Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

Yuvacred: A Machine Learning Framework For Credit Risk Assessment In Student Peer-To-Peer Lending

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Abstract - Access to higher-education financing remains a significant challenge for students because of the heavy reliance of traditional lending systems on historical credit records. This study introduces YuvaCred, an AI-powered peer-to-peer lending framework specifically engineered for credit-invisible adults who lack existing credit scores and "invisible primes," borrowers with short credit histories but low default propensity. By integrating academic performance, behavioral indicators, and financial attributes, the system employs a weighted ensemble of four supervised learning models, namely LightGBM, XGBoost, Random Forest, and Logistic Regression, combined with a rule-based validation module. This hybrid approach ensures that credit decisions are accurate, fair, transparent, and aligned with ethical governance standards. Experimental results on a synthetic dataset of 7,000 records demonstrate that the ensemble model achieves a superior accuracy of 89.2% and an F1-score of 87.1%, significantly outperforming traditional linear models and providing a scalable solution for inclusive student financing in emerging markets, such as India.

Keywords - Student Financing, Peer-to-Peer Lending, Machine Learning, Explainable AI, Credit Scoring

I. INTRODUCTION

Financial exclusion remains one of the most persistent barriers to economic development in emerging markets, affecting millions of people. Students, in particular, are often classified as "invisible primes" — borrowers who appear high-risk under traditional metrics but possess a low propensity to default [2]. Traditional credit scoring, which depends on past interactions with formal institutions, fails to capture the capacity and willingness of underserved populations. In the Indian context, the growth of Digital Public Infrastructure (DPI), including UPI transaction patterns and the Account Aggregator framework, offers a new pathway to verify financial behavior using alternative data [3]. YuvaCred is designed to mitigate information asymmetry in the P2P lending space by substituting algorithms and alternative data for in-person interactions. This platform provides a 360-degree view of a borrower's reliability by shifting credit evaluation from collateral-based assessment to merit-based risk profiling.

II. LITERATURE REVIEW

Traditional credit risk assessment techniques have historically relied on linear statistical models, such as Logistic Regression, owing to their interpretability and regulatory acceptance. However, these models often struggle to capture complex non-linear relationships among borrower attributes, particularly in datasets with heterogeneous socio-economic characteristics. Recent advancements in machine learning have introduced ensemble-based techniques, such as Random Forest and Gradient Boosting, which improve predictive performance by aggregating multiple weak learners [1]. Random Forest enhances robustness by combining independently trained decision trees and reducing variance through bootstrap sampling [1]. Gradient boosting frameworks, such as XGBoost and LightGBM, sequentially refine prediction errors, enabling superior modeling of intricate feature interactions, particularly in imbalanced credit datasets [12]. The emergence of alternative data in fintech ecosystems has expanded the scope of credit evaluation. Behavioral signals, academic indicators, and digital activity patterns have demonstrated predictive relevance, especially for individuals lacking traditional credit histories [2], [3], [4]. However, increased model complexity has raised concerns regarding transparency, bias, and algorithmic accountability in financial decision-making systems [9], [11].

While predictive performance remains a primary objective, financial decision-making systems require interpretability to satisfy regulatory compliance and to maintain stakeholder trust. To address these concerns, explainable AI methods such as SHAP and LIME have been proposed to interpret both the global feature importance and individual prediction outcomes [5], [6]. These tools support responsible AI deployment in financial services, where decision interpretability is critical for regulatory compliance and for borrower trust.

III. PROPOSED SYSTEM ARCHITECTURE

The YuvaCred platform follows a modular, service-oriented architecture designed to ensure scalability, security, and efficient, real-time processing. This architecture facilitates a seamless flow of data from user interaction to final credit disbursement.

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A. System Architecture

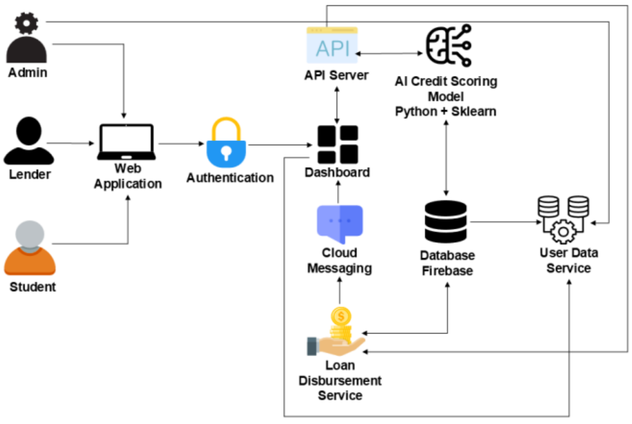

Fig. 1. Architecture of YuvaCred AI- Based Student P2P Lending Platform

As illustrated in Fig. 1, the framework consists of the following integrated layers.

