods. Journal of Combinatorial Optimization 45, 4. URL: https://doi.org/10.1007/s10878-022-00949-9, doi:10.1007/s10878-022-00949-9.

[14] Lim, B., Zohren, S., 2021. Time-series forecasting with deep learning: a survey. Philosophical Transactions of the Royal Society A 379, 20200209. doi:https://doi.org/10.1098/rsta.2020.0209.

[15] Liu, C.L., Hsaio, W.H., Tu, Y.C., 2019. Time series classification with multivariate convolutional neural network. IEEE Transactions on Industrial Electronics 66, 4788–4797. doi:10.1109/TIE.2018.2864702.

[16] Liu, Y., Gong, C., Yang, L., Chen, Y., 2020. Dstp-rnn: A dual-stage two-phase attention-based recurrent neural network for long-term and multivariate time series prediction. Expert Systems with Applications 143, 113082. doi:https://doi.org/10.1016/j.eswa.2019.113082.

[17] Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. Decentralized Business Review , 21260.

[18] Nava-Solis, A.R., Treviño-Saldívar, E.J., 2022. On-chain metrics and technical analysis in cryptocurrency markets, in: Rodríguez García, M.d.P., Cortez Alejandro, K.A., Merigó, J.M., Terceño-Gómez, A., Sorrosal Forradellas, M.T., Kacprzyk, J. (Eds.), Digital Era and Fuzzy Applications in Management and Economy, Springer International Publishing, Cham. pp. 122–129.

[19] Orte, F., Mira, J., Sánchez, M.J., Solana, P., 2023. A random forest-based model for crypto asset forecasts in futures markets with out-of-sample prediction. Research in International Business and Finance 64, 101829. URL: https://www.sciencedirect.com/science/article/pii/S027553192200215X, doi:https://doi.org/10.1016/j.ribaf.2022.101829.

[20] Oyedele, A.A., Ajayi, A.O., Oyedelec, L.O., Bello, S.A., Jimoh, K.O., 2022. Performance evaluation of deep learning and boosted trees for cryptocurrency closing price prediction. Expert Systems with Applications , 119233URL: https://www.sciencedirect.com/science/article/pii/S0957417422022515, doi:https://doi.org/10.1016/j.eswa.2022.119233.

[21] Rathore, R.K., Mishra, D., Mehra, P.S., Pal, O., HASHIM, A.S., Shapi'i, A., Ciano, T., Shutaywi, M., 2022. Real-world model for bitcoin price prediction. Information Processing Management 59, 102968. URL: https://www.sciencedirect.com/science/article/pii/S030645732200084X, doi:https://doi.org/10.1016/j.ipm.2022.102968.

[22] Ratre, S., Jayaraj, J., 2023. Sales prediction using arima, facebook's prophet and xgboost model of machine learning, in: Doriya, R., Soni, B., Shukla, A., Gao, X.Z. (Eds.), Machine Learning, Image Processing, Network Security and Data Sciences, Springer Nature Singapore, Singapore. pp. 101–111.

[23] Ren, Y.S., Ma, C.Q., Kong, X.L., Baltas, K., Zureigat, Q., 2022. Past, present, and future of the application of machine learning in cryptocurrency research. Research in International Business and Finance 63, 101799. doi:https://doi.org/10.1016/j.ribaf.2022.101799.

[24] Sandhu, R., Parimala, G., Nithiya, S., 2022. Lstm and cnn based stock price prediction app, in: 2022 7th International Conference on Communication and Electronics Systems (ICCES), pp. 1594–1601. doi:10.1109/ICCES54183.2022.9835919.

[25] Serena, L., Ferretti, S., D'Angelo, G., 2022. Cryptocurrencies activity as a complex network: Analysis of transactions graphs. Peer-to-Peer Networking and Applications 15, 839–853. URL: https://doi.org/10.1007/s12083-021-01220-4, doi:10.1007/s12083-021-01220-4.

[26] Siami-Namini, S., Tavakoli, N., Namin, A.S., 2018. A comparison of arima and lstm in forecasting time series, in: 2018 17th IEEE international conference on machine learning and applications (ICMLA), IEEE. pp. 1394–1401.

[27] Silva, T., Zhao, L., 2016. Machine Learning in Complex Networks. Springer International Publishing. URL: https://books.google.com.br/books?id=WdDurQEACAAJ.

[28] Soska, K., Dong, J.D., Khodaverdian, A., Zetlin-Jones, A., Routledge, B., Christin, N., 2021. Towards understanding cryptocurrency derivatives:a case study of bitmex, in: Proceedings of the Web Conference 2021, Association for Computing Machinery, New York, NY, USA. p. 45–57. URL: https://doi.org/10.1145/3442381.3450059, doi:10.1145/3442381.3450059.

[29] Svogun, D., Bazán-Palomino, W., 2022. Technical analysis in cryptocurrency markets: Do transaction costs and bubbles matter? Journal of International Financial Markets, Institutions and Money 79, 101601. doi:https://doi.org/10.1016/j.intfin.2022.101601.

[30] Wu, C.H., Lu, C.C., Ma, Y.F., Lu, R.S., 2018. A new forecasting framework for bitcoin price with lstm, in: 2018 IEEE International Conference on Data Mining Workshops (ICDMW), IEEE. pp. 168–175.