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Prediction of Credit Card Customer Repayment using LightGBM Classifier

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***Abstract*— This report discusses about the implementation and enhancement of defaulter prediction model, for predicting the future behavior of the customers using the recorded data of their past behavior and other demographic factors. This algorithm which has been chosen for this research is Ensembled Machine Learning Technique called LightGBM algorithm. This report also discusses about the methods which are already implemented for predicting the customer behavior, in various researches and their results were compared with the algorithm that is implemented in this research. It has been observed that LightGBM has more accuracy and area under ROC curve than the other algorithms, which helps to prove that the model which is adopted for predicting the defaulters of future credit card bill payment. And further the model is enhanced by the reduction the features to provide the business with more accurate result in understanding the future behavior of customer in the payment of bill.**

Keywords—Prediction, Defaulter, LightGBM, Accuracy, Feature Reduction.

I. Introduction

Forecasting the customers' behavior with the historical data has helped many industries to save their business from the future failure. This reason has resulted in recording the details of customers and their behavioral pattern towards their business, especially in Banking Sector. Especially in the business of Credit Card Issuing and Lending, they tend to maintain portfolio of their customers which helps to them analyze the data and to take necessary action whenever it is essential [1]. Business has been using the Machine Learning techniques to analyze their business data and to obtain the insights which could help them for future plans or strategies, in the field of Credit Card Business, these computer supported machine learning models were commonly used for predicting the future bill payment of the customer and credit scoring of the customers which would help them to classify the customer and their values. This prediction helped the business, especially loan lenders from bankruptcy. With the information obtained from these researches on the customer potential, two main actions can be implemented in the business

1) Identification of the customer accounts which has high probability of becoming defaulter in bill payment.
2) Develop policies which are appropriate for the different categories of the customer.

According to the perspective of Risk Management, predicting the probability of the customer to not pay the future payment is better than classifying customers as Risky and Non-Risky. Identification of probability of the customers behavior helps the lenders to take necessary steps such as intimating the customer about their due date of bill payment, taking necessary steps to provide the customer the knowledge about the advantages of paying their bills on-time, making an communication with the customer through any means in order understand their situation and provide certain assist that could encourage them towards paying the bills, and company could encourage the loyal customers with rewards and offers which could increase their interest towards being non-defaulter in payment and this could also help the business for retaining their customer.

The data [2] considered for this research is the dataset which has collected records of the customers in credit card lenders in Taiwan, for the time period between April 2005 and September 2005.The dataset has a record of 30,000 customers and 24 features that helps for prediction of the probability of the customers to become the defaulter. This data has been collected as result of the financial crisis that happened in Taiwan because of the excessive issues of credit cards to the customers, despite of their financial potential. This ultimately led to utilization of the credit by the customers more than their potential limit and resulted in debts which they could not afford, which led to bankruptcy for many banking sector businesses. The information of the credit card clients was collected to research and develop a machine learning or deep learning model which could help the business to identify and classify their customers. This research could also help the business to adopt an appropriate policies for the different category of customers depending on their historical data, credit scoring and other personal information, this could also help the firm in order to maintain their reputation and relationship with the customer.

Ensembled Learning [3] is one among the efficient and effective way of building a Machine Learning Model. It has been proved that adopting ensembled learning technique in a Machine Learning model has improved the performance of the model. The techniques which has been used in this research is one among the advanced ensembled learning technique called Boosting. This Boosting technique is a process that occurs in a sequence, where every subsequent model works on correcting the errors from previous model, on which it is dependent. This algorithm also does that task of grouping the weaker learners which could result in a strong learner that could result in boosting the overall result.

Gradient Boosting Decision Tree algorithm [4] is a popular Boosting technique in Machine Learning, which includes implementations such as pGBRT and XGBoost, but when it comes to the condition of huge datasets and feature dimension is high, their performance depreciates. And these processes are observed to consume more time since they have to scan all the data instances in each feature to gain the overall information and to decide the split points. In order to avoid this issue techniques like Gradient-based One-Sided Sampling (GOSS) and Exclusive Feature Bundling (EFB)

LightGBM algorithm has been developed. Light GBM models have the advantage of faster training speed, higher efficiency, lower memory usage, better accuracy than other boosting algorithm, supports parallel learning and compatibility with large dataset. These features have proved that adopting this algorithm for this research could provide a result which could effective and efficient for the business purpose.

