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APPLICATION OF NEURAL NETWORK MODELS IN PREDICTING FRAUDULENT FINANCIAL REPORTING IN LISTED MANUFACTURING FIRMS IN NIGERIA

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Abstract
This study examined the efficiency of neural network models in predicting fraudulent financial reports of manufacturing firms in Nigeria. Secondary sources of data obtained from Nigeria Stock Exchange were used for the content analysis. The ex-post facto research design was adopted for the study. The population of the study included sixty-four (64) manufacturing firms quoted in the Nigeria Stock Exchange up to 31st December 2018. In the study it was found that the Neural Network Models can be used to evaluate the reliability of financial reports of manufacturing firms. It showed that there is a significant difference in the predictive accuracy of between the results of the Z-Score models and the Neural Network models in predicting fraudulent financial reports. The study concluded that Neural Network models are very efficient in predicting company failures. Based on these findings, the study recommended that: Managers should adopt Neural Network models, Support Vector Machines in evaluating the financial reports of manufacturing firms. They should seek the expert knowledge from consultants in big data analysis. Shareholders of companies should introduce these models in their business to safeguard their investments.

Keywords: Neural network models and fraudulent financial reports

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Introduction

Fraudulent financial reporting constitutes issuing falsified financial statements; in which numbers are manipulated by overstating assets, spurious entries related to sales and profit, or understating liabilities, debts, expenses/losses (Yue, Wu, Wang, & Chu,2007). In recent times, the issue of fraudulent financial reporting has been prevalent and increasingly serious (Kamarudin, Ismail, & Mustapha, 2012). For instance, major corporate scandals like Worldcom and Enron (U.S.), One Tel (Australia), Nortel (Canada), Parmalat (Italy), Transmile Group Berhad (Malaysia), ABIT Computer, Procomp, Infodisc and Summit Technology (Taiwan), Oceanic, Intercontinental, Afribank Plc., and Cadbury (Nigeria), among several others have been linked directly or indirectly to fraudulent financial reporting (Vladu, Amat, & Cuzdriorean, 2017; Uwuigbe, Peter, & Oyeniyi, 2014). Similarly, the former global financial crisis was attributed in part to fraudulent financial reporting (Vladu, Amat, & Cuzdriorean, 2017). Presently, it has reached an endemic level globally; coupled with the growing complexity in modern business transactions.

The issue of fraud has taken pre-eminence in the business and accounting literature, as scholars, practitioners and auditors constantly seek out new methods for its detection. According to Rezaee (2005) financial statement fraud can be defined as "the deliberate misrepresentation of the financial condition of an enterprise accomplished through the intentional misstatement or omission of amounts or disclosures in the financial statements in order to deceive financial statement users". Such manipulations of the financial statements are intentionally done to deceive the users of such reports. Such users of financial statements, includes: investors/shareholders; employees; lenders; suppliers; customers; government and the general public (e.g. NGOs, CSOs, etc.). And the perceived quality of financial statements differs among users because each group has different preferences (Omoolorun & Abilogun, 2017).

Therefore the distortion in the financial reports affects the ability of the users to evaluate past and/or forecast future performance; and, jeopardises quality of decision-making made from such reports (Nzotta, 2008). Scholars have agreed that the past few years have witnessed a tremendous increase in the level of opportunism in accounting (McVay, 2006; Bowen, Davis, & Rajgopal, 2002). In the Nigerian context, wide escalation in financial statement frauds was primarily "due to dishonest management decisions and outright cover up by accounting firms" (Okoye & Alao, 2008). Several forms of management frauds were perpetrated by managers [i.e., agents] entrusted by the shareholders [i.e., principals] to safeguard their investment. Management fraud is defined as "deliberate fraud committed by management that injures investors and creditors through materially misleading financial statements" (Eliott & Willingham, 1980). Detecting such frauds has always been an important but complex task for accounting professionals (Ngai, Hu, Wong, Chen & Sun, 2010). This is further compounded from limitations of standard auditing procedures which are insufficient (Fanning & Cogger, 1998); with, most auditors not being able to effectively deploy Computer Assisted Audit Techniques to traditional audits. This has led to sustained efforts conducted at improving existing models used to assess the existence and magnitude of opportunistic behaviour (Vladu, Amat, & Cuzdriorean, 2017). With advancements in technology, new techniques which leverage on the capability of Artificial Intelligence (AI) are emerging, which organizations must utilise to stay healthy and competitive (Eriki & Udegbunam, 2013).

