AN IMPROVED MODEL FOR FINANCIAL INSTITUTIONS LOAN MANAGEMENT SYSTEM: A MACHINE LEARNING APPROACH

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ABSTRACT: *The inability of financial instructions, especially the Microfinance Banks, to forecast for the need of borrowers in order to make provision for them has been a cause for concern. Applications are made and most times the reply is that funds are not available. This paper demonstrated the design and implementation of neural network model for development of an improved loan-based application management system. The back propagation algorithm was used to train the neural network model to ascertain corrections between the data and to obtain the threshold value. The data was collected over a period of three years from UCL machine learning repository. The system was designed using object oriented methodology and implemented with Java programming language and MATLAB. The results obtained showed the mean squared error values 1.09104e-12, 5.56228e-9 and 5.564314e-4 for the training, testing and validation respectively. It was seen from the result that neural network can forecast the financial market with minimum error.*

KEYWORDS: *Neural Network, regression, Mean Square Error, Validation, and Forecasting.*

INTRODUCTION

Lack of planning and control of cash resources is the reason often given for the failure of many businesses. However, good forecasting can help to meet set goals. Faced with intense competition and rising demand for loans by borrowers, most banks are exploring ways to use their data assets to gain a competitive advantage over others (Hakimpoor et al., 2011). The business of lending is gradually becoming a major target for many banks; as a result, there is high competition among the financial institutions in this regard. With the increasing economic globalization and improvements in information technology, large amounts of financial data are being generated, stored and analysed, and in the light of changing business environments, managers are seeing the need for more flexible predictive models (Anupam, 2010). Financial forecasting describes the process by which firms plan and prepare for the future. The forecasting process provides the means to express its goals and priorities and to ensure that they are internally consistent. It also assists the firm in identifying the asset requirements and needs for external financing. (Etemadi et al, 2012)

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However, most of the processing of information that occurs in business is done by utilizing computers that process information sequentially from a single central processing unit. This processing unit generates results directly from the hard coding of the problem into the computer by a programmer (Mumtaz, 2011). Due to the need for improved and advanced processing, businesses have turned their focus to the idea that there is potential for information processing to take place through mechanisms other than traditional models. Such models are able to analyze bid data and extract meaning from the data. This is called data mining.

The aim of this paper is to model a loan financial management system with a supervised learning approach called Artificial Neural Network. The model will help the institutions to look ahead and make intelligent predictions that will sustain the lending system. The fundamental and technical variables were taken into consideration in order to obtain a high predictive accuracy.

RELATED LITERATURE

This work is inspired by a number of works available in the literature related to forecasting with neural network approach. The field of machine learning in forecasting has achieved remarkable growth in the last few decades. Such researches are: the ANN has been applied in addressing various managerial problems like sales forecasting, price elasticity modeling, brand analysis, new product acceptance research, and market segmentation and more (Hakimpoor et al., 2011).

Prediction is one of the profit criteria in action, which depends on experimental research. The best measuring method is the one which, for a specific purpose, has the highest predicting ability of the events (Pourzamani et al, 2010).

Mumtaz (2011), in his paper entitled “Estimating Financial Failure of the Turkish Bank using Artificial Neural network,” two models were developed for estimating the probable financial failure. The models include the logistic regression and the artificial neural network model. From his results it was shown that the artificial neural network model performed better than the logistic regression model for estimating financial failures of the bank.

Chiang et al. (1996) used neural network models to predict net cost of assets investment of companies at the end of the year. The results from neural network were compared with the results of the traditional econometric techniques and it was found out that neural networks performed better with small data than regression approach.

From the works of Shahin et al. (2001), Paulo et al. (2006) and Hakimpoor et al. (2011), it is obvious that ANN application in profitability prediction will contribute to the knowledge frontiers. The ANN has enjoyed wide application in industrial settings; some of these studies are as follows: Saanzogni and Kerr (2001) applied feed-forward ANN in evaluating milk production and Fast et al. (2010) investigated the use of the ANN in condition and diagnosis of a combined

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heat and power plant. It has been applied in controlling inventory in manufacturing systems (Gumus et al., 2000; Lin et al., 2009), as well as in quality control (Pacella et al., 2004).

