

Prediction of Cryptocurrency Price Index Using Artificial Neural Networks: A Survey of the Literature

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ABSTRACT

This paper initially presents a brief overview of the cryptocurrency and its history. We discuss the novel nature of literature attempting to create hybrid artificial neural network models to predict prices of cryptocurrency. For the remaining majority of the paper, we present the details of various hybrid artificial neural networks that have successfully been implemented to predict cryptocurrency prices in the form of a survey. Comparison of methods and results follow in the results section.

Keywords: artificial neural networks, cryptocurrency prices, prediction survey.

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I. INTRODUCTION

While the primarily well-known cryptocurrency, Bitcoin, was created by Nakamoto (Nakamoto, 2008), the idea of such secured peer-to-peer blockchain-based digital currency had been around for the last few decades. Cryptographer David Chaum initially introduced the idea in a 1983 paper whose initiative was to enhance the security of credit card transactions through a virtual system (Chaum, 1983). He also founded the first cryptocurrency, DigiCash, which went bankrupt after a decade.

Despite the absence of rapid growth in the first few years after its launch, Bitcoin has been growing extremely rapidly since 2017. It has frequently been experiencing price hikes, therefore attracting numerous investors. Its popularity has grown to a level that in addition to many private companies, a country has recently announced to be accepting it as a form of payment. Not to mention, researchers from central banks have been analyzing and debating on it since at least 2014.

The major factor distinguishing Bitcoin from other types of currency is its decentralization. That is, unlike other currencies, Bitcoin transactions are not processed and/or supervised by any government. Its money supply increases over time, though not linearly, by a reward process called "mining". Computers engage in solving mathematical equations through brute force, receiving bitcoins as a reward. Indeed, the classic supply and demand laws determine the exchange rate of Bitcoin prices to other currencies.

Similar to any other financial process, bitcoin prices could be predicted by artificial neural network methods. While the history of implementation of artificial neural network methods to predict other financial processes (e.g., stocks prices) is lengthy, the literature of prediction of cryptocurrency prices is not as much due to its novel nature.

Despite, over the last few years a growing number of researchers have attempted to create hybrid models of artificial neural networks that predict the price and/or price volatility of cryptocurrency prices, with a major focus on Bitcoin. This survey paper presents a number of research papers attempting to do so as well as their results. Comparison of methods and results follow in the results section.

II. THE ISSUE OF VOLATILITY

As elaborated on throughout the paper, numerous hybrid combinations and configurations of artificial neural network algorithms have been actively used for forecasting time-series data of various natures over the past few decades. Such algorithms often perform with substantial success and efficiency depending on the nature and context of the data. Forecasting techniques have a wide usage among the vast engineering literature, as well as financial engineering and economics. However, a repetitive argument in criticism of using neural networks for financial time-series predictions deals with the volatility of the data (Ghashami *et al.*, 2021).

Accordingly, the volatile nature of the data as well as the dependency of such financial measures on real-life events and shocks, which are hard to predict by nature, play a significant role in determination of stocks market prices. Such criticism is similarly applicable to cryptocurrency exchange rates as well. Ghorbani and Korzeniowski (2020) exemplify such case. We refer to Andersen *et al.* (2003) for addressing the issue of forecasting realized volatility. They create a framework for forecasting high-frequency time-series data; and due to continuous-time arbitrage-free price processes and the quadratic variation theorem, formal links are established between realized volatility and the conditional covariance

matrix. The links are further examined using data from spot exchange rates of multiple currencies and are found to perform well through a simple long-memory Gaussian vector autoregressive for logarithmic daily model. While the results are specific to a simple Gaussian autoregressive model and tested for limited data, the results may hold for forecasting any intraday time-series data with high volatility. Though the concept lies beyond the scope of this paper, some similar literature establishes models to predict the volatility of cryptocurrency price data using artificial neural networks.

III. BASIC MODELS

Earlier scholar works in price prediction (including but not limited to cryptocurrency) use linear regression optimization methods. Saad *et al.* (2018) implemented multiple regression-based models to predict Bitcoin prices using pre-2017 data points. The authors also use data from prices of other cryptocurrencies (Ripple, Litecoin, Dash, Ethereum) and provide a correlation matrix of their prices using the Pearson method.

The methods provided in Saad *et al.* (2018) are linear regression, random forest, and gradient descent. Data from 2016-2017 is implemented in the models and yields the following results (Table 1). The results include Root Mean Squared Error (RMSE), Mean Absolute Error value (MAE), and accuracy. Any unsatisfactory results may be due to the nature of the aforementioned methods.

