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An Application of Artificial Neural Networks in Predicting Customers' Loan Status in Nigeria (A Case Study of First Bank Nigerian PLC)

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Abstract: **Granting loans to customers is one of the most difficult decisions to be taken by banks because applicants are always categorized as good and bad .The aim of this paper is to examine the efficiency of the Artificial Neural Network to predict the credit risk of customers of the First Bank Nigerian Plc. The computations have been done by using MATLAB software. Number of samples was 131 including 81 creditworthy customers and 50 non creditworthy customers. In this paper, 11 independent (attribute) variables were used and 1 dependent variable. The result of the neural network model shows that out of 50 non creditworthy cases, 78.0% are correctly predicted as non creditworthy and 22.0% are predicted as creditworthy. Out of 81 creditworthy cases, 95.1% are correctly predicted as creditworthy and 4.9% are classified as non creditworthy. Overall, 88.5% of the predictions are correct and 11.5% are wrong classifications.**

Keywords: **Credit Scoring, Artificial Neural Network, Pattern Recognition, Bank.**

1. INTRODUCTION

One of the most important decision problems that require delicate care is granting of loans by a financial institution (bank or home loan business). Loan applicants can be categorized into good applicants and bad applicants. Good applicants are the applicants that are worthy of giving loans based on their very high probability of returning at the stipulated time, while bad applicants are those ones that should be rejected due to the small probability of the applicants ever returning the loan. A banking institution usually employs loan officers to make credit decisions or recommendations for the institution. These officers are given some hard rules to guide them in evaluating the worthiness of loan applications. After some period of time, the officers may gain some of their own experiential knowledge or intuition (other than those guidelines given from the institution) in deciding whether an applicant is loan worthy or not.

Traditionally, credits are granted based on a judgmental concept using past experiences of the credit officers. This approach suffers, however, from high cost of training credit officers; frequent incorrect decisions; long period of time required to evaluate the risk category of the client and make the credit granting decision; and different decisions may be made by different credit officers for the same case. Besides, there is widespread recognition that the capability of humans to judge the worthiness of a loan is rather poor (Glorfeld and Hardgrave, 1996). Some of the reasons for these are: (i) There is a large gray area where the decision is up to the officers, and there are cases which are not immediately obvious for decision making; (ii) Humans are prone to bias, for instance the presence of a physical or emotional condition can affect the decision making process. Also personal acquaintances with the applicants might distort the judgmental capability; (iii) Business data warehouses store historical data from the previous applications. It is therefore likely that knowledge is hidden in this data, which might be useful for assisting the decision making. Unfortunately, the task of discovering useful relationships or patterns from data is difficult for humans (Bakpo and Kabari, 2009). The reasons for such difficulties are the large volume of the data to be examined, and the nature of the relationships themselves that are not obvious.

Credit risk analysis is an important topic in financial risk management. Several different applications are presented in the finance and banking literature for credit risk analysis, such as bank loans, credit cards, mortgages, hire purchase, *etc.* (Lewis, 1992). Credit scoring is generally concerned with evaluating the potential risks corresponding to granting scores. Credit scoring models help lenders to decide who will get credit, how much credit they should get, and what additional strategies will enhance the profitability of the borrowers to lenders (Khashei and Mirahmadi, 2015)

Credit Scoring is a method of measuring the risk incorporated with a potential customer by analyzing his data (Lawrence and Solomon 2002). Usually, in a credit scoring system, an applicant's data are assessed and evaluated, like his financial status, preceding past payments and company background to distinguish between a "good" and a "bad" applicant (Xu, Chan et al. 1999). This is usually done by taking a sample of past customers (Thomas, Edelman et al. 2004).

Against this background, Artificial Neural Networks as an intelligent technology is proposed in this research in order to create a credit-scoring system that can meet the emerging needs and requirement of the loan management system. Recent developments in algorithms that extract rules from trained neural networks enable us to generate classification rules that explain the decision process of the network. The purpose of this work is to investigate whether these artificial neural network rule extraction techniques can generate meaningful and accurate rule sets for the credit-risk evaluation problem.

2. DATA AND METHODOLOGY

2.1 Data Used:

A real world credit dataset is used in this research. The dataset is extracted from the application forms of **First Bank of Nigeria, plc.** The dataset is referred to as "Credit Dataset". After preparing the dataset, it is used in the subsequent sections for conducting the analysis with Principal Component and Logistics Regression Analyses. The estimated credit scoring model is based on a binary logistic regression with principal components as exogenous inputs'.

