Neural Networks in Application to Cryptocurrency Exchange Modeling

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Abstract
Artificial neural networks are modern data science method. They are suitable for the cases of nonlinear dependency approximation, which is successfully applied in many fields. This paper compares the predictive capabilities of Back Propagation, Radial Basis Function, Extreme Learning Machine, and Long-Short Term Memory neural networks to determine which artificial intelligence algorithm is best for modeling the Bitcoin and Ethereum open price. The criterion for comparing network performance was the standard deviation, the mean absolute deviation, and the accuracy of predicting the direction of change of course. At the same time, in the study of time series, it is recommended to perform a comprehensive data analysis using regarded networks, depending on the length of the series and the features of the database.

Keywords [1]
Artificial intelligence; back propagation; radial basis function; extreme learning machine; long-short term memory; adaptive neural based fuzzy inference system; bitcoin; ethereum

1. Introduction

Stock prices and exchange rates prediction is recently one of the most important and relevant problems of quantitative finance. Special attention is paid to new financial instruments - cryptocurrencies. Price forecasting theory is one of the main topics of discussion in finance. With the evolution of behavioral finance, many economists believe that stock prices, albeit in part, can be predicted based on historical price patterns, which provides the basis for the development of fundamental and especially technical analysis as price forecasting tools.

Bitcoin is a type of digital currency that uses encryption techniques to control currency generation and verify funds transfers that operate independently of the central bank [1-3]. In [4] authors investigate the relationship between Bitcoin and conventional financial assets from a perspective on the connectedness of asset networks. Separating positive and negative returns in the bitcoin market reveals an asymmetric spillover pattern between bitcoins and conventional assets. Eom [5] focuses on the relation between bitcoin prices and trading volume. The findings imply that fundamental uncertainty generates more dispersion in heterogeneous beliefs among investors and leads to high trading and to speculative bubbles. In [6] authors explore the occurrence and timing of bubbles in the Bitcoin USD rates. Being a very new and innovative currency, Bitcoin exhibits unique features that makes it different from other currencies. Musiałkowska et al. [7] aimed to find, which of the assets: gold, oil or bitcoin can be considered a safe-haven for investors in a crisis-driven Venezuela. The authors look also at the governmental change of approach towards the use and mining of cryptocurrencies being one of the assets and potential applications of bitcoin as (quasi) money. In [8] authors examine the resilience of Bitcoin (BTC) to hedge Chinese aggregate and sectoral equity

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markets and the returns spillover to Altcoins onset the Novel Coronavirus outbreak. Overall, gold outperforms BTC in hedging and safe haven perspectives with respect to Chinese equity markets.

Ethereum is deservedly considered the "cryptocurrency №2" on the market. Basically, it is one of the most dynamic cryptocurrencies. For example, since the beginning of 2020, the number of ETH has increased by 145%. Meanwhile, in the case of BTC this figure has increased by only 13%. According to the analytical company Messari, the number of active Ethereum addresses is currently more than 500 000. Despite the larger number of users - more than 700 000 - bitcoin does not have such a large growth rate.

Ethereum is something more than just a digital currency. Thanks to the Solidity programming language in which the Ethereum platform is written, it compares favorably with other cryptocurrencies. Expanding the scope of Ethereum leads to an increase in demand.

Recently, the price of Ethereum has risen sharply and reached an all-time high. With the rise in the price and popularity of bitcoin, traders are also turning to other cryptocurrencies that can be used to make a profit. Therefore, Ethereum and Bitcoin do not compete with each other in any way.

The Ethereum price may be affected by various global news. For example, in June 2017, the Ethereum price collapsed after the news of an algorithm failure, as a result of which traders began to sell their positions and thereby exacerbated the fall. However, after a few seconds, the algorithms were restored, and the price went up again. As you can see, the volatility of digital currencies is enormous, and their rate can literally change at any time. At that moment, both ordinary people and investors closely followed the course of "ether", wondering how long the leap in cryptocurrency would be.

Any strong growth of the asset may sooner or later lead to a correction; this happens in the regular financial market, and it can happen in the cryptocurrency market.

