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Neuro-Fuzzy Model for Agricultural Loan Eligibility Assessment

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Abstract:
Background:*In most agricultural financing establishments, the existing credit facilities are prone to the risk of loss due to borrowers' default which is mostly blamed on lack of sound credit eligibility check. The negative effect of this is the reluctance ofmost financial institutions to disburse agricultural loans, thereby hampering national food security and the progress of the agricultural sector.*
Materials and Methods: *A neural network and fuzzy logic model for agricultural loan eligibility assessment was formulated. Data warehouse, fuzzy logic and neural network are the key components of the model. The data warehouse is for analysis and report on the assessment attributes and it is based on the multidimensional star schemas. The fuzzy logic component uses the fuzzifier to convert the crisp inputs into some linguistic variables based on some predetermined membership functions that are leveraged on some precedent and antecedent rules which are expressed with linguistic variables. The fuzzy set is used to facilitate the assignment of weights to variables and describe the attributes in terms of Very High, High, Average, Low or Very Low. The neural network structure of the model consists of input, hidden and output layers. The input layer comprises fifteen (15) data attributes and it is connected to the hidden layer of seven (7) nodes which are connected to a one (1) node output layer.The experimental study was carried out on a dataset that featured attributes on 310 prospective loan applicants.*
Results:*The general resultsfrom the research include weighted assessment scores for the experimental dataset and an adaptive platform that prioritizes objectivity in the assessment of agricultural loan eligibility.*
Conclusion:The managerial usefulness of the ensemble of neural network and fuzzy logic for the assessment of agricultural loan eligibility as well as an adaptive and expansive inferencing decision support system are established. The problems of missing platform, high error rates and mathematical complexities inherent with some similar models are also addressed.*

Key Word: *Agriculturalloan, credit, eligibility assessment, fuzzy logic, neural network.*

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I. Introduction

Agriculture has been described as the science, practice and occupation of cultivating land, raising of crops and rearing of animals. The development of Agriculture goes along with the development of an enduring economy which is considered a catalyst for the overall development of any nation. Agriculture has been established as a vital sector that propels food security, live sustenance, employment generation, economic development, industrialization and foreign exchange [1-5]. Increased agricultural production coupled with rise in the capital income is a sure way to increased industrial production as well as growth in the non-agricultural economy [6-7]. The current challenges confronting agriculture include lack of modern farm and harvesting tools, non-availability of credit facilities, activities of pest and rodents, vagaries of weather condition, poor investment on agricultural research and absence of modern storage and processing facilities [8-10]. Strong agricultural sector has been established as a sure means to reduction of poverty rates [11-13]. However, farmers in many places of the world cannot afford to purchase the necessary farm tools and inputs such as tractors, fertilizers, pesticides and improved seeds. Access to agricultural loan is therefore a surest way to achieving agricultural productivity, improved farmers' investment choices and provision of effective tools for risk containment [14]. Agricultural loan is an overdraft facility for meeting the cost of farming, cultivation and working capital activities for agro-business and associated activities [15]. It is a generally low interest loan for purchase of technical tools and inputs as well as efficient and effective management of farming businesses. One of the major roles of financial institutions to the agricultural development is to make simplified, easy, convenient, flexible repayment, low interest, hidden charge-free and quick processing credit funds available to the agricultural sector. Further benefits of agricultural loans include generation of economics of scales to farmers, provides farmers opportunity to venture to new fields of technologies and production, promotes sustainable agricultural practice, cater for the fledging manufacturing and production industry and achievement of national food security [1, 16].

Some of the major challenges to agricultural loan are inadequate records and statistics, risk of natural hazard, inability to provide collateral, misapplication and low repayment [16-18]. The market cluster for agricultural loan includes farmers and small agricultural entrepreneurs, actors along the value chain, rural infrastructure and research and development [17]. Agricultural loan eligibility requires a method of measuring the risk included with a potential customer by analyzing his or her data and the goal is to maximize the risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters [19]. Loan eligibility assessment is very important for financial institution to avoid losses that are connected to inappropriate loan approval decision [20]. Effective loan eligibility assessment involves development of terms and conditions to be satisfied by a borrower [21]. Eligibility evaluation involves the assessments of character, capacity or cash flow, residual capital, business viability, strength of assets and collateral, credit history, reference agency among others [22-23]. A loan eligibility scoring model classifies the applicant's information into good credit or bad credit. An application is classified into good credit if its associated risk is low and its repayment scale is high otherwise it is classified into bad credit and is rejected or dismissed [24]. Some of the underlying techniques for loan eligibility model include machine learning, decision tree, random forest, statistical, classifier ensemble, neural network, support vector machine, bagged chart, fuzzy logic, genetic algorithm, extreme e-learning machine and multivariate adaptive regression [25-29]. A neuro-fuzzy system combines parallel computation and learning abilities of neural networks with the human-like knowledge representation and explanation abilities of fuzzy systems. The neural networks and the fuzzy logic systems are often merged to leverage on their advantages for the elimination of their respective weaknesses [30]. A neuro-fuzzy system may be represented in form of a three-tier feed forward neural network in which the first tier are the input variables, the second tier comprises the fuzzy rules and the third tier composes of the output variables. It may also use five tiers in which the fuzzy sets are encoded in the units of the second and fourth tiers [31-35]. Neuro-fuzzy systems have been applied in process control, data analysis, data classification, imperfections detention and decision-making [36-38].

In the existing knowledge, specifically in eligibility assessment, little or no attention has been paid to agricultural loan eligibility as well as adaptive referencing. Furthermore, the existing eligibility assessment models suffered due to missing architectural framework, lack of sound analytical basis, mathematical intricacy, noticeable error margin between the forecast and actual results, lack of suitability for large population among others. This study was therefore motivated by the need to establish an agricultural loan eligibility model that promotes objective and bias-free assessment of applicants, establishes effectiveness and efficiency as well as meets users' satisfaction. The objective of the study was to formulate an adaptive neuro-fuzzy model that established merit-based agricultural loan candidates' assessment or rating as well as addressed some of the limitations of the existing related works. Contrary to other existing techniques, the proposed model centers on a 3-tier knowledge base comprising data warehouse, vague reasoning and neural network. It also blends cognitive and emotional filtering mechanisms to achieve adaptive inferencing. The new model made four significant contributions; namely, it made specific application of neural network and fuzzy logic to the assessment of agricultural loan eligibility, it established an adaptive and expansive inferencing structure, addressed the problems of missing platform, high error rates and mathematical complexities inherent with some similar models and established an eligibility assessment platform suitable for referencing in future research. The research was based on the hypothesis that the uncertainties (imprecision) with some of the standard, sentiment-prone and non-linear attributes for agricultural loan eligibility assessment require vague and predictive-based technique to handle. The experimental data was obtained from Nigeria's Incentive-Based Risk Sharing System for Agricultural Lending (NIRSAL). The dataset featured the information submitted by 310 prospective loan applicants between September 2019 and May 2020 and its key attributes include Age, Number of Dependents, Current Loan Amount, Civil Status, Current Loan Amount, Loan Purpose, Number of Current Loan, Annual Income, Year in Current Job, Intending Loan Amount, Number of Credit Problem, Number of Bank Accounts, Monthly Debt Repayment, Year of Credit History and Month Since Last Delinquent. The general results from the research include weighted assessment scores for the experimental dataset and an adaptive platform that prioritizes objectivity in the assessment of agricultural loan eligibility. Notably, the study established the usefulness and relevance of ensemble of neural network and fuzzy logic for attaining satisfactory and low error rate assessment.The following sections present the review of some related works, the neuro-fuzzy model and its implementation. The conclusion drawn from the research is also presented.