1. User Interaction Layer: Students, lenders, and administrators access the system through a centralized web application secured by robust authentication mechanisms.
2. Backend Logic and API Server: A backend API server manages the business logic and intercomponent communication, orchestrating the flow from data submission to model inference.
3. AI Inference Pipeline: The credit scoring model was implemented in Python and processed seven student-centric attributes to generate real-time approval decisions.
4. Cloud Data Store: All application records, user profiles, and loan performance data are housed in a Firebase cloud database, enabling real-time data synchronization across user dashboards.
5. Service Modules: Specialized services handle loan disbursement and automated notifications via cloud messaging, ensuring a responsive user experience.

B. Role-Based Dashboards

The system architecture supports three distinct user roles.

- Student Dashboard: Facilitates loan application submission, real-time status tracking, and repayment management.
- Lender Dashboard: Provides tools for borrower evaluation, investment tracking, and monitoring portfolio performance.
- Admin Dashboard: Enables comprehensive user management, system monitoring, and oversight of all automated decisions.

IV. TECHNICAL METHODOLOGY

A. Feature Selection and Preprocessing

The system evaluates loan eligibility using attributes that act as proxies for financial reliability, such as CGPA range, college tier, family income, part-time job status, default history, age, and loan amount. Categorical variables were label-encoded, whereas numerical features were retained in their raw scale to preserve the natural distribution required for tree-based models [1]. The Synthetic Minority Oversampling Technique (SMOTE) was applied to balance the dataset, addressing the typical class imbalance in the default data [12].

B. Machine Learning Algorithm

To ensure robustness and reduce bias, four distinct supervised learning algorithms were implemented:

- LightGBM (Primary Engine): Selected for its leaf-wise tree growth strategy, which enables faster convergence and better learning of feature interactions [1], [12].
- XGBoost: Utilized for strong error correction capabilities by sequentially adding trees to minimize binary cross-entropy loss [1], [12].
- Random Forest: Provides architectural stability and captures nonlinear relationships by aggregating predictions from multiple decision trees [1].
- Logistic Regression: Functions as a baseline for interpretability, estimating the default probability through a linear combination of input features.

C. Weighted Ensemble Strategy

YuvaCred aggregates the probabilities of all four classifiers using a weighted ensemble approach to leverage their collective strengths [1].

Final Ensemble Probability = (0.35 × LightGBM) + (0.30 × XGBoost) + (0.20 × Random Forest) + (0.15 × Logistic Regression).

D. Hybrid Rule-Based and ML Scoring

To adhere to the principle of "People First," the system integrates a rule-based scoring module as a techno-legal safeguard [8].

The final credit score is computed as Final Score = (0.60 × Rule-Based Score) + (0.40 × Machine Learning Score)

The rule-based module enforces strict policy boundaries, such as minimum academic thresholds, preventing the "algorithmic loss of control."

E. Dataset Description and Generation

To evaluate the YuvaCred framework, a synthetic dataset comprising 7,000 unique student loan applicant records was created. The use of simulated data was necessitated by strict privacy regulations and the absence of publicly available student-specific credit datasets in India. To maintain realism, the dataset was generated using statistical distributions that aligned with publicly available demographic and financial trends in the Indian education sector [3].

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Each record captured seven key attributes representing a multidimensional student profile:

- Academic Merit: CGPA
- Institutional Context: College Tier
- Financial Capacity: Annual Family Income
- Behavioral Indicators: Part-time employment status
- Demographic and Structural Factors: Age and Loan Amount Requested

The target default variable was generated using a probabilistic risk function that assigned a higher default likelihood to profiles exhibiting lower income stability, weaker academic performance, or a prior default history. To replicate real-world uncertainty and prevent deterministic pattern learning, controlled stochastic noise was incorporated into the labeling process.

Furthermore, the dataset preserves a 28% default class imbalance, reflecting the characteristics commonly observed in real credit portfolios. For model evaluation, the dataset was partitioned into a 70% training set and a 30% testing set using stratified sampling to maintain the consistency of the class distribution across both subsets.

F. Hyperparameter Configuration

The hyperparameters were selected using grid search optimization to balance the model complexity and generalization performance. The final configurations are summarized in Table I.