Big banks like J.P. Morgan Chase, as well as tech giants Microsoft and Intel, are already working on a business application for Ethereum, as the lack of middlemen makes Ethereum extremely attractive to entrepreneurs.

These cryptocurrencies (BTC and ETH) receive significant attention in [9-11]. The behavior of the cryptocurrency market in the conditions of the COVID-19 pandemic is considered. [9] is an overview of the available results on the cryptocurrency market, obtained using various methods of statistical physics using the multifractal formalism and the network approach in particular. A minimal spanning tree is considered as a network.

Artificial intelligence models, especially neural networks, have already found numerous applications in quantitative finance cases, such as predicting volatility. Within the supervised learning paradigm, neural networks are a useful tool for predicting prices as they do not require initial assumptions that distinguish them from traditional time series forecasting models such as ARIMA and its modifications.

Deep learning is coming to play a key role in providing big data predictive analytics solutions as data are becoming larger. In [12], authors provide a brief overview of deep learning, and highlight current research efforts and the challenges to big data, as well as the future trends.

One of the main benefits of deep learning is the ability to extract features from a large set of raw data without relying on any prior logic or rules. This makes deep learning particularly suitable for stock market prediction. In [13] the model was tested on high-frequency data from the Korean stock market.

In [14] authors demonstrated that deep learning is useful for event-driven stock price movement prediction by proposing a novel neural tensor network for learning event embeddings, and using a deep convolutional neural network to model the combined influence of long-term events and short-term events on stock price movements.

The type applications of Extreme Learning Machine (ELM) include classification and regression problems. In these problems, ELM has lower computational time, better performance, and generalization ability than the conventional classifiers, such as Back Propagation neural networks. In addition, ELM was also successfully applied on pattern recognition, forecasting and diagnosis, image processing, and other areas [15].

In recent years, deep artificial neural networks (including recurrent ones) have won numerous competitions in pattern recognition and machine learning. The historical survey [16] compactly summarizes relevant works, much of which were in the previous millennium. Shallow and Deep Learners differ in the depth of their ways of assigning credits that may be learning, of causation between actions and consequences.

Many modern scientific works are devoted to the research of the efficiency of using artificial neural networks. Adebiyi et al. [17] compared the predictive power of the ARIMA model and artificial neural networks in the context of Dell stock index modeling. Although the authors emphasize that both approaches are acceptable and sufficiently accurate for analysis, they nevertheless note that the artificial neural network model has shown better results. The results of similar studies are also presented in [18]. In [19] authors use support vector machine (SVM) learning algorithm to find whether it can predict Bitcoin prices and finds that SVM predicts five steps ahead Bitcoin prices for the short term, medium term, long term, and overall Bitcoin price level.

Chen et al. [20] examined which of the artificial intelligence algorithms best demonstrates itself when modeling the stock price index in the Chinese stock market. The authors investigated the predictive power of algorithms on time series of different lengths. The research concluded that it is advisable to use deep neural networks in predicting large data samples. Liashenko and Kravets [21] made a comparison of the predictive capabilities of Long Short Term Memory and Wavelet based Back Propagation neural networks for co-movement of time series for oil and gas prices, Dow Jones and US dollar indexes.

In [22], authors study the use of Support Vector Machines (SVM) to predict financial movement direction. SVM is a promising type of tool for financial forecasting. As demonstrated in empirical analysis, SVM is superior to the other individual classification methods in forecasting weekly movement direction of NIKKEI 225 Index.

This paper compares the predictive capabilities of different types of neural networks to determine the best artificial intelligence algorithm to model the price of Bitcoin and Ethereum opening.

This paper is a continuation of the research that was started in [23]. The method of fuzzy inference neural systems is additionally applied to the study of the exchange rate for Bitcoin and Ethereum. The time period from October 1, 2020 to October 8, 2020 with minute-by-minute data is considered.

