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Bitcoin USD Closing Price (BTC-USD) Comparison Using Simple Moving Average And Radial Basis Function Neural Network Methods

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Abstract—**Bitcoin is a decentralized electronic money that is not controlled nor insured by a central authority. Because it is still a young system, the price of Bitcoin is extremely unpredictable, making Bitcoin users and investors uneasy. A typical difficulty for investors and traders is predicting the future movement of the value of Bitcoin electronic money based on historical data. Because investors and traders only notice swings in global currency prices and make Bitcoin buy/sell decisions instinctively, they frequently make the erroneous buy/sell decisions. Many investors and traders suffered significant losses as a result of this error. Losses can be reduced by employing an algorithm that predicts the movement of the value of Bitcoin electronic money. Using a comparison of two methodologies, the Simple Moving Average and RBFNN, we will anticipate the closing price of Bitcoin USD (BTC-USD) from January 1, 2021 to January 31, 2021. The results obtained using the simple moving average method MSE = 0.01 percent and MAPE = 36.67 percent, and the results obtained using the RBFNN method MSE = 9.97 x 10-7 and MAPE = 9.97 x 10-5, indicating that the RBFNN method with an accuracy rate of 99.9995 percent is better than the simple moving average method in forecasting the closing price of bitcoin.**

Keywords—Prediction, Bitcoin, Moving Average, Radial Basis Function Neural Network

I. INTRODUCTION

The present monetary system is based on paper money, which has various benefits over previous kinds of money, including dispensability, transferability, durability, and rarity [1]. Today's finance, on the other hand, has severe flaws, such as unsupported currencies between countries, which means governments retain control over the currency. This can result in a variety of issues, such as hyperinflation and economic inequality [2]. The second point to consider is how people execute financial transactions. Everyone uses cheques, transfers, credit cards, or online tools like Amazon Pay to conduct financial transactions. Banking institutions or third-party intermediaries, such as credit card firms and financial institutions, are used to make payments. Fees for money transfers between nations are typically between 6% and 10% [3].

Individuals have lost control and ownership of their data as a result of this intermediate monopoly. Because of their accountability and order, society has built a sense of confidence in these organizations. More than 6 billion people transferred $200 trillion in value [3]. Even though these trusts are supported by government rules and legal contracts, they are readily ruptured, as seen by the billion-dollar dot-com bubble in the 1990s and the Real Estate Bubble in 2008 [4]. Public faith in the existing financial system, which risks probable hyperinflation, is shaky. As a result, a paradigm that develops trust among all stakeholders is required.

Bitcoin is a peer-to-peer (P2P) cryptocurrency that runs on open-source software. Bitcoin transactions are simpler than those using other digital currencies since they do not require a bank account, credit card, or an intermediary. Bitcoin is the first, largest, and most widely used cryptocurrency, and it can be found on a variety of cryptocurrency exchanges throughout the world. According to statistics from www.indodax.com, the price of Bitcoin was Rp. 8,757,600.00 on February 3, 2014, and Rp. 297,500,000.00 on December 07, 2017. Many people invest in Bitcoin as a long-term investment [6], [8], [9], [13], [14]. As a result, the value of Bitcoin in other currencies, such as the US Dollar, has increased. Buying and trading bitcoins entails various risks and losses, which should be mitigated to the greatest extent feasible. Investors make mistakes because they are not cautious while making investing selections. One method of investing and buying and selling transactions is to predict the price of Bitcoin electronic money. Historical Bitcoin price data will be evaluated by time to estimate the Bitcoin price, allowing investors to make purchasing and selling decisions on the worth of Bitcoin e-money [3], [7], [10]–[13], [15]–[24].

