

Analysis of the Use of Artificial Neural Network Models in Predicting Bitcoin Prices

Muhammad Sahi¹, Muhammad Faisal², Yunifa Miftachul Arif³, Cahyo Crysdiandian⁴

Abstract—Bitcoin is one of the fastest-growing digital currencies or cryptocurrencies in the world. However, the highly volatile Bitcoin price poses a very extreme risk for traders investing in cryptocurrencies, especially Bitcoin. To anticipate these risks, a prediction system is needed to predict the fluctuations in cryptocurrency prices. Artificial Neural Network (ANN) is a relatively new model discovered and can solve many complex problems because the way it works mimics human nerve cells. ANN has the advantage of being able to describe both linear and non-linear models with a fairly wide range. This research aims to determine the best performance and level of accuracy of the ANN model using the Back-Propagation Neural Network (BPNN) algorithm in predicting Bitcoin prices. This study uses Bitcoin price data for the period 2020 to 2023 taken from the CoinDesk market. The results of this study indicate that the ANN model produces the best performance in the form of four input nodes, 12 hidden nodes, and one output node (4-12-1) with an accuracy rate of around 3.0617175%.

Index Terms—Artificial neural network, bitcoin, predicting.

I. INTRODUCTION

In Indonesia, Bitcoin is still not recognized as a legal tender by the government, even so, the number of bitcoin and other cryptocurrency traders in Indonesia has continued to soar since the end of 2017 because the price of Bitcoin suddenly skyrocketed [1]. Bitcoin is a risky form of investment, but it can provide big profits if the decision of when to buy and when to sell can be managed properly [2]. The number of Bitcoins circulating in the world is currently around 17,000,000 while the algorithm that generates Bitcoins is only designed to produce 21,000,000 Bitcoins which are expected to run out in 2140 [3]. Due to the limited number of bitcoins, even though the exchange rate remains fluctuating, the Bitcoin exchange rate will certainly tend to increase from year to year.

The value of Bitcoin is very volatile and is purely influenced by supply and demand, in contrast to an ordinary currency whose exchange rate is heavily influenced by the central bank, the exchange rate of cryptocurrency is determined by the owners of the cryptocurrency itself. This is the main attraction for people to invest in Bitcoin. In Indonesia alone, in 2017 there were 700 thousand active Bitcoin traders and it is estimated that this will increase to 2 million in 2018 [4]. The ease of becoming a Bitcoin trader is also a factor in the development of investment in cryptocurrency because you don't need to be a big investor to be able to start trading. Bitcoin traders have touched many layers of society including students.

The main problem for Bitcoin traders is the uncertainty over the price of Bitcoin itself. This price uncertainty is more extreme than stock prices and foreign currencies because of their volatile nature. The price of Bitcoin is very volatile and can even change every minute because the supply and demand that goes up or down are controlled by the Bitcoin owners themselves [5]. In addition, the Bitcoin time series data from 2019 to 2021 is data that form patterns that tend to increase in extreme ways [6]. Therefore, to anticipate this, a prediction system is needed to estimate the price of Bitcoin in the future.

In several studies, the ANN method has been proven to be an effective tool for forecasting and a reference for making predictions using data that has many variables and no pattern [7]. In addition, ANN can also capture and infer invisible parts of the population, even if the sample data provided contains information that has a lot of noise [8]. Then, in a previous study that compared ANN and ARIMA in a case study, Bitcoin price forecasts showed that forecasting with ARIMA resulted in a larger error than ANN. So in this case ANN is superior to ARIMA [9].

Based on this information, research activities are needed related to the analysis of the use of artificial neural network models to predict bitcoin prices. In addition, this study aims to determine the best performance and accuracy of the ANN model using the Back-Propagation Neural Network (BPNN) algorithm in predicting Bitcoin prices. This research is expected to help traders and investors in making decisions to trade and invest in cryptocurrencies, especially Bitcoin.

