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A TIME DEPENDENT NEURAL NETWORK MODEL FOR THE PREDICTION AND FORECASTING OF BITCOIN PRICE

Agbedeyi O. D.[1*], Maliki S. O.[2], and Asor V. E.[3]

[1]Department of Mathematics and Statistics, Delta State Polytechnic, Ogwashi Uku, Nigeria.

[2,3]Department of Mathematics, Michael Okpara University of Agriculture, Umudike, Nigeria.

[*]Corresponding Author's Email: desmondagbededyi@gmail.com

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ABSTRACT: *In this research work, we developed a mathematical model of a digital currency market, involving daily closing price as a function of time. We proposed the Artificial Neural Network (ANN) model. We observed that our ANN model was able to predict the daily closing price of Bitcoin and also make six weeks forecast to a reasonable degree of accuracy. We equally observe that the time dependent ANN model can actually give digital currency traders and investors a clue on when to trade off their digital assets with minimum risk. We therefore, recommend that ANN model should be incorporated into digital currency trading platforms as a signal tool to enable digital currency traders take more informed and less risky trading decisions. From our findings, we would advise traders who wish to employ ANN model to consider a smaller time frame say a few weeks' time interval for their predictions. We observed also that ANN models have limitations when it comes to manual computation or implementation in Microsoft Excel, especially when dealing with very large input values. This is because of the saturation characteristic of our ANN inner layer activation function (viz; tanh function) which can lead to identical output values for different input values, making it difficult to replicate the ANN model's behavior. Furthermore, ANN models often involve complex interactions between multiple neurons, layers, and activation functions, which can be challenging to replicate manually.*

KEYWORDS: Digital Currencies, Artificial Neural Network, Bitcoin, Stochastic Modelling.

INTRODUCTION

The primarily well-known cryptocurrency, Bitcoin, was created by Nakamoto (Nakamoto, 2008), meanwhile, the idea of such secured peer-to-peer blockchain-based digital currency had been around for the last few decades. Cryptographer David Chaum initially introduced the idea in a 1983 paper whose initiative was to enhance the security of credit card transactions through a virtual system (Chaum, 1983).

Despite the absence of rapid growth in the first few years after its launch, Bitcoin has been growing extremely rapidly since 2017. It has frequently been experiencing price hikes, therefore attracting numerous investors. Hayes (2017) stated that there has been very little work on models predicting the market price of Bitcoin. The study created a regression model to identify potential factors that influence price.

Bitcoin is a peer-to-peer, global crypto-currency digital payment system in common use. It does not rely on specific institutions to issue, generated by computer algorithms, peer-to-peer transmission of digital currency, can be through the Internet global transactions.

Digital currencies are not issued by any central body and operate independently of regular banks. Many people do not consider them to be money, despite the fact that they have the potential to create extraordinarily strong competition for traditional money. However, many people are beginning to believe in cryptocurrencies. According to Gilpin (2014), Bitcoin was established to remove power away from the hands of the government and central bankers, and put it back in the hands of the people. Bitcoin is a revolutionary financial system established by and for the people, with everyone supposedly having equal power. People manage their own money, and the Bitcoin system's laws are enforced on everyone through mutual distrust. (Kelion, 2013).

Additionally, from inception of digital currency many individuals and institutional investors engage in digital currency markets for speculative purposes, hoping to profit from price changes. Bitcoin, created in 2009 by an unknown person or group using the pseudonym Satoshi Nakamoto, is the first and most well-known cryptocurrency. It introduced the concept of decentralized peer-to-peer transactions and a fixed supply limit of 21 million Bitcoins (Ying, 2020). Besides Bitcoin, thousands of alternative cryptocurrencies, often referred to as "altcoins," have been developed. Examples include Ethereum, Ripple (XRP), Litecoin, and many others, each with its unique features and purposes.

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How Bitcoin Works

Bitcoin has formed a system that covers the issuing (development), distribution and circulation of digital assets which is the main goal of a vast majority of the digital crypto-currency market.