II. Literature Review

The authors in[38] proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) for mortgage loan risk assessment. The research strived to address or mitigate the risk associated with mortgage lending and established a lending technique that can learn, adapt and incorporate existing knowledge of loan practices. The proposed model used neural network learning and adaptive capabilities for structural objective assessment of mortgage loan risk while Sugeno fuzzy inference technique, gradient descent and least square estimate learning algorithm were used for incorporating learning and adaptation. A generalized bell shape membership function (MF) was used to define the degree of membership of the input variables. The T-Norm operators were employed for computation of the antecedent part of the fuzzy rule base with each node presenting the firing strength of a rule. The aggregate output is diffuzified into a crisp form which represents the prediction result of a given mortgage loan application. The research model established a risk assessment method with the ability to learn the basic underling relationships among applicant's input variable and their corresponding target but lacks the analytic hierarchy process for multi-criteria decision-making.The authors in [28] presented a Principal Component Analysis (PCA) and Artificial Neural Network (ANN) model for credit risk assessment. The research centered on establishing accuracy as a strong criterion for loan profitability to lenders. The ANN and PCA models were trained for credit eligibility assessment. Attribute normalization was performed with a view to preventing the ANN from being dominated by the input attributes with large values as well as guaranteeing the independency of the principal components which are sensitive to the relative scaling of the original attributes. Predictive accuracy metric, confusion matrix and receiver operating characteristic were used for the performance evaluation. The research established a credit scoring model that attaches much importance to scoring attributes as well as promotes storage optimization but susceptible to computational complexities due to high influence of the ANN. In [39], a fuzzy logic model for credit risk rating is presented. The focus of the research was to address the problem of inaccurate risk rating that is synonymous with determination and prediction of credit eligibility. The fuzzy rules component of the model contains the expert knowledge of indicators relations and the if-then rules for calculating the profitability, debt-paying ability, operation ability andliquidity ability ratios. The model also uses Mamdani inference method for the reasoning process of input fuzzification, rule evaluation and output aggregation. The research established a model and a set of financial indicators for assessment of credit risk rating but failed to incorporate neural network for security enhancement coupled with its computational complexity.

A fuzzy logic model for the prediction of commercial banks financial failure is formulated in [40]. The research attempted to identify and address the causes of the recurrent financial failure of most commercial banks. The fuzzy logic model encompasses the membership functions, rule base, inference engine and fuzzy financial ratios which include capital adequacy, asset quality, earnings and liquidity ratios. The proposed model is suitable for determining the level of financial failure in commercial banks and proffers remedies, though it is susceptible to high error rate. The authors [25] presented an ensemble model for loan eligibility assessment. The model performs the estimation of the probability of default on loan request and Bank's performance scoring is based on an ensemble of time series, logistic regression and radial basis function. It also uses machine learning approaches to train and test its default parameters. The model is said to be suitable for predicting the credit risk of loan applicants, though no architectural framework. The authors in [41] presented a model for the evaluation of loan eligibility. The model combines the analytical power of data development analysis (DEA) and neuro-fuzzy. DEA was used to identify the important factors contributing to the success of a decision while fuzzy logic was used to create a rule-based system for the decision-maker. The Neuro-fuzzy model also integrates the performance values of a set of production units derived by ranking using DEA to create the *if-then* rules that handle fluctuating and uncertain scenarios. The model suitably identified bad units or decisions and offers significant improvements over statistical methods currently used by decision makers. However, its DEA component makes it unsuitable for very small-sized inputs such as income ratios.

III. Neuro-Fuzzy Model for Agricultural Loan Eligibility Assessment

The conceptualization of the proposed Neuro-Fuzzy model for agricultural loan eligibility assessment is presented in Figure 1. The model comprises of Knowledge Base (KB), Inference System (IS), Decision Support System (DSS) and the User Interface (UI). The KB is a repository of structured and unstructured knowledge on loan eligibility assessment. The structured knowledge are the organized facts, rules, events and attributes of applicants and it is formulated as a network of semantically related static and dynamic objects each of which is modelled in a relational form. The unstructured knowledge is the class of knowledge that is acquired through expert interactions, good practice, guesses and judgements.

Knowledge Base

The KB component of the model is viewed as an integrated collection of the data warehouse, fuzzy logic and neural network.

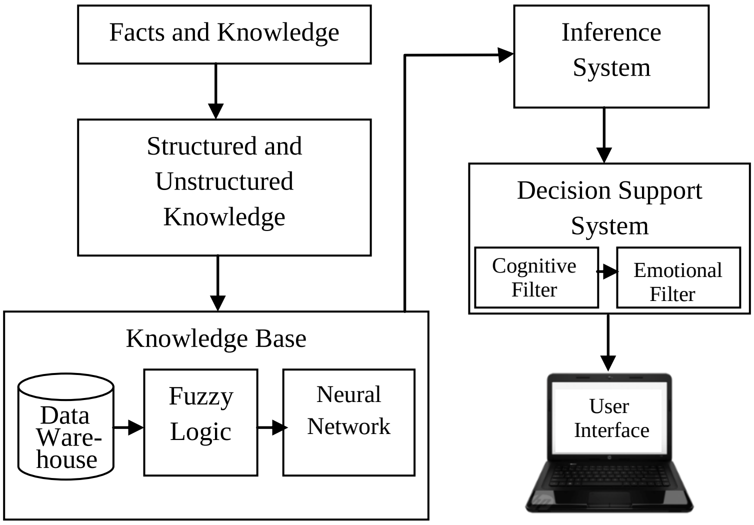

Figure 1: Architecture of the proposed system

Data Warehouse (DW)

This component of the KB is used for analysis and report on the major attributes of interest in the domain of agricultural loan eligibility assessment. Its design is based on the multidimensional star schema as shown in Figures 2. The schema featured Date, Loan, Customer, Account, and Timeframe as key dimensions with their respective attributes.

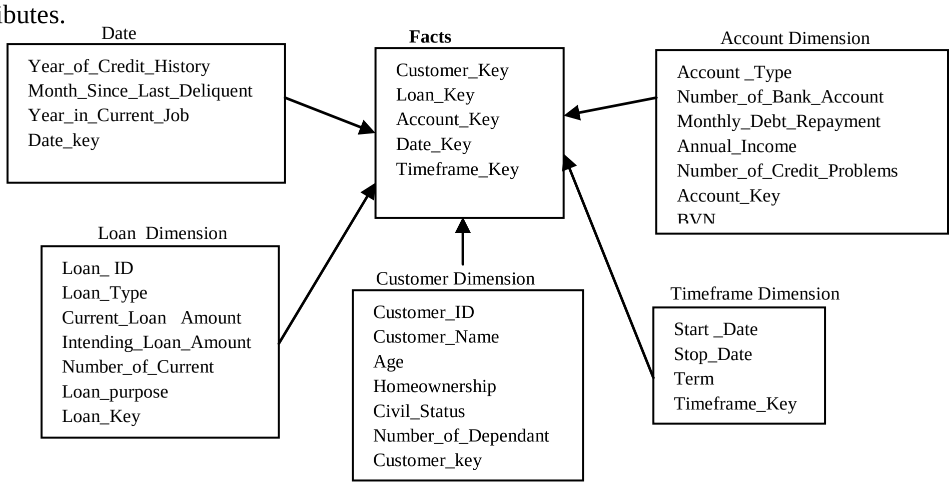

Figure 2: Star Schema of Agricultural loan attributes Fact Table

Fuzzy Logic

The fuzzy logic concept of the proposed system involves fuzzification and defuzzication as shown in Figure 3. During fuzzification, the fuzzifier converts the crisp inputs to linguistic variables using the membership functions stored in the fuzzy rule base. The fuzzy set is used to describe the attributes as *Very High, High, Average, Low or Very Low* criterion. The conversion to linguistic terms in the fuzzy domain is facilitated by the assignment of weights to variables. The assignment is based on the expected contribution of each variable to the domain of agricultural loan eligibility assessment as shown in Equation 1.

$$Weight(y) = \begin{cases} 0, & if y is nonsignificant \\ 1, & if y is lowly significant \\ 2, & if y is moderately significant \\ 3, & if y is highly significant \\ 4, & if y is very highly significant \end{cases} \quad (1)$$

y is the agricultural loan eligibility assessment variable.

