
Determining Solvency and Insolvency of Commercial Banks in Nigeria

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Abstract: This paper presents the application of artificial intelligence technique to develop a Multi-Layer Perceptron neural network model for determining the status (solvent or insolvent) of commercial banks in Nigeria. The common traditional classification techniques based on statistical parametric methods are constraint to fulfill certain assumptions. When those assumptions fail, the techniques do not often give sufficient descriptive accuracy in classifying the status of the banks. However, a class of feed-forward architecture of neural network known as Multi-Layer Perceptron (MLP) is not constraint by those parametric assumptions and offers good classification technique that competes well with the traditional statistical parametric techniques. In this study, data were sourced from the central bank of Nigeria and financial reports of the commercial banks in Nigeria. The banks specific variable of age, history of merger, time, total assets and total revenue are used as the input variables to the neural network. The solvency or insolvency as status are the two possible outputs of the neural network for each commercial bank in the period of 1994-2015. The developed MLP neural network model has 5 input neurons, 3 hidden neurons and 1 output neuron. Sigmoid activation function for the hidden neurons and “purelin” transfer function for the output neurons were utilized in training the MLP neural network. The results demonstrate that MLP neural networks are a viable technique for status classification of commercial banks in Nigeria.

Keywords: Artificial Intelligence, Multi-Layer Perceptron, Neural Network, Solvent, Insolvent, Transfer Function

1. Introduction

A bank serves as a conduit through which stabilization policy is transmitted to the economy at large. Therefore, the safety and soundness of banking industry is a very crucial prerequisite for economic stability, development and growth of any nation. Meanwhile, arising from a phenomenal increase in the occurrence of financial crises, efforts have been intensified to predict the health of banking system, with a view to empowering officials and market participants to recognize the symptoms of a financial crisis at an early stage.

In Nigeria, financial analyst assert that the recent Treasury Single Account (TSA) policy by the federal government would adversely affect the banking industry, a development that might lead to liquidity squeeze which may possibly cause another round of banks' failure. Bank failure is neither new nor peculiar to Nigeria. In fact, the phenomenon is almost as old as the industry. In spite of their best endeavors, bank failure still occur in older banking societies like Britain,

America, Spain, Indonesia, and many others till this moment.

However, the banking sector in the third world economies has been grossly under managed when compared with their counterparts in the developed countries of the world. This has made it imperative for Nigerian banks to sanitize and restructure their operational processes so as to be in line with the global trends, and to survive the depressed economy.

Conceptually, solvency of a bank is a static issue in that it characterizes a bank or a banking system at a point in time. Predicting financial unsoundness is, however, a dynamic exercise. A proactive measure of a banking system's health conditions should capture both the quantitative and qualitative determinants of bank insolvency.

Bank raises funds by attracting deposits, borrowing money in the inter-bank market, or issuing financial instruments in the money market or a securities market. The bank then lends out most of these funds to borrowers. However, it would not be prudent for a bank to lend out all of its balance sheet. It must keep a certain proportion of its funds in reserve so that it

can repay depositors who withdraw their deposits. Bank reserves are typically kept in the form of a deposit with a Central Bank. This behaviour is called “Fractional-Reserve” banking and it is a central issue of monetary policy. Two characteristics of this fractional-reserve banking remain the basis for present-day operations.

First, the banking system’s monetary liabilities exceed its reserves. This feature was responsible in part for Western industrialization, and it still remains important for economic expansion, though a risk of creating too much money is a rise in inflation. Second, liabilities of the banks (deposits and borrowed money) are more liquid—that is, more readily convertible to cash—than are the assets (loans and investments) included on the banks’ balance sheets. This characteristic enables consumers, businesses, and governments to finance activities that otherwise would be deferred or cancelled; at the same time, it opens banks to the risk of a liquidity crisis.

