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Research Article

# Neural Network-based Model for Forecasting the Macroeconomics on the Use of Blockchain and Cryptocurrency in Nigeria

**Eucharia Onyekwere, Francisca Nonyelum Ogwueleka* and Martins Ekata Irhebudhe**

*Department of Computer Science, Nigerian Defence Academy Kaduna, Nigeria*

***Corresponding Author:** Francisca Nonyelum Ogwueleka, Department of Computer Science, Nigerian Defence Academy Kaduna, Nigeria.

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## Abstract

Financial time series forecasting could be a daunting task due to inherent noise and non-stationarity. The most crucial and challenging factor in cryptocurrency forecasting is volatility. Cryptocurrency, particularly bitcoin, is not just used to make payments for goods and services; it is traded in exchange for other currencies. In this study, the Multilayer Perceptron (MLP) model with Backpropagation Algorithm written in Python programming language was developed to forecast the volatile time series data of the volume of bitcoin transactions in Nigeria for seven years. Three different models were designed and experimented with varying hidden layers and neurons for the forecast. In comparison, the ever-popular statistical model of Autoregressive Integrated Moving Average (ARIMA) was used as a point of reference for the Neural Network Models. The models were evaluated based on performance measures such as Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), which indicated that the best performing MLP model had an MSE of 0.007085, RMSE OF 0.000050 and MAPE of 1.274076. In comparison, the ARIMA model yielded an MSE of 0.092093, RMSE of 0.303468 and MAPE of 46.13.

**Keywords:** Cryptocurrency; Bitcoin; Blockchain; Artificial Neural Network; Multilayer Perceptron

## Introduction

During the mediaeval times, people produced all they needed to meet their physiological needs entirely by themselves and independent of others. After that, they started exchanging goods (trade-by-barter) or services when each man produced more than required for his family [1,2]. Realising the clumsiness of this method, they devised a general medium of exchange to overcome the challenges of trade-by-barter, which advanced into the use of cowries and other precious metals as a medium of exchange [3]. The use of cowries and other precious metals like gold grew and developed into fiat currency to solve the mutual coincidence of wants. In 2008, the history of digital currency began when an anonymous person or group of persons came up with Bitcoin, which operates on a digital ledger technology called the blockchain. As the name implies, blockchain is a technological innovation consisting of a sequence of 'blocks' of information or transactions interlocked (chain) by complex computational algorithms [4]. The advent of cryptocurrency and blockchain technology has moved the world to a different sphere of financial technological revolution through various cryptocurrency trading industry areas such as exchange, payments, mining and storage. In 2009, the cryptocurrency started gaining ground globally to the extent that in 2017, it was worth $91.073 billion US dollars [5], with an overwhelming increase of Bitcoin price over time. By the second quarter of 2021, the cryptocurrency market was worth $2.4 trillion [6]. The economic gap between African and developed nations is quite enormous. Since the well-known sources of revenue are failing, the continent needs to explore other means of generating revenue and create jobs to raise their economic status.

Financial time series forecasting is interdisciplinary and one of the most exciting applications with intricate behavioural patterns arising from political and psychological factors. Hence, quantitative computational models that can give better performance, especially in non-linear, multivariate and noisy data, are paramount to attain accuracy and speed in forecasting [7]. Artificial Neural Network (ANN) is a formulated representation of the human brain that tries to mimic the process of learning [8]. It is a state-of-the-art computational modelling tool in computer science used to analyse data and discover probabilities and relevant circumstances [9]. Neural Networks consist of simple computing cells known as 'processing units', otherwise called 'neurons', which are interconnected to perform some computations such as pattern recognition, natural language processing and computer vision [10]. ANNs are data-driven models; hence, they rely on input variables. Therefore, it is essential to identify a suitable and valuable variable for the in-sample training to attain a correct out-of-sample outcome. The framework presented in this study comprises three models of the Multilayer Perceptron characterised by varying numbers of layers and nodes. The objectives are: to apply several pre-processing techniques such as interpolation techniques to increase the number of observations, MinMaxScaler for standardisation of the data, and Adaptive Momentum (ADAM) optimisation techniques. To analyse the forecasting model with measures of performance using the root mean square error (RMSE) and mean absolute performance error (MAPE). And to compare the ANN model with the autoregressive integrated moving average (ARIMA) model. This study seeks to ascertain with precision and accuracy an ANN model that can forecast the viability and use of blockchain and cryptocurrency in Nigeria.