This report is divided into three sections,

(1) Techniques Applied, where the machine learning and deep learning techniques which are applied in past researches will be discussed.

(2) Technique Employed, this section covers the implementation of the LightGBM method for this research and about the data pre-processing, implementation, and evaluation of the result with the values from the techniques applied in the past.

(3) Conclusion, the result of the research will be discussed in both qualitative and quantitative perspective and their business importance is also discussed.

II. Applicable Techniques

There are several researches that has been done in the field of Banking sector. Machine Learning techniques, Deep Learning techniques were implemented on the customer data of the financial industries for many purposes mainly for two important uses, predicting the defaulters in credit bill payment and for credit scoring of the customers. The methods employed for such purpose were discussed in this section below.

A. *Machine Learning Models.*

The research [5] that has been conducted in comparing the performance of the Machine Learning algorithm such as Logistic Regression, rpart Decision Tree and Random Forest. This research also involves feature selection, dimensionality reduction and comparing the results of evaluation metrics of different machine learning model deployed in this research. And it has been concluded that the Random forest has performed better that other implemented models in this research which accuracy of 82% and Area under ROC curve to be 0.77. Another research [6] has been conducted to study the performances of other different classifiers and to obtain meaning pattern from the data. Data Mining techniques like BayesNet, , Naïve Bayes, Random forest, SMO and Meta-Stacking, are utilized for predicting the defaulters in credit card payment. The observation from this research has provided the knowledge that Random Forest has performed with better accuracy than the other employed methods. And further in addition to this research creation of subset good Correlation feature and Information Gain Selection models has also been adopted which has resulted in increased performance in Random Forest algorithm. This article [7] is about the research that involves in adopting a different approach towards the classification of customers depending on their past records. With the help of covariates of components, the researcher could get some knowledge about the impact of factors that helps in classification of customers. This research could help the in designing norms for the customers for the customers before getting a credit.

B. *Deep Learning Models.*

This journal [8] has claimed to be utilizing a novel method of prediction the customer behavior using the neural network along with grey incident analysis and Dempster-Shafer theory for predicting the defaulters. This method is implemented in two stages, first stage covers the implementation of the evolutional neural network model and the next stage functions the same but with selection of features before training the model. The process of feature selection is conducted in two different methods. First feature selection method uses the traditional & modified grey incident analysis to get the variable ranks. The other method uses the Dempster-Shafer theory, which can perform the fusion of data for variables obtained from the prior method. The integrated approach of Evolutional Neural Network model developed has produced the accuracy of 86.33% and the area under ROC curve 0.773.

Authors of this research paper [9] discusses about the performance of classification of the deep learning algorithms such as deep belief networks which has restricted Boltzmann machines and comparing their performance with other machine learning algorithms which has been already utilized for the purpose of predicting the defaulter in the customers. The method deployed in this research stands unique out of other techniques developed for the purpose of classifying the customers, because Deep Belief Networks has performed with an accuracy of 100% and this the AUC value as 1, which shows this this methods performs the best in prediction with Zero Error Rate. The research [10] involves in applying Discriminant Analysis, Neural Network, Logistic Regression and DEA-Discriminant Analysis, resulting that DEA-DA and Neural Network performing better in predicting the customer default. Measure of Goodness-of-fit involves cross-validation to obtain Accuracy Rate, Sensitive Rate, and hit rate.

This research [11] has utilized the Self-Organizing Map to clustering and visualizing the Bankruptcy pattern which many help the business and the researcher to understand the situation and to conduct further decisions to prevent the bank from such situation. The information utilized for this research is from the financial reports of the state of SMEs in the Podkarpacie region. This research has proved that SOM is efficient in providing the business about the financial pattern of the region which may help in predicting the investments in the business. About 16 patterns has been observed in which categories of classes like Bankrupt, in-liquidation and non-Bankrupt has been obtained. And the representation has been done with the help of Kohonen map.