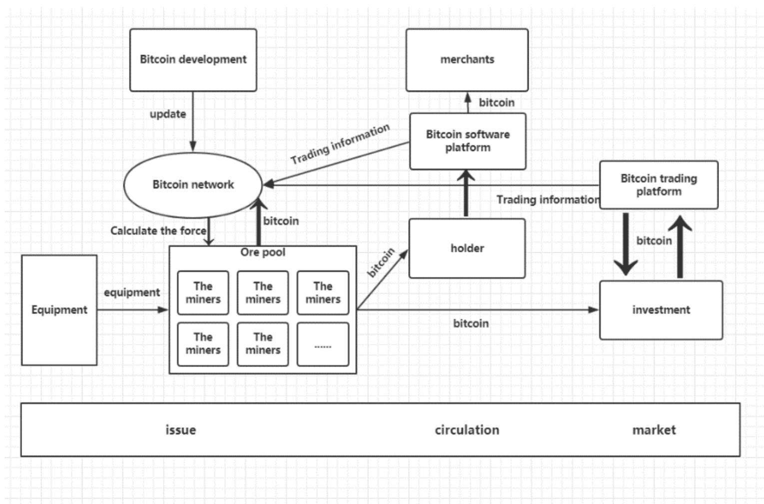

Fig. 1: Diagram of Bitcoin development, distribution and circulation in the digital market.

Currently, digital currency systems are not extensively utilized or recognized, and they face a number of obstacles that may limit their future expansion. As a result, their impact on financial services and the economy is currently modest, and it is probable that in the long run, they will remain a product for a small user base on the outskirts of conventional financial services. However, the operation of several digital currency schemes in recent years has demonstrated the possibility of employing distributed ledgers for peer-to-peer value transfers in the absence of a trusted third party. As a result, certain characteristics of distributed ledger technology may have the potential to increase the efficiency of payment services and financial market infrastructures (FMIs) in general.

Digital currency trading involves buying and selling various cryptocurrencies on online platforms, known as exchanges. Traders often use a combination of tools to analyze the market, execute trades, and manage their portfolios. Therefore, before using any tools for digital currency trading, it is essential to research and understand their features, fees, and security measures. Additionally, traders should practice good risk management and stay informed about market trends and regulatory developments.

Originally Bitcoin was not interesting to the general public since its purpose and usage were best understood by cryptographers, hackers, and mathematicians. It is generated by an algorithm, it is impossible to forge, it is somewhat anonymous, and because it is a peer-to-peer network, there are no additional costs from middlemen such as banks. In reality, these are the characteristics of a money that is ideally suited to our contemporary digital economy. Although the value of Bitcoin is based on

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speculation on future value as well as genuine, undeniable usefulness, the wild price swings seen recently are a natural reaction to the massive global interest in a pool of money that is relatively small in comparison to its government-backed peers. On this premises this study seeks to investigate the mathematical modelling of the digital currency market using Artificial Neural Network (ANN) with the Bitcoin as a case study.

Bitcoin showed a remarkable run up in price since 2016, especially in the latter half of 2017. This run up in price was so sudden and swift that many investors who held Bitcoin termed it as a 'lifetime opportunity'. However, Bitcoin price fell consistently and significantly, till it fell by 75% from its all-time high (Dec-2017). When invented and released for the first time in 2009 (3-Jan-2009), Bitcoin value was merely few cents but it is presently trading above $60,000.

Thus, we are motivated to study the price dynamics of Bitcoin and develop a neural network model that may give investors in Bitcoin adequate signal when to catch up the price hikes in Bitcoin to make good return in their investments.

This work is justified by the need to understand the dynamics of the Crypto currency market and the need for proper risk management in order to achieve a good return on investment in the cryptocurrency market through a reliable forecasting model.

In its early years, Bitcoin was known to a relatively narrow community of cryptography enthusiasts. The first time the currency made it into the mainstream media was probably in June. By 2013, Bitcoin started appearing to be an increasing speculative investment opportunity (Parham, 2017). Its price (i.e. exchange rate to the US dollar) increased from under $15 in Jan-2013 to over $1,200 in Dec-2013. During this time, Bitcoin also started gaining foothold in electronic commerce, when the Chinese search engine Baidu (world's 5th most visited site at the time) started accepting Bitcoin for payments. However, restrictions were put by the US government on digital currencies when it was revealed that Bitcoin was being used for payments in the illicit activities like drug trade by illegal websites like Silk Road.

Bitcoin started gaining popularity as it was touted as an instantaneous and anonymous way to make transactions, defying national boundaries, with no central bank and country as authority. Because of its anonymous nature, Bitcoins have been used in past in the criminal money laundering and tax evasion schemes (Nabilou, 2019).

