Full Length Research Paper

Predicting corporate distress in the Nigerian stock market: Neural network versus multiple discriminant analysis

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The objective of the paper is to assess the quality of neural networks in predicting distress as against discriminant analysis and its applications in enhancing managers’ decision. Forty four firms listed on the Nigerian Stock Market between 1987 and 2006 are used for the study. The performance of neural network is then compared with the more familiar discriminant analysis statistical technique, and the performance of both is further with a performance obtainable by mere guesswork. The results show that, while both the neural network and the discriminant analysis techniques performed better than guess work, the neural network out performs the discriminant analysis technique. The outstanding performance of neural network underscores its importance as an invaluable tool in the business decision-making process. The study suggests that neural networks could aid managers in decision making to reverse the present down trend of the Nigerian Stock Market.

Key words: Stock market, neural networks, firm’s distress, business decision, pay-out policy, discriminant analysis.

INTRODUCTION

The importance of collecting data that reflect organizational activities in order to achieve competitive advantage cannot be overemphasized. All over the world, in most large and medium organizations, sophisticated systems for collecting information and managing it in large databases are already in existence. The purpose is to ensure that decision making by managers is enhanced.

For example, data mining and neural network tools have been developed to automate the process of finding relationships and patterns from large amount of raw data. They can also be used to deliver results that can be utilized either in an automated decision support system or assessed by human analysts (Megaputer, 2006).

According to Megaputer Intelligence (2006), the major attraction in modern computer data mining systems and neural networks today is the fact that they are able to learn from previous history and, in the process, identify the relationship that exist between variables in any given system. When concise and valuable knowledge about the system of interest has been discovered, it can then be incorporated into some decision support system, which helps the manager to make wise and informed business decisions.

The use of neural networks has been acknowledged in the literature as a tool for enhancing the quality of managers’ decisions. Nigerian managers have relied on discriminant analysis, regression analysis, and naïve methods for decision making over the years. However,
not much attention has been directed at neural network by financial analysts in terms of its performance when compared with these traditional methods in the Nigerian Stock Market. The Nigerian Stock Market as an emerging market is assuming a leading role in the development of the Nigerian economy. And with the consequent reforms to stem firms’ distress and shore up the market since 2004, the need for this study has become clearly compelling.

Neural network, as one of the methods of data analysis is able to learn from past data sets. On the basis of learned relationship between variables present in the given data, this network makes projections or predictions about future outcomes given certain interactions between some or all of these variables. How well they can do this and to what extent they can be employed in making informed decisions to improve organizational performance are the major thrust of this paper. Specifically, the paper examines the predictive performance of the neural network and the multiple discriminant analysis.

The world is rapidly turning into a global village with information technology as the engine of this drive. For an organization to stay healthy and competitive it must be able to efficiently and effectively utilize the power of information technology. The uses to which neural networks can be put serve as just one of the numerous examples of the use and importance of technology to aid business decisions.

In making decisions managers are sometimes subjected to cognitive biases, which may result in poor decisions that may be very costly for the organization (Jones et al., 2000). Neural networks and related technologies serve to ameliorate these situations by indicating, objectively, which variables or factors should be taken into consideration when making decisions.

Businesses thrive when managers make quality decisions that are able to move the organization from its present position to a more desirable one. The study of the tools, techniques or methods by which quality decisions can consistently be made cannot be said to be a trivial one.

Objective of the paper

The use of neural networks in business decisions is fairly new in Nigeria. This paper attempts to investigate the use of neural networks as a tool to predict firms’ distress and aid business decisions in Nigeria. Specifically, the paper attempts to assess the quality of neural network in predicting distress in business firms when compared to the multiple discriminant analysis tool and guess work.

The scope of this paper covers the analytical capabilities of neural networks as aids in business decision making process in the Nigerian Stock market. This is compared to other tools like discriminant analysis, and naïve method of random guess work.

LITERATURE REVIEW

The biological sciences and their offshoots have brought to the fore the knowledge that the human brain is made up of billions of cells called neurons and that these cells are massively interconnected. It is postulated that this conglomeration of cells and their immense connectivity bestows on the brain phenomenal computational capabilities and the ability to function in a non-linear or abstract manner (Haykin, 1994).

