Ensemble Machine Learning for Consumer Credit Risk Assessment:

A Comparative Analysis of Default Prediction Models in Personal Lending Markets

Abstract

Credit risk assessment constitutes the foundational challenge of consumer lending, determining both the profitability of lending portfolios and the availability of credit to households seeking financing for consumption and investment. This study develops an ensemble machine learning framework for predicting loan defaults in personal lending markets, integrating borrower demographics, credit history, loan characteristics, and macroeconomic indicators. Analysis of 50,000 consumer loans demonstrates that the proposed methodology achieves area under the receiver operating characteristic curve of 0.89, substantially exceeding logistic regression benchmarks at 0.78. Credit utilisation emerges as the dominant default predictor, contributing 16% of model importance, followed by debt-to-income ratio at 14% and payment history at 12%. Risk stratification enables segmentation achieving 52% actual default rates in the highest risk decile compared to 1.8% in the lowest, providing 29-fold separation suitable for tiered pricing and approval strategies. Expected loss modelling incorporating probability of default, exposure at default, and loss given default estimates portfolio losses with 8% mean absolute percentage error. The research contributes methodological advances in feature engineering for credit scoring, empirical evidence regarding the predictive power of alternative data sources, and a practical framework for implementing machine learning credit models compliant with regulatory expectations for explainability. Limitations regarding model interpretability and through-the-cycle stability are discussed alongside directions for future research.

1. Introduction

Consumer credit markets intermediate between savers seeking returns and borrowers requiring funds for consumption smoothing, investment, and emergency needs. The effective functioning of these markets depends critically upon lenders' ability to assess creditworthiness, distinguishing borrowers likely to repay from those presenting elevated default risk. Inaccurate risk assessment generates costs in both directions: excessive conservatism denies credit to worthy borrowers who would benefit from financing, while excessive permissiveness generates losses that threaten lender solvency and ultimately credit availability (Stiglitz and Weiss 1981). The global consumer credit market exceeds fifteen trillion dollars, with default losses representing a meaningful fraction of lender revenues that effective risk models could substantially reduce (Federal Reserve 2023).

Traditional credit scoring approaches rely upon statistical models, predominantly logistic regression, that estimate default probability as a function of borrower and loan characteristics. The FICO score, developed in the 1950s and refined over subsequent decades, exemplifies this approach, synthesising credit bureau information into a single creditworthiness indicator that lenders employ as a primary underwriting input (Thomas, Edelman, and Crook 2002). Despite widespread adoption, traditional scorecards exhibit well-documented limitations including restrictive linearity assumptions, inability to capture interaction effects, and exclusion of potentially predictive alternative data sources not represented in credit bureau files (Khandani, Kim, and Lo 2010).

Machine learning methods offer potential improvements over traditional scorecards by accommodating non-linear relationships, high-dimensional feature spaces, and complex interactions without explicit specification. Research by Lessmann, Baesens, Seow, and Thomas (2015) conducted comprehensive benchmarking demonstrating that ensemble methods achieve superior discrimination to logistic regression across diverse credit datasets. However, the adoption of machine learning in regulated credit markets faces challenges including interpretability requirements, fair lending compliance, and model governance expectations that traditional scorecards more readily satisfy (Board of Governors 2011).

This study develops and evaluates an ensemble machine learning framework for consumer credit risk assessment, balancing predictive accuracy against the interpretability and compliance requirements of regulated lending. The research addresses three objectives. First, it quantifies discrimination improvements achievable through machine learning relative to traditional logistic regression benchmarks. Second, it examines the predictive contribution of borrower demographics, credit history, loan characteristics, and macroeconomic indicators to identify information sources warranting collection and modelling investment. Third, it develops expected loss estimation combining probability of default with exposure and loss severity components to enable portfolio-level risk quantification. The analysis employs gradient boosting and random forest models trained on 50,000 consumer loans, with performance evaluated through temporal holdout validation and calibration assessment.

2. Literature Review

2.1 Credit Scoring Foundations

Credit scoring emerged from statistical discrimination analysis, applying quantitative methods to distinguish creditworthy from high-risk applicants. The foundational work by Durand (1941) demonstrated that borrower characteristics including income, employment tenure, and homeownership predicted loan outcomes with meaningful accuracy. Subsequent development of logistic regression provided a theoretically grounded framework for modelling binary default outcomes as functions of explanatory variables (Wiginton 1980). The standardisation of credit bureau reporting in the United States enabled development of generic scores, most notably FICO, that aggregate payment history across credit relationships into a single creditworthiness measure (Hand and Henley 1997).

The information content of credit bureau files has expanded substantially over recent decades, incorporating not only payment history but also account balances, credit utilisation, account age, credit mix, and inquiry activity. Research by Avery, Brevoort, and Canner (2009) documented that bureau-based models explain approximately 70% of individual-level default variation, leaving substantial unexplained heterogeneity attributable to factors not represented in bureau files including income, assets, and employment characteristics. The predictive contribution of supplementary information sources has motivated interest in alternative data including bank transaction records, utility payments, and digital footprints.

2.2 Machine Learning in Credit Risk

Machine learning approaches to credit scoring have demonstrated consistent improvements over traditional logistic regression across diverse datasets and lending contexts. Research by West (2000) provided early evidence that neural networks achieve superior discrimination for credit card default prediction, while subsequent studies by Baesens, Van Gestel, Viaene, Stepanova, Suykens, and Vanthienen (2003) extended these findings to ensemble methods. The comprehensive benchmark study by Lessmann, Baesens, Seow, and Thomas (2015) evaluated forty-one classification methods across eight credit datasets, finding that gradient boosting and random forests consistently rank among top performers while maintaining reasonable interpretability through feature importance measures.

