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Intelligent System for Credit Risk Management in Financial Institutions

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ABSTRACT

Credit crunch is an alarming challenge facing financial institutions in Ghana due to their inability to manage credit risk. Failure to manage credit risk may lead to customers defaulting and institutions becoming bankrupt, making it a major concern for financial institutions and the government. The assessment and evaluation of loan applications based on a loan officer's subjective assessment and human judgment is inefficient, inconsistent, non-uniform, and time consuming. Therefore, a knowledge discovery tool is required to help in decision making regarding the approval of loan application. The aim of this project is to develop an intelligent system based on a decision tree model to manage credit risk. Data was obtained from the bank loan histories. The data is comprised of four hundred observations with seven variables: client age, amount requested, dependents, collateral value, employment sector, employment type, and results. The results of study suggest that the proposed system can be used to predict client eligibility for loans with an accuracy rate of 70%.

KEYWORDS

Artificial Intelligence, Credit Risk, Data Mining Algorithm, Decision Tree, Domain Expert, Expert System, Financial Institutions, Inference Engine, Knowledge Base

INTRODUCTION

Financial institutions such as banks are pursuing to advance their business operations with innovative technologies and intelligent or expert systems. This is to enable them to run their daily business processes such as solving, monitoring and credit risk management. Financial institutions have also undergone some changes due to globalization and use of new technology (Appiahene et al., 2019). This has created increased competition and further risks into the financial institutions. There are many evolving areas in the banking sector and one of the major areas is the risk management. Risk management in the banking sector has three vital areas; Market Risk Management, Credit Risk Management, Operations Risk Management (Kulkarni & Mali, 2015). Banks have been facing financial crises because lending loans to borrowers is one of the major ways to generate profit and this process is mostly done with the credit manager's subjective knowledge. When client or customer defaults there is loss of principal and interest, disruption to cash flow in the banking system, and increased

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collection cost. Several methods have been used in the time past for credit risk management. One of the major problems facing financial institution in Ghana is credit risk management. Inability to manage credit risk may lead to customers defaulting and institution becoming bankrupt, making it a major concern for the financial institutions and the government. Assessment and evaluations of loan applications are based on a loan officer's subjective assessment and mostly human judgment is inefficient, inconsistent, non-uniform and time consuming. Therefore, a knowledge discovery tool is required to help in decision making regarding the approval of loan application. There have been quite enormous numbers of research aimed at evaluating the application of statistical models to corporate data with a view to predicting business failure and credit default in Ghana. This issue has become increasingly important in recent years, in the mist of the current economic crisis popularly referred to as the credit crunch. This has raised the need to develop a robust and reliable model for predicting credit defaulters is important for the growth of every economy as it enables investors, auditors and other stakeholders to independently and fairly evaluates the risk of investment. The main objective is to develop an intelligent system based on decision tree algorithm to manage credit risk using Nsoatreman Rural Bank in Sunyani-Ghana as the case study. The rest of the paper is organized as follows; introduction, review of literature materials, methodology, results analysis and conclusion.

REVIEW OF RELATED WORKS

The application of artificial intelligence and machine learning systems for credit risk management has received extensive academic research in recent years. Credit risk means the probability of non-repayment of bank financial facilities granted to investors (Nazari, 2013; Weber et al., 2015). Credit risk management is defined as identification, measurement, monitoring and control of risk arising from the possibility of default in loan repayments (Kithinji, 2010; Wu et al., 2014). Poor credit risk management or evaluation constitutes the major reason financial institutions become bankrupt due to the huge amount of money being locked up when borrowers defaults. This is the reason why the development of a great variety of strategies to implement reliable prediction models has attracted considerable attention both from academicians and financial analysts over the last decades. Several researchers have explored and analyze the ability machine learning to develop models and software to forecast the credit risk. Alshatti (2015) investigated the impact of credit risk management on bank's financial performance, through ascertaining the credit risk management and financial performance indicators, and to find a pragmatic proof of the degree to which credit risk management affects banks' financial performance. Credit scoring has been acknowledged as a two-fold classification technique, distinguishing applicants into two groups: good credit and bad credit, based on features such as gender, age, occupation, and salary. These conclude the applicability of loans for applicants. There are two conventional classification techniques, statistical techniques and machine learning techniques (He et al., 2018).