TABLE I: RESULTS OF EXPERIMENTS OF THE THREE MODELS USED IN SAAD *ET AL.* (2018)

Method	Accuracy	RMSE	MAE
Linear Regression	0.9944	0.0113	0.0060
Random Forest	0.9272	0.0407	0.0115
Gradient Decent	0.9401	0.0369	0.0113

IV. IMPLEMENTATION OF LONG-SHORT-TERM-MEMORY (LSTM)

The majority of papers have analyzed the prediction of Bitcoin prices in an ANN-LSTM setting using different data. Zhengyang *et al.* (2019) uses Bitcoin price data from August 2015 to June 2019 to do so. The artificial neural networks are trained by gradient based back-propagation algorithm. Relations below depict the mathematical framework for nodes.

$$node = f(\sum_{i=1}^n w_i x_i),$$

where

$$f_{node} = \frac{1}{1 + e^{-node}}$$

Architecture of the LSTM mechanism is given in Fig. 1.

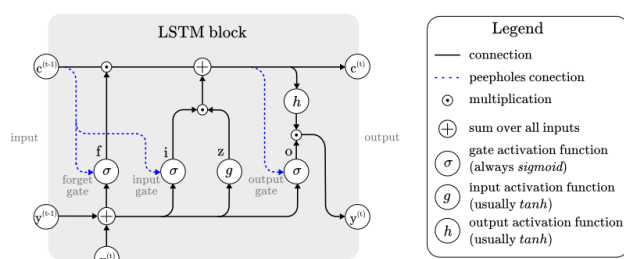


Fig. 1. Architecture of an LSTM block (Van Houdt *et al.*, 2020).

Zhengyang *et al.* (2019) uses multiple experiments that predict Bitcoin prices separately using ANN-LSTM, as well as a joint experiment of multiple cryptocurrencies. Accordingly, in the single prediction, with 20 nodes per layer and three layers in ANN, and training epoch number of 500 and batch size of 100 in LSTM, the model predicts a RMSE of 209 and a MAE of 99. In the LSTM single prediction, however, the RMSE and MAE values are 3894 and 2789, respectively. In the joint experiment, the resulting RMSE and MAE values are 137 and 30. The authors also argue that model error increases as the predictive time scale is larger.

A similar framework is used in Livieris *et al.* (2021), where the authors use a Convolutional Neural Networks (CNN) hybrid with LSTM to predict the prices of the three cryptocurrencies with highest market capitalization: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP). Their experiment implements three years (January 2017 to October 2020) of price data into a multiple-input deep neural network framework. The lags used in the experiment are 7 and 14 days, and the multiple models alter in the number of their convolutional layers (16 and 32, respectively) as well as the number of neurons in their dense layer (64 and 128, respectively). Finally, the MICDL model consists of 3 convolutional layers with 16 filters, each taking an input of a unique time-series data (average pooling of size 2), and a LSTM layer of 50 units. The experiment results are depicted in tables 2 through 4. Based on the data and further tests, the authors argue that MICDL is the most appropriate model in terms of performance prediction.

TABLE II: PERFORMANCE OF THE EVALUATED MODELS FOR ALL BTC DATA (LIVIERIS *ET AL.* 2021)

Model	Lag	MAE	RMSE	R-squared	Accuracy
1	7	169.81	256.68	0.953	55.03%
2		169.60	256.31	0.953	53.64%
MICDL		170.76	257.72	0.952	53.04%
1	14	171.29	262.33	0.950	53.53%
2		170.10	256.84	0.952	52.60%
MICDL		171.14	257.84	0.952	51.88%

TABLE III: PERFORMANCE OF THE EVALUATED MODELS FOR ALL ETH DATA (LIVIERIS *ET AL.* 2021)

Model	Lag	MAE	RMSE	R-squared	Accuracy
1	7	9.172	13.517	0.964	51.51%
2		9.302	13.591	0.964	48.85%
MICDL		9.233	13.551	0.964	50.86%
1	14	9.309	13.657	0.964	49.57%
2		9.196	13.539	0.964	50.38%
MICDL		9.146	13.492	0.964	51.11%

TABLE IV: PERFORMANCE OF THE EVALUATED MODELS FOR ALL XRP DATA (LIVIERIS *ET AL.* 2021)