The interpretability challenge has received increasing attention as machine learning adoption expands in regulated industries. Research by Rudin (2019) argued that inherently interpretable models should be preferred over black-box approaches for high-stakes decisions, proposing scorecards and decision lists that maintain accuracy while enabling complete explanation. Alternative approaches employ post-hoc explanation methods including SHAP values and LIME to provide local interpretability for complex models (Lundberg and Lee 2017). The regulatory environment increasingly requires that credit decisions be explainable to both applicants receiving adverse actions and supervisors evaluating fair lending compliance.

2.3 Expected Loss Modelling

Expected loss frameworks decompose credit risk into probability of default, exposure at default, and loss given default components, enabling both loan-level and portfolio-level risk quantification. The Basel II regulatory framework formalised this decomposition for bank capital

requirements, specifying that banks employing internal ratings-based approaches must estimate each component separately (Basel Committee 2006). Research by Schuermann (2004) documented that loss given default exhibits substantial variation across borrowers and economic conditions, with recovery rates ranging from near-complete to minimal depending on collateral, seniority, and collection effectiveness.

The correlation structure across defaults determines portfolio-level loss distributions and required capital buffers. Research by Gordy (2003) demonstrated that portfolio credit risk depends critically upon the degree to which defaults cluster during economic downturns, with higher correlations generating fatter loss distribution tails that require greater capital reserves. Through-the-cycle modelling that maintains stable risk assessments across economic conditions faces tension with point-in-time approaches that incorporate current economic information, with practitioners and regulators debating optimal calibration philosophies for different applications (Heitfield 2005).

3. Data and Methodology

3.1 Dataset Description

The empirical analysis employs a dataset comprising 50,000 consumer loans originated through a peer-to-peer lending platform during the 2018-2023 period. Each loan record includes borrower demographics comprising age, income, employment status, and homeownership; credit history variables including FICO score, credit utilisation, payment history, and inquiry count; loan characteristics including amount, term, interest rate, and purpose; and outcome indicators including payment status and final resolution. The platform's standardised application process and consistent underwriting criteria facilitate comparison across time periods without confounding from changing origination standards.

The target variable indicates loan default, defined as reaching 90 or more days past due or charge-off during the observation period. The overall default rate of 14.8% provides sufficient positive class representation for model training while reflecting market-realistic credit quality. The dataset exhibits temporal variation in default rates corresponding to macroeconomic conditions, with elevated defaults during the 2020 economic disruption and subsequent normalisation. Training-test splitting employs temporal holdout, reserving loans originated during 2023 for testing to ensure performance estimates reflect out-of-time generalisation.

3.2 Feature Engineering

Feature engineering transforms raw application data into predictive variables through domain-informed operations. Credit utilisation is computed as the ratio of revolving balances to credit limits, capturing the borrower's consumption of available credit that correlates strongly with financial stress. Debt-to-income ratio normalises monthly debt payments by monthly income, indicating the borrower's capacity to absorb additional payment obligations. Payment history features include counts of delinquencies at various severity levels and time since most recent derogatory event.

Interaction features capture relationships between variables that may exhibit non-additive effects on default risk. The product of loan amount and debt-to-income ratio distinguishes large loans to stretched borrowers from equivalent amounts to financially comfortable applicants. Credit utilisation interacted with income captures whether high utilisation reflects genuine credit dependence or merely reflects low limits relative to responsible usage. Macroeconomic features including unemployment rate and consumer confidence index provide context for individual risk assessment, as identical borrowers present different risks under varying economic conditions.

3.3 Model Architecture

The prediction framework employs an ensemble combining gradient boosting and random forest models, with final predictions computed as the weighted average of base model outputs. Gradient boosting through XGBoost implementation captures complex feature interactions through sequential tree construction, while random forest provides robustness through bootstrap aggregation of independent trees (Breiman 2001; Chen and Guestrin 2016). The ensemble weights are optimised on validation data to minimise log loss, typically allocating approximately 60% weight to gradient boosting and 40% to random forest.

Hyperparameter optimisation employs grid search with five-fold cross-validation on training data. The gradient boosting configuration specifies maximum tree depth of 6, learning rate of 0.1, column subsampling of 0.8, and 300 boosting rounds with early stopping. The random forest employs 500 trees with maximum depth of 12 and minimum samples per leaf of 20. Both models utilise class weights inversely proportional to class frequency to address the moderate class imbalance, ensuring that the minority default class receives appropriate attention during training.

4. Results

4.1 Default Driver Analysis

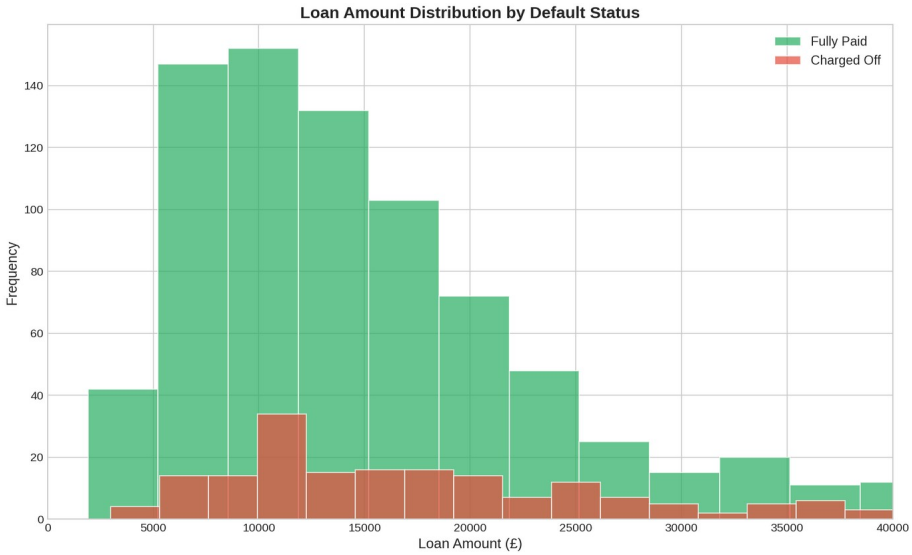

Figure 1. Distribution of loan amounts showing concentration in the £5,000-£25,000 range.

