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Effectiveness of Artificial Neural Network in Credit Risk Analysis

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Abstract

Artificial Neural Networks play an increasingly important role in financial applications for such tasks as pattern recognition, classification, and time series forecasting. In recent years, there has been an increase in the number of non – performing loans in kenya which has affected many financial institutions . In this paper, the researcher evaluates how neural network model can be used for loan default prediction. The prediction is performed by taking into consideration the financial and personal details provided by the potential customer. A multi-layer feed-forward neural network with back propagation learning algorithm was used for this purpose, the neural network is trained and tested using the dataset provided by several financial institution in kenya. Before training the neural network, Preprocessing is performed on the dataset in order to reduce the dimensionality of the dataset. Based on the results obtained from WEKA, it is inferred that neural network model outperforms other classifiers that are traditionally used by financial institutions for loan default prediction.

Keywords — Loan Default Prediction, Neural Network, Classifiers, Variables, Weka

1.0 INTRODUCTION

Along with the financial market, the credit business of banking industry is also rapidly expanding with extreme competition. At the same time, consumption method by the consumer has turned the consumer loan into major competitive market. According to banking laws, "Consumer loan" is defined as personal credits provided by financial institution which is played back by the method of installment payment and is generally provided for personal or family consumption, to pay certain expenses, such as medical cost, education cost, travelling cost or to pay some other accumulated debt taken with some other purpose of consumption. With increase in "Consumer loan" provided by financial institutions, the scenario of loan default is also increasing. With excessive competition in between different financial institutions to attract more consumers, it became important to not to deny the loan or simply provide the loan to consumer. To provide loan, it is important to know whether the consumer will be able to pay back the provided loan or not. Although, financial institutes provide "Consumer Loan" with extreme caution and after various affirmations, but still there are some cases in which consumer is not able to pay the loan back. Artificial neural network is computing systems made up of a number of simple ,highly interconnected processing elements which process information by their dynamic state response to external inputs. Artificial neural networks have been successfully used in a variety of business fields including marketing, accounting, management information systems, and production management (Cao and Parry, 2009). Most of the studies have used neural networks for predicting future stock behavior, financial crises, bankruptcy, exchange rate, and detecting credit card fraud. The granting of loans by banks is one of the key areas concerning decision problems that need subtle care (Handzi et.al, 2003). Neural Networks have successfully provided effective credit evaluations for supporting granting loans. Researchers are currently focusing on using neural network classification models and particularly back propagation neural networks in classifying loan applications into good and bad ones. This research attempts to explore whether using neural networks will provide more accurate personal loan decisions in selected Kenya commercial banks. In figure 1 a0 to an represents inputs to the neuron, the weights attached to each input are shown as w_{jo} to w_{jn} which are numerical indicators of the strength of each input S_j. this inputs multiplied by the weights are added together and compared with some threshold value to

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determine if the neuron should fire or not, this is processed by a threshold function $f(s_j)$.

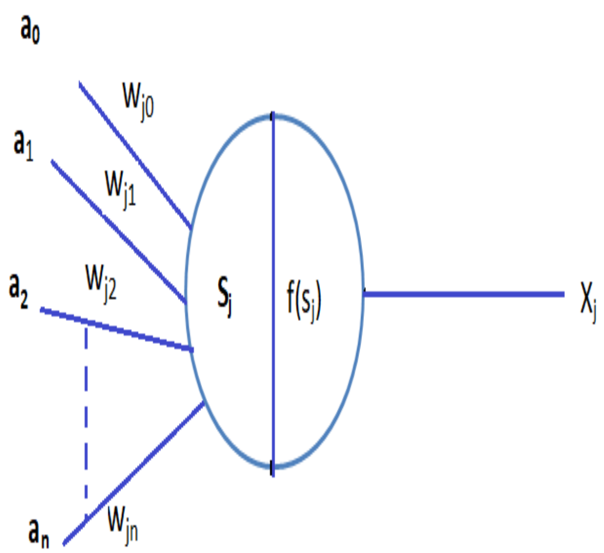

Figure 1 A classical neural Network.

