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A Hybrid System for Credit Risk Evaluation in Nigeria Micro-Finance Banks (A NIRSAL Micro-Finance Bank Ltd Lesson)

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Abstract

The Nigeria Incentive-Based Risk Sharing System for Agricultural Lending (NIRSAL Plc.) Microfinance Bank is facing financial risk due to non-performing loans, which may lead to loan losses. This is because poor decision-making procedures are employed when awarding these loans, potentially resulting in investors losing money on the borrowers' investments. To solve this issue, a hybrid system based on a belief network and fuzzy-inference model is being developed. Using inputs such as Loan_Request, Collateral_Value, Available_Cash, Average_Income, Deposit_Rate, Withdrawal_Rate, Average_Withdrawal, and Average_Deposit to produce 4 outputs: capital, character, capacity, and collateral. The fuzzy if/then rules are then utilized to assess the degree of credit risk and generate feasible suggestions. The Information used in this paper was obtained from NIRSAL Micro-Finance Bank. The work was executed with Java programming language, HTML, CSS, and MySql. The results of the experiment demonstrated that the mechanism accurately assessed the credit risk and produced the risk level needed for a potential suggestion that will minimize the risk level and the number of default loans incurred in Nirsal Micro-Finance Bank.

Keywords: Credit Risk, fuzzy rules, Belief Network, Nirsal Micro-finance Bank.

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I. Introduction

The focus of this paper is Nigeria's Incentive-Based Risk Sharing System for Agricultural Lending (NIRSAL Plc.), a credit risk assessment of its customers' creditworthiness. To identify and score credit risks for financial loan recommendation and approval, a hybrid system based on artificial intelligence—a Belief Network and fuzzy inference model—is employed. The primary responsibility of the NIRSAL Microfinance Bank is to enable the unrestricted flow of reasonably priced capital and investments to the agricultural industry and domestic resource utilization. Additionally, the Bank collects deposits, distributes them to investors and borrowers, and oversees the recovery of such loans. The bank's other business is protecting its customers' cash and other valuables. In addition, they offer loans, credit, and payment services like bank accounts, and money orders, cashier's checks, counterpart funds, and funds for governmental and non-governmental organizations. However, due to the inherent risk of potential loan losses (credit risk), default loans have historically been the main source of losses at Nirsal Microfinance Bank. Additionally, one of the challenges facing Nirsal microfinance banks is getting the banking system to comprehend the vast amounts of data that customers provide, deciphering ambiguous historical customer records, and figuring out how to extract valuable information to enhance financial decision-making.

Also, credit officers' subjective manual evaluations serve as the basis for evaluating loan requests. Such a judgment is unreliable and non-uniform, counterproductive, unfair, and therefore, unable to glean from previous financial endeavorsof clients. This can result in debt defaults and bankruptcies, which would prevent the nation's economic growth, GDP, and internally generated revenue (IGR). This has caused investors to lose money in NIRSAL Micro-Finance Banks and the public’s inability to access bank loans.

The database structure is described using a tree format by belief networks, also known as Bayes networks. Variables are represented by nodes, and conditional dependencies between variables are represented by branches to produced future events by the belief nets.

On the other hand, Fuzzy-inference systems enumerate all of the information and guidelines that are currently available. The knowledge is saved in a series of "if-then" statements.

The sets of data can be integrated to create the knowledge based that are uncertain and can use its linguistic ability to determine the membership rating to predict an output. [1] states that a hybrid system based on a Fuzzy-Belief Network is designed to model how the brain learns from the past and performs a particular task or function of interest. A Fuzzy-Belief Network hybrid system can imitate how decision-making occurs in humans that involves learning to recognize patterns, improve consistency, provide timely results and greater flexibility, having intermediate possibilities between variables that can also deal with imprecise, untruly, and uncertain data with the aid of knowledgeable rules and probability for an event occurring. It is the realization of these facts and the significance of a Belief-network & Fuzzy inference system in Micro-finance banks that this study seeks to develop a hybrid system-based Belief network and Fuzzy inference system to assist in decision-making regarding the challenges in Nirsal micro-finance banks to determine if a particular customer is qualified for a credit facility and the risk involved before such customer is granted a credit facility.

II. Review of literature

The Nigeria Incentive-Based Risk Sharing System for Agricultural Lending (NIRSAL Plc.), a banking financial institution founded in 2013 with the mission of facilitating the free flow of affordable financing and investments to the agricultural sector and other small and medium

businesses, is the parent company of Nirsal Micro-finance Ltd, also known as NMFB. One of the renowned schemes implemented by the Nirsal Micro-Finance bank is the Agriculture, Small, and Medium Enterprise Interventions Scheme (Asgmeis), which was initiated on the 9th of February 2017 by the banker's committee.