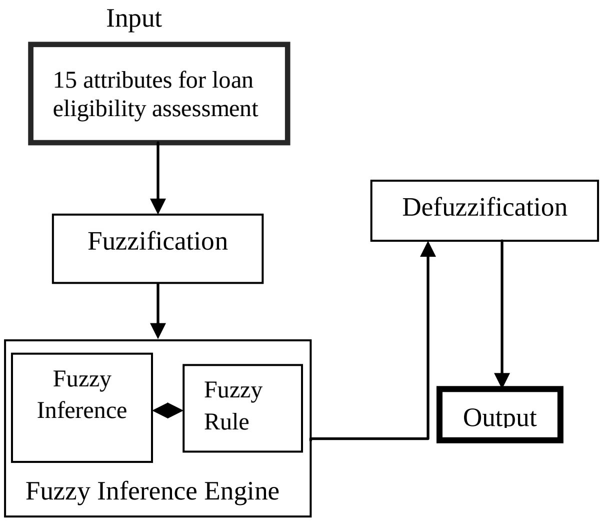

Figure 3: The fuzzy logic concept

The general form of the fuzzy set is expressed in Equation 2 with each element of the set mapped to its degree of membership.

$$A = \frac{\mu_A(x)}{x} : x \epsilon X \tag{2}$$

$\mu_A(x)$ is the degree of membership of *x* in a universe of discourse *X* in the fuzzy set *A*. The triangular MF is adopted for mapping the fuzzy set into linguistic values due to its fitness for recognition and classification [42]. The general form of a triangular MF is shown in Equation 3.

$$\mu_A(x) = \begin{cases} 0, \ if x < a \\ \frac{x-a}{b-a}, if a \leq x \leq b \\ \frac{c-x}{c-b}, if b \leq x \leq c \\ 0, if c \leq x \end{cases} \tag{3}$$

a,b,c are the parameters of the MF governing triangular shape. The degree of membership is used to map the output value specified in individual rules to fuzzy linguistic values *“Very Low”, “Low”, “Moderate”, “High” and “Very High”*. The linguistic values for variable, *y* with weight 1, 2, 3 or 4 are shown in Equations 4, 5, 6 and 7 respectively.

$$Var(y) = \begin{cases} VeryLow, if y < 0.1 \\ Low, if \ 0.1 \leq y < 0.4 \\ Moderate, if \ 0.4 < y < 0.6 \\ High, if \ 0.6 \leq y < 0.8 \\ VeryHigh, if \ 0.8 \leq y \leq 1.0 \end{cases} \tag{4}$$

$$Var(y) = \begin{cases} VeryLow, if y < 0.1 \\ Low, if \ 0.1 \leq y < 0.5 \\ Moderate, if \ 0.5 \leq y < 1.0 \\ High, if \ 1.0 \leq y < 1.5 \\ VeryHigh, if \ 1.5 \leq y \leq 2.0 \end{cases} \tag{5}$$

$$Var(y) = \begin{cases} VeryLow, if y < 0.1 \\ Low, if \ 0.1 \leq y < 0.9 \\ Moderate, if \ 0.9 \leq y < 1.5 \\ High, if \ 1.5 \leq y < 2.3 \\ VeryHigh, if \ 2.3 \leq y \leq 3.0 \end{cases} \tag{6}$$

$$Var(y) = \begin{cases} VeryLow, if\, y < 0.1 \\ Low, if\ 0.1 \leq y < 1.0 \\ Moderate, if\ 1.0 \leq y < 2.0 \\ High, if\ 2.0 \leq y < 3.0 \\ VeryHigh, if\ 3.0 \leq y \leq 4.0 \end{cases} \tag{7}$$

The MF for each point variable is subsequently derived. For instance, the MF for 1 weight variable is derived using Equations (9) to (12).

$$VeryLow(y) = \begin{cases} 0, & if\, y < 0 \\ \frac{y}{0.1}, & if\ 0 \leq y < 0.1 \\ 1, & if\, y \geq 0.1 \end{cases} \tag{8}$$

$$Low(y) = \begin{cases} 0, & if\, y < 0.1 \\ \frac{y}{0.3}, & if\ 0.1 \leq y < 0.4 \\ 1, & if\, y \geq 0.4 \end{cases} \tag{9}$$

$$Moderate(y) = \begin{cases} 0, & if\, y < 0.4 \\ \frac{y - 0.4}{0.2}, & if\ 0.4 \leq y < 0.6 \\ 1, & if\, y \geq 0.6 \end{cases} \tag{10}$$

$$High(y) = \begin{cases} 0, & if\, y < 0.6 \\ \frac{y - 0.6}{0.2}, & if\ 0.6 \leq y < 0.8 \\ 1, & if\, y \geq 0.8 \end{cases} \tag{11}$$

$$VeryHigh(y) = \begin{cases} 0, & y < 0.8 \\ \frac{y - 0.8}{0.2}, & if\ 0.8 \leq y < 1.0 \\ 1, & if\, y \geq 1.0 \end{cases} \tag{12}$$

The fuzzy input and output variables are used in the rule formulation and implication to guide the fuzzy inference. The operation ranges of the variables are presented in Table 1 [43-44]).

Table 1: The operation ranges of the variables

S/N	Variable		Normal range		Unit code
	Name	Code	Min	Max	
1	Customer ID	CUD	N/A	N/A	N/A
2	Customer Name	CUN	N/A	N/A	N/A
3	Current Loan Amount	CLA	10,000	10,000,000	Naira
4	Term	TEM	1	3	Number
5	Biometric Verification Number	BVN	N/A	N/A	N/A
6	Age	AG	18	60	Year
7	Annual Income	ANI	350,000	1,500,000	Naira
8	Years in Current Job	YIC	2	20	Year
9	Fixed/Moveable Assets	HOP	N/A	N/A	N/A
10	Intending Loan Amount	ILA	100,000	10,000,000	Naira
11	Number of Bank Accounts	NBA	1	5	Number
12	Number of Credit Defaults	NCD	1	2	Number
13	Civil Status	CIS	N/A	N/A	N/A
14	Number of Existing Loans	NEL	1	4	Number
15	Loan Purpose	LOP	N/A	N/A	N/A
16	Monthly Debt Repayment	MDR	1000	100,000	Naira
17	Year of Credit History	YCH	1	10	Year
18	Number of Dependents	NOD	2	4	Number

Fuzzy Rule base

The rule base for the system contains a set of *if-then* rules in which the *if* and the *then* parts involve linguistic variables. A rule fires if its '*very high',' high', 'moderate', 'low' or 'very low'*value evaluates to true, otherwise it does not fire. With reference to Table 1, the following are some of the associated *if-then* rules.

Rule 1: IF (CLA is *'very high')* AND (TEM is '*high'*) AND (AG is *'very low'*) AND (ANI is '*low'*) AND (YIC is *'very low'*) AND (ILA is *'very high'*) AND (MDR is '*high'*) AND (YCH is *'very high'*) AND (NBA is '*high'*) AND (NCP is '*high'*) AND (CIS is 'l*ow'*) AND (NEL is '*high'*) AND (NOD is '*high'*) AND (MDE is *'very high'*) THEN (OUTPUT is '*low'*)

Rule 2: IF (CLA is *'very low'*) AND (TEM is *'very low'*) AND (AG is *'moderate')* AND (ANI is '*low'*) AND (YIC is '*low'*) AND (ILA is *'moderate'*) AND (MDR is *'very low'*) AND (YCH is *'moderate'*) AND (NBA is *'very high'*) AND (NCP is '*low'*) AND (CIS is '*low'*) AND (NEL is *'moderate'*) AND (NOD is *'very low'*) AND (MDE is '*low'*) THEN (OUPUT is *'moderate'*)

Rule 3: IF (CLA is '*low'*) AND (TEM is *'very low'*) AND (AG is *'moderate'*) AND (ANI is *'very high'*) AND (YIC is '*high'*) AND (ILA is *'moderate'*) AND (MDR is *'very low'*) AND (YCH is '*low'*) AND (NBA is *'moderate'*) AND (NCP is *'very low'*) AND (CIS is '*high'*) AND (NEL is '*low'*) AND (NOD is '*low'*) AND (MDE is '*low'*) THEN (OUPUT is '*high'*).