Table 1: Credit Dataset Description

No.	Variable	Type	Scale	Description
1	Attribute1	Input Variable	Scale	Age of the Applicant
2	Attribut2	Input Variable	Nominal	Sex of the Applicant
3	Attribute3	Input Variable	Nominal	Ownership of residence
4	Attribute4	Input Variable	Nominal	Marital status
5	Attribute5	Input Variable	Nominal	Qualification
6	Attribute6	Input Variable	Nominal	Employment status
7	Attribute7	Input Variable	Scale	Length of service
8	Attribute8	Input Variable	Scale	Salary
9	Attribute9	Input Variable	Scale	Amount Request
10	Attribute10	Input Variable	Scale	Credit Amount
11	Attribute11	Input Variable	Nominal	Other borrowing
12	Attribute12	Output Variable	Nominal	Status of the Credit Applicant

The dataset contains 131 cases, 81 applicants are considered as "Creditworthy" and the rest 50 applicants are treated as "Non-creditworthy". The dataset holds 12 variables altogether. Among the variables, 7 variables are "Categorical" and the rest 5 variables are "Numerical". Moreover, there are 14 independent variables (input variables) and 1 dependent variable (output variable) in the dataset.

2.2 Artificial Neural Networks (ANNs):

Artificial Neural Networks are mathematical representations inspired by the human brain nerve cells and their communication and processing information techniques. The Neural Network is ideally composed of three layers, the input layer, the hidden layer, and the output layer. The input layer consists of input nodes which represent the system's variable. The hidden layer consists of nodes which facilitate the flow of information from the input to the output layers. The flow is controlled by weight factors associated with each connector. The output layer consists of nodes which represent the system's classification decision. The value of the output nodes is compared with cut-offs to determine the output and classify each case. The weight adjustment is known as training. The training process consists of running input values over the network with predefined classification output nodes. This process runs until the weight values are minimized to an error function. Testing samples are used to verify the performance of the trained network. In the context of credit scoring, numerous studies have proven that Neural Network perform remarkably better than any other statistical approach, such as logistic regression or discriminant analysis (Hu & Ansell 2007).

The underlying structure of an ANN is a directed graph, i.e. it consists of vertices and directed edges, in this context called neurons and synapses. The neurons are organized in layers, which are usually fully connected by synapses. In ANN, a synapse can only connect to subsequent layers. The input layer consists of all covariates in separate neurons and the output layer consists of the response variables. The layers in between are referred to as hidden layers, as they are not directly observable. Input layer and hidden layers include a constant neuron relating to intercept synapses, i.e. synapses that are not directly influenced by any covariate.

To each of the synapses, a weight is attached indicating the effect of the corresponding neuron, and all data pass the neural network as signals. The signals are processed first by the so-called integration function combining all incoming signals and second by the so-called activation function transforming the output of the neuron. The simplest multi-layer perceptron (also known as perceptron) consists of an input layer with n covariates and an output layer with one output neuron. It calculates the function

$$O(X) = f(\omega_0 + \sum_{i=1}^{n} \omega_i x_i) = f(\omega_0 + \omega^T X) \qquad (1)$$

Where ω_0 denotes the intercept, $\omega = (\omega_1, \ldots.., \omega_n)$ the vector consisting of all synaptic weights without the intercept, and $X = (x_1, x_2, \ldots., x_n)$ the vector of all covariates. The function is mathematically equivalent to that of Generalized Linear Model (GLM) with link function f^-. Therefore, all calculated weights are in this case equivalent to the regression parameters of the GLM.

To increase the modeling flexibility, more hidden layers can be included. However, Hornik et al. (1989) showed that one hidden layer is sufficient to model any piecewise continuous function. Such an MLP with a hidden layer consisting of J hidden neurons calculates the following function:

$$O(X) = f(\omega_0 + \sum_{j=1}^{J} w_j . h_j) = f(\omega_0 + \sum_{j=1}^{J} \omega_j . f(\omega_{0j} + \sum_{i=1}^{n} \omega_{ij} x_i)) \qquad (2)$$

Where $h_j = f(w_{0j} + \sum_{i=1}^{n} w_{ij} x_i), j = 1,2 \ldots J$

$$O(X) = f(\omega_0 + \sum_{j=1}^{J} \omega_j . f(\omega_{oj} + \omega_j^T X)) \qquad (3)$$

Where ω_0 denotes the intercept of the output neuron and ω_{0j} the intercept of the j_{th} hidden neuron. Additionally, ω_j denotes the synaptic weight corresponding to the synapse starting at the j_{th} hidden neuron and leading to the output neuron, $\omega_j = (\omega_{1j}, \ldots., \omega_{nj})$ the vector of all synaptic weights corresponding to the synapses leading to the j_{th} hidden neuron, and $X = (x_1, \ldots x_n)$ the vector of all covariates. This shows that the neural networks are direct extensions of GLM_s. However, the parameters i.e. the weights cannot be interpreted in the same way anymore.

