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Optimization of cryptocurrency price estimates by data preprocessing

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ABSTRACT

In the present study, we have tried to increase investment efficiency by using several cryptocurrencies and preprocessing them simultaneously on their price history while reducing the volume of calculations. The primary purpose is to preprocess the data and extract the feature of estimating the number of days by simultaneously considering several cryptocurrencies' price charts. For this purpose, bidirectional long short-term memory (BiLSTM) neural network is used. To predict the price, we can give different price ranges to the input of each neural network, so we have various neural networks for each desired period. Each neural network obtained for each input interval is called a strategy. With neural networks with different inputs and optimised outputs with a certain number of days calculated in the present study, we show the superiority of the introduced strategy. The optimal production we have achieved in the present study is the estimation of the next three days, along with the estimate of the price of the same day to reduce the error of the neural network system. In the introduced method, we come to several different strategies, some of which are more effective than similar research. In the present study, we design the neural network's output according to the need, but we use the main structure of the neural network from the most optimal networks in this field and do not change it. If we have a better neural network structure and replace it, we will have better final efficiency. According to the results, when we use the strategy of estimating the next three days with an input interval of 67 days, we achieve an efficiency of about 15% compared to similar research. Of course, we also compare it with another essential criterion based on the average efficiency during the simulation. The proposed method has a much higher position based on the above standard. Using the introduced method has several advantages, such as reducing the number of calculations, increasing efficiency, and reducing response time. This method can be used in any field of artificial intelligence related to time series.

Key words: Cryptocurrency, Neural network optimisation, Neural network preprocessing, Bidirectional long short-term memory (BiLSTM)

INTRODUCTION

The use of neural networks to predict prices has a long history, and much progress has been made. It has been used in various deep learning topics such as deep neural networks, short-term neural networks, and convolutional neural networks. Experiments have shown that although forecasting models perform slightly better than regression models for bitcoin price forecasting, LSTM-based models perform better for price forecasting. In addition, DNN-based models perform better for price forecast classification. A performance simulation model has also shown that classification models are more effective for algorithmic transactions than regression models (1).

Deep learning neural networks are also widely used to predict prices in academia and economics. There are many articles and achievements in this field. A neural network structure model with reasonable predictions with different confidence intervals has been used in this context. On the other hand, price forecasting has its complexities due to the nature of uncertainty. With the advancement of computer science, neural networks are used in various industrial fields (1). In addition to neural networks, traditional analysis and data are used as input for more accurate price forecasting (2). In addition to machine learning, statistical studies are also used for price forecasting. However, learning methods are more effective.

The following can be mentioned in the research: In (3), the author tries to challenge the efficient market hypothesis. The author argues that the purpose of stock price forecasting systems is to provide abnormal returns for financial market operators and provide a basis for tools that cannot continuously manage market movement (EMH). Although the efficient market hypothesis was predicted, sophisticated computing systems using machine learning algorithms are increasingly common in developing stock trading mechanisms. Several daily stock prices studies have presented the projected system schedules at fixed intervals regardless of the new model update. Using a machine learning technique called a support vector machine, studies in this field predict stock prices for large and small capital in three different markets and examine prices at daily intervals of up to one minute. (2) uses a long short-term memory neural network to utilise and improve the traditional business algorithms used in technical analysis. The reason for choosing this method is that the network can learn market behaviour and predict when a particular strategy is more likely to succeed. The research algorithm is performed using the Python programming language. The results showed that neural network prediction and traditional technical analysis work better than alone.

In another study, we see a different approach. One of the most challenging tasks when dealing with financial time series is predicting stock returns in a dynamic, complex, evolutionary, nonlinear, nebula, nonparametric, and chaotic manner. In addition, the stock market is susceptible to political factors, micro and macro conditions, and the expectations and insecurity of investors.

According to mainstream theory, it is impossible to predict the price of financial assets. They proposed a model based on flag patterns to identify uptrend patterns (4)(5)(6).

Related work

In source number (7), the author has examined the subject in terms of time series. There are several characteristics of time scale in financial time series, which due to different times, is an influential factor in the behaviour of traders. This paper proposes an end-to-end hybrid neural network, a model based on multiple time scale features taught to predict stock market price trends.

In source number (8), a different approach to data analysis is selected. Instead of analysing data based on numerical values, this paper uses data analysis as image processing. This paper proposes a business model using a two-dimensional convolution neural network based on CNN-TA processing algorithms based on the image algorithm.

Source (9) examines high-performance machine learning classification and regression models to predict bitcoin price movements and short- and medium-term prices. In similar work, machine-based classification has been studied for only one one-day period. At the same time, this paper goes beyond using machine-based learning models for one, seven, thirty, and ninety days.

Source (10) compares liquidity forecasts in the digital currency markets and Fiat between the two traditional time series methods, the moving average and root hysteroscopy, and the machine algorithm. These results show that KNN can better access the proposed digital currency system than the ARMA and GARCH models.

In Source (11), the author is looking for a tool to automatically predict the price of Bitcoin in the stock market due to fluctuations in Bitcoin digital currencies. This research study shows how to create a bitcoin stock market forecasting model using LSTM. Yahoo's financial need has been used for this purpose.

It should be noted that market complexities require a specific combination of parameters that may change in different market conditions and seasons for a tool. Many models show positive performance for specific experimental settings and a variety of parameters; however, their short-range accuracy may be a significant weakness of the approach used in this paper. A feature selector presented in (12) can be implemented to overcome these problems, a limited Boltzmann machine for extracting features from technical markers. The regression model implements a dynamic SVM based on retraining windows whose variable outputs, inputs, and training set size can be checked for specific machine learning models to determine the exact time a model should be replaced by better parameterisation (13).