Nany Salwa, Nidya Tatsara, Ridha Amalia, and Aja Fatimah Zohra researched estimating the price of virtual currencies such as Bitcoin in 2018. "Forecasting Bitcoin Prices Using the ARIMA (Autoregressive Integrated Moving Average) Method" [25] is the title of this study. The ARIMA approach is used in the study to predict the price of the Bitcoin cryptocurrency. The data utilized in this study is secondary data in the form of bitcoin price data 60 times between January 10 and March 10, 2018, to forecast bitcoin prices for the next 30 periods between March 11 and April 09, 2018. The results reveal that the bitcoin price data for 60 periods do not match the assumption of average stationarity, requiring a level 2 differencing method to make the data stationary. ARIMA(0,2,1), i.e. $Zt = - 0.9647Zt-1 + at$, is the resultant ARIMA model, which is suited for forecasting bitcoin price data. The ARIMA(0,2,1) model are predicting findings suggest that the bitcoin price would decline gently over the following 30 periods, and the forecasting results are close to the actual data.

The goal of this research is to compare the Simple Moving Average (SMA) and Radial Basis Function Neural Network (RBFNN) approaches for forecasting the closing price of the Bitcoin electronic money value against the US dollar (BTC-USD) from January 1, 2021, to January 31, 2021. The accuracy of each approach, such as Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE), is displayed for each procedure (MAPE). In the instance at hand, the approach with the lowest mistake rate or highest degree of accuracy is the best way. This study is supposed to aid investors in assessing Bitcoin price swings and making the best investment decisions.

II. Research methods

This study uses the following framework in Figure 1.

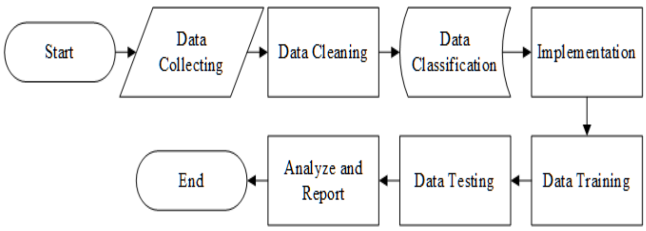

Figure 1. Flowchart of Research Thinking Framework

There are 7 stages of testing in this research:

1) Bitcoin Data Collection: Bitcoin data collection is the initial stage of this research. The data used in this research is during the period 1 January 2015 to 31 December 2020 obtained from finance.yahoo.com.

2) Cleaning of data: To create high-quality data, data cleaning involves examining the quality of data and modifying, updating, or removing data that is erroneous, incomplete, inaccurate, or has the wrong format in the database. Data cleansing is also known as scrubbing or cleaning data. Data cleaning is frequently utilized in industries that require large amounts of data, such as banking, insurance, retail, telecommunications, and transportation. Data cleaning is used in businesses to rectify data using algorithms to save time and money routinely. The data cleaning procedure is sometimes done manually and sometimes done automatically.

3) Data Classification: The outcome of a specific computation or quantity is Counting Data (Enumeration or Counting Data). The percentage of a particular quantity is included in the computed data. A measure that reveals the value of anything is called measurement data.

4) Implementation: A design for the created system begins at this point. The data classification from the previous step informs the system design. This step results in a complete system design, executed in the following stage. With MATLAB software and Microsoft Excel, the design findings will be realized as a simulation. For users, this step will be implemented (Investors and traders). This data will eventually be synced with the central server using real-time data.

5) Data Training: The use of the Simple Moving Average (SMA) and Radial Basis Function Neural Network (RBFNN) algorithms in the previous stage will be examined.

6) Data Testing: Data testing will be done at this step based on the data from the previous stage's application of the Training data test.

7) Analyze and Report: The testing procedure from steps 1 to 6 will be displayed at this stage, and the amount of accuracy and efficacy of the SMA and RBFNN algorithms will be calculated.

