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INTERPRETABLE LOAN APPROVAL PREDICTION USING REGULARIZED LOGISTIC REGRESSION AND GUARDRAILED DECISION SUPPORT

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ABSTRACT

Credit risk assessment and retail loan underwriting are high-stakes financial operations traditionally governed by manual appraisal, which exhibits significant latency, operational cost, and subjective variability across loan officers. While modern black-box machine learning models offer predictive accuracy, stringent regulatory compliance mandates (such as the Fair Credit Reporting Act, GDPR Article 22, and digital lending directives) necessitate auditable, intrinsically explainable decision workflows. This paper presents an end-to-end, interpretable machine learning framework for consumer loan approval prediction paired with an interactive, guardrailed decision-support system. Using a benchmark dataset of 4,269 loan applications, we implement a leakage-safe data engineering pipeline featuring two-sided percentile winsorization (1st/99th percentiles) and derived financial solvency ratios. We formulate a class-weighted, ℓ_2 -regularized Logistic Regression architecture encapsulated within a single scaling pipeline, optimized via stratified 5-fold cross-validation. On a held-out test partition ($n = 854$), the proposed model achieves an accuracy of 91.9%, precision of 95.1%, recall of 91.7%, F1-score of 93.4%, and a ROC-AUC of 0.974, dramatically outperforming the majority-class baseline (accuracy 62.2%). Hyperparameter sensitivity analysis reveals that the regularizer exhibits a broad plateau ($C \in [10^{-2}, 10^2]$), proving model stability. Coefficient-level attribution indicates that the CIBIL credit score is the primary determinant ($\beta = +3.63$), outweighing secondary asset and liability features by more than

five-fold. To prevent unsafe extrapolations in real-world deployment, we engineer a multi-layered defense-in-depth guardrail framework comprising input validation, distribution-drift warnings, out-of-distribution hard stops, sub-prime credit floors, and debt-to-income overrides. The resulting decision-support application provides transparent, per-applicant counterfactual explanations for responsible underwriting assistance.

INDEX TERMS: Credit scoring, loan approval prediction, logistic regression, interpretability, class imbalance, regularized learning, decision-support systems, financial technology.

I. INTRODUCTION

CONSUMER credit evaluation is a cornerstone of the commercial banking system. Every financial institution must systematically decide whether to approve or reject a retail credit application by evaluating an applicant's financial solvency, debt-servicing capacity, and historical repayment reliability. Traditionally, credit evaluation relies on manual underwriting, where credit officers evaluate income tax returns, bank statements, collateral documents, and credit bureau scores against institutional risk policies. While human oversight provides domain-specific intuition, manual underwriting is intrinsically slow, costly to scale, vulnerable to human cognitive fatigue, and prone to intra-reviewer inconsistency [1], [2].

To overcome these constraints, automated credit scoring models have been widely adopted across modern financial technologies. Over the past decade, supervised learning algorithms—ranging from Support Vector Machines (SVMs) and Random Forests to Extreme Gradient Boosting (XGBoost) and Deep Neural Networks—have demonstrated high discriminatory power in classifying credit default risks [2], [3]. However, in high-stakes retail lending, pure predictive accuracy is insufficient. Financial institutions are governed by stringent regulatory mandates, including the U.S. Equal Credit Opportunity Act (ECOA), the Fair Credit Reporting Act (FCRA), the European Union General Data Protection Regulation (GDPR Article 22 Right to Explanation), and the Reserve Bank of India (RBI) Digital Lending Guidelines. These frameworks legally require lenders to supply transparent, auditable adverse action notices that clearly explain the explicit factors driving an adverse decision.