There has also been much research into the algorithms used. For example, one type of research has optimised profitability. Researchers believe that investors' net profits can increase fast if they make the right decision to do one of three things: buy, sell or hold stocks. The correct action is related to stock market measurements. Therefore, defining the right step requires the unique knowledge of investors (14).

Because stock index price forecasting is widely used in both academic and economic fields and also index price forecasting is difficult due to uncertainty, various neural networks are used in multiple industrial areas to help us in Help increase productivity (16).

In the last decade, cryptocurrency has emerged in the financial sector as a significant factor in jobs and financial market opportunities. Accurate forecasts can help cryptocurrency investors make the right investment decisions and increase potential profits. In addition, they can also support policymakers and economic researchers in studying cryptocurrency market behaviours. In some studies, in addition to price and time analysis, dynamic analysis has been used; for example, in a study, it has been investigated that using emotion analysis and machine learning techniques to make predictions about the behaviours of markets. Market emotional forecasting focused exclusively on bitcoin behaviours. This article predicts the prices of digital currencies Bitcoin, Ethereum, Ripple, and Litecoin in the market using machine learning tools and data available on social networks. We compare price prediction output using neural networks, support vector machines, and random jungles while using Twitter messages and social media data as input features. The results show that cryptocurrency markets can be predicted using machine learning and emotion analysis; in a way, Twitter data alone can predict some digital currencies, and neural networks are also superior to other pricing models (15) (17)

Economists have continued their research by proposing several specific strategies and factors to find the best option for trading on the stock exchange. However, several investors lost their capital when they wanted to base their recommendations on these strategies. This means that the stock market needs more good research to ensure tremendous success for investors.

The importance of the present study is that we are not just dependent on neural networks and have used other powerful mathematical tools to achieve maximum efficiency. We are developing a scheme under which neural network forecasting works as a consultant.

Research Methods

In the present study, after collecting the data, we preprocess the data to form the neural network structure that we will use in the next step. In the present study, in addition to mathematical calculations, which are the basis of the research, a programming environment has been used to implement the computational process algorithm. The programming language used in this research is Python. Figure 1 shows the research process.

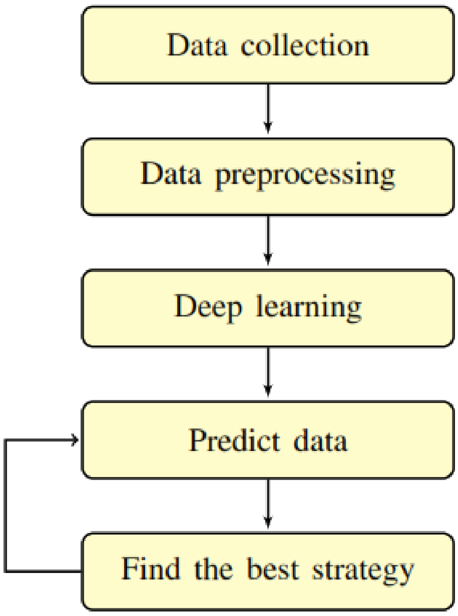

Figure 1- Research flowchart

Data preprocessing

The first part we look at is the data processing and neural network structure used in the simulation. The neural network used in the present study is BiLSTM, which is based on the source (18) of the formulas that describe the above structure.

$$H_F = F(W_{F1}X_T + W_{F2}H_T - 1) \quad (1)$$

$$H_B = F(W_{B1}X_T + W_{B2}H_T + 1) \quad (2)$$

Output function:

$$Y_1 = G(W_{O1}H_F + W_{O2}H_B) \quad (3)$$

Calculation of coefficients:

$$a_{ki} = \frac{\exp(a_{ki})}{\sum_{j=i}^{T_x} \exp(a_{ki})} \quad (4)$$

$$a_{ki} = \text{vtanh}\ (Wh_k + Uh_i + b) \quad (5)$$

$$C = \sum_{i=1}^{T_x} a_{ki} h_i \quad (6)$$

$$h_k = H(C, h_k, x_k) \quad (7)$$

The specifications of the neural network used to estimate the price of cryptocurrencies are as follows. The first layer consists of a BiLSTM architecture with 50 units and a sigmoid activation function in the three-layer network. The second layer is the LeakyReLU function with alpha 0.5. Moreover, the third layer is the Dropout function with parameter 0.1. To calculate the number of Epoch and Batch of the neural network, we extensively searched the neural network that estimates each cryptocurrency. According to the error rate, the best numbers were calculated in this search: the Bitcoin epoch is equal to 500, and the batch size is equal to 5. For Litecoin, Ethereum and Zedcoin, the epoch is 1500, and the batch size is 5. We experienced the slightest error in the above inputs. Also, the above values were mentioned in similar studies, but in the above research, we recalculated the values.

We used the actual process in the simulation and calculated the sales commission according to what is usually customary. Considering the fee makes a big difference in both strategy and calculation. When there is no commission, the best strategy is in small steps; the smaller the price range we analyse, the better we buy with the most nominal growth and the slightest drop in sales. However, in practice, this strategy does not give us good efficiency and may even reduce the principle of capital. Because the average commission paid for buying and selling may be more than our profit and ultimately have a negative profit percentage. So, we use an idea to solve this problem. Based on the cryptocurrencies we use, we calculate that we can get the most out of it by knowing the price forecast for the next few days. Another point is that because we use the neural network to predict prices, the more days we predict for the future, the more error we will have and the more calculations it will require. Therefore, finding the maximum optimal number of days can improve the estimates and the final efficiency.