## Review of Related Literature

Lahmiri and Bekiros [11] compared several artificial intelligence systems forecasting the chaotic intraday bitcoin market. They used models from three different sets: Firstly, are statistical models such as Support Vector Machine (SVR) and Gaussian Poisson Regression (GPR). Secondly, are algorithmic models such as Regression Trees (RT) and *k*-Nearest Neighbour (kNN). Lastly, are the ANN models, which includes; Feedforward Neural Network (FFNN), Bayesian Regularization Neural Network (BRNN) and Radial Basis Function Networks (RBFNN). The comparative evaluation reveals that ANN was unusually fast despite the big data with an overall lead and superior performance. Its intelligent models involve numerous parallel information-processing elements that take care of non-linear relationships between inputs and outputs despite the noisy and non-stationary data.

Similarly, Wang and Chen [12] used several machine learning and deep learning algorithms such as SVR for regression, Backpropagation Neural Network (BPNN), Radial Basis Function (RBF), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and two kernel functions; linear and sigmoid activation functions to carry out a comparative study on the price prediction of cryptocurrency based on multiple market sentiment. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were the two indicators used as evaluation criteria. The volume of cryptocurrency transactions was obtained from Binance and Huobi, China's two most significant cryptocurrency trading platforms. The Predictions were made on five cryptocurrencies; bitcoin (Btc), Ethereum (Eth), Tether USD (USDT), Ripple (XRP) and Litecoin (LTC). In the long run, the studies revealed that RBF is a better predictor than BPNN in terms of the neural network, although not as accurate as SVM, CNN and LSTM. However, SVM, CNN and LSTM take a longer time to learn and predict and out of the two deep learning algorithms, LSTM gave a better result. Hua [13] compared the prediction of bitcoin price in the US dollar in terms of two different models; the ARIMA and LSTM models. The price dataset was obtained from the Bitfinex website, which provides its users with an API to access real-time pricing information and 5-second interval trading data of 10000 prices observations. The dataset was split into 8000 and 2000 values of each 5 seconds for training and testing. After analysis, results show that both models performed well in predicting the price of bitcoin, although the LSTM performed better after an extra amount of time in data training. Nevertheless, ARIMA was equally efficient in predicting the price within a short span of time, but as the time increases, the precision rate declines.

Jang and Lee [14] performed a time series analysis of bitcoin prices by adopting the Bayesian Neural Network (BNN) model and comparing it with benchmark models such as linear regression and support vector regression models. Inputs for the BNN learning were obtained from three categories comprising 25 variables and two response variables; bitcoin price and bitcoin price volatility. Based on Root Mean Square Error (RMSE) and Mean Absolute Percentage

Error (MAPE), the performance of BNN exceeded Support Vector Regression and Linear regression models. They also observed that the error value was relatively low after removing excessive variables from linear correlation analysis despite using the 26 input variables rather than 16 input variables. Invariably, Support Vector Regression (SVR) models performed poorly in training and testing.

Alonso-Monsalve, Suárez-Cetrulo [15] explored the suitability of CNN with convolutional components as an alternative to Multilayer Perceptron in classifying the trend of cryptocurrency exchange rate using technical analysis. A comparison was made among four different neural network architectures: MLP, CNN, RBFNN, and hybrid CNN-LSTM to predict the rise of the most common cryptocurrencies (bitcoin, Ethereum, Litecoin, Dash, Monero, and Ripple) against the dollar. Similarly, [16] analyzed cryptocurrency market price with correlation analysis using cryptocurrency attributes and bitcoin. Data collected was normalized with min-max normalization and was subjected to analysis using Linear regression, Random Forrest, and Gradient Boosting. [17] examined the forecasting ability of ANNs with Bob-Jenkins and structural economic Modeling approaches to forecasting economic time series in African countries. [18] described known applications of artificial intelligence such as a neural network in predicting the growth of GDP of Eurozone countries up to the year 2025. He obtained data for the years 1960 – 2015 from the World Bank Server and used the Gaussian curve as the activation function in the hidden layer of the five radial basis function (RBF) networks.

## Methodology

In this study, three models of MLP were built and trained with a backpropagation (BP) algorithm as the forecasting models while using ARIMA as a benchmark for the MLP models.

Bitcoin transactions started gaining ground in Nigeria in 2013, and within that year, nothing much was done. The awareness and level of involvement started gathering momentum from 2014. Hence, weekly Data for the volume of bitcoin transactions was extracted from 2014 through to 2021, having only 326 observations. As the number of data seems grossly inadequate, the interpolation technique was implored to combat the inadequacies, thus converting the weekly data to daily data, making it up to 2318 observations.