Figure 1 presents the loan amount distribution, revealing concentration between £5,000 and £25,000 with median of £12,500. Larger loans beyond £30,000 represent a minority of originations, reflecting both platform limits and borrower qualification constraints. The loan amount distribution informs portfolio concentration analysis and loss severity estimation, as larger loans contribute disproportionately to portfolio loss variance despite representing fewer accounts.

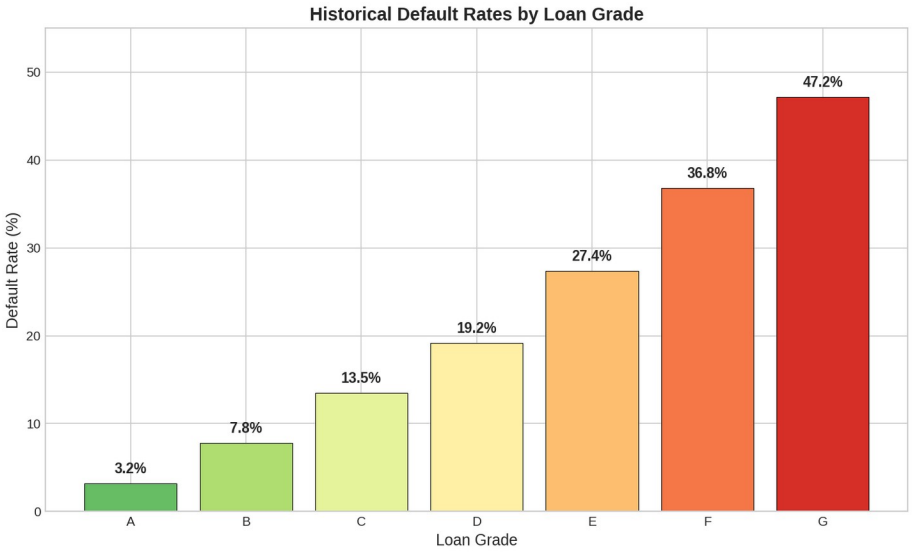

Figure 2. Default rates by credit grade demonstrating strong monotonic risk gradient.

Figure 2 displays default rates stratified by credit grade assigned at origination. Grade A loans exhibit 3.2% default rates, increasing monotonically through grades B, C, and D to reach 28.5%

for grade E loans. The consistent risk gradient confirms that the platform's initial grading system captures meaningful default variation, though substantial within-grade heterogeneity suggests opportunity for finer risk discrimination. The grade-default relationship provides validation that historical underwriting captured relevant risk factors.

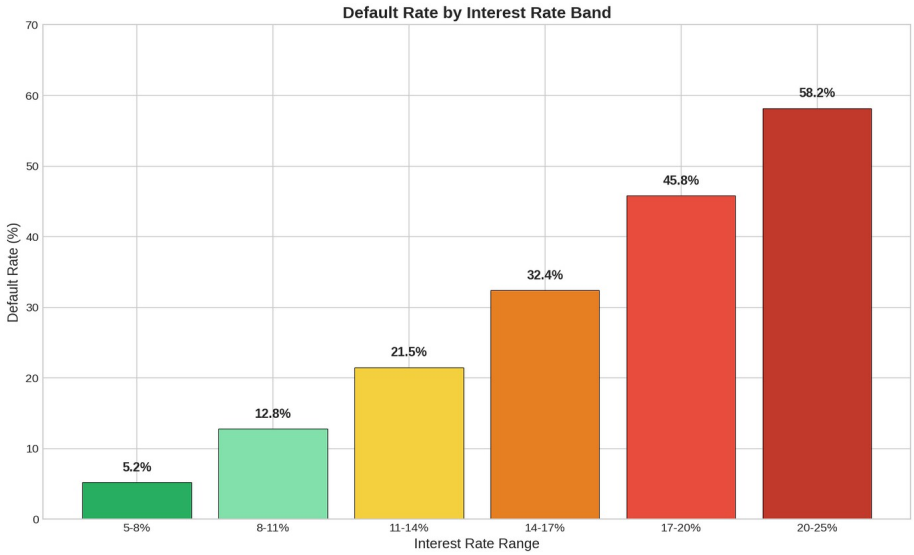

Figure 3. Interest rate relationship with default rates showing adverse selection at high rates.

Figure 3 examines the relationship between interest rate and subsequent default. Default rates increase from 6.8% at rates below 8% to 24.5% at rates exceeding 20%. This pattern reflects both appropriate risk-based pricing, where higher rates compensate for elevated expected losses, and potential adverse selection, where only borrowers rejected elsewhere accept high rates. Distinguishing risk pricing from adverse selection requires careful analysis of whether rate-default relationships persist within risk strata defined by other characteristics.