Biscontri and Park (2000) extended the ANN successes to lean production system while Mozer and Wolniewics (2000) examined its potential as a predictive model in the telecommunication industry. The ANN has the benefit of using multiple independent variables (inputs) in developing nonlinear equations for predicting one or more dependent variables (outputs). This is done by training patterns over several epochs with specified error range and then testing the proposed network, whereas multiple linear regressions (MLR) can only predict one dependent variable at a time as its output. The interrelationships among productivity, price recovery and profitability have been established by Phusavat and Aneksitthisin (2000) using MLR model. This paper explored the potentials of neural network as identified from the literature to model an improved loan management system for financial institutions.

MATERIALS AND METHODS

For the analysis and design of the new system, data from U&C Microfinance Bank Choba, Port Harcourt, Rivers State, Nigeria where the problem of Loan management system is absent and several crises have emanated as a result of that. The data collected were data reflecting the bank's Loan transactions from the period of five years and two months (16/02/2009-17/04/2014). The data was subjected to normalization to adjust the values and the distributions. The data were raw and given in large amount and figures, this form will not be convenient for neural network model to accept as an input. So each amount was divided by 10000000 (ten million), in other to have figures less than or equal to 1 (one) for the neural network to accept as an input. The data was used to train the proposed model in order to ascertain the pattern that exists within them and also to determine the threshold value of the model.

ANALYSIS OF THE PROPOSED SYSTEM

The fundamental and technical variables used in the model were obtained from the data. These variables include amount of loan granted, interest rate per annum, duration (date granted to the expiring date), principal paid, interest paid, principal past due, interest past due, pass and watch, doubtful, lost, bank's provision and total balance. A design of neural network model architecture of the system was made as shown in figure 1. The model consisted of twelve input variables, four intermediate variables and one output variable making up of a **12-4-1** topology. The twelve input variables were: $\mathbf{X1_1}$, $\mathbf{X1_2}$, $\mathbf{X1_3}$,...$\mathbf{X1_{12}}$. These were the fundamental and technical variables which formed the inputs to the model. The hidden layers of $\mathbf{X2_1}$, $\mathbf{X2_2}$, $\mathbf{X2_3}$ and $\mathbf{X2_4}$ were intermediate variables which interacted by means of weight matrices with adjustable weights to produce the output. The activation function was used to manipulate the inputs from the input layer in order to make the optimal prediction. The output layer contained one output from the model.

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The following were the input variables used in the model:

A*i* the Amount Granted*i*
I*i* the interest per annum*i*
L*i* loan Duration*i*
P*i* The principal paid*i*
E*i* The Interest paid*i*
R*i* Principal past Due*i*
R*i* Interest past Due*i*
W*i* Pass and Watch*i*
D*i* Doubtful*i*
O*i* Lost*i*
D*i* Bank provision*i*
T*i* Total Balance*i*

