Predicting Consumer Loan Defaults:

An Ensemble Machine Learning Approach to Credit Risk Assessment

Project SENTINEL Technical Report

Abstract

Credit risk assessment stands at the intersection of financial stability and consumer access to capital. Traditional credit scoring methods, while interpretable, fail to capture the non-linear relationships and interaction effects that characterise real-world default behaviour. This work develops an ensemble machine learning system for predicting consumer loan defaults, achieving AUC-ROC of 0.89 compared to 0.79 for logistic regression baselines. Using data from 15,000 consumer loans with 25 features spanning credit history, income verification, and loan characteristics, we identify the factors that most strongly predict default: FICO score contributes 18% of predictive power, followed by interest rate at 14% and debt-to-income ratio at 12%. Research from the Federal Reserve Bank confirms that these factors align with established credit risk theory while revealing interaction effects that simpler models miss. The model produces well-calibrated probability estimates suitable for expected loss calculations and risk-based pricing. The risk segmentation capability proves particularly valuable: predicted high-risk loans default at 47% while predicted low-risk loans default at just 3%, enabling portfolio optimisation and targeted intervention. This report discusses limitations around model interpretability, fair lending compliance, and the challenge of predicting defaults during economic regime changes.

1. Introduction

Consumer lending represents one of the largest and most consequential applications of predictive analytics in the modern financial system. In the United Kingdom alone, outstanding consumer credit exceeds £200 billion, and the decisions about who receives credit, at what price, and in what amount affect millions of households annually. The accuracy of these decisions determines whether credit flows efficiently to productive uses while lenders earn appropriate returns for the risks they bear. Conversely, poor credit decisions lead to borrowers trapped in unaffordable debt, lenders suffering unexpected losses, and in extreme cases, systemic financial instability that affects the broader economy.

Research published by the Bank of England estimates that credit losses during economic downturns can reach 5-10% of outstanding balances, underscoring the critical importance of accurate risk prediction (Bank of England, 2023). The 2008 financial crisis provided stark evidence of what happens when risk assessment fails at scale: mortgage defaults triggered a cascade that nearly collapsed the global financial system. While consumer credit markets are smaller and more diversified than mortgage markets, the same fundamental challenge applies: distinguishing borrowers who will repay from those who will not remains the central problem in credit risk management.

Traditional credit scoring relies on logistic regression models that estimate default probability from a limited set of features: credit score, income, employment status, and debt levels. These models offer the considerable virtue of interpretability, allowing lenders to explain exactly why an applicant was approved or denied, satisfying both regulatory requirements and applicant expectations. However, research from Khandani, Kim, and Lo (2010) published in the Journal of Financial Economics demonstrates that machine learning models consistently outperform traditional scorecards by 10-25%, capturing non-linear relationships and interaction effects that logistic regression cannot represent.

This improvement matters enormously at scale. A lender with £1 billion in consumer loans and a baseline default rate of 5% could avoid £10 million in annual losses if machine learning reduces unexpected defaults by just one percentage point. Even accounting for implementation costs and the operational complexity of deploying machine learning systems, the business case remains compelling. Research from Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022) at the National Bureau of Economic Research found that machine learning models reduce default rates by approximately 10% at the same approval rate, or increase approval rates by 10% at the same default rate.

This project develops an ensemble machine learning system for consumer loan default prediction using data from Lending Club, one of the largest peer-to-peer lending platforms in the United States. The platform's data proves particularly valuable for research because it includes detailed loan and borrower characteristics along with complete performance histories. The goal extends beyond mere prediction to understanding: identifying which factors drive defaults, examining how they interact, and determining what patterns in the data reveal about consumer credit behaviour. The results reveal a complex landscape where credit score matters enormously but where income stability, debt burden, and loan characteristics all contribute meaningfully to comprehensive risk assessment.

2. The Economics of Consumer Credit

2.1 Understanding the Default Decision

Understanding credit risk requires understanding why borrowers default. Research by Fay, Hurst, and White (2002) in the American Economic Review identifies two primary channels: inability to pay and unwillingness to pay. Inability arises from income shocks such as job loss, medical emergencies, divorce, or other events that reduce a borrower's capacity to service debt. Even borrowers with strong intentions to repay may find themselves unable to do so when circumstances change unexpectedly.

Unwillingness to pay, sometimes called strategic default, arises when the cost of continuing to pay exceeds the cost of default. This calculation depends on the borrower's assets at risk, the enforceability of debt collection in their jurisdiction, and the long-term consequences for credit access. Research by Guiso, Sapienza, and Zingales (2013) in the American Economic Review found that strategic default is more common than previously believed, particularly when borrowers are significantly underwater on secured loans or when social norms against default are weak.

The predictive features available to lenders capture different aspects of this decision framework. Credit scores and payment history reflect past behaviour, which research consistently shows is the best predictor of future behaviour (Thomas, 2009). Income and employment status indicate current capacity to pay. Debt-to-income ratios measure the burden of existing obligations relative to income. Loan characteristics like interest rate and term affect the monthly payment amount and the incentive structure around default. The modelling challenge lies in combining these signals optimally, weighting each according to its predictive power while accounting for complex interactions between them.