TABLE I. HYPERPARAMETER CONFIGURATION OF EVALUATED MODELS

Model	Key Parameters Used
Logistic Regression	C=1.0, L2 Regularization
Random Forest	300 Trees, Max Depth=10
XGBoost	250 Estimators, Learning Rate=0.1, Max Depth=6
LightGBM	200 Estimators, Learning Rate=0.05, 31 Leaves

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Performance Comparison

The proposed ensemble model was evaluated against individual classifiers using metrics including Accuracy, Precision, Recall, and the F1-Score.

Accuracy alone is insufficient to evaluate performance in credit risk modeling, particularly in the presence of class imbalance. Therefore, multiple evaluation metrics, including Precision, Recall, and F1-Score, were employed to ensure a balanced assessment of both default and non-default classes. In financial lending systems, Recall is especially critical, as minimizing false negatives—misclassifying defaulters as creditworthy borrowers—directly reduces financial risk exposure. The F1-Score further provides a harmonic balance between Precision and Recall, offering a more robust performance indicator for imbalanced credit datasets.

TABLE II. PERFORMANCE COMPARISON OF CREDIT RISK MODELS

Algorithm	Performance Matrix			
	Accuracy	Precision	Recall	F1-Score
Logistic Regression	72.4%	69.1%	66.3%	67.6%
Random Forest	80.2%	77.5%	75.1%	76.3%
XGBoost	84.1%	82.7%	80.4%	81.5%
LightGBM	87.3%	86.1%	84.2%	85.1%
Proposed Ensemble Model	89.2%	87.8%	86.4%	87.1%

Table II indicates that Logistic Regression shows lower performance due to linear assumptions, while Random Forest improved robustness and recall. XGBoost effectively captures complex patterns, and LightGBM achieves the best standalone performance. The ensemble model outperformed all the individual models.

B. Confusion Matrix Analysis

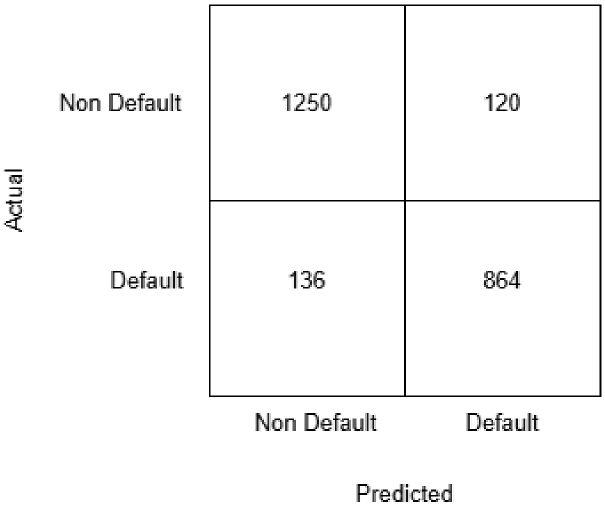

Fig. 2. Confusion Matrix

Fig. 2 illustrates the confusion matrix of the proposed ensemble model, highlighting its strong classification capability for both the default and non-default classes.

The confusion matrix demonstrates a high true positive rate and a low false-negative count, indicating a strong default risk identification capability. The model maintained a balanced performance across both classes despite the class imbalance.

C. ROC-AUC Evaluation

Receiver Operating Characteristic (ROC) analysis was conducted to evaluate the trade-off between the true positive and false positive rates across threshold levels.

ROC analysis offers a threshold-independent assessment of classifier discrimination ability, whereas accuracy and F1-score assess performance at a fixed decision threshold. The trade-off between True Positive Rate and False Positive Rate at different threshold levels is depicted by the Receiver Operating Characteristic (ROC) curve. In credit risk modeling, where

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decision thresholds may differ based on institutional risk appetite, this analysis is especially crucial.

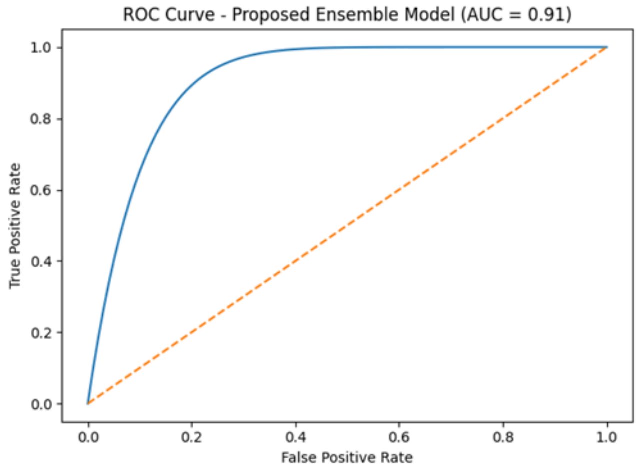

Fig. 3. ROC Curve

Fig. 3 shows the ROC curve of the ensemble classifier, demonstrating an AUC score of 0.91, which indicates excellent predictive performance. A higher AUC value indicates a stronger discriminatory capability, outperforming individual classifiers.