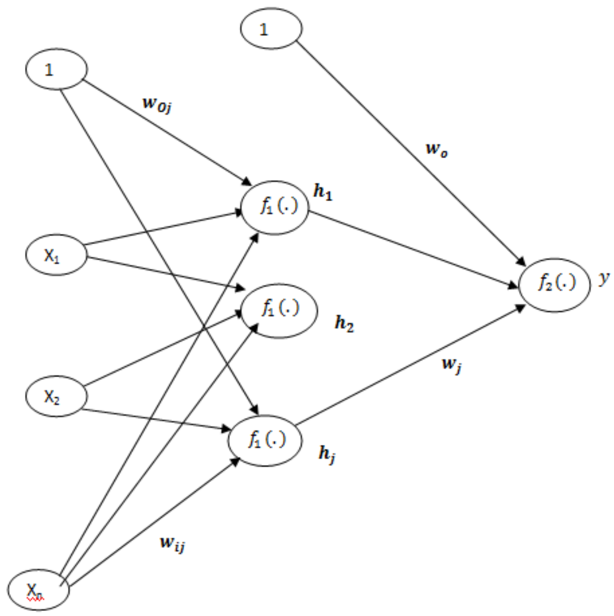

Figure 1: the Architecture of multi layer feed forward neural network with n covariates

3. RESULTS AND DISCUSSIONS

In this section, the MATLAB software was used to train the neural network model with the Backpropagation gradient based algorithm using the credit dataset. The dataset is sub-divided in to training (70%), validation (15%) and testing (15%). In all the cases, the samples have been randomly chosen as to cover the specified percentages. Figure 2 is the architecture of the neural network used where twelve (12) independent variables which otherwise known as attributes of the credit applicant, twenty (20) hidden neurons were also used in this research and one (1) dependent variable which is also known as applicant status. Figure 3 is the confusion matrix for the training, validation and testing samples. In this figure, for each case, the first two diagonal cells show the number and percentage of correct classification by the rained network. During the training, 29 applicants are correctly classified as non creditworthy. This corresponds to 31.9% of all 91 samples used for training. Similarly, 62 cases are correctly classified as creditworthy applicant. This corresponds to 68.1% of all samples used for training and there was none misclassification during the training. During the validation, of all 20 samples used, 5 cases were correctly classified as non creditworthy and 10 cases were correctly classified as creditworthy, zero (0) case was misclassified as creditworthy and 5 cases were misclassified as non creditworthy. During testing, of all 20 samples used, 5 cases were correctly classified as non creditworthy, 5 cases were correctly classified as credit worthy, 4 cases misclassified as creditworthy and 6 cases were misclassified as non credit worthy. Finally, when all samples are put together, that is, 131 samples, the performance of the trained model is that 39 cases corresponding 29.8% were correctly classified as non creditworthy, 77 cases corresponding 58.8% were correctly classified as creditworthy, 4 cases representing 3.1% were misclassified as creditworthy and 11(8.4%) cases were misclassified as non creditworthy.

Out of 43 non creditworthy applicants' predictions, 90.7% are correct and 9.3% are wrong. Out of 88 creditworthy applicants' predictions, 87.5% are correct and 12.5% are wrong. Out of 50 non creditworthy cases, 78.0% are correctly predicted as non creditworthy and 22.0% are predicted as creditworthy. Out of 81 creditworthy cases, 95.1% are correctly predicted as creditworthy and 4.9% are classified as non creditworthy. Overall, 88.5% of the predictions are correct and 11.5% are wrong classifications. Another useful tool for analysing pattern recognition network is called the Receiver Operating Characteristic (ROC) curve. To create this curve, we take the output of the trained network and compare it against a threshold which ranges from -1 to +1. Inputs that produce values above the threshold are considered to belong to Class 1, and those with values below the threshold are considered to belong to Class 2. For each threshold value, we count the fraction of true positives and false positives in the data set. This pair of numbers produces one point on the ROC curve. As the threshold is varied, we trace the complete curve, as shown in Figure 4.