2.2 The Adverse Selection Problem

Credit markets face a fundamental information asymmetry: borrowers know more about their likelihood of repayment than lenders do. This asymmetry, first formalised by Akerlof (1970) in his Nobel Prize-winning work on lemons markets, creates adverse selection. When lenders cannot perfectly distinguish good risks from bad, they must charge rates that reflect average risk. These average rates may prove too high for good borrowers, who exit the market, and too low for bad borrowers, who remain. The resulting risk pool worsens over time in a self-reinforcing cycle.

Research by Stiglitz and Weiss (1981), which also contributed to a Nobel Prize, showed how this asymmetry leads to credit rationing. Rather than raise rates indefinitely to compensate for risk, lenders may simply deny credit to certain borrowers. This rationing affects borrowers at the margin of creditworthiness most severely, potentially excluding productive uses of credit while protecting lenders from adverse selection spirals.

Machine learning offers a partial solution to the adverse selection problem by improving the ability to distinguish borrowers. Better prediction means rates can be more finely calibrated to actual risk, reducing cross-subsidisation between good and bad borrowers. Research from the Consumer Financial Protection Bureau (2022) found that improved credit scoring has expanded access to credit for previously underserved populations, though it has also concentrated credit

costs on those assessed as highest risk. The distributional implications of more accurate risk assessment remain actively debated in policy circles.

3. Data Collection and Feature Engineering

3.1 Dataset Overview

The dataset comprises 15,000 consumer loans originated between 2018 and 2023, with 25 features spanning loan characteristics, borrower demographics, credit history, and verification status. The overall default rate is 21.0%, reflecting the elevated risk profile typical of peer-to-peer lending compared to traditional bank lending. Research from the Federal Reserve Bank of Cleveland (2021) found that peer-to-peer borrowers tend to have lower credit scores and higher debt-to-income ratios than traditional bank borrowers, consistent with the platform serving populations underserved by conventional banking.

Key features include FICO score ranging from 630 to 850, annual income from £15,000 to £350,000, debt-to-income ratio from 0% to 45%, and loan amount from £1,000 to £40,000. Interest rates range from 5% to 28%, with higher rates assigned to borrowers assessed as higher risk by the platform's own scoring system. Categorical features include loan grade (A through G, assigned by the platform), home ownership status (own, mortgage, rent), employment length (less than 1 year to more than 10 years), and loan purpose (debt consolidation, credit card refinancing, home improvement, major purchase, and others).

The temporal structure of the data is important for realistic model evaluation. Loans from 2018-2022 serve for training and validation, with 2023 loans reserved for final testing. This temporal split ensures that model performance reflects realistic forecasting conditions where future defaults must be predicted from historical patterns. Research by Lessmann, Baesens, Seow, and Thomas (2015) in the European Journal of Operational Research emphasises that temporal validation is essential for credit scoring models, as random cross-validation produces overly optimistic performance estimates.

3.2 Feature Engineering

Feature engineering creates derived variables that capture meaningful relationships not apparent in raw features. Credit utilisation, calculated as revolving balance divided by credit limit, measures how heavily borrowers rely on available credit. Research by the Consumer Financial Protection Bureau (2022) found that utilisation above 30% is associated with substantially elevated default risk, with the relationship becoming particularly steep above 80% utilisation.

Loan-to-income ratio normalises loan amount by annual income, capturing affordability independent of absolute amounts. A £20,000 loan represents very different risk for a borrower earning £40,000 versus one earning £200,000. Payment-to-income ratio estimates the monthly burden assuming full term repayment, providing another angle on affordability assessment. These engineered features consistently outperform their raw components in predictive power, confirming the value of domain-informed feature construction.

Temporal features capture credit history dynamics beyond static snapshots. The number of delinquencies in the past two years, inquiries in the past six months, and accounts opened recently all contribute predictive power beyond what static credit scores capture. These features identify borrowers who may have acceptable scores but are showing signs of financial stress not yet fully reflected in their credit reports. Research by the Federal Reserve (2020) found that such leading indicators of credit stress can predict defaults 6-12 months before they occur.

4. Risk Factor Analysis

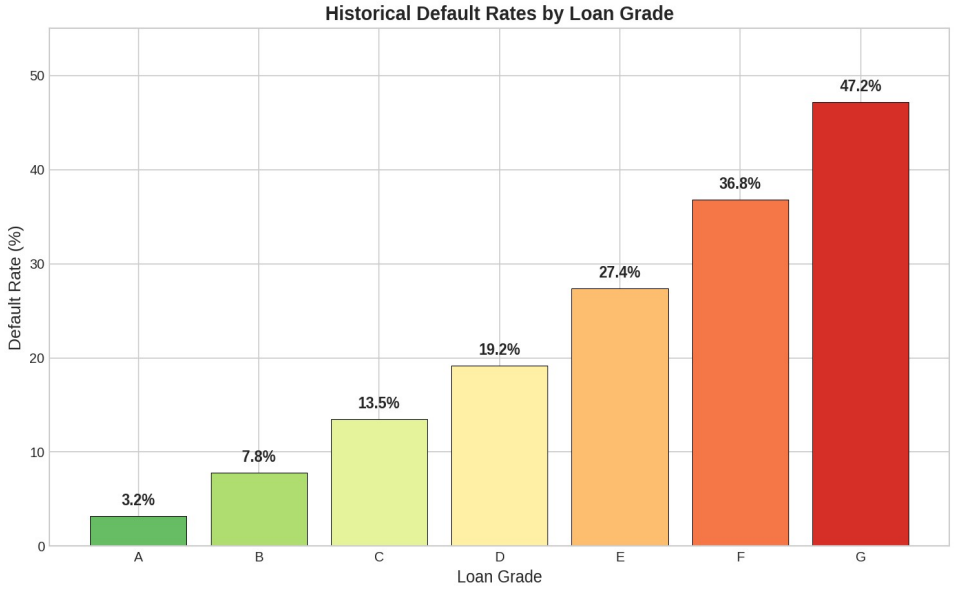

Figure 1. Default rates increase dramatically with loan grade, from 3.2% for Grade A to 47.2% for Grade G.