### Autoregressive integrated moving average (ARIMA)

The ARIMA model, also known as Box-Jenkins's method, is regarded as the most popular and best forecasting statistical method for time series data due to its ease in application and capability in analysing non-stationary data [19, 20]. It integrates the Autoregression model (AR) denoted as $p$, the Moving Average Model (MA) denoted as $q$, and the differencing parameter denoted as $d$. The differencing order is used in converting a non-stationary time series to a stationary series [19, 21]. According to [19] forecasting a time series data with the aid of the ARIMA model involves three main steps viz; Model-identification, Parameter Estimation, and Diagnostic Checking. The data is normalised and made stationary using a suitable differencing order during the identification process. At the same time, during parameter estimation, the model parameters are assessed with maximum likelihood function and information criteria (AIC & BIC).

### Multilayer perceptron (MLP)

The multilayer perceptron, a feedforward neural network, is a subclass of deep neural networks consisting of three layers; input, hidden, and output [22]. It is called feedforward, as the signal travels in one direction. When the input layer receives the signal to be processed, it passes through the hidden layer, the core processing layer, and the output layer that performs classification and forecast. Each neuron in any layer is directly connected to the neurons in the following layer, as shown in figure 1. Thus, moving the data in a forward direction.

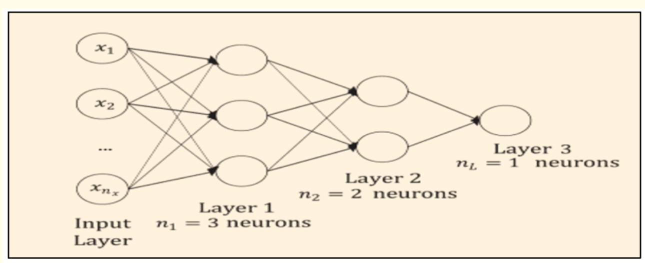


**Figure 1:** A feedforward neural network with two hidden layers.

To build a neural network, specific parameters that will affect the ANN performance need to be considered; these include the pre-processing techniques on the time series data, the network architecture, learning algorithm, and data splitting.

### Steps in building the artificial neural network

The input variable is the historical univariate weekly volume of bitcoin transactions in Nigeria. The Nigerian data obtained was limited; thus, decomposition and interpolation techniques were employed to increase the number of observations without necessarily affecting the accuracy of the result.

### Selection of parameters

Three numbered time series lagged terms represented as; $Y_{t-1}$, $Y_{t-2}$, and $Y_{t-3}$ were used as inputs. The learning rate was set at 0.01 to produce results at a minimum possible time, while Adaptive Momentum (ADAM) was employed to adjust the learning rate as training progresses automatically. Epoch size was set at 1000 with an Early Stopping Call Back Mechanism (ESCBM) to maximize training resources. Rectilinear Unit (ReLU) as shown in equation1:

$$f(x_i) = \max(0, x_i) = \begin{cases} x_i, x_i > 0 \\ 0, x_i < 0 \end{cases}, f^1(x_i) = \begin{cases} 1, x_i > 0 \\ 0, x_i < 0 \end{cases} \quad \text{--------------(1)}$$

### Splitting the data

The data was split into training and test data sets in a percentage of 80% to 20% for training and test sets, while 25% of the training set was set aside for validation giving training, tests, and validation sets in the ratio of 60: 20:20 respectively. It was also scaled down to the range of (0, 1) through the normalization/standardization processes. Normalizing the data gives all the points an equal weight, thereby allotting it equal importance. The normalization equation is thus expressed [23] in equation 2:

$$x_{ni} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad \text{-----------(2)}$$

Where,

$x_{ni}$ is the scaled input value of the actual data,

$x_i$ represents the Nigerian volume of bitcoin transactions, while $X_{\min}$ and $X_{\max}$ are the minima and maximum values of the unscaled data set.

The predicted values of the network which falls within the variation of (0, 1) are changed to actual values using the equation (3):

$$x_i = x_{ni}\left(x_{\max} - x_{\min}\right) + x_{\min} \quad \text{--------(3)}$$

### Hidden layer of the three Models

Three models were built with a unique number of hidden layers. Model 1 comprised one hidden layer and experimented with various nodes, while model 2 comprised two hidden layers and Model 3 with three hidden layers.

