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**Abstracts
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Credit Score Prediction System using Deep Learning and K-Means Algorithms

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Abstract. In financial markets, credit rating and risk assessment tools are used to minimize potential risk up to some extent for credit score. Nowadays, the banking and financial industry has experienced rapid expansion. Therefore, with this growth, the numbers of credit card applications with various credit products are increasing day by day because many people want to avail these services for their personal interest. The challenge here is to identify insights on the performance of a finance industry by using deep learning algorithms as they directly affect the viability of that industry. These industries have a limited number of resources and capital, which can be used to deliver the services among the customers. In this research work, we proposed prediction of credit scoring system using deep learning and K-Means algorithm for the financial industry. The scheme contains a predictive model which uses feature selection (FS) classification and deep learning applications simultaneously to train the proposed model to perform effectively. The scheme 1) pre-processing credit card data 2) uses a feature selection technique to minimize the dimension of data in order to obtain the finest training data 3) applies a deep learning algorithm to map the input weight with hidden biases to achieve excellent performance 4) Decision support system is used to enable the deep learning algorithm to provide a more accurate and intelligent decision. Furthermore, the proposed model is validated on different credit scoring dataset in real-world scenarios and is capable of improving the effectiveness and accuracy. The studies indicate that our predictive model performs well for credit scoring of existing customer and helps lenders to allocate funds in finance industry.

1. Introduction

Credit scoring model predictions have now become an important component of the commercial world. The important aspect of assets used in banking directly comes from the profit earned from the distribution of credit cards among the customers. Credit scoring efforts to isolate the consequence of diverse applicant's physical characteristics hooked on unlawful manner and non-payments [1, 2]. The best step of any banking system is to identify the worthy stakeholders from which they can get maximum profit from the investment in the assets. The field of banking is affecting the lives of the credit card holder loan holder by its services. Financial companies issued credit cards following a thorough verification and validation process, but there is no guarantee that the credit cards were granted to deserving candidates. Credit scoring is a conventional decision model and its main focus is on risk approximation approach associated with credit products such as credit card, loans, etc. and is estimated based on applicants' historical data which helps credit lenders in the granting of credit products. Currently, financial institutions are adopting various risk assessment tools and techniques for credit scoring systems to minimize the risk up to some extent [3]. The use of statistical tools for



analyzing customer credit data helps to find out the default customer [4]. The Number of compensations of credit scoring model incorporates such as establishing & fading credit risk and its concert is responsible for the profitability of the foundation [5, 6]. Various studies in the past have shown that ensemble-based approaches are effective in credit score assessment. In the credit risk system it uses empirical models for making decisions for both corporate and retail credit businesses. Literature review focuses on automatic estimation of defaulter using machine learning methods [7, 8]. The scoring can be divided into two, first one is behavioural scoring where dynamic portfolio administration processes are used which takes into the consideration of current consumers to examine their individual conduct standards. The second one is collection scoring which tries to classify clients into several clusters based on the change in their behaviours. Credit scoring systems are generally used to estimate loan default probability.

The prime objective of this research work is to find out the score for all the existing customers from a financial institute and helps lenders to allocate funds for a non default user by making use of good prediction. The scheme uses deep learning based algorithm to map the input weight with hidden biases and uses an effective classifier for taking intelligent decisions and perform a rigorous training to train the predictive model. Machine learning models finds patterns and relationships from the training data set and yields predictions about the future.

1.1. Credit Scoring Process

Credit scoring is a conventional decision model and its main focus is on risk approximation approach associated with credit products such as credit card, loans, etc. and is estimated based on applicants' historical data which helps credit lenders in granting credit products. Probability of Default (PD) prediction is carried out for generating credit score for individual customer to identify default when he visited bank for loan and check their credit score. The credit score is used by bank for credit bureaus.

1.2. Credit Risk

Credit risk is the risk of borrower who did not repay credit card amount or any other type of loan within the stipulated time.