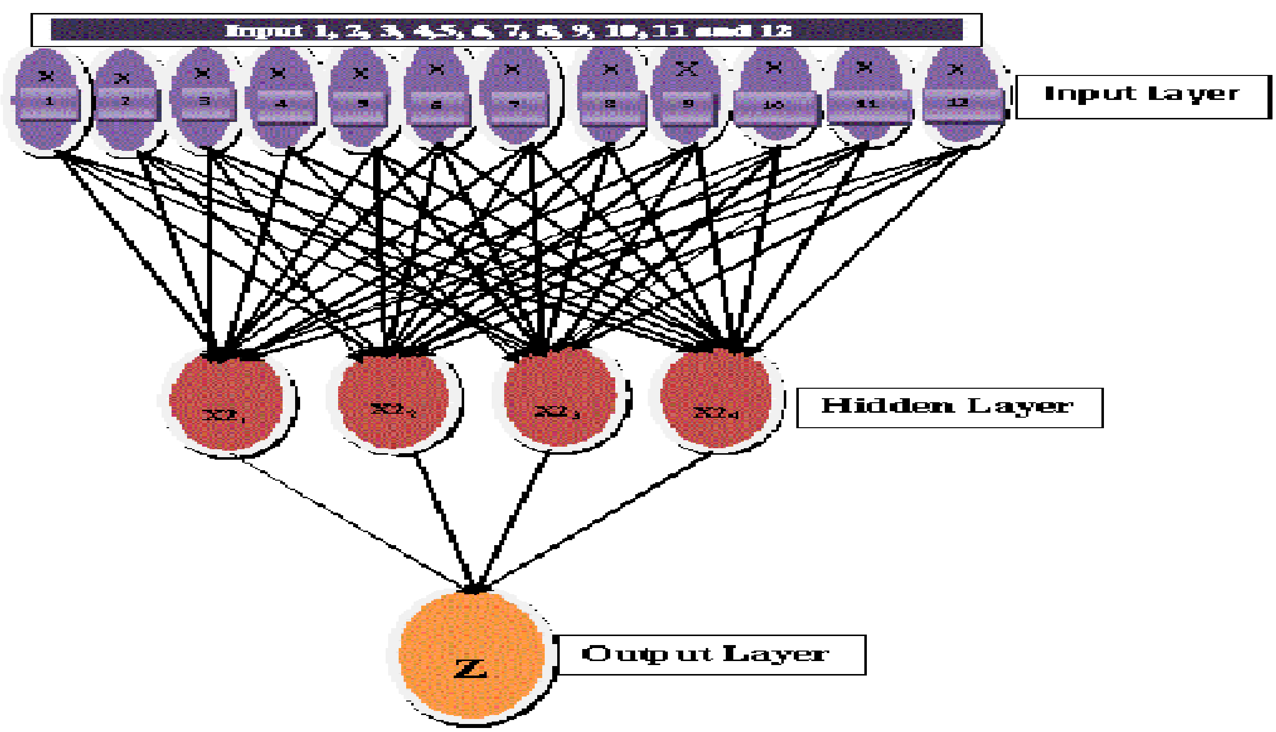

Figure 1. Neural Network Model of the System

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To train the model, a back propagation algorithm was used, each sample consists of two parts, the input and the target part (supervised learning). At the initial, the weights of the network were assigned random values within the range of -1 to 1. Then the input part of the first sample was presented to the network. The network computed an output based on: the values of its weights, and the number of its layers, the type and mass of neurons per layer. These were done to obtain net error. While propagating in forward direction, the neurons were activated using the sigmoid activation function.

The formula of **sigmoid activation** is:

$$f(x) = \frac{1}{1 + e^{-input}}$$

The back propagation algorithm was used to adjust the new weights during network training. The mathematical models of the back propagation algorithm can be represented as shown below.

The error in the output layer is calculated by using the formula in equation:

$$\delta_k = o_k \boldsymbol{(1 - o_k)(T_k} - o_k) \quad \ldots\ldots 1$$

Where

O_k is the calculated (actual) output expressed as

$$O_k = \frac{1}{1 + e^{-x_k}} \quad \ldots\ldots 2$$

T_k is the observed (True) output

The back propagation error in the hidden layer is calculated as

$$\delta_j = o_j \boldsymbol{(1 - o_j)} \sum_{\boldsymbol{k}} \delta_{\boldsymbol{k}} * w_{jk} \quad \ldots\ldots 3$$

Where w_{jk} is the weight of the connection from unit j to unit k in the next layer and δ_k is the error of unit k.

The weight adjustment formula in equation (4) is used to adjust the weights to produce new weights which are fed back into the input layer.

$$\boldsymbol{W_{new} = W_{old} + \eta * \delta * input} \quad \ldots\ldots 4$$

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Where η is a constant called the learning rate. The learning rate takes value between 0 and 1.

Experiments and Results

Series of experiments were done to have a good model that will predict with less error. 12-15-1 model was picked because its predicted values were closed to the actual value as compared to existing models. Matlab was used for the various experiments, the sample data were divided into training data (60%), validation data (20%), and testing data (20%). These sample data were used to train, validate, and to test the neural network model. Figure 2 shows the validation interface.