Complex ensemble and deep architectures function largely as “black-box” estimators. Although post-hoc explanation frameworks such as Local Interpretable Model-agnostic Explanations (LIME) [9] and SHapley Additive exPlanations (SHAP) [10] can approximate

local decision boundaries, they introduce computational latency, sampling variance, and potential fidelity divergence from the underlying model logic. Consequently, generalized linear models—most notably Logistic Regression—continue to serve as the global regulatory benchmark for credit scorecards [5], [6]. In a regularized logistic regression model, each parameter represents an uncorrupted, monotonically verifiable log-odds weight that is transparent to regulators, risk auditors, and consumers.

Despite their intrinsic interpretability, linear models deployed without protective scaffolding pose operational vulnerabilities. Linear models extrapolate unbounded sigmoid probabilities when presented with anomalous or out-of-distribution (OOD) feature vectors, and they can inherit historical correlation artifacts present within training corpora. Therefore, a critical engineering and scientific inquiry arises: How effectively can an optimized, regularized logistic regression pipeline perform on retail credit data, and what architectural safeguards must be constructed to guarantee safe, reliable decision-support deployment?

To address these challenges, this study provides the following primary contributions:

- **Leakage-Safe Preprocessing Pipeline:** We implement a mathematically rigorous data engineering workflow combining non-destructive percentile winsorization (1st and 99th percentiles) and financial ratio synthesis (R_{LTI} and R_{LTA}). All scaling parameters are isolated strictly within training cross-validation folds, precluding any optimistic performance leakage.
- **Comprehensive Imbalance-Aware Benchmark:** We evaluate the model against an uninformative majority-class baseline and an untuned benchmark across multiple threshold-independent and threshold-dependent metrics (Accuracy, Precision, Recall, F1, and ROC-AUC), proving that balanced cost-sensitive weighting effectively resolves class skew without artificial data generation.
- **Model Stability and Interpretability Analysis:** We document hyperparameter sensitivity over five orders of magnitude ($C \in [10^{-3}, 10^2]$) and perform coefficient-level feature attribution, confirming the overwhelming primacy of credit bureau scoring while transparently dissecting collinearity-induced artifacts.
- **Layered Defense-in-Depth Guardrail Framework:** We develop and stress-test a multi-stage production safeguard pipeline—comprising input validation, distribution-drift warnings (3σ), hard OOD rejection bounds, sub-prime floors, and domain business overrides—implemented within a real-time Streamlit decision-support application.

The remainder of this paper is organized as follows: Section II reviews relevant literature. Section III details the dataset, cleaning strategy, and feature engineering. Section IV

formalizes the mathematical methodology and evaluation framework. Section V outlines the system architecture and layered guardrail mechanisms. Section VI presents the empirical results, error analysis, and feature attributions. Section VII discusses operational limitations and ethical considerations. Finally, Section VIII concludes the paper and identifies future research trajectories.

II. RELATED WORK

A. Statistical Scoring and Machine Learning Baselines

The formal foundation of credit risk assessment originated with linear discriminant analysis, pioneered by Fisher and adapted by Altman [4] for corporate bankruptcy prediction. Over subsequent decades, Logistic Regression became the established standard for credit scorecards across commercial lending institutions [5], [6]. Its widespread adoption is primarily driven by its direct correspondence with credit scoring points: the log-odds of default scale linearly with individual borrower attributes, allowing risk managers to inspect and calibrate individual risk weights against regulatory standards.

In recent benchmarks, researchers have extensively investigated advanced non-linear estimators. In a comprehensive survey of 187 credit scoring publications, Louzada *et al.* [1] observed that ensemble methods (such as Random Forests and Gradient Boosted Decision Trees) frequently demonstrate superior classification metrics relative to individual statistical classifiers. Similarly, Lessmann *et al.* [2] benchmarked 41 classification algorithms across eight credit datasets, concluding that while ensemble architectures yield marginal gains in discriminatory power, well-tuned logistic regression baselines remain remarkably competitive, often exhibiting statistically indistinguishable performance when features are appropriately transformed.