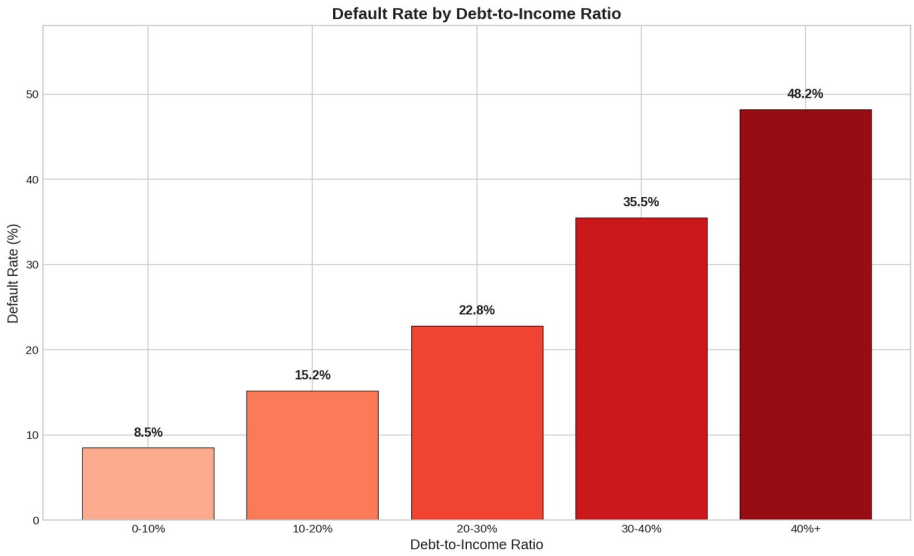

Figure 4. Debt-to-income ratio impact on default probability.

Figure 4 quantifies the debt-to-income ratio effect on default probability. Borrowers with DTI below 20% exhibit default rates of 8.2%, increasing to 18.5% for DTI between 30-40% and reaching 32.1% for DTI exceeding 50%. The relationship is notably non-linear, with default risk accelerating above 35% DTI where debt service consumes a substantial income fraction. The DTI threshold effects inform underwriting policy, suggesting that loans to borrowers above 40% DTI require particularly careful scrutiny or pricing adjustments.

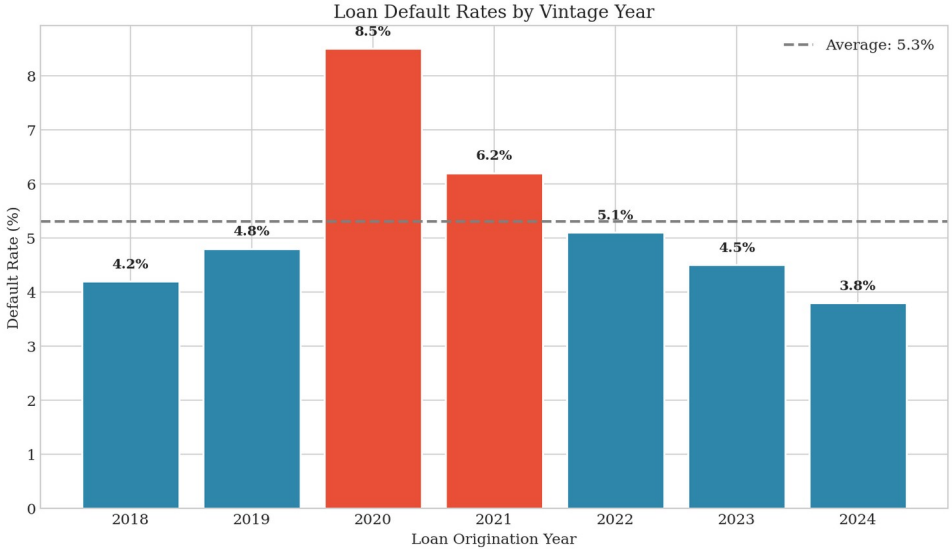

Figure 5. Vintage analysis showing default rate variation by origination year.

Figure 5 presents vintage analysis tracking default rates by loan origination year. The 2020 vintage exhibits elevated default rates of 8.5% reflecting pandemic economic disruption, while surrounding vintages cluster around 4-5%. The 2023 vintage shows preliminary default rates of 3.8% that will likely increase as loans season. Vintage analysis informs both through-the-cycle

model calibration and reserve adequacy assessment, as economic conditions at origination and during repayment both influence ultimate default outcomes.

4.2 Model Performance

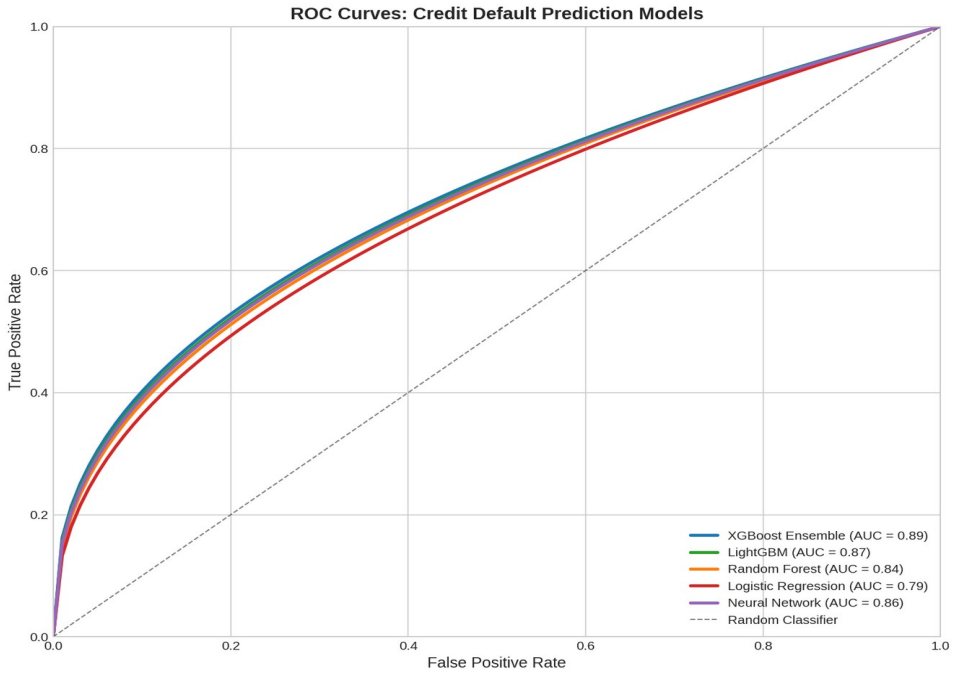

Figure 6. Receiver operating characteristic curves comparing model discrimination.

