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*Automated Credit Scoring System for Financial Services in Developing Countries*

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*Abstract***—The principle objective of this research is to carry out an intelligible evaluation of the automated credit scoring system for financial service applications. The investigation tries to identify the key determinants for constructing an automated model for credit scoring applications. It provides a comperative evaluation related to Statistical and Artificial Intelligence (AI) techniques that are used in favor of automated credit scoring. It also assists to highlight the most common and effective methods which are used in credit scoring system. Ours analysis revealed that improvements are necessary (in the existing credit scoring system) to effectively address all financial environments. Although credit scoring is highly in practice in developed countries, however in developing countries it is not implemented in many financial services. Eventhough, it has high prospect of selecting creditworthiness, but credit scoring industry is due for a major overhaul. Due to the revolution of information technology(IT) and big data it appears that new IT and big data, analytical tools can make credit scoring highly individualized, accurate, and able to provide informed decision for financial service applications.**

***Keywords: Credit scoring, applications, key determinants, methods, developing countries.***

* 1. INTRODUCTION

The incidence of lending and borrowing has related to human behavior from the Stone Age. So, credit has become substantial in daily life and it is an issue as old as trade and commerce. In general, credit refers to credit card, loans, gages, trade financing and bond etc. Credit assessment is the most troublesome effort for bank and other financial institutions. The traditional way to grant a credit card was made by human experts using prior experience and other directing logics. The 5 C’s of credit, that means the character, capacity, capital, collateral and conditions are the classic methods to follow in general. Heavy training costs, incorrect and inconsistent decisions for the same applications are some common traits of this method, which may result taking a wrong decision while granting credit. As a result, financial organizations may drop

creditworthy consumers or endure great capital wreck if the client eventually fail to pay [1] . Sometimes these monetary distresses can conduct to bankruptcy. These blunders have led to emergence more systematic and exact methods to assess the credit threat.

At this point, automated credit scoring has become a crucial tool for bank and other financial institutions to assess creditworthiness, reduce possibility of risks, make directional determinations, and improve the effectiveness and the financial stability. The core idea behind credit-scoring comprises the classification of potential customers into good quality applicants, who has the chance to repay the loan and bad quality applicants who has the possibility of failure to pay the loan.

Based on the literature, this study compares the effectiveness of different methods used in credit scoring system such as LDA, LR, KNN and DT and also the AI techniques such as Expert System, SVM, Fuzzy Logic, NN and GP. Moreover, it tries to highlight the main points of these methods and techniques. This work also points out some research works done in the field of credit scoring in developing countries. Furthermore, it gives some recommendations along with the possible approaches that can be taken to implement effective credit scoring in developing countries.

* 1. AMENITIES AND CHALLENGES OF CREDIT SCORING

1. *Amenities of Credit Scoring*

Credit scoring is used progressively in loan evaluation because of some obvious conveniences it possesses. As credit scoring models are based on expert systems and other artificial technology, it can make a decision very quickly as it demands less information. It reduces unnecessary variable to make a decision. Different credit experts can easily and clearly analyze the same information given the same weights which is a very important benefit of credit scoring. Scoring does the

loan endorsement process very promptly. It not only saves both time and cost of the bank and customers greatly but also reduces human involvement on credit assessment Mechanized credit scoring models are correct the preference when the result histories of just acknowledged application are considering but not all applications. They do this by expecting the execution of rejected application on the off chance that they had been acknowledged [3]. The operation of the credit scoring model can be observed, followed, and balanced whenever. By the aid of credit scores, monetary organizations are able to enumerate the risks allied with yielding credit to a particular applicant quickly. The weights in the model give a measure of the relative quality of every component's relationship with credit execution. Lenders use credit scores to find out who allows for a loan along with the interest rate [4]. Automated credit scoring has a lot of amenities that accumulate to the granters as well as the suppliers. To impart a pointed scrutiny of a person’s creditworthiness using scoring models, credit scores aid to minimize discrimination. This empowers credit suppliers to concentrate on just data that identifies with credit hazard and evade the individual subjectivity of a credit examiner. Enhanced objectivity in the advance endorsement procedure is another advantage of credit scoring. This objectivity aids lenders make sure for employing the equivalent underwriting benchmark to all borrowers paying little heed to race, sex, or different variables differ by law from being utilized as part of credit choices. By using credit scores, financial organizations can fix up their lending rate which they should placing their customers. Maximum-risk customers are imposed a higher lending rate. These assist financial organizations to conduct their accounts more effectively and fruitfully.