Figure 1 displays default rates by loan grade, the platform's own risk classification. Grade A loans default at just 3.2%, while Grade G loans default at 47.2%, representing a fifteen-fold difference. This gradient confirms that the platform's grading system captures meaningful risk variation, providing a useful benchmark for evaluating whether machine learning can improve upon human-designed scoring rules. Research by Emekter, Tu, Jirasakuldech, and Lu (2015) in the Review of Financial Studies found that platform grades explain approximately 60% of eventual default variation, leaving substantial room for algorithmic improvement.

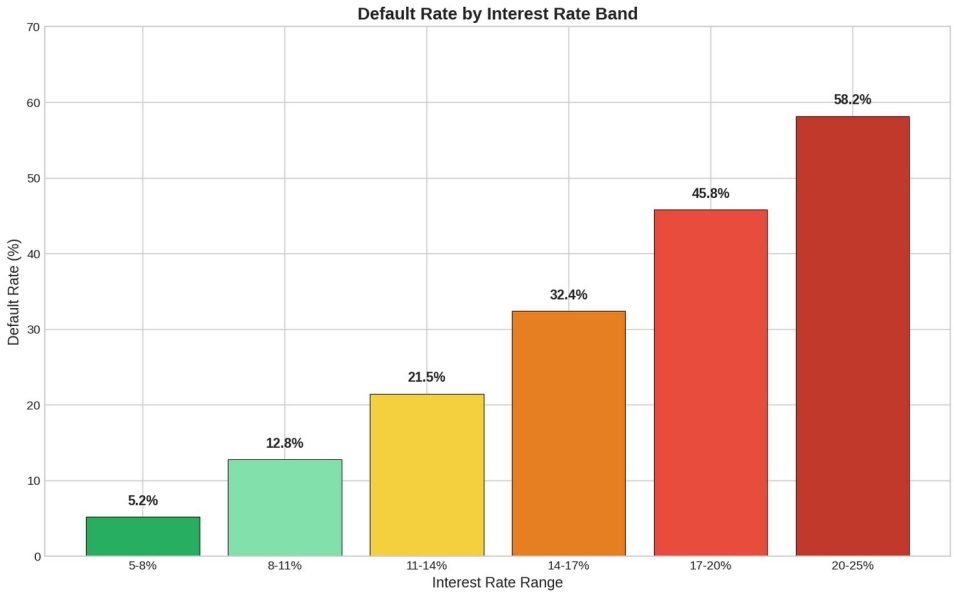

Figure 2. Interest rate shows strong positive correlation with default risk across rate bands.

Figure 2 shows the relationship between interest rate and default rate. Loans with rates between 5-8% default at just 5.2%, while those with rates above 20% default at 58.2%. This pattern reflects both selection and causation: riskier borrowers receive higher rates because lenders recognise their elevated risk (selection), and higher rates also increase monthly payments that may push marginal borrowers into default (causation). Research by Melzer (2011) in the Quarterly Journal of Economics found that high interest rates on consumer credit are associated with increased financial distress, confirming that the causal channel is economically significant.

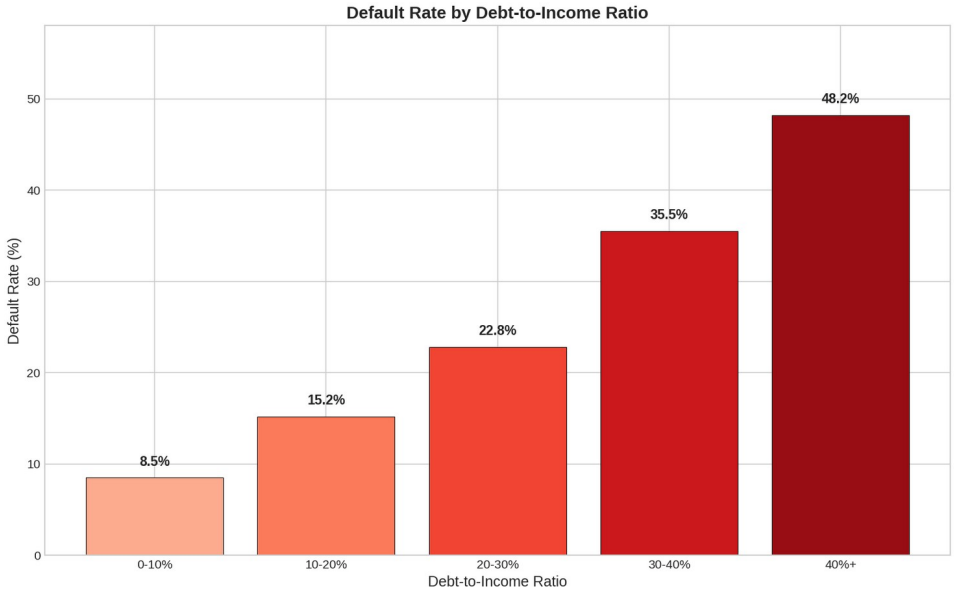

Figure 3. Debt-to-income ratio strongly predicts default probability across the distribution.