### Performance Measures

Performance measures are those standards used to evaluate the advantage of a network's architecture, learning algorithm, or applicability of the neural network. Performance Metrics used as expressed in equations 4, 5, and 5:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2 \quad \text{---------(4)}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2} \quad \text{----------(5)}$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left[\frac{A_t - F_t}{A_t}\right]100$$

------(6)

### Algorithm for the model

The algorithm for the Multilayer perceptron models trained with backpropagation and written in Python is in the following phases:

- Data Pre-processing
- Selection of suitable parameters, Training, and Testing
- Evaluating the Models
- Model Prediction.

Phase one: Data Pre-processing

- Interpolation of data
- Standardization of data with MinMaxScaler
- Split into samples

- X_train, y_train = split_sequence (train, n_steps)
- X_test, y_test = split_sequence (test, n_steps)
- Reshape 'train' and 'test' data
- 'For validation: ', train_size – int (train_size – train_size*.25)

Phase Two: Selecting suitable model parameters, Training, Testing and Evaluating the models

- Define model parameters
- EarlyStopping (Patience=20, monitor='val_loss'
- Return_model_1 (node=13, activation='relu')
- Model.compile (optimizer='adam', loss='mse', metrics = [keras. Metrics.RootMeanSquareError]
- Mape (actual, predict)
- Train_models (lower=3, upper=20, step=1)
- Model_1 = train_models ()

Same process is repeated for models '2' and '3'.

Phase Three: Evaluating the Models

- Model_1 = return_model_1(node=13)
- History = model_1.fit (x_train, y_train,)
- Epochs = 1000
- Shuffle = False, validation_split = 0.25,
- Callbacks = [early_stopping]

Same process repeated for models '2' and '3'.

Phase Four: Model prediction

- Model_1_predictions = model_1.Predict (x-test, verbose = 0)
- Model_1_preds_full = model_1.Predict(full_data_x, verbose = 0)

Same process is repeated for models '2' and '3'.

## Results and Discussion

The data which is the volume of bitcoin transaction from 2014 to 2021 was downloaded from [6] and graphically represented in figure 2.

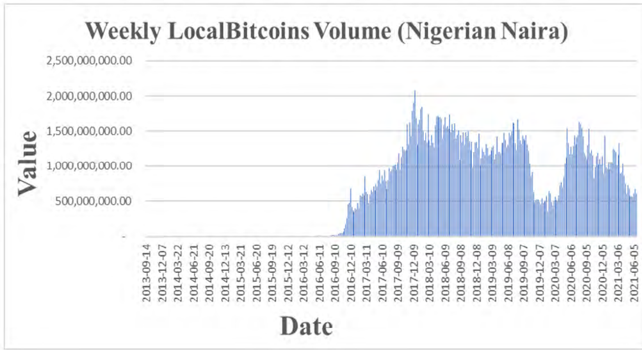


**Figure 2:** A graphical representation of the original data.

### Results of the ARIMA model

Table 1 summarises the model; The p, d, q values obtained for the best ARIMA model are 5, 1, 0. The prediction error estimator that provides quality models for the time series data is known as information criteria comprising AIC, BIC, and HQIC.

| Dep. Variable: | Scaled Vol | No. Observations: | 1854 |
|---|---|---|---|
| Model: | S. ARIMAX (5, 1, 0) | Log Likelihood | 9415.44 |
| Date: | Sat, 15 May 2021 | AIC | -18819 |
| Time: | 14:47:24 | BIC | -18786 |
| Sample: | 11-15-2014 - 12-12-2019 | HQIC | -18807 |

**Table 1:** Model specification and information criterion.

Table 2 is the covariance table, where the values under 'coef' are the weights of their respective terms. Model value for the AR term is represented as ar.L1 up to ar.L5 in the table. The column p>|z| stands for the p-value of each term; the value should ideally be less than 0.05 for the corresponding output to be significant. The best ARIMA model is ready for forecasting, considering the values obtained in the ADF statistic.

In this study, the best ARIMA model was determined based on the following criteria:

- ACF and PACF – The ACF determines the number of terms needed to remove any autocorrelation in the already made stationary series and the number of MA terms. The PACF

| | Coef | Std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| ar. L1 | 1.9208 | 0.022 | 87.002 | 0.000 | 1.877 | 1.964 |
| ar. L2 | -1.2868 | 0.060 | -21.624 | 0.000 | -1.403 | -1.170 |
| ar. L3 | 0.4162 | 0.085 | 4.911 | 0.000 | 0.250 | 0.582 |
| ar. L4 | -0.1944 | 0.071 | -2.724 | 0.006 | -0.334 | -0.055 |
| ar. L5 | 0.0379 | 0.029 | 1.306 | 0.192 | -0.019 | 0.095 |
| sigma2 | 2.252e-06 | 4.33e-08 | 52.008 | 0.000 | 2.17e-06 | 2.34e-06 |

**Table 2:** Table of covariance.

reveals a clear correlation between lags and the series, hence determining whether the lag is necessary for the AR term or not.