Therefore, this article aims to calculate the maximum period for predicting the price of cryptocurrencies, which can give the optimal result. The following is an example of how to do this. First, we consider a 60-day interval (this 60 day is an example, and any other break can be considered), and we determine the paramount price of the four cryptocurrencies in these 60 days. We use previous periods' recorded prices in this process and do not make any predictions. Then the simulation is performed by the following method. On the first day of 02/17/2021, we determine the exact price of four cryptocurrencies for the next three days based on the price history (these three days are an example to understand the trend, and we study several periods). Then, according to the cost of buying and selling, we calculate the price growth, which shopping model has the highest efficiency in the next three days, and based on that, we make the next day's purchase. For the next day, we repeat the above trend; we add one day to the start date, and three days later, we consider the price and calculate the most profitable purchase model. We repeat the same process for 60 days. Of course, in the last days, because we considered the forecast period to be 60 days, the number of forecast days decreases; for example, on the 58th day, the next two days are cited, and on the 59th day, the next day is mentioned. The following is a table example of this.

Table 1: Currency prices for four consecutive days

	BTC	ETH	ZEC	LTC
17/2/2021	52068.01	1893.59	164.14	232.72
18/2/2021	51241.23	1910.18	168.05	224.91
19/2/2021	55761.1	2016.34	176.58	243.55
20/2/2021	56541.2	1935.3	164.96	227.43

Table 2: Percentage change in the price of cryptocurrencies in four consecutive days

	BTC	ETH	ZEC	LTC
18/2/2021	−0.015879	0.008761	0.023821	−0.033560
19/2/2021	0.088208	0.055576	0.050759	0.082878
20/2/2021	0.013990	−0.040192	−0.065806	−0.066188

The above problem can be solved by the idea of finding the best path in graph modelling.

Graph modelling

The graph modelling method we use in the present study is that each cryptocurrency is converted to a vertex and the set of vertices forms the strategy in one step. Our step can be daily or hourly or any design model we consider. After the above modelling, our problem has become a network routing problem in which our goal is to calculate the best route. Determining the best way can vary depending on the graph. In our modelling, the percentage of efficiency per edge is defined. The final efficiency is obtained by multiplying all the efficiency, so the best path is when the multiplying value of edges is to the maximum. Finally, the best-calculated route gives us the best investment strategy. The introduced tools are among the most widely used tools in mathematical analysis. Moreover, they are strong backers of decision-making. In the above modelling, we also considered the transaction cost.

The best way to calculate the route is that the price of four cryptocurrencies per day is four vertices of a graph network. We ultimately connect to the other four vertices of the network model for the price of four cryptocurrencies the next day. According to the described process, the whole graph is formed according to the number of days we consider. That is, the total chart is 5 x 3 vertices, which is 4 out of 5 vertices for the price of four cryptocurrencies in one day, and one vertex for the case in which we have not included any cryptocurrencies in the asset that day (Because there is a case of not buying and selling the complete cryptocurrency to each series of 4, which is equivalent to 1 day, a vertex is added to this title). As a result, it has five vertices every day, and since we consider the next three days, we have 15 vertices, all 5 of which are connected by a directional edge from the day before to the next day. We link to all cryptocurrencies the next day and the fifth vertex from each cryptocurrency. The weight of the edges is equal to the sales commission plus the purchase between the two cryptocurrencies. Figure 1 shows a sample chart for three days.

After modelling based on the above process and finding the best path, we decided what strategy to choose on 2021/02/17. That is, what cryptocurrency to buy or not to buy at all. Of course, it should be noted that we were in fifth place on the first day of the simulation because we assumed we had no cryptocurrency in the first job. In this example, given the price of the next three days, our buying strategy in 2021/02/17 is ZEC.

So far, on 02/17/2011, we have decided to buy the ZEC. We are now on 2/18/2021, and we have the ZEC currency. Prepare the table from 2/19/2021 to 2/21/2021, and determine what strategy we have for today. Of course, this time, our plan is assumed to have ZEC, and the sales commission is also influential in our approach. Moreover, this process continues for a certain period, for example, 60 days.

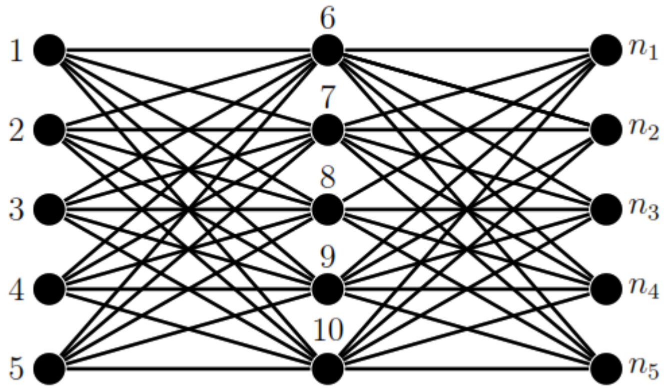

Figure 2 - Graph model to simulate a day

Formulas:

$$\text{Edge} = [(a_1, a_{26}, \dots, a_i), (a_1, a_{27}, \dots, a_i), \dots, (a_1, a_{25}, \dots, a_k)] \quad (8)$$

$$P_i = \prod_j^{\text{Edge}_i} a_k \rightarrow Beast\ Path = Max(P_i)\ _{i \subseteq Edge} \quad (9)$$

Because our goal is to find the efficiency, each edge that connects the vertices of the two networks has an efficiency weight that indicates a change in strategy from the first vertex to the second vertex; the best efficiency is obtained by multiplying the efficiency. The best route for us is when the weight of the edges is maximised.

Table 3 is displayed for a specific day, and this table continues until the number of days that the simulation is considered, for example, 60 days. In the second column, the table of numbers 0 to 3 shows the number of forecast days and the original price. The line with the number zero shows the price on the specified date, and lines 1 to 3 show the forecast for the next 1 to 3 days, which is the neural network's output. Moreover, according to the table above and the commission cost, we calculate our purchasing strategy for the next day.

Since this criterion has no extraordinary proof, we have to be satisfied with statistical data; we perform a hypothesis test for it.

Our zero assumption is that a maximum of 3 days is sufficient for our forecast.