Banks and Peer-to-Peer (P2P) platforms rely on credit scoring models for the purpose of estimating the credit risk of their loans, the incentive for model accuracy may differ significantly (Agosto et al., 2019). Credit risk assessment is led by the financial institution itself which, being the actual entity that accepts the risk, is concerned to have the most accurate possible model in banks whiles in a P2P lending platform, credit risk is determined by the platform, but the risk is fully endured by the lender (Agosto et al., 2019; Guo et al., 2016). Khemakhem and Boujelbènea (2015) did a comparative study to determine a discrimination model to detect financial distress of companies requesting credit from banks by means of a new approach based on artificial neural networks and compare the method to discriminant analysis to improve decision support for Tunisian bankers. They found that the percentage of correct classification, resulting from the application of artificial neural networks (82.55%) is better than discriminates analysis (74.4%).

The theory of artificial neural networks is widely used in finance and insurance problems (Ghatge & Halkarnikar, 2013). These authors used the theory of artificial neural networks and business rules to correctly determine whether a customer is default or not. The Feed-forward back propagation neural network is used to predict the credit default. The results of applying the artificial neural networks methodology to classify credit risk based upon selected parameters show abilities of the network to learn the patterns. As part of artificial intelligence, data mining techniques like classification and prediction can be applied to solve credit risk management to a great extent. Sivasree and Rekha (2015) introduce an effective prediction model for the bankers that help them predict the credible customers who have applied for loan; Decision Tree Induction Data Mining Algorithm was applied to predict the attributes relevant for credibility.

Recently, researchers have found that expert systems perform very well for this complex credit risk issues and unstructured problem when compared to more traditional statistical approaches. Mahmoud et al. (2015) presents an Expert System for Evaluating and Supporting Credit Decisions on the Banking sector (ESESCDB) uses the credit rating weights for each factor that affecting the decision of the credit. This work has established an expert system tool that aids the decision maker to issue the right decision with familiar and easy-to-use interface. Comparing and choosing most suitable approach in evaluating credit score, Hooman et al. (2018) presented a comprehensive literature survey on data mining methods, such as discriminant analysis, logistic regression, K-nearest neighbor, Bayesian classifier, decision tree, neural network, survival analysis, fuzzy rule-based system, support vector machine, and hybrid methods. The results showed that Decision tree has better logical relationship, flexibility, easy to interpret, efficiency. Using credit scoring as a mean to curb credit scoring, Pacelli and Azzollini (2011) explore the effectiveness of two credit scoring models Radial basis function (RBF) and Logistic regression (LR) model in evaluating credit applications and investigate the superiority of the RBF model over logistic regression in screening out potential defaulters. Their results suggest that the LR is more accurate and interpretive than the RBF model, although the RBF showed encouraging results for screening bad applications. However, the decision on the best model is up to the bank's management.

Two or more data mining algorithms can be integrated to develop better predictive model for evaluating credit risk. The Credit Risk Evaluating System uses the Decision Tree – Neuro Based Model. Kabari and Nwachukwu (2013) presented a system that uses an integration of decision tree and artificial neural networks with a hybrid of Decision Tree algorithm and Multilayer Feed-forward Neural Network with back propagation learning algorithm to build up the proposed model. Their research results indicate that Decision Tree-Neuro Based Models produced 88% success rate and better explanatory background are successful technology that can adapt to the present day loan application evaluation in commercial banks. Min and Lee (2014) paper presents a new method of credit scoring using Data Envelopment Analysis (DEA). As opposed to broadly know multiple discriminant analysis, logistic regression analysis, and neural networks, DEA require only ex post information to calculate credit scores. The discriminatory power of this method was also tested by comparing its results against those obtained by regression analysis and discriminant analysis, and by using actual bankruptcy cases and was positive.