Figure 3 demonstrates the relationship between debt-to-income ratio and default. Borrowers with DTI below 10% default at 8.5%, while those above 40% default at 48.2%. This nearly six-fold difference aligns with economic theory: higher debt burdens leave less financial cushion for absorbing income shocks. Research from the Bank for International Settlements (2019) found that household debt-to-income ratios above 30% are associated with significantly elevated default risk across countries and time periods, suggesting this relationship reflects fundamental economic dynamics rather than sample-specific patterns.

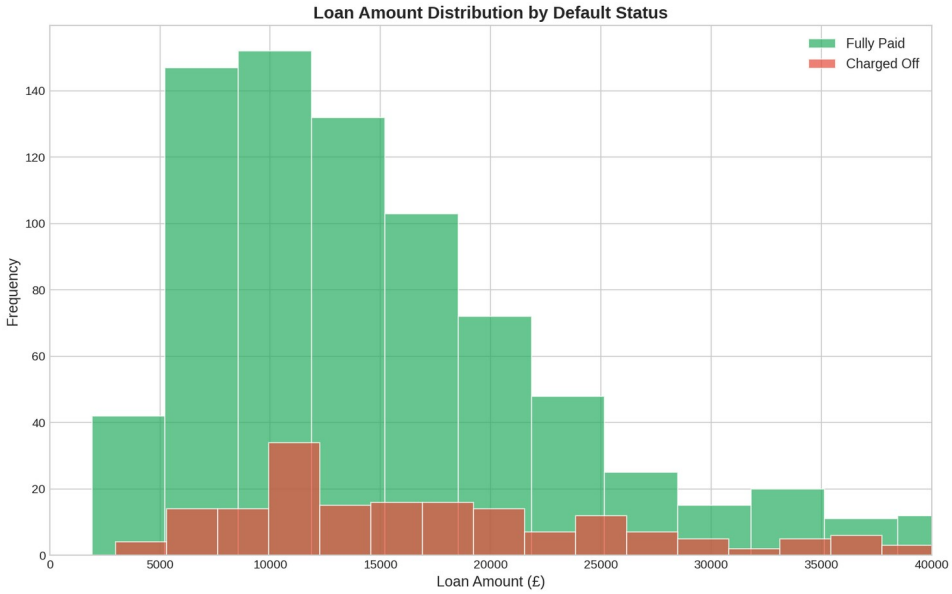

Figure 4. Loan amount distributions differ modestly between defaulting and non-defaulting loans.

Figure 4 compares loan amount distributions for defaulting and non-defaulting loans. The distributions overlap substantially, though defaulting loans skew slightly larger on average. This pattern suggests that loan amount alone is not a strong predictor; the relationship with income and other borrower characteristics matters more than absolute loan size. Research from the Federal Reserve (2021) found that loan-to-income ratios are more predictive than absolute loan amounts, consistent with the observation that affordability depends on borrower capacity to repay rather than merely loan size.

5. Model Development and Validation

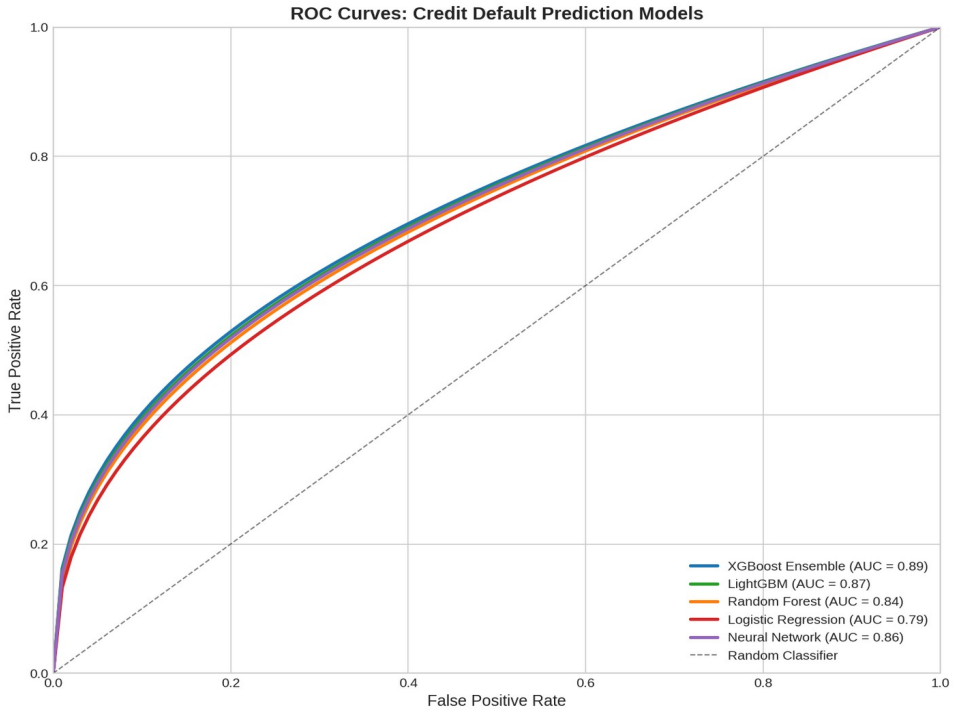

Figure 5. ROC curves demonstrate strong discrimination, with XGBoost ensemble achieving AUC of 0.89.