Received: 13 December 2022; Revised: 28 December 2022; Accepted: 28 July 2023

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II. RELATED WORK

Study [10] investigated the performance of machine learning techniques in cryptocurrency price predictions based on Support Vector Machines (SVM) and Artificial Neural Network (ANN). The main objective of this study is to conclude the application of machine learning to the historical price of Bitcoin compared to the price of gold and silver. The findings of this study indicate that SVM can provide better returns than buy-and-hold for gold and silver prices with a hit rate of around 57.41%. Meanwhile, ANN showed poor performance from both of them with a Hit rate of about 56.26%.

A cryptocurrency prediction study was also conducted by [11] in dimensional engineering sampling. This study aims to predict bitcoin prices using machine learning techniques such as Random Forest (RF), XGBoost, Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM), and Long Short-term Memory (LSTM) with 5-minute time intervals. . The findings of this study indicate that machine learning methods are superior to statistical methods in predicting Bitcoin prices with the best performance accuracy achievement of around 67.2% on the LSTM model. However, this study has limitations, especially in terms of data sources and analysis. Therefore, to conduct a more comprehensive study in the future related to Bitcoin price prediction, researchers need to collect price data with various details and with features that refer to a wider dimension.

Furthermore, the exploration of statistical methods and deep-learning methods was carried out by [12] to predict the future Bitcoin price. They compared two machine learning models, namely the Auto-Regressive Integrated Moving Average with eXogenous input (ARIMAX) and the Recurrent Neural Network (RNN) which were used to predict the Bitcoin time series. The findings of this study show that both models can optimally predict Bitcoin price with a fairly low mean square error of around 0.14% MSE. In addition, they can prove that the performance of the ARIMAX model is superior to the RNN model which is characterized by a lower error value of the ARIMAX model, which is around 0.00030187 MSE. However, this study only uses two comparison models. Therefore, in the next study they will compare the best method they can with other models.

On the other hand, [13] conducted a study through surveys related to the technology that resides in several Bitcoin networks and various machine learning prediction algorithms. They investigated various prediction-based algorithms, especially in the field of Bitcoin price which have been used by several researchers before. In addition, they also compared the accuracy of the performance between the methods used by previous researchers. Then, they got the best method, namely the ARIMA model used in their research. The results of their study show that the ARIMA model cannot perform well in predicting Bitcoin prices with an accuracy value of around 49%. This is due to the large volatility variations contained in the prediction and actualization of prices when measured in the short term. Therefore, it is necessary to use other machine algorithm models such as Artificial Neural Network (ANN) in further studies.

In general, information is one of the factors driving the movement of asset price volatility in financial markets, both symmetrically and asymmetrically [14]. They highlight and investigate volatility structures such as open price (OP), high price (HP), low price (LP), and close price (CP) and the characteristics of cryptocurrencies as investment assets or as digital currencies through the study of Bitcoin price predictions with models. Artificial neural network (ANN) based on its symmetric volatility structure. The findings from their study show that cryptocurrencies are digital currencies that investors tend to use as investment assets. In addition, the findings of their study show that ANN is an effective and adequate model for predicting Bitcoin prices with an accuracy rate of about 92.15% of the actual price. However, the volatility in it is not asymmetrically informative. Therefore, other attributes need to be used in further studies.

III. RESEARCH METHOD

This section describes the systematic steps in order to carry out this research so that it can be done easily and in an organized manner.

