Credit Risk Forecasting using Deep Learning

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Abstract - **Credit risk is the probability of incurring a loss due to a debtor's inability to repay debt. In this paper, we propose to create a Deep Neural Network Classifier (DNN) to forecast the credit risk. We also aim to study the performance of Deep Learning systems for Credit Risk Management on structured data. A comparative study of Credit Risk Forecasting systems using DNN, Logistic Regression, Linear Classifier and Random Forest classification models is conducted. The objective of the classification models is to identify and label the debtors associated with higher credit risk. The DNN Classifier achieves an accuracy of 91.57% and the area under the Receiver Operating Characteristics (ROC) Curve is 89.53%. Since the model is trained on data, which is updated periodically, the model can be utilized to predict future credit risk exposure as well.**

keywords - **Area Under Curve, Deep Neural Network, Linear Classifier, Precision, Recall, Receiver Operating Characteristics**

I. INTRODUCTION

Credit Risk Forecasting refers to the process of mitigating losses by predicting the propensity of default. The United States economy experienced a major financial bubble in 2008 which led to a period of financial uncertainty that had a catastrophic impact globally. Credit Risk can be indicative of such events and can help in assessing the health of the economy. Since 2008, several approaches have been adopted for Credit Risk Management that involve the use of Machine Learning algorithms for forecasting the likelihood of default. Current research has not fully explored the power of deep learning algorithms on structured data and for credit risk management. Whereas, our research efforts are aimed at creating a new and robust credit risk model using Deep Learning.

The paper of K. Y. Tam and M. Y. Kiang [1] introduces a neural network approach to perform discriminant analysis in business research. Using bank default data, the neural network approach is compared with linear classifier. Although, the neural network model is a promising method of evaluating risk, in terms of predictive accuracy, adaptability and robustness, it lacks interpretability and is difficult to explain.

The objective of the paper of T. S. Lee, C. C. Chiu, C.J. Lu and I. F. Chen [2] is to explore the performance of credit scoring by integrating the back propagation neural networks with traditional discriminant analysis approach. This approach is inconsistent in mapping complex non-linear relationships within the data.

Z. Huang, H. Chen, C. J. Hsu, W. H. Chen and S. Wu [3] introduce support vector machines (SVM), in attempt to provide a model with better explanatory power. However, it suffers from poor testing accuracy and a subpar Area under ROC curve. Current research techniques involve the use of Artificial Neural Networks, Support Vector Machines and Decision Trees for Credit Risk Assessment. However, there has been an absence of a unifying model with superior performance and interpretability.

The approach that we have opted for Credit Risk Forecasting is different from current research in the following ways:

1) The proposed Deep Neural Network model makes use of its excellent ability to map complex and non-linear relationships in the training data thereby allowing better pattern recognition
2) We have evaluated the predictions of the Risk model by the means of the Area under the Receiver Operating Characteristics (ROC) Curve instead of Accuracy due to an inherent class imbalance in the dataset.
3) A comparative study is made among four families of Machine Learning algorithms to show that Deep Neural networks are better equipped for Credit Risk Management.

The paper is organized in the following manner: Section I provides a brief introduction on Credit Risk Forecasting and Credit Risk Management. Section II provides detailed explanation on the methods used for creating the risk model. Section III explains the evaluation metric used in assessing the model. In Section IV, the neural network approach is studied. Section V covers The Implementation, Optimization. Results are discussed in sections VI. Conclusions are covered in section VII.

II. METHODOLOGY

The classification model is trained using Supervised Machine Learning Algorithms. The work presented in this paper is carried out on Lending Club's dataset, obtained from their website. Lending Club is an online lending platform that allows users to create non-collateralized debt obligations. The data comprises 3,54,951 observations of 74 variables. The amount of the loan requested by the applicant, the amount of loan granted by Lending Club, the installments made on the loan and the annual income of the debtor are some of the variables in the dataset. Notably, the dataset also has a record of the open credit lines, number of credit inquiries made, the days past default and the ratio of income to total debt obligations for that applicant. Another crucial predictor in the data is the "delinquency". Delinquency keeps track of all occasions when the applicant has missed the deadline to pay his installments. Among these 74 variables, the "loan_status" is the target variable that the risk model will try to predict. The model performs the task of binary classification and labels each applicant on their creditworthiness.

The label definition is as follows:
0 – Low Default Risk, Eligible for Loan
1 – High Default Risk, Not Eligible for a Loan

A) *Exploratory Data Analysis*

Exploratory Data Analysis encompasses the cumulative task of cleaning, transforming, visualizing and morphing the data to extract valuable insights. Anomalies and outliers in the data can affect prediction and they need to be transformed in such a way that they don't interfere with predictions. The target variable is analyzed during Exploratory Data Analysis. It is observed that there is an imbalanced distribution among the binary classes. This is referred to as a Class Imbalance. Class Imbalance can negatively impact the model by imparting a bias. Due to a Class Imbalance, the model will be biased towards identifying borrowers associated with a low Default Risk. Table1. shows the percentage of data belonging to each class of the target variable.