This journal [12] is about identifying the potential target customers with the help of applied neural network approach. This research involve in the process of categorizing and defining the target customers, collection and classification of the Eigenvalues of the data, preprocessing the collected data by converting the proportional scale and nominal values, selecting the appropriate neural model and subsequent parameters, and as the final step choosing the Eigenvalues of the data with high discriminability. The results show that neural network outperformed the decision tree and logistic regression. The paper proposed in [13] involves credit card default modelling with Bayesian Neural Network(BNN). The model is trained with Gaussian approximation and the initial

BNN model is trained by Hybrid Monte Carlo (HMC). The model of BNN which has Automatic Relevance Determination (ARD), performed better than the model without ARD. ARD Multilayer Perceptron has the weights associated with the distant class. The inputs with less relevancy will have high values of regularization parameter, whose weights will gradually reduce. HMC generates the sample by simulating the Markov Chain along the distribution as stationary, from the distribution of exact posterior.

C. Hybrid Models:

A hybrid approach has been followed in the research [14] of credit card scoring model, which uses an unsupervised deep learning method of Self-Organizing Map (SOM) to improve the capability of discriminant of feedforward neural network (FNN). This works in a process of the output obtained from the SOM is then transferred into the FNN model subsequently. The research published in ScienceDirect journals [15] is about the testing the performance of the dynamic models implemented for forecasting the defaulters in credit card clients. The testing parameters include the micro stress testing and macro stress testing, which depends on the size of the institutions considered for the analysis. Forecasting has been done with the dynamic model which is built to replicate the real-time scenario and the prediction is done with the help of the history of records provided as training dataset. Evaluation of the model developed for this research includes presenting the underlying hazard for the default, estimation of coefficient of the variables, model fit along with forecasting results which also includes the result of forecast at aggregate level, and finally concluded with the presentation of result of the stress test on the dynamic model. Hazard rate of the defaulter is presented to be reducing over the increase in the time period. The stress test of the model resulted that it performs well in predicting the risk of default for a short-term of time than the far future prediction. A survey on the implementation of hybrid and ensembled based techniques of computation in predicting the bankruptcy is conducted by the researchers of the journal [16].

The paper [17] propose a hybrid approach on predicting the failure of the established firms with the help of the historical data, along with implementing with combining rough set approach and neural network model. Rough set approach will identify the classification rules with the process knowledge induction with which the decision rules are selected along with minimal set of features. The researches have proposed the 2-Dimensional Reduction Algorithm which helps in preventing the overfitting problem and reducing the training time.

D. Unsupervised Learning Models.

Unsupervised learning technique of clustering is utilized in this research to credit card customers classification and analyzing them for predicting the financial risk of investment for the financial lending firms is studied in the research [18]. The unsupervised clustering analysis has been analyzed and the improved along with the ensembled learning technique and supervised learning technique. The research has also utilized the CLUTO clustering technique for categorizing the customers along with a couple of machine learning methods such as decision tree and multiple-criteria linear programming (MCLP) were utilized for increasing the efficiency of the model. Result inferred that the clustering has helped the stand-alone classification models for better performance. This research [19] has utilized the clustering technique for analyzing the risk of the customers of banking sector. Behavioral factors of the customers were clustered depending on the pattern of their customers from the record, this also includes identifying the parameters which do not contribute for the purpose of unsupervised learning, using the statistical methods.