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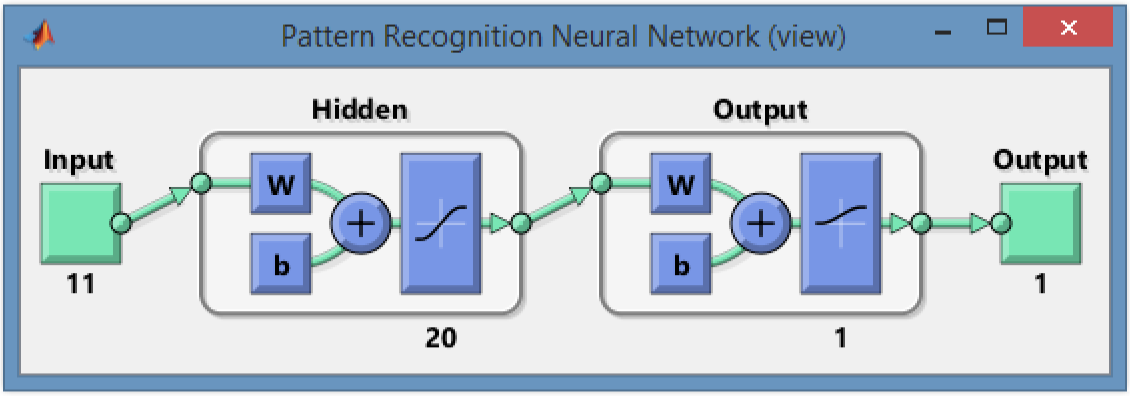

Figure 2: Neural Network Architecture

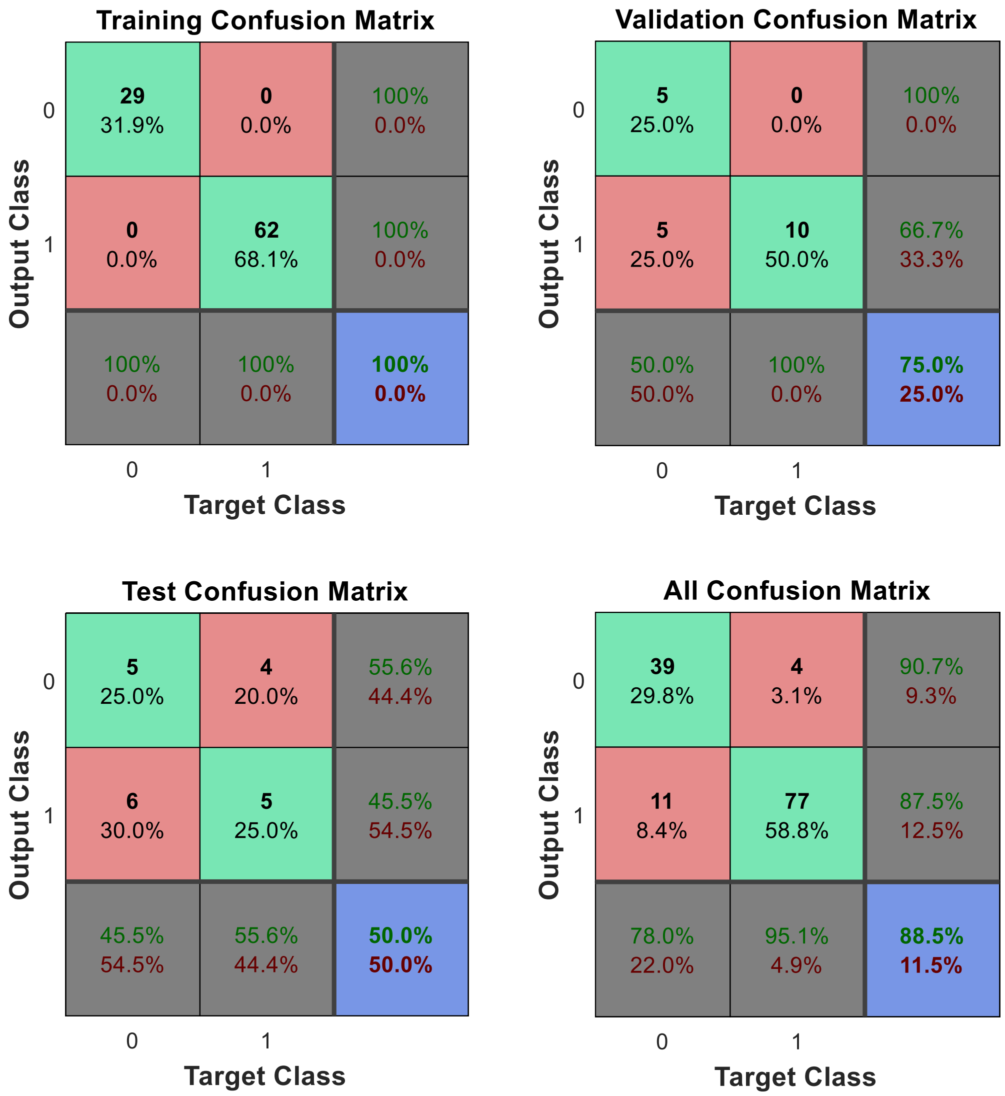

Figure 3: Confusion Matrices training, validation, testing and all samples.