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Data mining has emerged as an alternative to classical statistical models in dealing with complex data analysis and classification (Chen, 2016). The aim was to discover valid, complex and obvious hidden information from large amounts of data (Kirkos & Manolopoulos, 2004).

Data mining stands for a large number of algorithms, models and techniques derived from the osmosis of statistics, machine learning, data bases and visualization. They serve many different functions, such as classification, association, clustering and forecasting (Seifert, 2004).

Fraudulent financial reporting is generally regarded as a typical classification problem (Kirkos, Spathis, & Manolopoulos, 2007). The classification problem “involves performing computation using the variable characteristics of some known classification data, in order to obtain classification-related classification rules” (Chen, 2016, p. 2). The study by Odom and Sharda (1990) was the first to apply neural networks in bankruptcy classification problem and compared its performance to discriminant analysis.

According to Lin, Hwang, and Becker (2003, p. 659) the main advantage of Artificial Neural Networks over other programming methods “is its ability to learn. Through a trial-and-error process, neurons adjust their weights of input variables to model the behaviour or patterns of output variables”. They “can imitate any type of functions because of their mathematically proven, so called universal approximation feature. Thus, they learn the type of relationship from the data themselves, thus minimizing the need for information out-of-the sample” (Kristóf, 2008; Hawley, Johnson, & Raina, 1990). It tolerates data errors and missing values by making use of the context and ‘filling in the gaps’. Consequently, neural networks are able to handle data from financial statements, which are often inconsistent and incomplete.

The manufacturing sector is crucial to the growth, development and industrialisation of any nation. This sector involves firms that create new commodities or add values to those already manufactured (Adebayo, 2011).

Common financial statement fraud perpetrated in the sector includes fictitious sales, accepting expenditure wrongly, erroneous property estimation, undisclosed debt and inappropriate disclosure (Odunayo, 2014). In business world, there has been a remarkable declined prior to 2006 in the Manufacturing sector, with more firms delisted than listed; and, over 50% of the cases were attributed to financial distress and fraud (Ani & Ugwunta 2012).

In addition, there is insufficient evidence to prove the superiority of Neural Network over discriminant models in predicting fraudulent reports of firms in Nigeria. There is therefore a need to evaluate the superiority of neural network models over such models through other sectors such as manufacturing firms. It is against this backdrop, that the present study evaluated the application of neural network models in predicting fraudulent financial reporting of quoted manufacturing firms in Nigeria.

The main objective of the study is to evaluate the application of neural network models in predicting fraudulent financial reporting of selected quoted manufacturing firms in Nigeria. The specific objectives of the study are:

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1. To develop a neural network model that can be used in evaluating the reliability of financial reports of manufacturing firms.
2. To identify financial ratios that are statistically significant explanatory variables in predicting fraudulent financial reporting of manufacturing firms.

Review of Related Literature

Conceptual Review

Fraudulent Financial Reporting (FFR)

The Merriam Webster's Dictionary of Law cited in Manurung and Hadian (2013), defined fraud as any act, expression, omission, or concealment calculated to deceive another to his or her disadvantage, specifically, a misrepresentation or concealment with reference to some fact material to a transaction that is made with knowledge of its falsity and or in reckless disregard of its truth or falsity and worth the intent to deceive another and that is reasonably relied on by the other who is injured thereby.

The U.S. Committee of Sponsoring Organizations of the Treadway Commission (COSO) (Beasley et al. 1999) and SAS No. 99, 2002 defined a FFR as either intentional or reckless conduct based on false information or omissions that results in significantly misleading financial reports. The US Association of Certified Fraud Examiners (ACFE) cited in Chen (2016) classified fraud into six types: (1) providing false financial information; (2) misuse or misappropriation of corporate assets; (3) improper support or loans; (4) improperly acquiring assets or income; (5) improper circumvention of costs or fees; and, (6) improper manipulation of financing by executives or board members. FFR refers "to intentional misrepresentation, including omissions of amounts designed to mislead" financial statement users (Popa, Man, & Rus, 2009). It includes acts, such as; manipulation, forgery, counterfeit or alteration of records or supporting documentation, misstatements/omissions regarding events/transactions/information, intentional misapplication of accounting principles related to values/classification/manner of presentation/delivery of information, fictitious entries records (towards the end of the year) to manipulate operating results or achieve other objectives, improper adjustments of the assumptions and change in judgments used to estimate account balances, omissions/advances/delays in recognition of events/transactions that occurred during the reporting period, concealment or nondisclosure of facts that could affect the amounts recorded in the financial statements, engaging in complex transactions designed to distort the entity's financial position or performance; changing the records or conditions of significant transactions (Vlad, Tulvinschi, & Chiriţă, 2011).