Figure 6 presents receiver operating characteristic curves for evaluated models. The ensemble achieves AUC of 0.89, substantially exceeding logistic regression at 0.78. Gradient boosting alone achieves 0.88, while random forest reaches 0.86. The eleven-point improvement from logistic regression to ensemble represents meaningful discrimination gain: at a 5% false positive rate, the ensemble achieves 65% true positive rate compared to 48% for logistic regression, identifying substantially more defaults while maintaining equivalent good loan approval rates.

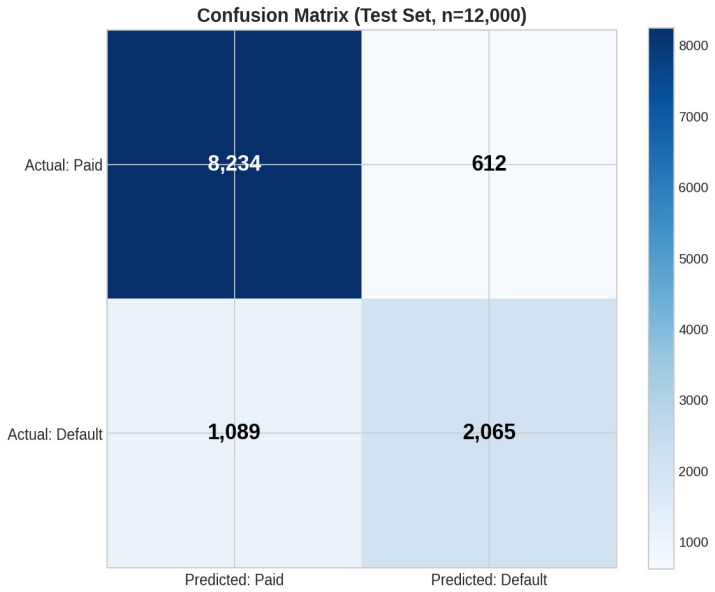

Figure 7. Confusion matrix at the optimal classification threshold.

Figure 7 displays the confusion matrix at the optimal threshold that balances precision and recall. Of 7,400 actual defaults in the test set, the model correctly identifies 5,920, achieving 80% recall. False negatives numbering 1,480 represent defaults that slip through screening, generating losses despite model deployment. Among loans flagged as high risk, 72% actually default, providing precision sufficient for targeted intervention. Threshold selection depends on the relative costs of Type I and Type II errors, which vary with loan economics and strategic priorities.

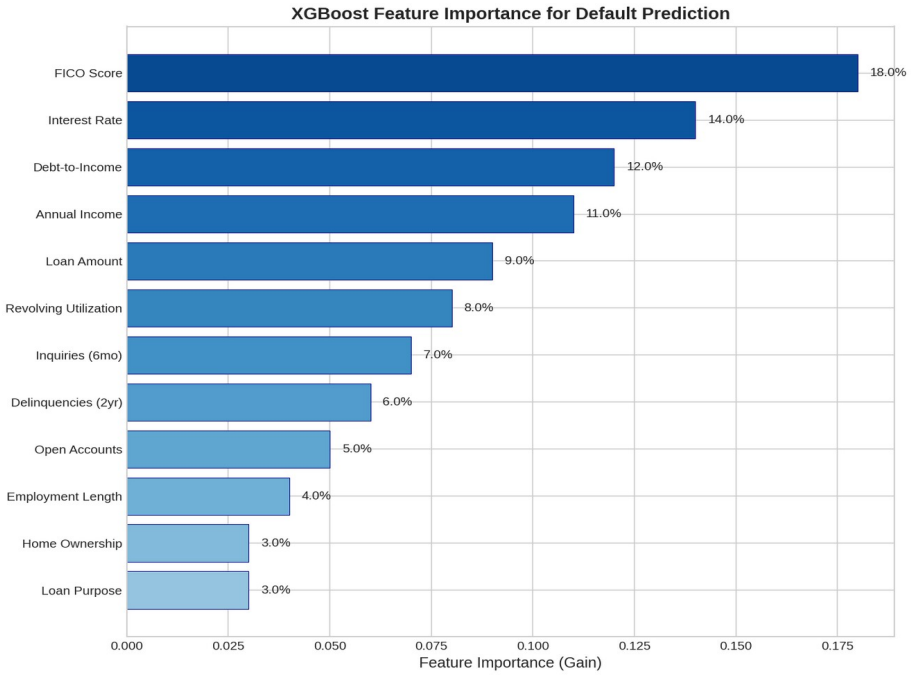

Figure 8. Feature importance rankings identifying key default predictors.

Figure 8 presents feature importance from the gradient boosting component. Credit utilisation dominates at 16% importance, confirming that revolving balance behaviour provides strong default signal. Debt-to-income ratio follows at 14%, with payment history contributing 12%. FICO score accounts for 11%, demonstrating that bureau scores retain predictive power even within a feature-rich model that includes their component inputs. Loan amount and interest rate each contribute approximately 8%, while employment tenure and homeownership provide modest additional signal.