Each cryptocurrency has its own rules concerning the maximum amount of money, currency production, privacy, transaction rates added to the blockchain, and the various mechanisms used by miners to compete among each other and earn rewards (Indera, Alrasheedi & Alghamdi, 2017).

Due to its unstable nature, cryptocurrency prediction is not an easy task. Interestingly, based on the information provided from the website www.coindesk.com, Bitcoin has more than 50% of the market share in the cryptocurrency market at the time of this study. Therefore, studying its prediction is of great importance and researchers are becoming focused on it.

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MATERIALS AND METHODS

Data Collection

The data for our model and analysis was collected from yahoo.com from the period January 2020 to June 2024 which is a period of four and half years.

Artificial Neutral Network

We introduce the concept of Artificial Neural Networks (ANN) in this section. We will employ ANN to analyze the dynamics of Bitcoin price. In particular we will attempt to build a predictive model for the Bitcoin prospect value calculation, taking into consideration the fact that price may differ greatly because of internal and external factors to Bitcoin. By internal factors we are presuming factors inside the Bitcoin security. By external we are referring to agents which influence indirectly the price of Bitcoin.

ANNs, also known as neural networks, are computational approaches used for machine learning, knowledge demonstration, and maximizing complex system outputs (Chen, Ursula, Walid, Changchuan and Mérouane, 2019). An Artificial Neural Network (ANN) mimics how biological nervous systems, such as the brain, process data. They study the neural structure of the mammalian cerebral cortex, but on a smaller scale. Many artificial intelligence scientists think that artificial neural networks are the best and perhaps the only hope for designing an intelligent machine. Artificial neural networks are designed similarly to the human brain, with neuron nodes connected in a web-like structure. Neurons are billions of cells that comprise the human brain. Neurons are made up of cell bodies that process information and transmit it to and from the brain. These networks draw inspiration from the biological neural system's ability to process input and develop knowledge. This approach focuses on developing novel information processing structures.

The neurons are highly linked and structured into layers. The input layer accepts data, and the output layer generates the final result. Secret (hidden) layers are often placed between the two. This structure makes it difficult to predict or understand the exact flow of data. Weight influences signal intensity at a link. Neurons transmit signals only when the aggregate signal reaches a specific threshold. The Activation Value is the weighted sum of the summing unit that determines the output based on the signal.

Artificial neural networks are increasingly employed to regulate and model complicated systems. A neural network can control an engine's input and learn the control function. According to Wu (2018), adaptive learning in these systems involves changing the weight of synapses to provide the appropriate response to incoming inputs. When training a neural network, it receives inputs and outputs based on a certain approach.

Neural networks can be utilized for pattern recognition, speech recognition, image processing, and text/image classification (Li, Zhien, and Zhijian, 2017). Neural networks have several uses, such as risk analysis, drone control, welding quality analysis, computer quality analysis, emergency room testing, oil and gas exploration, truck brake detection, loan risk assessment, spectrum detection, and drug detection. Applications include industrial control, error management, voice recognition,

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hepatitis detection, remote information retrieval, submarine mine detection, 3D object, handwriting, and face detection, among others. ANNs have various uses, including calculating known functions, approximating unknown functions, identifying patterns, and processing signals (Li *et al* 2017). Kavimani and Soorya (2017) propose employing artificial neural networks (ANNs) to model wear rate and friction coefficient in reinforced magnesium metal matrix composites, improving prediction accuracy depending on input parameter variations. Zain et al. (2010) used an Artificial Neural Network (ANN) to predict surface roughness in end milling operations. They found that using a high speed, low feed rate, and radial rake angle resulted in the best surface roughness value. Lalwani et al. (2020) used an advanced ANN system to predict the performance of wire electrical discharge machining of Inconel 718 Alloy, which improved the quality of machined parts. Khosravi, Koury, Machado, and Pabon. (2018) investigates the use of artificial neural networks to predict wind speed and direction, with the goal of improving wind turbine performance.

The neural network (NN) is a distributed processor that stores and connects experience information, similar to how the human brain learns to analyze input and solve problems through training. Neural networks are also known as stimulated neural networks (SNNs) or artificial neural networks (ANNs) (Abe, 2017). Neural networks are used in a variety of applications, including robotics, facial identification, medicine, speech recognition, economics, and manufacturing.

