PREDICTING MULTIVARIATE FINANCIAL TIME SERIES USING NEURAL NETWORK ALGORITHMS

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***[1]David Opeoluwa Oyewola, [2]Kuluwa A. Al-Mustapha,[3]Emmanuel Gbenga Dada, [1]Daniel Eneojo Emmanuel, [1]Alechenu Bernard, [1]Hussaini Sani Hudu**

[1,2]Department of Mathematics & Computer Science, Federal University Kashere, Gombe, Nigeria

[3]Department of Mathematics, Baze University, Abuja, Nigeria

[1]Department of Mathematical Sciences, University of Maiduguri, Maiduguri, Nigeria

*Corresponding author's email: davidakaprof01@yahoo.com

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Abstract: For applied researchers, the stock market has been a challenging task because of its very noisy existence and its time varies. Many scientists used neural network techniques effectively as a means of forecasting stocks. This paper examined stock forecasting for investors' use. Investors generally get losses because of unsafe intentions of investment and unpredictable assets. This paper considered four neural network model such as Feed Forward Neural Network (FFNN), Recurrent Neural Network (RNN), Cascade Forward Neural Network (CFNN) and Generalized Regression Neural Network (GRNN) to find efficient algorithms for predicting Nigerian Stock Exchange. Investigational findings demonstrate that our GRNN model has higher precision than FFNN, RNN and CFNN. We believe this finding will help stock investors to yield significant profit on Nigerian stock exchange.

Keywords: Forecast, feed forward neural network, cascade forward neural network

Introduction

With a population of more than 200 million, Nigeria needs capital resources for rapid and indeed productive economic growth and industrial development to be distributed from a variety of competing alternatives (Vargas *et al.*, 2017). This explains the purpose of this issue, which aims at appraising the bourses as vehicles or means of mobilization of funds in order to boost industrial growth in the country for diverse industries and investors. The bond market is a financial market subsector dealing with long-term securities and procedures for long-term financial investments. Consequently, capital broadly includes any service provided by financial institutions and facilities to mobilize long-term funds and channel each fund to a variety of end users' industrial or economic units. In the Nigerian capital markets the Nigerian Stock Exchange (NSE) is a significant regulator. In terms of investment avenues and divestment of various stocks and bonds, it is the pivotal growth of the Nigerian capital market. On the other hand, the capital market is the aspect which offers facilities for mobilizing and transferring securities-including long-term funds. It can be referred to as the market for government, industry and business loans in the short, medium, long and permanent periods (Ruder *et al*., 2016). The stock market can also be subdivided into the main and secondary markets (Ding *et al*., 2015). The main market is concerned with the sale of new securities first issued by the issuing companies and secondary markets with secondary securities or old securities. Capital provision is a strategic consideration to fuel business growth through equity markets (Leinweber and Sisk, 2011).

There have been serious questions about availability of funds for Industrial Growth since the Second World War, when the development policy of third-world countries took on an acceleration turn (Bengio *et al*., 2013). This depends in turn on the national income saving partnership, which both would raise to increase growth with a certain amount of savings. After these savings have been developed, institutions and policies need to further induce and enables household and the private sector to achieve economically justifiable savings, and how and where funds can be obtained. In this context, certain financial and non-financial institutions are structured to collaborate and cooperate to ensure the successful functioning of the capital market and this led to the creation of the Lagos stock market. In September 15, 1960, the Nigerian Stock Börse was incorporated; formerly known as the Lagos Stock Exchange. On 5 June 1961 three commercial securities, two federal government bonds and seven other securities, under the United Kingdom's stamp duty began exchange operations. There are three membership groups of stock exchange, namely founding members, ordinary members and trading members. There are other bodies approved by the stock exchange council to exchange shares, stocks and other securities. They are brokers and employers. The stock market is a key body in economic industrial growth, since it facilitates the intermediary of funds between financial institutions' savers and investors. A number of developing corrective measures, such as deregulation of the market, introduction of the second-tier market (SSM), promulgation of the 1988 decree of privatization and marketing, and the 1996 panel sale to brand review agencies have been introduced by the federal Government in order to improve the operating of the stock market. In terms of the market capitalization value of sold debt, the amount of trade and the number of operators, the stock market has greatly expanded across all of the developments. However, a very limited long-term source of funding. In this context, several problems related to the Nigerian stock market were found during this review. There is no infrastructure such as stable telecommunications network, data storage space, etc. The Nigerian Stock Bursary. If required, the information requested can be retrieved. The restrictive regulatory framework for securities and exchange commission's affects the amount and valuation of the offered securities. It is difficult to understand the degree to which a structured stock market has generated investment through the securities law, the presence of unregulated informed markets such as (meeting, issuing union and community group) along with the coexistence of modern financial institutions and Bank insurance firms and savings institutes. Furthermore, the lack of market operators and the low interest rate structure leads to market maladministration. For certain people it is almost difficult to understand investment possibilities because of the education gap between the population.