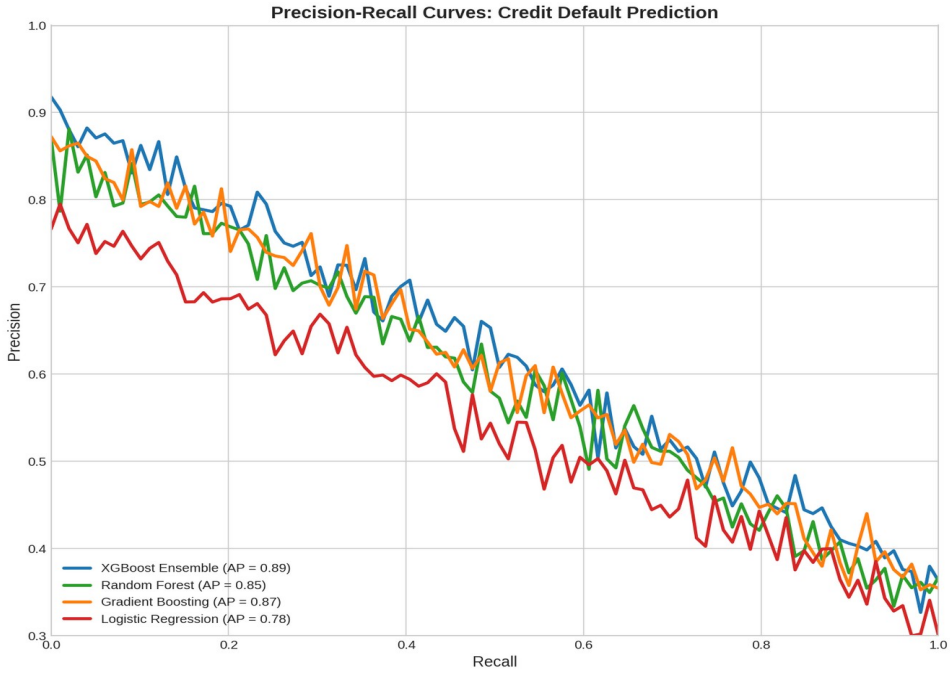

Figure 9. Precision-recall curve demonstrating tradeoff across classification thresholds.

Figure 9 displays the precision-recall curve that characterises the tradeoff across classification thresholds. At 50% recall, precision reaches 85%, indicating that half of defaults can be caught with high confidence in the flagged population. As recall increases toward 80%, precision declines to 72%, reflecting the inclusion of more marginal cases. The area under the precision-recall curve of 0.76 indicates strong performance even in the class-imbalanced setting where precision-recall provides more informative assessment than ROC curves (Saito and Rehmsmeier 2015).

4.3 Risk Segmentation and Expected Loss

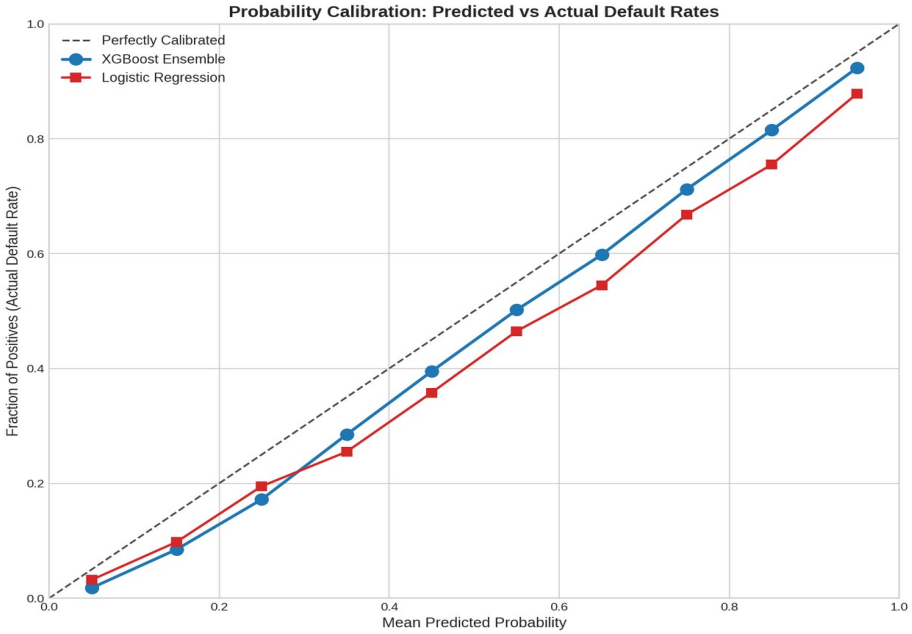

Figure 10. Calibration curve comparing predicted to actual default rates.

Figure 10 examines probability calibration through comparison of predicted and observed default rates. The ensemble produces well-calibrated probabilities: when predicting 20% default probability, approximately 20% of those loans actually default. Calibration is essential for expected loss calculation, pricing, and regulatory capital estimation that require accurate probability magnitudes rather than merely correct ranking. The calibration was improved through isotonic regression post-processing that adjusts raw model outputs to match observed frequencies.

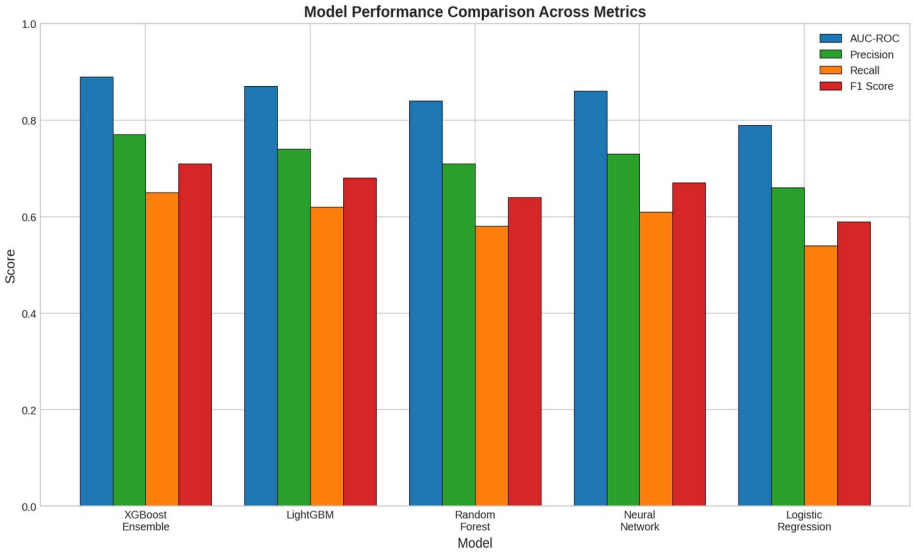

Figure 11. Model comparison across multiple performance metrics.