1.3. Internal rate of Return (IRR)

IRR is a technique which is used to find out the profitability of potential investments. There are other strategies to utilize when attempting to get an expected return, but the internal rate of return is the most commonly used calculation for determining the expected interest rate. This interest rate is used for assigning the loan for the borrowers. The IRR can have a negative training example.

1.4. Credit risk components:

Credit scoring model is a classification problem where the dependent variable is dichotomous and assigns "false" to failed loans and "true" to non-failed loans. Figure 1 shows the various credit risk components.

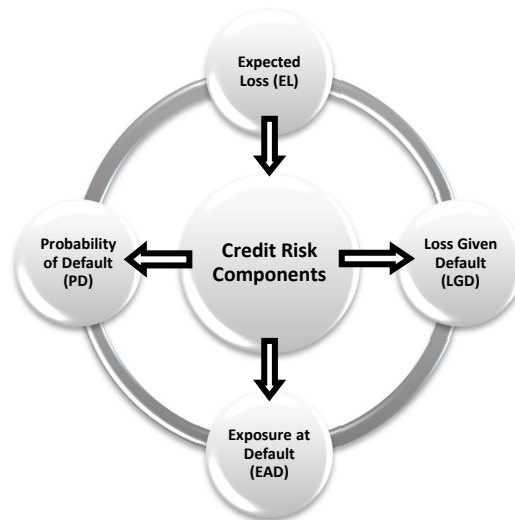


Figure 1. Components of credit risk scoring.

1.5. Probability of Default (PD)

In this a customer generally borrower will default on debit like credit card and mortgage loan over a time. It basically returns the expected probability of users who fail to repay the loan back to the bank. In this 0% and 100% percentage is used to represent the Probability. Greater probability shows the greater chance of default.

1.6. Exposure at Default (EAD)

Exposure at default is generally referred as the amount that the borrower has to pay back to the bank at the time of default.

1.7. Loss given Default (LGD)

Loss given default refers how much of the amount outstanding we expect to lose. LGD can be calculated by using the equation (1).

$$LGD = \frac{(\text{Exposure at Default} - \text{Present value}_{(\text{recovery})}) - \text{Present value}_{(\text{cost})}}{\text{Exposure at Default}} \quad (1)$$

1.8. Expected Loss (EL)

The expected loss is computed by multiplying PD by LGD and then further multiplying the product of these two by EAD. This can be calculated by using following equation (2).

$$EL = (PD \times LGD \times EAD) \quad (2)$$

The rest of the paper is structured as follows. Section I shows the introduction of credit scoring system. Section II represents the two-stage credit scoring system. Section III shows the literature survey of different credit scoring approaches. Section IV demonstrates the proposed predictive model for credit scoring. In section V the experiment set up has been elaborated. Finally section VI concludes the research paper.

2. Two-Stage Credit Scoring System

In two-stage credit scoring system two phases are being used to find out the best practices for filtering the customers' matches for a particular credit score. In the first phase, it basically predicts the total profit against the credit score for a loan holder by making use of probability of default attributes like credit history, period of loan, income, employment length etc. In the second phase, internal rate of return is used for identifying non-default loans with the help of other attributes such as highest IRR, capital budgeting etc. Figure 2 shows two-stage credit scoring system.