Recently, algorithmic trade has become a powerful trend in investment management due to the developments in computing power and computers' ability to process large quantities of data (Ruta, 2014). In combination with developments in computer and natural language (NLP) technology, unstructured text data has been used as a source of knowledge for investment strategies (Fisher *et al*., 2016). The most influential field of NLP sensation analysis, or opinion mining, was the field of NLP with the greatest impact in stock market prediction (Pang *et al*., 2008). In earlier work by Tetlock (2007) sentiment analysis was studied, which showed that media pessimism could influence both stock prices and trading volume. Similarly, Bollen *et al*. (2011) used a collective mood measurement method via Twitter feed and showed that the Dow Jones Industrial Average closing values were highly predictive. Other work has also provided social media data for stock market forecasting according to their findings (Nguyen *et al*., 2015; Oliveira *et al*., 2017, for example). In the literature a variety of systems focused on feature selection are proposed in relation to direct market price prediction from newspapers. Schumaker *et al*. (2012), using a Support Vector Regression Student to test feelings with characteristics deriving from a single sentence and measured in a positive/negative subjectivity scale, have developed the method, but the findings have been limited.With a selection process based on a contextual entropy model, Yu *et al*. (2013) achieved better accuracy in extending a seed words to discover related emotional words with their corresponding intensities from online stock news objects. Hagenau *et al*. (2013) used Chi-square and Bi-normal separation features with n-gram characteristics resulted in strong performance. As all sentimental analyses, the extent of negation can be a problem: Prolixes *et al*. (2016) recently proposed a method of reinforced learning to predict the extent of negation. Nuij *et al*. (2014), using an evolutionary algorithm to integrate trading rules by using technical indicators and events from the news with specialized impact ratings, introduced a different method in integrating news into stock trading strategies. Although they did not use an optimal methodology for collecting information from financial text data, the results of their findings showed that the news events are part of optimum trading strategies. Ding *et al*. (2014), used a two layer feed forward neural network as well as a linear SVM to address the issue of whether stocks will increase or decrease as a classification problem, has one of the main approaches that informed the model and assessment system in this article; they found that the Deep Learning model was more accurate. They also contrasted bag-of-words with structured events extracted through open knowledge extraction (open IE), which enhanced structured inputs. They noticed that for the price movements of the next day, the prediction was higher than the next week, and that in turn, it was better than anticipated in the next year. Ding *et al*. (2015) used a neural tensor network as input to their prediction models to learn both word embedding and organized events. They then used a deep convolutional multi-channel network — channels which match events on a different time scale — to forecast changes to the S&P 500 stock and the individual stock prices. Vargas *et al*. (2017) combined recurrent and convolution layers along with previously trained word vectors to predict even adjustments to the S&P 500 index. The design here was also multi-channel and had an input channel for technical analysis. The results of both work pieces surpassed the previous approaches to the manual feature engineering. In the sense of data shortages, Ding *et al*. (2014) and Ding *et al*. (2015) make use of general and back-of techniques, which may help resolve the above character level representations, as stated earlier. In addition, input at the level of the character is potentially complementary to other types of inputs or event representations, particularly the multi-channel architectures for the above work: Research such as Kim's (2014) showed that multiple input representations can be combined usefully and this kind has, for the particular purposes of character-level, word-level or other input, been achieved using this model such as Ruder *et al*. (2016). They intended to examine whether type of feedback at the character level may collect useful information for stock price forecasting. Artificial Neural Network has been attractive to new studies of the time series since the mid-1990s (Arévalo, 2016). Zhang *et al*. (2009) studied an improved S&P500 prevention model based on neural systems and Bacterial Chemotax Optimization (IBCO). Oyewola *et al*. (2021) proposed a natured-inspired algorithm, called Auditory Algorithm (AA) which follows the pathway of the auditory system to predict Nigerian stock exchange using Logistic Regression, Support vector machine, feed forward neural network, recurrent neural network, stochastic differential equation, geometric Brownian motion and AA. The result shows that AA perform better than other algorithms.

Methodology

Feed Forward Neural Network (FFNN)

Feed Forward Neural Network can be defined as a non-parametric estimate of mathematical models for the non-linear input data extraction (Rumelhart *et al*., 1986). The free network parameters are set and during this process, the input signal is transmitted over the network. It ends with the error signal calculation.

Equation for activation function (Sibi, 2013) of an i^{th} hidden neuron is given by:

$$h_i = f(u_i) = f(\sum_{k=0}^{K} w_{ki} x_k) \quad (1)$$

Where h_i is the i^{th} hidden neuron, $f(u_i)$ is the link function which gives non-linearity among input and hidden layer, w_{ki} is the weight in the ki^{th} entry in a ($K\times N$) weight matrix, x_k is the K input value.

$$y_j = f(u_j^1) = f(\sum_{i=1}^{N} w_{ij} h_i) \quad (2)$$

Where y_j is the j^{th} output value

Recurrent Neural Network (RNN)

The recurrent layers or hidden layers within the Recurrent Neural Network (RNN) consist of recurring cells with both past and current input with feedback connections influencing states. The recurring cell and network architecture differentiate RNN primarily. Different cells and internal connections enable RNN to have various capabilities. Networks consist of normal recurring cells, such as sigma cells and tanh cells, are used to investigate the Recurrent Neural Network (RNN). The basic recurrent sigma cell mathematical expressions are written as follows:

$$h_t = g_n(W_{xh} X_t + W_{hh} h_{t-1} + b_h) \quad (3)$$

Where h_t is the hidden layer at t^{th} instant, g_n is the function, W_{xh} is the input to hidden layer of weight matrix, X_t is the input at t^{th} instant, h_{t-1} is the hidden layer at $t-1$ instant, b_h is the bias or threshold value hidden to output layer equation is given as :

$$Z_t = g_n(W_{hz} h_t + b_z) \quad (4)$$

whereas Z_t is the output vector, W_{hz} is the hidden to output layer weight matrix, b_z is the bias or threshold.

Cascade Forward Neural Network (CFNN)

Cascade Forward Neural Networks (CFNN) is a distinct and more complex neural network class than feed forward neural network. In CFNN, weighted ties between the input layer and the output layer as well as each hidden layer are introduced, which allow us to understand the difficult data patterns and take the direct effect of inputs on outputs into account. The output layer is, for example, connected directly to the input level and to the hidden layer in a network of three layer network. By using incremental search methods on hidden units and the average square error criterion an optimum network structure can be achieved.

The mathematical equation is given as:

$$y = \sum_{i=1}^{n} f^i(w_i x_i) + f^o(\sum_{j=1}^{K} w_j^o f_j^h(\sum_{i=1}^{n} w_{ji}^h x_i)) \quad (5)$$

Where f^i is the activation function from the input layer to the output layer, $w_i^i$is weight from the input layer to the output layer. In the event a bias is added to the input layer and the activation function of each neuron in the hidden layer is f^h then equation (2) becomes

$$y = \sum_{i=1}^{n} f^i(w_i x_i) + f^o\left(w^b + \sum_{j=1}^{K} w_j^o f^h\left(w_j^b + \sum_{i=1}^{n} w_{ji}^h x_i\right)\right) \quad (6)$$

Generalized Regression Neural Network (GRNN)

GRNN is one of the most popular neural networks, and is a form of supervised feed forward neuronal network (FFNN). It was initially presented in 1991 by Donald F. Specht. Specht's GRNN is linked to his classifier of the Probabilistic Neural Network (PNN). GRNNs are known, as PNN networks, for their ability to train in small data sets quickly. GRNN applications can produce constant valuable outputs instead of categorizing data such as PNN. Bayesian post-probabilities are a major by-product of the GRNN network. The GRNN trainings are very fast, since data must only be transmitted once, in contrast to many other PNN, where the data can be propagated to and from time to time until an acceptable error is found (Spetch, 1998). GRNN consists of layers of input, hidden, summing and splitting. When GRNN is trained, every single pattern is stored. It will be able to generalize for new inputs following training GRNN with suitable trainings. GRNN output is calculable by (7) and (8).

$$D_i = (X - X_i)^T (X - X_i) \quad (7)$$

$$\hat{Y} = \frac{\sum_{i=1}^{N} Y e^{(-D_i/2\sigma^2)}}{\sum_{i=1}^{N} e^{(-D/2\sigma^2)}} \quad (8)$$

Where D_i is the Euclidean distance between the input X_i and the training sample input X, Y is the training sample output, $\sigma$is the smoothing parameter of GRNN.