1.1 PROBLEM STATEMENT

Credit scoring systems has not been commonly used in kenya commercial banks. Generally, the bank employs loan officers to make credit decisions or recommendations for the bank. The lending officer usually makes approval for applications that are worthy of giving a loan. These officers are given some guidelines to direct them in evaluating the worthiness of loan applications depending on the borrowers' characteristics. This practice is inefficient, inconsistent and non-uniform. The increase in consumer loans defaults and competition in kenya banking market is high , most of the Kenyan commercial banks are reluctant to use artificial intelligence software technologies in their decision-making routines. Generally, bank loan officers rely on traditional methods to guide them in evaluating the worthiness of loan applications. A checklist of bank rules and regulations, conventional statistical methods and personal judgment are used to evaluate loan applications. Furthermore, a loan officer's credit decision or recommendation for loan worthiness is biased. After some experience, these officers develop their own experiential knowledge or intuition to judge the worthiness of a loan decision. Given the absence of neutrality, such judgment is biased, ambiguous, and nonlinear and humans have limited capabilities to discover useful relationships or patterns from a large volume of historical data (Handzic et al., 2003). Generally, loan applications evaluations are based on a loan officers' subjective assessment. Therefore, a knowledge discovery tool (expert system) is needed to assist in decision making regarding the application. Furthermore, the complexity of loan decision tools and variation between applications is an opportunity for an artificial neural-computing tool to provide learning capability that does not exist in other knowledge based methods.

1.2 OBJECTIVES:

This study aims to evaluate whether neural network is effective in credit decision modeling kenya commercial banks. This is the first empirical research of its kind in kenya that addresses this issue of using artificial neural networks in credit risks. Neural networks with their capability of capturing nonlinear and complex relationships are a powerful alternative to the conventional forecasting and classification methods. Neural networks are consistent paradigms of the nonparametric approach in financial modeling due to their ability to correctly classify and predict consumer loan defaults. The purpose of using the neural network algorithm in bank loan decisions is to simplify a loan officer's job, to control it and to achieve more efficiency and productivity (Curry and Moutinho, 1993). This study explores the power of using NNs in banks for loan approval.

1.2.1 SPECIFIC OBJECTIVES

i. To recognize neural networks as an qualifying tool for evaluating credit applications to support loan officers in decision making.
ii. Show the role played by different variables in risk evaluation.
iii. To outline the contests of using neural networks in credit risk evaluation

1.3 CREDIT RISK VARIABLES

Credit risk variables are defined as those variables which influence Consumer credit. According to Updegrave (1987) there are eight key factors of the credit risk that influenced the credit or short-term loan. These factors are: Number of creditors, declared bankruptcy or not, previous payment records, consumer's income, work/resident duration, occupation, age, consumer possess the saving account or checking account. Similarly, according to Steenackers and Goovaerts (1989) the key factors which may have influenced the credit loan are borrower's age, district, resident/work duration, owner of phone, whether working in public sector, house ownership, monthly income and it has also been pointed that loan duration and its numbers also have a significant relationship with paying back the loan to financial institution. Thus, it can be said that there are different variables which influence the loan default scenario which also includes demographic variables. In addition, as rightly pointed out by Chiang, Chow, and Liu (2002) there are various individual characteristics such as attitude of borrower which also influences the default risk behavior of the borrower. In this study the following variable were considered they include :- credit rating, consumer income, debt-income ratio, job occupation, house ownership, Gender, Age, marital status, No of dependents, no of loans, County among others as shown in table 1.

2.0 LITERATURE REVIEW

There are several model in existence that are used in credit risk prediction. In this process It is important to use correct model from various different models present because the model chosen plays a crucial role in determining efficiency, accuracy and precision of the system. Predictor variables provide data which influences the credit loan risk but predicting models uses this data to predict whether the particular instance may be loan default instance or not. However, from various models, there is no specific model which can be said as the best model. Currently, the various models which are frequently used for prediction purposes include statistic-oriented models such as Discriminant Analysis (DA) and Logistic Regression (LR). Neural Networks (NN) , genetic algorithms (GA) are also used for this purpose. Sueyoshi (1999) used mathematic programming viewpoint to create a predictor system. This system integrated the programming concept of the integer with data Development analysis in order to create new and innovative kind of Data development Analysis.