One of the most popular lessons to handle forecasting difficulties is the Radial Basis Function Neural Network (RBFNN). Newrbe and newrb are the two functions that makeup RBFNN. In terms of the learning process, they are nearly identical. The distinction is that newrbe contains as many neurons as the number of inputs created, whereas newrb only forms one neuron every iteration. The neuron with the minor overall error will be considered a new neuron. The network error will then be rechecked, and if the network error is modest enough, the iteration will be terminated. However, if the network problem persists, the next neuron will be added, and so forth. The number of neurons in the hidden layer will not always match the number of input vectors in the newrb function; in other words, not all input layers in the data can be used for modeling. The following is the Radial Basis Function Neural Network (newrb) calculating algorithm:

a) Find || $Xij - Xkj$ || Euclidean distance. where i, k = 1, 2, …, n and n are the number of observations j = 1, 2, …, p and p are the number of predictor variables

$$\|x_{ij} - x_{kj}\| = D_{ik} = \sqrt{\sum_{j=1}^{n} (x_{ij} - x_{kj})^2} \quad (1)$$

b) Finding $\varphi_{ik} = \varphi\|x_{ij} - x_{kj}\|$ activation results with a radial basis function of the data distance multiplied by the bias.

$$\varphi_{ik} = e^{-(b1 * D_{ik})^2} \quad (2)$$

c) Finding layer weights and layer bias weights, w_t and b_l by solving the following linear equations which can be solved by the Least Square method.

$$\varphi_{11} w_1^{(2)} + \varphi_{12} w_2^{(2)} + \cdots + \varphi_{1n} w_n^{(2)} + b2 = d_1$$
$$\varphi_{21} w_1^{(2)} + \varphi_{22} w_2^{(2)} + \cdots + \varphi_{2n} w_n^{(2)} + b2 = d_2$$
$$\cdots$$
$$\varphi_{n1} w_1^{(2)} + \varphi_{n2} w_2^{(2)} + \cdots + \varphi_{nn} w_n^{(2)} + b2 = d_n \quad (3)$$

Equation (3) when arranged in matrix form is as follows:

$$\begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} & 1 \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \varphi_{n1} & \varphi_{n2} & \cdots & \varphi_{nn} & 1 \end{bmatrix} \begin{bmatrix} w_1^{(2)} \\ w_2^{(2)} \\ \vdots \\ w_n^{(2)} \\ b2 \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix}$$

Two layers of networks may be created using the newrb function. Radbas neurons make up the first layer, whereas purelin neurons make up the second. The radbas layer has no neurons initially. Thus the methods below are repeated until the network has the tiniest defect. The procedure is as follows:

- Simulate the network
- Enter the vector that has the most significant error
- Add radial basis neurons with the same weight
- Redesigned purelin layer to minimize errors

Moving Average is a predictive indicator model utilized in trading and investment strategies. In statistics, a moving average is a formula used to examine data points by constructing a series of averages from various subsets of the entire data set. Moving average (MA) is a stock indicator utilized frequently in technical analysis. Calculating the moving average of a stock's price aims to streamline price data by providing a constantly updated average price. By calculating a moving average, the effect of random short-term changes on stock prices can be diminished over time.

The Formula for SMA is:

$$SMA = \frac{A1 + A2 + \ldots + An}{n} \quad (4)$$

Dimana:
A_n = the price of an asset at periods n
n = the number of total periods

III. Results and Analysis

The bitcoin USD prediction algorithm utilizes the bitcoin price input variable in this method. Before commencing the training phase of the Radial Basis Function Neural Network approach, input and target data are normalized on a scale of 0 to 1 before training. This normalization aims to produce data with smaller file size and accurately represent the original data without altering its properties. The following table contains instances of normalization outcomes:

	DATA HARGA BITCOIN TAHUN 2016						
Hari ke	Januari	Februari	Maret	April	Mei	Juni	Juli
1	0.006347	0.00874	0.006764	0.00845	0.008423	0.009444	0.012485
2	0.006421	0.008846	0.006812	0.008078	0.008424	0.009319	0.013568
3	0.007315	0.008807	0.006656	0.007718	0.008442	0.009363	0.013691
4	0.007309	0.008708	0.007337	0.007966	0.008532	0.009766	0.013769
5	0.007544	0.009712	0.007232	0.008195	0.008511	0.009729	0.014135
6	0.008238	0.009545	0.006884	0.008183	0.008488	0.00973	0.013825
7	0.008308	0.00935	0.006887	0.008214	0.008404	0.009797	0.014
8	0.008235	0.009363	0.006777	0.008293	0.008372	0.009464	0.013757
9	0.0095	0.009379	0.006867	0.008451	0.008447	0.009528	0.013856
10	0.008913	0.008937	0.007062	0.008102	0.008478	0.009598	0.014871
11	0.00887	0.008822	0.006993	0.008186	0.008572	0.00963	0.017162
12	0.009231	0.00875	0.007152	0.008269	0.008522	0.00963	0.018258
13	0.009965	0.006461	0.007416	0.008282	0.008541	0.009696	0.017606
14	0.009604	0.007266	0.007949	0.008289	0.008729	0.009578	0.017915
15	0.009644	0.007084	0.007705	0.008414	0.008759	0.009564	0.020407
16	0.009906	0.007253	0.007958	0.00803	0.008649	0.009593	0.019803
17	0.009861	0.00701	0.008265	0.008061	0.00869	0.009042	0.020057
18	0.009179	0.0084	0.008475	0.008176	0.00893	0.009179	0.020319
19	0.009039	0.008054	0.00842	0.00816	0.009134	0.009197	0.019398
20	0.008967	0.007091	0.008988	0.008326	0.009413	0.009063	0.01695
21	0.009169	0.007264	0.009044	0.008324	0.009285	0.00923	0.014502
22	0.009606	0.007802	0.009008	0.008267	0.009443	0.009294	0.015469
23	0.009629	0.007411	0.008418	0.008294	0.00973	0.009419	0.016903
24	0.008298	0.007426	0.008564	0.008321	0.00983	0.009551	0.016897
25	0.00849	0.007524	0.00855	0.008627	0.009991	0.010247	0.015656
26	0.008471	0.007015	0.008814	0.008539	0.009249	0.01221	0.016555
27	0.008843	0.006986	0.008827	0.008271	0.009399	0.012078	0.016268
28	0.008622	0.006944	0.008861	0.008212	0.00961	0.012343	0.016021
29	0.008759	0.006615	0.009006	0.008279	0.009375	0.012257	0.017182
30	0.00889		0.008917	0.008322	0.009498	0.012449	0.017284
31	0.008859		0.008531		0.009248		0.018235

Figure 2. Bitcoin Price Normalization Results in 2016

This prediction approach employs the Radial Basis Function Neural Network and Simple Moving Average techniques to compare the accuracy of its predictions to the Mean Square Error and MAPE values.

The training data for the bitcoin USD forecast is variable bitcoin price input data from 2015 to 2020. The goal data consists of bitcoin price information from 2016 through 2020. The value is achieved after training the Radial Basis Function Neural Network and Simple Moving Average system. The most minor Mean Square Error (MSE) in a Radial Basis Function Neural Network.