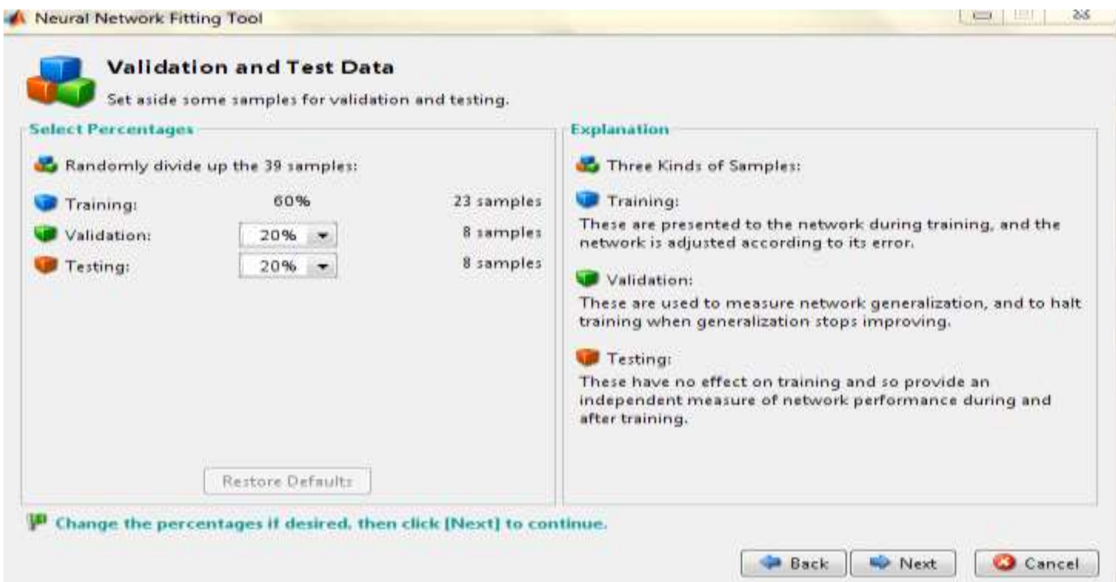

Figure 2: The validation and testing interface.

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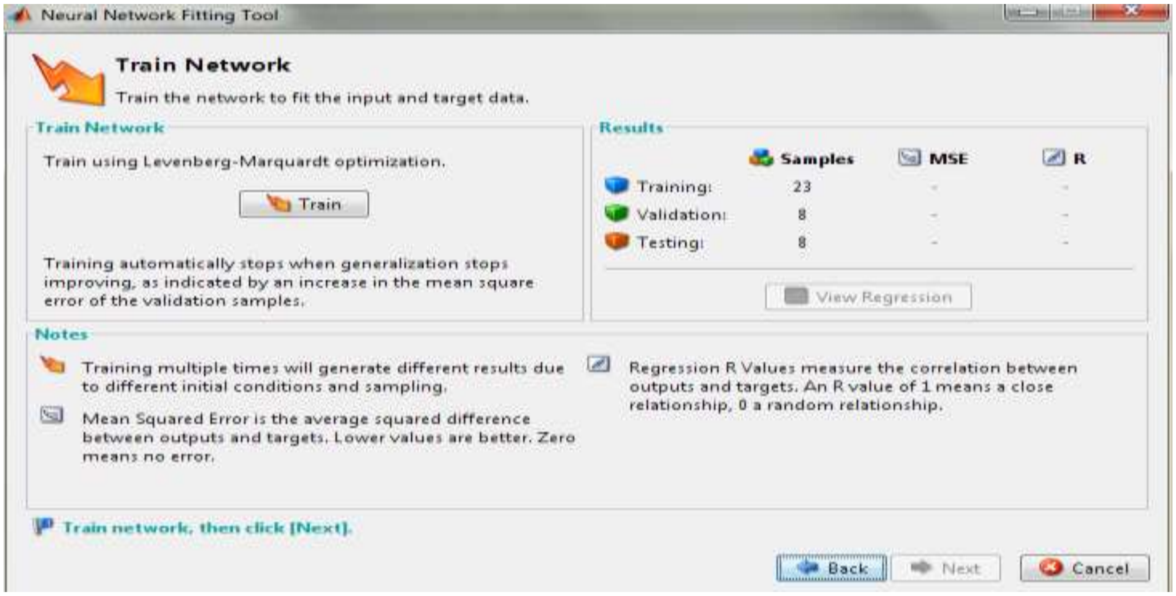