When depositors en masse request payment, the inability of a bank to respond because it lacks sufficient liquidity means that it must either break the promise to pay their depositors or the bank fails. A key role of the central bank in most countries is to regulate the commercial banking sector to minimize the likelihood of a run on a bank, which could undermine the entire banking system. The central bank will often stand prepared to act as lender of last resort to the banking system to provide the necessary liquidity in the event of a widespread withdrawal of funds. This, however, does not provide a permanent safety net to save any bank from collapse, as was demonstrated by the Agbonmagbe (established in 1945), National Bank of Nigeria, (established in 1933), Africa Continental Bank, (established in 1945).

After the global economy recession of 2008/2009, where many international corporation and financial institutions needed a bail out by government to remain in business, many of the banks operating in Nigeria were found to be distressed. Many of the banks have high ratio of portfolio at risk and are gradually unable to meet payment obligations to both depositors and creditors as they fall due, hence, bank distress was inevitable. The first bank distress was recorded in 1930 when the first indigenous bank, Commercial and Industrial Bank established in 1929 went into liquidation with total deposit liabilities of twenty three thousand (23,000.00) British pound sterling. Bad management, lack of trained manpower, inadequate working capital, poor record keeping and accounting system are among the factors that led to its liquidation. More than Eighty years after, those factors still remain major issues facing the banking industry in Nigeria today. A study carried out by the World bank in 1989 on Nigerian Banks identified poor lending; mismatching of assets and liabilities; weak and ineffective internal control; inadequate policies; lack of standard practices and strategic planning as the major factor responsible for the persistent crises in the Nigeria banking industry [1]. After the first banking crisis of 1930, crises have been a regular feature of the Nigeria banking industry. The banking crisis of the 1950s prompted the colonial government to initiate the first banking

ordinance of 1952 which took effect in 1954. Since then, so many reforms had taken place in the sector but the crises never stopped.

The 1995 banking crisis is another major turning point in the industry when 57 commercial and merchant banks went into distress within a space of three months leaving the whole nation in panic. The same trend of the 1990s was about to repeat itself in 2004 when the regulator quickly step in with bank consolidation reforms. In his address on 6th July, 2004, the former Central.

Bank Governor said “the Nigerian banking system today is fragile and marginal. Our vision is a banking system that is part of the global change, and which is strong, competitive and reliable. It is a banking system which depositors can trust, and investors can rely upon. Evolving such a banking system is a collective responsibility of all agents in the Nigerian economy.” He highlighted factor such as persistent illiquidity, weak corporate governance, poor assets quality, insider abuses, weak capital base, unprofitable operations, and over-dependency on public sector funds, among others, necessitated the 2004 reform [2].

The banks were expected to inject fresh funds where applicable, but most importantly they were encouraged to enter into merger/acquisition arrangements with other relatively smaller banks thus taking the advantage of economies of scale to reduce cost of doing business and enhance competitiveness locally and internationally. This forced the existing 89 banks into voluntary mergers and acquisitions to meet up with the N25 billion minimum capital base. At the end of the exercise in 2005, 25 banks emerged, but the merger of Stanbic IBTC a year later brings the total number of banks operating in the nation to 24. Immediately after the 2005 consolidation exercise there were concern over the state of the industry and the state of readiness of the regulator to meet the challenges of the outcome of the exercise. Reference [3] commented that the regulatory authority must re-engineer its supervision department and man it with qualified and experienced personnel to carry out this assignment in a professional manner.

The automation of the process for the rendition of returns by banks and other financial institutions through the enhanced Financial Analysis Surveillance System (e-FASS) must be driven and implemented with all sense of purpose. The Code of Corporate Governance for Banks in Nigeria post consolidation must be fully implemented to sanitize and reposition the banking industry. The consolidation exercise was expected to diversified the shareholding structure of the bank, by removing the overwhelming dominance of some pioneer chairman, MD/CEO and instituted a tight code of corporate governance in the industry, with the goal of stemming the tide of banks distress in the country, unfortunately, on August 14th 2010, the current Governor of CBN sacked five managing directors of Nigerian banks, injected N620 billion (approximately \$4.1 billion from the CBN, representing 2.5 per cent of Nigeria’s entire 2010 GDP of \$167 billion) into the affected banks to prevent systemic failure in the Industry.