The aggregate number of rules is obtained from $k = M^P$, M is the number of MFs and P is the number of input parameters. This design established five (5) MFs and fifteen (15) input parameters, resulting in k = 5^{15} possible rules. The rules for any three variables is 3^3 = 27 while its fuzzy composition is presented in Table 2 (H-High, L=Low, M-Medium).

Table 2: Typical fuzzy rule composition for three variables

Rule No.	**VAR-1**	**VAR-2**	**VAR-3**	**Activity**
1	H	H	H	H
2	H	H	L	H
3	H	H	M	H
4	H	L	H	M
5	H	L	L	M
6	H	L	M	M
7	H	M	H	H
8	H	M	L	H
9	H	M	M	M
10	L	H	H	M
11	L	H	L	M
12	L	H	M	M
13	L	L	H	L
14	L	L	L	L
15	L	L	M	L
16	L	M	H	L
17	L	M	L	L
18	L	M	M	L
19	M	H	H	M
20	M	H	L	M
21	M	H	M	M
22	M	L	H	M
23	M	L	L	L
24	M	L	M	L
25	M	M	H	M
26	M	M	L	M
27	M	M	M	M

Neural Networks (NN)

The NN structure of the proposed system consists of input layers, hidden layers and output layer. The input unit comprises fifteen (15) data attributes of agricultural loan eligibility assessment. It is connected to the hidden layer of seven (7) nodes towards attaining a better and an acceptable performance level [45]. The single node output layer is where the assessment of the indices for agricultural loan eligibility takes place. The assessment is based on the connection weights of the hidden layer and a sigmoid transfer function. The difference between the obtained and desired outputs is the error term which is used for the adjustment of the connection weights using back propagation algorithm.

Neuro-Fuzzy Inference System

The inference system consists of one (1) input layer, five (5) hidden layers and the one (1) output layer. The fuzzy inferencing is based on the mapping of the inputs to output in fuzzy space using Gaussian linguistic variables membership functions *very low, low, moderate, high and very high.* The general form of the fuzzy rule for the inference system is given by:

$$Rule\ 1: If(x_1 is A_1) AND \dots AND (x_n is A_n)\ THEN (f_1 = p_1 x + \cdots + p_z x + r_1) \quad (13)$$

$x_1 \dots x_n$ are the input variables, $A_1 \dots A_n$ is the input fuzzy set, $f_1$is the fuzzy output. The design parameters for the inference system training are represented by p, q and r respectively.

The first layer of the inference system is the input layer consisting of z-number of neurons. The first hidden layer comprises of adaptive nodes. The outputs layer is the fuzzy membership grade of the inputs, which is expressed as:

$$O_{1,i} = \mu_{A_i}(x_1), \quad i = 1, 2, \dots P \quad (14)$$

P is the number of linguistic variables, $A_i$is the linguistic variable, x_1 is the first input and $\mu_{A_i}(x_1)$ is the fuzzy membership function. The second hidden layer consists of fixed nodes and its output is a result of multiplier effect (w_i) with the fuzzy inputs. It involves intersection operator (t-norm) that is based on the AND operator to fuzzify the inputs as follows:

$$O_{2,i} = \mu_{A_i}(x_1)^* \mu_{B_i}(x_2), \quad i =, 2, \dots P \quad (15)$$

The third hidden layer comprises fixed nodes and its output is a standard union of the multiplied fuzzy inputs effects in the last layer. Its operation is based on the union (max) and the s-norm operators that use the OR operator to fuzzify the outputs from the second layer as shown in Equation (16).

$$O_{3,i} = \mu_{A_i}(x_1)^{\oplus} \mu_{B_i}(x_3), \quad i =, 2, \dots P \quad (16)$$

The fourth hidden layer performs normalization and its output is a normalized firing strength or weights. It comprises of adaptive nodes that adapt to changes in the product of normalized firing strength and nth order polynomial. The normalized firing strength is given as:

$$O_{4,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2 + w_3 + \cdots + w_z}, \quad i = 1, 2, 3, \dots, z \quad (17)$$

$w_1, w_2, \dots, w_z$ are the normalized weights. The fifth hidden layer results in an adaptive node whose output is the subsequent product of the normalized firing strength and a first order polynomial. The output of this layer ($\bar{w}_i f_i$) is given by:

$$O_{5,i} = \overline{w_i}(p_1 x_1 + q_2 x_2 + \cdots + p_z x_z + r_1), \qquad i = 1, 2, \dots., z \quad (18)$$

p, *q* and *r* are the consequent parameters.

The output layer consists of one single fixed node and it performs the summation of all subsequent node outputs based on Equation (19).

$$O_{6,i} = \frac{\sum_i \overline{w_i} f_i}{\sum_i \overline{w_i}} \quad (19)$$

Decision Support System

The Decision support system consists of the cognitive filter and emotional filter. While the former analyzes the output of the inference system based on the objective judgment on loan eligibility criteria, the latter performs analysis using subjective factors. The objective output of the system can be '*not eligible', 'fairly eligible' or 'highlyeligible'* based on the rating scale. Output of a subjective analysis includes decision to favour one particular gender, decision to give priority to youth and decision to approve on basis of national character, geographical spread and political affiliation.

IV. Experimental Study

The proposed model was implemented in Microsoft Windows 8 Operating System environment on Pentium IV Personal Computer System 2.0 GHZ Duo Core Processor with 8 GB of RAM and 1TB HDD. Python 3, Pandas 1.0.3, Jupiter notebook 1.0.0, Tensor flow 1.14.0, NeuroSolutions 7.0 and Matlab version 7 were the frontends while MySQL database from Wamp Server 2.2 served the backend. The experimental data was obtained from Nigeria Incentive-Based Risk Sharing System for Agricultural Lending (NIRSAL) in Akure, Nigeria. The dataset featured the information submitted by 310 prospective loan applicants between September 2019 and May 2020 and its subset is shown in Figure 4.