E. Data Imbalance:

[20] describes about the review about the techniques used to handle the in the customer related data for financial sectors. Data Imbalance plays key role in affecting the efficiency of the performance of the prediction model. The dataset considered for this analysis has the data imbalance where most of the customers falls under the non-defaulter's case and the defaulters case contributes 4% among the overall record of customers. The methods utilized for the process of class imbalance correction are Random under-sampling, Random over-sampling, and few hybrid methods, Synthetic Minority Oversampling Technique (SMOTE), TOMEK, Wilson's Edited Nearest Neighbor Rule (ENN), other method in the combination of TOMEK Links & SMOTE and other combination of SMOTE + ENN. The researcher has utilized the modelling techniques such as Logistic Regression, Decision Tree, Random Forest and Naïve Bayes are implemented to analyze the data obtained from the methods implemented to overcome Data Imbalance. The result has shown that hybrid techniques implemented to prevent data imbalance has helped in most of the cases to obtain more efficiency.

F. Ensemebled Learning Models.

The research [21] discuss about utilization of boosted decision tree approach along with Bayesian hyper-parameter optimization for scoring the credit of the customers of the banking sectors. The hyper parameter optimization technique has been developed with TPE algorithm as its base. The model has been evaluated with five different datasets and few parametric evaluation metrics. The Ensembled method in which the structure can be split into sequential and parallel ensembles model has been developed for credit scoring the customers. To improve the performance of the ensembled method highlighting the hyperparameter tuning, developing the sequential models, and key focus on the learning efficiency of the models. Model-based feature selection is utilized to avoid redundancy of the variables. Hyper-parameter of the XGBoost model has been tuned adaptively with the help of Bayesian hyper-parameter optimization for training the model.

Light GBM classification model has also been proven to be performing better than the many other machine learning methods in predicting the customers' default as per the journal [22]. The research. This research involved in implementing Logistic Regression, Neural Networks, Support Vector Machine, XGBoost and Light GBM algorithms among which Light GBM has proven to be efficient in predicting the customers' behavior. The efficiency of the model is evaluated with the metrics like

AUC, Precision (Correct Rate) and F1 score which is shown in the table below in Fig.1

methods	Logistic	Neural Networks	SVM	Xgboost	LightGBM
AUC	0.7228	0.7735	0.7230	0.7792	0.7904
Correct rate	79.19%	81.76%	81.90%	81.95%	82.29%
F_1	88.08%	88.83%	89.15%	89.10%	89.34%

Fig.1 Comparison of Evaluation metrics of the models for prediction.

The occurrence of the error in the prediction is evaluated and compared with the values of other implemented models which proves the same that Light GB performs better than the other models.

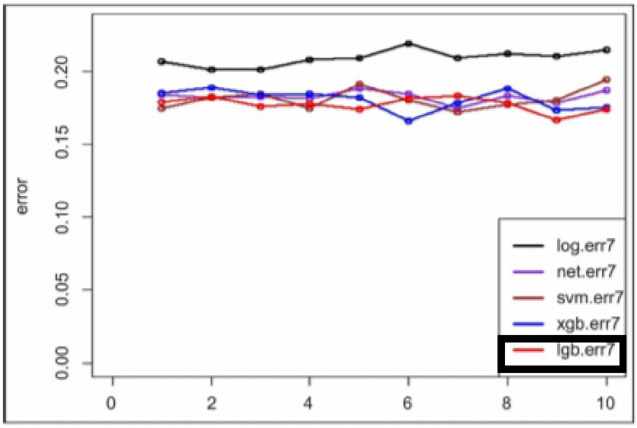

Fig. 2 Comparison of Seven times 10-fold Cross Validation Error rate of the implemented models.

methods	Logistic	Neural Networks	SVM	Xgboost	LightGBM
The mean of 10 times 10-fold CV error rate	0.2091	0.1824	0.1810	0.1805	0.1771

Fig.3 Comparison of mean of ten times 10-fold Cross Validation Error rate of the implemented models.

The graph in Fig.2 and table in Fig,3 shows that the occurrence of error in the Light GBM model is lesser than other machine learning models. This provides a strong proof for utilizing the model for the business purpose where the occurrence of mistakes in decision must be lower.

