

A Probabilistic and Ensemble Learning Framework for Credit Risk Assessment

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Abstract—Credit risk refers to the possibility of financial loss when a borrower fails to repay a loan or meet contractual obligations. In India, the rise in Non-Performing Assets (NPAs) has made credit risk assessment a major challenge for banks. Traditional scoring models rely on heuristic-based credit rules and manual evaluations, which can introduce bias and result in inefficient decisions. To address these challenges, Machine Learning (ML) models provide a data-driven, automated solution that can handle complex feature interactions and deliver higher accuracy. In this paper, we propose a probabilistic and ensemble learning framework for credit risk assessment, combining Logistic Regression for probability estimation with Random Forest for robust classification through ensemble voting.

Index Terms—credit risk, machine learning, ensemble learning, logistic regression, random forest, banking, NPA

I. INTRODUCTION

Credit risk refers to the possibility of financial loss when a borrower fails to repay a loan or meet contractual obligations. In India, the rise in Non-Performing Assets (NPAs) has made credit risk assessment a major challenge for banks. Traditional scoring models rely on heuristic-based credit rules and manual evaluations, which can introduce bias and result in inefficient decisions. To address these challenges, Machine Learning (ML) models provide a data-driven, automated solution that can handle complex feature interactions and deliver higher accuracy. In this paper, we propose a probabilistic and ensemble learning framework for credit risk assessment, combining Logistic Regression for probability estimation with Random Forest for robust classification through ensemble voting.

II. LITERATURE REVIEW

Credit risk prediction has been widely studied in both academia and industry. Traditional approaches have primarily relied on logistic regression and scorecard-based models due to their interpretability and ease of implementation [1]. However, recent research shows that machine learning (ML) techniques, particularly ensemble methods, provide improved predictive power by capturing nonlinear feature interactions and reducing overfitting [2], [3].

Do and Simioni [4] compared Random Forest and Logistic Regression for credit scoring on rural household data and found that Random Forest achieved higher predictive accuracy. Sivasankar et al. [5] proposed a weight-adjusted boosting ensemble with rough set-based feature selection,

achieving significant performance improvements over baseline classifiers. Perera and Premaratne [6] demonstrated that an ensemble of classifiers improves the forecasting of loan default risk compared to traditional single models. Another recent study combined Random Forest, AdaBoost, and SMOTE-ENN with SHAP explainability, improving model transparency and performance on imbalanced datasets [7].

In the Indian banking context, the Reserve Bank of India (RBI) has issued regulatory principles for the use of credit risk models, highlighting the growing adoption of ML-based risk assessment systems among commercial banks and NBFCs [8]. RBI has also cautioned lenders against over-reliance on algorithmic models, emphasizing the need for model validation, bias detection, and explainability [8]. These guidelines indicate that Indian banks are actively exploring ML-based credit scoring systems, with large lenders and fintech platforms integrating probabilistic and ensemble methods into their credit workflows.

Despite these advancements, few studies explicitly integrate probability-calibrated models (e.g., Logistic Regression) with ensemble learners (e.g., Random Forest) into a unified framework tailored to banking operations. Our work addresses this gap by presenting a hybrid approach that combines calibrated probabilistic predictions with robust ensemble classification, providing both interpretability and superior predictive accuracy for credit risk assessment.

III. METHODOLOGY

A. Dataset and Preprocessing

We utilized a publicly available credit dataset containing demographic attributes, income details, loan amount, credit history, and repayment status of applicants.

- **Handling Missing Values:** Median imputation was used for numerical attributes, while mode imputation was used for categorical variables.
- **Categorical Encoding:** One-hot encoding was applied to convert categorical variables into numerical format.
- **Feature Scaling:** Min-Max normalization was used to ensure numerical features lie on a comparable scale.

B. Probabilistic Model – Logistic Regression

Logistic Regression was employed to estimate the probability of default. The probability that a borrower defaults given predictors X is given by:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}} \quad (1)$$

C. Ensemble Model – Random Forest

Random Forest, an ensemble of N decision trees, was used to improve classification robustness. Each tree $h_i(X)$ produces a class prediction, and the final class is determined by majority voting:

$$\hat{Y} = \text{mode}\{h_1(X), h_2(X), \dots, h_N(X)\} \quad (2)$$

This ensemble approach reduces variance, captures nonlinear interactions, and mitigates overfitting compared to a single decision tree.

D. Evaluation Metrics

Model performance was assessed using the following metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

Where TP, TN, FP, FN represent true positives, true negatives, false positives, and false negatives respectively. ROC-AUC measures the model's ability to discriminate between defaulters and non-defaulters across all possible classification thresholds.

IV. RESULTS

The performance of the proposed probabilistic and ensemble framework was evaluated using a publicly available loan dataset. Table I summarizes the evaluation metrics for Logistic Regression, Decision Tree, and Random Forest classifiers.

TABLE I
PERFORMANCE COMPARISON OF CLASSIFICATION MODELS

Classifier	Acc. (%)	Prec.	Rec.	F1	AUC
Logistic Regression	78.3	0.76	0.74	0.75	0.81
Decision Tree	80.1	0.78	0.76	0.77	0.83
Random Forest	82.0	0.80	0.90	0.795	0.87

V. DISCUSSION

The experimental results indicate that combining probabilistic and ensemble learning improves credit risk prediction performance. While Logistic Regression provides interpretable probability estimates useful for threshold-based decision-making, Random Forest enhances robustness and captures complex, nonlinear interactions among features, consistent with prior studies [4], [5]. The superior performance of Random Forest aligns with Do and Simioni [4], who observed ensemble methods outperforming single classifiers in credit scoring tasks.

The hybrid approach provides both interpretability (through probability estimates) and predictive strength (through ensemble voting), making it suitable for real-world banking applications in India.

Limitations of the study include reliance on a single publicly available dataset, which may not capture the diversity of Indian banking data. Further work could explore multi-bank datasets, incorporate additional financial indicators, and test other ensemble approaches such as XGBoost or AdaBoost.

VI. CONCLUSION

This paper presents a probabilistic and ensemble learning framework for credit risk assessment. Random Forest, as part of the ensemble, achieved the highest accuracy (82%) and ROC-AUC (0.87), demonstrating its effectiveness in identifying high-risk borrowers. Logistic Regression complements the ensemble by providing probability estimates, enabling data-driven decision-making and risk scoring.

The proposed framework can be integrated into banking systems to improve loan approval decisions, reduce default rates, and support automated credit scoring in Indian banks. Future research may focus on enhancing model explainability, incorporating alternative ensemble methods, and validating performance on diverse datasets.

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