- AIC and BIC –The model yielded AIC of -18819 and BIC of -18786, the lowest values obtained.

Considering the AIC and BIC values, ARIMA model 5, 1, 0 was selected as the best.

Table 3 shows the actual, forecasted, and difference between the two values. Revealing that the model performed well from the beginning as the predicted values are very close to the actual values. In contrast, the predicted values from the later years are much lower than the actual values giving a poor performance. The loss function for the ARIMA is as follows:

- MSE for the ARIMA model: 0.09209306610070739
- RMSE for the ARIMA model: 0.3034683939073514

This evaluation was done based on the ability of the ARIMA model to accurately predict whether the volume of bitcoin transactions will appreciate or not.

| Sample Period | Predicted Value | Actual Value | Difference |
|---|---|---|---|
| 13/12/2019 | 4.51E+08 | 4.51E+08 | 1.11E+05 |
| 14/12/2019 | 4.54E+08 | 4.55E+08 | 1.11E+06 |
| 15/12/2019 | 4.60E+08 | 4.63E+08 | 3.75E+06 |
| 16/12/2019 | 4.67E+08 | 4.76E+08 | 8.92E+06 |
| 17/12/2019 | 4.75E+08 | 4.93E+08 | 1.77E+07 |
| ... | ... | ... | ... |
| 16/03/2021 | 4.81E+08 | 1.22E+09 | 7.44E+08 |
| 17/03/2021 | 4.81E+08 | 1.16E+09 | 6.83E+08 |
| 18/03/2021 | 4.81E+08 | 1.09E+09 | 6.07E+08 |
| 19/03/2021 | 4.81E+08 | 9.98E+08 | 5.17E+08 |
| 20/03/2021 | 4.81E+08 | 8.94E+08 | 4.13E+08 |

**Table 2:** Table of covariance.

## Results of the ANN model

The data was first pre-processed based on the ANN procedure; Figure 3 shows the original data with missing data points before interpolation. Figure 4 shows the data plots after applying the interpolation technique. The pre-processing procedure also involves checking the number of times the learning algorithm will work through the entire dataset (epoch); each observation in the training dataset has been exposed to the internal model parameter, thereby updating it. The ANN model performance was assessed using MSE, RMSE and MAPE. Each training cycle (epoch) calculates its loss (MSE), the lower the loss, the better.

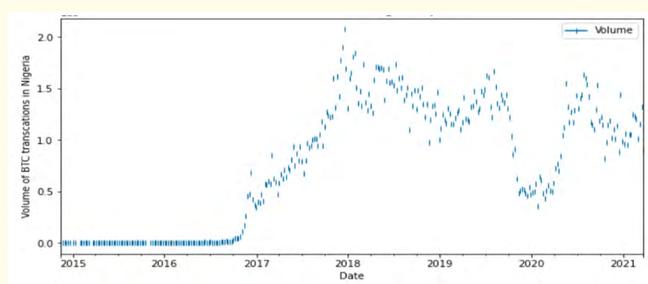


**Figure 3:** Plot of data with missing points.

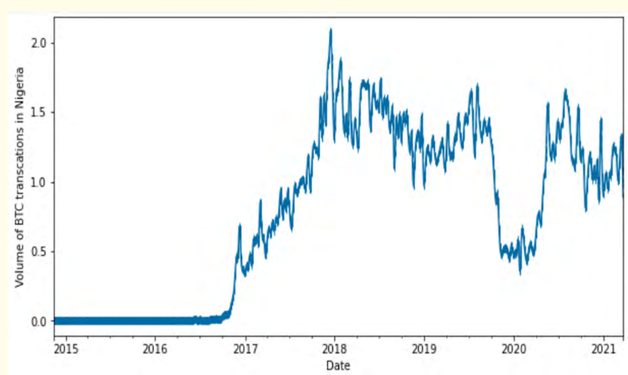


**Figure 4:** Plot of data after interpolation.

**Citation:** Francisca Nonyelum Ogwueleka*., et al.* "Neural Network-based Model for Forecasting the Macroeconomics on the Use of Blockchain and Cryptocurrency in Nigeria". *Acta Scientific Computer Sciences* 4.4 (2022): 72-82.