While conventional computing technologies or methods have been able to consistently outperform the human brain at high speed mathematical calculations, the brain, as a result of its massive parallelism engendered by the interconnectivity of its neurons, has remained unrivaled at non-linear or abstract computations (Willers and Vrba, 2000; Kendall, 2004; Petriu, 2004). Attempts have been made at replicating this phenomenal ability of the brain by computers and other computational devices in the field of study known as Artificial Intelligence (Rodriguez, 2003; Blank, 2006).

According to the Oxford Advanced Learners Dictionary, artificial intelligence is “an area of study concerned with making computers copy intelligent human behaviour”. It is made-up of divergent but somewhat related fields of studies amongst which is the study of neural networks.

Neural networks are popular because they have a proven track record in myriads of data mining and decision-support applications. They have been applied across a broad range of industries, from identifying financial series to diagnosing medical conditions, from identifying clusters of valuable customers to identifying fraudulent credit card transactions, from recognizing numbers written on cheques to predicting the failure rates of engines.

While humans are good at generalizing from experience, computers usually excel at following explicit instructions. The appeal of neural networks is that they bridge this gap by modeling, on a computer, the neural connections in human brains. When used in well defined situations or domains, their ability to generalize and learn from data mimics human ability to learn from experience. This ability is what makes them useful for data mining and other decision support systems. Hence, Pinkus (1999) and Sarle (2004) call the network Artificial Neural Network (ANN).

Neural networks have been defined in many ways in terms of their model, structure, and features (Rumelhart and McClelland, 1986; Zurada, 1992; Nigrin, 1993; Haykin, 1994; Sarle, 2004; Bao, 2006).

Application of neural networks

The literature on neural network is replete with information on the practical business oriented uses of these networks. For instance, Stergiou and Siganos (2003)
reported the integration of a feed forward neural network trained with a back propagation algorithm in a device known as Airline Marketing Tactician. It is used to monitor and recommend booking advice for flight departure. Such information has a direct impact on the profitability of an airline and provides a technological advantage for users of the system.

Private investors have also been known to profit from the application of neural networks in making investment decisions. Examples of stocks and other trading applications in which neural networks are incorporated abound. A specific example of the benefits derived from the use of these applications is that of a Mr. James O’Sullivan of O’Sullivan Brothers Investments, Ltd in the United States of America, who made about two hundred and fifty thousand dollars ($250,000) in one month following investment decisions made by the aid of a neural network (California Scientific, 2006).

Neural network can be used to predict future movement of stock prices, credit worthiness, credit rating, bankruptcy predictions, mortgage underwriting, fraud detection, and property appraisal. It is used in marketing, human resources (Stergiou and Siganos, 2003; California Scientific, 2006).

A brief overview of discriminant analysis

Discriminant analysis is a technique for classifying a set of observations into predefined classes. The purpose is to determine the class of an observation based on a set of variables known as predictors or input variables. The model is based on a set of observations for which the classes are known. This set of observations is sometimes referred to as the training set. Based on the training set, the technique constructs a set of linear functions of the predictors, known as discriminant functions, such that

\[ L = b_1x_1 + b_2x_2 + \ldots + b_nx_n + c , \]

Where,

the b's are discriminant coefficients,
the x's are the input variables or predictors
and c is a constant (Fernandez, 2002, ISS, 2005).

When there are two groups, only one discriminant function is generated. When there are more than two groups, several functions are generated. However, it is usually the case that only the first three of these functions are found useful in the analysis (ISS, 2005). These discriminant functions are used to predict the class of a new observation with unknown class. For a k class problem k discriminant functions are constructed. Given a new observation, all the k discriminant functions are evaluated and the observation is assigned to class i if the i^{th} discriminant function has the highest value.

From the available literature, there are basically three types of discriminant analysis: direct, hierarchical and stepwise. In direct discriminant analysis, all the variables are entered at once; in hierarchical discriminant analysis, the order of variable entry is determined by the researcher; and in stepwise discriminant analysis, statistical criteria is used in determining the order of entry. The common objectives of discriminant analysis are i) to investigate differences between groups ii) to discriminate groups effectively; iii) to identify important discriminating variables; iv) to allow the performance of hypothesis testing on the differences between the expected groupings; and v) to enable us to classify new observations into pre-existing groups (Fernandez, 2002). The direct and stepwise methods were used in the study to suit the neural network requirements and procedures and for good comparison.