2. Methodology

Back Propagation Neural Networks (BP) is by far one of the most used and most popular models. The basic idea behind the BP algorithm is to divide the learning process into two steps: direct signal propagation and reverse error propagation. At the stage of direct signal propagation, input information is supplied from the input layer to the output layer through a hidden layer. Network weights are fixed during the direct signal transmission. During the backpropagation stage, the error signal that does not meet the accuracy requirements is propagated step by step, and the error is divided among all neurons in each layer. The weights are dynamically adjusted according to the error signal [24]. The most common algorithm for finding weights that minimize error is the gradient descent method. The Back Propagation method is used to find the steepest descent direction [25].

Back propagation is probably the most well-studied neural network learning algorithm and is a starting point for most people looking for a network-based solution. One of its drawbacks is that it often takes many hours to prepare for problems in the real world, and therefore many efforts have been made to improve the training time [26].

Radial Basis Function Neural Networks (RBF) are three-layer artificial neural networks, each hidden layer neuron using a radial basis function as an activation function [20, 27]. The radial basis function is a function of variables whose value depends on the distance to the origin of the coordinate system. The simplest training algorithm for this network involves using the gradient descent method. The criterion for optimizing the model is to minimize the root mean square deviation. You can also use clustering methods to determine the initial centers and the least squares method to find the initial weights [28]. Extreme Learning Machine (ELM), as a relatively new algorithm for training three-layer neural networks, is very fast and efficient. Weights are tuned using mathematical operations, which eliminates long learning processes with adjusting network parameters using iterative methods [15, 29].

The network parameters, such as input weights, biases are randomly generated and doesn't need to be transformed. At the same time, the output weights could be find in analytical way using the inverse operation. The number of hidden neurons is the only thing, that must be priorly determined by the researcher. This approach greatly simplifies the learning process and, as a result, is much faster compared to the other algorithm with less human interaction [15].

Fuzzy inference neural systems are a combination of neural network algorithms and fuzzy inference systems (FIS). FIS is a logical system that uses an algorithm for obtaining fuzzy inferences based on fuzzy assumptions. Implementation of neural network algorithms allows to optimize the parameters of such a system. There are many possible architectures of the neural system of fuzzy inference. In this work, we used an adaptive neural based fuzzy inference system (ANFIS), the structure of which allows us to solve regression problems [30, 31]. Hybrid algorithms that combine gradient descent and least squares methods are used to train networks of this type. However, the method of applying different types of the Differential Evolution branches is more popular [32].

Long-Short Term Memory Neural Networks (LSTM) are a special type of recurrent neural networks (RNN) that can study long-term dependencies. All RNN have the form of a chain of repetitive neural network modules. In a standard RNN, this repeating module has a simple structure of one layer. LSTM also has such a chain structure, but the repeating module has four layers [21, 33, 34].

The LSTM module (or cell) has 5 main components, which allows you to model both long-term and short-term data:

- the state of the cell is the internal memory of the cell, which stores both short-term memory and long-term memory;
- hidden state - this is the initial status information calculated for the current logon;
- input gateway - determines how much information from the current incoming stream enters the cell's state;
- "forget gate" - determines how much information from the current input and the previous state of the cell goes to the current state of the cell;
- output gateway - decides how much information from the current state goes into a hidden state.

3. Results

The future of bitcoin is very unpredictable. There are many possible options for its further development. There is an opinion that bitcoin has the potential to become a world currency. To do this, it must perform the functions of a medium of exchange, unit of account, and accumulation of value. The first of them cryptocurrency partially executes. Bitcoin is a means of accumulation in the sense that it can be sold and stored for future use. The tricky part is achieving a steady value for cryptocurrency, as its price is based mainly on the supply and demand relationship. At the same time, the price of bitcoin is very volatile.

Bitcoin has the potential to become an adjunct to the global financial sector as one way to transact with other global currencies. It is a widespread, decentralized database, designed to reach consistent and reliable agreement on transactions between independent network members [35].

If bitcoin can to some extent become a more controlled and stable currency, this way of transferring money globally has a great prospect, since it does not require the involvement of intermediaries. Other positive features of this cryptocurrency include its global availability, the ability to create multifunctional accounts, and the simplification of crowdfunding.

