Interpretable Machine Learning Models for Credit Risk Assessment

Md Al Mahedi Hassan
Department of Computer Science and Engineering
JAIN (Deemed-to-be University)
Bengaluru, India
mahedialhassan2000@gmail.com

Rakshit Govind T
Department of ECE
BMSIT&M
Bengaluru, India
rakshitgovind982@gmail.com

Usman Muhammad Mansur
Department of Computer Science and Engineering
JAIN (Deemed-to-be University)
Bengaluru, India
muhammadmansur737@gmail.com

Roshan Jha
Department of Computer Science and Engineering
JAIN (Deemed-to-be University)
Bengaluru, India
roshanjhazha825@gmail.com

Md Forkan Hossain Fahim
Department of Computer Science and Engineering
JAIN (Deemed-to-be University)
Bengaluru, India
forkanfahimhossain@gmail.com

Mahesh T R
Department of Computer Science and Engineering
JAIN (Deemed-to-be University)
Bengaluru, India
trmahesh.1978@gmail.com

***Abstract*— For lending organizations, determining a borrower's creditworthiness is essential to determining their capacity to repay loans. The prediction of credit scores using feature engineering and machine learning techniques is the main emphasis of this study. Using the Kaggle Family Credit Default Risk dataset, the AUC scores of several machine learning models are compared. Modern machine learning techniques, including well-established methods like Random Forest and Linear Support Vector Machines, can be effectively applied to credit scoring. Ensemble models, such as LightGBM, offer advantages like improved predictions and increased stability, making them well-suited for this specific use case. Combining predictions from multiple models often results in less noisy outcomes compared to using a single model, outperforming other techniques like XGBoost, SVMs, and logistic regression.**

Keywords*— *credit risk prediction, Machine Learning, LightGBM, XGBoost algorithm, SVM.

I. Introduction

Assessing credit risk is a vital responsibility within the financial services and lending sector. The capacity to appropriately evaluate the credit worthiness of persons and institutions has far-reaching ramifications for both financial stability and societal well-being. Traditional credit risk assessment systems, such as the commonly used FICO score, have been useful for decades. However, the developing financial landscape, along with the rising complexity of data and the requirement for transparency, has resulted in an increased demand for creative and interpretable solutions [1].

This work proposes a conceptual risk assessment approach that may be further divided into fuzzy comprehensive evaluation, credit rating determination, weight determination, analysis, and index selection.

The world is getting closer to a cashless society because to recent technology and e-commerce advancements, such as In India, the demonetization policy has led to a preference for card-based or digital payments in both traditional and online grocery and pharmacy stores. This shift away from cash payments is driven by a desire to reduce the inconvenience of dealing with physical currency. Due to the rising popularity of online purchasing, the COVID-19 epidemic has also pushed the adoption of credit card payments and other alternative payment methods [2].

Credit cards are convenient and user-friendly, but their history is marred by instances of exploitation, resulting in financial and emotional losses for countless individuals. Given that they can be issued in a matter of minutes, credit cards are often seen as "free" money by the public. Using credit cards may lead to customers overspending by up to 100% over what they otherwise would, according to several research. The situation is exacerbated by the fact that credit card debt accrues significant interest over time, making repayment increasingly challenging as the balance increases and interest rates climb. These conditions might lead to credit card debt that is easily unmanageable. [3].

Credit risk assessment is essential in the financial industry and for organizations in general for a variety of reasons. Here are some of the most essential reasons for credit risk assessment: Credit risk assessment assists lenders and creditors in mitigating potential financial losses associated with lending money to individuals or businesses. Effective credit risk assessment contributes to lending institutions' overall financial stability [4]. It contributes to the prevention of high default rates and guarantees that banks and financial institutions remain financially healthy and capable of serving their customers. Credit risk evaluations guide lending, investment, and underwriting rules. It serves as the foundation for calculating interest rates, loan approval, and credit limitations. Accurate credit risk assessments assist financial firms in making informed business decisions. Credit risk assessment that is accurate can lead to more successful lending and investing activity. Financial organizations can charge appropriate interest rates and fees by effectively measuring risk, which can lead to higher profitability; Credit risk assessment is critical for preserving the asset quality of a financial organization. A bank can lower the chance of non-performing loans, write-offs, and distressed assets by recognizing and managing credit risk. Credit risk assessment also assists financial institutions in diversifying their loan and investment portfolios. They can design portfolios with a mix of low, medium, and high-risk assets to balance total risk by recognizing the credit risk associated with different assets [5].