Figure 3: Train Network interface of Neural Network Fitting Tool

Figure 3 is the interface for network trained. The training was done using the lavenberg-Marquardt back propagation. The network was trained to fit the input and the target. This implied that the network would map between data of numeric inputs and set of numeric target. The training automatically stops when generalizations stop improving as indicated by an increase in the mean square error of the validation samples. The trained network shows the mean squared error and the regression of the training, validation and testing. The mean squared error is the average squared difference between outputs and targets. The lower values are better, and zero means no error. The higher the value, the greater the error and the lower the value, the lesser the error. The regression values measure the correlation between output and targets. A regression value of 1 means a close relationship and 0 means a random relationship.

Table 1: Performance Analysis of the Prediction

	Samples	Mean Squared Error	Regression
Training	799	1.09104e-12	0.999999
Validation	266	5.56228e-9	0.999999
Testing	266	5.564314e-4	0.932578

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Table 2: Result from Different Neural Network Structure of the Prediction

Date	Prediction with different Number of Hidden neurons									
	Actual	12-11-1	12-12-1	12-13-1	12-14-1	**12-15-1**	12-16-1	12-17-1	12-18-1	12-19-1
2007	**0.140**	0.139998	0.14001	0.139435	0.140002	**0.140000**	0.143461	0.139990	0.135763	0.15014
2008	**0.088**	0.087999	0.08807	0.087993	0.087987	**0.087995**	0.083076	0.088050	0.087901	0.00559
2009	**0.096**	0.096000	0.09598	0.095800	0.096000	**0.089829**	0.091445	0.096000	0.043391	0.30067
2009	**0.280**	0.280014	0.28006	0.279763	0.280264	**0.280000**	0.277401	0.280000	0.279970	0.11066
2010	**0.095**	0.095000	0.09496	0.095005	0.095000	**0.093165**	0.095622	0.095000	0.094999	0.33971
2010	**0.200**	0.200001	0.19993	0.200011	0.200027	**0.200010**	0.199059	0.199994	0.200163	0.02657
2011	**0.130**	0.129999	0.13003	0.130013	0.129979	**0.130000**	0.129839	0.130023	0.129984	0.13037
2011	**0.026**	0.025999	0.02597	0.026005	0.025994	**0.026000**	0.025149	0.025997	0.025982	0.20023
2012	**0.340**	0.339990	0.34008	0.339990	0.339421	**0.340040**	0.345464	0.339738	0.339980	0.09565
2012	**0.110**	0.110000	0.11009	0.110002	0.110009	**0.110000**	0.111134	0.110000	0.110000	0.28209
2013	**0.300**	0.300000	0.29982	0.300278	0.303936	**0.300001**	0.294878	0.300001	0.300260	0.13533
2014	**0.005**	0.005000	0.00501	0.005010	0.005002	**0.005000**	0.005641	0.005002	0.005002	0.08836
2014	**0.150**	0.150000	0.14993	0.149998	0.150012	**0.149998**	0.151227	0.149997	0.150011	0.14095