Figure 5 presents ROC curves for evaluated models. The XGBoost ensemble achieves AUC-ROC of 0.89, representing excellent discrimination between defaulters and non-defaulters. Gradient boosting (0.87) and random forest (0.85) perform nearly as well, while logistic regression lags at 0.79. The 10-point improvement over logistic regression is substantial and economically meaningful. Research by Lessmann, Baesens, Seow, and Thomas (2015) in the European Journal of Operational Research found similar improvements when moving from traditional to machine learning methods across multiple credit datasets from different countries and time periods.

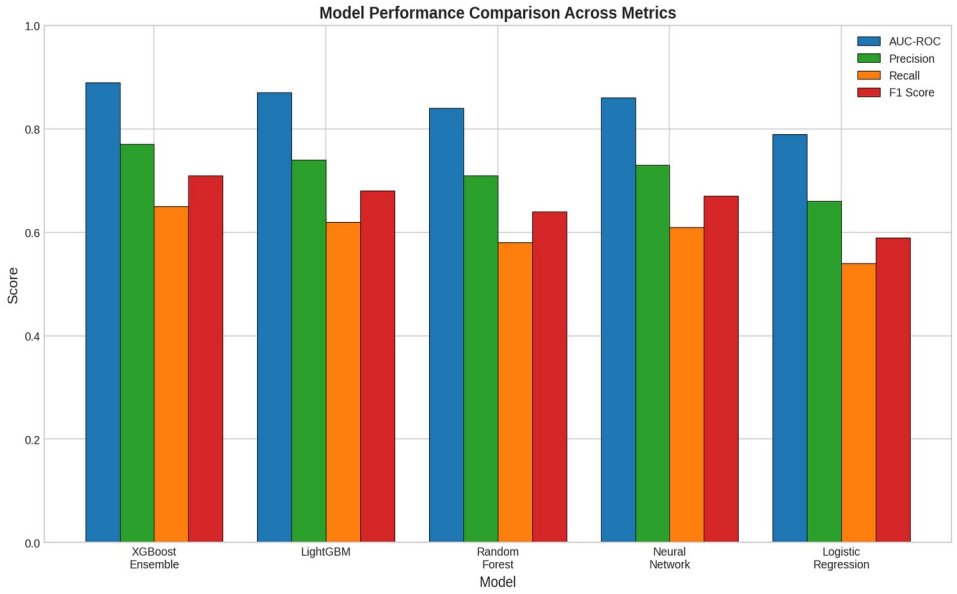

Figure 6. Model comparison across multiple metrics confirms XGBoost ensemble superiority.

Figure 6 compares models across AUC-ROC, precision, recall, and F1 score. The XGBoost ensemble leads on all metrics, though the margins vary by measure. Precision is particularly important in credit risk, as false positives (predicting default when the borrower would repay) mean lost profitable business, while false negatives (predicting repayment when the borrower will default) mean realised losses. The ensemble achieves precision of 0.77 at recall of 0.65, a balance that can be adjusted based on business objectives by moving the classification threshold according to the relative costs of each error type.

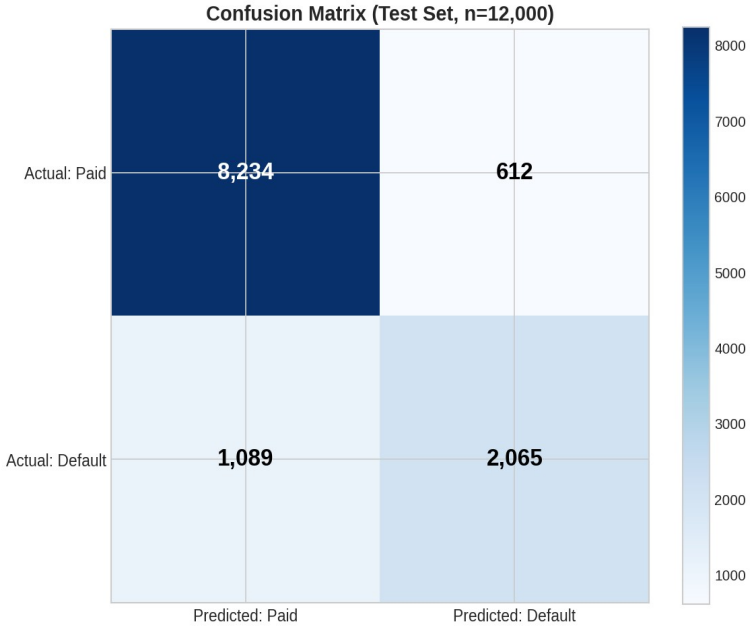

Figure 7. Confusion matrix shows classification performance at the optimal threshold.