Training Algorithms for Neural Network

This study evaluated training algorithms to assess the three output out of the four neural networks. We have used the Levenberg-Marquardt algorithm as training algorithms for Feed Forward Neural Network (FFNN), Recurrent Neural Network (RNN) and Cascade Forward Neural Network (CFNN). The training algorithms considered was used for weighting adjustments of RNN, CFN and FFN model used in this research.

Levenberg Marquardt (LM)

The Levenberg-Marquardt algorithm combines the fastest descent technique with the Gauss-Newton technique and searches for optimal parameters with accuracy. In the previous case the algorithm of the most rapid descent linear model is used and in the last case the convergence is a square one (Levenberg, 1944; Marquardt, 1963). The algorithm of Levenberg-Marquardt is an iterative method in which the vector of unknown parameters is calculated by equation during step *K+1*:

$$x_{k+1} = x_k^T - [J^T(x_k,t)J(x_k,t) + \mu_k I]^{-1} J^T(x_k,t)y(x_k,t) \quad (9)$$

With the error:

$$I_2 = \int_0^T y^2(x_k,t)dt \quad (10)$$

Where: $y(x_k,t) = \int_0^t k(t-\tau)u(\tau)d\tau \quad (11)$

$$J(x_k,t) = \begin{bmatrix} \frac{\partial y(x_k,t_1)}{\partial x_1} \frac{\partial y(x_k,t_1)}{\partial x_2} & \cdots & \frac{\partial y(x,t_1)}{\partial x_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial y(x_k,t_n)}{\partial x_1} & \cdots & \frac{\partial y(x_k,t_n)}{\partial x_m} \end{bmatrix} \quad (12)$$

Where

$k = 1,2,\ldots p$; p is the number of iteration loops; $J_{n\times m}$ is the Jacobian matrix; $I_{m\times n}$ is the unit matrix; μ_k is the scalar and its value changes during iteration; $x = [x_1, x_2, \ldots, x_m]$ is the model parameters searched for.In the event that the parameters of the vector are not optimum ones, and the value of error (11) is not at the minimum level. At this point:

$$J^T(x_k,t)J(x_k,t) \ll \mu_k I \quad (13)$$

can be accepted and this leads to the steepest descent method, then we have:

$$x_{k+1} = x_k^T - \frac{1}{\mu_k} J^T(x_k,t)y(x_k,t) \quad (14)$$

In the event the value of coefficient μ_k is small, it implies that the values of the parameters of

vector x are close to the optimum solution. At this point:

$$J^T(x_k,t)J(x_k,t) \gg \mu_k I \quad (15)$$

which means that the Levenberg-Marquardt algorithm is reduced to the Gauss-Newton method:

$$x_{k+1} = x_k^T - [J^T(x_k,t)J(x_k,t)]^{-1} J^T(x_k,t)y(x_k,t) \quad (16)$$

Back propagation is utilized to calculate the Jacobian J with respect to the weight and bias variables x. Each variable is adjusted according to Levenberg-Marquardt.

Technical Indicators

In order to monitor stock prices and establish trade regulations, researchers and investors have used various types of technical indicators for buying-selling decisions. Five well-known technical indicators are selected as model inputs for this study: RSI, DPO, MACD, EMA and CMO. The technical indicators are established as follows from historical prices:

Relative Strength Index (RSI)

RSI is a typical measure of momentum that determines if the stock will be overpurchased or oversold. A stock is stated to be overbought as demand incredibly increases the price. This is generally interpreted as an indication that the stock has been overly priced and the price will most likely fall. A stock is said to be overpurchased if the price falls unambiguously below the true value. This is a consequence of panic sales. The price after an oscillator varies from 0 to 100, and when the RSI is over 70, the stock could be overbooked, if the RSI is under 30 then the stock could be overbooked..

The mathematical formula for calculating RSI is:

$$RSI = 100 - \frac{100}{1 + (\sum_{i=0}^{n-1} \frac{Up_{t-i}}{n}) / (\sum_{i=0}^{n-1} Dw_{t-i}/n)} \quad (17)$$

Where Up_t is the upward-price-change and Dw_t is the downward-price-change at time t

Detrended Price Oscillator (DPO)

The decreased price oscillator shows the difference between a preceding price and a simple moving average. Cycles with their peaks and troughs are simply to be identified. By counting the time between peaks or troops, cycles can be evaluated. Detrended price oscillator is calculated by mathematical equation:

$$DPO = C_t - SMA(\frac{n}{2} + 1) \quad (18)$$

Where C_t is the closing price at time t, SMA the simple moving average, $n = 21$

Moving Average Convergence Divergence (MACD)

Moving Average Convergence Divergence (MACD) is a specialized indicator created by Gerald Appel in late 1970. It is used to detect changes in the strength, direction, dynamics and length of a stock price trend. The MACD calculates the difference in closing prices from two Exponential Moving Averages (EMA). This distinction is distinguished by a moving average contrast after some time. Recent changes in stock price include EMA. The MACD line describes changes in stock pattern.

The equation for calculating MACD is:

$$MACD = EMA_{12}(C_t) - EMA_{26}(C_t) \quad (19)$$

$$S_L = EMA_9(MACD) \quad (20)$$

Where C_t is the closing price at time t, $EMA_n = n = 9$, 12 and 26 day Exponential Moving Average. When the $MACD$ goes below the S_L, it indicates a sell signal. When it goes above the S_L, it indicates a buy signal.