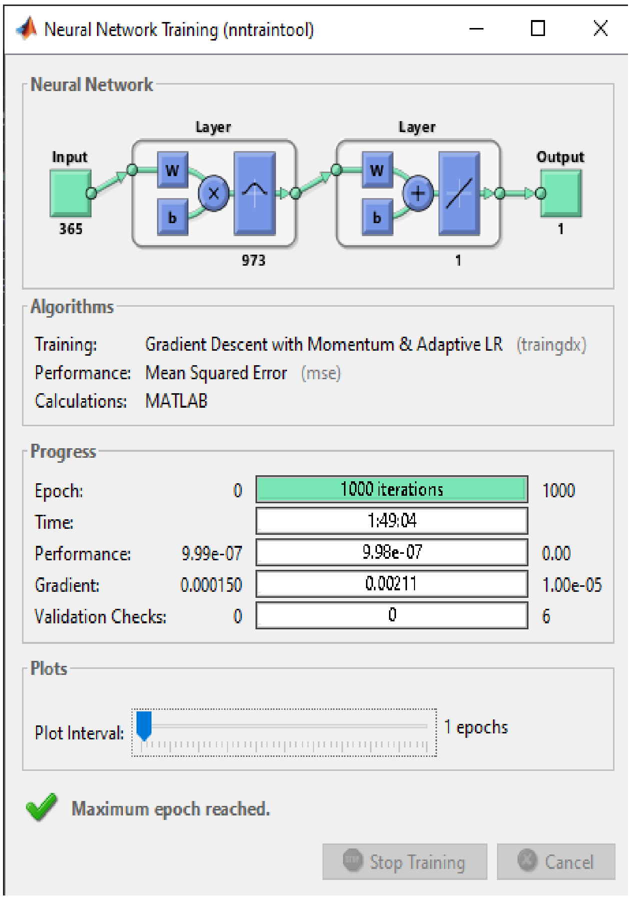

Figure 3. RBFNN Neural Network

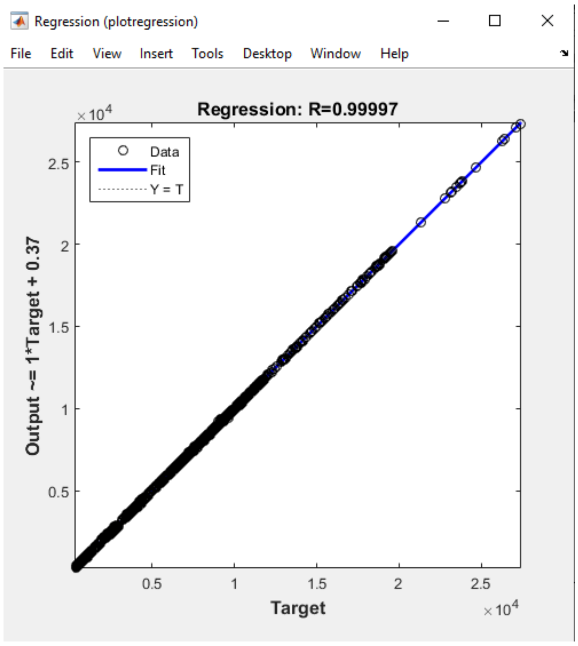

Figure 4. Training Accuracy of Radial Basis Function Neural Network

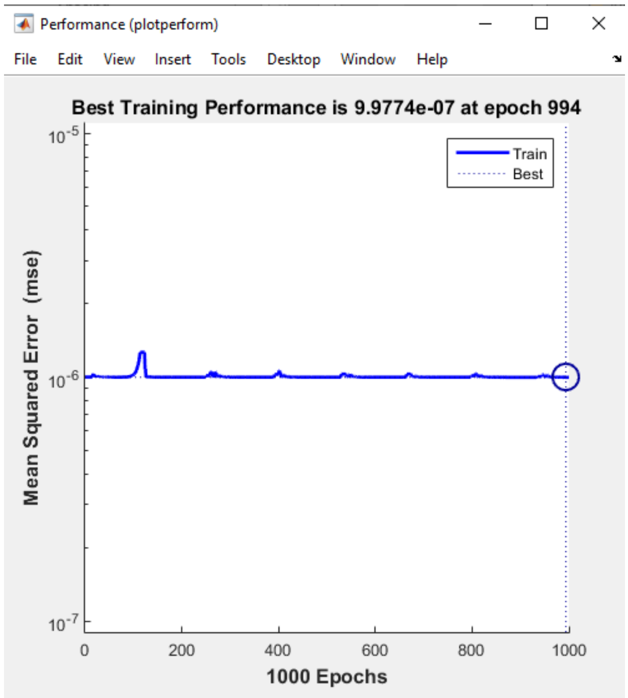

Figure 5. Radial Basis Function Neural Network Training Performance

Figure 6. Comparison Graph of Training Data with Training Targets Radial Basis Function Neural Network