1. *Challenges and Restrictions of Credit Scoring:*

In spite of credit scoring has profound advantages, its few defects ought to likewise be noted. As credit scoring is a mechanical framework for investigating the advance candidate, so that there is an opportunity to break down and decipher some information inaccurately. Credit risk can never be weighed precisely, and any model that anticipates it, is erroneous. It additionally might change overnight. Example: The possessor of an industry succumbs and there is nobody qualified to supplant him. While developing a credit scoring model utilizing a one-sided example of buyers and clients who have been result credit, one of the significant issues can appear [46]. This might happen on the grounds that just the good customers are represented as the sample is one-sided and rejected customers will not be incorporated into the information for developing the model. The credit scoring system that use this example may not execute efficiently on the overall inhabitants while the record used to assemble the model is apart from the record that the model will be applied to. Therefore, if a credit scoring model has not every possible variable, usually it will a credit scoring model has every possible variable in it and it is frequently updated, normally it

will be unable to classify some customers or unable to provide sufficient outcome. In statistical credit scoring, it requires a lot of data on each loan and also requires a consultant to manage and to monitor everything. It can reject faulty applications, but it cannot modify them. It is also susceptible to misuse[47]. Forces a dichotomous result, for example, either the borrower inability to pay or not is another feedback of credit scoring. Along these lines, a scope of the possible outcomes can be incorporated, as every now and again the borrower declares an issue with payments, and the loan terms can be renegotiated. In addition, credit scoring models are too excessive to purchase and prepare credit analyst furthermore fluctuate starting with one market then onto the next. Now and again a credit scoring framework might dismiss the trustworthy purchaser as a result of exchanging his/her employment or address. In spite of the confinements mentioned above, there is no hesitation that credit scoring will keep on being a noteworthy instrument in the foreseeing credit risk in consumer lending.

* 1. APPLICATIONS OF CREDIT SCORING

Be that as it may, utilizations of credit scoring have been generally utilized as part of various regions, together with osmosis between various factual methods utilized as a part of expectation purposes and order issues. These may be arranged into bookkeeping and finance, promoting, building and assembling, health and prescription, and general applications. However, not every one of these applications is generally utilized equally. In the early years, money related organizations utilized credit scoring basically to settle using a credit card choice for advance applications. Nonetheless, the utilization of credit scoring has developed from settling using credit card choices to settling on choices identified with lodging, protection, fundamental utility administrations, and even employment. In the field of bookkeeping and finance, financial institutions utilized scoring primarily to settle on layaway choices for loan applications. Here, credit scoring is also used for different purposes such as bankruptcy prediction and bankruptcy classification, financial distress[2], scoring applications[3] and so on. Credit scoring applications in saving money segments have extended amid the last couple of decades [4]. The assessment of new customer loan is a standout amongst the mainly essential uses of credit scoring models and has pulled in consideration over the last several decades [3]. Crediting small & medium enterprises (SME) and microfinance have been decided by credit scoring also [5]. In option to choices on individual credit applications, monetary organizations now make utilization of credit score assessments to put credit limits, oversee accessible records, and gauge the benefit of customers. Credit scoring models have additionally been utilized as a part of the protection business to settle on the uses of new protection approaches and the re- establishments of existing policies. There is considerable utilization of credit scoring in the home loan industry too [6].