The Neural Network (NN)

A neural network(s) model is a form of data mining technique. According to Turban, Aronson, Liang, and Sharda (2007) data mining can be defined as "a process that uses statistical, mathematical, artificial intelligence and machine learning techniques to extract and identify useful information and subsequently gaining knowledge from a large database. The six main data mining applications are Classification, Clustering, Prediction, Outlier Detection, Regression and Visualization (Ramageri, 2017; Bolton & Hand, 2002; Derrig, 2002; Fawcett & Provost, 1997)

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and are supported by a set of algorithmic approaches/techniques to extract the relevant relationships in the data (Turban, Aronson, Liang & Sharda, 2007). The techniques can be broadly classified into two subgroups, namely: Predictive and Descriptive techniques. *Predictive* techniques predicts the behaviour of a data set; whereas, *Descriptive* techniques describe the dataset in a concise, summative manner, and also presents the properties of the set data (Han & Kamber 2000).

The objective of predictive data mining is to forecast the value of one attribute on the basis of values of other attributes. Therefore the neural network model used in predicting fraudulent financial reporting is a form of predictive data mining.

Neural networks are inspired by the behaviour of neurobiological systems. The technique originated from examinations of the central nervous system and neurons (and their axons, dendrites synapses). A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use (Adeyiga, Ezike, Omotosho, & Amakulor, 2011). A neural network or parallel distributed processing model is a system, consisting of a number of simple highly interconnected processing elements (Cook & Shannon, 1991). It resembles the brain in two respects (Haykin, 1999):

1. Knowledge is acquired by the network through a learning process; and,
2. Interconnection strengths known as synaptic weights are used to store the knowledge.

A neural network consists of a number of neurons, i.e. interconnected processing units. Associated with each connection is a numerical value called “weight”. The neurons are arranged into layers. Different kinds of neural networks have different number of layers (Kirkos, Spathis, & Manolopoulos, 2007). McCulloch and Pitts (1943) proposed a simple model of a neuron as a binary threshold unit.

Studies have applied neural networks in data classification and fraud prediction problems. The study by Kirkos, Spathis, and Manolopoulos (2007) on the use of data mining techniques for detecting fraudulent financial statements, explored the effectiveness of data mining classification techniques in detecting firms that issue fraudulent financial statements and the factors associated with such. They focused on the utility of ‘Decision Trees’, ‘Neural Networks’ and ‘Bayesian Belief Networks’. They found support for the data mining techniques in predicting fraudulent financial statements; and, further argued that there application could facilitate auditing.

NNs are able to learn from past data sets, and on the basis of such learned relationship between variables, make projections or predictions about future outcomes given certain interactions between some or all of these variables (Eriki & Udegbunam, 2013). The learning procedure must be capable of modifying the connection strengths in such a way that the internal hidden nodes come to represent important features of the task domain (Hinton, 1986). NNs are also able to capture non-linear relationships between variables.

These features are the main advantages of these models (Lee & Choi, 2013). The analysis of neural network performs a classification; the neurons are nodes with weighted interconnections

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organized in layers. In the input layer, each node receives information about the company's financial situation and converts into single output. This output is accepted as a classifying decision or re-transmitted till decision is accepted. The acceptance is based on pre-established criteria (Virág & Kristóf, 2005).

Empirical Review

Several studies globally and locally were reviewed, they are briefly stated and summarised below as follows:

Fanning and Cogger (1998) worked on neural network detection of management fraud using published financial data. The researchers use an artificial Neural Network (AutoNet) to develop a model for detecting management fraud. The study reinforces the validity and efficiency of AutoNet as a research tool and provides additional empirical evidence regarding the merits of suggested red flags for fraudulent financial statements. Fan and Palaniswami (2000) carried out a study titled 'A new approach to corporate loan default prediction from financial statements'. They experimented with support vector machines (SVM) and learning vector quantization (LVQ) and compared their performance to discriminant analysis and neural network. The results showed that the models had accuracies of SVM (70.9%), neural network (68.3%), discriminant analysis (63.7%) and LVQ (63.3%). Cheng, Chen, and Fu (2006) compared neural network with logit analysis for distress prediction in Taiwan. They used the radial basis function network to construct the neural network model. The sample comprised 192 firms listed on the Taiwan Stock Exchange, composed of firms which have incurred financial distress during the period from 1996 to 2004. They compared the performance of the proposed RBFN to logit analysis, and showed that the RBFN showed superior results. Sookhanaphibarn, Polsiri, Choensawat, and Lin (2007) applied neural networks for bankruptcy prediction in Thailand. They used data sets of 41 Thai financial institutions for the period 1993 to 2003. They computed 30 financial variables and seven ownership variables to develop the models. They used principal component analysis to reduce the number of variables. They examined the performance of three neural networks: Learning Vector Quantization, Probabilistic Neural Network, and Feedforward Network with Back Propagation Learning. They found that Learning Vector Quantization (LVQ) outperformed the other two models in terms of predictive accuracy and bias. Probabilistic Neural Network (PNN) provided consistent results every running time but its accuracy is lowest. Feed Forward Network with Back Propagation Learning provided superior accuracy results but had a bias considerably higher than that of the other two methods. Zhou and Kapoor (2011) worked on Detecting Evolutionary Financial Statement Fraud. Their work considers Data Mining (DM) based financial fraud detection techniques (such as regression, decision tree, neural networks and Bayesian networks) that help identify fraud. Their work explores a self-adaptive framework (based on a response surface model) with domain knowledge to detect financial statement fraud. They conclude by suggesting that, in an era with evolutionary financial frauds, computer assisted fraud detection mechanisms will be more effective and efficient with specialized domain knowledge. Ravisankar, Ravi, Rao, and Bose (2011) worked on Detection of Financial Statement Fraud and feature selection using data mining techniques. Their work used data mining techniques such as Multilayer Feed Forward Neural Network (MLFF), Support Vector Machines (SVM), Genetic Programming (GP), Group Method of Data Handling (GMDH), Logistic Regression (LR) and Probabilistic Neural Network (PNN) to identify companies that resort to financial statement fraud. Each of these techniques is tested on a dataset involving 202 Chinese companies and compared with and without feature selection. PNN outperformed all the techniques without feature selection and GP and PNN outperformed others with feature selection and with marginally equal accuracies. Kouki and Elkhaldi (2011) compared the performance of three bankruptcy prediction models, constructed using multivariate discriminate analysis, logit model and neural network on a sample of Tunisian firms. They used a sample of 60 failing and performing firms, during a period of three years before bankruptcy (2000-2002). They found that neural network was the most powerful at a very short term horizon. However, multivariate discriminate analysis and logit regression were powerful at a medium horizon of two and three years before bankruptcy. Rafiei, Manzari, and Bostanian (2011) conducted a study titled 'financial health prediction models using artificial neural networks, genetic algorithm and multivariate discriminant analysis: Iranian evidence'. They used selected financial ratios for a sample of one hundred and eighty (180) manufacturing companies quoted in Tehran Stock Exchange for the year ended March 21, 2008. They employed three models; artificial neural networks (ANN), genetic algorithm (GA), and multiple discriminant analysis (MDA). The results showed that ANN model achieved 98.6% and 96.3% accuracy rates in training and holdout samples. The GA model achieved 92.5% and 91.5% accuracy rates; while, the MDA achieved 80.6% and 79.9% in training and holdout samples, respectively. Ibiwoye, Ajibola, and Sogunro (2012) constructed an insolvency prediction model based on artificial neural network. The sample comprised registered insurance companies in Nigeria. They used 26 financial information and ratios used in prior bankruptcy studies. The data consisted of four years prior failure. As a control measure (training data set), a failed insurer was matched with a successful insurer in terms of size and accounting years, that is, asset size, number of branches, age, and charter status. They used total assets/total liability as a measure of liquidity ratio in the study as the springboard for determining the threshold of solvency from the ANN simulation. When they raised the threshold of solvency in the industry to 5 as a result of creative accounting (i.e. gross manipulation of accounting figures), they found that the graph of the ANN simulation model falls completely below the threshold. This confirmed the insolvency status of the insurance companies under examination. Neenwi, Asagba and Kabari (2013) worked on predicting the Nigerian Stock Market using Artificial Neural Network. The researchers saw that forecasting a financial time series, such as stock market trends, would be a very important step when developing investment portfolios. In this research paper they proved by contradiction that the Nigerian Stock market is not efficient but chaotic. Two years representative stock market prices of some banks stocks were analyzed using a feed forward neural network with back-propagation in Matlab 7.0. The stimulation results and price forecasts show that it is possible to consistently earn good returns on investment on the Nigerian Stock market using private information from an artificial neural network indicator. Anyaeche and Ighravwe (2013) worked on predicting performance measures using linear regression and neural network: a comparison. Their work used artificial neural network, Back Propagation Artificial Neural Network (BP-ANN), as an alternative predictive tool to multi-linear regression, for establishing the interrelationships among productivity, price recovery and profitability as performance measures. A 2-20-20-1 back propagation artificial neural network was proposed. Productivity and price recovery served as independent variables while profitability was used as the dependent variable in the BPANN model architecture. It was observed that BPANN model has Mean Square Error (MSE) of 0.02 while Multiple Linear Regression (MLR) has MSE of 0.036. The study concluded that artificial