Table 1
Class Imbalance Table

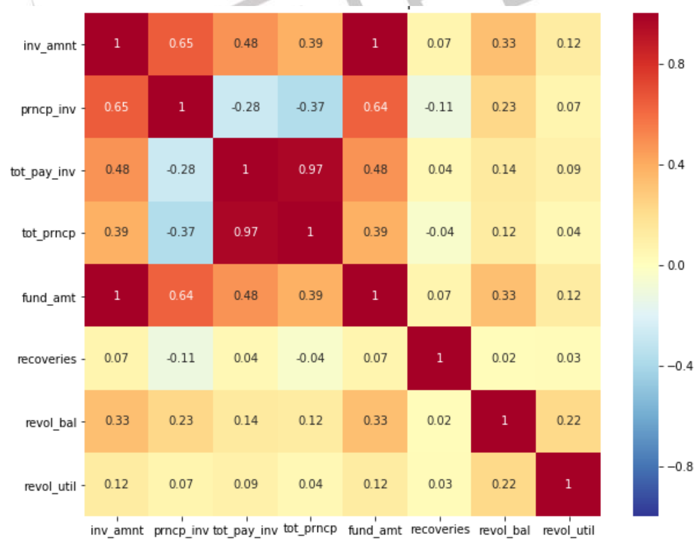
LABEL	0	1
PERCENT OF INSTANCES	92.41%	7.59%

The bias will throw off the accuracy of predictions. Class Imbalance can be rectified either by Under sampling, Oversampling or training the model on a well-balanced training data set. In this paper, we train the model on a slightly well-balanced dataset, to offset the bias caused by class imbalance.

B) *Data Preparation*

Every Machine Learning model is only as good as the data it is trained with. To ensure optimum and precise predictions, it is essential to train the model on a dataset that is not riddled with redundancies. *Data Cleaning* refers to the task of purging the data of missing values by either omission or imputation. Columns with more than 50% missing values are dropped. Since the amount of data sacrificed doesn't explain most of the variance, it won't affect the predictions. Variables like description of the loan, URL of the website from which the loan was granted, employment title and zip codes are removed since these columns contain an enormous number of categories and will not aid the predictions. *Correlation* is a statistical measure to assess how a pair of variables are related to each other. A feature correlated with the target variable is important as it aids the predictions. Multi-collinearity increases harmful bias, thereby limiting accuracy. Figure 1 shows the Correlation heatmap for a few features from the dataset.

Fig.1 Correlation Heatmap



In this paper, for treating correlation, a benchmark value of the Pearson Correlation coefficient is set. Features possessing Karl Pearson's Correlation coefficient greater than 0.9 indicate strong positive correlation and one of these features is dropped, thereby reducing the dimensionality of the data. Inter-feature correlation makes the data more complex and retards the learning rate. Therefore, a DNN will train faster on data with lower dimensionality. For *Categorical Features*, A Label Encoding tool has been used for dealing with categorical data. Label Encoder basically changes the data type of characters to integers. “Term” is the feature that describes the duration of the loan period, i.e. ‘36 months’ or ‘60 months.’ Similarly, the ‘verification_status’, ‘payment plan’ and ‘application type’ columns are Label Encoded as well. Label Encoding cannot be performed for all categorical features in a dataset. Features with many categories can be treated by grouping them, if they retain their individual properties in a parent group. ‘Loan_status’, ‘homeownership’ and ‘employment length’ are some of the features in which the data is grouped together. Purpose of loan indicates the reason for which the loan request is being issued. It has 13 different categories which are grouped into debt consolidation, educational, small businesses and others. Table 2 indicates how data in the Loan Status column is aggregated.

Table 2
Grouping Status of Loan Column

Loan Status	Transformed Data
‘CURRENT’, ‘ISSUED’	CURRENT
‘FULLY PAID’, ‘EARLY PAYMENT’	PAID
‘DEFAULT’, ‘CHARGED OFF’, ‘IN GRACE PERIOD’, ‘LATE (16-30) DAYS’, ‘LATE (31-120) DAYS’.	DEFAULT

III. Deep Neural Net Classifier

Neural networks are modelled to function like the human brain. A neural network aims to replicate the cognitive skills which humans possess [4],[5]. Neural networks consist of multiple layers. The layers are made up of neurons, which resemble the ones in the human brain. First, the data is fed to an input layer, which is connected to a single or multiple hidden layer(s) and these hidden layer(s) are connected to the output layer by the means of weights [6]. When the neural net is trained, the weights constantly change in order to fit the training data and minimize training loss.