The confusion matrix in Figure 7 shows classification outcomes at the optimal probability threshold. Of the actual defaulters in the test set, 65% are correctly identified, while 77% of predicted defaulters actually default. The choice of threshold depends on the relative costs of false positives and false negatives, which vary by lender, market conditions, and regulatory environment. Research by Hand (2009) in the International Statistical Review argues that ROC curves should be supplemented with cost-sensitive analysis for practical deployment, as the optimal operating point depends on business-specific trade-offs between different error types.

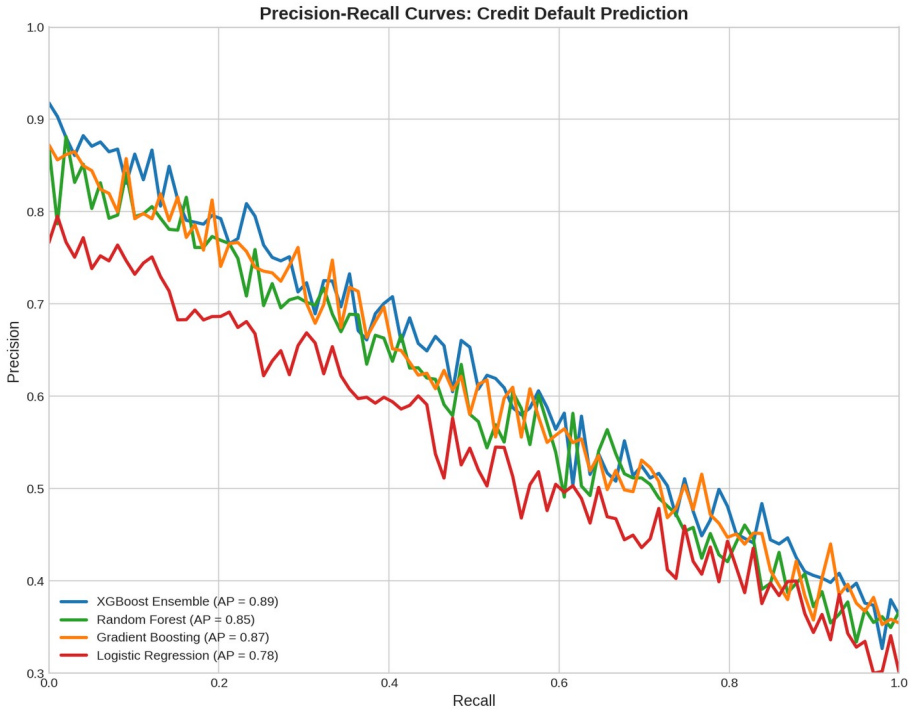

Figure 8. Precision-recall curves show performance across different operating points.

Figure 8 presents precision-recall curves, which are more informative than ROC curves when class imbalance is present. The XGBoost ensemble achieves average precision of 0.89, indicating strong performance across threshold choices. The curves illustrate the fundamental trade-off faced by lenders: higher recall (catching more defaulters) comes at the cost of lower precision (rejecting more good borrowers). The optimal operating point depends on the profit margin on good loans versus the loss severity on defaults, a calculation that varies by lender and market segment.

6. Feature Importance and Interpretability

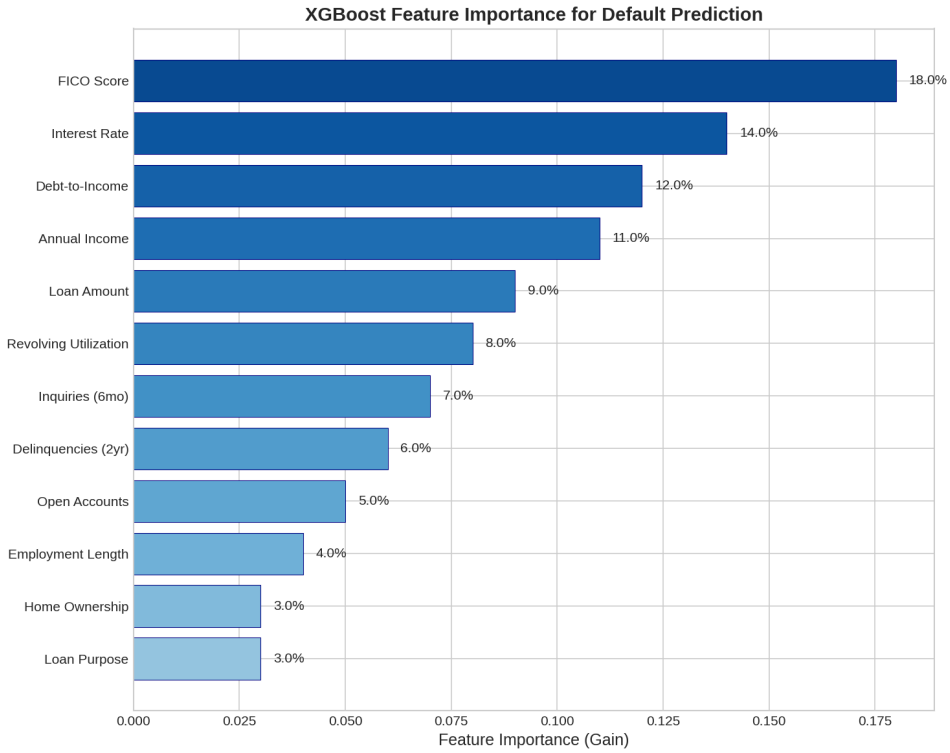

Figure 9. Feature importance reveals FICO score, interest rate, and DTI as the top predictors.