The neurons of a layered artificial neural network are organized into layers. According to Vishwakarma (2021), the most basic architecture is a single-layer feed-forward network with input and output nodes. A multi-layer feed-forward neural network differs from others in that it has multiple hidden layers with computation nodes known as hidden neurons (Aizenberg, 2017). The network can retrieve higher-order statistics from input by using hidden layers.

Artificial neural networks (ANNs) have been used to solve complex pattern identification tasks, including stock market prediction. One of the most challenging limitations in time series data analysis is predicting and tracking stock performance. For decades, several machine learning techniques have been used to forecast financial time series. Despite the popularity of automated trading systems based on Artificial Intelligence (AI), few cases have successfully utilized the existing approach.

Many studies have examined the digital currency marketing using the Bitcoin as a case study. Cryptographic techniques are used by these currencies to control the generation of new units and secure transactions. With potential advantages like quicker transactions, less costs, increased financial inclusion, and improved security, digital currencies are important innovations in the financial sector overall. They do, however, also present difficulties with acceptance, volatility, scalability, and regulatory compliance. Peer-to-peer networking allows for direct user-to-user transactions without the involvement of middlemen like banks or payment processors. Since its launch, Bitcoin has attracted a lot of interest and users, acting as a store of wealth in addition to a digital currency. It has spurred creativity in the financial sector and resulted in the creation of a large number of other cryptocurrencies and blockchain-based apps. But it also has issues with mainstream adoption, scalability, and regulatory uncertainty.

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The Artificial Neural Network Model

In this section, we present the Artificial Neural Network (ANN) model for Bitcoin using time series data obtained online (Yahoo.com).

RESULTS AND DISCUSSION

In this section and in the subsequent sections, we present and analyze Bitcoin closing price as a function of time.

ANN prediction of BTC daily closing price using trading day/time

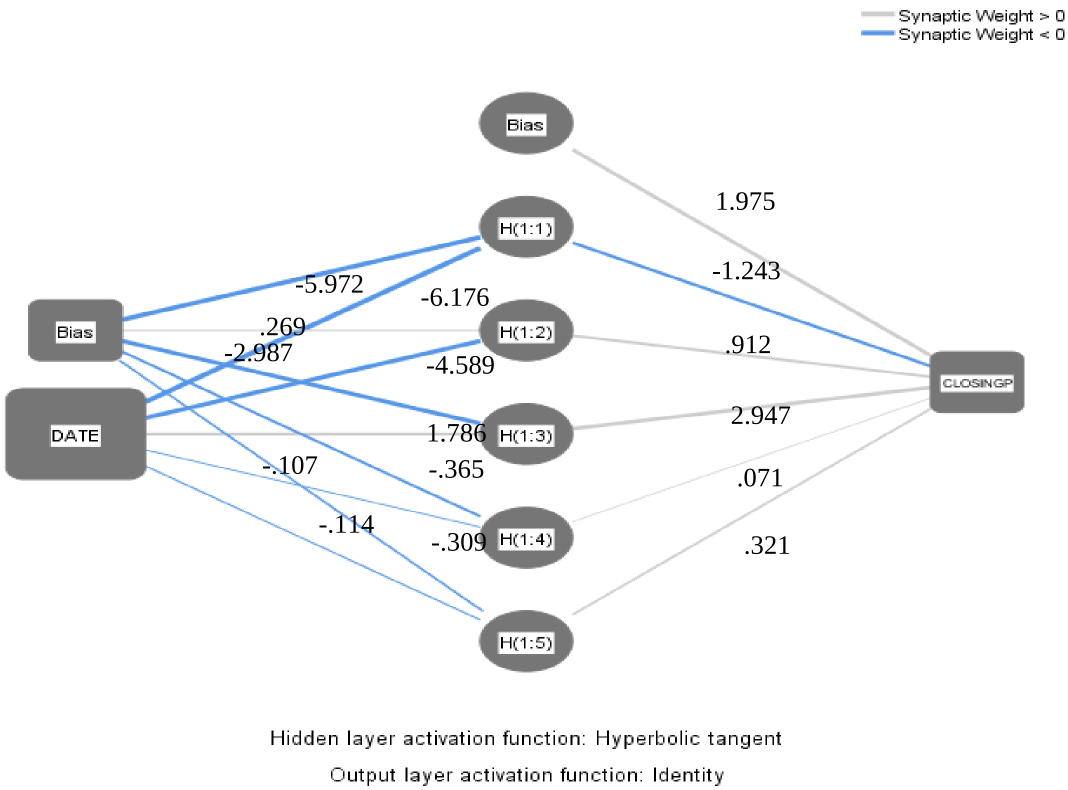

Fig. 2 ANN network diagram for time dependent model

The network diagram in Fig. 2 shows that we have one input which is Date(time). We have five nodes in the hidden layer, five hidden weights, five bias in the hidden layer, five output weights and one bias in the output layer. The input layer activation function is the hyperbolic tangent and the output layer activation function is the identity function