The opposite assumption is that a maximum of 3 days is not enough.

We sample completely randomly at different time intervals and with the same duration to prove it. Assuming a 5% alpha, we test the idea hypothesis. If our null hypothesis is confirmed, it can be used to determine neural network constraints. Repeat this process for 1 to 10 days. Ten days mean that we know our purchasing strategy in the 60-day simulation period by knowing the information for the next ten days. Based on the results obtained in all simulations, considering the next three days is enough to predict. Of course, in some simulations, we even reached two days. In the following, we will analyse the above results.

Table 3 - The table below shows the calculations for December 17th.

		$btcd$	$ethd$	$ltcd$	$zecd$	$N.A-$
$2021-02-17$	0	52068.010	1893.590	232.720	164.140	0.0
	1	54238	1803	242	151	0.0
	2	55032	1778	268	158	0.0
	3	51039	1930	298	143	0.0

Calculate the number of days for strategy

We calculate and check the simulation at different time intervals based on the abovementioned method. Knowing the information in the next few days can achieve maximum efficiency.

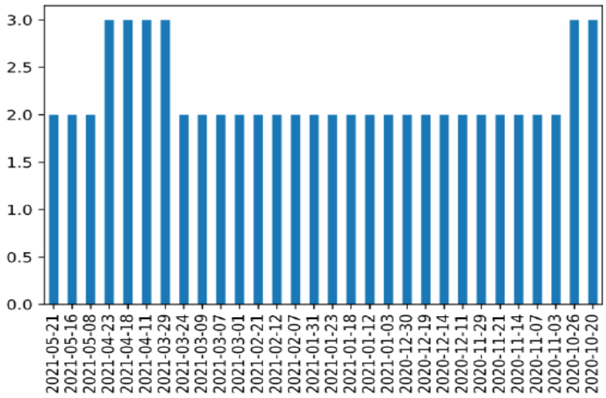

Figure 3: Number of days required for maximum efficiency in different simulation intervals

Figure (3) shows the date of the horizontal axis at which the 60-day interval has ended. The above experiment was performed in 30 different time intervals, and as can be seen, the highest performance occurred for 2 or 3 three days. Because the above criterion has no specific proof to test the hypothesis, we have performed simulations in 30 different time intervals so that we can test the hypothesis on it. Finally, assuming 5% alpha, we reach three days of forecasting.

Neural network design and training

Now that the first step to predicting the coming days has been determined, it is enough to consider the output of the next three days, select the neural network that has been known as the best neural network so far in the articles, and change it. The next step is to determine the number of days before the last price to give input to the neural network and generate output. Also, since the final strategy is to use multiple neural networks and integrate their output, a period of 20 to 70 days is considered the neural network's input.

We can see the price forecast for the next three days and the 40-day interval in the output charts. In the charts above, blue is the actual price. Orange is the forecast price for the same day. Green, red and purple are the forecast prices for the next one to three days, respectively, plotted in the graphs with the appropriate time shift. We see a behavioural model of the neural network for forecasting in each currency. For example, forecasts move away from the original price in the bitcoin cryptocurrency over time, and most predictions are higher than the actual price. However, in the Ethereum cryptocurrency, before the middle of the chart, the maximum price is above the forecast price, and after that, it comes down to the forecast prices.

In the charts, the forecast chart for the coming days is transferred to the number of days in the title of the same chart to compare the difference between the forecast price and the paramount price on the vertical axis. The best-case scenario for charts is when all the lines are drawn match.

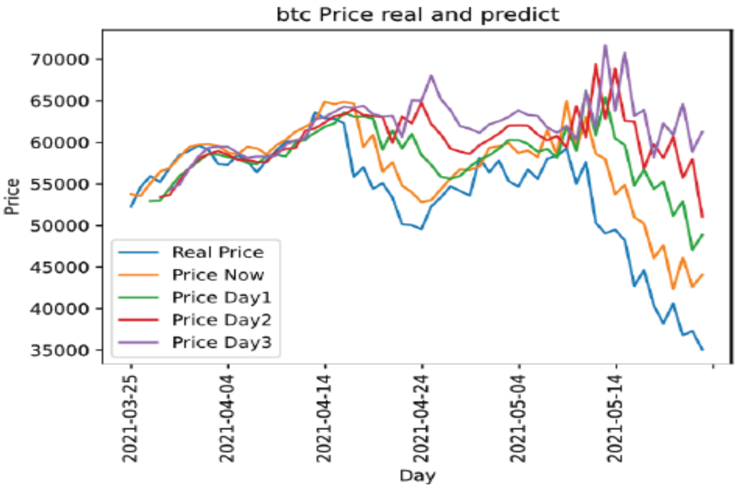

Figure 4: Prices of bitcoin cryptocurrency along with forecast prices with appropriate time transfers

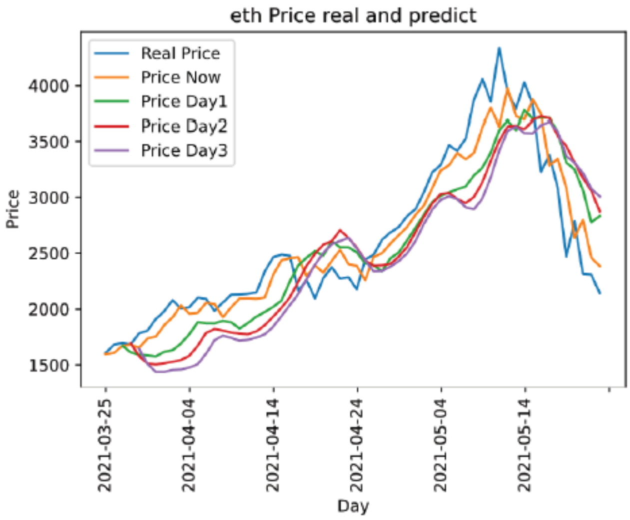

Figure 5: Ethereum cryptocurrency prices along with predicted prices with appropriate time transfer