The highest cryptocurrency value at market is considered hedge against inflation because its supply is limited and its monetary policy is pre-programmed to reduce its rate of expansion by 50 percent every four years.

The day of halving the rewards of miners for the extraction of new coins is called the day of halving. The halving procedure reduces the number of new bitcoins that are paid for the completion of each new block on the blockchain. This means that the supply of new bitcoins will decrease. In traditional financial markets, lower supply at a steady demand tends to lead to higher prices. As halving also reduces the number of new bitcoins and the demand remains constant, this procedure also leads to an increase in the price of bitcoins. Bitcoin has historically come up with new price highs just before or after the next halving. Every halving lowers bitcoin inflation.

But a periodic decline in the bitcoin chasing rate can be more profound than any short-term price changes for the currency to function. Reward block is an important component of Bitcoin that ensures the security of this leaderless system. As remuneration drops to zero over the coming decades, it could potentially destabilize the economic incentives underlying bitcoin security.

A unique aspect of bitcoin is that the programmed block reward decreases over time. This is different from the norm for modern financial systems where central banks control the money supply. Unlike the twice-reduced bitcoin premium, the dollar supply has increased about three-fold since 2000.

In order to simulate the bitcoin and ether exchange rate, we used high-frequency Gemini cryptocurrency data. A database of every-minute BTC and ETH exchange rates for the period from October 01, 2020 to October 08, 2020 was downloaded for research. The minute change in the cryptocurrency rate from October 01, 2020 to October 8, 2020 shows significant fluctuations during the period. This allows us to draw some conclusions about the suitability of neural networks for forecasting in the case of high accuracy of the obtained forecast.

Using neural network learning algorithms, it is necessary to prepare the data, which involves reducing the difference between the threshold and the actual data. Typically, data is normalized before using it on a neural network. After calculations, an operation back to normalization is performed.

Three criteria are used to estimate the forecasting accuracy of a study: root mean squared error (RMSE), mean absolute percentage error (MAPE), and directional accuracy (DA) [35].

RMSE characterizes the standard deviation between the predicted and actual values:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t-1}^{N}(\hat{y}_t - y_t)}, \tag{1}$$

where y_t and $\hat{y}_t$ – the actual and predicted price according to time t, N – the length of the test dataset.

MAPE estimates the accuracy of the forecast in percentage terms and is defined as

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{\hat{y}_t - y_t}{y_t}\right|. \tag{2}$$

RMSE and MAPE are used to measure prediction accuracy. The smaller they are, the higher the accuracy of the model.

The accuracy of predicting the direction of course changing is defined as

$$DA = \frac{1}{N}\sum_{t=1}^{N} D_t, \qquad D_t = \begin{cases} 1, & (y_{t+1} - y_t)(\hat{y}_{t+1} - y_t) \geq 0, \\ 0, & (y_{t+1} - y_t)(\hat{y}_{t+1} - y_t) < 0. \end{cases} \tag{3}$$

The closer DA is to one, the higher the accuracy of forecasting the direction of price change.

During the study, the database was initially divided into 5 consecutive sets of 2200 values (small datasets).These sets contain data on Bitcoin open price for the periods from October 01, 2020 (00:00 a.m.) to October 02, 2020 (00:39 p.m.), from October 02, 2020 (09:19 a.m.) to October 03, 2020 (09:59 p.m.), from October 03, 2020 (06:39 p.m.) to October 05, 2020 (07:19 a.m.), from October 05, 2020 (03:59 a.m.) to October 06, 2020 (04:39 p.m.) and from October 06, 2020 (01:19 p.m.) to October 08, 2020 (01:59 a.m.). In the next step, 2 medium datasets of 5500 values were used. These sets consist data on Bitcoin open price of the periods from October 01, 2020 (00:00 a.m.) to October 04, 2020 (07:39 p.m.) and from October 04, 2020 (11:19 a.m.) to October 08, 2020 (06:59 a.m.). At the final stage, the whole time series (large dataset) containing 11000 values was considered. This set contains data on Bitcoin open price for the period from October 01, 2020 (00:00 a.m.) to October 08, 2020 (03:19 p.m.).

