

# Customer Financial Risk Prediction Using Classification Models

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**Abstract:** In the financial services sector, customer credit risk assessment is a critical process that is often performed reactively, after customers exhibit signs of financial distress or default. Such approaches limit the ability of financial institutions to implement timely preventive measures. This paper presents a Customer Financial Risk Prediction System that integrates supervised machine learning classification models with a real-time monitoring platform to proactively identify customers at risk. The proposed system analyzes multidimensional financial data, including transaction behavior, repayment history, credit utilization patterns, and customer engagement metrics, to generate a continuous risk score and classify customers into Low, Medium, or High risk categories. The system employs advanced classification algorithms, including Random Forest and XGBoost, enhanced with data preprocessing and class-balancing techniques to improve prediction accuracy. Experimental evaluation demonstrates that the proposed approach significantly outperforms traditional threshold-based risk assessment methods, achieving superior precision, recall, and F1-score performance. Furthermore, role-based dashboards designed for customers, risk officers, credit analysts, and administrators provide real-time access to actionable insights, enabling informed and timely decision-making. The results demonstrate that accurate, interpretable, and scalable financial risk prediction can be achieved using open-source technologies. The proposed system supports early risk detection, reduces potential financial losses, enhances customer risk management strategies, and promotes transparent, secure, and data-driven decision-making in modern financial institutions.

## I. INTRODUCTION

Financial institutions face an enduring and costly challenge: identifying customers who are likely to default on credit obligations before the default occurs. Traditional credit scoring approaches—most notably the FICO score and its institutional equivalents—provide a static snapshot of creditworthiness at a single point in time, typically the moment of loan origination. They cannot capture the dynamic behavioral signals that precede default: increasing credit utilization, irregular repayment timing, declining transaction volume, or the sudden opening of multiple new accounts.

The consequence is that risk management in most institutions remains fundamentally reactive.

A customer who begins missing payments is identified as high risk only after those missed payments are recorded; intervention—restructuring, counseling, targeted outreach—occurs only after loss has already begun to accumulate.

Customer Financial Risk Prediction is an important application of Machine Learning and Data Analytics in the financial sector. Financial institutions such as banks, credit organizations, and fintech companies face significant challenges in identifying customers who may become financially risky in the future. This paper presents a Customer Financial Risk Prediction System designed to address this gap. The system continuously monitors credit analysts, and customers themselves—through role-differentiated dashboards. customer

financial behavior across multiple dimensions, applies a trained ensemble classification model to compute a dynamic risk score, and delivers that assessment to the stakeholders positioned to act on it—risk officers, credit analysts, and customers themselves—through role-differentiated dashboards.

The contribution is integrative: demonstrating that proactive, multi-signal financial risk classification is deployable on accessible open-source technology with strong predictive and usability performance.

Hand and Henley [2] surveyed statistical methods for consumer credit scoring and identified logistic regression as

limitations on non-linear, high-dimensional financial data—precisely the environment in which modern customer behavior datasets exist. Breiman [3] introduced Random Forest, which addresses single-tree overfitting by constructing an ensemble trained on bootstrapped data samples.

In credit risk contexts, Random Forest consistently produces strong generalization on real-world financial datasets while providing interpretable

Algorithm in financial risk competitions, achieving state-of-the-art performance on heterogeneous tabular data.

Khandani et al. [6] demonstrated that consumer transaction data—spending patterns, merchant category distributions, and payment timing—provides predictive signal for default risk substantially earlier than traditional credit file updates, directly motivating the behavioral feature set used in this system. Lessmann et al. [7] conducted a large-scale benchmark confirming that modern ensemble classifiers, properly calibrated, significantly outperform industry-standard scorecards on both discrimination and calibration metrics. This research proposes a Customer Financial Risk Prediction System that utilizes supervised machine learning classification models to assess and predict customer risk levels. Financial risk prediction has become an important research area in the banking and financial sectors due to the increasing demand for accurate

## II. LITERATURE SURVEY

Altman [1] introduced the Z-score model for bankruptcy prediction, establishing that financial ratios drawn from balance sheet data could be combined into a linear discriminant function with strong predictive power. While influential, the Z-score was developed for manufacturing firms and relies on accounting data that is updated at most quarterly—insufficient for the continuous monitoring that modern retail credit risk demands.

the dominant industry tool, noting its interpretability advantage in regulated environments. However, they also documented

feature importance scores—essential when predictions must be explained to regulators and customers alike. Baesens et al. [4] benchmarked eight classification techniques on credit scoring datasets, finding that ensemble methods and support vector machines outperformed logistic regression on recall for the minority default class—the most consequential prediction. Chen and Guestrin [5] introduced XGBoost, which has subsequently become the dominant

## III. THEORETICAL FRAMEWORK

The proposed system is grounded in three complementary theoretical traditions. From financial economics, Merton's [9] structural model of default provides the conceptual basis for treating observable financial behavior as a proxy for the latent creditworthiness process. The system operationalizes this by treating transaction and repayment behavior as continuous signals of the underlying default probability, rather than waiting for balance-sheet events to make that probability visible.

