

Predictive Modeling of Credit Default Risk Using Ensemble Learning

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ABSTRACT

Credit default risk assessment is a critical task in the financial sector, enabling lenders to evaluate borrower reliability and minimise financial losses. Traditional statistical models, such as logistic regression, often struggle to capture complex nonlinear relationships within high-dimensional financial datasets. Recent advancements in machine learning, particularly ensemble learning techniques, have demonstrated improved predictive performance and robustness in credit risk modelling. This paper presents an ensemble learning-based framework for predicting credit default risk using structured financial and behavioural data. The proposed system integrates feature engineering, class imbalance handling, and multiple ensemble algorithms, including Random Forest, Gradient Boosting, and Extreme Gradient Boosting. Experimental evaluation demonstrates improved accuracy, recall, and Area Under the ROC Curve compared to single-model baselines. The framework provides a scalable and reliable solution for financial risk management systems.

Keywords: *Credit Risk Prediction, Default Risk Modelling, Ensemble Learning, Machine Learning, Financial Analytics, Classification*

I. INTRODUCTION

Credit risk management is essential for financial institutions to ensure profitability and stability. Assessing the likelihood of borrower default helps lenders make informed decisions regarding loan approvals, interest rates, and credit limits. Traditional credit scoring models rely heavily on linear statistical techniques, which may not adequately model complex borrower behaviour patterns.

Recent developments in machine learning have enhanced predictive modelling capabilities in financial analytics. In 2023 and 2024, studies demonstrated that ensemble learning methods outperform traditional single classifiers in credit risk prediction tasks [1], [2]. Ensemble techniques combine multiple weak learners to produce a stronger predictive

model capable of capturing nonlinear relationships and interactions among features.

Handling class imbalance, where default cases are relatively rare compared to nondefault cases, remains a significant challenge. Advanced ensemble frameworks incorporating cost-sensitive learning have shown improved detection of high-risk borrowers [3]. Motivated by these advancements, this study proposes an ensemble learning-based framework for predictive modelling of credit default risk.

II. RELATED WORK

Recent research from 2023–2026 highlights substantial improvements in financial risk

prediction using ensemble models. In [1], a gradient boosting-based credit scoring system achieved superior predictive accuracy compared to logistic regression. Similarly, [2] introduced a hybrid ensemble framework combining Random Forest and boosting algorithms for enhanced default risk detection.

Class imbalance in credit datasets has been addressed using oversampling and cost-sensitive learning strategies. A 2024 study in [3] proposed imbalance-aware ensemble methods to improve recall for minority default classes. Explainable AI approaches for credit scoring were explored in [4], ensuring regulatory compliance and transparency.

Deep ensemble architectures integrating neural networks and tree-based models were investigated in [5], demonstrating improved generalisation across diverse financial datasets. Scalable big data frameworks for financial risk modelling were discussed in [6], enabling real-time credit evaluation systems.

These advancements provide a strong foundation for developing an ensemble-based predictive model for credit default risk.

III. METHODOLOGY

The proposed framework consists of data preprocessing, feature engineering, ensemble model training, evaluation, and deployment.

The dataset includes structured financial records such as borrower demographics, credit history, income level, loan amount, repayment history, outstanding balances, and transaction behaviour. The dataset is divided into training, validation, and testing sets.

Data preprocessing involves handling missing values, outlier detection, normalisation of numerical features, and encoding categorical variables. Since credit default datasets are typically imbalanced, the Synthetic Minority Oversampling Technique and class-weighted learning are applied to improve minority class detection.

Feature engineering includes generating derived financial ratios such as debt-to-income ratio, credit utilisation ratio, and payment-to-income ratio. Correlation analysis and feature

importance techniques are used to identify influential variables.

Multiple ensemble algorithms are implemented, including Random Forest, Gradient Boosting, and Extreme Gradient Boosting. Hyperparameter tuning is conducted using cross-validation to optimise performance. The final ensemble model may combine predictions using weighted averaging or stacking techniques.

The workflow of the system is described as follows:

- Credit Dataset Collection
- Data Cleaning and Preprocessing
- Feature Engineering
- Class Imbalance Handling
- Ensemble Model Training
- Performance Evaluation

Evaluation metrics include accuracy, precision, recall, F1score, and Area Under the ROC Curve. Special emphasis is placed on recall for default cases to minimise financial risk.

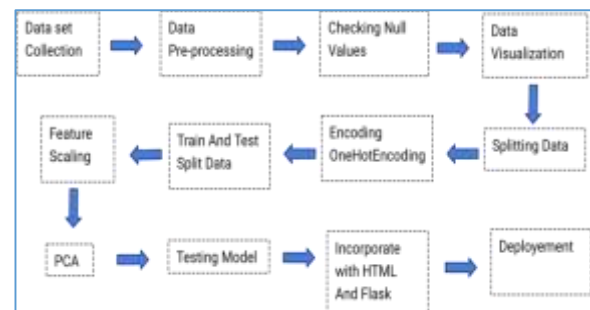


Fig 1: Methodology

IV. RESULTS AND DISCUSSION

Experimental results indicate that ensemble models significantly outperform single classifiers in predicting credit default risk. Gradient Boosting and Extreme Gradient Boosting demonstrate strong predictive performance due to their ability to capture complex feature interactions.

The ensemble framework achieves a high Area Under the ROC Curve, indicating strong

discriminative capability between default and nondefault cases. Feature importance analysis reveals that credit utilisation ratio, repayment history, and debt-to-income ratio are key predictors of default risk.

Cost-sensitive training improves recall for default cases, reducing false negatives. The system demonstrates robustness across different validation folds, indicating good generalisation performance.

However, interpretability remains an important consideration in financial applications. Integration of explainable AI tools ensures transparency and regulatory compliance.



Fig 2: Data Entry Interface for Financial Risk Prediction System



Fig 3: Prediction Result Display Interface of the Financial Risk Prediction System

V. CONCLUSION AND FUTURE WORK

This paper presented an ensemble learning-based framework for predictive modelling of credit default risk. The proposed system achieves improved predictive accuracy and robustness compared to traditional models.

Future work includes integrating deep neural ensemble architectures, incorporating real-time

transaction data for dynamic credit scoring, implementing federated learning for privacy-preserving financial modelling, and enhancing explainability for regulatory transparency. This proctoring is 90% accuracy.

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