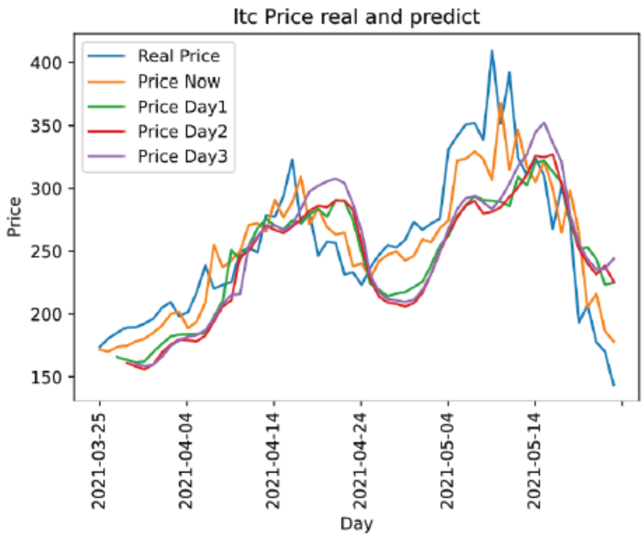

Figure 6: Litecoin prices along with projected prices with appropriate time transfer

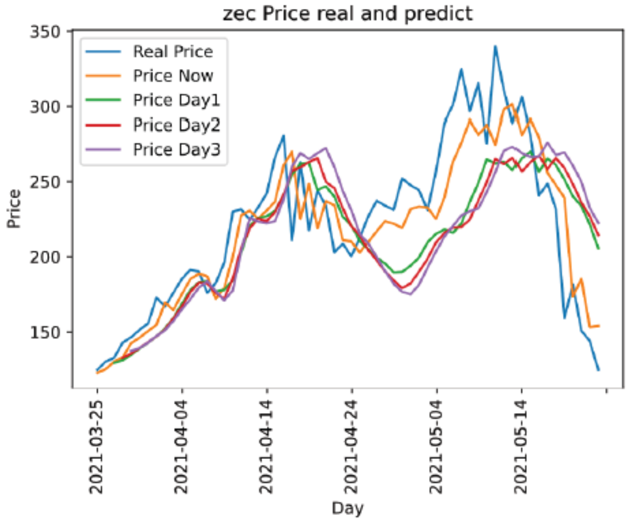

Figure 7: The price of Zcash along with the predicted prices with a suitable time transfer

Simulations and results

To compare the strategies, we use accurate simulation to consider the wage work of each transaction in reality. There is no difference between the result of the above research and practical sales. If there is a difference according to the purchase price range, Sales may differ slightly from the price we have calculated because we use the maximum and minimum prices. However, the actual user may not be able to do all the transactions at the desired prices and trade close to the above prices. However, it is expected that there will be no significant difference in the end.

Before expressing the simulation results, we used indices to draw the following diagrams so that we would explain them first.

Explanation of Indices

X1_X2_X3_X4

X1: This number indicates the number of neural network outputs. One output is the price forecast for the same day, and the other outputs are forecasting for the coming days, which in this study are two numbers, 2 and 4.

X2: This number represents the simulation interval which is equal to 40.

X3: This symbol indicates the type of definition fee applied for accurate simulation of prices. We used two modes, P1 and P2, where P1 has all the commissions and is for the case where all the cryptocurrencies are in our strategy, and P2 is for the case where the cryptocurrencies are traded individually.

X4: This symbol either contains a number or the phrase 'other' with the currency name. When it is a number, it refers to the number of neural network inputs .It relates to the 60-day information for the cryptocurrency used in the simulation of similar research when it is other.

Investment simulation using a neural network designed for different input parameters between 20 to 70 days is presented separately below. For example, with the price of the last 20 days, we predict the next three days and simulate the strategy for 40 days.

The following diagrams show the step-by-step efficiency of each strategy during the simulation. Efficiency is calculated based on the total daily value of the cryptocurrency and cash.

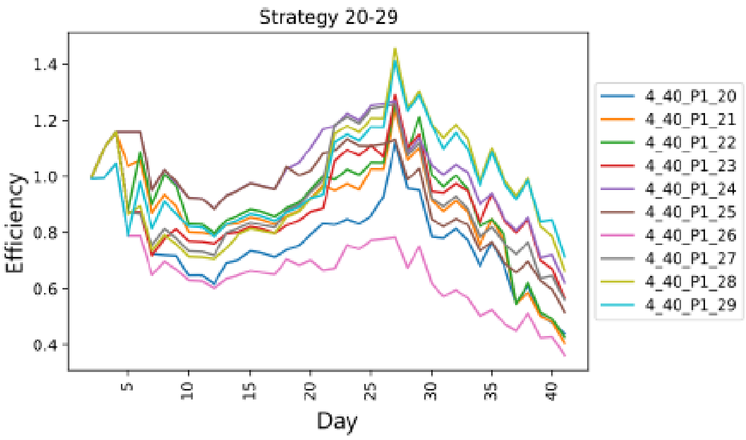

Figure 3: Efficiency on a day-to-day basis for the first strategy of the 20-29 drawing range