Exponential Moving Average (EMA)

Exponential Moving Average (EMA) is used in conjunction with the Simple Moving Average and EMA responds faster than the moving average to recent price value. Additionally, EMA is used to process different metrics, such as the Moving

Average Convergence (MACD) and so on. The moving average exponential of n days is computed as:

$EMA_t = C_t \times \propto\ + EMA_{t-1} \times (1 - \propto)$ (21)

Where EMA_t is the exponential moving average at time t, $\propto$ is the exponential smoothing Factor given as $\propto = 2 \div (n + 1)$

Chande Momentum Oscillator (CMO)

Tushar S. Chande developed the Chande's Momentum Oscillator (Labs, 2016). The oscillator of Chande Momentum is an updated Relative Strength Index (RSI). Where the upward movement of the RSI is divided by net movement (up / + down), the CMO divides the aggregate by net movement (up - down / (up + down)). The values above 50 show a buy signal and the values below 50 display a sell signal.

The equation for computing CMO is:

$$CMO = 100 \times \frac{\sum_{i=0}^{n-1} Up_{t-i} - \sum_{i=0}^{n-1} Dw_{t-i}}{\sum_{i=0}^{n-1} Up_{t-i} + \sum_{i=0}^{n-1} Dw_{t-i}} \quad (22)$$

Where Up_t is the upward-price-change and Dwt is the downward-price-change at time t.

Performance Evaluation

We assess prediction performance utilizing three measures: Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Scaled Error (MASE).

Mean Absolute Error (MAE)

Consider a set of target or actual returnsr_t^n and their predicted values$\hat{r}_t^n$

MAE is defined as follows:

$$\frac{1}{n}\sum_{n=1}^{n} |r_t^n - \hat{r}_t^n| \quad (23)$$

Root Mean Square Error (RMSE)

RMSE is defined as:

$$\sqrt{\frac{1}{n}\sum_{n=1}^{n} (r_t^n - \hat{r}_t^n)^2} \quad (24)$$

Mean Absolute Scaled Error (MASE)

MASE is defined as follows:

$$\frac{1}{n}\sum_{n=1}^{n} \left(\frac{|r_t^n - \hat{r}_t^n|}{\frac{1}{n-m}\sum_{n=m+1}^{n} |r_t^n - r_{t-m}^n|}\right) \quad (25)$$

Where m is the seasonal period of return r_t^n

Target and Input data

Our analysis is similar to that in (David *et al*., 2019). However, we use the regular closing price and resolve our task with technical indicator in Section 3.7. We suggest the use of a technical predictor to produce good results as it was used to model time series (Rajashree *et al*., 2016) and in stock decision systems (Luckyson, 2016). Stock data are collected from the Nigerian Stock Exchange (NSE) consists of Access Bank, First City Monument Bank (FCMB), Fidelity Bank (FIDELITY), Stanbic Bank (STANBIC) and Zenith Bank was used traversing from January 2015 to December 2020.

In this analysis, stock data is used to evaluate the performance output. The dataset spans five financial years, 1324 business days included. To analyses the stock market datasets, for example the training and research datasets are split in two sets. For example, the model input is a matrix of five parameters such as RSI, DPO, MACD, EMA, STOCH. Daily Stocks with closing prices of Access Bank, First City Monument Bank (FCMB), Fidelity Bank (FIDELITY), Stanbic Bank (STANBIC) and Zenith Bank was used in this research.

If we let the daily closing price at time-step t be $c_d^i(t)$ since we are using technical indicator as our input data with an integration of daily closing price, then our model or hypothesis is given by the following equations

$$Y_{t+1}^i = F\left(\left(RSI_{c_d^i(t)} \dots, RSI_{c_d^i(t-n)}\right)^T, \left(DPO_{c_d^i(t)} \dots, DPO_{c_d^i(t-n)}\right)^T, \left(MACD_{c_d^i(t)} \dots, MACD_{c_d^i(t-n)}\right)^T, \left(EMA_{c_d^i(t)} \dots, EMA_{c_d^i(t-n)}\right)^T, \left(CMO_{c_d^i(t)} \dots, CMO_{c_d^i(t-n)}\right)^T\right) \quad (25)$$

Here F is the predicted function which our deep learning is modeling and,Y_{t+1}^itakes the value of the stock closing price of Access Bank, First City Monument Bank (FCMB), Fidelity Bank (Fidelity), Stanbic Bank (STANBIC) and Zenith Bank. Those classes are defined according to the daily closing price of stock i for all the stocks in the list.

Results and Discussion

Here we make an account on how the experiments were conducted and present the results that we obtained. Data from the Nigerian Stock Exchange (NSE) was used for this study and Access Bank (ACCESS), First City Monument Bank (FCMB), Fidelity Bank (FIDELITY), Stanbic Bank (STANBIC) and Zenith Bank was gathered for the period 1 January 2015 to 31 December 2020 for each of the stock.

Figure 1 is the daily closing price of Access Bank spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate. Fig. 2 is the daily closing price of FCMB Bank spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate.

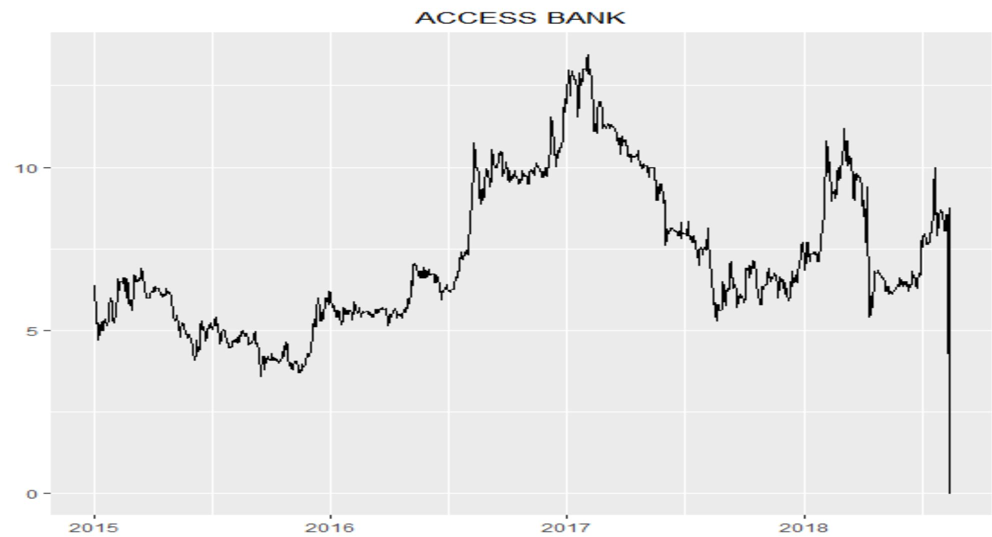

Fig. 1: Daily closing price of Access Bank (ACCESS)