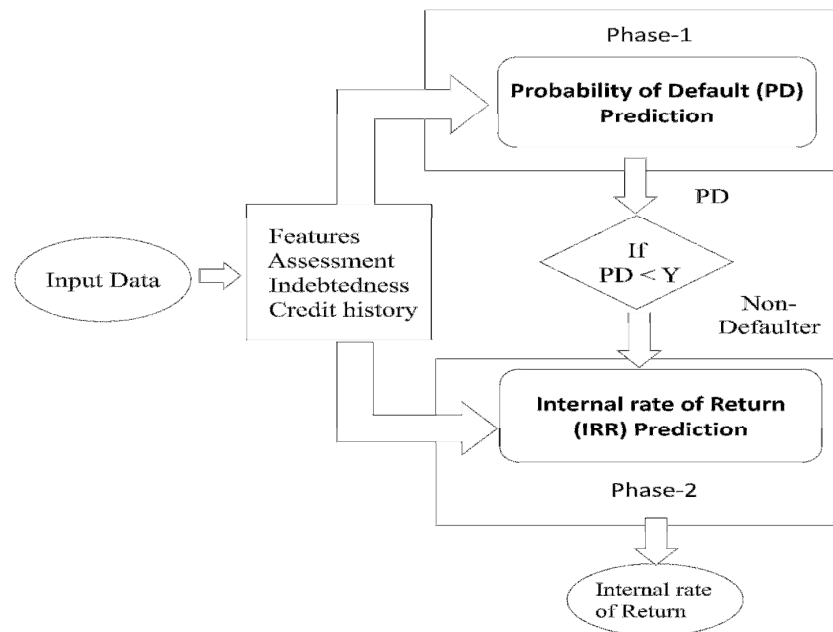


Figure 2. Two-stage credit scoring system.

The following equation (3) is used for calculating internal rate of Return (IRR). An IRR calculation is totally dependent on the same formula as NPV does. In this formula the annual return makes the net present value equal to zero.

$$NPV = \sum_{t=1}^T \frac{C_t}{(1 + IRR)^t} - C_0 \quad (3)$$

The motivation of our research is build a reliable predictive model for credit scoring which helps lenders to allocate funds in financial institutions based on the credit score. The model shows accurate outcomes even if the dataset is imbalanced and improves feature selection process by adopting deep neural network which makes balanced dataset. The scheme uses decision tree classifier to assign new weight for every class in the predictive model with respect to accuracy. The model is validated on different credit scoring dataset in real-world scenarios and is capable of improving the effectiveness and accuracy for training data and ensures that the training data is balanced.

3. Literature Review

In this section, we have shown the literature review of various credits scoring model based on machine learning algorithms for financial sector. Louzada *et al.*, have conducted a methodologically formal comprehensive survey of binary classification methods for credit scoring financial research [9]. Their major objective of conducting a literature review is to suggest a new approach for ranking in credit scoring, particularly with hybrid techniques, where there is a similarity in predictive results. Xu *et al.*, suggested EGHE, a novel ensemble credit scoring model that combines an effective feature selection algorithm, a novel ensemble approach, and a GFSS-based weighting approach for single

ELM classifiers [10]. They also introduced a new weighting approach for constructing the GFSS theory-based ensemble credit scoring model. Liberati and Camillo have examined the use of personal values as new knowledge to improve credit risk ratings [11]. Their findings show that non-linear classifiers forecast credit risk considerably better than KDAs. They also discovered that psychological characteristics improve the efficacy of screening approaches. They have concluded that when financial statements and credit applicants' banking records are used, the findings indicate slight changes in misclassification errors. Based on their findings, Papoukova and Hajek proposed a two-stage consumer credit risk model on the topic of ensemble learning [12]. They introduced an MC metric for forecasting loans with fixed exposures to assess the success of PD models.

Cinca *et al.*, have proposed profit scoring DSS for Peer-to-Peer lending [3]. According to their research, clients with a high risk of default can also be successful. Profitability considerations vary from default factors. Wang *et al.*, have proposed a two-phase hybrid solution based on filtering and a multiple population genetic algorithm-HMPGA [13]. This hybrid approach incorporates the wrapper approach into the filter approach in order to obtain some critical prior knowledge. Furthermore, instead of the conventional genetic algorithm, the authors have used MPGA in this paper to prevent the issue of premature convergence. Zhao *et al.*, proposed a high performance credit rating model based on MLP neural networks in this article [14]. The MLP model has 9 secret units that were conditioned using the BP algorithm. In their research, this credit rating model achieves an accuracy of 87%, which is 5% better than the best findings of previous work on the German dataset. The authors have also demonstrated that our approach is applicable to other credit datasets, such as the Australian credit dataset. Ala'raj *et al.*, have proposed a new classifier consensus-based combination method for combining multiple classifier systems (MCS) with different classification algorithms [15]. Their experimental findings, analysis, and comparative analyses show that the proposed combination approach outperforms all base classifiers. The authors have also validated the model using five real-world credit score datasets. Abellan *et al.*, have presented Credal Decision Trees, a novel procedure for building decision trees that handles imprecision differently than traditional procedures [16]. They have also highlighted how the Bagging scheme on this category of decision trees outperforms the findings obtained using the best approach previously proposed for datasets related to bankruptcy prediction and credit rating. This affirmation is backed up by a series of mathematical analyses. Kaveh Bastani *et al.*, have proposed wide and deep learning for peer-to-peer lending [17]. They have used two-stage scoring method for giving benefits to the lenders for deciding to whom they can give their fund in financial market.