Model	Lag	MAE	RMSE	R-squared	Accuracy
1	7	0.005	0.007	0.960	48.97%
2		0.005	0.007	0.958	49.61%
MICDL		0.005	0.007	0.958	49.07%
1	14	0.005	0.007	0.962	49.34%
2		0.006	0.009	0.936	49.23%
MICDL		0.007	0.009	0.953	49.23%

Another research paper with prediction models featuring LSTM is Jaquart *et al.* (2021). The paper focuses on short-term movement predictions of the cryptocurrency market and attempts the question using an LSTM and GRU (Gated Recurrent Units) approach. Their prediction horizon being 1-60 minutes, they provide cryptocurrency price data from 2019

in an extremely volatile period.

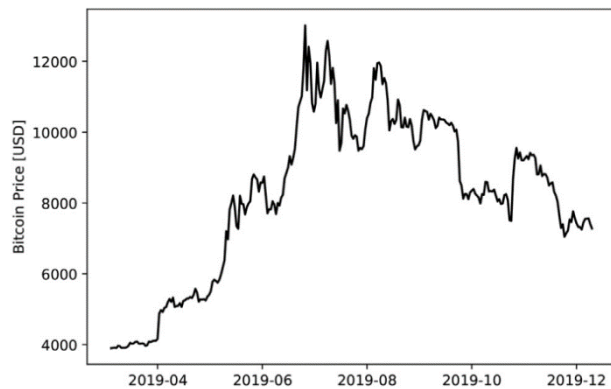


Fig. 2. Bitcoin price volatility in 2019 (Jaquart *et al.* 2021).

The model implements feedforward, LSTM and GRU, tree-based, and random forest artificial neural network techniques, with LSTM/GRU number of memory blocks of 64, 128, 256, and 512. Feedforward neural networks (FNN) process information in a single direct

ion, with three layers of input, a variable number of hidden layers, and an output layer. The activation function in equation 3 determines the result. Here, $g(n)$ is the activation function, $W(n)$ is the weight matrix for the connections between layer $n - 1$ and layer n , and $b(n)$ is the bias for layer n . The recurrent neural network model used is depicted in Fig. 3. Finally, the accuracy results are given in Table V.

$$a(n) = g(n) (W(n)^T a(n-1) + b(n))$$

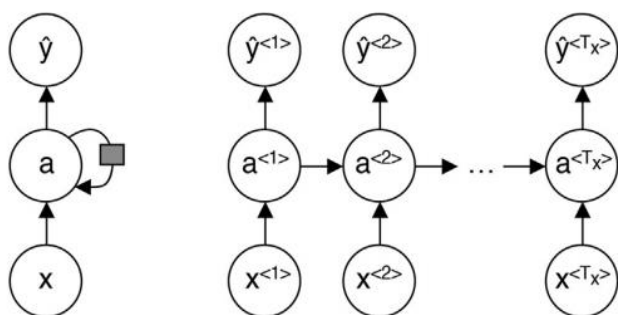


Fig. 3. RNN Structure. Jaquart *et al.* (2021).

TABLE V: ACCURACY OVERVIEW AMONG METHODS JAQUART *ET AL.* (2021).

Model	1-Min Pred.	5-Min Pred.	15-Min Pred.	60-Min Pred.
GRU	0.518411	0.524562	0.536490	0.556653
LSTM	0.519286	0.524931	0.531967	0.560067
FNN	0.509438	0.521988	0.520820	0.529587
LR	0.511272	0.517926	0.519595	0.538552
GBC	0.511093	0.529268	0.537282	0.557026
RF	0.511947	0.526662	0.534641	0.556356
E (All)	0.514626	0.526092	0.537863	0.557579

Using the accuracies and binomial distribution, the authors provide the probability of prediction models to have a true accuracy of 50% in Table V. In conclusion, they argue that RNN and GBC models are the most appropriate for predicting the short-term bitcoin market.

TABLE VI: BINOMIAL PROBABILITIES FOR TRUE MODEL ACCURACY OF 50% (JAQUART *ET AL.* (2021)).