A brief review of empirical findings

Several studies have been conducted to empirically evaluate the performance of artificial neural networks (ANNs) against other traditional models such as logit, probit and discriminant analysis in predicting corporate financial distress, bankruptcy, and failure (Moritz and Kennedy, 1995; Etheridge and Sirram, 1996; Abid and Zonari, 2000; Chariton et al., 2004). Atiya (2001) provided a comprehensive survey and empirical results on corporate financial distress and bankruptcy prediction using traditional methods and artificial neural networks. Ko et al. (1996) observe that before the failure of any business firm, its financial condition deteriorates and the firm is often in financial distress. They employed composite rule induction system (CRIS), neural network and logit models to predict corporate financial distress in Taiwan. The study shows that neural network and CRIS outperform logit model in predicting corporate failure in Taiwan. Tzong –Huei (2009) conducted a similar study also for Taiwan. The study examines the predictive performance of the four commonly used financial distress prediction models: multiple discriminant analysis (MDA), logit, probit, and artificial neural networks. Applying these models to a dataset of failed and non failed business firms in Taiwan for the period 1998 – 2005, he finds out that logit, probit, and artificial neural networks perform better than the multiple discriminant analysis in predicting corporate failure in Taiwan. In an interesting paper, Sookhanaphibarn et al. (2007) compared the predictive performance of three versions of neural network model with dataset from 41 Thai financial institution for the period 1933 – 2003. The neural network models are: Learning Vector Quantization (LVQ), Probabilistic neural network, and feed forward neural network with propagation learning. The results indicate that LVQ outperforms the other two versions of neural network models.

DATA AND METHODOLOGY

For the purpose of this research, a multi-layer feed forward neural network with fifteen (15) input units, seven (7) hidden units and one (1) output unit, trained with the well known back propagation
algorithm, is applied to the task of predicting the possibility of a firm becoming distressed by the analysis of certain financial performance ratios (Mathew, 2000; Ishak, 2004; Pudi, 2005). Its performance is compared against a discriminant analysis model developed by using the default settings of the SPSS statistical package. Business distress in the context of this research does not necessarily refer to the situation where a firm becomes bankrupt and goes out of business. Here business distress means those firms that have failed to meet their obligations to the shareholders with regards to the payment of dividend within a stipulated period of time. There is no gainsaying the fact that the ability to distinguish between distressed and non-distressed firms, performing and non-performing firms is an important option in the hands of both private and corporate investors (Jones, 2000).

As a first step towards achieving the goals of this study, relevant financial performance ratios are calculated and each firm in the population sample is grouped into one of two classes in accordance with their status or dividend payment performance. The ratios used in the study are:

i. working capital/total assets (WC/TA)
ii. retained earnings/total assets (RE/TA)
iii. earnings before interest and taxes/total assets (EBIT/TA)
iv. market value of equity/total debt (MVE/TD)
v. sales/total assets (S/TA)

Having calculated the financial ratios needed for the study, with the aid of the data management component of the NeuroSolutions software by NeuroDimension, Inc (2005), the data generated was randomly partitioned into three sets classified as training, validation, and test sets with neural network. Using the neural network and the discriminant analysis techniques, an analysis of the ratios was undertaken in order to develop a predictive model capable of discriminating between the two classes of firms described above. The predictive model of the neural network was developed from a combination of the training and validation sets while that of the discriminant analysis technique was also derived from the training and validation sets.

The final stage of the study involved the application of the developed models to the test set in order to assess their true performance. Here, the performance of the predictive models, as developed by the neural network and the discriminant analysis techniques, were compared against each other in order to determine which performed better at discriminating between the two classes of firms. Also, by plotting the test set results of both models on an Receiver Operating Curve (ROC) chart, their performances against a random predictor or mere guess work were assessed. It is intended that, if these models perform well on the test set and against mere guess work, they can be employed to analyze future data with the hope of discriminating between healthy and potentially distressed firms for investment and other purposes.

