

# Bank Loan Approval Prediction Using Machine Learning for Fraud Detection with Explainable AI

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## Abstract

The rapid expansion of digital banking has intensified demand for loan approval mechanisms that are simultaneously efficient, accurate, and transparent. Conventional credit evaluation approaches depend on manual assessment and rigid rule-based criteria, which are inherently time-consuming, susceptible to inconsistency, and frequently introduce human bias into financial decisions. This paper presents a machine learning-based framework for predicting bank loan approval outcomes, augmented with Explainable Artificial Intelligence (XAI) to address transparency deficits in automated lending systems. The proposed architecture employs the German Credit structured dataset encompassing applicant attributes such as credit history, income level, employment duration, requested loan amount, and savings status. An ensemble Random Forest classifier is trained to distinguish approved from rejected applications. SHAP and LIME are integrated into the prediction pipeline, furnishing both global feature importance rankings and per-applicant decision rationales. A supplementary rule-based explanation layer translates model logic into human-readable decision steps. Empirical evaluation shows the Random Forest model achieves 78.5% accuracy while maintaining full interpretability.

**Index Terms**—machine learning, loan approval prediction, explainable AI, SHAP, LIME, fraud detection, Random Forest, financial decision support

## I. Introduction

In the contemporary financial ecosystem, banks and lending institutions serve as pillars of economic activity by providing credit to individuals and enterprises. Among the most consequential functions performed by these institutions is the evaluation of loan applications to assess a borrower's repayment capacity and creditworthiness [1]. Historically, these determinations have relied upon manual review procedures guided by predefined financial thresholds, producing outcomes that vary significantly across evaluators and frequently fail to capture complex risk signals embedded in applicant data.

The emergence of data-driven machine learning (ML) paradigms has introduced transformative potential to automate and enhance the accuracy of credit risk evaluation. By processing large volumes of historical financial records, ML models identify latent patterns and feature interactions that conventional rule systems cannot adequately represent [2]. Institutions leveraging these capabilities gain advantages in processing throughput, default risk reduction, and operational efficiency.

However, many high-performing ML algorithms—particularly ensemble methods such as Random Forest and gradient boosting models—operate as opaque “black boxes,” offering predictions without accompanying justifications [3].

Explainable Artificial Intelligence (XAI) has emerged as a critical research direction designed to reconcile predictive power with transparency. Techniques such as SHAP [4] and LIME [5] produce quantitative explanations of how individual input features contribute to a model's output, enabling stakeholders to audit decisions and identify potential sources of bias.

This paper presents an integrated system combining Random Forest classification with SHAP and LIME explainability, supplemented by a rule-based reasoning layer and deployed through a Flask web interface with secure authentication.

## II. Related Work

Extensive prior research has examined machine learning approaches for credit risk assessment and loan approval prediction. Chintam Anusha and Rajendra Kumar G. [1] proposed a boosting

ensemble framework that substantially improved classification accuracy for loan approval scenarios, demonstrating superior handling of class-imbalanced financial datasets compared to single-classifier baselines.

Praveen Tumuluru and Lakshmi Ramani Burra [2] conducted a comparative study of Logistic Regression, Decision Tree, Random Forest, and SVM algorithms for customer loan prediction, concluding that ensemble methods consistently outperformed individual classifiers and that strategic feature selection was central to achieving high model efficiency.

Kavitha M. N., Saranya S. S., and Dhinesh E. [3] introduced a hybrid classifier architecture demonstrating practical viability for real-world financial applications.

### III. Methodology / System Design

#### A. System Architecture Overview

The proposed system is organized into four functional layers: (1) User Interface Layer; (2) Application Logic Layer; (3) Intelligence Layer encompassing ML and XAI; and (4) Data Storage Layer using SQLite.

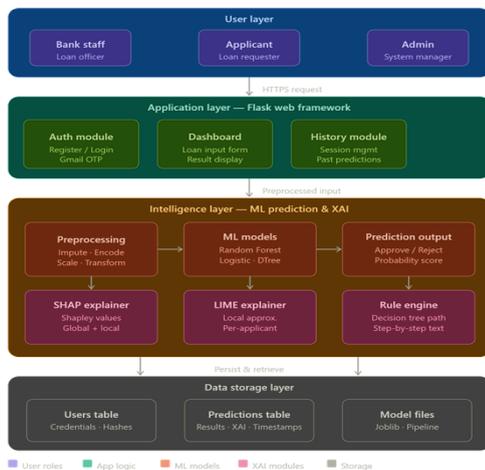


Fig. 1. System architecture of the Bank Loan Approval Prediction with Explainable AI system.