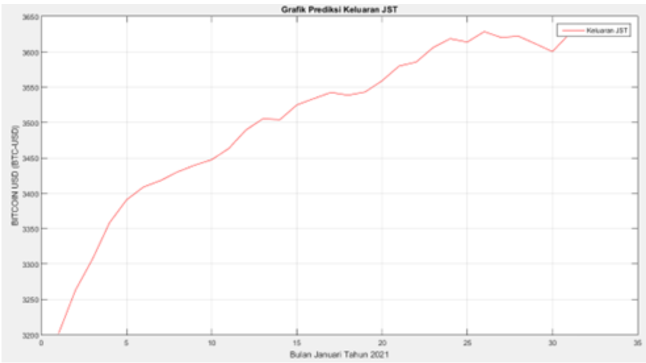

Figure 7. Bitcoin Price Prediction in January 2021

Figure 8. Simple Moving Average Chart

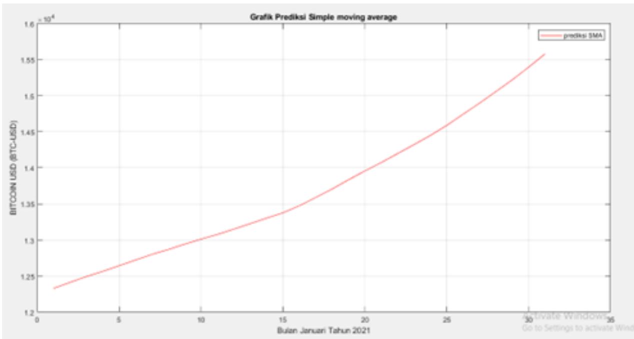

Figure 9. Simple Moving Average Bitcoin Price Prediction in January 2021

This investigation uses the traingdx training function. Considering the size of the correlation coefficient and the little amount of inaccuracy produced. The results of the forecast are then generated:

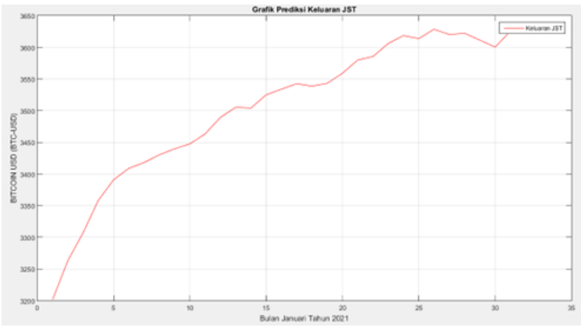

Figure 10. RBFNN Bitcoin Price Prediction in January 2021

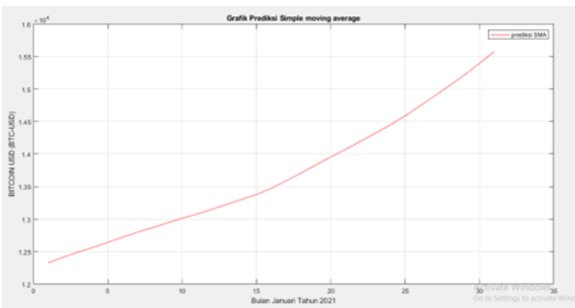

Figure 11. Simple Moving Average Bitcoin Price Prediction in January 2021

The accuracy of the radial basis function neural network approach with multiple training functions is 99.9995 percent, based on the data acquired and evaluated from the two articles without consideration of data beyond the scope of the papers' study. In comparison, the accuracy of the simple moving average approach is lower. This indicates that the radial basis function neural network technique is superior to the simple moving average method by 63.280 percent.

IV. Conclusion

Using the radial basis function neural network approach with the traingdx function is preferable to using the basic moving average method because the radial basis function method has a greater accuracy rate, which may reach 99.9995 percent.

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