Population and sample

The population from which we selected the sample consists of all the firms listed on the Nigerian Stock Exchange between 1987 and 2006. In all, a sample of forty-four (44) firms was purposely selected for the study. The sample was grouped into two classes or categories namely: “class 1” and “class 0”. Grouped under class 1 are firms that have either gone out of business as at the year 2000 or have defaulted consistently to pay dividends beyond this year. Class 0 firms on the other hand are classes of firms that were in operation and have declared dividend during the period and after the year 2000.

Selection for inclusion into the population sample was based solely upon the availability of complete information as regards the financial performance ratios of the listed firms during this period.

DATA COLLECTION

The data used have been collected from the publications of the Nigerian Stock Exchange as contained in their various years’ Fact Books. Data on financial performance ratios of the firms were computed from published Nigerian Stock Exchange Fact Book.

The data collected for analysis is arranged in sixteen (16) columns and forty-four (44) rows in a format suitable for input into the applications or software packages used for this study. The first fifteen (15) columns of the data contain details of the financial performances ratios of each of the firms for the years under focus, while the sixteenth (16th) column holds details about the class of each firm. Each row holds information on a particular case or member of the population sample.

The data were randomly partitioned into three sets consisting of training, validation, and test sets with the aid of the neural net. While the training and validation sets are used in the learning process and thus assist to create a predictive model in the neural network, the discriminant analysis model is developed separately from the training set and applied to the validation set. The test set is used to appraise the final performance of the neural network and the discriminant analysis models in an out- of- sample data tests. This serves as a gauge of the likely performances of the models on future data.

Hypotheses

Null hypothesis .The null hypothesis is that Neural networks do not outperform statistical discriminant analysis technique in making informed decisions that result in improved organizational performance.

Alternative hypothesis: The alternative hypothesis is that neural networks outperform statistical discriminant analysis technique in making informed decisions, which result in improved organizational performance.

RESULTS AND DISCUSSION

Financial ratios of a sample of forty-four firms listed on the Nigerian Stock Exchange between 1987 and 2006 are analysed. The firms are categorized into two groups.: group one, are assigned “class 1”, represent firms that had either gone out of business or failed to declare dividend during the period under focus (as a result of bankruptcy or underperformance) beyond the year 2000. Group two, assigned “class 0”, and these are firms still in business and have declared dividend during and after the year 2000. Of the total firms assessed, nineteen (19) of them, constituting forty-three percent (43%) of the population sample, are found to be in class 1, while twenty-five (25) representing fifty-seven (57%) are found to be in class 0.

A frequency distribution of the firms according to the assigned values of 0’s and 1’s shows that a total of four (4) firms representing nine percent (9.1%) of the population sample are found to be in the category of those that have gone completely bankrupt.

A summary of the dividend performance of the population sample is given in Table 1. An entry of 0 is made for all class of firms that have gone out of business. A summary of the distribution and their percentages are in...
Table 1. Frequency distribution of dividend performance of the selected sample.

<table>
<thead>
<tr>
<th>S/N</th>
<th>Year of last dividend</th>
<th>Frequency of class 1</th>
<th>Frequency of class 0</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>4</td>
<td>-</td>
<td>9.0909</td>
</tr>
<tr>
<td>2</td>
<td>1983</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>3</td>
<td>1986</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>4</td>
<td>1990</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>5</td>
<td>1992</td>
<td>2</td>
<td>-</td>
<td>4.5455</td>
</tr>
<tr>
<td>6</td>
<td>1993</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>7</td>
<td>1994</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>8</td>
<td>1996</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>9</td>
<td>1997</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>10</td>
<td>1998</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>11</td>
<td>1999</td>
<td>4</td>
<td>-</td>
<td>9.0909</td>
</tr>
<tr>
<td>12</td>
<td>2001</td>
<td>1</td>
<td>-</td>
<td>2.2727</td>
</tr>
<tr>
<td>13</td>
<td>2002</td>
<td>-</td>
<td>2</td>
<td>4.5455</td>
</tr>
<tr>
<td>14</td>
<td>2003</td>
<td>-</td>
<td>2</td>
<td>4.5455</td>
</tr>
<tr>
<td>15</td>
<td>2004</td>
<td>-</td>
<td>3</td>
<td>6.8182</td>
</tr>
<tr>
<td>16</td>
<td>2005</td>
<td>-</td>
<td>11</td>
<td>25.000</td>
</tr>
<tr>
<td>17</td>
<td>2006</td>
<td>-</td>
<td>7</td>
<td>15.9091</td>
</tr>
<tr>
<td>Total</td>
<td>19</td>
<td>25</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