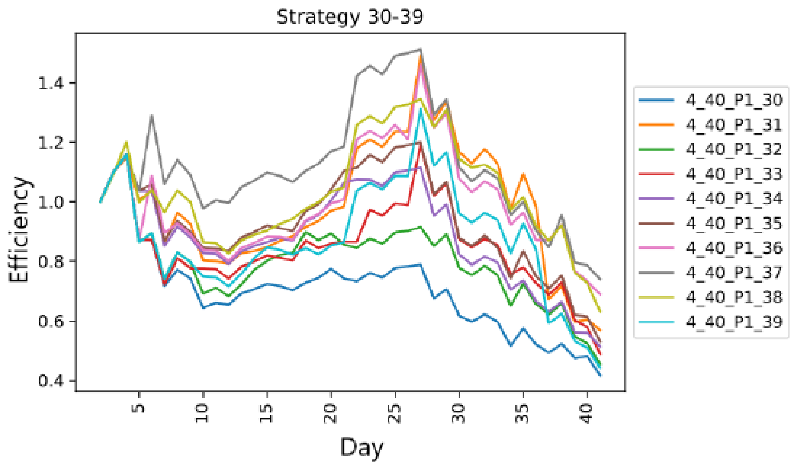

Figure 4: Efficiency on a day-to-day basis for the first strategy of drawing 30 to 39

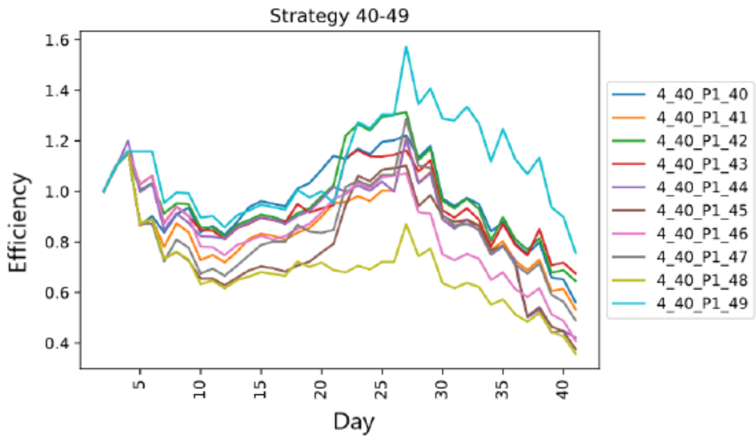

Figure 5: Efficiency on a day-to-day basis for the first strategy of drawing 40 to 49

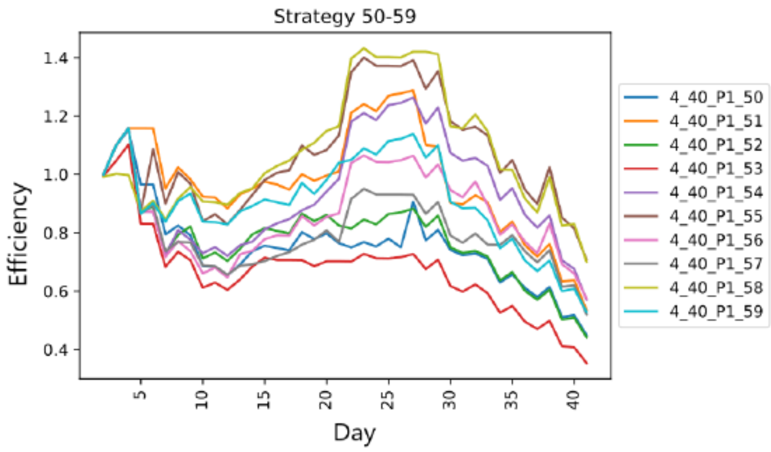

Figure 6: Efficiency on a day-to-day basis for the first strategy of drawing 50 to 59

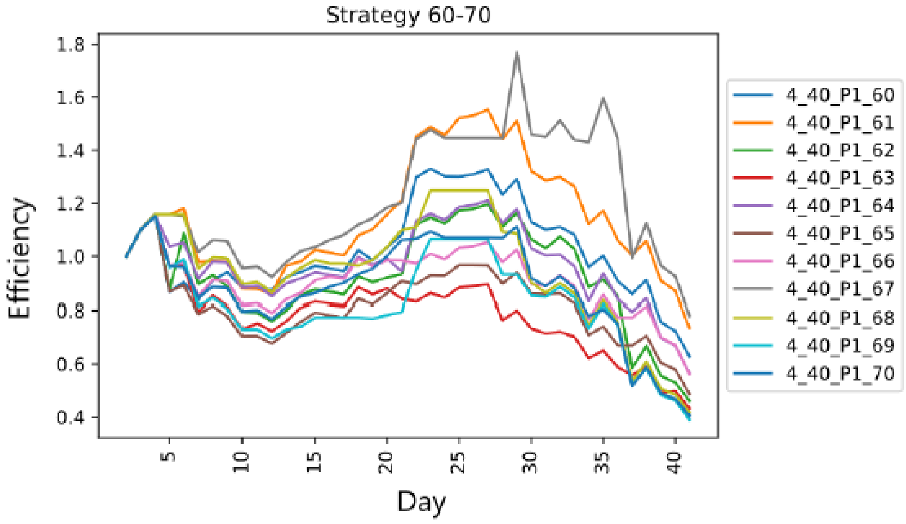

Figure 6: Efficiency on a day-to-day basis for the first strategy of drawing 60 to 70

In Figures (7 to 12) we have shown the results of other researchers whose research results are mentioned until 2020. We have used the best neural network structure proposed in the above source in the present study. We also used the proposed neural network alone for comparison with the present study. To compare the results of other people's research with the designs presented in the present study, based on the proposed structure of the above source, we have performed the simulation in the same range to compare with the criteria introduced. The following Figures, 7 to 12 of the Y-axis show the efficiency of the strategies used in the research simulation.

Figure 7: All cryptocurrencies

Figure 7 shows the strategy efficiency for predicting a future day for four simultaneous codes. Of course, in similar research, there are no multiple digital currencies, and sales are made for a specific digital currency. This simulation was performed to compare with the results of the present study. Below is a chart of the efficiency of investment in each digital currency separately.