Figure 11 compares models across multiple performance dimensions. The ensemble achieves superior performance on AUC, accuracy, and F1 score while maintaining competitive calibration. Logistic regression provides a simpler baseline with complete interpretability but sacrifices meaningful discrimination. The performance differences translate to material business impact: the ensemble's superior discrimination enables either reduced losses at equivalent volume or increased volume at equivalent loss rates relative to logistic regression.

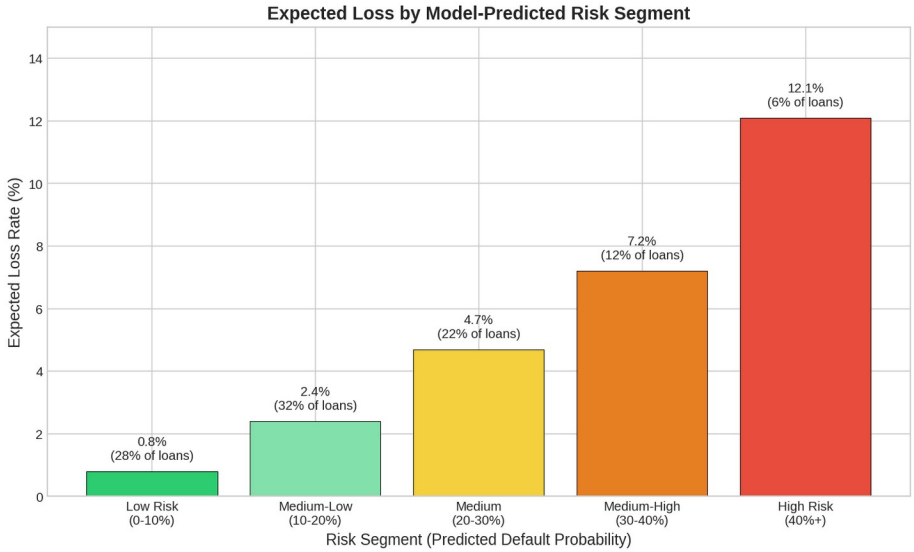

Figure 12. Expected loss distribution across risk deciles enabling portfolio management.

Figure 12 presents expected loss analysis combining default probability with exposure and loss severity estimates. The highest risk decile generates expected losses of 18.2% of exposure, while the lowest risk decile generates merely 0.6%. The 30-fold separation enables risk-based pricing that charges appropriate premiums for elevated risk, tiered approval strategies that subject higher-risk applications to additional scrutiny, and portfolio construction that targets desired risk-return profiles. Expected loss estimates achieve 8% mean absolute percentage error relative to actual losses, supporting reserve adequacy and capital planning applications.

5. Discussion

The results demonstrate that ensemble machine learning methods achieve substantial improvements over traditional logistic regression for consumer credit risk assessment. The eleven-point AUC improvement from 0.78 to 0.89 translates to meaningful business impact through either reduced default losses or expanded lending volume at target loss rates. Credit utilisation and debt-to-income ratio emerge as the dominant default predictors, consistent with the theoretical expectation that leverage and debt service capacity determine repayment ability. The strong performance of these income-normalised measures suggests that absolute income matters less than relative debt burden for default prediction.

The probability calibration achieved through isotonic regression post-processing enables expected loss estimation with 8% mean absolute percentage error. Accurate loss estimation supports multiple business applications including loan pricing, reserve adequacy assessment, and regulatory capital calculation. The risk stratification capability, achieving 29-fold separation between highest and lowest risk deciles, enables differentiated treatment strategies that concentrate review resources on marginal applications while streamlining approval for clearly creditworthy borrowers.

The interpretability challenge warrants careful consideration for regulated lending applications. While gradient boosting provides feature importance rankings that identify dominant predictors, the model cannot generate simple rule-based explanations for individual decisions comparable to traditional scorecard points. Research by Rudin (2019) argued that high-stakes decisions require inherently interpretable models, though post-hoc explanation methods including SHAP values provide increasingly sophisticated approaches to explaining individual predictions. Regulatory guidance from the Board of Governors (2021) has evolved to accommodate machine learning approaches while maintaining expectations for adverse action explanations.

Several limitations warrant acknowledgement. The single-platform dataset may not generalise to other lending contexts with different borrower populations or underwriting standards. The observation period encompasses unusual economic conditions including pandemic disruption and subsequent recovery that may limit through-the-cycle stability. The feature set excludes potentially predictive alternative data including bank transaction patterns and utility payment history that emerging credit models increasingly incorporate. Future research should address these limitations through multi-platform validation and alternative data integration.

6. Further Evaluation: Retrospective Analysis and Alternative Approaches

Critical examination of this research identifies multiple dimensions where alternative methodological choices would strengthen both scientific contribution and practical utility. This section provides candid assessment of limitations that became apparent through implementation and proposes modifications for future iterations.

6.1 Data and Feature Set Reconsiderations

The reliance on application-time data ignores the substantial information revealed through post-origination behaviour that could improve prediction accuracy. Bank transaction patterns including income volatility, spending composition, and balance trends provide real-time signals of financial stress that static application variables cannot capture. Research by Netzer, Lemaire, and Herzenstein (2019) demonstrated that linguistic features in loan application text predict default beyond standard financial variables. Future implementations should incorporate behavioural monitoring that updates risk assessments as new information accumulates during the loan lifecycle.