Chen and Huang (2003) analyzed credit risk by using actual borrower's data of UCI Database as the sample and analyzed it on DA, Classification and Regression Tree (CART) and BPN to discover that each and every one of them has their own specialty. Noh et al. (2005) used data of credit card center of South Korea to create a new predicting model of credit risk while considering time-dependent characteristics and considered this data as predicting variables, and then adapted survival analysis (SA) to compare capability with LR and NN. LR and NN have better precision rate for good borrower, but SA got better sensitivity of predicting default borrower.

Lee et al. (2006) conducted a research by using data of credit customers in Taiwan, compared different models created applied using CART, DA, NN, MARS and LR models and the research concluded that MARS and CART have better average accuracy for classification than the other 3 compared models. Thus, DA and LR can be used to analyze the predicting variables that may influence loan default significantly. NN has better adaptability than other predicting models and this model is able to construct non-linear model and can better adapt predicting variables than other models.

3.0 METHODOLOGY

In this study, data was provided by Kenya commercial banks which were used to identify the most significant attributes that may be of influence in loan default. Most influencing variables are highlighted which can further be used as input variables in the predicting model ,less significant influencing characteristics are omitted. This leads to significant decrease in preprocessing time and also improves efficiency and provides efficient system. The dataset provided by Kenya commercial Bank is unstructured and with lots of dimensions, some of which are correlated to each other and hence. To counter this problem the research used dimension reduction techniques on the data set collected as shown in the Figure

This study builds a neural network that simulated the physical neural process by which human learning takes place and intuition is formed. The researcher used a multilayer feed-forward neural

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network model. By using a supervised back propagation learning algorithm to train the net with a set of cases from the banking sector, the Neural Network will learn by example after being given a sufficient number of input/output cases . A neural network has three layers: the input layer , the hidden layer(s) and the output layer as shown in figure 2.

Hidden layers form a processing bridge between source and destination (Shaaf, 1996). The most significant elements in the NN are: The neuron (the processing element) which has an input (a) or more and only one output and the interconnection between the processing elements which are represented by weights (Pollard, 1990). Each input is associate with some weight (w) . There are three basic phases of NN learning, recalling and testing. The system is trained on historical examples of input and output variables. During this learning process, the system learns to recognize patterns by constructing the relationship between inputs and outputs coming up with the final output. Then, a comparison between the actual and desired output occurs and errors are calculated (Shaaf, 1996). The errors are used to adjust the weights so that the variation between source values and target values is minimized. The concept of learning by example is the most important concept for training the network. Since the neural network provides output on the basis of its prior training, the training must be representative of the targeted population. Then the learned pattern can be used in the testing phase to examine the accuracy of the network.

This procedure is based on the neural network methodology for designing a credit-scoring model that can be used by Kenya Commercial banks for decision making regarding loans. Credit scoring is the key in reducing the credit risk on loan applications. This includes determining the financial strength of the borrowers, approximating the probability of default and reducing the risk of non-payment to an acceptable level. Credit scoring employs a model of evaluating a set of variables to determine creditworthiness of similar loan applications. A combined score is calculated relative to the value of each variable. The result will be compared to a threshold point. If the score exceeds the threshold point, the application is approved; if not, the application is rejected (Tafti and Nikbakht, 1993). However, the scoring cannot totally remove the loan officer. The selection of cutoff scores is a subjective decision. The evaluation of applications that have scores between the accepted scores and rejected scores is an individual judgment (Malhotra and Malhotra, 2003). Credit scoring models have the potential in reducing the inconsistency of credit decisions and adding effectiveness to the lending risk assessment practice. Moreover, in addition to their role in the loan approval process, credit scoring models assist on loan pricing, loan monitoring, determining the amount of credit, credit risk management and the assessment of loan portfolio risks. Credit scoring is widely applied in consumer lending mainly in credit cards and mortgage lending (Limsombunchai et al., 2005). However, there are some challenges associated with scoring consumer credits-