Fig. 2: Daily closing price of FCMB Bank

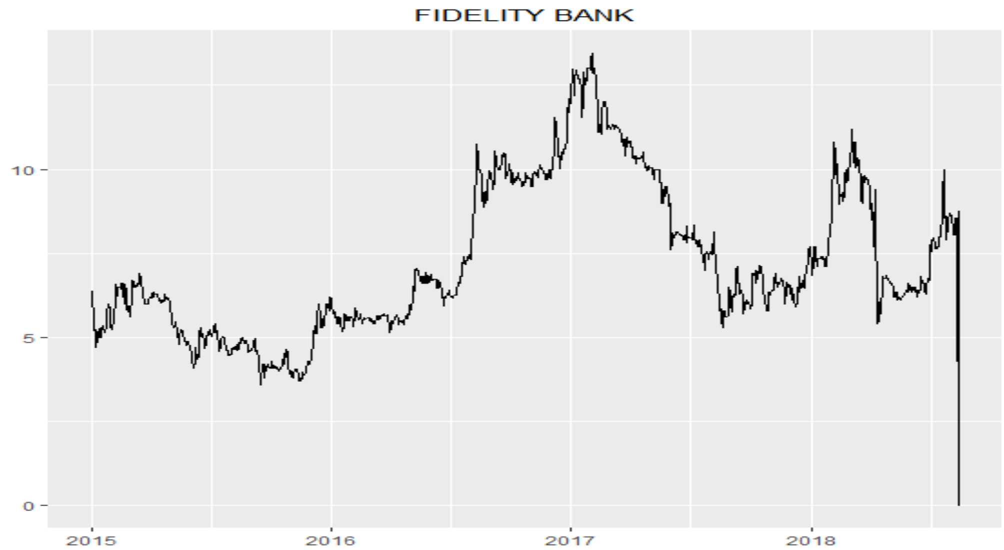

Fig. 3: Daily closing price of Fidelity Bank

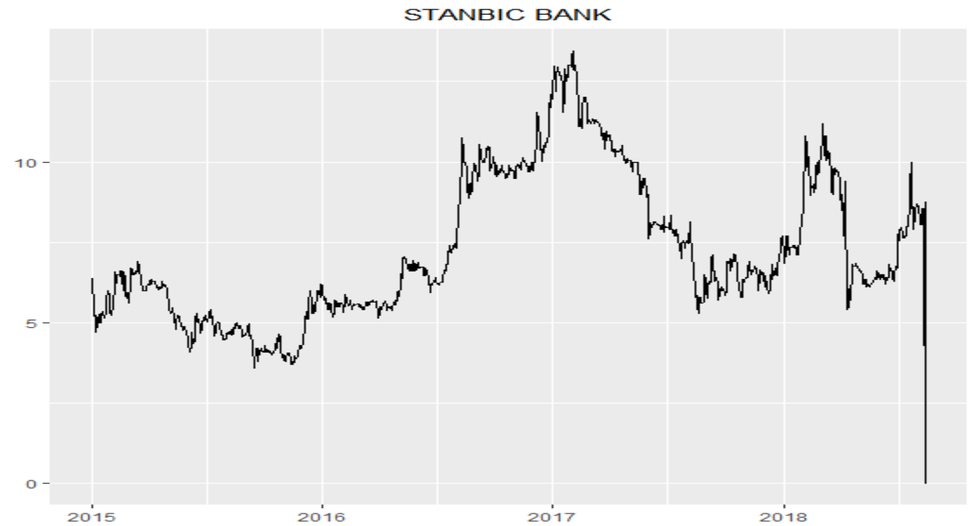

Fig. 4: Daily closing price of STANBIC Bank

Fig. 5: Daily closing price of Zenith Bank

Figure 3 is the daily closing price of Fidelity Bank spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate. Fig. 4 is the daily closing price of Stanbic Bank spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate. Fig. 5 is the daily closing price of Zenith Bank spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate.

Table 1 summarizes the statistical analysis of the five selected stocks such as ACCESS, FCMB, Fidelity, STANBIC and Zenith Bank. STANBIC has the highest maximum values while FCMB has the lowest maximum values. The mean values of STANBIC bank is higher than the other stocks considered in this research.

Table 1: Summary statistics of five stock market

Stocks	Minimum	Median	Mean	Maximum
ACCESS	0.00	6.60	7.26	13.45
FCMB	0.00	1.73	1.86	3.80
FIDELITY	0.00	1.62	1.66	3.99
STANBIC	0.00	33.00	32.04	53.25
ZENITH	0.00	18.70	19.49	33.51

Table 2: Summary statistics of five selected technical indicator

Stocks	Technical indicator	Minimum	Median	Mean	Maximum
Access	Rsi	4.67	49.62	50.24	99.35
	Cmo	-84.16	-1.32	0.59	97.37
	Dpo	-0.89	-0.00	-0.00	2.21
	Ema	3.91	6.51	7.27	12.86
	Macd	-13.18	-0.09	0.16	10.76
FCMB	Rsi	0.00	47.31	48.62	100.00
	Cmo	-100.00	-5.26	-2.36	100.00
	Dpo	-0.39	0.00	-0.00	0.49
	Ema	0.81	1.72	1.79	3.29
	Macd	-15.22	-0.82	-0.05	24.61
Fidelity	Rsi	0.00	47.31	48.62	100.00
	Cmo	-100.00	-5.26	-2.36	100.00
	Dpo	-0.39	0.00	-0.00	0.49
	Ema	0.81	1.71	1.79	3.29
	Macd	-15.22	-0.82	-0.05	24.61
Stanbic	Rsi	0.00	53.37	52.12	100.00
	Cmo	-100.00	1.32	2.94	100.00
	Dpo	-4.90	-0.02	-0.01	7.10
	Ema	13.82	32.98	32.00	50.75
	Macd	-8.26	0.37	0.18	10.35
Zenith	Rsi	0.69	48.69	49.20	100.00
	Cmo	-93.54	-4.14	-1.27	100.00
	Dpo	-3.25	0.01	-0.00	4.24
	Ema	11.35	18.55	19.49	31.42
	Macd	-12.53	-0.13	0.09	9.13

Table 2 is the summary statistics of five selected technical indicators such as RSI, CMO, DPO, EMA and MACD. CMO and MACD have the lowest value while RSI and CMO has the highest value as shown in Table 2.