The three ANN models: Model 1, Model 2, and Model 3, is made up of the following network architectures Model 1 comprises one hidden layer, model 2 consist of 2 hidden layers, and model 3 with three hidden layers. Table 4 shows the performance measures for model 1 in which the network structure that gave the most accurate prediction is 15-1; that is, fifteen hidden neurons as it returned the lowest MSE and RMSE.

| Network Structure | RMSE | MSE | MAPE |
|---|---|---|---|
| 15-1 | 0.007085 | 0.000050 | 1.274076 |
| 10-1 | 0.007911 | 0.000063 | 1.246433 |
| 16-1 | 0.007995 | 0.000064 | 1.429024 |
| 4-1 | 0.008097 | 0.000066 | 1.234492 |
| 6-1 | 0.009205 | 0.000085 | 1.500674 |
| 3-1 | 0.010396 | 0.000108 | 2.023749 |
| 11-1 | 0.010728 | 0.000115 | 2.01501 |
| 19-1 | 0.013638 | 0.000186 | 3.128011 |
| 5-1 | 0.014757 | 0.000218 | 2.546807 |

**Table 4:** Result of the performance measures of Model 1.

Table 5 shows the results for model 2. The best architecture with the smallest MSE and RMSE that produced the most accurate result is 21-10-1, twenty-one neurons in the first hidden layer, ten in the second hidden layer, and one in the output layer.

Table 7 presents findings from out-of-sample test data over the three different network models. Models one and two seem to be better predictors than model three, as there is no significant difference in their values. The low performance of model 3 could be attributed to overfitting since the data is not large enough to be fit into more than two hidden layers. Table 8 depicts the level of accuracy of the three different models using the three performance measures of RMSE, MSE and MAPE. The network structure with better performance for each model is highlighted.

| Network Structure | RMSE | MSE | MAPE |
|---|---|---|---|
| 21-10-1 | 0.007474 | 0.000056 | 1.18337 |
| 15-7-1 | 0.009247 | 0.000085 | 2.019694 |
| 19-9-1 | 0.010698 | 0.000114 | 2.10339 |
| 9-4-1 | 0.011113 | 0.000124 | 1.868094 |
| 7-3-1 | 0.011778 | 0.000139 | 2.398296 |
| 17-8-1 | 0.013667 | 0.000187 | 2.848943 |
| 13-6-1 | 0.029932 | 0.000896 | 4.783924 |
| 11-5-1 | 0.030135 | 0.000908 | 7.064968 |
| 5-2-1 | 0.226625 | 0.051359 | 38.101917 |

**Table 5:** Result of the performance measures of model 2.

In model 3, the architecture that gave the most accurate result is 21-10-7-1; twenty-one neurons in the first hidden layer, ten in the second, seven in the third hidden layer, and one in the output layer, as shown in table 6.

| Network Structure | RMSE | MSE | MAPE |
|---|---|---|---|
| 21-10-7-1 | 0.014055 | 0.000198 | 2.807695 |
| 13-6-4-1 | 0.015552 | 0.000242 | 2.660966 |
| 9-4-3-1 | 0.016705 | 0.000279 | 2.984883 |
| 17-8-5-1 | 0.019554 | 0.000382 | 3.945387 |
| 19-9-6-1 | 0.024074 | 0.00058 | 3.861536 |
| 15-7-5-1 | 0.024134 | 0.000582 | 4.577049 |
| 7-3-2-1 | 0.226625 | 0.051359 | 38.101909 |
| 11-5-3-1 | 0.226625 | 0.051359 | 38.101909 |
| 5-2-1-1 | 0.226625 | 0.051359 | 38.101917 |