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Table 1 Model Summary

Training	Sum of Squares Error	61.986
	Relative Error	.112
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.34
Testing	Sum of Squares Error	28.581
	Relative Error	.099

Dependent Variable: Closing Price
a. Error computations are based on the testing sample.

Table 2 Parameter Estimates

Predictor		Predicted Hidden Layer 1 H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	Output Layer CLOSINGP
Input Layer	(Bias)	-5.972	.269	-2.987	-.365	-.309	
	DATE	-6.176	-4.589	1.786	-.107	-.114	
Hidden Layer 1	(Bias)						1.975
	H(1:1)						-1.243
	H(1:2)						.912
	H(1:3)						2.947
	H(1:4)						.071
	H(1:5)						.321

Table 1 show that ANN used 34 micro seconds for the training while the relative error for this model was 9.9%. That is to say about 90.1% of the daily closing price of Bitcoin was accurately predicted using time. This shows our ANN model performance was good using Time as the independent variable.

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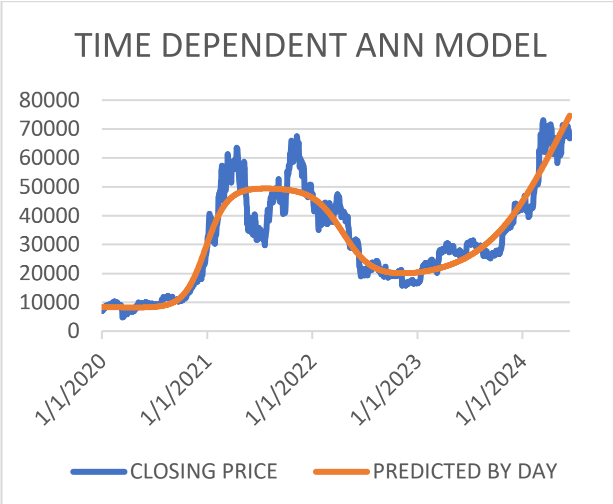

Fig. 3: Chart for ANN prediction and Bitcoin daily closing price

Fig.3 agrees with Table 1 that ANN was able to use trading time to predict the closing price of Bitcoin up to 91.1% accurately with 9.9% relative error.

Combining Fig 3 and the parameters estimate on Table 2, we have the ANN model for the time dependent variables for predicting Bitcoin closing price below.

Here is the ANN equation for one independent variable, 5 nodes in the hidden layer, 5 input biases, and 5 output weights with one output bias:

$$P(t) = B_{kk} + W_{kj} tanh\ (W_{ji} X_{ik} + b_{jk}) \qquad (2.1)$$

Which gives

$$\mathrm{P(t)} = 1.975 + (-1.243 \quad .912 \quad 2.947 \quad .071 \quad .321)\ \mathrm{tanh}\left(\begin{pmatrix}-6.176\\-4.589\\1.786\\-.107\\-.114\end{pmatrix} t + \begin{pmatrix}-5.972\\.269\\-2.987\\-.365\\-.309\end{pmatrix}\right)$$

(2.2)

Where $k = 1, i = 1, 2, \ldots. N, j = 1, 2, \ldots M,$ N is the number of input variable, M is the number of nodes, t is trading day (time) which is the input variables and

- P(t) is the output vector (1x1)- daily closing price, - B_{kk} is the output bias vector

- W_{kj} is the weight matrix for the output layer, - W_{ji} is the weight matrix for the hidden layer

- X_{ik} is the input vector, and - b_{jk} is the bias vector for the hidden layer

Note that matrices above are obtained from Table 2 and are defined as follows:

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- W_{ji} = [w1; w2; w3; w4; w5] , - W_{kj} = [w1 w2 w3 w4 w5] , - B_{jk} = [b1; b2; b3; b4; b5]

- B_{kk} = [b1], and - X_{ik}= [x1].