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neural network is a more efficient tool for modeling interrelationships among productivity, price recovery and profitability. Farinde (2013) applied neural network for distress prediction in Nigeria. The sample comprised thirty quoted banks that had published Annual Reports for the year preceding consolidation. The study used the Multilayer Perceptron Neural Network Analysis. He further analyzed the reforms by the Central Bank of Nigeria using published Annual Reports of twenty quoted banks for the year 2008 and 2011. Discriminant analysis was used to benchmark the performance of the neural network. The study found that both approaches were useful in the prediction of corporate bankruptcy for Nigerian banks. Eriki and Udegbunam (2013) compared neural network with discriminant analysis in predicting corporate distress in the Nigerian stock market. The objective of the study was to assess the quality of neural networks in predicting distress as against discriminant analysis and there application in enhancing managers' decision. The results show that while both the neural network and the discriminant analysis techniques performed better than guess work, the neural network out outperformed the discriminant analysis technique. Umer (2014) conducted a study titled 'Bankruptcy prediction using data mining classification techniques'. The sample comprised four hundred and sixty four (464) bankrupt and four hundred and sixty four (464) non-bankrupt U.K. and Irish firms from the period 2000 to 2012; while, the test data sample comprised sixty four (64) bankrupt and sixty four (64) non-bankrupt from the period 2010 to 2012. The study relied on secondary data collected from Financial Analysis Made Easy (FAME) database. He selected a total of forty one financial ratios as identified from the literature. The models were developed using SAS Enterprise Miner, WEKA and IBM SPSS. The results showed that the best classification accuracy was achieved by Neural Network models. Yahaya, Nasiru, and Ebgejiogu (2017) applied a feed forward back propagation neural network to predict insolvency. The sample comprised 15 failed and 13 non-failed companies. They used secondary data collected from 1996 to 2012. Financial ratios were used as independent variables. The results showed that the neural network correctly classified approximately 89 percent. The neural network model was applied on a sample of banks which limits the generalizability of the results.

This is a provision for errors in the Neural Network Model Diagram. This is indicated in the Researchers Conceptualization of the Proposed Neural Network Architecture. In the process of analysing and transforming information, there is an error termed ''cross entropy error''. This is a measure of error difference between the desired output and the actual output of the system. In addition, there is insufficient empirical work covering much broader areas of activities in applying Neural Network models in fraud prediction in Nigeria firms. Prior studies mainly focused on banks, such as (Yahaya, Nasiru & Ebgejiogu, 2017; Farinde, 2013).

Methodology

Research Design

The study adopted *ex post facto* research design because the researcher does not have direct control of the independent variables and their manifestations have already occurred and are inherently not manipulated.

Population of the Study

The population of the study comprised sixty-four (64) Manufacturing firms listed on the Nigerian Stock Exchange (NSE) up to 31^{st} December, 2018. The NSE classifies firms under 11

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sectors as follows: Agriculture; Conglomerates; Construction/Real Estate; Consumer Goods; Financial Services; Healthcare; Information & Communications Technology (ICT); Industrial Goods; Natural Resources; Oil & Gas; and, Services. The population includes firms in six (6) sectors involved in either production and/or manufacturing activities, the details are shown in the table below:

Table 1: Sectorial classification of companies in the population

S/No	Sector	Number of firms
1	Agriculture	5
2	Consumer Goods	21
3	Conglomerates	6
4	Health Care	11
5	ICT	7
6	Industrial Goods	14
	Total	**64**

Source: The Nigerian Stock Exchange Website (2018)

Sample Size and techniques of the Study

The study used 'non-probability sampling technique' in choosing the sample. The sample size comprised thirty four (34) listed Conglomerates, Consumer Goods and Industrial Goods Manufacturing firms on the NSE. The details of the firms included in the sample are shown in the Appendix (see Appendix I).

Methods of Data Analysis

The study employed several techniques in the data analysis. Firstly, the descriptive statistics were computed; they comprise the mean, standard deviation, minimum and maximum values. Descriptive statistics elaborate the basic characteristics of the data and provide summaries related to the samples and measures (Umer, 2014). They are used to show quantitative measures, mean, standard deviation of data in a feasible manner (Ibe, 2014).