**Table 6**: Performance measures of Model 3.

| Sample Period | Actual Values | Model One Predictions | Model Two Predictions | Model three Predictions |
|---|---|---|---|---|
| 2019-12-16 | 4.759497e+08 | 4.748469e+08 | 4.427046e+08 | 6.869574e+08 |
| 2019-12-17 | 4.928126e+08 | 4.843223e+08 | 4.586732e+08 | 6.869574e+08 |
| 2019-12-18 | 5.127151e+08 | 4.984122e+08 | 4.789123e+08 | 6.869574e+08 |
| 2019-12-19 | 5.283683e+08 | 5.166074e+08 | 5.020604e+08 | 6.869574e+08 |
| 2019-12-20 | 5.385576e+08 | 5.350977e+08 | 5.192869e+08 | 6.869574e+08 |
| ... | ... | ... | ... | ... |
| 2021-03-16 | 1.224950e+09 | 1.280444e+09 | 1.263306e+09 | 6.869574e+08 |

| | | | | |
|---|---|---|---|---|
| 2021-03-17 | 1.163462e+09 | 1.250593e+09 | 1.206180e+09 | 6.869574e+08 |
| 2021-03-18 | 1.087836e+09 | 1.207732e+09 | 1.131435e+09 | 6.869574e+08 |
| 2021-03-19 | 9.980721e+08 | 1.151859e+09 | 1.042005e+09 | 6.869574e+08 |
| 2021-03-20 | 8.941695e+08 | 1.082975e+09 | 9.378903e+08 | 6.869574e+08 |

**Table 7:** Actual values vs predictions of the three models.

| | Network Structure | RMSE | MSE | MAPE |
|---|---|---|---|---|
| MODEL 1 | 15-1 | 0.007085 | 0.000050 | 1.274076 |
| | 10-1 | 0.007911 | 0.000063 | 1.246433 |
| | 16-1 | 0.007995 | 0.000064 | 1.429024 |
| | 4-1 | 0.008097 | 0.000066 | 1.234492 |
| | 6-1 | 0.009205 | 0.000085 | 1.500674 |
| | 3-1 | 0.010396 | 0.000108 | 2.023749 |
| | 11-1 | 0.010728 | 0.000115 | 2.015010 |
| | 19-1 | 0.013638 | 0.000186 | 3.128011 |
| | 5-1 | 0.014757 | 0.000218 | 2.546807 |
| MODEL 2 | 21-10-1 | 0.007474 | 0.000056 | 1.183370 |
| | 15-7-1 | 0.009247 | 0.000085 | 2.019694 |
| | 19-9-1 | 0.010698 | 0.000114 | 2.103390 |
| | 9-4-1 | 0.011113 | 0.000124 | 1.868094 |
| | 7-3-1 | 0.011778 | 0.000139 | 2.398296 |
| | 17-8-1 | 0.013667 | 0.000187 | 2.848943 |
| | 13-6-1 | 0.029932 | 0.000896 | 4.783924 |
| | 11-5-1 | 0.030135 | 0.000908 | 7.064968 |
| | 5-2-1 | 0.226625 | 0.051359 | 38.101917 |
| MODEL 3 | 21-10-7-1 | 0.014055 | 0.000198 | 2.807695 |
| | 13-6-4-1 | 0.015552 | 0.000242 | 2.660966 |
| | 9-4-3-1 | 0.016705 | 0.000279 | 2.984883 |
| | 17-8-5-1 | 0.019554 | 0.000382 | 3.945387 |
| | 19-9-6-1 | 0.024074 | 0.00058 | 3.861536 |
| | 15-7-5-1 | 0.024134 | 0.000582 | 4.577049 |
| | 7-3-2-1 | 0.226625 | 0.051359 | 38.101909 |
| | 11-5-3-1 | 0.226625 | 0.051359 | 38.101909 |
| | 5-2-1-1 | 0.226625 | 0.051359 | 38.101917 |

**Table 8:** Performance measures of Models 1, 2 and 3.

Figures 5, 6, and 7 are plots of the three models, illustrating each model's actual values and predicted value as indicated, thereby showing the level of accuracy at a glance. The graph shows that Model 3 (Figure 8) performed very poorly compared to the other two models. The structural architecture comprises three hidden layers. Small data does not do well in a Model with numerous hidden layers, unlike Models 1 and 2, which are one and two hidden layers, respectively. The graphical illustration of Figure 7 proves that Model 2 gave a better performance out of the three models. Network model one with a network structure of one hidden layer and fifteen neurons has the minutest MSE and the lowest RMSE, but Model 2 has the lowest MAPE. Similarly, considering Figures 6 and 7, Figure 7 seems to be very close-fitting with the actual value; hence Model 2 is better.