In this study, we explore the field of credit risk assessment using interpretable ML models. The examine the models, approaches, and strategies that have been established to achieve a balance between interpretability and forecast accuracy as the scan the field of current research. The discourse delves into the obstacles and constraints encountered by scholars and professionals in this pursuit, and they offer perspectives on prospective avenues for further investigation in this field [6-7].

II. Related Work

The LS-SVM ensemble was created by Firman Aziz and Armin Lawi to improve the SVM method's performance accuracy. They used a dataset of credit from Taiwanese consumers, making sure to precisely balance the information to guarantee that default and non-default classes were equally represented. The findings showed that the classification prediction accuracy of the Least Square SVM ensemble varied by 1.7% when compared to the SVM and Least Square SVM approaches, with only a 0.6% difference between the latter two [8].

On a credit dataset, Taiwanese researchers used logistical regression, the random forest, and decision-making algorithms. They pre-processed the data and used Correlation-based Feature Selection (CFS) to choose pertinent characteristics. Among these methods, the random forest algorithm exhibited the highest accuracy, achieving an 82% accuracy rate and a 77% area under the curve, outperforming the others [9].

In the bank risk management is crucial for organizing asset activities. It involves analyzing credit portfolio quality and classifying loans based on varying credit risk levels and potential loss amounts. Each bank sets its own standards for credit analysis, risk identification, and classification indicators, based on NBU requirements, international recommendations, and economic conditions. The applicability of theoretical research depends on the bank's credit risk management features, which determine the applicability of such research. [10]

In fraud detection credit card fraud is a significant concern for financial institutions, consumers, and companies, causing significant monetary and reputational damage [11]. ML, a technique that analyzes large datasets, can identify unusual buying patterns and dubious behavior patterns, such as frequent purchases or repeatedly compromised credit card information. This helps to detect fraudulent activities and prevent credit card theft, thereby enhancing overall security and trust.[12]

III. Methodology

This section provides the workflow of the proposed methodology. Figure 1 depicts the workflow of the proposed model.

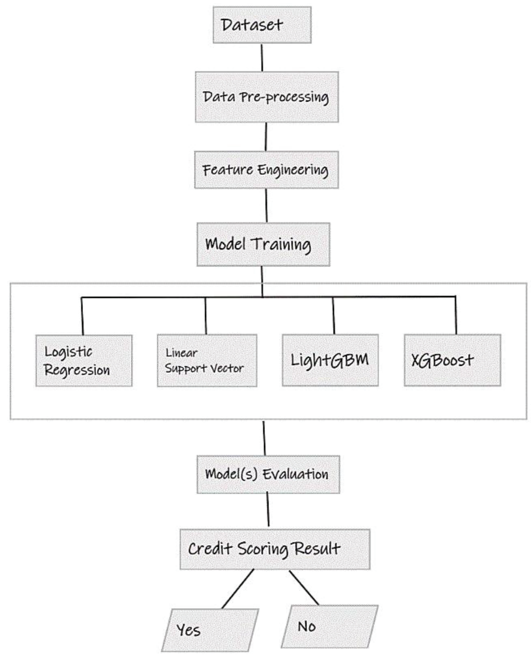

Fig. 1. Experiment Process

TABLE I. Dataset Description

Name of Attributes	Description
ID	User ID
Limit_Bal	Amount of the given credit (NT dollar)
Sex	Gender(1=male,2=female)
Education	Education(1=graduateschool,2=University,3=others)
Marriage	Marital status(1=married,2=unmarried)
Age	Age(year)
Pay_1 – Pay_5	The repayment status from April to September 2005
Bill_Amt1 to Bill_Amnt6	Amount of bill statement from April to September ,2005
Pay_Amt1 to Pay_Amt 6	Amount paid in September,2005
Default_Payment_Next_Month	Amount to be paid next month

A. Dataset

The set of data, which consists of thirty thousand instances with twenty-four integer and real-valued attributes, is derived from user-made transactions using credit cards [13]. Notably, this dataset contains a binary variable, where 'Yes' is denoted as 1 and 'No' as 0, representing the default payment outcome. Although it has been utilized by multiple researchers, the dataset remains non-anonymized. Table I presents the variables of interest from the dataset [14].

B. Data Pre-processing

It runs quick tests on the data to lessen the impact of outliers in the sample. The dataset is currently free of missing values, requiring no further processing to address such issues. But since the id column is useless for this investigation, it will be eliminated. A small number of variables will also be changed from numeric to factor. It'll evaluate variables like education, marital status, and income to combine the unknowns and improve the interpretation of the data.

