CREDITPATHAI: A MACHINE LEARNING FRAMEWORK FOR PREDICTING LOAN DEFAULT RISK AND OPTIMIZING RECOVERY STRATEGIES

By: Sayantani Das

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Abstract

Loan default prediction is a critical component of modern financial risk management. Traditional credit scoring systems are increasingly inadequate in capturing the complexity of borrower behaviour, resulting in inefficiencies in risk prediction and subsequent recovery processes. This research introduces **CreditPathAI**, an end-to-end machine learning–driven loan recovery framework capable of predicting borrower default probability and mapping those predictions to personalized recovery strategies. The pipeline integrates a robust ingestion mechanism, preprocessing automation, baseline and advanced ML modelling (Logistic Regression, XGBoost, LightGBM), and hyperparameter optimization, culminating in a best-model selector. With the inclusion of an Action Recommendation Engine and API-ready design, CreditPathAI moves beyond typical academic ML projects toward a scalable, production-grade solution.

1. Introduction

The rapid growth of digital lending ecosystems has resulted in unprecedented volumes of borrower data, making traditional analytical techniques insufficient for accurate default prediction. Loan default not only affects financial institutions' profitability but also influences long-term portfolio stability and regulatory compliance. Classical models such as logistic regression offer simplicity and interpretability but fall short when dealing with nonlinear patterns, multicollinearity, and heterogeneous borrower attributes.

Machine learning has emerged as a powerful tool capable of modelling complex borrower behaviours, enhancing discrimination between high- and low-risk clients, and enabling proactive decision-making. However, many existing studies focus narrowly on prediction accuracy without considering the broader workflow, including data preprocessing, model scalability, action recommendation, or integration into live systems.

CreditPathAI addresses these gaps by proposing a holistic framework for loan default prediction and recovery optimization. The system is designed to:

- Handle large borrower datasets,
- Automate all major steps of preprocessing and evaluation,
- Compare multiple ML models under a unified pipeline,
- Recommend risk-based borrower interventions, and
- Prepare the foundation for an event-driven, API-enabled production deployment.

This study contributes a complete, industry-inspired workflow that aligns with modern FinTech credit risk practices.

2. Literature Survey

Credit risk prediction has been extensively studied in financial analytics, with early research predominantly relying on statistical models including logistic regression and discriminant analysis. Addo et al. [1] demonstrated that modern machine learning methods significantly enhance classification performance by capturing non-linear feature relationships. Logistic regression, while considered a cornerstone in classical credit modelling, has shown limitations when handling complex borrower feature sets [6], [14].

Ensemble learning, particularly boosting algorithms such as XGBoost and LightGBM, has emerged as the leading approach for structured financial datasets. Chen and Guestrin's foundational work on XGBoost [2] established its efficiency and scalability in large-scale risk modelling. Studies by Yeo [3] and Ding et al. [4] further validated gradient boosting's superiority over traditional approaches for loan default prediction, highlighting its robustness in imbalanced datasets.

Debt recovery optimization is another evolving field. Zhang and Zhou [5] demonstrated how predictive modelling can refine the prioritization of delinquent accounts, improving both recovery rates and resource allocation. Benchmark studies by Lessmann et al. [6], Brown & Harris [7], and Louzada et al. [8] emphasize the value of evaluating credit models using metrics beyond accuracy, including AUC-ROC, recall, and confusion matrices, which are crucial for minimizing false negatives in risk-sensitive applications.

While these studies contribute greatly to the field, they often lack fully automated ingestion pipelines, high-cardinality handling, model comparison workflows, or integrated recovery recommendation components. CreditPathAI distinguishes itself by offering a complete and modular architecture combining all these capabilities.

3. Technologies Used

CreditPathAI utilizes a multi-layered technology stack designed for scalability, interpretability, and production readiness:

1. Python (Core Language)

Used for entire ML pipeline development, data processing, and model experimentation.

2. Pandas & NumPy

Essential for dataset manipulation, cleaning, encoding, and numerical operations across millions of records.

3. Scikit-learn

Provides the backbone for preprocessing pipelines, Logistic Regression, train-test split, metrics, and hyperparameter utilities.

4. XGBoost

A high-performance gradient boosting library used to identify complex borrower behaviour patterns.

5. LightGBM

A fast, leaf-wise gradient boosting framework optimized for large-scale tabular data.

6. Matplotlib & Seaborn

Used for generating ROC curves, confusion heatmaps, and borrower feature distributions.

7. FastAPI (Milestone 5)

A scalable API framework enabling real-time loan risk scoring and model serving.

8. Docker (Optional)

Useful for containerizing ML models and APIs for deployment.