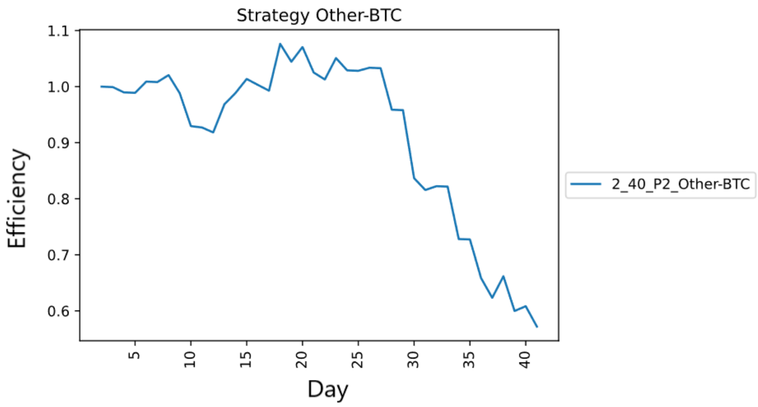

Figure 8: Bitcoin cryptocurrency

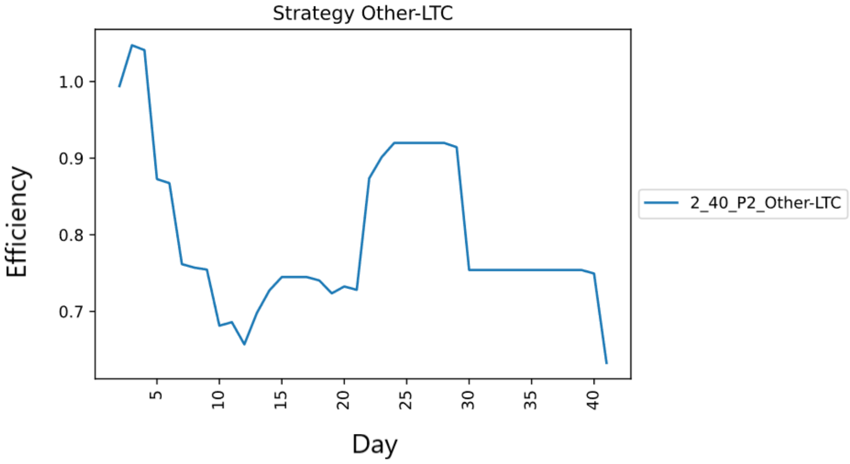

Figure 8: Litecoin cryptocurrency

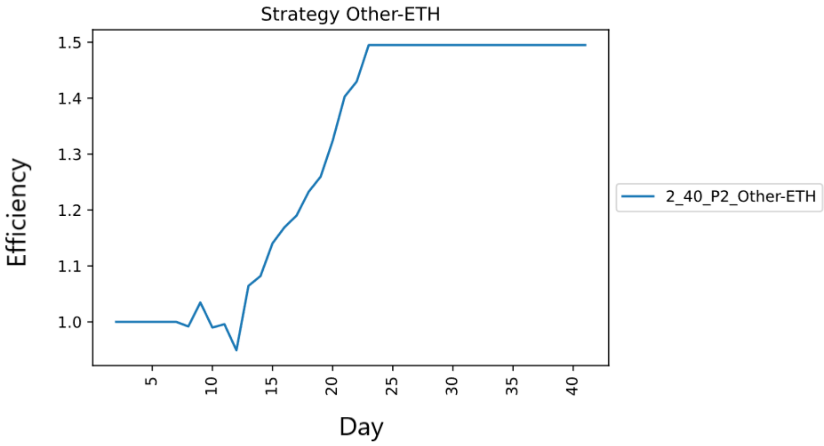

Figure 8: Ethereum cryptocurrency

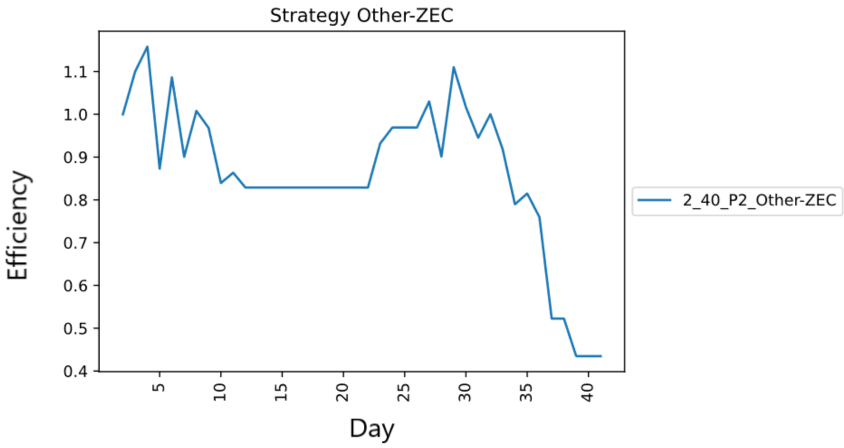

Figure 8: Zcash cryptocurrency

We compare the results based on two criteria. The first criterion is the final efficiency; the second criterion is the average efficiency. We rank according to the above criteria. Finally, according to the ranking and the average numerical value of the efficiency or final efficiency, we show that the suggestions presented in the present study are superior to similar studies.

The first method is network modelling and calculating the best route. We defined several strategies and simulated each one over 40 days based on the above suggestions. Now let us compare which method can be suitable for our goal.