The study of various research papers in literature review state that feature selection (FS) classification enhances the performances of the predictive model to provide optimal solution. Deep learning based applications provides a prominent way to achieve effectiveness. Decision support system helps to find out the combination of classifiers which provides more accurate and intelligent decisions for an instance.

4. Proposed Credit Scoring System

In this section, we have shown the prediction of credit scoring model using deep learning and K-Means algorithm for the financial institutions. Basically, credit scoring refers to the model for assisting the finance industry for decisions making and also identifies the various risk associated to it. In this risk analysis it is very important to find out the risk for an applicant for decision-making. Contrariwise, credit scoring data may contain noise i.e. unrelated data or redundant data or sometimes the data may contain missing values which breaks down the performance of model. Therefore, our proposed predictive model uses feature selection (FS) technique for selecting the important features from the training data. This improves the effectiveness of the model because now the model works on finest training data. The model is trained using deep neural network which works well for unseen training examples and allows a learning model to learn for a low dimensional embedding of input vector and weight vector with each categorical instance. Figure 3 represents the deep neural network with hidden layers used in proposed approach.

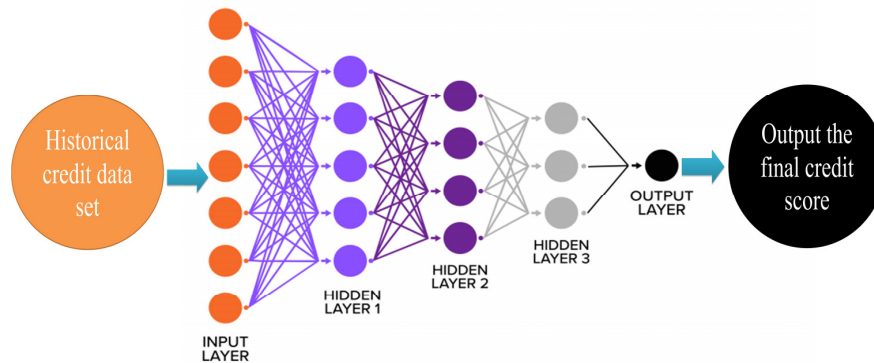


Figure 3. Deep neural network with hidden layers used in proposed approach.

The model can make accurate prediction for any new instance even though the data contains missing values. It uses activation function i.e. ReLU which is used to operate as a threshold function. This function uses boolean method for classifying the instance which works on input vector and weight vector. The cost function is used to reduce the squared error. On the other hand a decision tree is used for classification. These, when combined, yield the best results for making predictions and credit rating. To achieve balanced dataset the predictive model uses algorithm 1.

4.1 Algorithm 1:- Pre-processing of Dataset

Input: Credit scoring dataset $DataSet_{cr}$.

Output: Balanced dataset for training and testing $Bal_{DataSet_{cr}}$.

Step1: Pre-processing of data.

Step2: Removing irrelevant data and noise.

Step3: Identify the outliers from the dataset.

Step4: Evaluating the missing values and duplicate values.

Step5: Fixing the missing values that may lead to inconsistency by using fillers.

Step6: Data validation.

4.2 Algorithm 2:- Proposed credit scoring algorithm

Input: Credit scoring dataset $Bal_{DataSet_{cr}}$ from Algorithm 1.

Output: Final credit score for individual customer $Cust_{score}$.