Table 1 Loan Risk Factors

Variable Code	Variable description	Variable Coding
X_1	Age	Integer values btw 18-100
X_2	Consumer income	0 if income <30k, 1 for 30<=100k and 2 for income>=100k
X_3	House ownership	1 for yes 0 for none
X_4	No of existing loans	0 for none, 1 for existing loans
X_5	Credit rating	0 for bad 1 for good
X_6	Guarantor	0 for no guarantor 1 for guarantor
X_7	Gender	0 for female 1 for Male
X_8	Loan size	0 for less than 100k, 1 for more than 100k
X_9	Marital status	1 for married 0 for not married
X_{10}	No of dependents	0 for none 1 for dependents
X_{11}	Purpose	Qualitative (car, mortgage, marriage)

The loan risk factors are further shown as a neural network in figure 2 with eleven variables, the figure shows the input layers, hidden layers and the output Xj.

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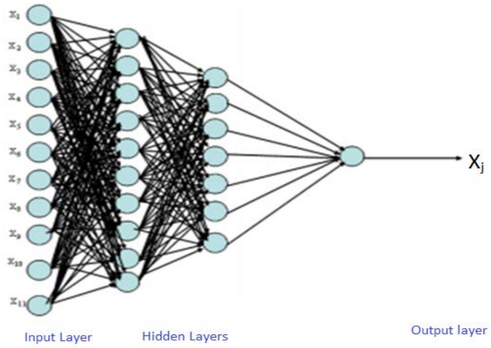

Figure 2: Input, hidden and output layers

4.0 RESULTS AND DISCUSSIONS

This chapter gives an analysis; interpretations of the research findings based on machine learning algorithm namely Artificial Neural Network. An experiment was done to examine 1000 customers with the selected variables in table 1. The data was collected from both primary and secondary data selected from both banks and individuals. The experiments were conducted using WEKA, a data mining tool. This analysis was done with reference to the objectives aforementioned in the research objectives. These findings were used to explain the results and future work. The experiment gave an accuracy of 99.3%. The figure 4.0 gives statistical summary of the experiment conducted including the confusion matrix.

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=== Summary ===

Correctly Classified Instances         993               99.3    %
Incorrectly Classified Instances         7                0.7    %
Kappa statistic                          0.9832
Mean absolute error                      0.012
Root mean squared error                  0.0841
Relative absolute error                  2.8505 %
Root relative squared error             18.3471 %
Total Number of Instances             1000

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 1.000    0.023    0.990      1.000    0.995      0.983    0.982     0.986     good
                 0.977    0.000    1.000      0.977    0.988      0.983    0.982     0.985     bad
Weighted Avg.    0.993    0.016    0.993      0.993    0.993      0.983    0.982     0.986