Clustering algorithms have been widely used in financial risk analysis, presented an MCDM-based approach to evaluate clustering algorithms and indicate that the repeated-bisection method leads to good 2-way clustering solutions on the selected financial risk data sets (Kou et al., 2014). Zhang et al. (2016) used public dataset from a leading online P2P platform in China to study the loan default and constructed a credit scoring model by fusing social media information credit information based on decision tree.

Mohammadi and Zangeneh (2016) proposed a model that was very effective and leads a system to be able to correctly classify the inputs with high Accuracy and outperforms the other two, with C4.5 decision tree followed by Linear Regression. Khemakhem and Boujelbènea (2015) explored two techniques and concluded that an artificial neural network is better than discriminates analysis individually, but neural approach and discriminant analysis are two complementary techniques. Discriminates analysis allows us to select the most relevant variables and the neural network can resume variables and calculates the lowest error rate. Hamid and Ahmed (2016) implemented three algorithms j48, bayesNet and naïve Bayes using Weka application to build a predictive model that can be used to predict and classify the customers into good or bad loan by investigate customer behaviors and previous pay back credit. J48 algorithm is best because it has high accuracy of 78.4% and low mean absolute error. Sudhakar et al. (2016) in a study explored the performance of two-step credit scoring or combined credit scoring models which is very useful and accurately classifies the loan applications using traditional credit scoring and improved behavior scoring using Logistic regression, Multilayer Perceptron Model, Radial basis neural network, SVM and decision trees (C4.5) approaches.

Addo et al. (2018) built binary classifiers based on machine and deep learning models on real data in predicting loan default probability and noticed that the tree-based models are more stable than the models based on multilayer artificial neural networks. Measuring the prediction performance of four machine learning algorithms to predict Loan Default Prediction: Logistic Regression, K-Nearest Neighbors (KNN), the tree-based classifier, Classification and Regression Tree (CART) and Random Forest (RF) using the metric Area Under the Curve (AUC), F1 score, Recall, Precision, Accuracy using the ROC Curve, which plots the true positive rates against false positive rates (Kumar, 2018). Applying different approach Min and Lee's (2014) paper presents a new method of credit scoring using Data envelopment analysis (DEA). Different from the machine learning algorithms like logistic regression analysis, and neural networks, DEA requires only ex post information to calculate credit scores. The empirical results suggest that this new approach can serve as an encouraging substitute for augmenting current credit scoring methods used by commercial banks and credit industry.

The predictive performance of four techniques for predicting mortgage defaults compared namely; Boosted Regression Trees (BRT) and Random Forests (RF) under machine learning algorithm and Logistic Regression (LR) and semi-parametric Generalized Additive Models (GAMs) from statistical models. These techniques were assessed using the H-measure and performance differences on four large real-life datasets were evaluated using an appropriate statistical testing procedure. The results of the empirical study showed that BRT performed significantly better than LR. Although BRT and GAMs were first and second in the overall ranking (Fitzpatrick & Mues, 2015). Other algorithms also perform well in credit risk and scoring, (Harris, 2015) introduced the use of the CSVM for credit scoring. Their study compares the CSVM with other nonlinear SVM based techniques and shows that the CSVM can achieve cutting edge performance coupled with its comparatively cheap computational cost makes it an interesting algorithm in the credit scoring space. Jin and Zhu (2015) explores the characteristics of loan and its applicant. The empirical result of their study shows that the term of loan, annual income, the amount of loan, debt-to-income ratio, credit grade and revolving line utilization play an important role in loan defaults. And SVM, Classification and Regression Tree (CART) and Multilayer perceptron (MPL)'s prediction performance are almost equal. Sullivan et al. (2018) recommend improving the framework of logistic regression using information from decision trees and rules extracted from various short-depth decision trees built with different sets of predictive variables (singletons and couples) are considered as predictors in a penalized or regularized logistic regression.