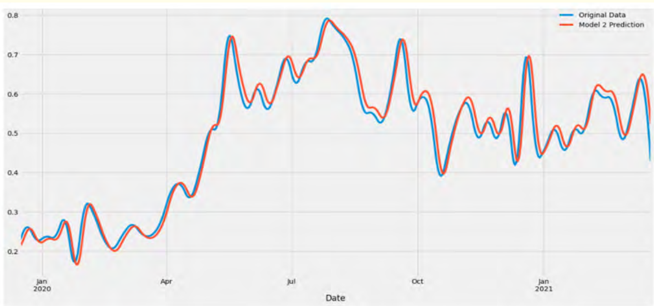


**Figure 5:** Comparing actual values with predicted values from Model 1.


**Figure 6:** Comparing actual values with predicted values from Model 2.

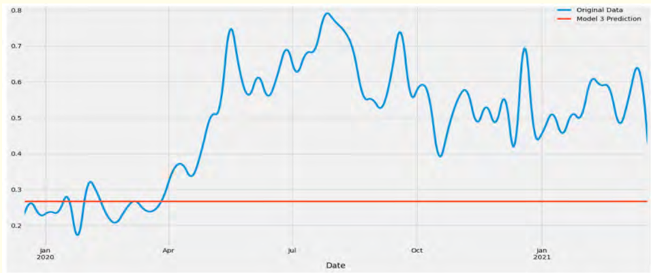


**Figure 7:** Comparing actual values with predicted values from Model 3.

## Comparison of the ANN Model with ARIMA

Table 9 depicts the comparison of the ANN and ARIMA models based on the performance metrics. The results show that all the ANN models performed far better than the ARIMA model. Considering the error loss of both techniques, the MSE, RMSE and MAPE of all the ANN models are lower than that of the ARIMA.

| Model type | MSE | RMSE | MAPE |
|---|---|---|---|
| ANN Model 1 | 0.007085 | 0.00005 | 1.274076 |
| ANN Model 2 | 0.000056 | 0.007474 | 1.18337 |
| ANN Model 3 | 0 .014055 | 0.000198 | 2.807695 |
| ARIMA | 0.092093 | 0.303468 | 46.13 |

**Table 9:** Comparison of ANN Models with ARIMA Model

Table 10 presents the forecasted values of the ARIMA model and the ANN model. It is eminent that there are marked discrepancies between the ARIMA and the ANN values.

| | Date | Actual Values | Predicted Values |
|---|---|---|---|
| | 13/12/2019 | 450887400 | 450762300 |
| | 14/12/2019 | 454987100 | 453820000 |
| | 15/12/2019 | 463341200 | 459464200 |
| | 16/12/2019 | 475949700 | 466743000 |
| | 17/12/2019 | 492812600 | 474633200 |
| ARIMA | … | … | … |
| | 16/03/2021 | 1224950000 | 403570500 |
| | 17/03/2021 | 1163462000 | 403416900 |
| | 18/03/2021 | 1087836000 | 403263500 |
| | 19/03/2021 | 998072100 | 403110000 |
| | 20/03/2021 | 894169500 | 402956700 |

| | | | |
|---|---|---|---|
| ANN | 16/12/2019 | 475949700 | 442704600 |
| | 17/12/2019 | 492812600 | 458673200 |
| | 18/12/2019 | 512715100 | 478912300 |
| | 19/12/2019 | 528368300 | 502060400 |
| | 20/12/2019 | 538557600 | 519286900 |
| | ... | ... | ... |
| | 16/03/2021 | 1224950000 | 1263306000 |
| | 17/03/2021 | 1163462000 | 1206180000 |
| | 18/03/2021 | 1087836000 | 1131435000 |
| | 19/03/2021 | 998072100 | 1042005000 |
| | 20/03/2021 | 894169500 | 937890300 |

**Table 10:** Comparison of the estimated value of both ARIMA and ANN models.

### Summary of the two forecasting techniques

The two techniques used in this experiment are ARIMA and ANN. Similarly, the data used for both methods is the volume of bitcoin transactions in Nigeria for seven years. The ARIMA model did well in the earlier years, but the accuracy rate decreases as time appreciates. The uniqueness of this study is in the MLP models that were developed in forecasting the volatile data of bitcoin transactions. Model 1 comprises one hidden layer, Model 2; two hidden layers and Model 3, three hidden layers. The three neural network models were experimented with various multiple nodes to obtain the model with better performance.

## Conclusion

In this study, the ability of ANN in volatility forecasting was demonstrated, whereby the multilayer perceptron was applied on the very high volatile bitcoin and cryptocurrency market. The ANN produced improved stability by offering lower error margins and directional accuracy. Hence, ANN's capability will be of great interest and benefit to the world of financial technology and government regarding macroeconomic forecasting since it has been proven to be better suited in forecasting macroeconomics.

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