C. Feature Engineering

Feature selection will be done prior to starting the data analysis. By selecting the most significant variable to employ during modelling, this approach lowers the total number of variables. For this task, it will utilize Correlation-based Feature Selection (CFS) method.

D. Model Training

Logistic regression is a useful model when a researcher wants to evaluate a categorical response variable with a binary outcome, like in this assignment where the findings are expected to be either "Yes" or "No" about default payment. This technique quantifies the disparity between the observed outcomes and the predicted values based on the training data.

Logistic regression is a computationally efficient model because it can be learned quickly. It is especially beneficial for large datasets and real-time applications. Logistic regression is resistant to noise and performs well even when the model's assumptions are not entirely met [15]. It is less likely to over fit, particularly when the number of characteristics is small. Through the coefficient values, logistic regression provides insight into the importance of each feature in the classification process. This can aid in feature selection and engineering.

In evaluating credit risk, Linear SVM is an essential tool. In order to categorize borrowers as either high or low credit risk, it creates an ideal linear border, maximizing the margin that separates these categories. The regularization parameter (C) controls this profit maximization, which decreases overfitting and increases model generality. Utilize measures like F1 score, ROC-AUC, accuracy, precision, recall, and recall to assess performance. In the research literature, credit risk evaluation is frequently examined in relation to the efficacy of linear SVM in producing discrete decision boundaries as well as parameter tuning, feature selection, and data preparation.

In high-dimensional feature spaces, linear SVM works well. It performs especially well when there are more features than training examples. Linear SVM can be utilised for binary as well as multi-class classification applications. SVMs are extended to handle multiple classes using techniques such as one-vs-one and one-vs-all. While Linear SVM is intended to handle linearly separable data, it may be easily modified to accept non-linear data by employing kernel methods. Popular kernels, such as polynomial and radial basis function (RBF), can be used.

Based on decision trees, LightGBM is a gradient boosting ensemble approach utilised by the Train Using AutoML tool [4]. Regression and classification challenges can be handled with LightGBM, a decision tree-based technique. High performance with distributed systems is the focus of LightGBM's optimization. Because LightGBM generates decision trees that develop leaf wise, just one leaf is divided based on the gain given a condition. Leaf-wise trees may over fit, particularly when working with smaller datasets. Reducing the depth of the tree can aid in preventing overfitting.

LightGBM is built on the gradient boosting framework, which is a highly effective ensemble learning technique. To make predictions, it sequentially creates an ensemble of weak learners (typically decision trees). LightGBM is lightweight and efficient, making it one of the quickest gradient boosting implementations accessible. This speed is achieved using strategies like histogram-based learning and gradient-based one-side sampling.

Extreme Gradient Boosting, or XGBoost, is a strong machine learning approach that is important for credit risk assessment. It is an ensemble learning technique commonly employed for both classification and regression tasks. XGBoost creates a robust predictive model by combining multiple decision trees, each of which iteratively corrects the mistakes of its predecessors. Its main advantages are excellent prediction accuracy, feature selection and robustness against overfitting. XGBoost's ability to handle imbalanced datasets and adjust for missing values is particularly valuable in credit risk assessment, where data quality and class imbalances are common challenges. Its strong performance and reliability make it a popular choice for improving the accuracy and reliability of credit risk forecasts.

XGBoost is a robust and adaptable machine learning algorithm commonly used in various applications. It is an important tool for data scientists and machine learning practitioners due to its speed, accuracy, regularization capabilities, and adaptability. XGBoost frequently provides cutting-edge prediction performance. It is a preferred pick for many machine learning competitions because to its high accuracy. XGBoost is intended to be fast and efficient. It is designed to handle parallel processing, tree pruning, and cache-aware access patterns. When compared to many other machine learning methods, this leads in faster training and prediction times. L1 (Lasso) and L2 (Ridge) regularization are included into XGBoost, which helps reduce overfitting and enhances model generalization. XGBoost can automatically handle missing data by making smart decisions on how to proceed.

E. Model(s) Evaluation

A crucial step in creating the prediction model is assessing how well these machine learning algorithms work. A number of statistical indicators, including F-measure, accuracy values, and the precision of classification, will be evaluated in order to evaluate the calibre of the findings.