METHODOLOGY

The Decision Tree

A decision Tree is one of the most popular classification technique. It is a structure that includes a root node, branches, and leaf nodes. Each internal node denotes a test on an attribute, each branch denotes the outcome of a test, and each leaf node holds a class label. The topmost node in the tree is the root node. R programming language can be used to generate the decision tree based on data collected or historical data. Decision tree are self-explanatory and can be easily converted to set of rules so after generating the decision tree model for easy decision making. There are different decision tree algorithms based on how to select the attributes and pruning mechanism for creating tree. While making decision tree, at each node of tree there is a decision or split. Based on decision or split, the information gain corresponding to it is calculated. Information gain is used to decide which feature to split on at each step in building the tree.

Divide the dataset into, D, as a training set of class-labeled tuples. Suppose the class label attribute has m different values to define m different classes $C_i \left(i = 1,\ldots,m\right)$. Set $C_{i,D}$ as the set of tuples of class C_i in D. $|D|$ is the number of tuples in D, and $|C_{i,D}|$ is the number of tuples in $C_{i,D}$. Set node N store the tuples of partition D. The attribute of the highest information gain is chosen as the splitting attribute of the node N. Firstly, the information entropy (expected information) needed to classify the tuple in D is given by:

$$info\left(D\right) = -\sum_{i=1}^{m} p_i \, log_2\left(p_i\right) \tag{1}$$

Suppose we use some attribute *A* to divided tuples in *D*. According to the training dataset, A has v distinct values $\left\{a_1, a_2 \;\ldots,\; a_v\right\}$. Using attribute *A*, tuples in *D* can be divided into *v* partitions or subsets $\left\{D_1, D_2 \;\ldots,\; D_v\right\}$. In order to get an accurate classification, the information needs to be measured by:

$$info_A\left(D\right) = -\sum_{j=1}^{v} \frac{\left|D_j\right|}{\left|D\right|} x\, info\left(D_j\right) \tag{2}$$

where $\frac{\left|D_j\right|}{\left|D\right|}$ is the weight of the jth division. Then, the information gain equals to the difference between the original information demand and the new demand:

$$Gain\left(A\right) = info\left(D\right) - info_A\left(D\right) \tag{3}$$

Both C4.5 and C5.0 algorithms are improved to ID3, in which gain ratio is used to overcome the characteristics that biased toward tests with many outcomes, and they can deal with continuous attributes. The gain ratio is defined as:

$$GrainRate\left(A\right) = \frac{Grain\left(A\right)}{Splitinfo_A\left(D\right)} \tag{4}$$

where $Splitinfo_A\left(D\right)$ is defined as:

$$Splitinfo_A\left(D\right) = -\sum_{j=1}^{v} \frac{\left|D_j\right|}{\left|D\right|} x\, log_2\left(\frac{\left|D_j\right|}{\left|D\right|}\right) \tag{5}$$

The Study Area and Data Collection

The Nsoatreman Rural Bank was founded in October 1984 at Nsoatre as a private rural-based banking institution in the Brong Ahafo Region. Nsoatreman Rural Bank is headquartered at Nsoatre in the Sunyani west district off the Berekum road. Apart from the Head Office, the bank's catchment area extends to Jinijini in the Berekum West District (22 kilometers from the head office), Sunyani (19 kilometers from the head office), Chiraa in the Sunyani West District and Yamfo in the Tano North District (both 38 kilometers from the head office) and Techiman (83 kilometers from the head office). There are over 415,352 populations in the current operating districts; the bank has over 50,219 clients from different background and embarking on different business. It has been in operation since 1984. The study targeted Nsoatreman rural bank Sunyani branch and type of loan clients, mostly apply which includes Individual susu loan, farmers' loan and salaried loan.