The initiative supports the Federal Government's policy measures to promote Agricultural Businesses and SMEs for sustainable economic development and employment generation in various sectors including agriculture, education, health, services, ICT, manufacturing, mining, creative industry, fashion, design, crafts, and entertainment. [2] (https://www.cbn.gov.ng/FAQS/FAQ.asp?category=Microfinance, 2023).

III. Review of Related literature

Early detection, evaluation, and management of credit risk in Nirsal Micro-finance Bank will better the operation of the bank and its sustainability. This section will explore various methodologies developed in the past and their shortcomings. [3]used a regression model to assess the effects of credit risk mitigation (CRM) regarding the profitability of banks. The study makes use of data from five years' worth of records on profits, non-performing loan volume, and total credit. It demonstrates that the volume of credit and non-performing loans have no bearing on the total profits that banks have gathered. Thus, Regression models are statistical and cannot hold high thresholds of data.

[4] developed a support vector machine (SVM) loan evaluation model to find possible consumer loan clients. The study reveals that vector support machine (VSM) outperforms neural network models in generalization, but its complexity makes it challenging for many humans to understand.

[5] introduced a rule extraction technique for comprehension credit scoring using SVM, retaining SVM accuracy while allowing human interpretation, resulting in a small performance lost compared to SVM.

The ability of rule induction software, fuzzy logic, neural networks, and genetic algorithms, and rough sets to classify credit risk was scrutinized by [6], determined that the fuzzy/genetic approach performed better than the rough set and neuro-fuzzy techniques.

[7] suggested putting in place a system for managing credit risk that is built around creative scoring methods. To establish credit lines and thereby reduce credit risk, her thesis proposes a credit scoring system, three distinct model types are covered: behavioral scorecards, early detection scorecards, and application scorecards.

They were constructed using current, accurate data from a German credit card company. Logistic regression has been utilized to validate the models that were constructed using a training sample. The models have been compared using validation charts and information values. In closing, the author suggests potential directions for future research and expresses hope that the method presented in this thesis can help avert financial disasters in the future to some extent.

[8] investigated the methodologies used by credit union credit scoring models developed using neural links and more conventional methods like discriminant analysis and logistic regression. They examined data samples with eighteen variables gathered from three credit unions and demonstrated that while neural networks performed better overall in classifying loans (bad and good), logistic regression was superior in identifying bad loans.

To classify credit loan applications, and filtering to boost; ensemble averaging; multi-layer perceptions. They discovered that committee machine models were superior and that filtering outperformed ensemble averaging.[9]

Research was done by [10] to determine how well the Z-score and neuro-fuzzy models predicted corporate bankruptcy. The transaction statements of 132 publicly traded companies were used by the writers for their research (25 of which filed for bankruptcy). The authors forecasted the company's likelihood of bankruptcy in 1, 2, and 3 years using both quantitative and qualitative data as input data. The Z-score model and the results obtained using the quantitative data were identical. However, when qualitative data from the neuro-fuzzy model were used, the outcome was noticeably better.

Thus, these techniques were proposed mostly not in Nigeria banking sector without using the customer's financial record of the Nirsal micro-finance bank credit rating criteria (character, collateral, capacity, and capital) 4Cs and learning from traceable records with no information sharing among other banks about customer credit risk history using their Bank Verification Number (BVN) as a unique mode of identification and customers past indebtedness.

IV. Methodology

Design of the hybrid system for the credit risk Evaluation

This work employs a hybrid belief network and fuzzy inference framework, renowned for its ability to learn from historical data and accurately approximate nonlinearities.

The system consists of a Bayes belief network and fuzzy inference engine fragments, representing probabilistic relationships among variables in expert systems. It includes the raw input layer and the fuzzy inference segment as shown in Fig 1.