III. TECHNIQUE EMPLOYED

The method utilized for developing a prediction model in this research is Ensemble learning method, which are the meta algorithms that combines more than one machine learning techniques into one model for prediction. Gradient Boosting is the ensembled learning techniques utilized in this research. Ensembled learning techniques [3] has been proven to be efficient in developing a robust model for the prediction, since it utilizes the knowledge acquired from the machine learning model which has been executed on the data and then performs the learning and prediction.

Boosting is the process that takes place in a sequential manner where the model subsequentially attempts to rectify the error occurred in the previous model. Boosting method combines the number of weak learners from the previous model to form a group as a strong learner, this process takes place by adjusting the weights of the learners where more weightage has been provided to the weak learners than the stronger ones.

Gradient Boosting Model (GBM) has been performed with the parameters which are tuned for further improving the performance in training the model. The hyperparameter tuning includes parameters like learning_rate, n_estimators and subsamples. Evaluation of parameters has been done with the metrics like loss, Area under curve, random state, and various other metrics. Light GBM is a distributed, highly performing gradient boosting framework which operates based on the decision tree algorithm. This framework is mainly used for ranking the attributes, classifying, and performing efficient machine learning tasks. Since the Light GBM model develop repeatedly in the same leaf as shown in Fig.4, the loss can be reduced than the other level-wise algorithm, which is commonly used in decision tree algorithm. This property of the Light GBM framework helps the model to achieve accuracy than the other boosting algorithm.

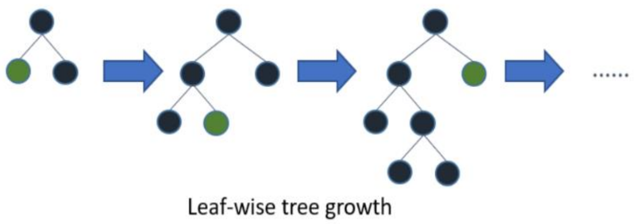

Fig.4 Diagrammatic representation of working of Light GBM

Since the Light GBM works by splitting the single leaf continuously the complexity increase as the process continues and may even cause overfitting of the performance of the model. This constrain of overfitting of the model can be reduced by using the parameter max-depth which limits iterations of the leaf increment. Several advantages like its compatibility with larger datasets, lesser memory usage and reduced training speed and increased efficiency has proven to be supporting the idea using the Light GBM algorithm for this research.

IV. IMPLEMENTATION OF PROPOSED TECHNIQUE

The implementation of the proposed Light GBM algorithm on the dataset is conducted in three different sections.

- Initially, the process starts with exploring the raw dataset and removing the used attributes which do not contribute for the prediction efficiently and the null values are neglected, this process is done as a part of Data Wrangling. The huge difference in the number of the Defaulters and Non-Defaulters in the output feature is corrected with the help of under-sampling technique.

- Second section discusses about the implementation of the Light GBM algorithm which hyper-parameter tuning on the cleaned dataset, and the parameters which can produce the better result for the Light

GBM classifier was identified and optimized parameter will be fed to the Light GBM classifier, which helps the model to perform better in the prediction. Further to enhance the performance Feature Selection was also performed which has resulted with identifying the important features of the customers which contribute for the prediction of defaulters and the other features were removed. After this process, the implementation of the model with parameter optimization is repeated in order to obtain the better prediction result.

- Final section discusses about the Evaluation of the performance of the model in predicting the defaulter in credit card bill payment.

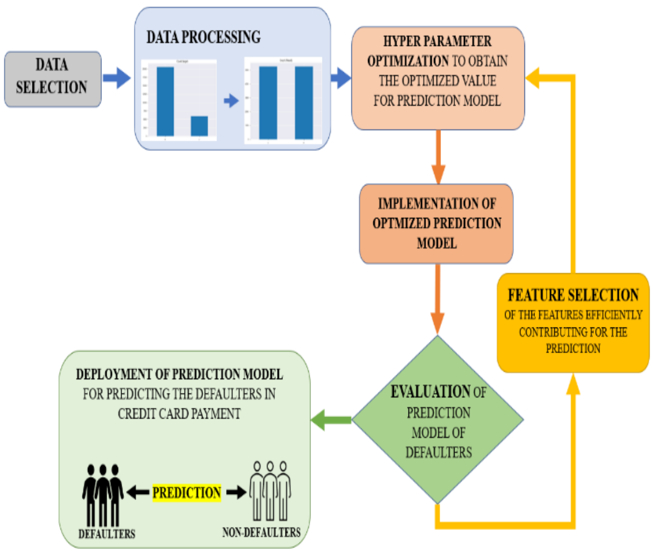

Fig.5 Implementation of Light GBM algorithm for Prediction of Credit Card Defaulters