* 1. BASIC FACTORS OF CREDIT SCORING

The purpose of the variable selection in the credit scoring model is to obtain a role model with low dimensionality. The exactness of the model might enhance by utilizing a formal technique for picking the most suitable customer variables and the many-sided quality of the model might decrease by disposing of the non-significant variables. So, variables selection may affect the performance of the model. Predetermined scores, looked into the customer's financial record and reliability was the base to minimize the likelihood of wrongdoing and default for credit experts. A new applicant is determined by some attributes such as sex, age, marital condition, dependents, telephone, credit card, learning level, job and duration at present address. These characteristics are broadly practiced in constructing scoring models [7][8]. The working of scoring models likewise utilizes length of staying at present employment, bank account, total credit, credit duration, purpose of loan, house proprietor, car owner, month to month pay, mortgage, guarantees etc [7]. In some cases spouse’s individual information, like salary, no of child, age and others has been integrated in the list of variables More variables, for example, worst record status, time in vocations, time with bank and others are less every now and again utilized as a part of building scoring models [9]. To decide individual credit scoring debt, length, credit history, payment history, types of credit and new credit are utilized. To fabricate scoring models there is no ideal number of variables that ought to be utilized. The choice of the variables contrasts from study to think about relying upon the way of information. For example,[8] applied forty-one variables, and twenty-nine variables have been utilized by[10]. Therefore, the danger system and the credit society of the organizations ought to be transformed by a part scoring model.

* 1. THE METHODS OF CREDIT SCORING MODEL

Credit scoring optimization is a rising topic now a day where different researchers are using different techniques for choosing the right applicant and reducing credit loss. In order to obtain a satisfactory credit scoring model, numerous methods have been proposed. In this paper, four statistical techniques have been discussed; these are DA, LR, KNN and DT. In the other hand this study also discussed five Artificial Intelligence (AI) techniques: Expert System, SVM, Fuzzy Logic, NN and GP. A short description of these techniques is discussed in this section.

1. *Statistical and Optimization approaches:*

**Discriminant Analysis (DA)** is generally used for modeling sorting tasks as a statistical technique. Fisher proposed that - DA is a classification and discrimination tool which was one of the first methods that applied to make credit scoring models by comparing between those loans which was defaulted and those which was not. DA’s base assumption is that, the

explanatory variables are distributed as a multivariate normal distribution with a common variance covariance matrix for each given class of response variable [25][26].

**Logistic Regression (LR)** is derived from linear regression. It is more suitable for fraud detection problems. Where other statistical tools failed to fit in, it can fit several kinds of distribution functions such as Gamble, Poisson, and normal distributions [27]. Another quality of this method is that, it does not need normal distribution variables and also the linearity of relationship between dependent and independent variables is not assumed in this method. The disability of LR is, it cannot properly resolve the problems of non-linear and interactive effects of explanatory variables [28].

**K-Nearest Neighbor (KNN)** has some fascinating features in credit scoring. For example, it is feasible to exceed the problem of population drift by using KNN, because it strongly updates by dropping older cases and by adding new candidates to the design [29][30]. But these methods have not been practiced largely in the credit scoring industry, because its predictive accuracy is extremely affected by the measure of distance and the cardinality of the neighborhood [31].

**Decision Tree (DT)** is a classification technique used in stimulant automated credit scoring models [32]. In order to solve the classification issues, a tree-like chart of choices and their conceivable results is used mostly. The root node of this tree is the highest node which a decision should tackle it. On an attribute or input variable, a test is done in each inward node. The leaf nodes speak to the classes and every branch taking after the node prompts the aftereffect of the test. Over fitting can be a problem of using this method.

1. *Artificial Intelligence techniques:*

**Expert System (ES)** is one of the traditional methods in accessing credit scoring. They were designed to replicate the way of thinking of human experts. In an ES the credit decision is bestow upon the local or branch lending officers [33]. In the decision making process the expert’s expertise, subjective judgment and weighting of certain key factors play an important role. The advantages of using ES for credit analysis are speed and accuracy, both which far surpass human capacity.

**Support Vector Machine (SVM)** is a learning system that uses a linear model to map into a higher dimension feature space from the input vector using a kernel so that there is a linear reparability between the two groups [35]. Examples from the training that are close to the maximum margin hyperplane are named support vector. Normal distribution and continuity – this kind of data structures are not required which is the main advantage of SMV [39]. One of the main disadvantages of SVM is that it is sensitive to outliers or noises in the training sample due to overfitting.