For small sets, the first 2000 values are used to train neural networks, the remaining 200 are used to estimate prediction accuracy. For medium and large data sets, this proportion remains unchanged: 90% for training; 10% to estimate forecasting accuracy. There is no unified method for determining the most appropriate number of neurons in networks. The network structure used in the work is purely experimental. The BP, RBF and ELM networks contain a single hidden layer consisting of 50 neurons. In the case of ANFIS network there were 20 nodes each one standing for the single Takagi-Sugeno rule. The LSTM network contain a single hidden layer consisting of 50 LSTM-cells. The size of sliding window is equal to 5. The number of training cycles for each network is 150.

Figure 1 and Figure 2 show the results of predicting BTC and ETH rates for the large dataset respectively. The actual data and data modeled by the ELM, RBF, ANFIS, BP and LSTM networks are represented in different color lines.

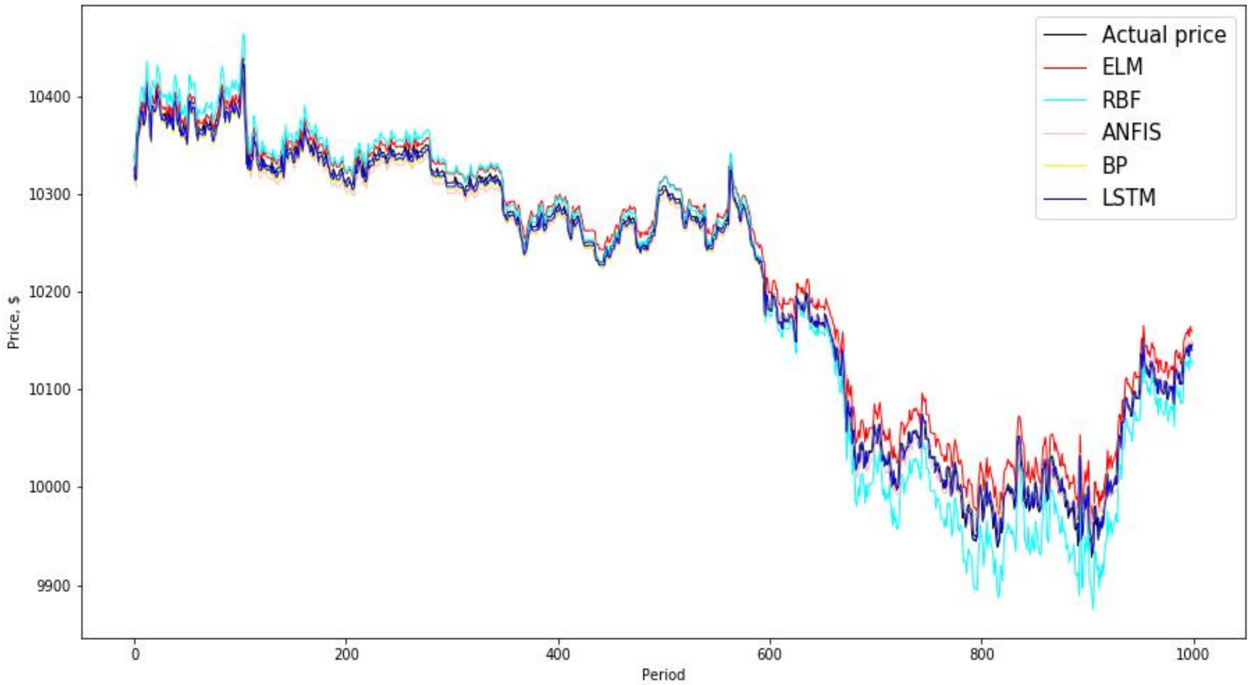

Figure 1: actual and predicted Bitcoin exchange rate (large dataset)