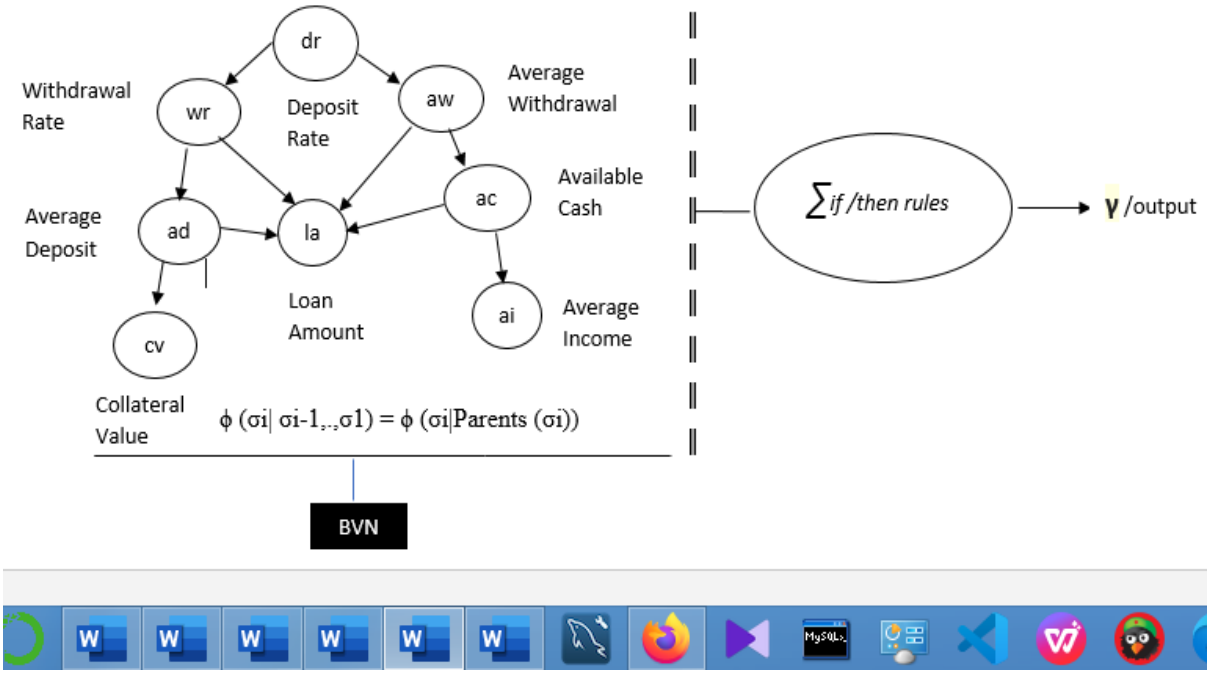


Fig 1: The proposed hybrid system Architecture

Figure 1 shows the layer of input with eight nodes representing deposit_ rate (dr), withdrawal_ rate (wr), loan_amount (la), available_cash (ac), average_deposit (ad),

collateral_value (cv), average_income (ai), and customer BVN. The joint belief network probability distribution equation ϕ(yi|yi-1,....,y1) = ϕ(yi |Parents(yi)) is used to ascertain probabilities, which the inference system if/then rules are used to determine customer the credit worthiness.

The combined probability distribution is used to calculate the probabilities of different combinations of input variables σ1, σ2,σ3 ,.., σn(n=8). This equation is used to determine the probabilities of customer transactions as inputs for a fuzzy inference system, forming the inputs/output membership.

This implies that,
[σ1,σ2, σ3,....., σn].....(1),

it can be written in the following way in terms of the joint probability distribution.
ϕ[σ1| σ2, σ3,....., σn]ϕ[σ2, σ3,....., σn].....(2)
ϕ[σ1| σ2, σ3,....., σn]ϕ σ2|σ3,....., σn]....ϕ[σn-1|σn]ϕ σn].....(3)

In general, for each variable Xi, we can write the equation as:
ϕ σi|σi-1,....., σ1) = ϕ(σi|Parents(σi)) .....(4). As the Belief network probability notation.

P(dr) = 0.09 — Where, P(dr): Deposit rate probability
P(wr)=0.32 — P(wr): Withdrawal rate probability
P(aw): Average Withdrawal Probability
P(aw) = 0.80 — P(ad): Average Deposit probability
P(ad) = 0.05 — P(la): Loan Amount Probability
P(la)= 0.75 — P(ai): Average Income Probability
P(ai)= 0.75 — P(ac): Available Cash Probability
P(ac)= 0.07 — P(ca): Collateral value probability
P(cv)=0.70

The flexible fuzzy inference fragment uses input like capital, character, capacity, and collateral, and links each set membership to a corresponding rule using fuzzy if/then rules. The defuzzification/output layer combines these rules resulting in the output y, which is a single fuzzy operation union.

The Fuzzy inference segment uses the if/then fuzzy rule to assess the credit risk parameters to determining customer risk levels. Notation used for the linguistic variable in the fuzzy rule are: ʉ = Very poor, ɻ= low, Very Low = ƀ, ʍ=Medium, ɠ=Good, ɦ= High, = And, ɥ= Very high.

Input membership values	**Output rating Value**
Very poor <=0.30	Very High <=1.00
Low >=0.25 and <=0.50	High >=0.50 and <=0.60
Medium >=0.50 and <0.65	Good <=0.30 and <=0.40
High >=0.65 and <=0.80	low >=0.23 and <=0.30
very High >=0.80	Very low <=0.10 and 0.12

Application Status: Risk Rejection, Value; S<=0.40, Risk Acceptance Value; >=0.50 and <=1.00.

$(\alpha_1, \beta 1)[\cap][U]\ (\alpha_2, \beta 2_)\ [\cap]\ [U]\ (\alpha_n, \beta n) \longrightarrow \gamma$

γ is the output, ∩ and U are AND and OR logic operators, and (α1, β1) are fuzzy rules in the fuzzy inference notation. α and β are

linguistic variables, which are read as though α is β. For instance, if (capital, h) is read as though capital is high.