According to reference [4], the financial system, with banks as its major component, provide linkages for the different sectors of the economy and encourage high level of specialization, expertise, economies of scale and a conducive environment for the implementation of various economic policies of government intended to achieve non-inflationary growth. Banks play a vital role in the Nigerian economy as they perform the crucial role of financial intermediation by mobilizing deposits from the surplus units and channeling same to the deficit units of the economy to facilitate trade, production and capital formation.

Table 1 provides the list of 40 failed banks which were closed, having had their licenses revoked by the Central Bank of Nigeria, between 1994 and 2006.

Table 1. List of Closed Financial Institutions under Liquidation.

S/NO	BANKS IN LIQUIDATION	DATE OF CLOSURE
1	Abacus Merchant Bank Ltd	Jan. 16, 1998
2	ABC Merchant Bank Ltd	Jan. 16, 1998
3	All States Trust Bank Plc.	Jan. 16, 2006
4	Allied Bank of Nigeria Plc	Jan. 16, 1998
5	Alpha Merchant Bank Plc	Sept. 08, 1994
6	Amicable Bank of Nigeria Plc.	Jan. 16, 1998
7	Assurance Bank of Nigeria Plc	Jan. 16, 2006
8	Century Merchant Bank Ltd.	Jan. 16, 1998
9	City Express Bank Plc	Jan. 16, 2006
10	Commerce Bank Plc	Jan. 16, 1998
11	Commercial Trust Bank Ltd	Jan. 16, 1998
12	Continental Merchant Bank Plc	Jan. 16, 1998
13	Coop. & Commerce Bank Plc	Jan. 16, 1998
14	Credit Bank Nig. Ltd	Jan. 16, 1998
15	Crown Merchant Bank Ltd.	Jan. 16, 1998
16	Financial Merchant Bank Ltd.	Jan. 21, 1994
17	Great Merchant Bank Ltd.	Jan. 16, 1998
18	Group Merchant Bank Ltd.	Jan. 16, 1998
19	Highland Bank of Nigeria Plc	Jan. 16, 1998
20	ICON Ltd. (Merchant Bankers)	Jan. 16, 1998
21	Ivory Merchant Bank Ltd.	Dec. 22, 2000
22	Kapital Merchant Bank Ltd.	Jan. 21, 1994
23	Lead Bank Plc	Jan. 16, 2006
24	Lobi Bank of Nig. Ltd.	Jan. 16, 1998
25	Mercantile Bank of Nig. Plc.	Jan. 16, 1998
26	Merchant Bank of Africa Ltd.	Jan. 16, 1998
27	Metropolitan Bank Ltd.	Jan. 16, 2006
28	Nigeria Merchant Bank Ltd.	Jan. 16, 1998
29	North-South Bank Nig. Plc.	Jan. 16, 1998
30	Pan African Bank Ltd.	Jan. 16, 1998
31	Pinnacle Commercial Bank Ltd.	Jan. 16, 1998
32	Premier Commercial Bank Ltd	Dec. 22, 2000
33	Prime Merchant Bank Ltd.	Jan. 16, 1998
34	Progress Bank Ltd.	Jan. 16, 1998
35	Republic Bank Ltd	29-Jun-95
36	Rims Merchant Bank Ltd.	Dec. 22, 2000
37	Royal Merchant Bank Ltd.	Jan. 16, 1998
38	Trade Bank Plc	Jan. 16, 2006
39	United Commercial Bank Ltd.	Sept. 8, 1994
40	Victory Merchant Bank Ltd.	Jan. 16, 1998

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The Federal High Court issued orders for them to be wound up and appointed the Nigeria Deposit Insurance Corporation (NDIC) as Liquidator of the banks.