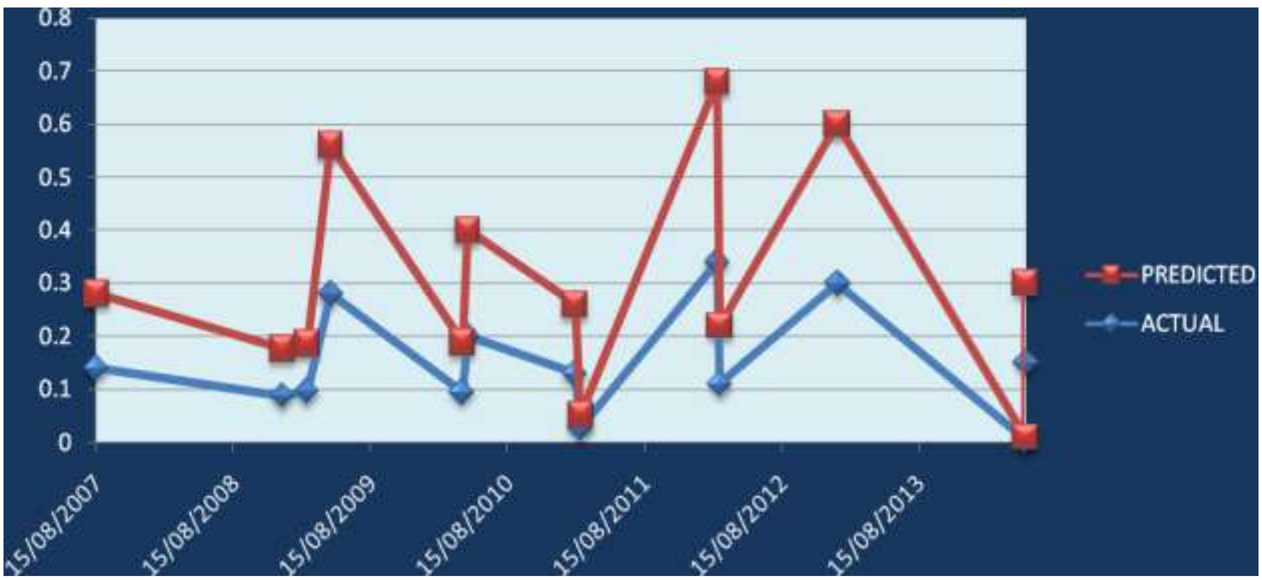

Figure .5: Graphic Representation of the Actual and the Predicted Value

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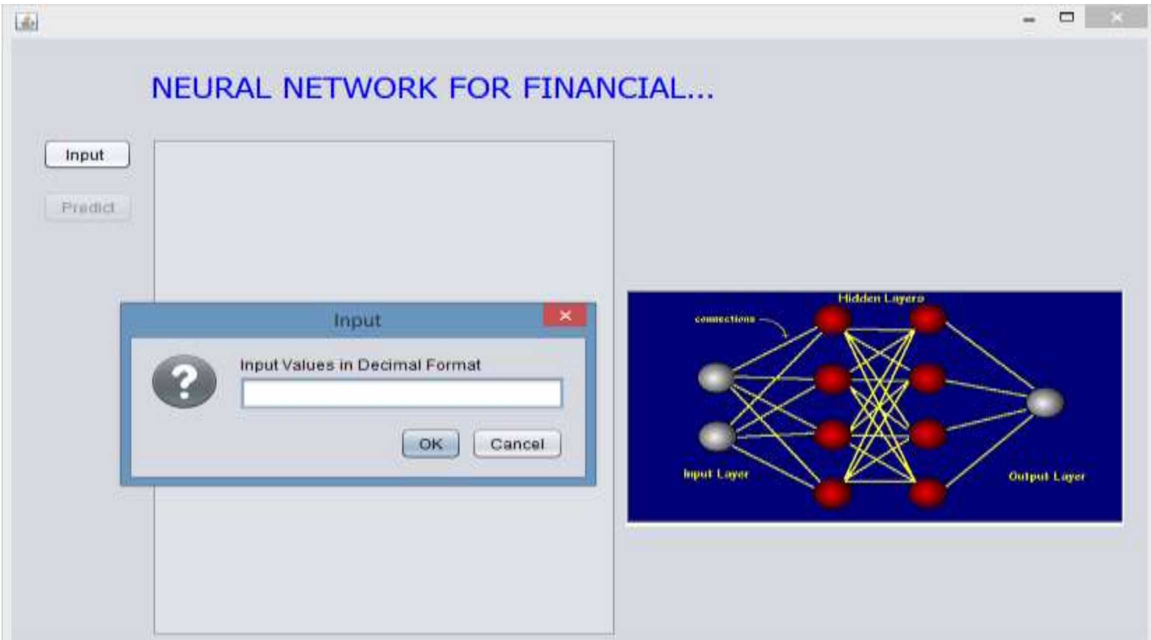

Figure 6: Input Interface.