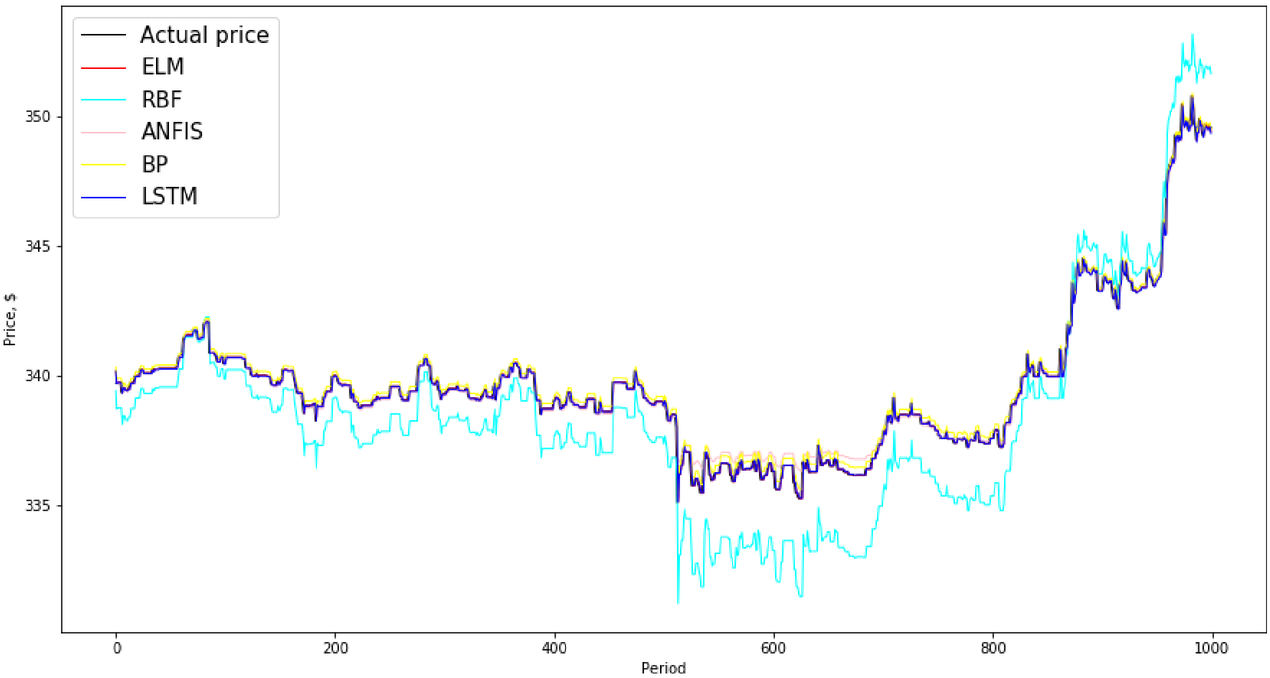

Figure 2: actual and predicted Ethereum exchange rate (large dataset)

The Table 1 and Table 2 present a comparison of the Bitcoin prediction accuracy for different length datasets and for all neural networks used.

When forecasting on small datasets, the LSTM network has the smallest average values of root mean square error and average absolute percentage error (11.9951 and 0.00079, respectively), outperforming all other networks by these indicators.

The BP and ANFIS networks also show good results The ELM, BP and LSTM networks have the highest accuracy in predicting the direction of course changing (0.562, 0.539, 0.539).

The results show that the LSTM and BP networks perform best when forecasting on medium datasets.

They have the smallest RMSE (12.8999 and 13.4224, respectively) as well as the smallest values of the MAPE (0.00082 and 0.00092). The ANFIS network and the ELM network show the best results (0.562 and 0.555) in terms of forecasting accuracy.

As for forecasting on a large dataset, the LSTM network performs best with the smallest RMSE and MAPE (10.8444 and 0.00074, respectively), ahead of the BP network (11.5678 and 0.00084), ANFIS network (13.7243 and 0.00105). The ANFIS and LSTM networks demonstrate good results in DA predicting (0.585 and 0.577).