=== Confusion Matrix ===

   a   b   <-- classified as
 700   0 |   a = good
   7 293 |   b = bad
```

Figure 4 Detail accuracy by Class.

4.1 CONCLUSION

The whole purpose of this research is to automate the banking process of selecting qualified loan applicants who are not risky . In the future work warning systems can help a bank or any other financial institutions to reduce their losses and increase their profits. The model accuracy can be increased by training it with datasets of banks of different countries from East Africa and the world so that the model would be able to incorporate region or community-specific parameters, that sometimes play a huge role in the case of loan default prediction. The accuracy and precision of the model can be further increased by adding more hidden layers as well as the number of perceptron in each layer within a certain threshold value.

REFERENCES

Abdou, H. A., & Pointon, J. (2011). Credit scoring, statistical techniques and evaluation criteria: a review of the literature. *Intelligent Systems in Accounting, Finance and Management*, *18*(2-3), 59-88.

Abellán, J., & Mantas, C. J. (2014). Improving experimental studies about ensembles of classifiers for bankruptcy prediction and credit scoring. Expert Systems with Applications, 41(8), 3825–3830.

Akkoç, S. (2012). An empirical comparison of conventional techniques, neural networks and the three stage hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) model for credit scoring analysis: The case of Turkish credit card data. European Journal of Operational Research, 222(1), 168–178.

Berry, M. J. A., & Linoff, G. (2004). Data mining techniques: For marketing, sales and customer relationship management (2nd ed.). Indianapolis: wiley Publishing.

ISSN 2229-5518
Bhattacharyya, S., Jha, S., Tharakunnel, K., & Christopher, J. (2011). Data mining for credit card fraud: A comparative study. Decision Support Systems, 50(3), 602–613.

Braga, A. de P., Carvalho, A. P. de L. F., & Ludermir, T. B. (2000). Redes neurais artificiais: Teoria e aplicações. Rio de Janeiro: LTC. Chaia, A. J. (2003). Modelos de gestão de risco de crédito e sua aplicabilidade ao mercado brasileiro. Dissertação de Mestrado. FEA/USP.

Cao, Qing, and Mark E. Parry. "Neural network earnings per share forecasting models: A comparison of backward propagation and the genetic algorithm." *Decision Support Systems* 47.1 (2009): 32-41.

Chang, S.-Y., & Yeh, T.-Y. (2012). An artificial immune classifier for credit scoring analysis. Applied Soft Computing, 12(2), 611–618. Chawla, N. V. (2005). Data mining for imbalanced datasets: An overview. In Data mining and knowledge discovery handbook (pp. 853–867). New Jersey: Springer.

Chen, S. C., & Huang, M. Y. (2011). Constructing credit auditing and control & management model with data mining technique. Expert Systems with Applications, 38(5359-5365).

Chiang, R. C., Chow, Y. F., & Liu, M. (2002). Residential mortgage lending and borrower risk: the relationship between mortgage spreads and individual characteristics. *The Journal of Real Estate Finance and Economics*, *25*(1), 5-32.

Eletter, S. F., & Yaseen, S. G. (2010). Applying neural networks for loan decisions in the Jordanian commercial banking system. *International Journal of Computer Science and Network Security*, *10*(1), 209-214.

Silva, M., Moutinho, L., Coelho, A., & Marques, A. (2009). Market orientation and performance: modelling a neural network. *European Journal of Marketing*, *43*(3/4), 421-437.

Steenackers, A., & Goovaerts, M. (1989). A credit scoring model for personal loans. *Insurance: Mathematics & Economics*, *8*(1), 31-34.

Updegrave, W. L. (1987). How lender size you up. Money. [2]

Steenackers, A., & Goovaerts, M. J. (1989). A credit scoring model for personal loans. Insurance: Mathematics and Economics, 8(1), 31–34.

Yeh, I. C., & Lien, C. H. (2009). The comparisons of data mining techniques for the predictive accuracy of probability of default of credit card clients. *Expert Systems with Applications*, *36*(2), 2473-2480.

Moon, T. H., & Sohn, S. Y. (2010). Technology credit scoring model considering both SME characteristics and economic conditions: The Korean case. *Journal of the Operational Research Society*, *61*(4), 666-675.

Tsai, C. F., & Wu, J. W. (2008). Using neural network ensembles for bankruptcy prediction and credit scoring. *Expert systems with applications*, *34*(4), 2639-2649.

Shaaf, Mohamad, and G. Rod Erfani. "Air pollution and the housing market: A neural network approach." *International Advances in Economic Research* 2, no. 4 (1996): 484-495.

Tafti, M. H., & Nikbakht, E. (1993). Neural networks and expert systems: new horizons in business finance applications. *Information Management & Computer Security*, *1*(1), 22-28.

Hsieh, N. C. (2005). Hybrid mining approach in the design of credit scoring models. *Expert systems with applications*, *28*(4), 655-665.