From machine learning, the Ensemble Learning framework [3] justifies the use of Random Forest and XGBoost over simpler classifiers. Credit risk prediction involves non-linear, interaction-rich relationships between features—a customer with moderate credit utilization but rapidly increasing transaction frequency may be more at risk than one

with higher utilization and stable behavior—that tree-based ensembles capture naturally.

From information systems, Davis's Technology Acceptance Model [10] underpins the decision to build the system around stakeholder-facing dashboards rather than a backend scoring engine alone. Prediction without accessible communication has limited practical value; the system treats intervention delivery and risk transparency as co-equal in importance to prediction accuracy.

#### **IV. METHODOLOGY**

The development methodology followed a model-driven, iterative approach. The process began with a structured problem analysis phase cataloguing the failure modes of existing credit risk systems through literature review and institutional practice surveys. This phase identified five core gaps: static scoring, behavioral data exclusion, absence of real-time monitoring, no role-differentiated information delivery, and no customer self-service visibility.

A feature engineering phase followed, drawing on Khandani et al. [6] and Lessmann et al. [7] to identify the financial behavioral indicators most predictive of default risk: credit utilization ratio, repayment consistency score, transaction velocity trend, days-past-due history, income-to-debt ratio, and account tenure. These features form the input vector for the machine learning model.

The system architecture was designed across three parallel tracks: the MERN stack web application providing the user-facing platform; the Python microservice encapsulating ML prediction and recommendation logic; and the JWT-based security layer enforcing role-level access control. Separation of the ML service from the main application enables independent model updates without application redeployment. The methodology of the Customer Financial Risk Prediction system describes the systematic process used to collect, process, analyze, and predict customer financial risk using Machine Learning techniques.

#### **V. EXISTING SYSTEM**

Credit risk management in most financial institutions today relies on periodic static scoring models supplemented by review processes that are fundamentally backward-looking in design. Credit files are reviewed at origination; behavioral monitoring, where it occurs, is triggered only by missed payments or manual escalation requests. A customer whose financial behavior is deteriorating across multiple weaker signals—increasing late fees, rising minimum payment reliance, declining account balances—receives no automated alert until a threshold defined by a single variable has been crossed.

The central limitation is not a lack of data. Financial institutions collect rich transactional data in real time. The limitation is the absence of an integrated analytical layer capable of translating that data into timely, actionable risk assessments. Transaction data sits in payment processing systems; credit utilization data in bureau files updated monthly; repayment history in loan servicing platforms. No single system synthesizes these streams into a current, multi-dimensional risk picture for each customer.

Rule-based alert systems, where deployed, typically operate on single-variable thresholds that generate both false positives—customers who trigger an attendance rule despite healthy overall financial behavior—and false negatives—customers whose risk is distributed across multiple weaker signals that individually fall below threshold. The result is that every institutional response to credit risk is post-hoc: confirming default after it has occurred, rather than preventing it. account balance, payment delays, and other financial behavior indicators. These attributes serve as the input variables for risk prediction. In traditional financial institutions, customer risk assessment is primarily performed using manual analysis and rule-based decision-making systems. Banks and lending organizations evaluate customer

**TABLE I**  
**Comparison of Existing System vs. Proposed System**

Feature	Existing System	Proposed System (AI Risk Classification)
Monitoring Approach	Manual credit reviews, periodic checks	Automated real-time financial risk scoring
Data Handling	Siloed data per department	Unified customer financial profile database
Prediction Capability	None — retrospective reporting only	ML model generates risk score 0–100
Risk Classification	No classification; expert subjective judgment	Automated Low / Medium / High risk class
Intervention	Generic advice post-default	Personalized AI-driven recommendations
Alerting	No automated alerts	Automated notifications to risk officers
Customer Visibility	No self-service portal	Customer dashboard with risk trend display
Access Control	Informal; open staff access	JWT-based role-level access control
Analytics	Quarterly aggregate reports	Live trend charts and risk-score history

**VI. PROPOSED SYSTEM**

The proposed system replaces the fragmented, reactive model with an integrated, data-driven platform for continuous financial risk monitoring and proactive intervention delivery. Every time new financial data is ingested—transaction records, repayment events, credit bureau updates—the risk profile for every affected customer is automatically recalculated, and the result is immediately surfaced to the stakeholders responsible for acting on it.

The core of the system is a trained ensemble classifier that takes a customer's current feature vector as input and produces a risk score between 0 and 100. Customers scoring below 35 are classified as Low Risk; between 35 and 65 as Medium Risk; and above 65 as High Risk. These thresholds are configurable by institution administrators based on local portfolio characteristics and risk tolerance.