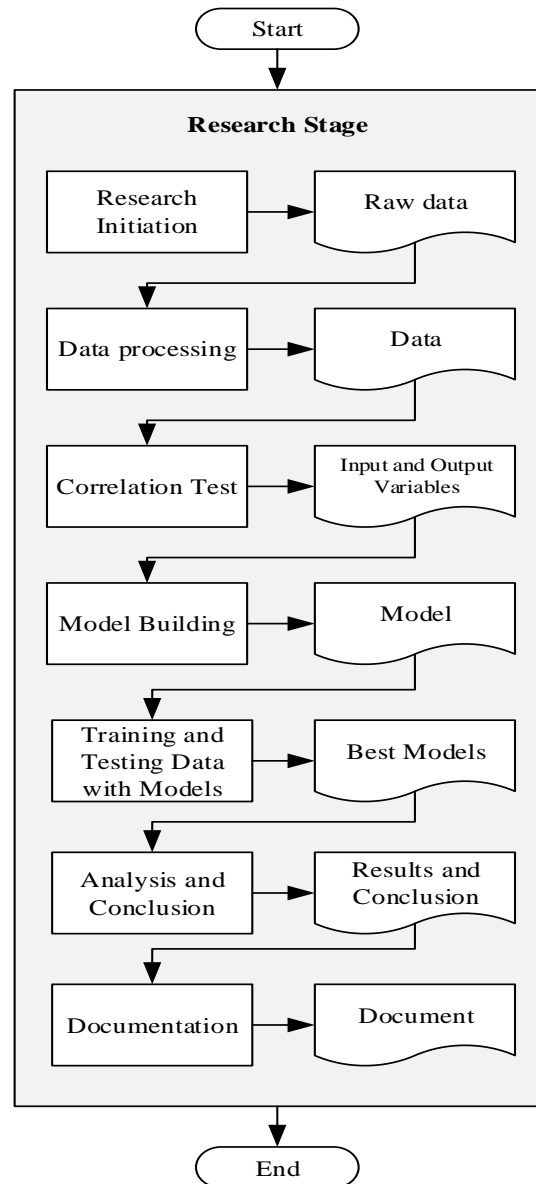


Fig. 1. Research Stage

Research initiation is the initial stage of this research. At this stage identification of problems is carried out, searching for case studies and background problems as well as searching and collecting data related to the research topic. At this stage, a literature study was also carried out on the topic of the final project problem. Identification of the problem is done by looking for problems with Bitcoin traders and investors regarding the price of Bitcoin. After the problem is found, seek knowledge about forecasting and Back-propagation Neural Networks from sources in the form of papers, journals, or books.

The next stage is data processing. At this stage, the data that has been obtained is daily bitcoin price data starting from December 1, 2020, to January 31, 2023, sourced from CoinDesk. Meanwhile, the amount of data obtained was 791 which was divided by around 80% or 633 data for training data and 20% or 158 data for testing data.

Next, double-checking is carried out to find out the completeness of the time series data that has been obtained and whether there are blank or missing data, and if there is will fill in or replace the missing data following statistical rules. At this stage, a data correlation test was carried out between the high price, low price, and open and close price of the previous period against the output data, namely the close price. The results of the correlation test are taken into consideration in determining the input variables in the experimental scenarios carried out.

After the correlation test phase is completed, the next stage is the modeling stage where at this stage the model is built with the input parameters determined based on the results of the correlation test and the output parameters for the next closed price period. From the selected input variable, one output is obtained by using:

$$Y_{n+1} = ((M_1, M_2 \dots M_n) (N_1, N_2 \dots N_n) (O_1, O_2 \dots O_n)) \quad (1)$$

where Y_{n+1} is the output and M_n , N_n , and O_n are the n_{th} -period inputs and f is the sigmoid function [15].

The parameters used in this forecasting include a combination of the transfer function, training function, momentum, learning rate, and the number of hidden layer nodes. The model is created using nodes with a range of n to $3n$ where n is the number of input variables. The number of $n-3n$ nodes was chosen because of its good performance [16]. The hidden layer nodes start from node n to $3n$ of the number of input nodes

$$(h(n), h(n+1), \dots, h(3n)) \quad (2)$$

where $h(n)$ is n nodes in the hidden layer, then $h(n+1)$ is $n+1$ nodes in the hidden layer, and $h(3n)$ is $3n$ nodes in the hidden layer. Initial weight will be allocated randomly. To determine the epoch, a trial and error method is used to determine the smallest error rate of the iterations. After all the steps above are done, then the next step lastly is to document the results of study.

IV. RESULT

In this section, there are 4 important points that will be explained based on the results of the research that has been done, namely parameter trials, scenarios, best models, and actual comparisons with forecast models.

A. Test Parameter

The first thing to do is try to check the parameters using the `nnool` command in Matlab [17]. `Nntool` is the command to run the neural network tool in Matlab. Through `nnool` it can be estimated how the neural network works according to the parameters that have been previously determined. The first thing to determine is to determine the epoch by looking at the performance graphs generated after training the data with `nnool`. The epoch is determined after the performance graph begins to converge or decline and then level off. To find the epoch, an experiment was carried out using `nnool` with an epoch of 100.