Figure 6 is the daily closing price of ACCESS Bank and five technical indicator such as RSI, CMO, DPO, EMA and MACD spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate but none can predict the accuracy of the stock.

Figure 7 is the daily closing price of FCMB Bank and five technical indicator such as RSI, CMO, DPO, EMA and MACD spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate but none can predict the accuracy of the stock.

Figure 8 is the daily closing price of FIDELITY Bank and five technical indicator such as RSI, CMO, DPO, EMA and MACD spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate but none can predict the accuracy of the stock.

Figure 9 is the daily closing price of STANBIC Bank and five technical indicator such as RSI, CMO, DPO, EMA and MACD spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate but none can predict the accuracy of the stock.

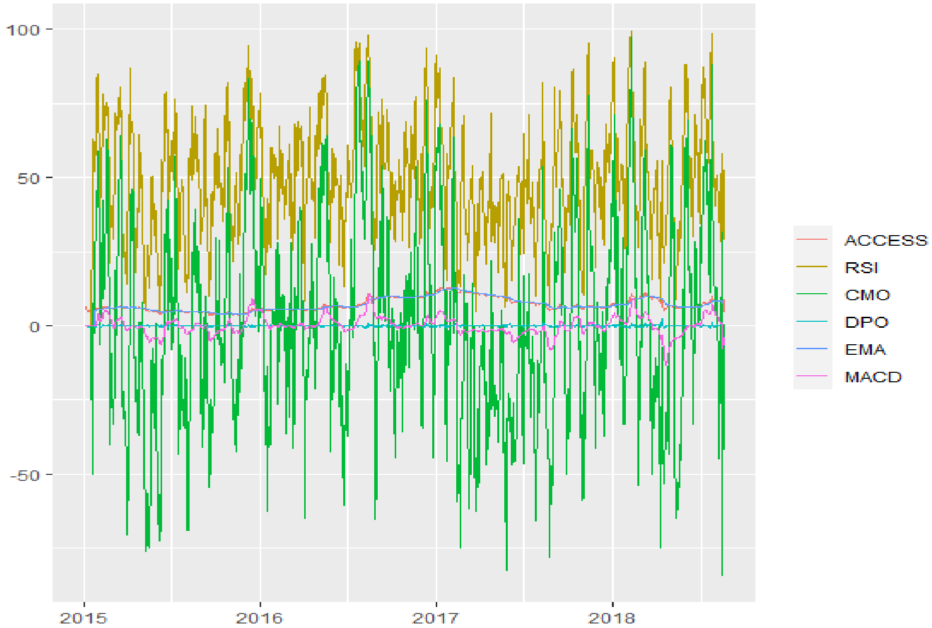

Fig. 6: Daily closing price of Access Bank, RSI, CMO, DPO, EMA and MACD

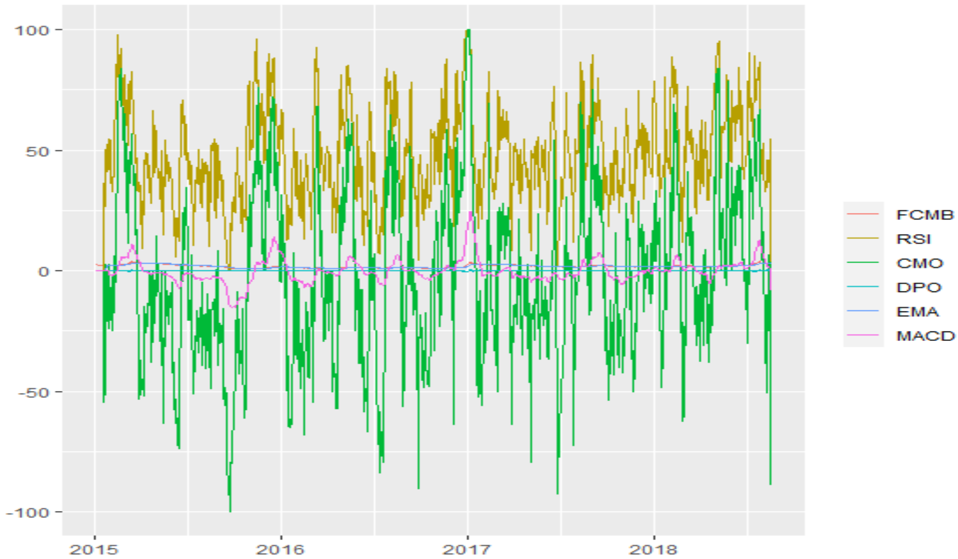

Fig. 7: Daily closing price of FCMB Bank

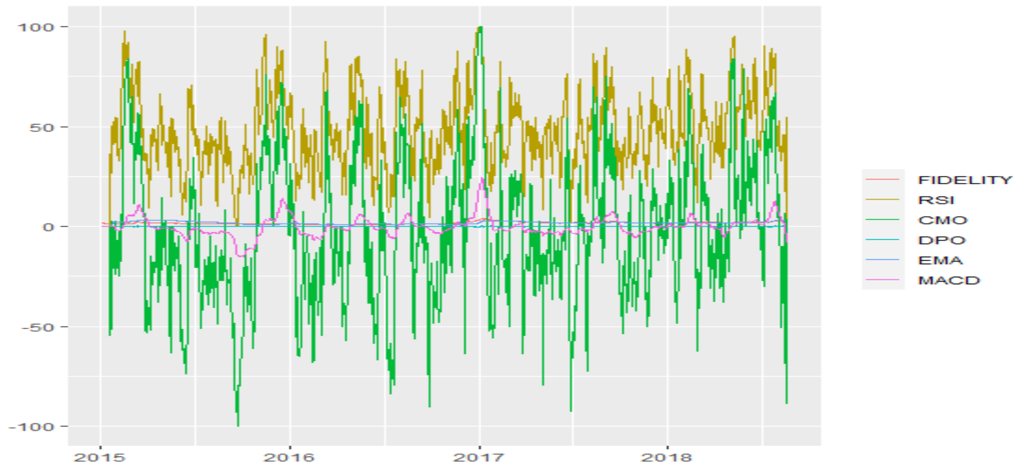

Fig. 8: Daily closing price of Fidelity Bank

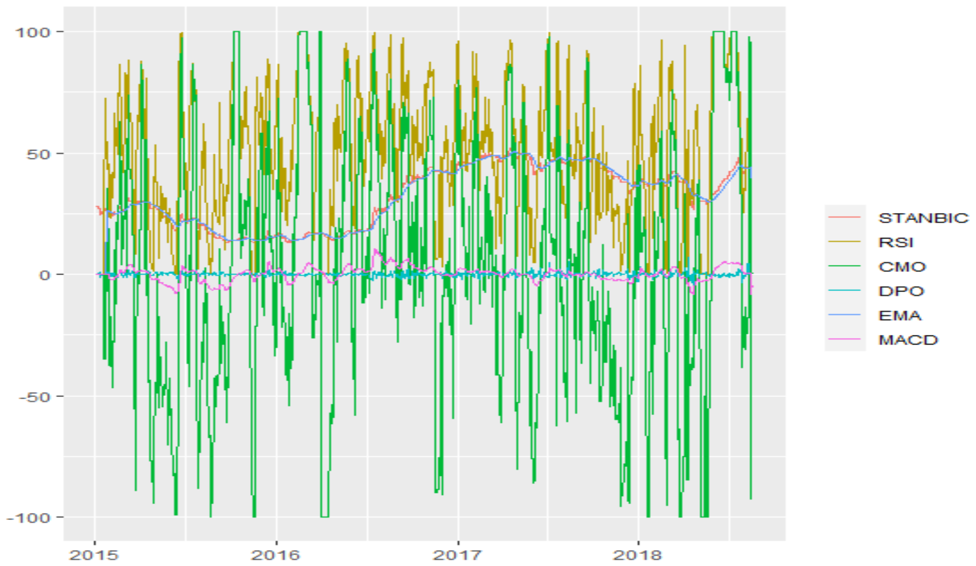

Fig. 9: Daily closing price of STANBIC Bank

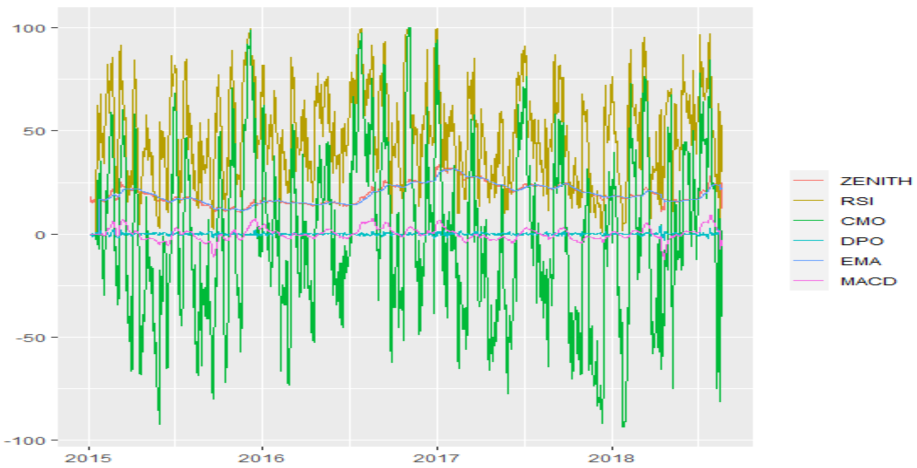

Fig. 10: Daily closing price of Zenith Bank