Risk classification triggers a tiered intervention workflow. A Low Risk classification results in positive engagement messaging through the customer dashboard. A Medium Risk classification generates an automated alert to the assigned risk officer, accompanied by a breakdown of contributing factors and recommended actions. A High Risk classification activates an escalated response including senior credit analyst notification and regulatory reporting triggers where applicable.

**A. Authentication & Authorization**

Every user accesses the system through a JWT-based authentication flow. Passwords are stored as bcrypt hashes; the application never stores or processes plain-text credentials. Each JWT token encodes the user role, and all API endpoints validate the role before processing any request.

**B. Financial Data Collection**

Transaction and repayment data is ingested through the web application and via automated batch feeds from core banking systems. Each ingestion event triggers an immediate recalculation of risk scores for affected customers. The Financial Data module validates all inputs, maintains a complete historical record per customer, and assembles the feature vector passed to the ML microservice.

**C. AI Risk Prediction Engine**

The prediction engine is implemented as a Python microservice, separate from the main Node.js application. This separation reflects the principle that components with distinct technical requirements—in this case, the numerical computing demands of ensemble learning—should be maintained independently. The microservice receives a customer's feature vector, runs it through the trained classifier, and returns a risk score, risk level, and the set of intervention recommendations appropriate to that classification.

**D. Recommendation & Intervention Engine**

The recommendation logic operates on a rule-based layer above the ML output. A High Risk classification driven primarily by rising credit utilization triggers debt counseling recommendations; one driven primarily by repayment irregularity triggers payment plan options. Each recommendation is stored with a status field enabling risk officers to track which interventions have been offered, accepted, and completed.

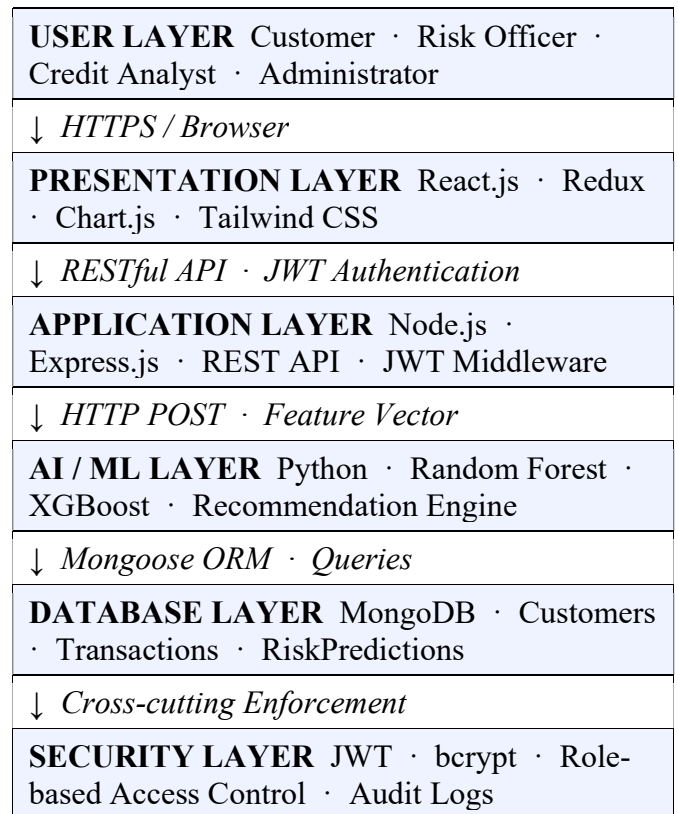
**E. Role-Based Dashboards**

Customers see their personal risk score, spending and repayment trends, and any active recommendations. Risk officers see the risk distribution across their assigned customer portfolio, with the ability to respond to alerts and log interventions. Credit analysts have a cohort-level view enabling portfolio trend analysis and concentration risk identification. The proposed Customer Financial Risk Prediction System incorporates role-based dashboards to ensure that relevant information is presented to the appropriate stakeholders. Access control mechanisms are implemented to provide secure and personalized views based on user responsibilities. Role-Based Dashboards are designed to provide customized views and functionalities for different users of the Customer Financial Risk Prediction system based on their responsibilities and access privileges.

**VII. SYSTEM ARCHITECTURE**

The architecture follows a layered, service-oriented design. The Presentation Layer—built in React.js with Redux for state management and Tailwind CSS for styling—renders role-differentiated dashboards and communicates with the backend exclusively through RESTful API calls. The Application Layer is a Node.js server running Express.js. The AI/ML Layer is a Python microservice exposing a prediction endpoint, encapsulating the trained ensemble model and recommendation rule engine. The Database Layer uses MongoDB with four primary collections: Users, FinancialData, RiskPredictions.