A. *Data Wrangling*

As first step of implementation, the dataset [23] considered for this research has been extracted and loaded in the python environment and further the raw data is explored visually for the attributes and their data types. The column of Customer ID is dropped as it does not contribute for the prediction. Further the null values in the dataset is checked and found that there are no null values in the dataset. Presence of outliers can affect the efficiency of the prediction model to a great extend so the outliers are checked and removed. The huge class imbalance in the Predicted output is rectified with the help of Random-oversampling technique, where the class with lesser count will be repeated number of times to compensate the class with higher count as shown in fig.6. Then the dataset is separated into two, the feature that help for the prediction and, the feature to be predicted. And the obtained data is split into test and train data for evaluation purpose. The test set will be provided to the trained prediction model without the result value in order to make the prediction of defaulters from the customer data and the performance will be evaluated with the result values of the test data in order identify whether the model has predicted the defaulters class correctly.

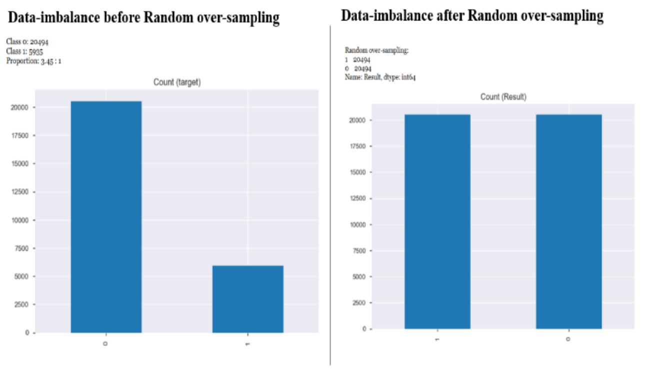

Fig. 6 Random over-sampling of class imbalance.

B. *Development of Prediction Model.*

1. *Implementation of Prediction model without Feature Reduction.*

First, the Light GB model is implemented with hyper parameter optimization performed before the prediction and the best performing optimum parameters are selected and the Light GB model is developed with the parameters obtained from the parameter optimization which shows the value of learning_rate as 0.2 and n_estimators as 38. Then the Light BG model is implemented with values set in parameter and the prediction of the model is evaluated with the test set data. Evaluation has resulted that accuracy of the prediction is 76%. And the ROC curve resulted that model could predict the defaulters correctly in 75% of the cases. To further increase the quality of the prediction. The Feature importance graph is plotted as shown in Fig.7, which shows the influence different features of customer behavior in predicting the future payment of the credit card bill.