Figure 10 is the daily closing price of Zenith Bank and five technical indicator such as RSI, CMO, DPO, EMA and MACD spans from 1st January, 2015 to 31st December, 2020. The graph shows changes in prices, over time, which moves forward at a consistent rate but none can predict the accuracy of the stock.

Figure 11 shows the Actual value of the closing price and the predicted value of the Neural Networks. Generalized Regression Neural Network (GRNN), Feed Forward Neural Network trained with Levenberg Marquardt (FFNN), Cascade Forward Neural Network trained with Levenberg Marquardt (CFNN), Recurrent Neural Network trained with Levenberg Marquardt (RNN).

Figure 12 shows the Actual value of the closing price and the predicted value of the Neural Networks. Generalized Regression Neural Network (GRNN), Feed Forward Neural Network trained with Levenberg Marquardt (FFNN), Cascade Forward Neural Network trained with Levenberg Marquardt (CFNN), Recurrent Neural Network trained with Levenberg Marquardt (RNN). Fig. 13 shows the Actual value of the closing price and the predicted value of the Neural Networks. Generalized Regression Neural Network (GRNN), Feed Forward Neural Network trained with Levenberg Marquardt (FFNN), Cascade Forward Neural Network trained with Levenberg Marquardt (CFNN), Recurrent Neural Network trained with Levenberg Marquardt (RNN).

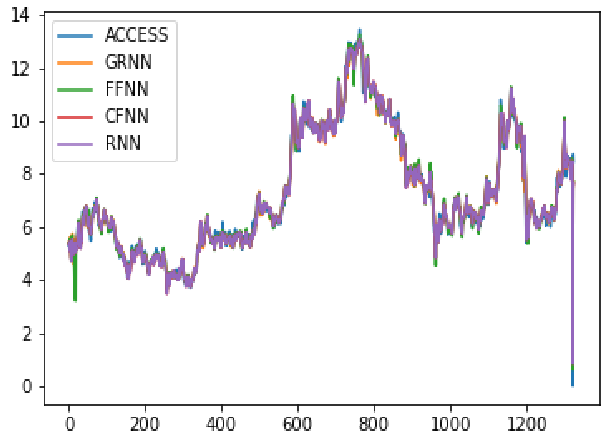

Fig. 11: Actual price (Access Bank) and predicted price (GRNN, FFNN, CFNN, RNN)

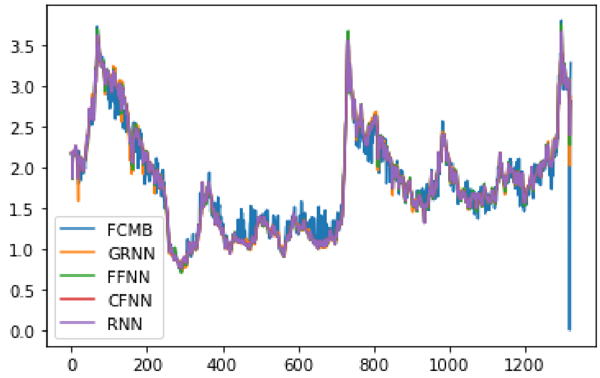

Fig. 12: Actual price (FCMB Bank) and predicted price (GRNN, FFNN, CFNN, RNN)