Step1: Features selection based on deep learning network.

Step2: Removing irrelevant features from the feature selection.

Step3: Decision tree based classification is applied on these selected features.

Step4: Selection of classifiers given by decision tree by using equation number (5).

Step5: Calculate credit score for individual customer using μ and σ by equation (6), (8), and (9).

Step6: Build the predictive model

Step7: Test the model for minimizing the error by using stochastic gradient descent.

Step 8. Final credit scores for individual customer $Cust_{score}$.

Algorithm 2 shows the complete overview of the proposed credit scoring system predictive model. To make a prediction the model uses a predictor to compare individual data vector with the prediction vector. This predictor gives the output in the form of boolean valued function i.e. true for successful prediction and false for unsuccessful prediction.

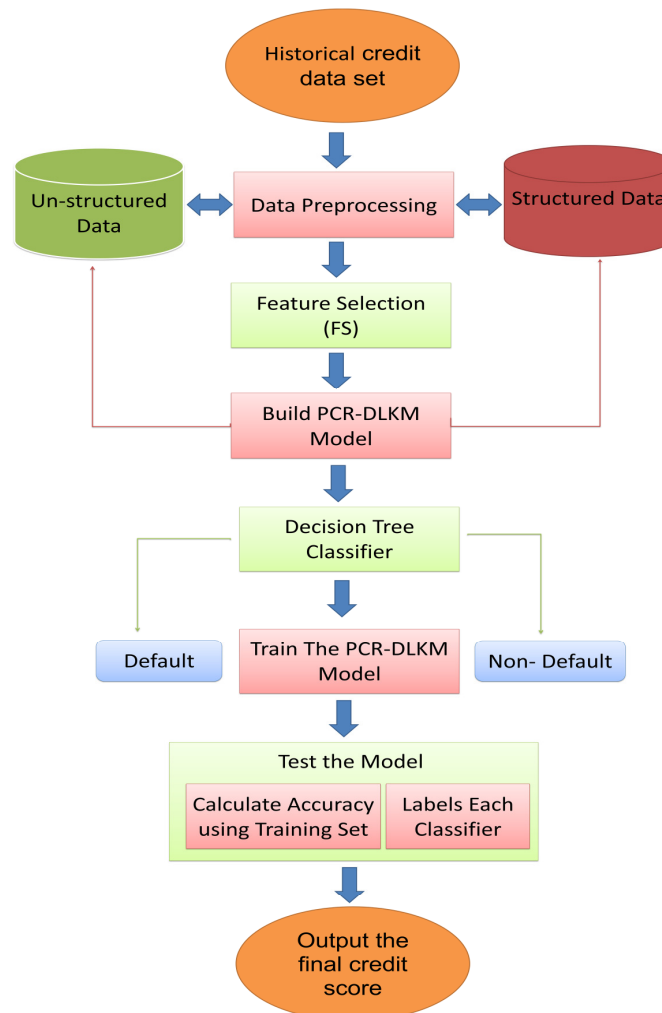


Figure 4. Block diagram of the proposed predictive model.

Figure 4 depicts the block diagram of the proposed credit scoring system predictive model which make a prediction for credit scoring strategies using deep neural network. First, historical credit data set is collected from the database. Data pre-processing is performed to convert unstructured data into structured data for training and testing purpose. Second, feature selection is used for selecting a set of dominant features. After feature selection the trained model is prepared using the k-means algorithm for classification. Lastly, the predictive model is tested in real-world scenarios by using credit scoring dataset for a credit score. The predictive model focuses on predicting the credit score for an individual customer associated to a financial industry to classify default and non-default customers by analyzing customer's behavior. This model also enables lenders by providing default and non-default customer which helps them for their future investments. Decision tree learning is used to classify new weight for every class in the predictive model with respect to accuracy which helps in the process of

classification. The model mainly consists of historical credit data set, data pre-processing, feature selection and decision tree classifier. Deep neural network based algorithms are one of the mostly used methods for credit score [18-21].