**Fuzzy Logic** is an extension of multivalued logic. Many parameters are used for determining the credit scoring which are usually vague, difficult to define, and even conflicting.

Fuzzy set theory was developed to handle this kind of situation, and improving the accuracy of credit scoring [36]. Fuzzy rule based system provides explanation when deriving the credit score, while most of credits scoring models do not explain how the results obtained.

**Neural Network (NN)** contains a large number of nodes by links. By finding the complex pattern between input and output variables, NN can predict the outcome of new independent data of input. The feed-forward NN containing back-propagation (BP) is largely used for credit scoring, where the pre-layer gives signals to the neurons and output them to the next layers without feedback. The strong learning ability and no assumptions about the relationship between input variables are the main advantages of NN. Also they act as black boxes as it is difficult for humans to interpret the way

neural networks reach their decision [8][42]. A disadvantage of NN is that a number of parameters like the network topology must be defined analytically.

**Genetic Programming (GP)** is a search heuristic that imitates the process of natural evolution [7]. Genetic Algorithms (GA) provide the solution in the form of a string. Every string is the encoded binary, real etc., version of a candidate solution. To compute a whole generation of new strings, standard GA applies genetic operators such as selection, crossover and mutation on an originally random population [40].

Table I provides a detail of different statistical approaches along with AI technologies used in various articles by the researchers. This table incorporates the analysis, references and important features of all those given methods.

TABLE I. CORERELATIVE STUDY OF DIFFERENT METHODS OF AUTOMATED CREDIT SCORING FROM PUBLISHED RESEARCH

|  |  |  |
| --- | --- | --- |
| **APPROACHES** | **METHODS** | **COMMENTS** |
| **Statistical approaches (SA)** | **LDA**  [24][25][26] | It is still one of the most broadly established techniques to classify customers’ credit score as good or bad by using linear functions. However, DA cannot properly deal with non-linear problems. |
| **LR**  [3][27][28] | It performs well on big dataset. However, this method can be applied on a small dataset or a data set with a short repayment history, but the quality of the scoring model can decrease. |
| **KNN**  [25][29][30][31] | It enables modeling of irregularities in the risk function over the feature space and a fairly intuitive procedure and can be used dynamically but its predictive accuracy is extremely affected by the measure of distance and the cardinality of the neighborhood. |
| **DT**  [32] | It solves both classification and regression problems. As like LR, it needs big dataset in order to get dependable predictions. |
| **AI**  **technologies** | **Expert System**  [33][34] | It does not end up with a score card which gives weights to each answer instead it classifies the consumers into groups, each group being homogeneous in its default risk. |
| **SVM**  [35][39][41] | It produces global optimal solution and can work well with few samples but selecting kernel and its parameters is a tricky issue. |
| **Fuzzy Logic**  [36] | It can derive human understandable rule and has low computational requirement but random choice of membership function can bias the result. |
| **NN**  [8][37][42] | It is good at function approximation, forecasting, classification, clustering and optimization tasks but demands a lot of training data and training cycles. |
| **GP**  [7][40] | It can perform better than traditional techniques such as MLP, CART, C4.5 and Rough set. However it is difficult to come out with a generic model for all class of problems. GP also requires good processing power. |

Based on the literature, table II compare the effectiveness of different methods used in credit scoring system. It compares the accuracy (percentage of correctly classified instances) of the methods. The vast majority of the studies that concentrated on correlation between various strategies for credit scoring have found that artificial intelligence techniques, for example,

neural networks, genetic programming and fuzzy algorithms are superior to the conventional ones taking into account the average correct classification rate criterion. However, the more straightforward classification methods, for example, LDA and LR, additionally have a decent performance in this context.

TABLE II. A COMPARISON OF DIFFERENT METHODS (SA AND AI) USED IN CREDIT SCORING SYSTEM (BASED ON THE LITERATURE).