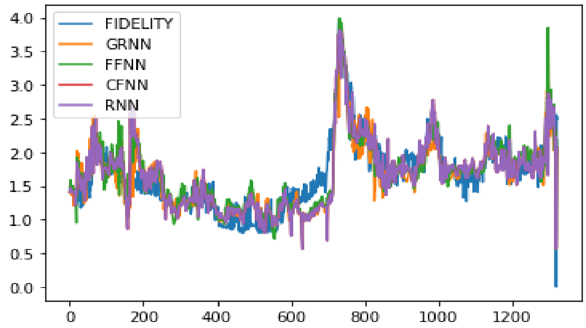

Fig. 13: Actual price (Fidelity Bank) and predicted price (GRNN, FFNN, CFNN, RNN)

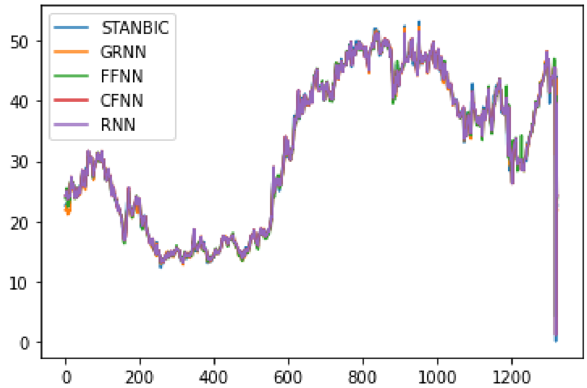

Fig. 14: Actual price (STANBIC Bank) and predicted price (GRNN, FFNN, CFNN, RNN)

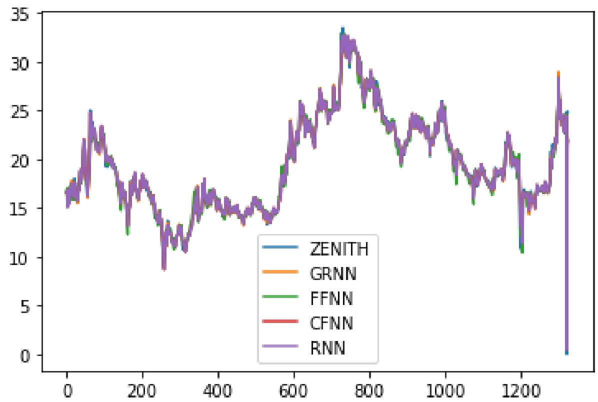

Fig. 15: Actual price (Zenith Bank) and predicted price (GRNN, FFNN, CFNN, RNN)

Figure 14 shows the Actual value of the closing price and the predicted value of the Neural Networks. Generalized Regression Neural Network (GRNN), Feed Forward Neural Network trained with Levenberg Marquardt (FFNN), Cascade Forward Neural Network trained with Levenberg Marquardt (CFNN), Recurrent Neural Network trained with Levenberg Marquardt (RNN). Fig. 15 shows the Actual value of the closing price and the predicted value of the Neural Networks. Generalized Regression Neural Network (GRNN), Feed Forward Neural Network trained with Levenberg Marquardt (FFNN), Cascade Forward Neural Network trained with Levenberg Marquardt (CFNN), Recurrent Neural Network trained with Levenberg Marquardt (RNN).

Table 3: Performance evaluation of neural network

Stocks	Model	RMSE	MSE	MASE
ACCESS	GRNN	0.09377503*	0.008793756	0.1597294
	FFNN	0.2335441	0.05454283	0.3698005
	CFNN	0.1702483	0.02898449	0.3368855
	RNN	0.1487324	0.02212132	0.3362116
FCMB	GRNN	0.1047422	0.01097092	0.6548399
	FFNN	0.07439965	0.005535308	0.3650465
	CFNN	0.07354533*	0.005408915	0.2820383
	RNN	0.07863925	0.006184131	0.3213356
FIDELITY	GRNN	0.1194555*	0.01426961	0.7897255
	FFNN	0.2935867	0.08619318	2.734817
	CFNN	0.2834055	0.08031865	2.684531
	RNN	0.2857971	0.08167996	2.560297
STANBIC	GRNN	0.9292105*	0.8634322	0.08677182
	FFNN	1.387894	1.926249	0.3912144
	CFNN	1.043255	1.08838	0.4228247
	RNN	0.9781284	0.9567352	0.3732491
ZENITH	GRNN	0.08998707*	0.008097674	0.0370226
	FFNN	0.3475467	0.1207887	0.272697
	CFNN	0.5944032	0.3533152	0.3859936
	RNN	0.331397	0.109824	0.2607107

Table 3 shows four Neural Network we used in this research such as Generalized Regression Neural Network (GRNN), Feed Forward Neural Network (FFNN), Cascade Forward Neural Network (CFNN), Recurrent Neural Network (RNN) The performance of each of the Neural Network were tested using Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Scaled Error (MASE) for different Neural Networks. The * indicated the overall best training algorithms selected in each neural network. This shows that GRNN performs better than the remaining three neural networks.

Conclusion

This study showed a neural network technique for designing effective stock trading strategies that could provide investor with attractive benefit. The model integrated technical analysis with machine learning technology to generate stock trading decisions effectively. In this analysis, four neural networks such as Feed Forward Neural Network (FFNN), Recurrent Network (RNN), Cascade Forward Neural Network (CFNN), and Generalized Regression Neural Network (GRNN), including Levenberg-Marquardt, are considered for stock trading decision techniques.

The results show that the three Neural Networks best complement the test data and we see the best results in the prediction output from their performance metrics. For generating stock trading decisions, the four neural network approach has been used. The experimental results show that the GRNN model is higher than that of the three neural networks such as Feed Forward Neural Network (FFNN), Recurrent Neural Network (RNN) and Cascade Forward Neural Network (CFNN).The results show that the GRNN model can correctly predict the stock market, which is higher than other models considered in this analysis. Therefore, it is much more profitable to take a trade decision using combinations of technical indicators with machine intelligence system, instead of taking trading decisions based on simple technical indicators. Further work will be done to optimize the model structure by using effective algorithms for optimization including differential evolution, particle swarm optimization, genetic algorithms and soon.

Conflict of Interest

The authors declare that there is no conflict of interest reported in this work.

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