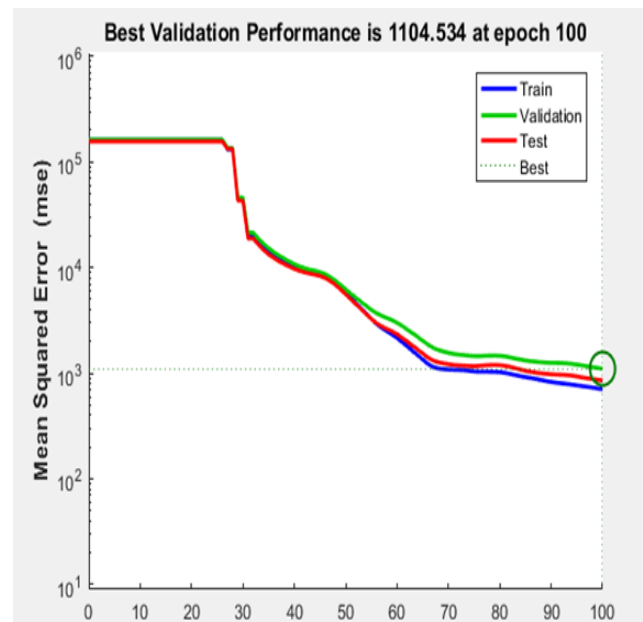


Fig. 2. Data performance

Experimental results as shown in Fig. 2. The performance graph continues to decline after epoch 100, but the gap between train and test is widening. This can result in overfitting and high data errors, so an epoch of 100 is still considered not good [18]. For maximum results, we must look for epochs at convergent points with the smallest possible distance between the train and test to avoid overfitting. By considering these factors, epoch 80 is used to get maximum results.

B. The Scenario

The scenario is done using Matlab software. Scenarios 1 to 3 are carried out using a script that has been written before. Scenarios are carried out by trial and error, where trials are carried out by trying all combinations of the existing and previously mentioned parameters [19]. Three

trials were carried out for each scenario. Of the three trials, the best will be selected based on the MAPE value [20]. Of the three scenarios carried out, it will be seen which scenario produces the smallest MAPE and will produce the best model.

Scenarios are carried out starting from input data for one period and will continue to be added. Scenario trials will be terminated if the MAPE chart has decreased. To ascertain whether the resulting MAPE is indeed the smallest MAPE result, two more trials are carried out by increasing the data input period. have achieved good results. The output results from the trial are stored with code in the format A_B_C_D_E. Each code represents a certain parameter. Explanation of the output storage code can be seen in Table 1. A is the code for the training function, B is for the transfer function, C is for momentum, D is the learning rate and E is for the number of nodes.

Table 1.Storage Code

Code	Parameter	Value
A	Training Function	1 = trainlm
		2= traindx
		3= traingda
B	Transfer Function	1 = logsig
		2 = tansig
		3 = purelin
C	Momentum	1 = 0.1
		9 = 0.9
D	Learning Rate	1 = 0.1
		9 = 0.9
E	Amount HiddenNodes	n-3n

Each code has a value denoted by a number. This number represents the type of parameter used in the trials that have been carried out. The following table describes the value of each parameter.

Table 2.Parameter Explanation

Number of inputs nodes	Number of hidden nodes	Number of models resulting from
1	3	6561
2	5	10935
3	7	15309
4	9	19683
5	11	24057

Code A has three values denoted by the numbers 1-3. Value 1 for code A represents training function training, value 2 represents training function training, and value 3 represents training function training. Code B has three values which are denoted by the numbers 1-3. Code B represents the transfer function parameters. Number 1 for code B represents logsig, number 2 represents tanding, and number 3 represents purelin. Codes C and D have nine values denoted by numbers 1-9 which represent momentum and learning rate with values 0.1-0.9. So if code C or D has a value of 3, then the value of the momentum and learning rate is 0.3.

C. Best Models

The best model is searched based on the MAPE value. The model that has the lowest MAPE value will automatically be the best model [21]. Of the three scenario trials that have been carried out, the best model is the model from the three scenario trials as shown in Table 3.