Model	1-Min Pred.	5-Min Pred.	15-Min Pred.	60-Min Pred.
GRU	4.18E-30	5.66E-52	6.19E-11	8.44E-265
LSTM	7.65E-33	1.75E-53	1.99E-86	2.28E-297
FNN	3.08E-09	4.64E-42	7.17E-38	7.02E-74
LR	1.92E-12	1.26E-28	8.99E-34	6.90E-124
GBC	4.18E-12	6.67E-73	9.47E-12	2.93E-268
RF	9.31E-14	7.30E-61	4.23E-10	4.75E-262
E (All)	1.05E-19	2.22E-58	2.40E-12	1.94E-273

V. IMPLEMENTATION OF GENERAL ALGORITHMS

A subgroup of literature attempt to predict cryptocurrency prices using hybrid techniques of General Algorithms. Here, Radityo *et al.* (2017), and Sin *et al.* (2017) are briefly discussed. The former employs backpropagation neural network (BPNN), genetic algorithm neural network (GANN), genetic algorithm, backpropagation neural network (GABPNN), and neuro-evolution of augmenting topologies (NEAT). The complete results of experiments in Radityo *et al.* (2017) are given in Table VII.

TABLE VII: RESULTS OF BPNN, GANN, GABPNN, NEAT EXPERIMENTS (RADITYO *ET AL.* 2017).

Method	MAPE	Training Time (s)
BPNN	1.998 ± 0.038	347 ± 63
GANN	4.461 ± 0.49	467 ± 345
GABPNN	1.883 ± 0.066	1539 ± 558
NEAT	2.175 ± 0.096	470 ± 363

In Sin *et al.* (2017), a hybrid model of Genetic Algorithm based Selective Neural Network Ensemble (GASEN) is implemented to predict the next day change in the direction of the price of Bitcoin. Used data spans 2 years of time-series Bitcoin prices, and the number of epochs for each MLP was set as 30. The authors report the classification function to be represented by relation 4. Accordingly, the results are satisfactory in the sense that using the certain given datapoints, a simulation of investment would yield positive profit. They further report that GASEN was able to perform with a “consistent accuracy of around 58% to 63%” (Sin *et al.* 2017).

$$y = \frac{2}{1 + e^{-2x}} - 1$$

VI. GREY SYSTEM THEORY

Grey system theory is an optimization method using a first-order differential equation to model the time-series data trend of nonlinear nature. GM (n, m) refers to a grey prediction model with n degrees of differential equations and m variables. Faghih Mohammadi Jalali *et al.* (2020) uses a GM (1,1), namely a classical grey model to predict Bitcoin prices and measure efficiency of their proposed method. In order to more accurately depict results, they divide the data into 8 parts and attempt to compute predictions separately. The first five parts each consist of 4 days of time-series data, and the latter three parts each consist of 6 months of time-series data. For the former set of groups, the resulting MAPE values are 0.34%, 1.66%, 1.04%, 1.13%, and 0.22%, respectively. For the latter set of groups, the resulting MAPE values are

13.67%, 15.60%, and 9.45% respectively. Due to the strong MAPE resulting values, the authors find the results significant. They further argue that non-statistical methods such as grey system theory are suitable for prediction of such prices.

VII. DISCUSSION AND CONCLUSION

As shown in the previous sections, the purpose of this survey paper is to present and compare multiple research papers that employed multiple artificial neural network-based approaches to predict cryptocurrency prices. Noting the pros and cons of each of the methods presented (in terms of time elapsed, prediction accuracy, MAPE, and R-squared), it appears that in a holistic manner the methods used in Jaquart *et al.* (2021), and the MICDL method in Livieris *et al.* (2021) are of significant efficiency.

Due to the novel nature of this literature, all papers written in the area span solely to the last few years. Therefore, it's expected that many additional papers be written in the near future. There exist many aspects of cryptocurrency price forecasting with no existent research papers at the time. One area of possible further work, for instance, is to focus solely on implementing data from less volatile cryptocurrencies (e.g., Ethereum, XRP, Chainlink, etc.) into the same frameworks. Indeed, many other frameworks could be implemented to forecast and/or measure the prediction efficiencies as well.

It should also be noted that another subgroup of related literature uses some similar and/or the same methods presented throughout this survey to predict the volatility, rather than future prices, of cryptocurrencies. This lies beyond the scope of this paper and is a possible area of research and/or another survey paper of existing literature.

Due to the prominent recent increase in the popularity and price of cryptocurrencies (including but not limited to Bitcoin), introduction to the history and technicalities of cryptocurrency is of essential importance to policymakers and other economic agents. The first transaction using bitcoins was to buy a pizza in 2011, which would have been worth over \$5 million today. With such quick turnover, agents need to catch up quickly (Charandabi *et al.* 2021).

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