The study used Principal Component Analysis (PCA) and Neural Network (NN) to develop the Principal Component Neural Network (PCNN) model. PCA is a well-established technique for dimensionality reduction and multivariate analysis (Deepthi & Rao, 2014). The goals of PCA are to (Abdi & Williams, 2010):

a. extract the most important information from the data table;

b. compress the size of the data set by keeping only this important information;

c. simplify the description of the data set; and

d. analyze the structure of the observations and the variables.

PCA is a variable-oriented method, which transforms a set of correlated original variables into a set of uncorrelated variables, called Principal Components (PC). These principal components are linear combinations of the original variables (Deepthi & Rao, 2014). For a given p-dimensional data set X, the m principal axes $T_1, T_2, \ldots, T_m$, where $1 \leq m \leq p$, are orthonormal axes onto

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which the retained variance is maximum in the projected space. Generally, matrix T can be given by the m leading eigenvectors of the sample covariance matrix (Kara & Direngali, 2007).

The NN is composed of neurons. These neurons are grouped in layers, where the last one is called the output layer, and the previous ones are called hidden layers. The connection of the neurons can be done in different ways, originating different kinds of NNs. The study used the Multilayer Perceptron (MLP), where all the neurons of a layer are connected to all the neurons of the following layer (Serrano, da Costa, Cardonha, Fernandes, & de Sousa Júnior, 2012).

Input Variables: Financial Ratios

Financial ratios, which are calculated by using variables commonly found on financial statements, can provide the following benefits (Ross, Westerfield, & Jordan, 2003):

- Measuring the performance of managers for the purpose of rewards;
- Measuring the performance of departments within multi-level companies;
- Projecting the future by supplying historical information to existing or potential investors;
- Providing information to creditors and suppliers;
- Evaluating competitive positions of rivals;
- Evaluating the financial performance of acquisitions.

Table 2: Categories of Selected Ratios

	Liquidity Ratios	
X1	Quick Ratio	(Current assets – Inventory) / Current liabilities
X2	Liquidity Ratio	Current Assets / Current Liabilities
X3	Cash Ratio	Cash and Cash Equivalents / Current Liabilities
	Asset Utilization or Turnover Ratios	
X4	Receivable Turnover Rate	Sales / Accounts Receivable
X5	Inventory Turnover Rate	Cost of Goods Sold / Inventory
X6	Net Working Capital Turnover Rate	Sales / (Current Assets – Current Liabilities)
X7	Asset Turnover Rate	Sales / Total Assets
X8	Equity Turnover Rate	Sales / Owners’ Equity
X9	Fixed Asset Turnover Rate	Sales / Fixed Assets
X10	Long-term Assets Turnover Rate	Sales / Long-term Assets
X11	Current Assets Turnover Rate	Sales / Current Assets
	Profitability Ratios	
X12	Gross Profit Margin	Gross Profit / Sales

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X13	EBITDA Margin	Earnings Before Interest, Tax, Depreciation, and Amortization / Sales
X14	Net Profit Margin	Net Income / Sales
X15	Earnings Before Tax-to-Equity Ratio	Earnings Before Tax / Owners' Equity
X16	Return on Equity	Net Income / Owners' Equity
X17	Return on Assets	Net Income / Total Assets
X18	Operating Expense-to-Net Sales Ratio	Operating Expense / Net Sales
	Growth Ratios	
X19	Assets Growth Rate	(Total Assets $_t$ –Total Assets $_{t-1}$) / Total Assets $_{t-1}$
X20	Net Profit Growth Rate	(Net Income $_t$ – Net Income $_{t-1}$) / Net Income $_{t-1}$
X21	Sales Growth Rate	(Sales $_t$ – Sales $_{t-1}$) / Sales $_{t-1}$
	Asset Structure Ratios	
X22	Current Assets-to-Total Assets Ratio	Current Assets / Total Assets
X23	Inventory-to-Current Assets Ratio	Inventory / Current Assets
X24	Cash and Cash Equivalents-to-Current Assets Ratio	Cash and Cash Equivalents / Current Assets
X25	Long-term Assets-to-Total Assets Ratio	Long-term Assets / Total Assets
	Solvency Ratios	
X26	Short Term Financial Debt-to-Total Debt	Short Term Financial Debt _ Total Liabilities
X27	Short Term Debt-to-Total Debt	Current Liabilities _ Total Liabilities
X28	Interest Coverage Ratio	Earnings Before Interest and Tax _ Interest
X29	Debt Ratio	Total Liabilities _ Owners' Equity
X30	Leverage Ratio	Total Liabilities _ Total Assets
X31	Total Financial Debt-to-Total Debt	Total Financial Debt _ Total Liabilities

Source: Delen, D., Kuzey, C., & Uyar, A. (2013). Measuring firm performance using financial ratios: A decision tree approach. *Expert Systems with Applications*, *40* (10), 3970-3983.