A Deep Neural Network is essentially a neural network with several hidden layers. Due to its complex architecture and ability to map complex relationships, DNNs are better at pattern recognition, as compared to the traditional machine learning algorithms. Neural networks possess an activation function, a cost function and an Optimizer. Activation Functions are used to determine the output of a neural network. An Optimizer is used to specify, analyze and update the hyperparameters of a neural network in order to generate the best fitting model. The cost function is a metric to evaluate the loss incurred during predictions. The objective is to arrive at a minimum value of loss to achieve accurate predictions. In our research, we have selected the Gradient Descent Algorithm for evaluating cost functions. After applying and comparing the Deep Neural network on various activation functions and optimizers, the minimum amount of loss was obtained when a Rectified Linear Unit (ReLu) activation function [7] was used along with an AdaGrad Optimizer. Adagrad is an optimizer which stresses specifically on parameterized learning rates, which are computed relative to the frequency of updating parameters during training. Higher frequency of updates implies that the update size is smaller [8]. A Deep Neural network classifier is deployed using TensorFlow’s Estimator API in accordance with the above-mentioned parameters. The DNN will use the variables from the dataset as feature vectors and periodically update its weight according to the expected output. The performance of the DNN is evaluated by the Area under ROC Curve. We have also compared the performance of Deep Learning system with traditional Machine Learning algorithms to ascertain if the former performs better than the latter, both in practice and theory.

DNNs have been extensively used for image, audio and video data. However, it’s uses in determining creditworthiness on default loan data has been limited. Our proposed DNN model aims to improve the existing loan disbursal systems and minimizes the cash shortfalls associated with high risk debtors.

IV. Implementation And Optimization

The data is collected from Lending Club’s website and stored in a comma separated value(.csv) file format. Data Engineering is carried out on the dataset as mentioned in section II to obtain the transformed dataset on which machine learning is performed. After normalizing the training data, we carry out a train test split. The data is split with 70% constituting the training data. The data is also validated using Folded Cross Validation. The number of folds is 10 and the epoch is set at 1000. This implies that the weight updating will occur over 1000 iterations on the training vectors. Another parameter which needs to be set is the number of hidden layers in the DNN. We begin with sixteen hidden layers containing 64 neurons each. It is important to choose the appropriate number of layers for the model. Accuracy is not guaranteed by simply adding more hidden layers to the model. The likelihood of overfitting skyrockets if layers are added blindly. The training occurs in 5000 steps and the loss is measured every hundred steps. The objective is to minimize the training loss while achieving a high Area under Receiver Operating Characteristics (ROC) Curve. The Area under the ROC curve obtained in the classification report is indicative of the performance of the model. The report also generates precision, recall and F1-scores for the model. Table V is the classification report for the model before optimization. The DNN achieves an AUC of 60.65%. The DNN performed poorly because the hyperparameters were not fine-tuned to aid the model's predictions. Table 3 presents the initial results for the unoptimized DNN.

Table 3
Classification Report for Unoptimized DNN

Accuracy	92.43%
Area Under ROC Curve	60.65%
Precision	0.86
Recall	0.92
F1-Score	0.89
Global Steps	5000

Optimization is the process of altering the hyperparameters of the model in order to improve performance and robustness of a system. Optimization is carried out using GridSearchCV, which uses loops to determine the best possible hyperparameters over a wide range of values for number of layers, units in each layer and the number of epochs. Although the process is time consuming, we have observed that it returns the best possible values for tuned hyperparameters.

The data split has been changed to 80% for training, 15% for testing and 5% for validation. The number of epochs is increased to 2000 from the original 1000. The number of folds for validation is kept unchanged. The units in the DNN are reduced to 32 per layer. The number of hidden layers is changed to 32. Training is carried over for 1000 steps and the loss is measured every 100 steps. The model not only took lesser time to train but also had a reduced loss. Table 4 shows the report of the optimized Deep Neural Network model.

Table 4
Classification Report for Optimized DNN

Accuracy	91.57%
Area Under ROC Curve	89.53%
Precision	0.89
Recall	0.88
F1-Score	0.88
Global Steps	1000

Although there was a small drop in the accuracy, the optimized DNN has achieved a significantly greater Area under ROC curve. The hyperparameter tuning ensured a reduction in the number of False Positives that were being predicted by the model, thereby augmenting the precision. However, a tradeoff occurs with a drop in the number of false positives. The number of false negatives is observed to increase, thereby decreasing the recall score. Opting for a higher precision implies that the model won't approve the loan to high risk clients, thereby saving the company a lot of money, which would've been lost on a possible Non-Performing Asset (NPA). However, the consequent increase in false negatives implies that a debtor who could be eligible for a loan, won't be approved by the model. This could adversely affect the approval ratings for the company. The trade-off can be resolved by appropriately deciding if a corporation want's a higher precision or recall score. In the next section, we discuss why Area under ROC curve has been chosen to evaluate the performance of the model.