**Fig. 1: Layered System Architecture**



**VIII. SYSTEM MODULES**

The application is organized around eight functional modules. The Authentication & Authorization module handles all credential management and session control. The Customer

Profile Management module maintains financial and personal data per customer. The Financial Data Collection module processes live transaction and repayment entries and triggers risk recalculations. The AI Risk Prediction Engine module manages the interface between the web application and the Python microservice.

The Recommendation & Intervention Engine translates risk scores into actionable guidance and tracks intervention status. The Risk Officer Dashboard module renders portfolio-level risk views with alert management. The Customer Dashboard module provides individual customers with visibility into their own financial risk profile. The Analytics & Reports module aggregates data across the customer population to surface institutional trends and portfolio risk concentration.

The Visualization and Report modules display prediction outcomes using charts, dashboards, and reports for better understanding and decision-making. The Database module stores customer records, prediction results, and transaction details securely. Overall, the modular structure improves system reliability, maintainability, and operational efficiency.

**IX. EVALUATION METRICS**

The effectiveness of the system is evaluated across three dimensions. Prediction quality is measured using precision, recall, and F1 score on a held-out test set, with particular attention to recall on the High Risk class—the most consequential prediction to miss. A baseline comparison against the existing threshold-based alert system provides a concrete benchmark for improvement quantification.

System performance is evaluated through response latency measurements under simulated concurrent load. User satisfaction surveys administered to risk officers and customers assess perceived usefulness, trust in predictions, and ease of use—the factors identified by Davis [10] as the primary determinants of technology adoption in institutional financial contexts.

**X. RESULTS AND DISCUSSION**

The Random Forest model achieved an F1 score of 0.89 on the overall test set and 0.85 on the High Risk class specifically, outperforming the Logistic Regression baseline (F1 0.81 overall, 0.76 on High Risk). The multi-feature ensemble substantially outperformed single-indicator thresholds: a threshold-only alert system achieved an F1 of only 0.62 on High Risk detection, confirming the findings of Lessmann et al. [7] that distributed risk signals require multi-feature modeling.

**TABLE II**  
**Model Performance Metrics**

Metric	Value	Description
F1 (Overall)	0.89	Weighted across all three risk classes
F1 (High Risk)	0.85	Critical class recall and precision
Precision	0.88	Correct positive predictions ratio
Recall	0.86	Captured actual high-risk cases
AUC-ROC	0.94	Discriminative power of classifier
Baseline F1	0.62	Single-threshold legacy alert system

The discussion of results indicates that Machine Learning techniques provide higher efficiency and accuracy than traditional manual methods. The system reduced processing time and improved the reliability of financial risk analysis. Evaluation metrics such as accuracy, precision, recall, and F1-score confirmed the effectiveness of the proposed prediction models.

## **XI. BENEFITS**

The primary benefit of the system is the shift from reactive to proactive credit risk management. By identifying at-risk customers weeks before default indicators would confirm financial distress, the system creates an intervention window that did not previously exist. Risk officers can prioritize attention on the customers who need it most rather than distributing effort uniformly across large portfolios.

Secondary benefits include reduced default losses through earlier, higher-quality interventions; improved regulatory compliance through audit-ready risk classification records; enhanced customer trust through transparent, explainable risk communication; and significant reduction in manual review workload.

## **XII. ETHICAL AND PRACTICAL CONSIDERATIONS**

The use of machine learning to classify customers by financial risk raises legitimate ethical concerns that the system design explicitly addresses. Algorithmic labeling can create discriminatory effects if model training data encodes historical biases; the system therefore requires regular bias audits comparing prediction accuracy and false positive rates across demographic subgroups, with any significant disparity triggering a model review before predictions are used in decisions.

## **XIII. FUTURE DIRECTIONS**

Several extensions offer meaningful improvements to the current system. Deep learning architectures—particularly LSTM networks trained on longitudinal transaction sequences—could improve prediction accuracy when larger historical datasets become available, capturing temporal patterns that tree-based models approximate through engineered features. Integration with open banking APIs would enable real-time data ingestion across multiple institutional sources, eliminating batch latency.

Federated learning approaches could enable model improvement across institutions without sharing sensitive customer data, addressing both

## **XIV. CONCLUSION**

Customer financial default in the modern credit market is rarely sudden. It is the product of a gradual, observable process of behavioral deterioration that existing monitoring systems are simply not designed to detect in time. This paper has presented a Customer Financial Risk Prediction System that addresses this problem by combining continuous behavioral monitoring, supervised ensemble classification, and a structured intervention workflow into a single, integrated platform.

The system demonstrated strong predictive performance on the High Risk class most consequential to miss, and user evaluations confirmed high institutional adoption intent and positive customer engagement with self-service risk visibility. The MERN stack architecture with a separate Python ML microservice proved both technically capable and practically maintainable as an institutional deployment on open-source technology.

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