From Fig 3, we observed that ANN was able to use the input variable Date(time) to accurately predict the closing price of Bitcoin and also give a clue to traders or investors when to buy or sell off their Bitcoins.

We observed that when the closing price of Bitcoin deviate significantly from the ANN model, it will indicate a buy or sell signal (over bought or oversold). If it deviates above the ANN model, traders are advised to take a sell order but if it deviate below the ANN model, traders are advised to take a buy order.

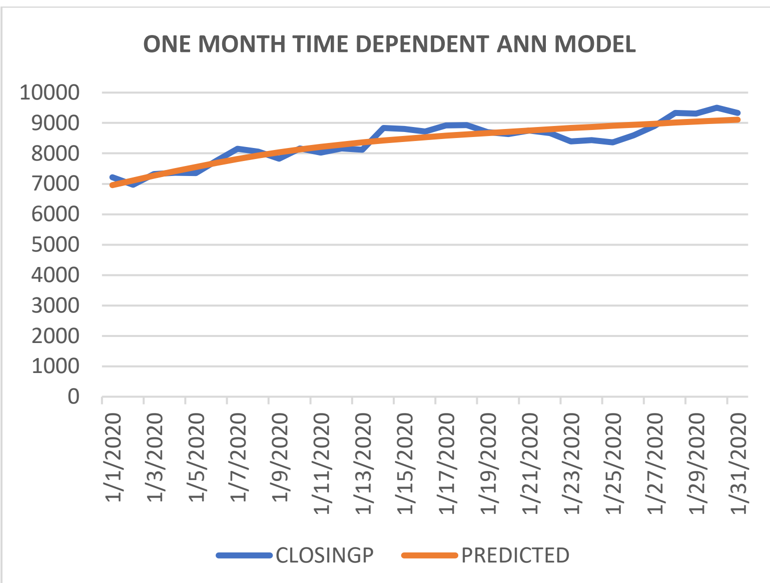

Fig. 4 Chat for ANN one month prediction and Bitcoin daily closing price

Using our time dependent ANN model, we did a one-month prediction of the daily closing price of Bitcoin as shown in Fig 4 to have a closer look at the market trend. The essence of this was to determine the trend and know exactly when to enter the market as a new trader or an investor in digital currencies. The one-month prediction shows us that traders or investors are to wait till price deviate significantly from the ANN model before placing an order (buy or sell). Investors or traders are also advised to pull out their funds as soon as price move significantly away from the ANN model or when price touches the ANN model. They can then wait for the next signal before placing a trade.

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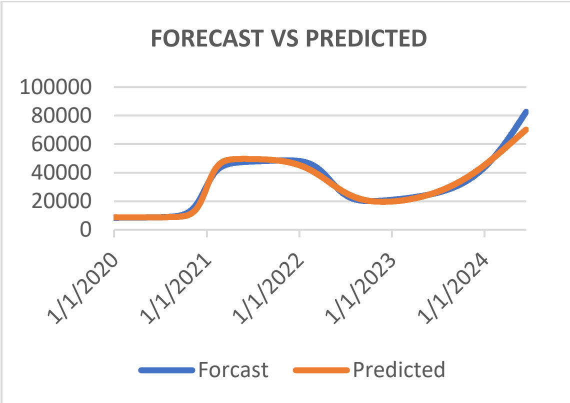

Fig. 5 Chat for ANN forecast and prediction

We went further to forecast the daily closing price of Bitcoin using our time dependent ANN model and the result is plotted against our ANN prediction after six weeks as shown in Fig. 5. The result shows that there is a deviation (or a significant difference) between the forecast value and the predicted value by ANN. On further investigation, we found out that this deviation was a result of the relative error in the forecast value. Because there was no observed value for ANN for the forecast period, ANN presented the forecast values as calculated. Thus, to get the accurate forecast, we have to subtract the relative error from the forecast value to bring it to the actual daily closing price predicted. We are subtracting the relative error because our result already show that the model was over stating the actual value of the Bitcoin daily closing price as indicated by positive relative error.