The work complied with the guidelines adopted from [11] Gafa et al (2019):

Rule21:*IF*(Collateral.ψ)∩(Capital.ψ)∩(Capacity.ψ)∩(Character.ψ) *THEN* (risk.ϐ), (Accept)

Rule 31: *IF(*Collateral.ϐ)∩(Capital.ϐ)∩(Capacity.ϐ)∩(Character.ψ) *THEN*(risk ψ), (Reject)

Rule 34: *IF(*Collateral.ψ)∩(Capital.ψ)∩(Capacity.ψ)∩(Character.ʍ) *THEN* (risk.ϑ), (Accept)

Rule 28: *IF*(Collateral.ψ)∩(Capital.ψ)∩(Capacity.ψ)∩(Character.ϑ) *THEN* (risk.ϥ), (Accept)

Rule 9: *IF*(Collateral.ψ)∩(Capital.ψ)∩(Capacity.ψ) ∩(Character.ʉ) *THEN* (risk.ϥ), (Accept)

Rule10: *IF(*Collateral.ψ)∩(Capital.ψ)∩(Capacity.ɦ)∩(Character.ψ)*THEN* (risk.ϑ), (Accept)

Rule 41: *IF(*Collateral.ψ)∩(Capital.ψ)∩(Capacity.ʍ)∩(Character.ψ) *THEN* (risk.ϑ), (Accept)

Rule 20: *IF*(Collateral.ψ)∩(Capital.ψ)∩(Capacity.ʍ)∩(Character.ψ)*THEN* (risk.ϥ), (Accept)

Rule40: *IF(*Collateral.ψ)∩(Capital.ψ)∩(Capacity.ϑ)∩(Character.ψ) *THEN* (risk.ϥ),(Accept)

Rule51: *IF(*Collateral.ψ)∩(Capital.ψ)∩(Capacity.ϐ)∩(Character.ψ)*THEN* (risk.ϥ), (Accept)

Rule 44: *IF(*Collateral.ψ)∩(Capital.ɦ)∩(Capacity.ψ)∩(Character.ψ)*THEN* (risk.ϐ), (Accept)

Rule 30: *IF*(Collateral.ψ)∩(Capital.ʍ)∩(Capacity.ψ)∩(Character.ψ)*THEN*(risk.ϥ),(Accept)

Rule 33: *IF(*Collateral.ψ)∩(Capital.ϑ)∩(Capacity.ψ)∩(Character.ψ)*THEN*(risk.ϥ), (Accept)

Rule 14: *IF(*Collateral.ψ)∩(Capital.ψ)∩(Capacity.ψ)∩(Character.ψ)*THEN*(risk.ɦ), (Reject)

Rule 65: *IF(*Collateral.ɦ)∩(Capital.ψ)∩(Capacity.ψ)∩(Character.ψ)*THEN*(risk.ϑ), (Accept)

It can be deduced that; the fuzzy rule is linguistics in nature and is capable of giving a detailed and accurate explanation of events.

The fuzzy inference segment is shown in Equation 5.

$$\begin{aligned} &\text{IF } \alpha 1 \text{ is } \beta\ 1 \\ &\text{AND } \alpha 2 \text{ is } \beta\ 2 \\ &\ldots \\ &\text{AND } \alpha m \text{ is } \beta m \\ &\text{THEN } \gamma = f(\alpha 1, \alpha 2, \ldots, \alpha m) \end{aligned} \qquad (5)$$

Where the train data of the belief network segments is represented by the values β 1, β 2,..., β m, and the fuzzification inputs are represented as collateral, capital, character, and capacity (α1, α2,... αm). Are fuzzy sets which range from $y = \begin{cases} 1, & 0.5 \le f(\alpha) \le 0.9 \\ 0, & otherwise \end{cases}$

γ is the result of applying fuzzy rules for the customer credit portfolio, which can be approved or denied. Thus, from Equation 5, before the fuzzy rules do the evaluation using the If/Then concept, the criteria to be evaluated i.e α1, α2. . . αm (collateral, capital, character, and capacity) must be the input of membership fuzzy sets; β 1, β 2, . . . , β m (Non-crispy values) boundaries/rating. Then the fuzzy inference engine selects the interwoven events α1, α2. . . αm (Collateral, Capital, Character, and Capacity) and compares them with the targeted output to produce an output.