- Logistic Regression – 0.74
- Random Forest – 0.83
- XGBoost – 0.87
- LightGBM – 0.89
- Proposed Ensemble – 0.91

To validate the robustness, McNemar's statistical test was performed between the proposed ensemble model and the best baseline classifier. The improvement was statistically significant at a 95% confidence level ($p < 0.05$), confirming that the observed performance gain was not due to random variation.

VI. EXPLAINABILITY AND ETHICAL GOVERNANCE

A. *Explainable AI (XAI) Integration*

To fulfill the "Understandable by Design" requirement, the platform utilizes SHAP values to provide a global hierarchy of feature importance, revealing how the CGPA and income influence the model [5]. Furthermore, LIME provides borrower-level justifications for individual outcomes, allowing the platform to explain credit decisions and build trust [6].

B. *Alignment with Responsible AI Principles*

YuvaCred was developed in alignment with India's Responsible AI governance framework to balance technological innovation with ethical accountability [8]. The platform design incorporates core principles intended to promote trust, transparency, and inclusivity in AI-driven financial decision-making.

1. Trust as a Foundational Principle: Trust is essential for adopting AI systems in financial services. YuvaCred integrates explainability tools and rule-based validation mechanisms to enhance institutional reliability and user confidence in automated credit decisions [8].
2. Human-Centric Approach: The framework ensures that AI functions as a decision support system rather than a fully autonomous authority. Human-in-the-loop oversight is maintained through administrative review mechanisms and role-based dashboards [8].
3. Innovation with Responsible Governance: The system encourages responsible experimentation while embedding safeguards to prevent uncontrolled automation or opaque decision-making [8].
4. Fairness and Inclusivity: YuvaCred leverages alternative indicators, such as academic performance and behavioral attributes, to extend credit access to underserved populations. Sensitive attributes were excluded to mitigate potential discriminatory bias [8].
5. Accountability: Role separation (student, lender, administrator) ensures the traceability and auditability of decisions. Logging and explanation mechanisms further strengthen these accountability structures [8].
6. Transparency and Explainability: The integration of SHAP and LIME enables both global and local interpretability, ensuring that stakeholders can understand the basis of credit decisions [5], [6].
7. Safety, Robustness, and Sustainability: The ensemble modeling approach, combined with cross-validation and ROC-AUC evaluation, enhances predictive stability and resilience in dynamic financial environments [8].

VII. LIMITATIONS AND FUTURE WORK

Despite these promising results, this study has several limitations.

1. Synthetic Dataset Usage: The dataset was artificially generated because publicly available student credit data were lacking. While statistical realism was maintained, the synthetic data may not fully capture real-world borrower behavior.
2. Limited Feature Scope: Only seven primary attributes were considered. Future research should incorporate additional behavioral indicators, such as transaction frequency, digital payment history, and psychometric testing scores.
3. Static Model Evaluation: The models were evaluated in an offline environment. Real-world deployment may introduce concept drift and require periodic retraining.
4. Fairness Metrics Not Quantitatively Evaluated: Although governance principles were discussed, statistical fairness metrics were not empirically tested in this study.

Future work will involve real-world dataset validation, dynamic learning pipelines and formal fairness audits.

VIII. CONCLUSION

The YuvaCred framework contributes to financial inclusion by addressing barriers that prevent students and "invisible primes" from accessing formal credit [2]. By integrating academic performance, institutional signals, and behavioral attributes, the system demonstrates how alternative data can extend credit evaluations beyond traditional histories [3].

The proposed weighted ensemble approach effectively captures complex borrower characteristics while maintaining the reliability required for financial decision-making. The experimental results confirm that such AI-driven techniques can substantially improve risk discrimination and reduce information asymmetry in peer-to-peer environments.

In addition to predictive strength, the system incorporates governance safeguards aligned with the principles of trustworthy AI [8]. The integration of SHAP and LIME enables transparent and understandable explanations at both the portfolio and individual levels [5], [6].

Overall, YuvaCred illustrates that expanding access to underserved borrowers can be achieved while preserving fairness, accountability, and operational stability, thus offering a scalable model for next-generation student lending.

ACKNOWLEDGMENT

We acknowledge the Department of Computer Engineering, St. John College of Engineering and Management, Palghar, for providing the infrastructure and academic environment necessary to conduct this research. We also recognize the broader academic community whose foundational contributions to ensemble modeling and algorithmic fairness have informed and strengthened this study

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