5. Experiment Setup

In this section, we have demonstrated the performance of proposed credit scoring model using deep learning and K-Means algorithm for making a prediction. The predictive model is able to predict the credit score for every individual customer associated with a financial industry. The predictive model uses different credit scoring datasets <https://www.kaggle.com/c/home-credit-default-risk/data>. The above dataset is fed into model for calculating the performance of the proposed scheme. The dataset is based on the boolean valued functions which classify the training examples either positive or negative classes. The model uses average values i.e. mean (μ) and standard deviations (σ) measures which are performed on different datasets. In the process of classification to find out the classifier the model make use of Accuracy (ACC), Root Mean Squared Error (RMSE) of probability of default (PD) and area under curve (AUC). The values were calculated as follows: to calculate accuracy the equation (4) is used which is based on the confusion matrix shown in (Table 1).

Table 1. Confusion matrix for probability of default (PD).

Target Function	Positive	Negative
Default (Negative)	FN	TN
Non-default (Positive)	TP	FP

0.1. Accuracy

Accuracy can be is defined as the measures of percentage of correct predictions for the test data from a given dataset [21-25]. Accuracy can be calculated by using equation (4).

$$\text{Accuracy (ACC)} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

0.2. Decision tree classifier

This classifier is used to apply k-means yields k to supports the original data points [12]. For making dynamic cluster k-means clustering algorithm is used. The process of classification can be done by making use of equation (5).

$$J(v) = \sum_{i=1}^c \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2 \quad (5)$$

0.3. Rectified linear activation function (ReLU)

ReLU is the activation function which is used in deep neural network. ReLU returns 0 if the function got negative value and return the value back if the function got positive value. Equation number (6) shows the formula for calculating ReLU.

$$f(x) = \max(0, x) \quad (6)$$

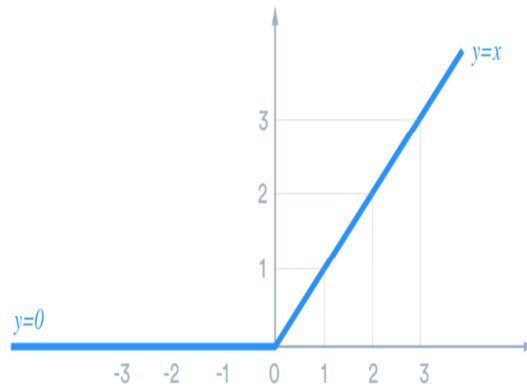


Figure 5. ReLU activation function used in deep neuron network.

0.4. Area under Curve (AUC)

AUC curve enables to visualize how well our machine learning model is performing classification. It can be used only for boolean valued function to classify an example. It is also known as AUROC i.e. area under the receiver operating characteristics used for any classification model's performance. Figure 7 shows the AUC curve which is cumulative percentage of bad customers for the dataset.

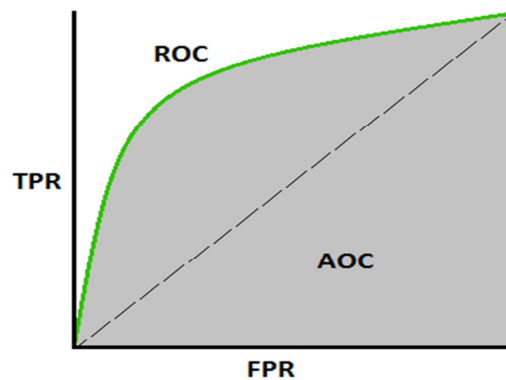


Figure 6. AUC curve.