Table 3. Best Models

Number Scenario	Input Nodes	Best Models	Mape Test
1	2	2_3_1_2_4	3.8737979
2	1	1_3_5_3_1	366814
3	4	1_3_2_5_12	3617175

The best model produced is in scenario 3 trials with 4 input nodes. It looks like in the picture the best MAPE value from each scenario.

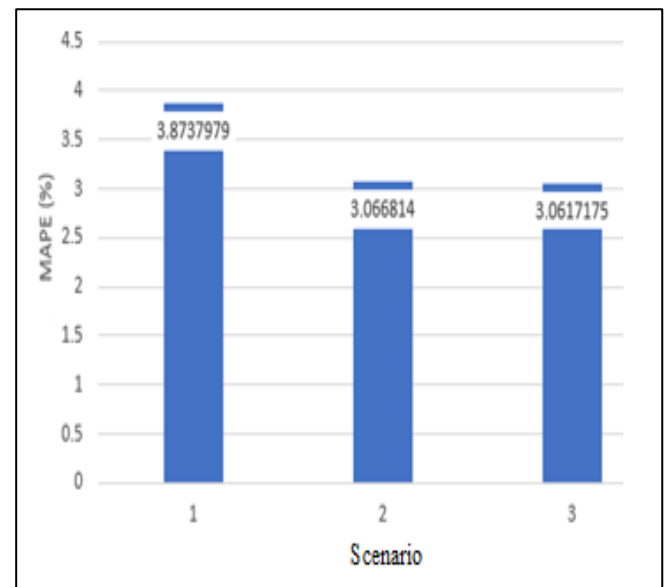


Fig. 3. Comparison chart between trials

Scenario 3 has the best MAPE value of 3,0617175% with model 1_3_2_5_12. The model uses the parameters train function trainlm, transfer function purelin, momentum 0.2, learning rate 0.5 and 12 hidden nodes.

D. Actual Comparison with Forecast Models

After finding the best model, then the model output data is compared with the actual data [22]. A comparison of forecast data with actual data can be seen in the Fig. 4.



Fig. 4. Graph comparison of forecast data with actual data

It can be seen from Fig. 4 that forecast data and actual data do not have too much difference. This is because the error for the best MAPE model is small, namely 3.062%. Previous research [10] investigated machine learning techniques by comparing the Support Vector Machines (SVM) model with ANN which obtained the result that the ANN model obtained an accuracy value of around 57.41% and could perform better than the SVM model in predicting bitcoin prices. Meanwhile, [14] obtained an accuracy value of around 92.15%.

Based on these findings, it can be concluded that the ANN model used in this research can be developed and performs better than the ANN model used in previous research. Even though you get a standard accuracy value, you can get an accuracy value of around 92.15%. Based on this, it can be synthesized that the ANN model in this study can be built and performs better than the use of the ANN model in previous studies.

V. CONCLUSION

Based on the results of the analysis that has been carried out, several conclusions can be drawn that the ANN model can be applied to a case study of Bitcoin price forecasting with an accuracy level of around 3.0617175%. In addition, the best model produced using the ANN structure is (4,12,1) with detailed parameters including function training using trainlm, transfer function uses purelin, momentum 0.2, learning rate 0.5, and uses epoch 80 to get better results than epoch 100.

This research has several limitations. First, the data used only uses bitcoins which may make our results less variable. Further research can consider the use of other cryptocurrencies such as Ethereum (ETH), Solana (SOL), TRON (TRX), and so on. Second, we assume that using more than one hidden layer will improve model performance. Thomas *et al.*, [23] states that the use of two hidden layers is better than one hidden layer. Therefore, we recommend using two hidden layers in future research. Third, other factors and models such as the General Regression Neural Network (GRNN) can be used to test the performance of models in predicting cryptocurrencies.

ACKNOWLEDGMENT

Our thanks go to Mr. Muhammad Faisal, Mr. Cahyo Crysdiyan, and all lecturers of the Informatics Masters Program at UIN Maulana Malik Ibrahim Malang who have helped provide direction and guidance in the process of carrying out this research.

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