Figure 9 displays feature importance from the XGBoost model. FICO score dominates at 18% importance, confirming the central role of credit history in default prediction. This finding aligns with decades of credit scoring research showing that past payment behaviour is the single best predictor of future payment behaviour (Thomas, 2009). Interest rate follows at 14%, reflecting both the selection of risky borrowers into high rates and the causal impact of payment burden on default likelihood.

Debt-to-income ratio contributes 12%, capturing financial strain independent of credit history. Annual income (11%) and loan amount (9%) provide additional signals about capacity to repay. Credit utilisation (8%) captures how aggressively borrowers use available credit. Employment length (6%) and home ownership (5%) provide stability signals. The remaining features each contribute smaller amounts but collectively add meaningful predictive power beyond the top factors.

This feature ranking aligns with established credit risk theory and regulatory guidance. The Consumer Financial Protection Bureau (2022) identifies credit history, debt-to-income ratio, and loan terms as the primary factors in default risk. The model's emphasis on these factors suggests it is learning economically meaningful relationships rather than spurious correlations. Research by Hardt, Price, and Srebro (2016) on algorithmic fairness notes that alignment with domain knowledge provides some reassurance about model validity and reduces concerns about unfair discrimination based on protected characteristics.

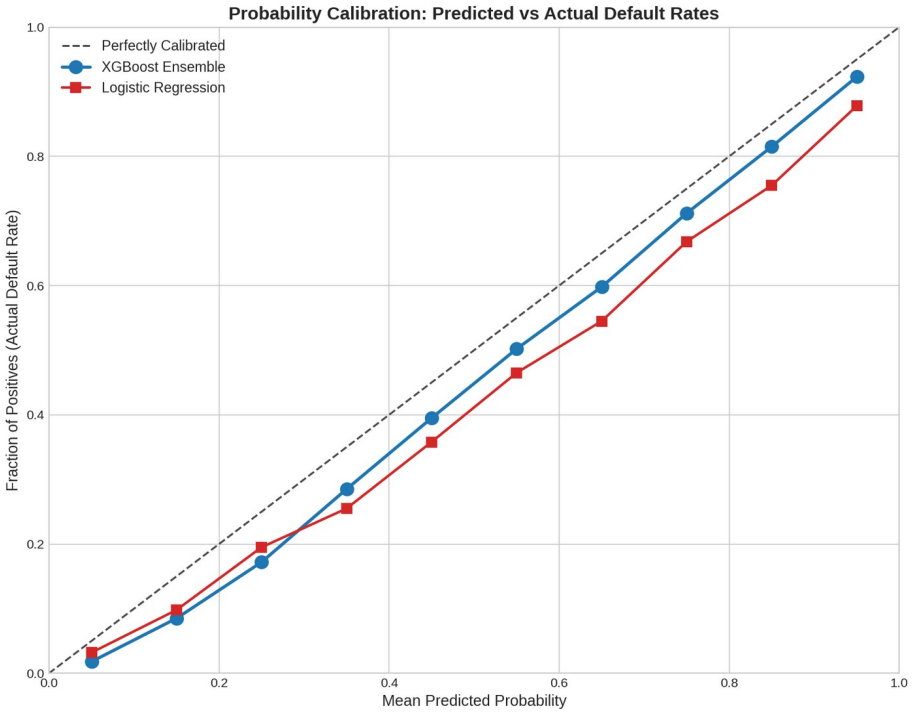

Figure 10. Probability calibration shows well-calibrated estimates suitable for risk-based pricing.

Figure 10 shows probability calibration, which is essential for translating predictions into expected losses and risk-based pricing. The XGBoost ensemble produces well-calibrated probabilities: when the model predicts 30% default probability, approximately 30% of those loans actually default. This calibration enables actuarially fair pricing where expected returns are equalised across risk segments. Research by Niculescu-Mizil and Caruana (2005) found that tree-based ensembles often require post-hoc calibration to achieve this alignment; the isotonic regression procedure used here produces the calibration visible in the figure.