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Research  Work | ***West (2000)***  **[37]** | ***Lee et al. (2002)***  **[38]** | ***Baesens (2003)***  **[39]** | ***Ong et al. (2005)***  **[40]** | ***Yu et al. (2008)***  **[41]** | ***Tsai (2009)***  **[42]** | ***Chuang (2009)***  **[43]** | ***Wang (2012)***  **[44]** |
| Methods |
| **LR** | 81.8 | 73.5 | 79.3 |  | 73.2 | 84.7(avg) | 76.5 | 71.6 |
| **LDA** | 79.3 | 71.4 | 79.3 | 80.8 |  | 76.8 | 76.0 |  |
| **DT** | 77.0 |  | 77.0 | 78.4 |  |  |  | 69.0 |
| **NN** | **82.6** | 73.7  (**77.0**)  hybrid LDA and NN | 79.4 | 81.7 | 77.2 | **92.7** | **79.5** | 71.5 |
| **CART** | 76.9 |  |  |  |  |  | 77.5 |  |
| **KNN** | 76.7 |  | 78.2 |  |  |  |  |  |
| **GP** |  |  |  | **82.8** |  |  |  |  |
| **SVM** |  |  | **79.7** |  | **78.8** |  |  | **72.4**  (avg ) |

* 1. CREDIT SCORING IN DEVELOPING COUNTRIES

The goal of credit scoring is to measure the financial risk of the loan, so that the loan provider can make credit lending decisions quickly and objectively. Human judgment of creditworthiness can be time consuming whereas credit scoring gives advancers to find out credit worthiness in lesser time. Because of this advantage banks in developed nations as US, UK and Europe have been using credit scoring techniques with higher success rate [45]. In the developed world, they have large credit scoring firms like Equifax, Experian and TransUnion to reduce the cost of identifying creditworthy applicants. On the other hand, the lack of proper data and reliable information about the credit or monetary history of bank clients in the developing countries credit scoring can be difficult to deal with. A credit scoring system that fulfills the developing countries’ need is yet to be discovered. Currently they are trying to find out an automated credit scoring technique which works best for them. In some of these countries, already have started to use credit scoring system which has been designed by developed nations and many of them are working to create their own credit scoring systems to give loan in the industrial area[15]. However, credit scoring has not been practiced effectively in small financial areas like mortgages, credit cards or personal loans. It is expected that integration of automated credit scoring system in developing countries could bring benefit to the financial sector as well as economy. As the financial organizations can determine whether there is a risk or not to grant the loan to the customer. Moreover, in developing countries small and medium enterprises (SMEs) are thought to be an important source of innovation and employment because of their flexibility in responding to new market opportunities and their potential for growth. Many developing countries have already commenced to practice automated credit scoring as a tool for their economic development.

Table III, gives an idea of adaptation of credit scoring methods and innovation being used for developing countries.

* 1. PROSPECT OF CREDIT SCORING IN DEVELOPING COUNTRIES

In developing countries, financial system is mostly microfinance. Therefore, prospect in credit scoring in developing country is related to adaptation of credit scoring in microfinance.

Some recommendations for micro-lenders and microfinance institutions in developing countries:

* 1. The quantity of distributed credit scoring contemplates for microfinance is constrained. There is a need to broaden the geographical range of credit scoring examines towards Eastern Europe-Central Asia and Middle East-North Africa as little quantities of studies have been distributed in these regions.
  2. The oppressive force execution of credit scoring frameworks for microfinance remains excessively feeble, making it impossible to legitimize a complete inversion of the conventional credit process towards scoring. However, credit scoring ought to end up a refinement instrument in the present procedure as it has effectively ended up being steady, simple to utilize, furthermore to have a specific discriminatory power. Enhancements of the discriminatory power by means of model mixes reject induction examination and more pragmatic confirmation, may bit by bit build the part of credit scoring in the credit process.

As there is no compatible credit scoring solution in developing countries, efficient approaches to implement better credit scoring system should be taken into consideration. Possible approaches that can be taken to implement effective credit scoring in developing countries are:

* + - Pointers of conduct got from cellphone transaction records can be prescient of loan payment [48]. To gage the prescient nature of the strategy, research has been made where joined bank information from loans have been completed with borrowers' cell telephone records. It predicts who among these people wound

up repaying their loan, in light of how they utilized their cellphones before taking a loan. The examination additionally found that the prescient accuracy of the technique approaches that of credit scoring strategies utilizing conventional information as a part of more created settings.