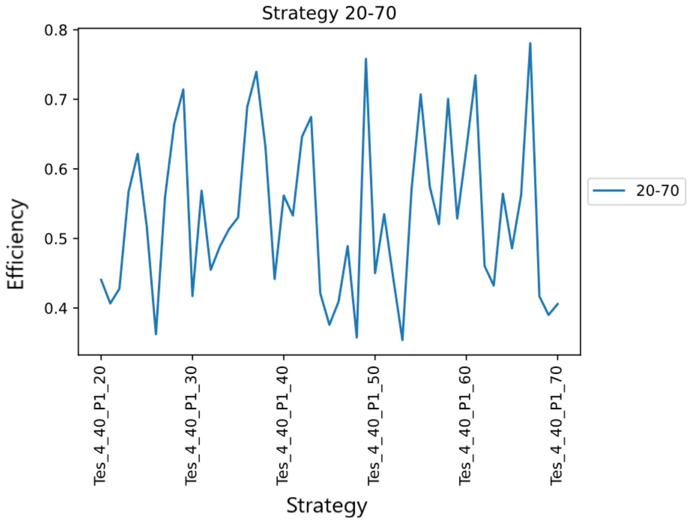

Figure 13: Comparison of the final efficiency of the first method

Figure 13 compares the average efficiency of strategies in the simulation interval. In this method, the efficiency diagram during the 40-day integral simulation is taken, and we compare the number obtained from the above integral. The point in the above charts is that the strategy diagram has shifted down one unit along the y-axis, so we see a negative value in the above graphs.

The shift can be explained as follows: Strategies whose integral value is negative, the efficiency of strategies in the desired range is often less than one, and we have been more at a disadvantage than profits, and strategies that have a positive value. This means the method efficiency more than once in the desired period, and we have been more profitable.

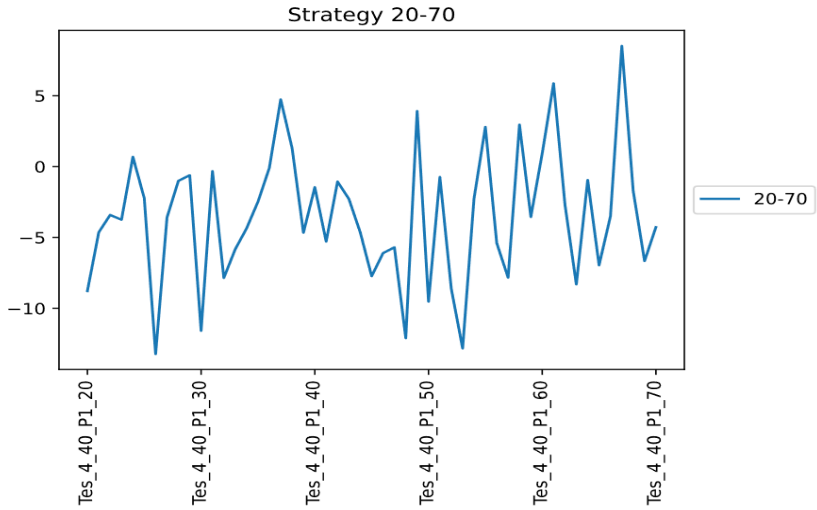

Figure 13: Comparison of the final efficiency of the second method

One strategy may have a higher final efficiency than others, but it does not perform well. This means that a design based on the computational error may significantly reduce efficiency in the last days of the simulation but generally performs well during the simulation. We consider efficiency during the strategy to be a more important criterion because the number of forty days is the time we have to consider for the above research. We practically do not work in a specific interval, forcing us to Look at the average performance of strategies and use it as a benchmark. The sequence of strategies in terms of performance and efficiency is presented in Table 4.

As can see in Table 4, the first rank is allocated to individual sales in Ethereum cryptocurrency, but this is a coincidence because this cryptocurrency has had good upward behaviour in this period and if the same behaviour for another cryptocurrency thing happened like bitcoin. The position of the single strategy of Bitcoin and Ethereum had shifted. However, the strategy that won second place considered all behaviour of this cryptocurrency so that it would be more reliable.

Table 4 Ranking 9 the first strategy and the best similar research strategy

Ranking based on the second method			Ranking based on the first method		
Value	Strategy	Rank	Value	Strategy	Rank
1.494958	2_40_P 2_Other − ETH	1	11.41253	2_40_P 2_Other − ETH	1
0.780752	4_40_P1_67	2	8.514011	4_40_P1_67	2
0.758212	4_40_P1_49	3	5.869663	4_40_P1_61	3
0.739611	4_40_P1_37	4	4.744598	4_40_P1_37	4
0.734493	4_40_P1_61	5	3.920266	4_40_P1_49	5
0.714177	4_40_P1_29	6	2.964249	4_40_P1_58	6
0.707197	4_40_P1_55	7	2.800841	4_40_P1_55	7
0.700765	4_40_P1_58	8	1.318159	4_40_P1_38	8
0.688944	4_40_P1_36	9	0.936103	4_40_P1_60	9
0.632844	2_40_P2_Other−LTC	13	-2.3877	2_40_P1_Other−All	22

Discussion

We have already explained the conditions of the first rank. Given our lack of knowledge about the future price, it does not make sense to use only one particular cryptocurrency, and the performance of the Ethereum cryptocurrency in the simulation interval has led to high efficiency. If strategies with the suffix "other" were in the top 10, it could be said that the proposed method is not efficient except for the first rank, which is due to the proper performance of the cryptocurrency; the rest of the rankings are dedicated to our strategy. In the present study, we increased the yield by examining the number of predictable days and finding the optimal state. This is one of the strengths of the present study compared to other studies.

Conclusion

We answered what new methods or changes could be made in similar research to increase efficiency. For this purpose, we suggested using the forecast for the next few days and limiting the number of predictable days. As seen in the text, ideally, this can maximise our efficiency. If the neural network is more robust and predicts the price better, we can use this maximum capacity more. In a way, we are limiting the neural network that indicates this. This limitation has several advantages. The first advantage is that we will have fewer errors in calculations when we have less output. The second advantage is the number of computations. Limiting the output of the neural network we teach makes it smaller and requires less computing power. At the same time, we could use all the predictive capacity in the neural network.

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