9. React + Plotly (Planned for Milestone 6)

Frontend tools for building interactive dashboards for credit analysts.

4. Dataset Description

CreditPathAI utilizes two combined datasets:

- Kaggle Loan Default Dataset
- Microsoft R Server Loan Credit Risk Dataset

The unified dataset includes:
LoanID, Age, Income, CreditScore, LoanAmount, LoanTerm, DTIRatio, MonthsEmployed, NumCreditLines, Education, EmploymentType, MaritalStatus, HasMortgage, HasDependents, LoanPurpose, HasCoSigner, InterestRate, Default.

After cleaning and encoding, the final ML-ready dataset contains 249,999 rows and 26 features, with zero missing values.

CreditPathAI incorporates two major datasets: the Kaggle Loan Default Dataset and Microsoft R Server Credit Risk dataset. These were merged and standardized to create a unified borrower dataset of **249,999 rows and 18 primary features**, later expanded to 26 through one-hot encoding.

5. Methodology

5.1 Data Ingestion & Cleaning

- Removal of duplicates
- Median imputation for numeric attributes
- Mode-based handling of missing categorical values
- Filtering invalid borrowers (e.g., Age < 18, Income ≤ 0)
- One-hot encoding for selected categorical fields
- Generation of data quality KPIs

5.2 Preprocessing Pipeline

- Scaling numerical variables with StandardScaler
- Encoding categories using OneHotEncoder
- Unified Column Transformer to avoid data leakage

5.3 Baseline Model

- Logistic Regression
- Provides reference accuracy and AUC for comparison

5.4 Advanced Models

- XGBoost and LightGBM classifiers
- Robust for tabular, imbalanced datasets
- Feature interactions handled effectively

5.5 Hyperparameter Tuning

- RandomizedSearchCV used on XGBoost
- Optimized n_estimators, depth, learning rate, sampling parameters

5.6 Model Selection

- AUC-ROC used as final selection criterion
- Best model saved as best_model.pkl

6. Unique Contributions of CreditPathAI

1. **Automated ingestion pipeline with complete data quality profiling**
2. **Dynamic high-cardinality detection in categorical variables**
3. **Fully unified preprocessing across all models**
4. **Separated visualization scripts to eliminate redundant training**
5. **Automatic best-model selection based on AUC metrics**
6. **Action Recommendation Engine mapping risk scores to recovery steps**
7. **FastAPI-based scoring API enabling deployment readiness**
8. **Scalable architecture that supports future MLOps integration**
9. **Industry-grade KPI reporting integrated from Milestone 1**
10. **Planned React dashboard for operational use by credit analysts**

7. Results & Analysis

Experimental results show that boosting methods significantly outperform logistic regression in predicting loan defaults. The tuned XGBoost model achieved the highest AUC-ROC score, indicating strong discriminatory power between default and non-default borrowers.

Key Observations:

- **Logistic Regression** offered interpretability but underperformed on non-linear patterns.
- **XGBoost** delivered superior detection of high-risk borrowers, improving recall for default class.
- **LightGBM** performed competitively but slightly below tuned XGBoost.
- Confusion matrix analysis showed reduction in false negatives—crucial for financial risk minimization.
- ROC curves exhibited improved threshold sensitivity, useful for setting business cutoffs.

Feature distribution plots (LoanAmount, CreditScore, DTIRatio) further helped interpret borrower behaviour, revealing patterns associated with delinquency.

8. Conclusion and Future Scope

CreditPathAI demonstrates the effectiveness of combining structured data pipelines, boosting-based algorithms, and actionable insights to enhance credit risk modelling and loan recovery operations. Its modular architecture, preprocessing automation, and unified evaluation make it suitable for real-world FinTech deployment.

Future Scope Enhancements:

1. **Integration of SHAP or LIME explainability**
   To interpret model decisions for regulatory compliance (RBIs guidelines, EU AI Act, etc.).
2. **Incorporation of behavioural and transactional features**
   Enabling detection of early delinquency signals through spending patterns and cash flow changes.
3. **API-driven deployment with real-time scoring**
   Allowing financial institutions to integrate CreditPathAI into existing loan origination systems.
4. **Automated re-training and MLOps integration**
   Using MLflow, Docker, and CI/CD for continuous improvement.
5. **Hybrid ensemble models**
   Combining gradient boosting with neural networks for even better prediction accuracy.
6. **Advanced Recommendation Engine**
   Leveraging reinforcement learning or policy optimization to automate intervention workflows.
7. **Interactive risk dashboard**
   Real-time tracking of portfolio performance, recovery effectiveness, and borrower risk distribution.

These enhancements position CreditPathAI as a scalable, next-generation AI solution for intelligent loan risk assessment and automated recovery pathways.

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