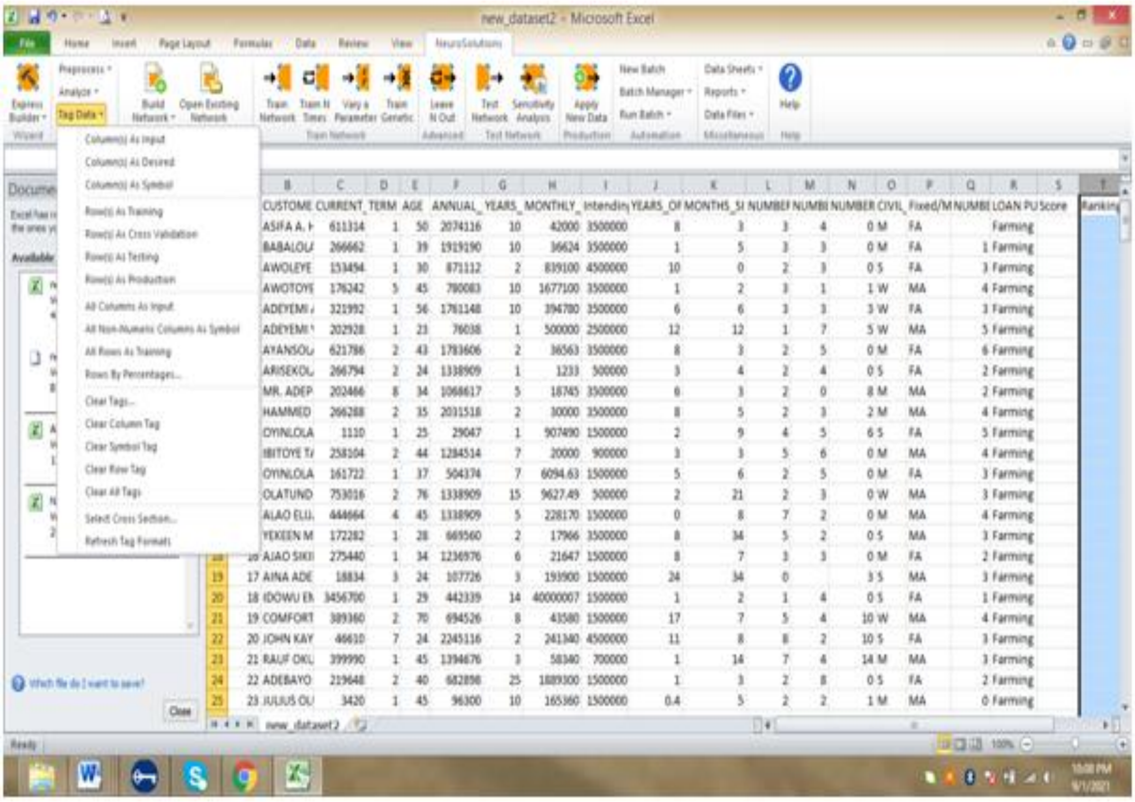

Figure 4: Experimental dataset

The dataset was divided into three parts; namely training, validation and testing subsets in the ratio of 8:1:1 respectively which translates to 248 records for training, 31 records for validation and 31 records for testing. During Neuro Solutions pre-processing of the dataset, Column ‘A’ was designated as *Symbol* and it contains data that do not participate in the preliminary neural network training used for input-output sensitivity determination. Columns ‘E’ to ‘R’ were designated as *Input* and contain data for initial network training to determine data patterns and the significance of each input contributions to output. Column ‘S’ was designated as *Desired* or the *Output* column. Rows 2 to 249 were tagged as ‘*Training’ data*, rows 250 to 280 were tagged as cross validation and rows 281 to 310 were designated as testing dataset. The “Train Network” menu of the Neuro Solution is shown in Figure 5.The training network window enables the entry of trial name, number of epochs and cross validation parameters. The number of epochs specifies the number of times the complete presentation of data should be made for training. The NN training and validation curve for 100 epochs which depicts the training and cross validation Mean Squared Error (MSE) is presented in Figure 6.

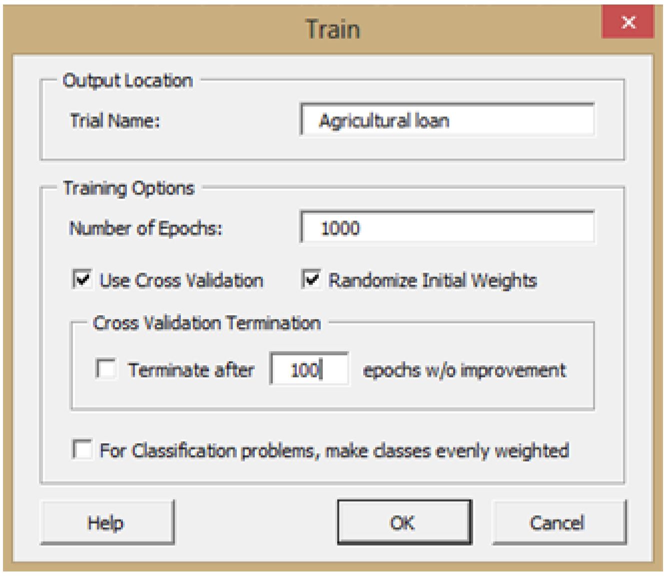

Figure 5: Preliminary Training Network Window

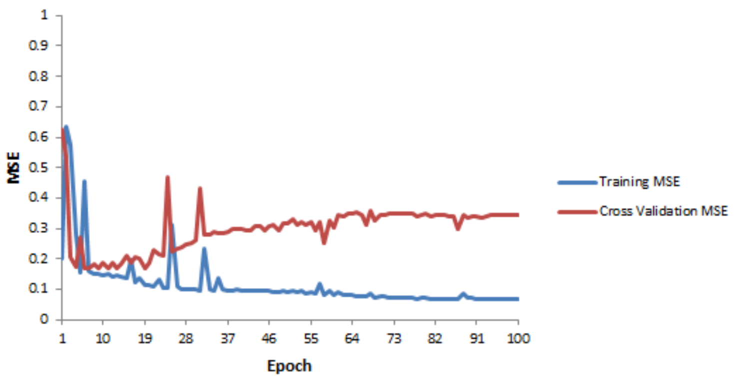

Figure 6: Training and Validation MSE

As shown in Figure 6, at epoch 1,the training and validation errors begin at 0.62 and 0.61 respectively. The errors decrease in the same direction till epoch 6. At epoch 7, the validation MSE starts to increase from 0.17 to 0.225 while the training MSE continues to decrease from 0.17 to 0.05. This shows that NN is over specializing on the training data at epoch 6. The best weights for updating model parameters are obtained at epoch 6. The attributes weights and scores are presented in Table 3.

Table 3: Attribute weight and scores

SN	Attribute	Code	Weight	Class	Score
1	Age	AGE	15	18-25	4
				26-35	5
				36-45	3
				46-59	2
				>=60	1
2	Year of Credit History	YCH	15	0-1	1
				2-4	2
				5-7	3
				8-9	4
				>=10	5
3	Year of Credit Job	YIC	15	0-2	2
				3-5	3
				6-10	5
				11-19	4
				>=20	1

4	Annual Income	ANI	15	<=350k	1
				>350 &<=500k	2
				>500k &<=750k	3
				>750k &< =1m	4
				>1m	5
5	Current Loan Amount	CLA	15	<=1m	5
				>1mk &<=2m	4
				>2m &<=5m	3
				>5m &<= 7.5m	2
				>7.5m	1
6	Intending Loan Amount	ILA	15	<=1m	5
				>1mk &<=2m	4
				>2m &<=5m	3
				>5m &< =7.5m	2
				>7.5m	1
7	Monthly Dept Repayment	MDR	15	<=1m	5
				>1mk &<=2m	4
				>2m &<=5m	3
				>5m &< =7.5m	2
				>7.5m	1
8	Civil Status	CIS	15	<=1m	5
				>1mk &<=2m	4
				>2m &<=5m	3
				>5m &<= 7.5m	2
				>7.5m	1
9	Loan Purpose	MDR	15	Crop farming	5
				Tree farming	4
				Rearing of animal	3
				Poultry	2
				Fishing	1
10	Fixed/Movable Asset	FMA	7	Value >loan request	5
				Value <loan request	2
11	Term	TEM	15	<1 Year	5
				>1years &<=1.5years	4
				>1.5 years &<=2 years	3
				>2 years &<=2.5 years	2
				>2.5 years	1
12	Number of Active Bank Accounts	NBA	15	<2	5
				>=2	10
13	Number of Loan Default	NLD	15	0	10
				>=1	5
14	Number of Active Loans	NEL	15	0	10
				>=1	5
15	Number of Dependent	NOD	15	<=3	3
				>3 &<=6	4
				>6	8

Based on the values displayed in Table 3, the scores derived for the dataset presented in Figure 4 are shown in Figure 7. Customer id and names merely served informative purposes and do not contribute to the rating process.