V. Evaluation of The Model

The Credit Risk model performs binary classification and labels the debtors affiliated with higher default risk. The area under the Receiver Operating Characteristic (ROC) curve is selected as the evaluation parameter for the model. The ROC curve is a graph of the True Positive Rate (TPR) plotted against the False Positive Rate (FPR). These are derived from a Confusion Matrix. A Confusion Matrix is used in statistical classification to judge the performance of a classification algorithm [9]. Table 5 depicts the general layout of a confusion matrix along with formulas of the metrics used for evaluation.

Table 5
Confusion Matrix

		ACTUAL LABELS	
		0	**1**
PREDICTED LABELS	**0**	TRUE POSITIVE(TP)	FALSE POSITIVE(FP)
	1	FALSE NEGATIVE(FN)	TRUE NEGATIVE(TN)

The following statistical parameters are obtained from the confusion matrix:

1) False Positive Rate (FPR): False Positive rate or fall-out is the probability of a false alarm [10][11].

$$\text{FPR} = \frac{FP}{FP+TN}$$

2) True Positive Rate (TPR): True Positive rate or *Recall (R)* is the probability of detection [10][11].

$$\text{Recall (R)} = \frac{TP}{TP+FN}$$

3) Precision (P): Precision is defined as the Positive Predicted Value, [10][11].

$$\text{Precision (P)} = \frac{TP}{TP+FP}$$

4) F1-Score: The weighted average of Precision and Recall is known as the F1 score [10][11].

$$\text{F1-Score} = \frac{2\times(P\times R)}{P+R}$$

Where P is the Precision and R is Recall.

The implicit goal of the Area Under Curve (AUC) is to deal with cases in which the target distribution is highly skewed and to avoid overfitting of a single class. Since the target variable that the algorithm will train against is biased towards '0', extremely high accuracy can be achieved if all cases are predicted as '0'. Hence, accuracy can be misleading while evaluating a classifier trained on skewed data. Therefore, the AUC is used to evaluate the model.

VI. COMPARATIVE STUDY OF ALGORITHMS

The approach of this paper advocates the use of some traditional Machine Learning algorithms along with a Deep Learning model. Another driving force behind this paper is to observe the performance of Deep Neural Networks on structured data, in the Retail Banking domain. The families of classification algorithms that were selected are Generalized Linear models, Discriminative Classifiers, Ensemble methods [12] and Deep Neural Networks.

Out of the four families of classification algorithms presented in this paper, an algorithm from each category was chosen. Logistic Regression, an algorithm belonging to the generalized linear models [13] is chosen as the baseline model. Apart from the Random Forest Classifier and A Deep Neural Net classifier, a Linear Classifier, belonging to the family of Discriminative Classifiers [14] is also used to forecast credit risk. From the results presented in Table 6, it can be concluded that the Deep Learning model that has been created is best suited for predicting Credit Risk. The model achieves an accuracy of 91.57% and an AUC of 89.53%. Table 6 demonstrates how the algorithms performed in predicting the Credit Risk based on the Area under the ROC.

Table 6

Performance of Classification Algorithms

Model	AUC
Logistic Regression	74.03%
Linear Classifier	71.51%
Random Forest	86.57%
Deep Neural Network	89.53%

VII. CONCLUSION

The Credit Risk Forecasting model was created and trained on a Deep Neural Network model and Lending Club's data. Based on the results of the classification report, the risk model showed potential to predict Credit Risk precisely.

The ability to analyze, predict and make informed decisions about the implications surrounding Credit Risk will have a widespread influence. If Credit Risk, a measure of the propensity of default can be measured to a high level of precision, creditors will end up making statistically sound decisions. By knowing the credit risk of a debtor, creditors can adjust their lending policies and select their approach towards Credit Risk Management in the light of economic fluctuations and the general instability in the financial markets.

Due to the influence of the Credit Risk model on lending firms, the model needs to be continuously improved. Lending firms need to provide a greater number of data points to train the credit risk model. By providing new features and by researching new machine learning algorithms, the performance of the model can be significantly improved.

Additionally, this model can be used to generate a probability score [0 to 1] to estimate Credit Risk. Automated Lending firms can also use this model to allow debtors to create personal non-collateralized loans and get them approved instantly without having to fill forms or standing in long queues. This greatly improves the customer experience while ensuring the absence of cash shortfalls associated with high default risk.

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