The list in table 1 of closed financial institutions does not contain the names of the under-listed banks whose licenses were revoked by the Central Bank of Nigeria because the Federal High Court is yet to issue winding up orders and appoint the Corporation as Liquidator for the banks. Due to court actions instituted by some of the banks challenging the revocation of their licenses, the Corporation was unable to conclude the closing exercise and initiate the payment of insured deposits to depositors of the banks. These include:

- (1) Savannah Bank of Nigeria Plc., license revoked Feb. 16, 2002
- (2) Peak Merchant Bank Limited, license revoked Feb. 28, 2003
- (3) Triumph Bank Plc., license revoked Jan. 16, 2006
- (4) Eagle Bank Plc., license revoked Jan. 16, 2006
- (5) Liberty Bank Plc., license revoked Jan. 16, 2006
- (6) African Express Bank Ltd., license revoked Jan. 16, 2006, (NDIC appointed Provisional Liquidator)
- (7) Fortune Bank Plc., license revoked Jan. 16, 2006, (NDIC appointed Provisional Liquidator)
- (8) Gulf Bank of Nigeria Plc., license revoked Jan. 16, 2006
- (9) Hallmark Bank Plc., license revoked Jan. 16, 2006
- (10) Societe Generale Bank of Nigeria Plc., license revoked Jan. 16, 2006

As a consequence, the assessment of the financial condition of banks in any nation should be seen as a fundamental goal for regulators of the financial institution in that nation which Nigeria is not an exception. Nigerian economy has so far been faced with national and global economic challenges and as such, the financial institutions, especially the banking sector has an option of sanitizing and restructuring its operational processes in order to survive the depressed economy, as well as embarking on a consolidation exercise which would have some wider structural effects on the industry and on the economy as a whole. Basically, banking is a service industry operated by human beings for the benefit of the general public while making returns to the shareholders. As such, it is natural that the services provided thereof by the industry cannot be 100% efficient; thus, there is always room for improvement.

The aim of this study is to utilize the artificial intelligence concept to develop a Multi-Layer Perceptron neural network that can be used to assist in identifying the solvency or insolvency status of commercial banks in Nigeria.

2. Data and Methods

The data used in training the MLP were obtained from CBN (Central Bank of Nigeria) statistical publications and bank financial statements. The population of commercial banks used for the study is the 40 failed banks listed in Table 1 and the 25 commercial deposit money banks that survived the N25 billion recapitalization exercises imposed by CBN (Central Bank of Nigeria) in year 2004. It covers a period of ten (10) years from 1994 to 2004. The independent variables used as the input to the neural network are age, history of merger, time, total assets and total revenue. While, solvent (1) and insolvent

(0) are the two possible outputs of the neural network signifying the status for each commercial bank in the research period.

The population of banks listed on the Central Bank of Nigeria publications using banks specific variable of age,

assets and revenue for the period of 2005-2015. During these period of study, 25 banks are listed which are the deposited banks listed by CBN in 2005. Among these 25 banks, 9 banks experienced the event (liquidation) while 16 Banks were censored.

Table 2. Data on the 25 deposit commercial banks in Nigeria in the year 2005.

S/No	Bank names	Status	Time	Merger	Age	Revenue (NBillions)	Asset (NBillions)
1.	Access Bank Plc	0	10	0	26	258	2590
2.	AfribankPlc*	1	7	0	52	0.24	1010
3.	Diamond Bank Plc	0	10	1	25	6.22	1750
4.	EcoBank	0	10	0	29	542.71	1770
5.	Equitorial Trust*	1	7	1	21	0.15	0
6.	FCMB	0	10	0	33	109.3	1160
7.	Fidelity Bank Plc	0	10	0	27	146.9	1232
8.	First Bank Plc	0	10	0	121	293	4170
9.	First Inland Bank*	1	7	1	5	0.633	3
10.	GTBankPlc	0	10	0	25	280.1	2520
11.	IBTC-Chartered*	0	10	1	10	6.87	125
12.	Intercontinental Bank*	1	7	1	22	261	261
13.	NIBank	1	2	0	27	0.124	0
14.	Oceanic Bank	1	7	0	21	74.9	1300
15.	Platinum-Habib Bank*	1	7	1	6	0.022	6
16.	Skye Bank*	0	10	1	25	129.24	1200
17.	North Omega Bank	1	2	0	15	0.002	0
18.	Spring Bank Plc	1	7	0	7	34	201.3
19.	Standard Chartered Bank*	0	10	1	16	2.1	12
20.	Sterling Bank*	0	10	1	56	130.6	799.5
21.	UBA Plc*	0	10	1	66	247.2	2750
22.	Union Bank Plc*	0	10	1	98	118.4	1059
23.	Unity Bank Plc*	0	10	1	9	78.8	429.6
24.	Wema Bank Plc*	1	10	1	70	20.87	350.638
25.	Zenith Bank	0	10	0	25	432.5	4010

Source: CBN publication 2006 and Bank financial statement 2015

Key: *Asterix* (*) signifies banks that have been merged.