Data Flow Chart

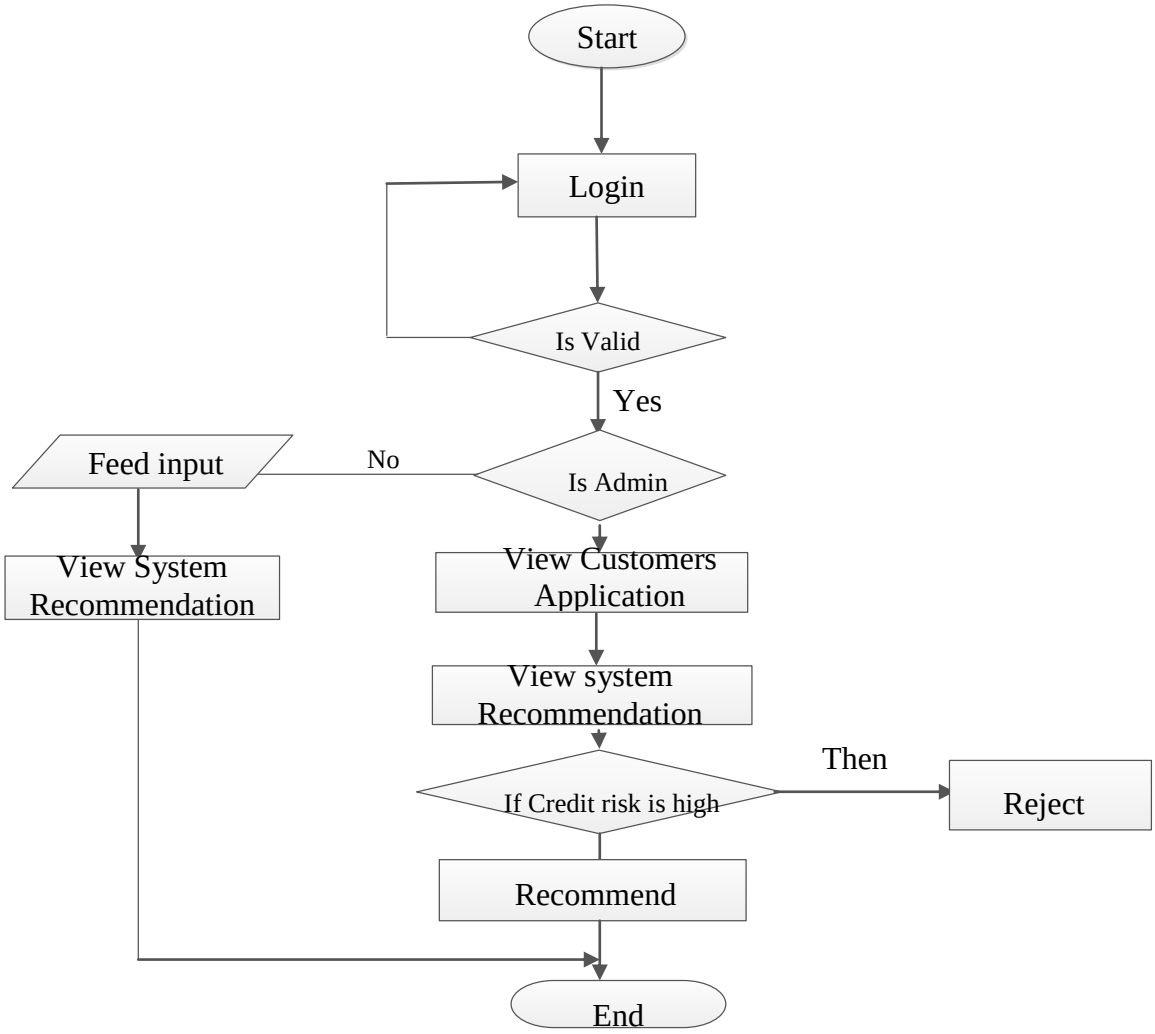


Fig 2: Showing the Flowchart of the Proposed Soft Computing Framework

From Figure 2, When a loan is requested after validation of the user credentials, the hybrid system trains the customer's vague historical financial data to extract the credit risk criteria with the aid of a belief network and it's been evaluated to determine the credit risk level using the fuzzy if/then rules with a decision for acceptance or rejection if the risk level is low or high. The admin then logs in to view the loan recommendation status.