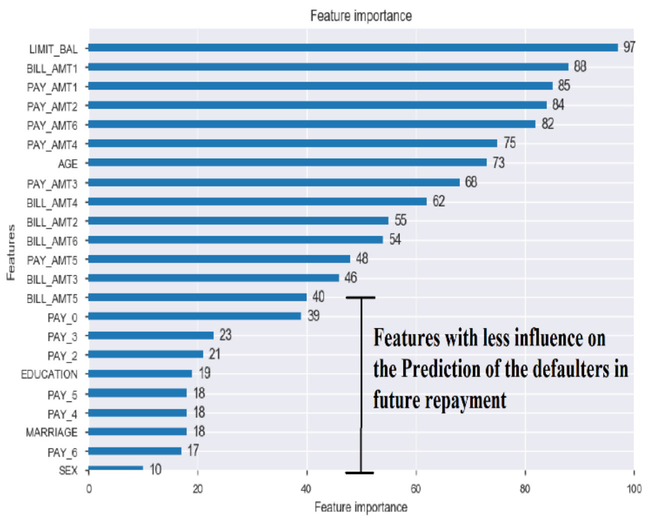

Fig.7 Feature Importance Graph

2. *Implementation of Prediction model with Feature Reduction.*

With the information about the contribution of the features of customer behavior for prediction, the features are reduced by keeping a threshold point, which is kept as 40 here and the features with the importance value lesser than 40 are removed from the consideration for training the prediction model of Light GB. After reducing the features, the parameter optimization is performed again in order to obtain the best parameter values with the reduced features. With the optimized values of learning_rate of 0.2 and n_estimator of 34 the Light GB model is trained again for the prediction and the prediction of defaulters is performed which resulted that Accuracy of the model in performing prediction has increased to 84% and the ROC curve resulted that the model performed better which correcting predicting about 84% of the customer cases about their future payment which has been shown in the Fig.7.

C. *Evaluation*

Evaluation of the model is conducted with the help for test sample of the dataset and metrics like accuracy, ROC curve, null accuracy, precision, and recall are utilized in this research for evaluating the efficiency of the prediction. The accuracy of the model helps to identify the quality of the prediction obtained from the model for the dataset. Accuracy of the Light GBM model without feature reduction is 75% which has been increased to 84% after feature reduction. And the null accuracy which is the accuracy that can be achieved by predicting the most frequent classes alone is 77%. Accuracy of the model is more than the null accuracy which shows that the model performs the prediction by not just performing the frequent classes. The ROC curve has been plotted for the model as shown in Fig.8 shows that the curve has 84% of the area under it, which shows that the model has predicted most of the customer future payment information. Precision of the model in predicting the default customers is 0.85 which makes this model suitable for prediction of the customer repayment to the bank sector business.

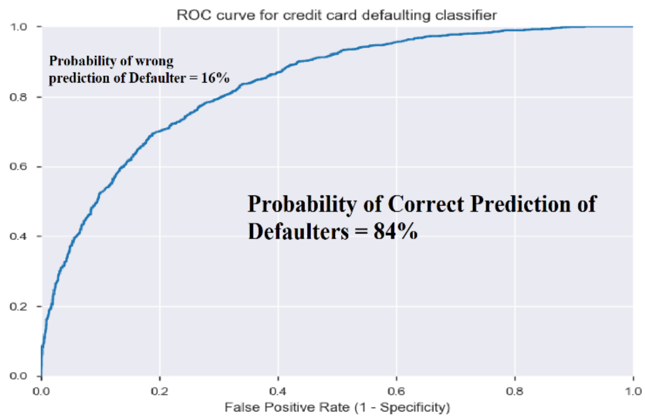

Fig.8 AUC ROC curve of Light GBM after Feature Selection.

V. Conclusion

From the knowledge acquired from the research [22] that the performance of Light GBM is better than the other machine learning algorithms in predicting the customer behavior with the historical behavior pattern of the bill, this model is implemented in this research for predicting the defaulters in the credit card bill payment for the future month. The classification algorithm has been further enhanced with hyper parameter optimization and by reducing the less influencing features of customer data for training the model. Evaluating the model has proved that the model has produced the value of efficiency desired to implement the model for the business which could help them to forecast the behavior of customers and to make decision which could prevent business from hassles. And further the feature reduction technique has provided an information about the features of the data which has less influence for making the prediction of customer behavior, which could help the business to concentrate more on recording the essential features of customers correctly which could help the developed model to provide efficient results after deployment in the company.

With the developed model the customers behavior will be predicted with the max accuracy, which helps the business understand the customers better before providing the loan or the credit limit for the new customers, which could help the firm to maintain the customer relationship better without any discrepancies. And for the current customers if the probability of the customer becoming the defaulter is high in their future bill repayment of their debts, suitable steps can be taken by providing the list of customers as leads to the customer relationship management, where they can provide certain offers, discounts or rewards for the customers in order to increase their interest towards the repayment

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