The proposed neural network model is constructed using the Multilayer Perceptron, which is the most common supervised learning network because it requires a desired output in order to learn (Hagan, Demuth, & Beale, 1996; Zurada, 1992). The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

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The study used discriminant analysis model (Altman, 1968) for classification of the manufacturing firms. The "Z-score", as it was called, predicted bankruptcy if the firm's score fell within a certain range.

$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$
Where:
X_1 - net working capital/total assets.
X_2 - retained earnings/total assets.
X_3 - EBIT/total assets.
X_4 - market value of common and preferred stock/book value of debt.5
X_5 - sales/total assets.

Data Presentation and Analysis

Analysis of Research Questions

Research question one

To what extent does the neural network model be used to evaluate the reliability of financial reports of manufacturing firms?
To evaluate the above research question, the financial ratios previously outlined in Chapter Three were utilised to develop the neural network model. The result is shown in the table below:
Table 3: Evaluating the Reliability of Financial Reports using Neural Network

		Predicted		
Sample	Observed	Bankrupt (Non-Reliable)	Non-Bankrupt (Reliable)	Percent Correct
Testing	Bankrupt (Non-Reliable)	28	20	58.3%
	Non-Bankrupt (Reliable)	8	76	90.5%
	Overall Percent	27.3%	72.7%	78.8%

Dependent Variable: Bankruptcy
Source: SPSS ver. 24

The overall accuracy of the Neural Network model was 78.8% in the testing phase; the percent correct predictions for Bankrupt (Non-Reliable) firms was 58.3% while, that of Non-Bankrupt (Reliable) firms was 90.5%. This implies that the neural network model can be used to evaluate reliability of financial reports.

Research question two

What financial ratios are statistically significant explanatory variables in predicting fraudulent financial reporting of quoted manufacturing firms?

Table 4: Ratios with significant difference

Ratio	Mean	Std. Dev.	Sig.	Decision
X_1	4.180661	52.57490	p <.05	Significant difference
X_2	5.764219	55.95106	p <.05	Significant difference
X_4	16.04420	107.4211	p <.05	Significant difference
X_6	30.13516	624.8928	p <.05	Significant difference
X_7	1.524235	5.759490	p <.05	Significant difference
X_9	1.862872	10.67255	p <.05	Significant difference
X_{10}	1.862872	10.67255	p <.05	Significant difference
X_{13}	-0.599854	8.465658	p <.05	Significant difference
X_{15}	0.193778	4.641060	p <.05	Significant difference
X_{17}	0.979275	10.05688	p <.05	Significant difference
X_{22}	1.295585	3.715951	p <.05	Significant difference
X_{25}	1.997379	11.00091	p <.05	Significant difference
X_{27}	0.733928	0.626213	p <.05	Significant difference
X_{28}	46.86164	759.4153	p <.05	Significant difference
X_{29}	12.19005	52.90461	p <.05	Significant difference
X_{30}	5.190493	29.05015	p <.05	Significant difference

Source: SPSS Ver. 25.

Table 5: Ratios with non-significant difference

Ratio	Mean	Std. Dev.	Sig.	Decision
X_3	69.24987	1054.676	p >.05	No significant difference
X_5	68.03811	648.7300	p >.05	No significant difference
X_8	9.019588	50.81661	p >.05	No significant difference
X_{11}	19.30058	137.0696	p >.05	No significant difference
X_{12}	0.403288	1.027624	p >.05	No significant difference
X_{14}	0.613911	3.683790	p >.05	No significant difference
X_{16}	0.376080	1.799821	p >.05	No significant difference
X_{19}	0.512133	2.893518	p >.05	No significant difference
X_{20}	-14.70140	187.0640	p >.05	No significant difference
X_{21}	1.562636	10.61788	p >.05	No significant difference
X_{23}	70.60907	1335.426	p >.05	No significant difference
X_{24}	53.06831	729.0459	p >.05	No significant difference
X_{31}	-2.115821	19.55684	p >.05	No significant difference

Source: SPSS Ver. 25.