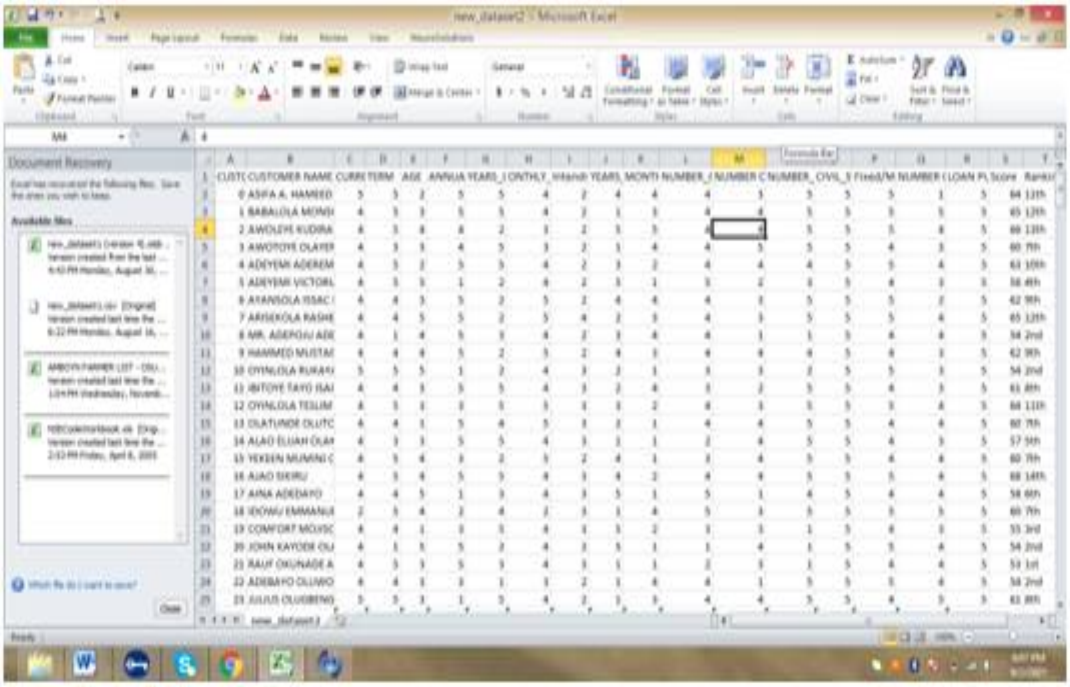

Figure 7: Scores derived from the dataset

Neuro- Fuzzy Implementation

The implementation of the Neuro-Fuzzy component was based on combination of Sugeno fuzzy inference, gradient descent and least – square estimate learning techniques. In the testing process, 248 records were used for training, 31 records for validation and 31 records for testing. The degree at which the output of the system matches the actual data set was used to evaluate the system decision ability. A triangular membership function based on Sugeno Fuzzy Inference System (SFIS) was used to classify the input and output variables as '*very low'*, *'low'*, *'moderate'*, *'high' and 'very high'*. The membership function plot for *Age* is shown in Figure 8.Relevant rules were formulated for deductive reasoning. The rule set was evaluated from five (5) MF and fifteen (15) attributes of loan eligibility assessment leading to 5^{15} possible rules. Figure 9, Figure 10 and Figure 11 present the inference system rule editor, fuzzy rule analysis viewer and surface view of attributes respectively.

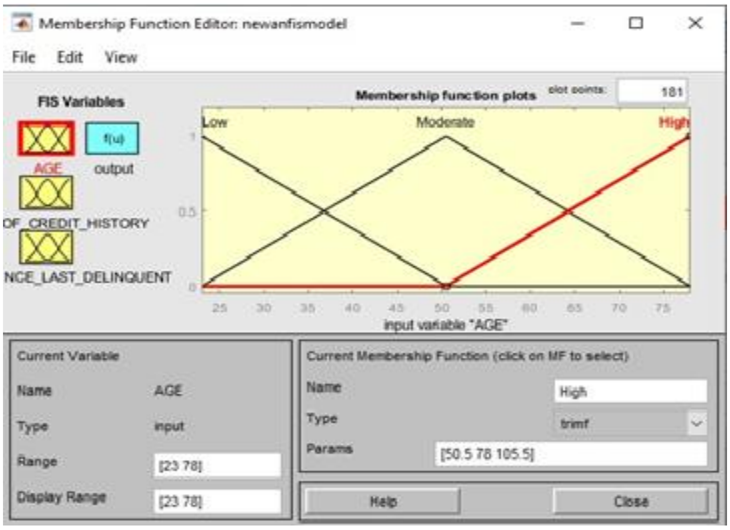

Figure 8: The membership function plot for attribute *Age*

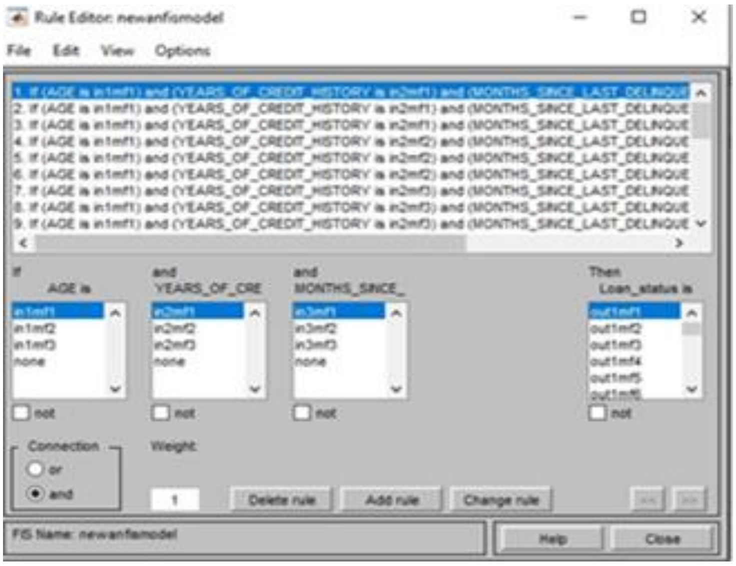

Figure 9: Inference System Rule Editor

Figure 10: Inference system fuzzy rule analyzer

Testing and Validation

The system was trained using a forward pass (least-square estimate method) and hybrid learning algorithm (least-square estimate and gradient descent method). In forward pass, the node outputs go forward and the consequent are identified by the least-square method while in backward pass, the error signals propagate backward and the premise parameters are updated by gradient descent. The training error and epochs were set to 0 and 990 respectively and the training process end when the goal of the training error was achieved. The membership function parameters of the inference system were adjusted during the training process thereby increasing its performances. With the forward pass algorithm selected as the training algorithm, the training started from epoch 0 with error value of 2.456564 and pass through a constant value at all point to epoch 990 with the same error value which implies that there is no model over-fitting as shown in Figure 12.

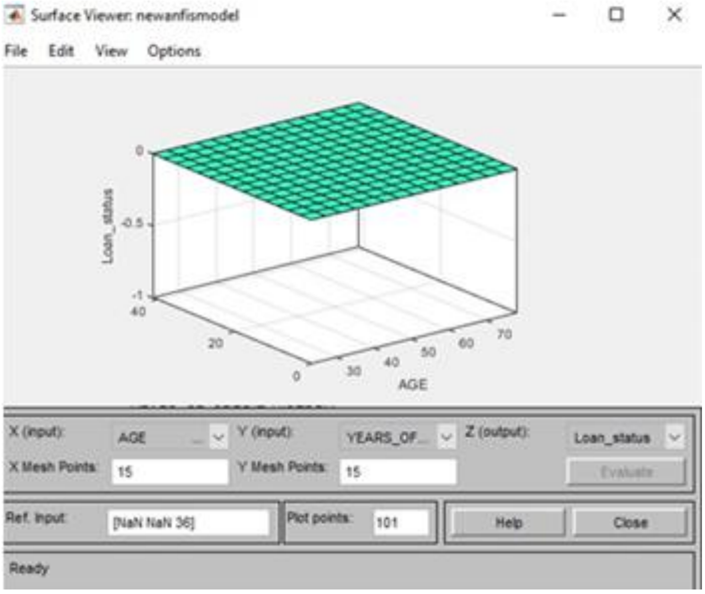

Figure 11: Inference system surface view of attributes

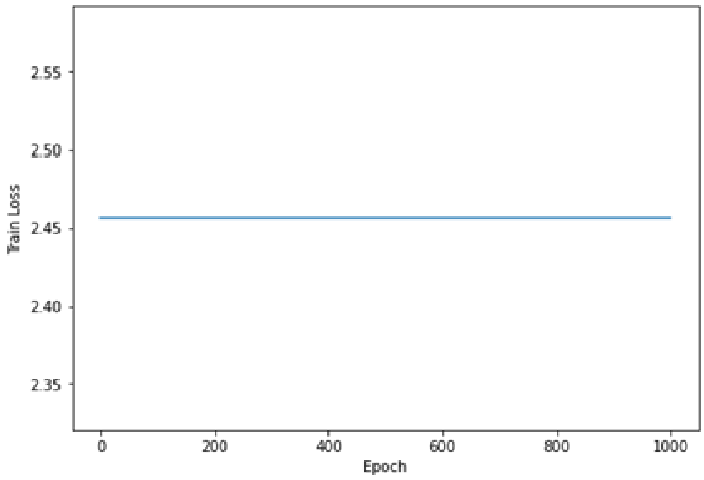

Figure 12: Inference system training error

The trained inference system output (predicted data) against the validation dataset (target value) is presented in Figure 13. The inference system's output is represented with plus (+) sign while the validation data is represented with asterisk (*) sign. It is established that the inference system has been trained with the appropriate sets of membership function value.