Database Design

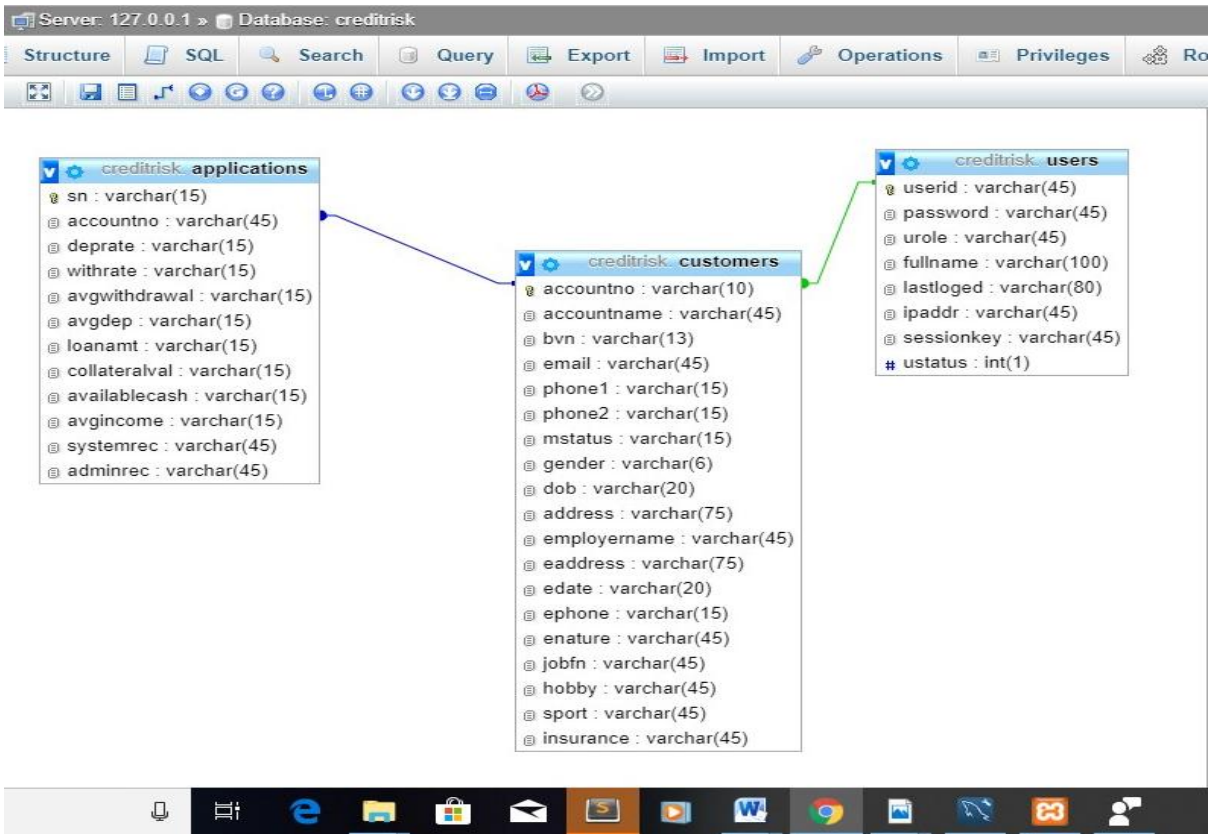


Fig 3: Showing the Soft Computing Framework Database

The database comprises of three relations viz; credit risk criteria, customers' personnel details, and the users in the credit risk evaluation system which are related by their primary key (i.e Account Number and User ID) as shown in Fig 3. The field names represent the fields in the tables, the data type represents the type of data to be accepted by the field and the length represents the maximum number of characters that can be entered in a field. Information on clienteles' credit criteria, phone numbers, account numbers, E-mails, and customers' full names received from the interfaces are kept on file in the database for usage for credit risk level rating.

V. Result

Two experiments were conducted to analyze customer credit risk criteria data, using eight inputs. The results show that the hybrid system can come out with possible recommendations, depending on inputs and results from various data sets.

An overview of the data and the corresponding outcomes are shown in Tables 1 and 2. The hybrid system's inputs and corresponding results, along with a potential recommendation, are shown in the table below.

Experiment 1

In this experiment, a customer files a loan application as shown in Fig 4. The hybrid system then fetches the customer's financial historical data and does the training concerning the customers' input data to determine the customer credit risk level.

In Fig 5, the system admin then logs in and views the system's possible recommendation based on the evaluation. In this experiment, the hybrid system accepts the loan application. As a result, the loan officer also approves of the loan facility. Therefore, the loan facility will be granted to the customer.