Back-propagation algorithm is chosen in this study to model the MLP network architecture. A 3 hidden layer with sigmoid activation function and an output layer with purelin transfer function were also used. Also a Resilient Back propagation "trainrp" is used to train the model. Resilient Back-propagation is known to eliminate the effects of the magnitudes of the partial derivatives. Only the sign of the derivative can determine the direction of the weight update; the magnitude of the derivative has no effect on the weight update. The size of the weight change is determined by a separate update value [5].

2.1. Artificial Neural Network

Artificial Neural Networks (ANN) are a bio-inspired mechanism of data processing that enables computers to learn technically similar to a brain and even generalize once solutions to enough problem instances are taught [6]. Modern neural networks are non-linear statistical data modeling tools. They are usually used for classification and to model complex relationships between inputs and outputs.

In the recent years, the applications of ANN techniques have found wide potential use for feature classification and data compression [7, 8, 9, 10, 11]. Here we analyze data of commercial banks in Nigeria in order to in classify the data

into dichotomous groups based on their age, history of merger, time, total assets and total revenue. These banks specific variable are obtained from the CBN publication 2006 and Bank financial statement 2015. The variables are used to develop the classification model. ANN offers an alternative robust computer based techniques to address such important economic challenge and problems.

2.2. Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) neural network is an aspect of artificial intelligence that can be used as classification and prediction system, often capable of modeling complex relationships between variables. It allows prediction of an output object for a given input object. MLP is a popular network architectures used in most of the researches [12]. In MLP, the weighted sum of the inputs and bias term are passed to activation level through a transfer function to produce the output, and the units are arranged in a layered feed-forward topology called Feed Forward Neural Network (FFNN).

Basically, all ANN has three layers: input layer, hidden layer(s) and output layer(s). The hidden layer vastly increases the learning power of the MLP. The transfer or activation function of the network modifies the input to give a desired output. The transfer function is chosen such that the algorithm requires a response function with a continuous, single-valued

with first derivative existence. Choice of the number of the hidden layers, hidden nodes and type of activation function plays an important role in model constructions [13, 14, 15].

2.3. Back-Propagation Algorithm

The MLP network is trained using one of the supervised learning algorithms of which the best known example is back-propagation, which uses the data to adjust the network's weight and threshold so as to minimize error in its predictions on the training set. We denote by W_{ij} the weight of the connection from unit U_i to unit U_j . It is then convenient to represent the pattern of connectivity in the network by a weight matrix W whose elements are the weights W_{ij} . The pattern of connectivity characterizes the architecture of the network. A unit in the output layer determines its activity by following a two-step procedure [16].

- 1) First, it computes the total weighted input X_j , using the formula:

$$X_j = \sum_i Y_i W_{ij} \tag{1}$$

Where X_j is the activity level of the j^{th} unit in the previous layer and W_{ij} is the weight of the connection between the i^{th} and the j^{th} unit.

- 2) Secondly, the unit calculates the activity Y_j using some function of the total weighted input. Typically we use the sigmoid function:

$$Y_j = (1 + e^{-x_j})^{-1} \tag{2}$$

Once the activities of all output units have been determined, the network computes the error E , which is defined by the expression:

$$E = \frac{1}{2} \sum_i (Y_i - d_i)^2 \tag{3}$$

Where Y_j is the activity level of the j^{th} unit in the top layer and d_j is the desired output of the j^{th} unit.