The data were obtained from the bank's relational database of clients' loan history. The data comprises of four hundred (observations) clients who applied for the loan. The above number was enough to help us to study and observe the trend to reach our conclusion and aid our decision making. The data used for the decision tree include seven variables, client's age, amount requested, dependents, collateral value, employment sector, employment type, results. The age of the client, amount requested, number of dependence and collateral value are continuous and independent variables, Employment sector, employment type is categorical and independent variables, but the results are categorical variable and dependent variable. Table 1 below shows sample of the dataset used for the study, where PV=Private Sector and GVT=Government Sector, V1, V2, V3, V4, V5, V6, V7 represent age, Amount Requested, Dependence, Collateral value, Employment Sector, Employment type and Results respectively.

The System Architecture of the Existing Credit Approval Process

When it is required to obtain credit scoring, one has to undergo a process of evaluation before the credit score is sanctioned. This process is called as credit evaluation, which may take time, but concludes in either an approval or a rejection. Before a potential debtor wants to obtain credit, he or she must be evaluated on certain areas. The credit evaluation process involves credit report, character, capacity, cash flow, and collateral. Figure 1 describes the existing workflow credit approval process the bank uses.

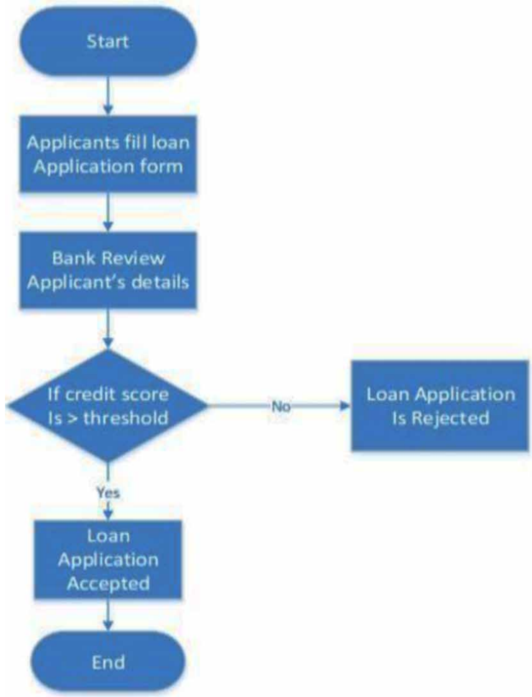
The System Architecture of Proposed Intelligent System

The proposed system and system model focuses on predicting the credibility of customers for loan repayment by analyzing their credit history. The input to the model is the customer credit history collected. Based on the output from the classifier, the decision on whether to approve or reject the

Table 1. Sample of data

Age	Amount Requested (GH ₵)	Dependence	Collateral Value (GH ₵)	Employment Sector	Employment Type	Results
V1	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**
45	4850	4	5980	PV	Permanent	low
40	6000	5	8400	PV	Permanent	low
38	6450	5	30000	PV	Permanent	high
51	2800	1	3500	PV	Permanent	low
47	8620	6	8000	PV	Permanent	default
29	4800	0	3975	GVT	Permanent	default

Figure 1. Demonstrating the classical or existing manual system for evaluating loan application



customer request can be made. Decision Tree Algorithm data mining technique is used to generate the relevant attributes and also make the decision on the model. Architecture of the proposed system is as shown in Figure 2. Figure 3 shows a proposed system flowchart.

ANALYSIS OF RESULTS

Figure 4 shows the home page of the Intelligent System for Credit Risk Management.

Figure 2. Showing the system architecture of the bank credit risk management software