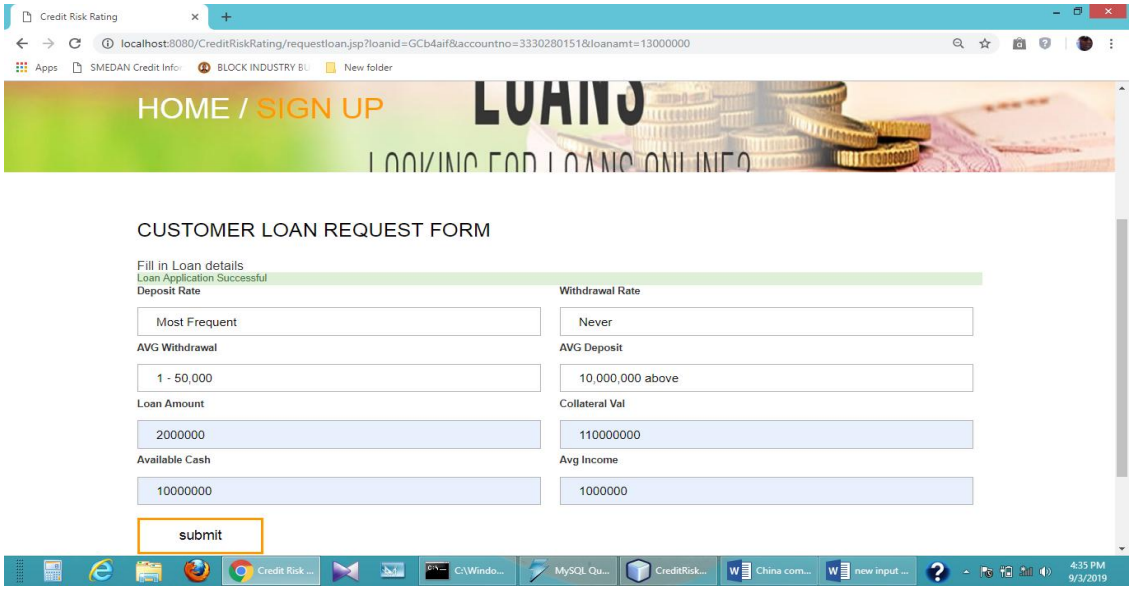


Fig 4: Input Data for Experiment 1

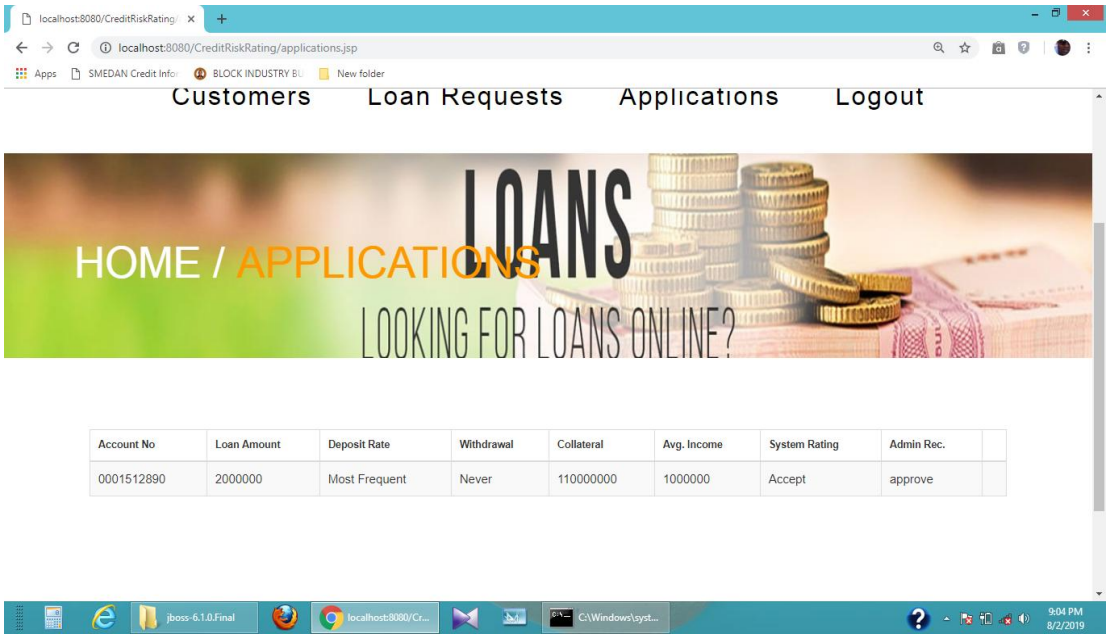


Fig 5: Output Result for Experiment 1

Experiment 2

This experiment shows another customer data with corresponding inputs as displayed in Fig 6. The hybrid system also does another training based on the customer's past financial transaction to determine the credit strength for the recommendation.

In Fig 7, the hybrid system after evaluation rejected the customer loan application which the loan admin also objected to the loan application.