* + - * Involving social media in credit scoring can be a fruitful way in developing country. A huge number of people use Facebook and tracking their social media activity can help lenders calculate the risk factors. However there are negative sides of this as well. The utilization of "big data" in advertising to target

particular shopper gatherings is as of now a questionable practice, for the most part since couple of customers ever acknowledges they are being tracked.

* + - Microfinance industry faces a big challenge on building long-term relationship with their clients. Usually, first credits are small and short-term loans. As a result, to enter the market, a special arrangement is needed. If all the terms are fulfilled by the client, they can provide clients higher amounts. It gives the client an incentive to stay with the institution.

TABLE III. SUMARRY OF RESERARCH WORK THAT CONSIDER DEVELOPING COUNTRIES FOR PRACTICING AUTOMATED CREDIT SCORING

|  |  |
| --- | --- |
| **Country Name** | **Adaptation of credit scoring** |
| **Bangladesh**  [11] | Investigates the effect of the MFI program mediation on the moneylender interest costs in northern Bangladesh and found that moneylender financing costs increment with the rate of households borrowing getting from MFIs in the town. |
| **India**  [12] [13] | They attempted to decide how far back these forecast models can anticipate that the organizations would get into financial related distress. |
| Many different methods including the hybrid model of GA, Fuzzy c-means algorithm and MARS are conceptualized for prediction of bankruptcy. From the study it was visible that hybrid models work better than other static bankruptcy models. |
| **Pakistan**  [14] [15] | Karachi stock exchange's non financial listed companies data were studied. Moreover it was evident that Abbas model and Altman's Z Score model was an effective tool to verify the financial stability of the company. |
| To predict bankruptcy in Pakistan the most considerable financial ratios were acknowledged. |
| **Malaysia**  [16] | Examine the determinants of credit hazard and demonstrated that the liquidity proportion was huge in deciding credit hazard previously, then after the fact income administration was balanced. |
| **Iran**  [17] [18] | The data of diferent firmsof an organization was reviewed and a data mining model was invented to specify the non bankrupt and bankrupt firms. |
| Tried to predict the failure or survival of Iranian marketplaces depending on financial ratios. In favor of this purpose GP and MDA were used. |
| **Ghana**  [19] | Loan default rate in micro finance institues are still high.A fuzzy logic based approach is provided to credit scoring in order to reduce the loan default. |
| **Nepal**  [20] | Demonstrated that credit risk management is an imperative indicator of bank financial execution. In this way achievement of bank execution relies on upon danger administration. |
| **Sudan**  [21] | LR and DA works superior on predicting future loss.A new method has been proposed using these models to foresee bank’s failure. |
| **Vietnam**  [22] | Utilized a way to deal with the present shortcomings in credit scoring forms and gives a hypothetical establishment of credit scoring value. |
| **Turkey**  [23] | Redesigned the quantitative analysis utilized as a part of the financial execution modules of best in class credit scoring techniques. |

VIII. CONCLUSION

Credit scoring is a broadly utilized method that helps banks and other financial establishments to choose whether to allow credit to buyers who applied for loan. Nonetheless, with progression of technology, the technique for credit score should be redesigned. Utilizing enormous information to decide lower, customized rates on credit cards and loans will advantage monetarily dependable individuals in a way the present framework does not, permitting reliable borrowers to pay less and escape obligation speedier. Also, fabricating a client base of monetarily mindful individuals will advantage banks - decreasing the dangers of misrepresentation, and additionally default and sparing organizations cash over the long haul. Putting resources into the fate of stable people

similarly puts resources into the fate of a stable financial industry and national economy. It is the ideal opportunity for the financial framework to grasp a bigger extent of markers to decide budgetary obligation; basically, the old methods for assessment can not stay aware of better approaches for living and working. This begins with social affair a superior comprehension of buyers to make financial arrangements that fit their individual needs. Instruments are being created that will make lending more productive to both the banks and the borrowers. Equipped with capable software and refined data science, the eventual fate of the financial industry lays on the capacity to bring educated individual finance into the current period.

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