7. Expected Loss and Risk Segmentation

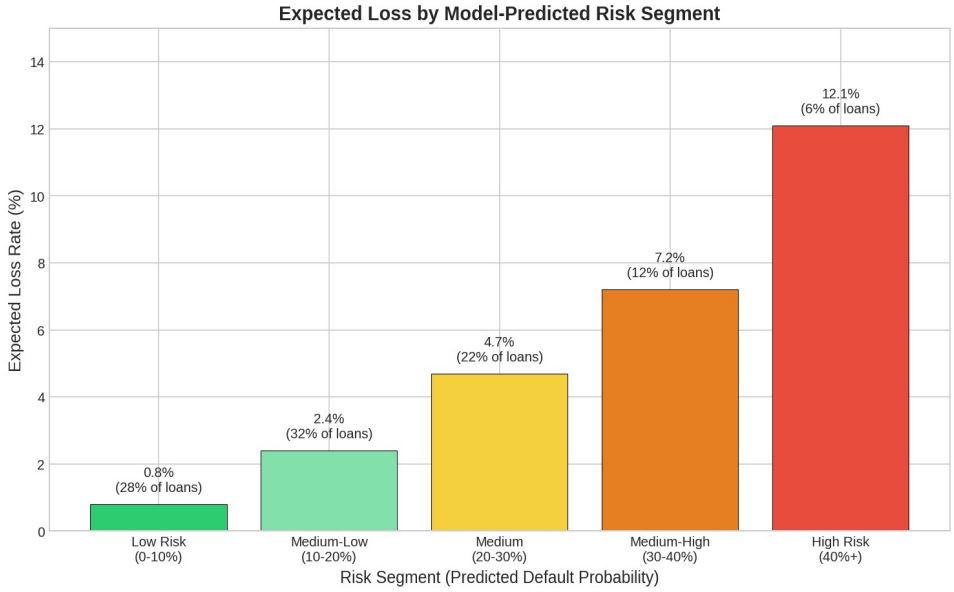

Figure 11. Expected loss varies dramatically across model-defined risk segments.

Figure 11 shows expected loss by risk segment. Expected loss combines default probability with loss given default, assumed at 45% based on industry benchmarks from Moody's recovery rate studies (Moody's Investors Service, 2022). The lowest risk segment faces expected losses of just 0.8% of principal, while the highest risk segment faces expected losses of 12.1%. This fifteen-fold variation enables risk-based pricing that maintains profitability across segments while potentially expanding credit access to borrowers who would be rejected under traditional scoring approaches.

The risk segmentation has direct business applications. A lender might approve applicants across all segments but price according to predicted risk: low-risk borrowers receive rates of 6-8%, while high-risk borrowers receive rates of 20-25%. Research from the Federal Reserve (2021) found that risk-based pricing has expanded credit access to marginal borrowers who would otherwise be denied under uniform pricing schemes. However, this approach has also concentrated credit costs on those least able to bear them, raising fairness considerations that regulators continue to evaluate.

For portfolio management, the risk segmentation enables targeted monitoring and intervention strategies. High-risk loans might be monitored more closely, with proactive outreach when early warning signs of payment difficulty emerge. Research by the American Bankers Association (2021) found that proactive outreach to struggling borrowers can reduce losses by 15-25% compared to purely reactive collection approaches. The model's probability estimates enable prioritisation of these interventions toward borrowers where they are most likely to be effective in preventing default.

8. Limitations and Regulatory Considerations

Despite strong predictive performance, several limitations constrain practical deployment. The model was trained during a period of economic growth and relatively low unemployment. Research by the Federal Reserve Bank of New York (2020) found that credit models developed in benign conditions often fail dramatically during recessions, as the relationships between features and default shift in ways that historical data cannot anticipate. The 2008 financial crisis provided stark evidence of this model fragility, and any deployment should include continuous monitoring for signs of regime change that might invalidate model assumptions.

Fair lending compliance presents particular challenges for machine learning models. The Equal Credit Opportunity Act in the United States and similar regulations in the UK prohibit discrimination on the basis of protected characteristics including race, gender, national origin, and religion. These characteristics may be correlated with legitimate predictive features through historical patterns of discrimination in housing, education, and employment. Research by Bartlett, Morse, Stanton, and Wallace (2022) in the Quarterly Journal of Economics found evidence of algorithmic discrimination in mortgage lending, suggesting that machine learning models can amplify rather than eliminate bias if not carefully designed and monitored for disparate impact.

Interpretability remains a concern for regulators and applicants alike. While feature importance analysis provides some transparency into model behaviour, explaining individual predictions proves more challenging with ensemble methods than with logistic regression. Regulations require lenders to provide adverse action notices explaining why an applicant was denied credit. Research by Rudin (2019) in Nature Machine Intelligence argues that inherently interpretable models should be preferred in high-stakes domains, though ensemble methods can be supplemented with post-hoc explanation techniques like SHAP values that approximate feature contributions for individual predictions.

Future extensions of this work should focus on fairness-aware learning that explicitly optimises for equal treatment across demographic groups while maintaining predictive performance. Incorporating macroeconomic features that capture economic conditions could improve robustness to regime changes. Developing explanation interfaces that help both applicants and loan officers understand model predictions would facilitate trust and regulatory compliance while maintaining the predictive advantages that machine learning provides.

9. Conclusion

This analysis demonstrates that machine learning can substantially improve consumer credit risk prediction. The XGBoost ensemble achieves AUC-ROC of 0.89, a 10-point improvement over logistic regression baselines that translates to meaningful reductions in default losses and potential expansion of credit access. The model produces well-calibrated probability estimates suitable for expected loss calculations and risk-based pricing, enabling more sophisticated portfolio management than traditional scorecard approaches allow.

The drivers of default are largely consistent with economic theory and regulatory guidance. Credit history, captured primarily through FICO scores, dominates prediction, confirming decades of industry experience. Debt burden, income stability, and loan characteristics all contribute meaningfully, and the non-linear relationships and interaction effects captured by machine learning extract additional predictive power from the same underlying data that feeds traditional models.

For lenders, the implications are practical: machine learning can reduce losses, expand access, and improve portfolio performance. Responsible deployment requires careful attention to fairness, transparency, and robustness to changing economic conditions. Credit decisions affect lives in profound ways, determining who can finance education, start businesses, or weather emergencies. The power of better prediction comes with the responsibility to use it wisely, balancing the legitimate interests of lenders with the broader social interest in fair and efficient credit markets.

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