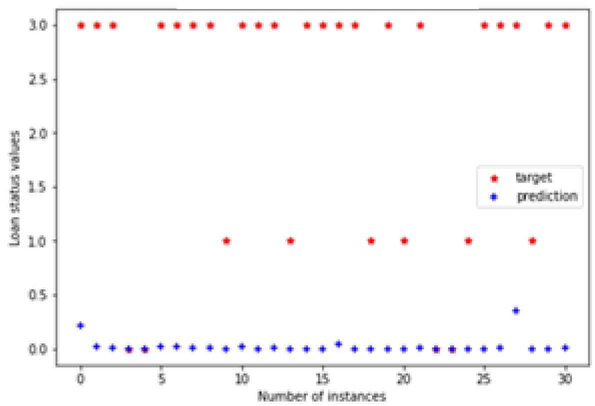

Figure 13: The predicted data against the validation data

The test of the performance of the trained inference system using the testing dataset is presented in Figure 14. The plus (+) signs represent the predicted outputs of the trained system while the asterisk (*) sign represents the testing data (target). It is observed that most of the testing and the validation datasets are far apart. Out of the thirty-one validation data, 6 data pairs match with the system output while 25 data pairs failed to match, resulting in an error value of 2.456564 between the computed and the desired output. This value indicates that the inference system is not well trained. The error values recorded for varying number of epochs are presented in Table 4.

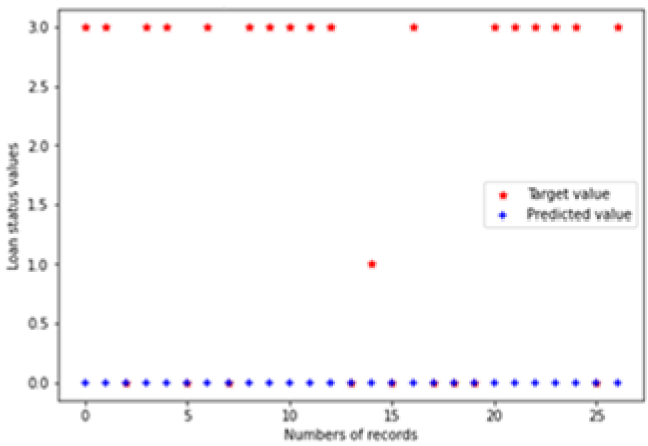

Figure 14: Inference system output testing data

Table 4: Error values recorded for varying number of epochs

SN	Number of Epochs	Training Error	Validation Error	Testing Error	Average Error
1	0	2.456564	2.480376	2.437061	2.458000
2	100	2.456564	2.480376	2.437061	2.458000
3	200	2.456564	2.480376	2.437061	2.458000
4	300	2.456564	2.480376	2.437061	2.458000
5	400	2.456564	2.480376	2.437061	2.458000
6	500	2.456564	2.480376	2.437061	2.458000
7	600	2.456564	2.480376	2.437061	2.458000
8	700	2.456564	2.480376	2.437061	2.458000
9	800	2.456564	2.480376	2.437061	2.458000
10	900	2.456564	2.480376	2.437061	2.458000

11	990	2.456564	2.480376	2.437061	2.458000

As shown in the Table 4, the inference system training, validation and testing errors from epoch 0 to epoch 990 are constant with an average error of 2.458000. The Hybrid learning algorithm applies the least-squares method and the backpropagation gradient descent method for training and adjustement of membership functions and consequent parameters. The training chart using the hybrid learning algorithm is depicted in Figure 15 showing how the training error decreases gradually from epoch 0 to epoch 990 with the training error value of 0.10234. The validation and testing errors are depicted in Figure 16 and 17 respectively, while the summary of training, testing, validation and average errors from epoch 0 to 1000 are presented in Table 5.

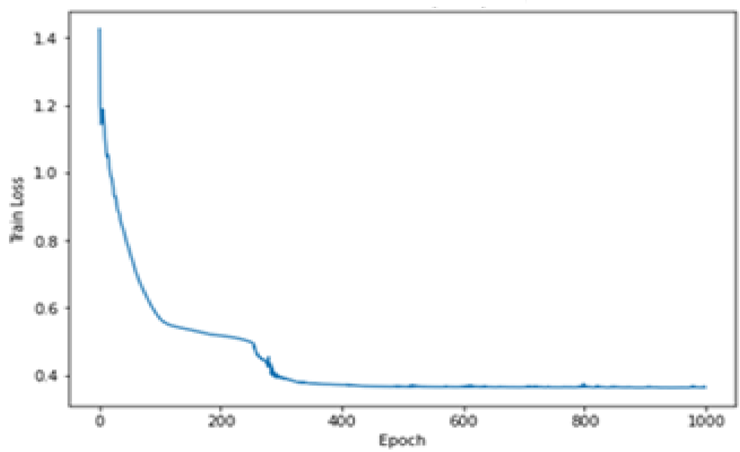

Figure 15: Inference system training with Hybrid algorithm

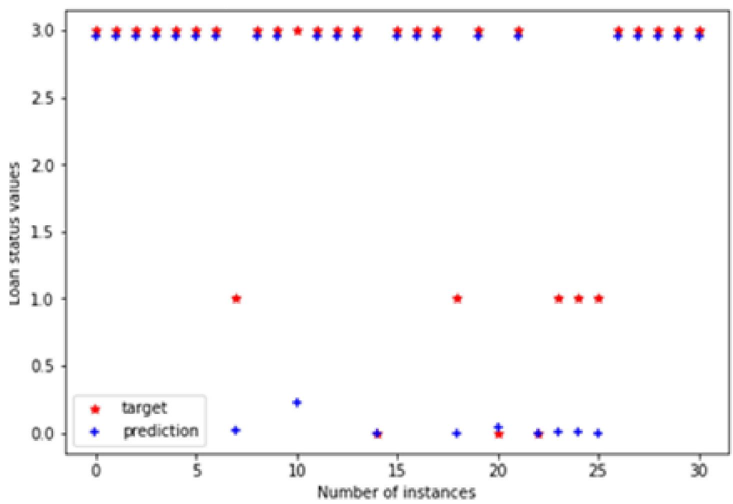

Figure 16: Inference system validation with Hybrid algorithm

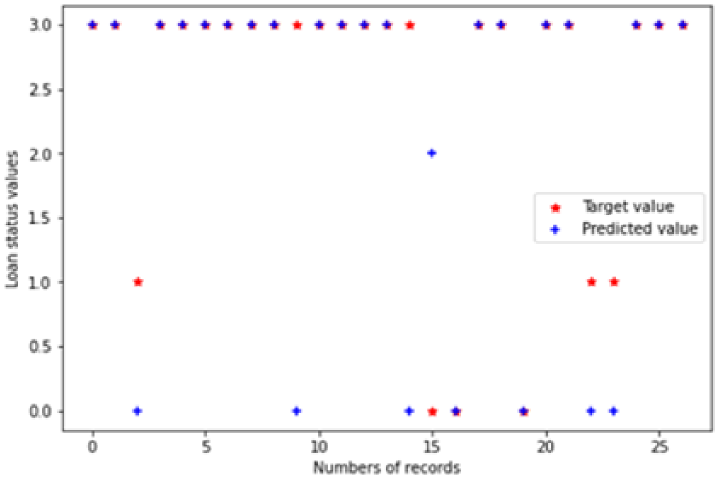

Figure 17: Inference system testing with Hybrid algorithm

Table 5: Training, testing, validation and average errors for hybrid algorithm

Number of Epochs	Training Error	ValidationError	Testing Error	Average Error
0	1.266394	1.403323	1.282128	1.317281
100	0.306463	0.292103	0.324107	0.307557
200	0.238180	0.248431	0.258719	0.244093
300	0.228625	0.246535	0.245670	0.243891
400	0.205398	0.250489	0.244082	0.233323
500	0.19228	0.253540	0.274615	0.240145
600	0.180804	0.247855	0.272338	0.233665
700	0.165057	0.222226	0.271796	0.219693
800	0.159747	0.219173	0.288269	0.222396
900	0.149789	0.166836	0.320803	0.212476
990	0.142137	0.156745	0.334697	0.211193

According to the values shown in Table 5,the inference system training, validation and testing errors decrease in the same direction in steps of 0 epochs until epoch number 400 while at epoch number 500, the training and validation errors continue to decrease while the testing errors start to increase from epoch 800. An average error of 2.458000was observed at epoch 990 in the forward pass learning algorithm while an average error of 0.211193was observed for epoch 990.A comparison of hybrid learning with forward pass algorithm shows that the inference system learning is relatively faster to implement than forward pass algorithm and requires a few number of training epochs to converge. The quick convergence and fast reduction in training error observed in the hybrid learning algorithm is due to the integration of least square strategy in the forward phase and backpropagation gradient descent method in the backward phase. It is also observed that the testing and validation datasets of the hybrid algorithm are very close to the trained inference system output compare to that of the forward pass algorithm. This suggests that the trained system would perform well on the loan eligibility assessment.