The back-propagation algorithm consists of the following steps [16]:

- (1) Compute how past the error changes as the activity of an output unit is changed. This error derivative (EA) is the difference between the actual and the desired activity.

$$EA_j = \frac{\partial E}{\partial Y_j} = Y_j - d_j \tag{4}$$

Compute how fast the changed. This quantity output of a unit changes error changes as the total input received by an output unit is (EI) is the answer from step (i) multiplied by the rate at which the as its total input is changed.

$$EI_j = \frac{\partial E}{\partial X_j} = \frac{\partial E}{\partial Y_j} \times \frac{\partial Y_j}{\partial X_j} = EA_j Y_j (1 - Y_j) \tag{5}$$

- (2) Compute how fast the error changes as a weight on the connection into an output unit is changed. This

quantity (EW) is the answer from step (ii) multiplied by the activity level of the unit from which the connection emanates.

$$EW_{ij} = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial X_j} X \frac{\partial X_j}{\partial W_{ij}} = EI_j Y_j \tag{6}$$

- (3) Compute how fast the error changes as the activity of a unit in the previous layer is changed. This crucial step allows back-propagation to be applied to multilayer networks. When the activity of a unit in the previous layer changes, it affect the activities of all the output units to which it is connected. So to compute the overall effect on the error, we add together all these separate effects on output units. But each effect is simple to calculate. It is the answer in step (iii) multiplied by the weight on the connection to that output unit.

$$EA_i = \frac{\partial E}{\partial Y_i} = \sum_i \frac{\partial E}{\partial X_j} X \frac{\partial X_j}{\partial Y_i} = \sum_j EI_j W_{ij} \tag{7}$$

By using steps (ii) and (iv), we can convert the EAs of one layer of units into EAs for the previous layer. This procedure can be repeated to get the EAs for as many previous layers as desired. Once we know the EA of a unit, we can use steps (ii) and (iii) to compute the EWs on its incoming connections. Figure 2, shows graphic representation of this learning cycle.

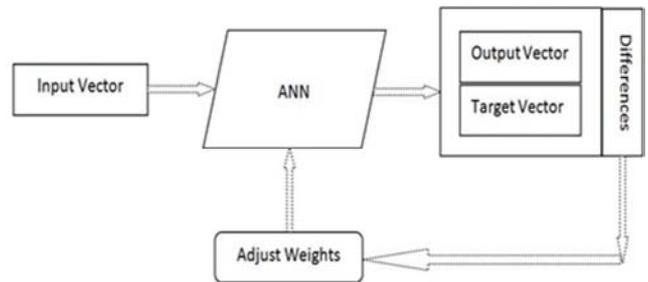


Figure 1. Diagram illustrating Learning Cycle in the Neural Network.

Back-propagation algorithm is chosen in this study to model the MLP network architecture. A 3 hidden layer with sigmoid activation function and an output layer with purelin transfer function were also used. This kind of network can be used as a general function approximator. It can approximate any function with a finite number of discontinuities arbitrarily well, given sufficient neurons in the hidden layer [5]. Resilient Back-propagation “trainrp” was used to train the model. This is because Resilient Back-propagation, eliminate the effects of the magnitudes of the partial derivatives. Only the sign of the derivative can determine the direction of the weight update; the magnitude of the derivative has no effect on the weight update. The size of the weight change is determined by a separate update value [5].

3. Results and Discussion

A random sample of 50% of the study data was used for the network training, while 25% each for validation and testing of

the network respectively. Training data were used to train the application; validation data were used to monitor the neural network performance during training and the test data were used to measure the performance of the trained application. A confusion matrix will be generated as part of the result as shown in Table 3.

Table 3. Illustration of Confusion Matrix.

		Predicted	
		Negative	Positive
Actual	Negative	θ_1	θ_2
	Positive	θ_3	θ_4

The entries in the confusion matrix have the following meaning in the context of our study: θ_1 is the number of correct predictions that an instance is negative, θ_2 is the number of incorrect predictions that an instance is positive, θ_3 is the number of incorrect of predictions that an instance negative, and θ_4 is the number of correct predictions that an instance is positive.