Table 1

Estimations of Bitcoin prediction accuracy for small datasets

Period	Criteria	ELM	RBF	ANFIS	BP	LSTM
10.02.2020	RMSE	27.6312	46.4687	54.0078	17.0421	20.0403
09:20 a.m.-	MAPE	0.00167	0.00360	0.00337	0.00089	0.00116
00:40 p.m.	DA	0.518	0.518	0.533	0.558	0.518
10.03.2020	RMSE	15.0129	29.6364	11.1039	12.1093	10.5088
06:40p.m.-	MAPE	0.00115	0.00229	0.00082	0.00091	0.00076
10:00 p.m.	DA	0.578	0.467	0.508	0.477	0.477
10.05.2020	RMSE	8.2870	12.9826	10.1526	9.9648	8.2914
04:00 a.m.-	MAPE	0.00055	0.00101	0.00072	0.00072	0.00055
07:20 a.m.	DA	0.578	0.568	0.573	0.568	0.528
10.06.2020	RMSE	8.9711	27.8788	9.5168	12.8711	10.2621
01:20 p.m.-	MAPE	0.00065	0.00256	0.00067	0.00104	0.00078
04:40 p.m.	DA	0.563	0.573	0.568	0.573	0.543
10.07.2020						
(10:40 p.m.)-	RMSE	17.1493	39.1333	11.8923	10.9708	10.8728
10.08.2020	MAPE	0.00138	0.00362	0.00076	0.00074	0.00071
(2:00 a.m.)	DA	0.573	0.518	0.513	0.518	0.573
Average	RMSE	15.4103	31.2200	19.3347	12.5916	11.9951
	MAPE	0.00108	0.00262	0.00127	0.00086	0.00079
	DA	0.562	0.529	0.539	0.539	0.528

The Table 3 and Table 4 demonstrate a comparison of the Ethereum prediction accuracy for different length datasets and for all neural networks used.

The LSTM and ELM networks show the best results in average values of RMSE and MAPE for large and small datasets.

As for medium datasets, the ELM and ANFIS networks have the smallest value of these indicators. The RBN network has the highest DA (0.791 and 0.744) on large and small datasets.

The ELM and ANFIS networks show the best results (0.781 and 0.780) in terms of forecasting accuracy on medium datasets.

Table 2
Estimations of Bitcoin prediction accuracy for medium and large datasets

Period	Criteria	ELM	RBF	ANFIS	BP	LSTM
Medium datasets						
10.04.2020	RMSE	25.8733	31.3168	31.3168	18.5265	17.8129
11:20 a.m.-	MAPE	0.00200	0.00265	0.00122	0.00129	0.00116
07:40 p.m.	DA	0.515	0.507	0.553	0.515	0.507
10.07.2020						
10:40 p.m.-	RMSE	7.9310	13.8389	13.8389	8.3182	7.9869
10.08.2020	MAPE	0.00048	0.00118	0.00106	0.00055	0.00048
07:00 a.m.	DA	0.595	0.573	0.571	0.573	0.559
Average	RMSE	16.9021	22.5778	22.5778	13.4224	12.8999
	MAPE	0.00124	0.00191	0.00114	0.00092	0.00082
	DA	0.555	0.540	0.562	0.544	0.533
Large datasets						
10.07.2020						
10:40 p.m.-	RMSE	19.9173	25.3625	13.7243	11.5678	10.8444
10.08.2020	MAPE	0.00161	0.00192	0.00105	0.00084	0.00074
03:20 p.m.	DA	0.520	0.574	0.585	0.574	0.577