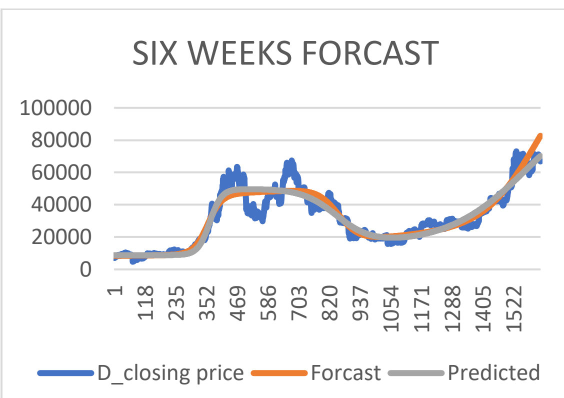

Fig. 6 Chat for Bitcoin daily closing price, ANN forecast and prediction

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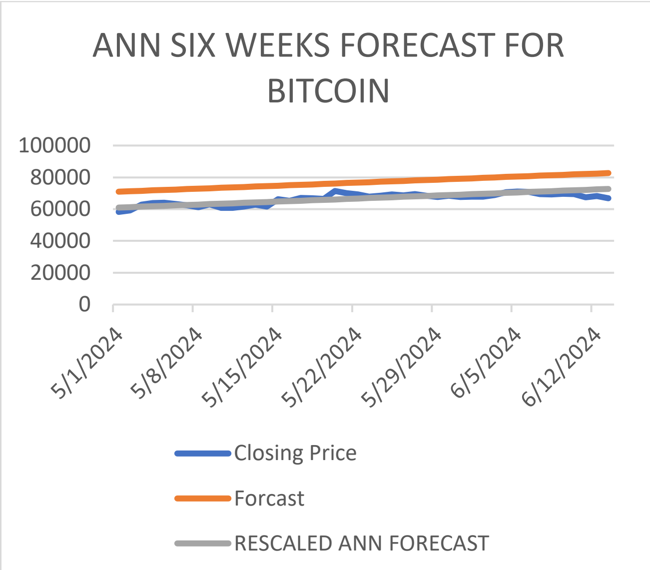

Fig. 7 Chat for Bitcoin daily closing price and ANN six weeks forecast

Fig. 7 shows the ANN forecast for six weeks, the actual closing price for six weeks and the rescaled forecast which is forecast minus relative error. Clearly, the recalled is a best fit for bitcoin daily closing price and can be used to make a good trading or investment decision.

SUMMARY AND CONCLUSION

The study was designed to investigate Mathematical Modeling of the Digital Currency using Bitcoin as a case study. Secondary data was used for data analysis and was collected from yahoo.com. The data was coded in excel spreadsheet and analyzed with SPSS version 24 using ANN. Based on the finding the study reveals time can be used to model or predict the daily closing price of digital currencies. Thus, we deployed the time dependent ANN model to make predictions and six weeks forecast for Bitcoin daily closing price.

The study therefore concludes that time dependent ANN model can be used to both predict and forecast digital currency prices. But it is important to note that the period of forecast should not be too long because of the high volatility nature of the digital currency market. In our work, our six weeks forecast was adequate within the period under review.

It is also important to note that ANN MODELS has limitations when it comes to manual calculation or implementation in Excel, especially when dealing with very large input values. This is because of saturation of the tanh function which can lead to identical output values for different input values, which makes it difficult to replicate the ANN model's behavior manually or in Excel. Additionally, ANN models often involve complex interactions between multiple neurons, layers, and activation functions, which can be challenging to replicate manually or in Excel.

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Thus, we propose that for future research, the manual computation or replication of the ANN prediction in Excel should be look into since a neural network model is a computational framework designed to simulate the behavior of the human brain's interconnected neuron structure through machine programing.

RECOMMENDATIONS

Based on the findings of the study the following recommendations were made.

1. ANN can be used to model the dynamics of order flows and market microstructure, helping traders understand the impact of large trades on prices and develop strategies to minimize market impact. We therefore recommend that traders take advantage of ANN to minimize the risk of losing their equity in the digital currency market.

2. ANN help in understanding the liquidity dynamics of digital currency markets, which is essential for executing large trades without significant price slippage. In this regard, we recommend proper understanding of ANN model predictions before considering investing or trading in digital currencies using ANN models.

3. We recommend that ANN model should be built into digital currencies trading platforms to run in real time with the digital currency prices to serve as one of the signal tools like SMA etc to help investor make more informed decisions.

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