Standard terms such as the accuracy, sensitivity and specificity of the model were estimated using the following relations [17]:

$$Accuracy = \frac{\theta_1 + \theta_4}{\theta_1 + \theta_2 + \theta_3 + \theta_4} \quad (9)$$

$$Sensitivity = \frac{\theta_4}{\theta_3 + \theta_4} \quad (10)$$

$$Specificity = \frac{\theta_1}{\theta_1 + \theta_2} \quad (11)$$

Note that, in this work, classification of Insolvent Bank (0) data as Solvent Bank (1) is considered as False Positive (FP) and classification of Solvent Bank (1) data as Insolvent Bank

(0) is considered False Negative (FN). True Positive (TP) and True Negative (TN) are the cases where the Solvent Bank (1) is classified as Solvent Bank (1) and Insolvent Bank (0) classified as Insolvent Bank (0) respectively.

Table 4. Performance of MLP using Resilient Back-Propagation Training Function.

Actual Value			
MLP	Solvent Bank (1)	Insolvent Bank (0)	Total
Prediction	TP = 19	FP = 2	21
False Negative	FN = 3	TN = 1	4
Total	22	3	25
		Accuracy	97.99%
		Sensitivity	95.79%
		Specificity	99.13%

The results shows the accuracy of 97.99% when resilient back-propagation was used as the training function. The accuracy is very important index as it is the ratio that indicates how well the model identifies both the true positive and true negative points divided by the total points. Also, the model show sensitivity of 95.79% and specificity of 99.13%. The model was subject to a cross validation with the hold-out data not used for training. This is to serve as a preliminary test of

the classification ability of MLP neural network. The classifications accuracy, sensitivity and specificity have shown that the model has good classification capability. Hence, we furthermore compute the other metrics from their original numbers such as weighted accuracy, G-mean, and F-measure to evaluate the performance of the network. The F-Measure or balanced F-score, a measure which combines precision and recall is the harmonic mean of precision and recall, because recall and precision are evenly weighted. The geometric mean (G-Mean) is the only correct mean when averaging normalized results that is, results that are presented as ratios to reference values [18]. These metrics are functions of the confusion matrix and have been widely used [19, 20, 21] for comparison and they are defined as follows:

$$G - Mean = \sqrt{TP \times TN} \quad (12)$$

$$\text{Weighted Accuracy} = \alpha \times TP + (1 - \alpha) \times TN \quad (13)$$

$$F = \frac{(\alpha^2 + 1) \times P \times TP}{\alpha^2 \times P + TP} \quad (14)$$

Where, α has a value from 0 to infinity and is used to control the weight assigned to TP and P.

It is worth mentioning here that for any classifier, there is always a trade-off between TP and TN; and the same applies for recall and precision. In applications such as oil exploration, where drilling a well is capital intensive, it is desirable to have a classifier that gives high prediction accuracy over the TP class, while maintaining reasonable accuracy for the TN class. Weighted Accuracy is often used in such situations. Weights can be adjusted to suit the application. Here we use equal weights for both TP and TN; i.e., $\alpha = 0.5$.

Table 5. Metrics Performance Measurement.

Indices	MLP
G-Mean	135.07
Weighted Accuracy	133
F-Measure	1.19

Table 4 presents the metric measures of the training function. The results shows that based on these three metrics (F-Measure, G-mean and weighted accuracy). Resilient Back-propagation achieve good performance.

4. Conclusion

In this study, we presented the application of MLP neural network in classifying the status of commercial banks in Nigeria. The training data are of two known categories, Solvent and Insolvent Banks. Resilient Back-propagation training functions was used in a 3 hidden layer with sigmoid activation function and an output layer with purelin transfer function. Some set of data not used in training session are used to test the network for cross validating the model.

From our results, we can conclude that MLP have shown good performance considering the prediction accuracies.

However, we found that using MLP with Resilient Back-propagation as a training function is computationally efficient with accuracy of above 97.99% in classifying commercial banks data. Additional study to explore other training algorithm need to be carried out to establish the full potential of MLP in this area.

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