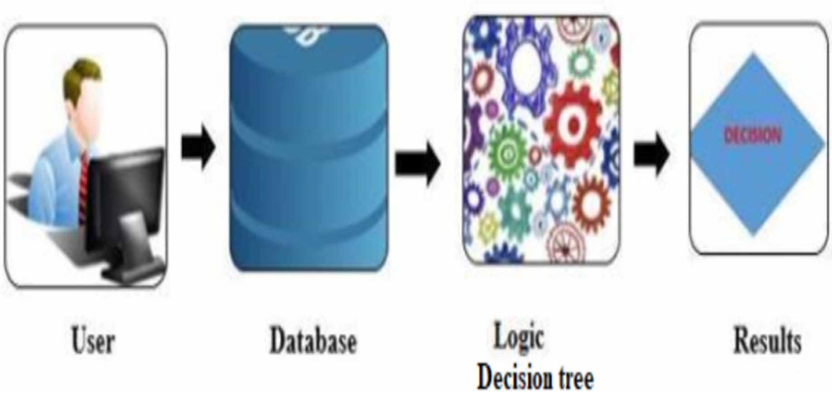


Figure 3. Proposed system flowchart

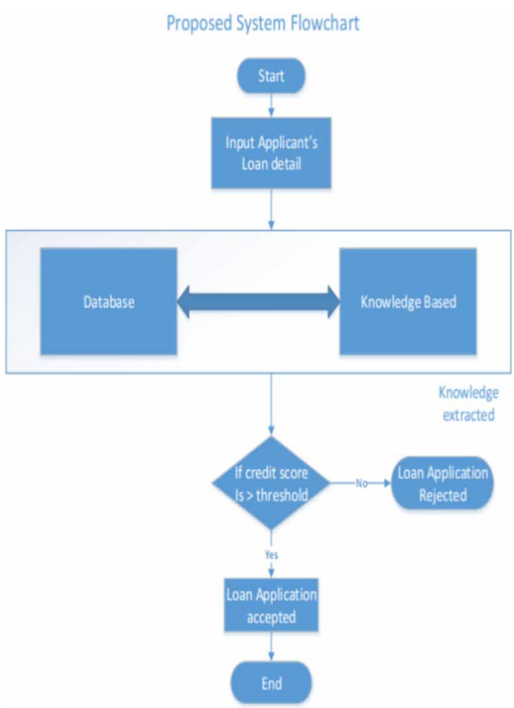


Figure 4. Home page

The Confusion Matrix and Statistics of the Decision Tree Model in System

Overall Statistics Accuracy: 0.7009

In Table 2, the leading diagonal shows observations that were correctly classified and correctly predicted in the decision tree model. The other values are observations that were classified and predicted otherwise. Default means clients who are classified that they could not repay their loans, high are clients who are classified that they repay their loans, therefore they can be granted loans, low and moderate are clients who has a minimum chance to repay their loans. Out of the 400 observations, 117 representing the 30% was used for testing. The model was able to predict 2 observations correctly as default out of the 7 classified as default, 72 was correctly predicted as high out 76 being classified as high, in the low classification 5 out 16 was predicted correctly, lastly 3 out 18 was correctly predicted as moderate.

The results from the proposed decision tree model suggest that decision tree as a data mining algorithm can be used to predict clients' eligibility for loans with an accuracy rate of 70%. The proposed system and the decision tree model helped the Loan officer to evaluate twice the number of clients' loan application form as compared to the existing manual system.

There were many predictor variables that could be used to evaluate client eligibility for loans, but age, number of dependents, employment, payback period and security for the loan such as collateral and the contribution being made are best.

CONCLUSION

In this technology driven era where computer algorithms are designed to evaluate huge data like clients' loan history. It is important that banks and financial institutions in developing countries should focus applying knowledge discovery tool like artificial intelligence in assessing and evaluating clients' loan application. Although the dimension of the dataset this work is not high enough, our model has good classification accuracy. In conclusion, the main objective of this project was to develop an intelligent system to manage credit risk and generate a decision tree model. The logic behind the system is, rules are drawn from the decision tree model generated, and also the loans officer's view of evaluating eligibility for giving loans. To actually confirm that decision tree algorithm can be used to predict loans defaulters, R programming language was used to generate the decision tree model. The Intelligent system was developed to assist the process of credit risk management to prevent bankruptcy, enable knowledge to be modeled and re-used in different areas of the financial institution, and speed up processes and make correct and consistent decision.

Table 2. Confusion Matrix and statistics

Prediction	Default	High	Low	Moderate
Default	2	0	0	0
high	1	72	9	9
low	3	1	5	6
moderate	1	3	2	3

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