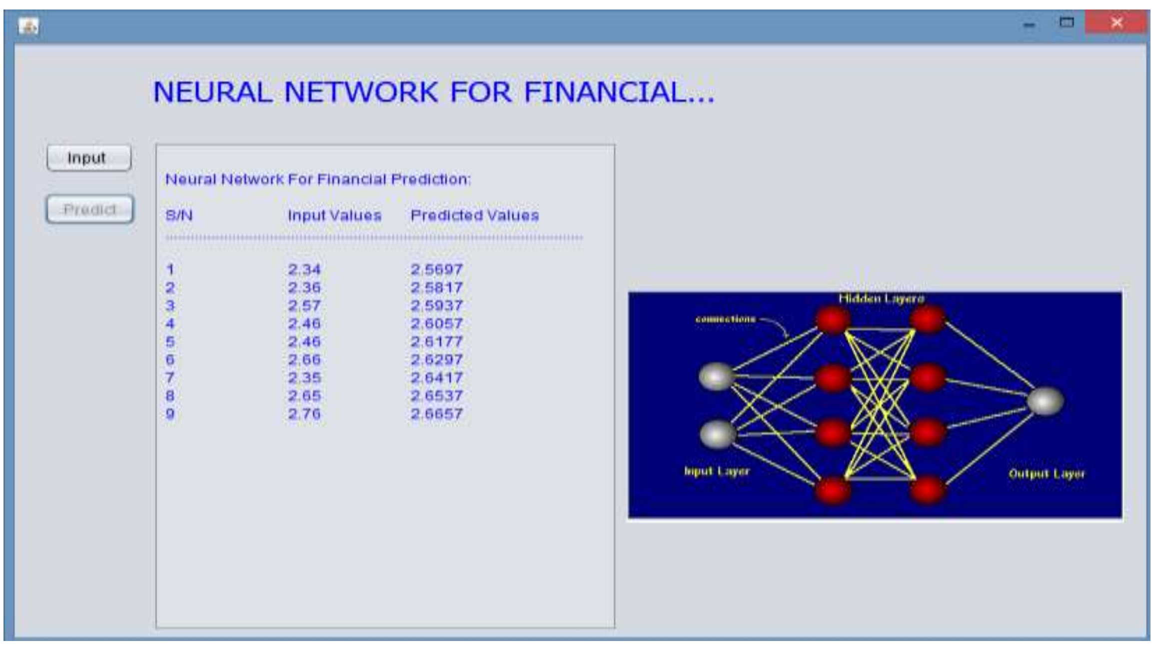

Figure 7: The Predicted result from the application.

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DISCUSSION OF RESULTS

The mean squared error (MSE) and regression (R) values analysis were used to describe the performance of the productiveness of the model. The mean square error of training, validation and testing used 799, 266 and 266 samples respectively. From results in Table 1, the mean squared error values of 1.09104e-12, 5.56228e-9 and 5.564314e-4 respectively show that the prediction was done with minimum amount of error, which was verified in Table 2.

The regression value measures the correlation between outputs and targets. A Regression value of 1 means a close relation; 0, a random relationship. The regression values 0.999999 in the training, 0.999999 in the validation and 0.932578 in the testing show that the output has a close relationship with the targeted prediction in Table 1.

The neural network structures for different hidden neurons were compared using their respective actual and predicted values. The result shows that the neural network structure of 12 - 15 – 1 model gives the optimal predicted value of the best network model in Table 2.

Figure 3 shows the graphic representation of the measurement between the actual value and the predicted value. The different actual values were compared with the predicted values using a line graph. The graph demonstrated the progression of the prediction. The predicted values are higher than the actual values.

Figure 6 and 7 shows the implementation interfaces of the application which consists of the “input bar”, and the “Prediction bar”. The Input bar allows the user to enter the data. The prediction bar depicts the predicted values. Once the input is entered successfully, it projects a message indicating a prompt to proceed to the prediction; the predicted values are displayed when the bar for prediction is processed. The predicted values demonstrate the closeness of predicted values.

CONCLUSIONS

An improved method of predicting the demand of borrowers in the financial loan management system has been developed. This model has the ability to make predictions and provisions are made for future demand of borrowers which has solved the problems inherent in their present management of loans. The model has minimum amount of error, which is used as performance yardstick to measure a good predictive model. This model, if adopted by the bank, will increase its profitability and clear the uncertainty involved in the business and level the playing field for investors who meet the criteria to acquire loans for business. It will help the banks to make provision for loan for borrowers before they make their demand since they are always aware of the amount that will be demanded.

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