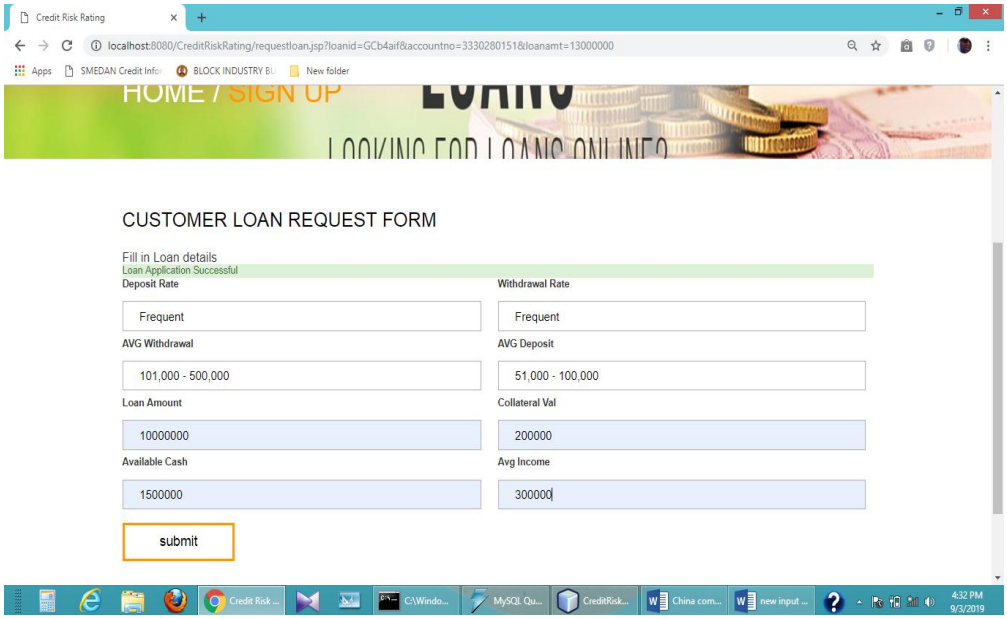


Plate 6: Input Data for Experiment 2

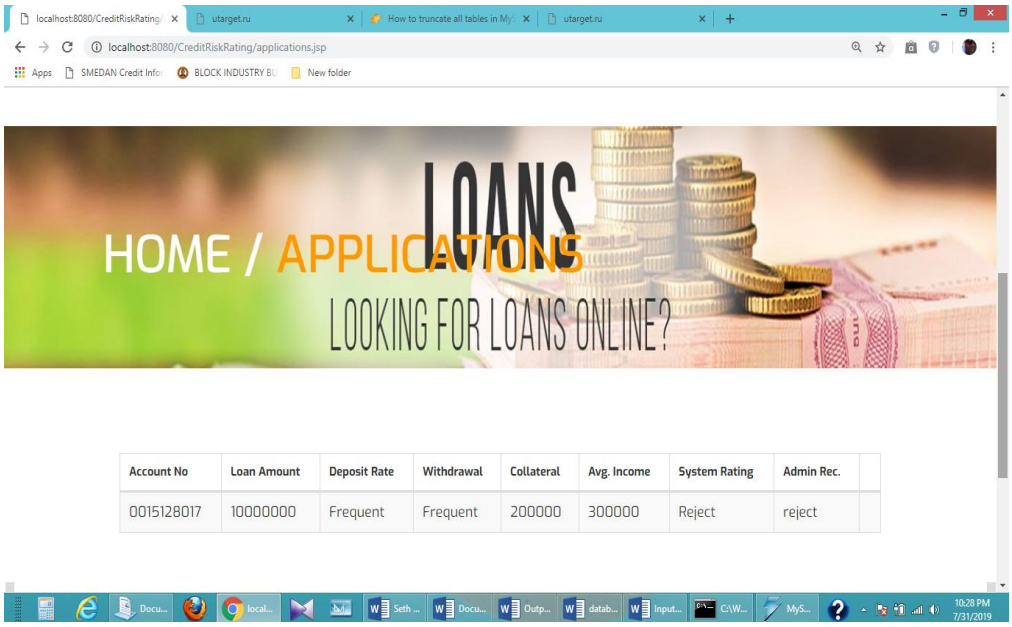


Fig 7: Output Result for Experiment 2

Table 1: Summary of Customer Input Values for Loan Applications

Exp	Dept-Rate	With-Rate	Av- Withr	Loan- Amt	Avgr-Cash	Avg- Deposit	Colla-Value	Avgr-Income
1	Frequent	Most Frequent	51,000-100,000	350,000	120000	1-50,000	500000	85000
2	Frequent	Frequent	101,000-500,000	10000000	1500000	51,000-100,000	2000000	300000

Table 2: Summary of Customer Output for Loan Applications

Experiment	Acct. Number	System rating	Loan Admin recommendation
3	0015128017	Approve	Approve
4	0051512890	Reject	Disapprove

VI. Discussion of Result

Two experiments conducted yielded input values and outputs in Tables 1 and 2. The data in Table 1 represents the Deposit_Rate, Withdrawal_Rate, Average_Withdrawal, Average_Deposit, Loan_Amount, Collateral_Value, Available_Cash, and Average_Income. Experiment 1 resulted in a customer loan application Approved and recommended based on historical financial records. Experiment 2 resulted in loan disapproval due to non-compliant credit criteria.

VII. Conclusion and Recommendation

The system outperforms other models such as Z-score, Takagi-Sugeno, Excel Spreadsheet, discriminant analysis, logic regression, and Mamdani Evolutionary software in its ability to accurately predict credit risk ratings for microfinance banks. These models do not, however, have the requisite threshold for risk rules.

The hybrid Belief network-fuzzy base model uses historical customer (i.e Deposit rate, Withdrawal rate, average withdrawal, average deposit, loan amount, available cash, average income, and BVN) information to evaluate loan applicants' financial transactions, assessing risk levels for loan recommendations. The results also show that the belief-fuzzy inference system is a scalable, reliable, and stable technique and is a significant Artificial intelligence technique for predicting credit risk ratings.

VIII. Recommendation

It is advised that Nirsal Micro-Finance banks use the system to manage credit risk in unclear financial data. Additional artificial intelligence models and statistical tools can be added later on.

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