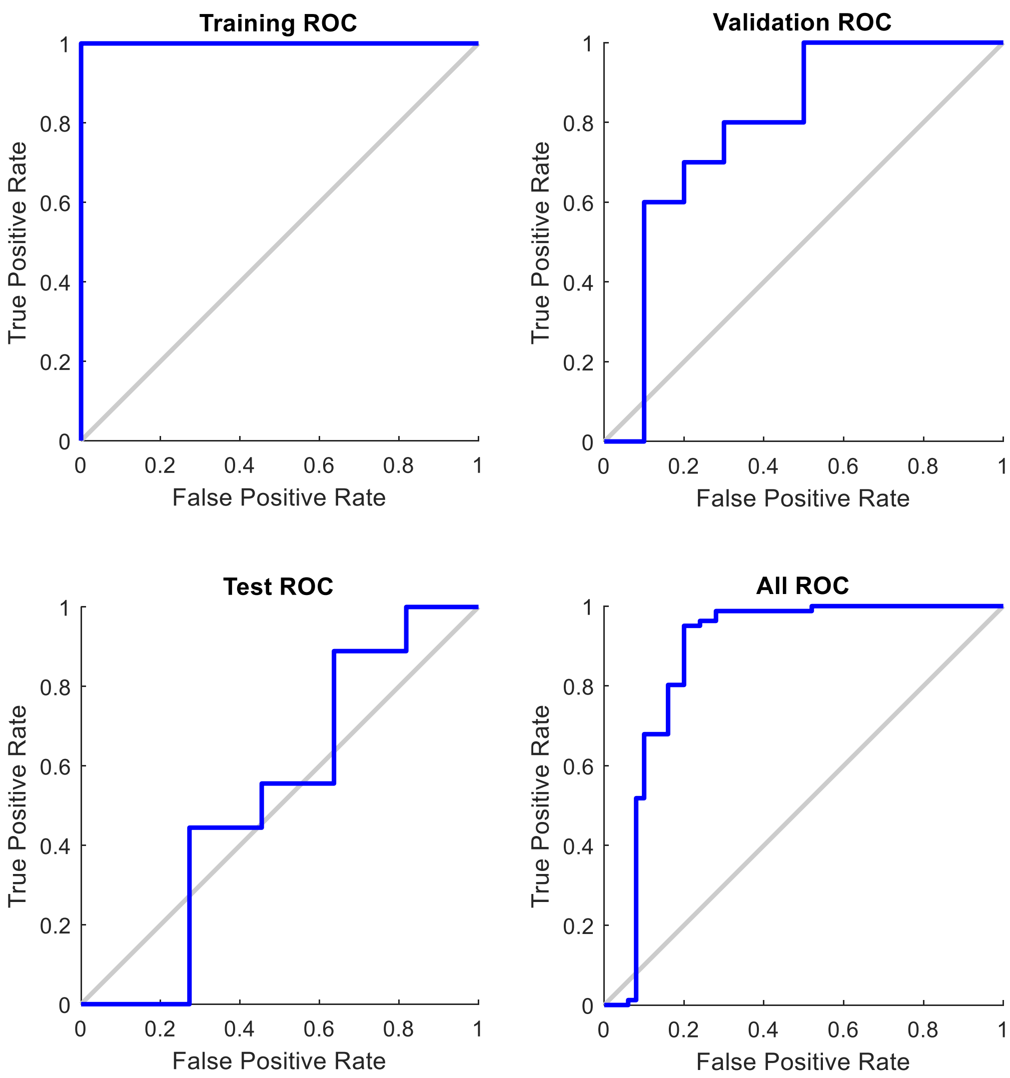

Figure 4: Receiver Operating Curve (ROC) for training, validation, testing and all samples

4. CONCLUSION

In this paper, we have presented an application of artificial neural network to predict first bank customers' credit risk. After determining of required variables, the collected data were entered into the model. Results show that out of 50 non creditworthy cases, 78.0% are correctly predicted as non creditworthy and 22.0% are predicted as creditworthy. Out of 81 creditworthy cases, 95.1% are correctly predicted as creditworthy and 4.9% are classified as non creditworthy. Overall, 88.5% of the predictions are correct and 11.5% are wrong classifications. Based on the conclusion drawn, the paper recommends that banks should be using artificial neural network technology in determining who gets loan because its predictive ability.

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