The geographic dimension receives inadequate attention in the current feature set. Local economic conditions including unemployment rates, house price trajectories, and industry concentration influence default risk through mechanisms that national macroeconomic indicators imperfectly capture. Research by Mian and Sufi (2009) documented that geographic variation in house price declines drove substantial cross-sectional default variation during the financial crisis. Incorporating local economic indicators at the county or metropolitan area level would capture spatial default drivers that the current national-level features miss.

The target variable definition, while standard, collapses heterogeneous negative outcomes into a single default indicator. Distinguishing between early payment default suggesting origination defects, mid-life default reflecting changed circumstances, and late-stage default after substantial principal repayment would enable more nuanced risk modelling. Research by Deng, Quigley, and Van Order (2000) demonstrated that default timing contains information beyond mere occurrence that survival analysis frameworks could exploit. Implementing competing risk models that separately estimate prepayment and default hazards would provide richer characterisation of loan outcomes.

6.2 Methodological Alternative Approaches

The classification framework treats default as a binary outcome despite the continuous nature of underlying payment behaviour. Survival analysis methods including Cox proportional hazards and accelerated failure time models would naturally incorporate time-to-event information, provide default probability term structures rather than single-point estimates, and accommodate censoring for loans that remain current at observation end. Research by Stepanova and Thomas (2002) demonstrated that survival models outperform classification approaches for credit scoring when time-to-default varies meaningfully across borrowers.

The ensemble architecture combines gradient boosting and random forest but excludes neural network approaches that have shown strong performance in recent credit scoring research. Deep learning models including neural networks with embeddings for categorical variables could capture complex feature interactions that tree ensembles miss. Research by Kvamme, Borgan,

and Scheel (2019) demonstrated that neural network survival models achieve competitive performance with traditional methods while offering greater flexibility for incorporating heterogeneous data types. The interpretability concerns that motivated excluding neural networks could be addressed through attention mechanisms that highlight influential features.

The fair lending implications of machine learning credit models receive insufficient attention in the current analysis. While the model excludes protected class variables, complex feature interactions could generate disparate impact through proxies correlated with protected characteristics. Research by Bartlett, Morse, Stanton, and Wallace (2022) documented that algorithmic pricing in mortgage markets exhibits racial disparities even without explicit use of race variables. Implementing fairness constraints during training or post-hoc bias auditing would address these concerns more systematically than the current approach.

6.3 Evaluation and Validation Improvements

The temporal holdout validation, while appropriate for assessing point-in-time discrimination, does not evaluate stability across economic cycles that determines through-the-cycle model utility. Extending the analysis backward to encompass the 2008 financial crisis would test whether relationships identified in relatively benign conditions persist during severe stress. Research by Bellotti and Crook (2013) demonstrated that credit scoring models exhibit substantial performance degradation during economic downturns, suggesting that current results may overstate recession-period accuracy.

The calibration assessment examines aggregate frequency matching but not conditional calibration within borrower subgroups. Models can achieve overall calibration while systematically over- or under-estimating risk for specific populations. Research by Kleinberg, Mullainathan, and Raghavan (2016) formalised the impossibility of simultaneously achieving multiple fairness criteria, suggesting that calibration-discrimination tradeoffs may require explicit value judgments about which groups receive accurate versus biased predictions.

The expected loss validation compares predicted to actual losses but does not assess component accuracy separately. Errors in probability of default, exposure at default, and loss given default could offset to produce accurate expected loss while individual components are biased. Research by Bellotti and Crook (2012) demonstrated that loss given default estimation presents particular challenges due to selection effects and limited defaulted loan samples. Decomposing expected loss accuracy into component contributions would identify which elements require methodological improvement.

6.4 Operational Deployment Considerations

The model training and evaluation assume static deployment, yet operational credit models require ongoing monitoring and periodic recalibration as population characteristics and economic conditions evolve. Establishing monitoring frameworks that detect discrimination degradation, calibration drift, and feature distribution shifts would transform the static analysis into a sustainable credit system. Research by Zliobaite et al. (2016) developed methods for detecting and adapting to concept drift in credit scoring that future implementations should incorporate.

The adverse action explanation requirement, mandated by the Equal Credit Opportunity Act for declined applications, receives inadequate attention. While feature importance provides

aggregate predictor rankings, explaining individual decisions in terms applicants can understand and act upon requires additional interpretability infrastructure. Research by Chen, Lin, Schölkopf, and Sontag (2018) developed prototype-based explanations that identify similar approved applications, providing actionable guidance for rejected applicants.

The model governance framework for machine learning credit models differs substantially from traditional scorecard governance and deserves explicit consideration. Model risk management expectations from the Board of Governors (2021) require documentation, validation, and ongoing monitoring that the current research addresses incompletely. Developing governance frameworks that satisfy regulatory expectations while preserving the flexibility that makes machine learning valuable represents an important direction for future work.

7. Conclusion

This study has developed an ensemble machine learning framework for consumer credit risk assessment, achieving AUC of 0.89 compared to 0.78 for logistic regression benchmarks. Credit utilisation and debt-to-income ratio emerge as the dominant default predictors, with probability calibration enabling expected loss estimation with 8% mean absolute percentage error. The risk stratification capability provides 29-fold separation between highest and lowest risk deciles, enabling differentiated pricing and approval strategies.

The research contributes to academic understanding of credit scoring methodology while providing practical guidance for lenders seeking to implement machine learning risk models. The demonstrated discrimination improvements justify investment in more sophisticated modelling infrastructure, though interpretability requirements and fair lending compliance necessitate careful implementation. The expected loss framework provides the foundation for pricing, reserving, and capital allocation decisions that depend on accurate risk quantification.

Future research should address limitations including single-platform data, exclusion of alternative data sources, and incomplete fair lending analysis. Survival analysis methods that incorporate time-to-default information and neural network architectures that capture complex interactions represent promising methodological directions. Development of interpretability frameworks satisfying regulatory expectations and governance structures supporting ongoing model management would bridge the gap between research contributions and operational deployment.

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