0.5. Mean Squared Error (MSE)

MSE is basically used to measure by taking the average of the square of the difference between the original and predicted values of the data. MSE can be calculated by using equation number (7).

$$MSE = \frac{1}{N} \sum_{i=1}^N (Original - Predicted)^2 \quad (7)$$

0.6. Root Mean Squared Error (RMSE)

RMSE is the mathematical function which is used to calculate the errors which occur when a prediction is made on a dataset. RMSE can be calculated by using equation number (8).

$$RMSE = \sqrt{\frac{\sum_{i=1}^N \|y(i) - \hat{y}(i)\|^2}{N}} \quad (8)$$

0.7. Standard Deviation (SD)

Standard deviation (σ) is basically used to measure dispersion of the data with respect to mean, or how the data is spread out. Standard deviation is calculated using equation (9).

$$Var(N) \approx \frac{1}{N-1} \sum_{i=1}^N (xi - \mu)^2$$

$$\sigma \approx \sqrt{Var(N)} \quad (9)$$

To predict a credit score for an existing customer from finance industry; the predictive model makes use of confusion matrix to classify instance with the help of values shown in table 1. The prediction is giving false negative (FN) and true negative (TN) values then the model classifies it as default (Negative). This is considered as bad prediction and customer accurately labeled as bad (default). On the other hand if the model gives true positive (TP) and false positive (FP) values then it is classified as non- default (positive). This is considered as good prediction and customer accurately labeled as good (non-default). Figure 7 shows the proportion of bad customers and good customers which are distributed.

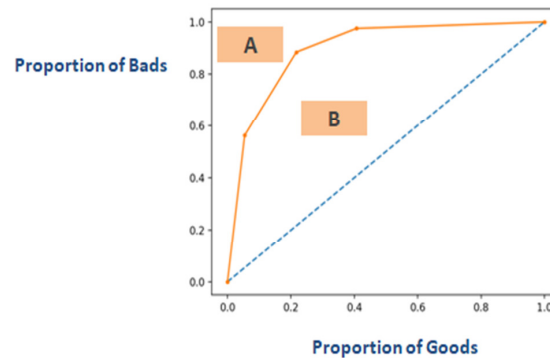


Figure 7. Number of default and non-default customer for the dataset.

Table 2 represents various attributes of customer which is used to finding out the patterns so that the prediction can be made. Attributes description used in the dataset are shown in the table 2. These features selection are very crucial and used to judge customer behaviour applied for credit score. The predictive model predicts a credit score to classify default and non-default customer based on customer behaviour and helps lenders to allocate funds in finance industry.

Table 2. Represents the description of attributes used in the dataset.

S.R	Feature selection based on customer behavior for credit score	Description of attributes
1	employment_period	No. of year borrower working from credit report.
2	open_account	Open trade line
3	credit_history_length	Age of the borrower of credit from report.
4	public_record	No. of derogatory
5	annual_income	Borrower's income in a year.
6	loan_policy	1 if the customer meets the loan underwriting criteria, and 0 otherwise.
7	type_of_purpose	This refers to the purpose of the loan.
8	grade	It define the category of credit score in grade from class A to class G. Class A no risk class G more risk.

Fig.8 shows the credit score of various existing customer for a financial institution with total population. The performance of the model is influenced by existing studies by Xu *et al.* [10] and Bastani *et al.* [17]. These existing schemes focuses on using deep neuron network for similar purpose and hence tested over same dataset. It can be seen from Fig.8 that model produces a good credit score

from existing approaches. The model gives an approximately 87% accurate prediction for identifying default and non-default customer. Fig.9 shows the total number of default customer represented by value “0” and non-default customer represented by value “1”. Fig.10 shows the number of default customer increases as the loan distributed over the customer. Moreover, it is less likely for lenders or investors to predict a wrong prediction for allocating the fund using the proposed predictive model as the model is trained and tested in such a way. Therefore, a higher degree of prediction is offered by the proposed predictive model.