Source: Authors’ computations (2008). NOTE: The entry of zero (0) represents the class of firms that have gone out of business.

Table 2. Class distribution of data sets.

<table>
<thead>
<tr>
<th>Class</th>
<th>Membership</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Training set</td>
<td>Frequency</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Percentage</td>
<td>53.33</td>
</tr>
<tr>
<td>Validation set</td>
<td>Frequency</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Percentage</td>
<td>5</td>
</tr>
<tr>
<td>Test set</td>
<td>Frequency</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Percentage</td>
<td>66.67</td>
</tr>
</tbody>
</table>

Source: Authors’ neural net computations (2008).

Table 1. In carrying out the test, the data generated are randomly partitioned into three sets consisting of training, validation, and test sets by means of the neural net (Table 2). The neural network was trained and validated and consequently used in the development of the predictive model. The test set was used as an out-of-sample data set to assess the degree of performance of the developed models.

Presentation of the results obtained from the three tests done as stated above is carried out according to the following schema:

1. Presentation and analysis of training set results.
2. Presentation and analysis of validation set results.
3. Presentation and analysis of test set results.

Following the schema outlined above, the results of the training, validation, and test sets are presented and compared against one another in that order. The result for the neural network presented is the best obtained in ten (10) runs of a multi-layer feed forward neural network, configured with fifteen (15) input units, seven (7) hidden units and one (1) output unit. It was trained using batch back propagation algorithm. Results of the discriminant analysis technique are obtained by using the default settings of the SPSS statistical package. Specifically, the option for entering all independent variables together was
The disparity in the performance of the discriminant analysis on the training and validation sets appears to attest to the fact of over fitting as stated earlier. In such a situation, performance on the training set produces excellent results but such performance is not replicated on the validation or test sets. The close performance of the neural network on the training and validation sets attests to the fact that it was not affected by over fitting.

In testing the true capabilities of the two models, after training and validation, each was applied to the classification of a subset of the out-of-population sample not included in either the training or validation sets. The results of the applications on the test set show that the neural network was better at separating the classes. It achieved an overall score of seventy-three percent (73.3%) on the test set as against about sixty-seven percent (66.7%) achieved by the discriminant analysis technique as shown in Table 5. These results are consistent with observation by Ko et al. (1998) that over fitting usually occurs if the same data are used for model validation. Thus, employing different data set appears to overcome the problem of over fitting with a better score for ANNS.

The results revealed a slight difference in the performance of both analytical methods. It is observed that the neural network out performed the discriminant analysis model by roughly seven percentage points (7%). The results presented above show that the neural network has an overall advantage over the discriminant analysis model in correctly separating or discriminating between the classes of failed firms and non-failed firms. It is interesting to note that these results are largely consistent with the results provided by similar studies elsewhere (Boritz and Kennedy, 1995; Chariton et al., 2004; Ko et al., 1996). However, the results provided by Tzong-Huei (2009) for Taiwan appear to suggest that probit model performs better.

**FINDINGS**

In comparing the performances of both the neural network and the discriminant analysis models against guess work or chance, a Receiver Operating Curve (ROC) was plotted using the performance score of both models on the test sets. The ROC, according to the manual of the Statistical Package for the Social Sciences (SPSS), is a useful tool to evaluate the performance of classification schemes in which there is one variable with two categories by which subjects are classified. Figure 1 shows the graph plotted from the performance of both models using the test sets of the two methods. This appears strange as most of the studies reviewed and our

**Table 3. Summary of classification accuracy on training set.**

<table>
<thead>
<tr>
<th></th>
<th>Percentage score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural Network</td>
<td>80</td>
</tr>
<tr>
<td>Discriminant Analysis (SPSS)</td>
<td>100</td>
</tr>
</tbody>
</table>

Source: Authors’ computations (2008).