F. Credit Scoring Result (Yes/No)

Credit scoring results in a binary classification outcome, typically expressed as "Yes" or "No" regarding an applicant's creditworthiness. "Yes" in this case means that the applicant is qualified for the sought credit and is judged creditworthy, implying a decreased chance of default. On the other hand, a response of "No" indicates a greater credit risk, indicating that the applicant would not get the credit or might get it under more restrictive conditions. Decision trees, logistic regression, and support vector machines are examples of machine learning models that can help lenders make more educated credit decisions. These models are taught to anticipate these "Yes" or "No" outcomes by analyzing a variety of personal and financial characteristics.

IV. Results and Discussion

This section presents the results. The dataset offers a thorough analysis of the performance of five distinct machine learning algorithms when it comes to assessing credit risk. Two versions of the dataset were considered: the "Actual Dataset" and the "Normalized Dataset." The accuracy metric was used to gauge the models' predictive power, with higher accuracy indicating superior performance in distinguishing between creditworthy and non-creditworthy borrowers.

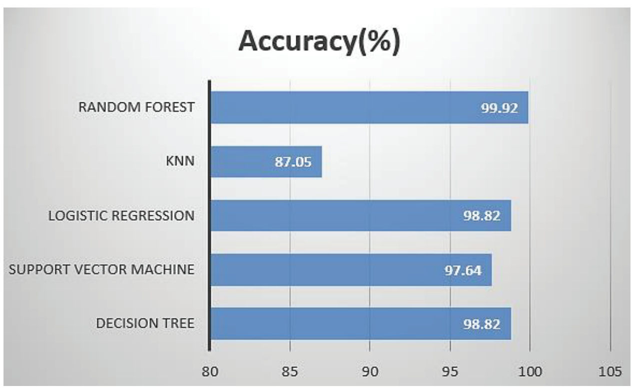

Fig. 2. Actual Dataset

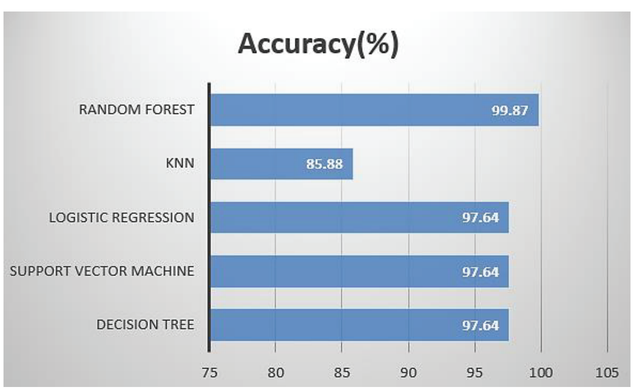

Fig. 3. Normalized Dataset

Across the algorithms tested, some key trends emerged. Decision trees and random forests exhibited remarkable robustness, maintaining high accuracy levels on both the actual and normalized datasets. This suggests that they are well-suited for credit risk assessment tasks and may offer a reliable solution for financial institutions.

Logistic regression, while highly accurate on the actual dataset, experienced a slight decrease in accuracy after dataset normalization. This reduction in performance underscores the importance of considering the effects of data preprocessing on model accuracy.

Support-vector machines (SVM) demonstrated consistent performance on both datasets, suggesting that SVM is less sensitive to dataset normalization. SVM's ability to maintain accuracy regardless of data scaling positions it as a reliable choice for credit risk assessment.

In contrast, K-nearest neighbors (KNN) exhibited a notable decline in accuracy when applied to the normalized dataset, indicating its sensitivity to data scaling. This emphasizes the necessity of careful feature scaling considerations when employing KNN for credit risk assessment.

Overall, the choice of machine learning algorithm significantly influences the accuracy of credit risk assessment models. Researchers and practitioners in the financial sector should consider factors such as interpretability, robustness to data preprocessing, and sensitivity to scaling when selecting the most appropriate algorithm for their specific use case. Additionally, further investigations into the trade-offs between model complexity and interpretability would provide a more comprehensive understanding of model performance in credit risk assessment.

V. Conclusion

Using a data-set created from credit card activities, the investigated the use of interpretable machine learning models in credit risk assessment in this work. The results imply that interpretable models that provide transparency, regulatory compliance, and fairness in lending decisions are logistic regression and linear support vector machines. While sophisticated models such as XGBoost demonstrate greater accuracy, interpretability and complexity are balanced by methods such as SHAP values, which offer insights into the algorithms' predictions. These models improve the calibre of financial management and credit risk assessment when assessed using pertinent statistical criteria. All things considered, interpretable machine learning models have the power to transform credit risk assessment and advance more open and responsible financial management procedures.

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