System Evaluation

The experimental data for the evaluation of the system were derived based on administration of a questionnaire that featured related questions on users' experiences and responses were based on a five point scaled variables; namely '*Strongly Agree' (SA)*, '*Agree' (A), 'Fairly Agree' (FA), 'Indifferent' (ID)*, and '*Don't*

Agree' (DA). The Questionnaire alongside responses for 200 applicants and personnel recruitment agents that were randomly surveyed is presented in Table 6.

Table 6: Questionnaire on users' experiences

Index	**SA**	**A**	**FA**	**ID**	**DA**	**TOTAL**
The system drawn correct conclusion with accuracy	148	45	5	2	0	200
The user interface is friendly and flexible	148	42	8	2	0	200
The operational system is highly responsive	134	49	15	2	0	200
The system promotes ease of use and is scalable	129	63	7	1	0	200
The system's inferencing is accurate	141	43	11	2	1	200
The system meets user's satisfaction and feedback	147	42	5	4	2	200
The system is recommended for use	159	39	0	1	1	200
The system promotes objectivity above subjectivity	152	37	7	1	3	200

The evaluation of the system was based on *Accuracy* (ϑ), *Precision* (ι), *Recall* (λ) and *F-measure* (κ). While *Accuracy* presents how a measurement comes to its true value and it is important because bad equipment or facility, poor data processing or human error can lead to misleading results that deviate from the truth, *Precision* on its own shows the closeness among a series of measurements of same attribute to each other. Precision also qualifies the number of positive predictions that really belong to positive class. *Recall* qualifies the number of positive class predictions made out of all positive examples in a dataset while *F-Measure* gives a mono score that balances the concerns of precision and recall in a single number. Accuracy, Precision, Recall and F-measure are obtained as follow:

$$\vartheta = (\omega + \psi) * (\omega + \chi + \tau + \psi)^{-1} \tag{20}$$

$$\iota = \omega A * \vartheta(\omega A + \tau C)^{-1} \tag{21}$$

$$\lambda = \omega A * (\omega A + \chi B)^{-1} \tag{22}$$

$$\kappa = 2\iota\lambda(\iota + \lambda)^{-1} \tag{23}$$

$\vartheta$is the number of applicants that satisfy all criteria and loan request successful, $\chi$is the number of applicants that satisfy certain criteria but loan request not successful, $\tau$is the number of applicants that do not satisfy certain criteria though loan request successful and $\psi$is the number of applicants that do not satisfy certain criteria and loan request unsuccessful. The measure of 95%, 77.47%, 76.42% and 82.25% were recorded for *Accuracy*, *Precision*, *Recall* and *F-measure* based on the data obtained from the 200 surveyed individuals. These values show the acceptability and practical function of the proposed system**.**The comparison of the proposed system based on four metrics; namely *Flexibility*, *Accuracy*, *Scalability* and *User Feedback* with other related works is presented in Table 6. While 0 implies not available, 1 means available. It is evident from Table 7 that the output from the current study possessed all the metrics while output from each of the other studies failed to possess one metric or the other.

Table 7: Comparison of Research Work with other Existing System

Attribute	Asogbon*et al.* [38]	Hamdy and Hussein [28]	Ahmed and Ahmed [40]	Goyal and Kaur [25]	Malhotra and Malhotra [41]	Current system
Flexibility	1	1	1	0	1	1
Accuracy	1	1	1	0	1	1
Scalability	0	0	0	1	0	1
User Feedback	0	0	1	1	1	1

V. Conclusion

In some countries of the world, the current agricultural loan facilities are associated with risk of loss resulting from borrower's failure to payback. This risk is often attributed to the failure of most creditors to carrying out reliable credit eligibility check on loan applications. The resultant effect of this is the widespread apathy towards disbursing agricultural loan. The existing process of agricultural loan eligibility assessment by most financial institutions and agencies is based on tabulation and direct analysis. This process requires direct submission of interest by the applicants which may be individuals or corporates. The submission involves filling of application form and attachment of relevant and supporting documents as well as payment of processing fee. The eligibility criteria for most financial institutions and agencies which bear very high resemblance to the attributes presented in this research are subjected to managerial scrutiny towards ascertaining the genuineness of the applications, the associated risks and the ability for effective and efficient loan utilization and servicing [46].

In Nigeria for instance, the tabulation and analysis for loan eligibility assessment is purely manual which subjects the process to several human factors including lack of timeliness and subjectivity. The need for a total deviation and a shift towards online application and processing that is timely, objective and placed all the applicants on equal opportunities formed the basis of this research.

The research work explored and applied the concept of neural network and fuzzy logic to formulate a model for agricultural loan eligibility assessment. A data warehouse component of the model is used for analyzing and reporting the major attributes of interest in the domain of agricultural loan eligibility assessment and its design is based on the multi-dimensional star schema. The fuzzy logic component of the model consists of fuzzifier which is used for converting the crisp inputs to linguistic variables via some predefined membership functions in the fuzzy rule base. The rule base contains some *precedent* and *antecedent* rules that involve linguistic variables. The fuzzy set is facilitated by the assignment of weights to variables and it is used to describe the attributes in terms of *Very High, High, Average, Low* or *Very Low*. The neural network structure of the model consists of input, hidden and output layers. The input layer comprises fifteen (15) data attributes of agricultural loan eligibility assessment and it is connected to the hidden layer of seven (7) nodes towards attaining a better and an acceptable performance level. In essence, the fuzzy logic component of the system will provide managers of agricultural loans the opportunity of using linguistic expressions to handle assessment criteria or attributes that are vague and imprecise in nature with simplicity and high understandability. It will equally offer effective solutions to complex issues such as human character and integrity and some processing uncertainties like personnel fitness and availability. The neural network component on its own is designed to promote error-free and adaptive application of the system by agricultural loan managers based on training and learning experiences.

The implementation of the model with an agricultural loan request dataset established its ability to promote an automated, more objective, less subjective and bias-free decision on loan eligibility. The system was trained using a forward pass (least-square estimate method) and hybrid learning (least-square estimate and gradient descent method) algorithms. The training established that the model experienced no over-fitting. It was also established that the model was properly trained with the appropriate sets of membership function values. The test of the performance of the model using the testing and validation components of the dataset revealed that most of the components are close to each other, suggesting that the trained inference system performs well on the dataset. Out of the 31 validation data, 6 data pairs match with the output while 25 data pairs failed to match, resulting in an error value of 2.456564 between the computed and the desired outputs. During survey-based evaluation, the system recorded 95%, 77.47%, 76.42% and 82.25% for *Accuracy, Precision, Recall* and *F-measure* respectively. These values buttressed the acceptability and practical function of the proposed system. Furthermore, comparative analysis of the proposed system with other related works based on *Flexibility, Accuracy, Scalability* and *User Feedback* showed that the proposed model did very well for all the metrics. Future research focuses on applying the model for loan eligibility assessment in other non-agricultural establishments.

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