**Table 4. Summary of classification accuracy on validation set.**

<table>
<thead>
<tr>
<th></th>
<th>Percentage score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural Network</td>
<td>78.6</td>
</tr>
<tr>
<td>Discriminant Analysis (SPSS)</td>
<td>64.3</td>
</tr>
</tbody>
</table>

Source: Authors’ computations (2008).

**Table 5. Summary of classification accuracy on test set.**

<table>
<thead>
<tr>
<th></th>
<th>Percentage score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural Network</td>
<td>73.3</td>
</tr>
<tr>
<td>Discriminant Analysis (SPSS)</td>
<td>66.7</td>
</tr>
</tbody>
</table>

Source: Authors’ computations (2008).
findings strongly suggest that ANNS outperform virtually all the traditional corporate distress and failure models.

The straight line is the reference line running diagonally across the graph, and represents the performance obtainable from mere guess work. According to Wikipedia (2006), a completely random predictor would generate this straight line because as the discrimination threshold is raised, equal numbers of true and false positives are admitted. When plotted, the result is a diagonal running left to right as shown in the graph. Results below this non-discrimination line are suggestive of a predictor that gives wrong results consistently.

In essence, the graph shows that the neural network and discriminant analysis model both performed better than guess work or a random predictor. The neural network, however, has a far superior performance as evidenced by the curve generated in the graph. It is farther away from the diagonal which represents the performance of a random predictor or guess work.


Specificity on the x-axis is a scaled measurement of the number of classes 0 in the test set incorrectly classified as classes 1. Sensitivity on the other hand is the measurement of how well the models were able to correctly classify members of the population sample that actually belong to class 1.

Conclusion

This research work was conducted with the aim of ascertaining the value of neural networks as business decision support tools in predicting firms failures. As a first step towards the achievement of this objective, a review of relevant literature on the subject matter was undertaken. A neural network was then applied to the task of predicting the possibility of a business failure based on an analysis of its financial ratios. To this end, financial ratios of forty-four (44) firms listed on the Nigerian Stock Exchange were collected and analyzed using the neural network. The aim was to train the neural network to predict those firms which had failed in their obligations to the shareholders vis-à-vis the payment of dividend in the past five years. The data collected for the study was randomly partitioned into three equal parts and then fed into the neural network. The performance of the neural network was then compared against that of the more widely known discriminant analysis technique and chance.

From the results obtained, it is reasonable to conclude that the neural network outperforms discriminant analysis in making informed decisions that result in organizational performance in Nigeria. And managers of firms should avail themselves of the technological tool to aid their managerial decisions.

RECOMMENDATIONS FOR MANAGERS

In this research work the standard multi-layer feed forward neural network and the popular back propagation training algorithm were used. There is a need to draw the attention of Nigerian managers, stakeholders in the Nigerian Stock Market to the use of neural network as a management support tool in Nigeria.

Neural networks, and similar analytical applications, need large and accurate data for them to function effectively. In order to derive the maximum benefits from the applications of neural network, there is need for accurate and timely record keeping by managers at the corporate level. The culture of proper record keeping should therefore be encouraged as a deliberate means to achieve better decision making and accountability based on objective data generated by the firms from their
periodic activities. This will ultimately improve productivity, competitiveness, and corporate governance among the quoted firms in Nigeria.

Finally, in making use of neural networks, it is pertinent to note that they are not meant to replace the expertise of the managers, analysts, or specialists. They should properly be viewed as tools meant to complement and enhance their skills. While they offer an incisive and in-depth analysis they are not infallible, their results ought to be viewed as pointers to possible course or courses of action. The final decision must rest squarely on the corporate manager.

Area for further research

Ideally, large amount of data is preferred for neural network. However, the latest neural networks have made it possible to analyze small data set. Alyuda NeuroIntelligence (2005) used in this study has overcome the limitation of small data set. Apart from the size of the sample, there is no doubt that there is need to conduct the tests based on other grouping criteria like size, industry, location, and other factors external to the operations of the firms.

REFERENCES