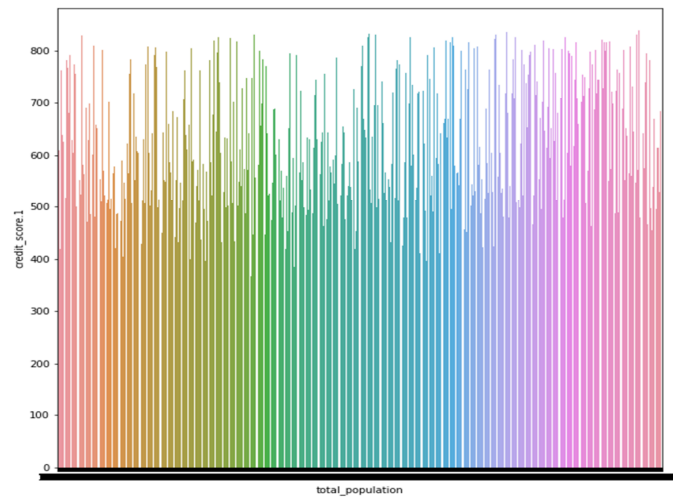


Figure 8. Credit core of proposed predictive model against total population.

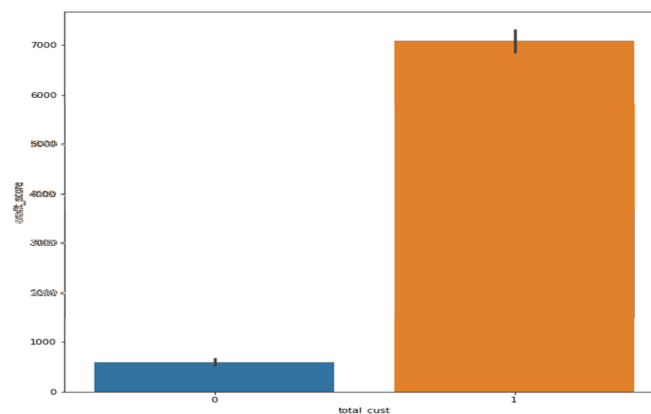


Figure 9. Total number of default with value “0” and non-default with value “1” customer.

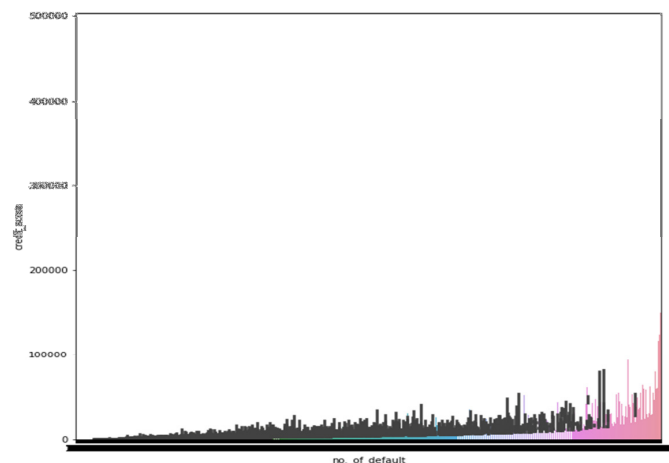


Figure 10. Default customer with value “0” increasing with the increase in fund distribution.

6. Conclusion

This research study come about a predictive model which uses deep neural network along with decision tree classifier for finding out the default and non-default customer for a finance industry. The model helps the lenders or investors to take a decision for allocating funds to a particular non-default customer involve in financial institution. The model uses credit score dataset to make a prediction about the customer with a great accuracy. The main contribution of this research work is to analyze and classify credit scoring strategies based on the customer behaviour. The predictive model would be very useful for the financial institute for predicting the credit score for the existing customers which helps the lenders from huge financial loss. Deep neural network helps the predictive model to make a prediction by using activation function and uses root mean square function to minimize the error. The model not only predicted the probability of default but also gives profit to the lenders. In the process of credit scoring the role of dependent variable is very crucial because it assign “0” for the default loans and “1” to non-default lone. Additionally, this paper uses efficient feature selection method, ReLU activation function for weighting method and decision tree classifier for labeling the class to improve the efficiency of the predictive model to make a prediction about credit score. The best part of the scheme is to predict accurate credit score with credit risk for the lenders by making use of performance indicators such as accuracy, mean, standard deviations, root mean squared error, probability of default and area under curve were implemented on different credit scoring dataset in real life scenarios. The simulation results shows that the predictive model is efficient accurate in credit scoring system.

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