Table 3
Estimations of Ethereum prediction accuracy for small datasets

Period	Criteria	ELM	RBF	ANFIS	BP	LSTM
10.02.2020	RMSE	0.6762	0.9730	0.7213	0.7227	0.3296
09:20 a.m.-	MAPE	0.00178	0.00270	0.00191	0.00193	0.00067
00:40 p.m.	DA	0.668	0.638	0.668	0.668	0.668
10.03.2020	RMSE	0.2815	0.3970	0.1966	0.2057	0.1579
06:40p.m.-	MAPE	0.00071	0.00099	0.00037	0.00048	0.00022
10:00 p.m.	DA	0.794	0.839	0.769	0.794	0.799
10.05.2020	RMSE	0.1758	0.9182	0.2115	0.2888	0.1883
04:00 a.m.-	MAPE	0.00033	0.00245	0.00043	0.00070	0.00036
07:20 a.m.	DA	0.714	0.709	0.734	0.779	0.779
10.06.2020	RMSE	0.5219	0.7267	0.4866	0.4557	0.4523
01:20 p.m.-	MAPE	0.00103	0.00168	0.00085	0.00082	0.00079
04:40 p.m.	DA	0.653	0.678	0.638	0.613	0.608
10.07.2020						
(10:40 p.m.)-	RMSE	0.1709	0.4701	0.2035	0.1744	0.1851
10.08.2020	MAPE	0.00025	0.00121	0.00037	0.00028	0.00037
(2:00 a.m.)	DA	0.839	0.854	0.854	0.829	0.814
Average	RMSE	0,3653	0.6970	0.3639	0.3695	0.2626
	MAPE	0.00082	0.00181	0.00078	0.00084	0.00048
	DA	0.734	0.744	0.733	0.737	0.734

Table 4
Estimations of Ethereum prediction accuracy for medium and large datasets

Period	Criteria	ELM	RBF	ANFIS	BP	LSTM
Medium datasets						
10.04.2020	RMSE	0.2272	0.3065	0.3065	0.2311	0.2486
11:20 a.m.-	MAPE	0.00030	0.00064	0.00043	0.00035	0.00045
07:40 p.m.	DA	0.739	0.731	0.737	0.715	0.713
10.07.2020						
10:40 p.m.-	RMSE	0.1949	0.8891	0.8891	0.2122	0.2260
10.08.2020	MAPE	0.00041	0.00244	0.00032	0.00049	0.00054
07:00 a.m.	DA	0.822	0.826	0.822	0.822	0.822
Average	RMSE	0.2111	0.5978	0.5978	0.2217	0.2373
	MAPE	0.00035	0.00154	0.00038	0.00042	0.00049
	DA	0.781	0.779	0.780	0.769	0.768
Large datasets						
10.07.2020						
10:40 p.m.-	RMSE	0.2620	1.7972	0.3634	0.3213	0.2641
10.08.2020	MAPE	0.00035	0.00458	0.00069	0.00072	0.00038
03:20 p.m.	DA	0.781	0.791	0.782	0.784	0.774

4. Conclusion & Discussion

In general, any deflationary collapse can be seen as a rise in the price of Bitcoin. The start of deflation may be associated with large job losses due to the outbreak of the coronavirus and the fall in oil prices. The prospect of a collapse in deflation intensified as oil prices fell. However, the demand for cash may not have a significant negative impact on the price of bitcoin, since deflation will also increase the purchasing power of the cryptocurrency. The increased purchasing power is likely to lead to an increase in demand for bitcoins, as cryptocurrency is already being used as a means of payment.

Moreover, the appeal of cryptocurrency as a medium of exchange is likely to continue to grow as technology becomes more prevalent in consumers' daily lives due to the coronavirus pandemic. In addition, if central banks are willing to do their best to overcome deflation, the real or inflation-adjusted bond yields are likely to remain negative or negligible at best. As a result, zero-return assets like gold and bitcoins can attract more buyers.

Cryptocurrencies market behavior forecasting is rather challenging. The non-linear relationship between transaction data and unpredictable market fluctuations makes prediction difficult. The shift in the exchange rate and the periodic fall in the bitcoin exchange rate are also associated with numerous cases of fraud, speculative transactions and market regulation problems. For example, in Germany, it was announced that from 2020, local banks will be allowed to offer the sale and storage of cryptocurrencies in accordance with new legislation. The new law could encourage investors to invest in cryptocurrencies, so bitcoin quotes have a chance to rise.

To demonstrate the impact of sample size on learning and network performance, we divided the sample into data sets of different lengths and compared the results obtained at each.

We have found that sample size affects forecasting results. The best results in bitcoin and ethereum exchange rate modeling were demonstrated by the LSTM network. Particularly striking is its advantage when forecasting on large datasets. This fact is due to the deep architecture of this type of network. However, when studying time series, it is recommended to perform a comprehensive data analysis using appropriate networks, depending on the length of the series and the specificity of the database.

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