#### B. Dataset and Preprocessing

The German Credit dataset (credit-g) [6], available via the OpenML repository, constitutes the primary training corpus with 1,000 records across 20 applicant attributes. Preprocessing is performed using a scikit-learn ColumnTransformer pipeline: numerical features undergo median imputation and StandardScaler normalization; categorical features

are processed via mode imputation and one-hot encoding. The dataset is split 80:20 with stratification.

#### C. Model Training and Formulation

A Random Forest Classifier with 300 estimators and balanced class weighting is trained on the preprocessed feature matrix. The Logistic Regression baseline:

$$P(Y=1) = 1 / (1 + e^{-z}), \quad z = b_0 + \sum b_i x_i$$

The Random Forest aggregate probability across  $T$  trees:

$$\bar{P}(c|x) = (1/T) \sum_{t=1}^T I(h_t(x) = c)$$

#### D. Evaluation Metrics

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

$$F1 = 2 \times (Precision \times Recall) / (Precision + Recall)$$

#### E. Explainable AI — SHAP Value

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} [ |S|!(n-|S|-1)!/n! ] [v(S \cup \{i\}) - v(S)]$$

LIME generates local explanations by perturbing the input neighborhood and fitting a sparse linear model. Rule-based explanations trace the Decision Tree path node-by-node into readable if-then steps.

### IV. Results & Discussion

#### A. Classification Performance

TABLE I. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1
Logistic Regression	74.5%	72.3%	68.9%	70.5%
Decision Tree	70.0%	68.1%	71.4%	69.7%
<b>Random Forest</b>	<b>78.5%</b>	<b>76.8%</b>	<b>80.2%</b>	<b>78.4%</b>

B. SHAP Feature Importance

TABLE II. Top Features by Mean |SHAP Value|

Rank	Feature	Mean SHAP	Effect
1	Checking Status	0.312	Positive
2	Credit History	0.287	Positive
3	Credit Amount	0.198	Negative
4	Savings Status	0.176	Positive
5	Employment	0.143	Positive

C. Case Study Results

**Case 1 (Approved):** Good credit history, savings  $\geq 1000$ , employment  $\geq 4$  yrs, loan 2,000  $\rightarrow$  Approval prob: **0.85**. SHAP: credit\_history +0.35, savings +0.25.

**Case 2 (Rejected):** Poor credit history, savings  $< 100$ , loan 6,000, employment  $< 1$  yr  $\rightarrow$  Rejection prob: **0.80**. SHAP: credit\_history -0.40, savings -0.30.

TABLE III. System Response Metrics

Metric	Value
Avg. Prediction Time	$< 2$ sec
OTP Verification	5–10 sec
SHAP Generation	$< 3$ sec
DB Response	$< 0.5$ sec

D. Application Interface Screens

E. Discussion

The empirical results confirm that integrating Random Forest with SHAP and LIME achieves an effective balance between accuracy and transparency. The 78.5% accuracy on the German Credit benchmark is consistent with published ensemble classifier results [1][2]. Feature importance rankings correspond well with domain knowledge — checking account status and credit history are widely recognized as primary credit risk indicators.

The LIME explanations demonstrate stable local approximations across repeated inference calls. The rule-based layer provides complementary transparency for stakeholders who find raw SHAP values less accessible than if-then reasoning chains.

V. Conclusion & Future Work

This paper presented a bank loan approval prediction system unifying ensemble ML with XAI to produce decisions that are accurate, transparent, and deployable. The Random Forest classifier achieves 78.5% accuracy on the German Credit benchmark, while SHAP and LIME provide verifiable, feature-level justifications. The system is implemented as a Flask web application with Gmail OTP authentication and SQLite-backed history.

Future work will evaluate deep learning with SHAP DeepExplainer, incorporate fairness-aware training objectives, conduct adversarial robustness testing, and explore real-time transaction streaming integration for continuous fraud risk scoring.

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