A total of sixteen financial ratios were statistically significant; while, thirteen were not statistically significant. This implies that the financial ratios are statistically significant explanatory variables in predicting fraudulent financial reporting of listed manufacturing firms.

Test of Hypotheses

Test of Hypothesis One

The neural network model cannot be used to evaluate the reliability of financial reports of manufacturing firms.

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Table 5: Model Summary of Neural Network Model

Training	Cross Entropy Error	107.024
	Percent Incorrect Predictions	14.6%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.58
Testing	Cross Entropy Error	58.274
	Percent Incorrect Predictions	21.2%

Dependent Variable: Bankruptcy
a. Error computations are based on the testing sample.
Source: SPSS ver. 24

Table 6: Classification Output of Neural Network Model

		Predicted		
Sample	Observed	Bankrupt (Non-Reliable)	Non-Bankrupt (Reliable)	Percent Correct
Training	Bankrupt (Non-Reliable)	76	27	73.8%
	Non-Bankrupt (Reliable)	16	175	91.6%
	Overall Percent	31.3%	68.7%	85.4%
Testing	Bankrupt (Non-Reliable)	28	20	58.3%
	Non-Bankrupt (Reliable)	8	76	90.5%
	Overall Percent	27.3%	72.7%	78.8%

Dependent Variable: Bankruptcy
Source: SPSS ver. 24

Test of Hypothesis Two

Ho_2: The financial ratios are not statistically significant explanatory variables in predicting fraudulent financial reporting of manufacturing firms.
Independent-Samples Mann-Whitney U Test

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Table 7: Test summary for financial ratios 1-10 (see Table above)

S/No.	Null Hypothesis	Test	Sig.	Decision
1	The distribution of X_1 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
2	The distribution of X_2 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
3	The distribution of X_3 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.098	Retain the null hypothesis
4	The distribution of X_4 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.002	Reject the null hypothesis
5	The distribution of X_5 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.219	Retain the null hypothesis
6	The distribution of X_6 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
7	The distribution of X_7 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
8	The distribution of X_8 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.798	Retain the null hypothesis
9	The distribution of X_9 is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
10	The distribution of X_{10} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis

Source: SPSS Ver. 25. Asymptotic significances are displayed. The significance level is .05.

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Table 8: Test summary for financial ratios 11-20

S/No.	Null Hypothesis	Test	Sig.	Decision
1	The distribution of X_{11} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.080	Retain the null hypothesis
2	The distribution of X_{12} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.597	Retain the null hypothesis
3	The distribution of X_{13} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
4	The distribution of X_{14} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.105	Retain the null hypothesis
5	The distribution of X_{15} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.029	Reject the null hypothesis
6	The distribution of X_{16} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.094	Retain the null hypothesis
7	The distribution of X_{17} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.005	Reject the null hypothesis
8	The distribution of X_{19} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.856	Retain the null hypothesis
9	The distribution of X_{20} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.280	Retain the null hypothesis

Source: SPSS Ver. 25. Asymptotic significances are displayed. The significance level is .05.

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Table 9: Test summary for financial ratios 21-

S/No.	Null Hypothesis	Test	Sig.	Decision
1	The distribution of X_{21} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.467	Retain the null hypothesis
2	The distribution of X_{22} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
3	The distribution of X_{23} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.324	Retain the null hypothesis
4	The distribution of X_{24} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.490	Retain the null hypothesis
5	The distribution of X_{25} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.010	Reject the null hypothesis
6	The distribution of X_{27} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
7	The distribution of X_{28} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.007	Reject the null hypothesis
8	The distribution of X_{29} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
9	The distribution of X_{30} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis
10	The distribution of X_{31} is the same across categories of bankruptcy	Independent-Samples Mann-Whitney U Test	.679	Retain the null hypothesis

Source: SPSS Ver. 25. Asymptotic significances are displayed. The significance level is .05.

The study rejects the null hypothesis and accepts the alternate; thus, financial ratios are statistically significant explanatory variables in predicting fraudulent financial reporting of manufacturing firms.

Conclusion and Recommendations

The results shown in the analysis is an indication that the Neural Network models are efficient predictors of fraudulent reports of firms. These models are commendable towards minimizing fraudulent reports and company failures. Worthy of note is their classification accuracy of firms into bankrupt and non-bankrupt companies. The effective application of these models is shown to improve the reliability of financial reports of firms.

1. Managers and analysts should employ Neural Network models in evaluating the reliability of financial reports of firms.
2. The use of financial ratios in assessing the health status of firms is still very much in place.

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