B. Class Imbalance and Performance Evaluation

Retail credit datasets are intrinsically characterized by class imbalance, as solvent applications typically outnumber rejected or defaulting applications. Training naive classifiers on skewed data induces majority-class bias, where the model achieves high nominal accuracy by defaulting to the dominant class while failing to identify high-risk rejections [7].

Techniques to counteract class imbalance span data-level re-sampling (such as the Synthetic Minority Over-sampling Technique, SMOTE [7]) and algorithm-level cost-sensitive learning. While SMOTE synthesizes minority instances via nearest neighbors, it risks introducing synthetic samples into borderline decision spaces and altering the underlying calibrated

probability distribution. Conversely, cost-sensitive learning assigns inverse class-frequency penalty weights directly to the loss function, preserving the original empirical feature distribution. Furthermore, Fawcett [8] highlighted that under skewed base rates, standard accuracy is an invalid indicator of performance, necessitating evaluation via Receiver Operating Characteristic (ROC) analysis, Precision, Recall, and the harmonic F1-measure.

C. Explainability and Production Reliability in Financial ML

As machine learning models are integrated into regulated environments, Explainable Artificial Intelligence (XAI) has emerged as an imperative field of inquiry. Post-hoc explanation mechanisms, including LIME [9] and KernelSHAP [10], compute local attribution vectors by perturbing inputs around an instance. However, Slack *et al.* [11] demonstrated that post-hoc perturbation explainers can be unstable, computationally burdensome for real-time inference, and vulnerable to adversarial manipulation.

In response, recent financial computing literature advocates for “inherently interpretable by design” models for core decision-making [12]. Rather than approximating an opaque model post-hoc, an intrinsically interpretable model—such as regularized logistic regression—is directly auditable. Nevertheless, deployment in production requires robust guardrails. In financial systems engineering, out-of-distribution (OOD) inputs, covariate shift, and statistical extrapolation represent primary modes of failure. Our work bridges this gap by combining an intrinsically interpretable classifier with a formal, deterministic guardrail architecture.

III. DATASET AND PREPROCESSING

A. Dataset Description

The empirical analysis is conducted using the public Loan Approval Prediction Dataset [14], encompassing 4,269 historical retail credit applications. Each record comprises twelve predictive features and one binary target label (`loan_status`). The features span demographic profiles, requested loan specifications, financial solvency metrics, and credit bureau scores within the Indian financial ecosystem:

- **Demographics:** Number of dependents (`no_of_dependents` $\in [0, 5]$), education status (`education` $\in \{\text{Graduate}, \text{Not Graduate}\}$), and employment nature (`self_employed` $\in \{\text{Yes}, \text{No}\}$).
- **Loan Terms:** Requested loan amount (`loan_amount`) and repayment duration (`loan_term` $\in [2, 20]$ years).

- **Income and Assets:** Annual income (income_annum) and four categorized asset classes: residential property (residential_assets_value), commercial property (commercial_assets_value), luxury assets (luxury_assets_value), and liquid bank deposits (bank_asset_value). All monetary values are denominated in Indian Rupees (INR).
- **Credit Bureau Score:** Credit Information Bureau (India) Limited (CIBIL) score, ranging continuously on the standard scale [300, 900].
- **Target Variable:** Binary indicator where loan_status = 1 denotes an Approved application ($n = 2,656$, 62.2%) and loan_status = 0 denotes a Rejected application ($n = 1,613$, 37.8%).

B. Data Cleaning and Integrity Verification

A rigorous preliminary audit of the raw dataset was performed:

- 1) **String Sanitization:** Leading and trailing whitespace was stripped from all column headers and categorical string values.
- 2) **Completeness and Uniqueness:** Missing-value analysis confirmed complete data coverage (zero null or NaN fields). Verification against duplicate rows identified no redundant entries. The unique application identifier (loan_id) was decoupled from the feature set to eliminate arbitrary indexing bias.
- 3) **Domain Boundary Integrity:** Numerical fields were audited against physical domain constraints. Twenty-eight records exhibited anomalous negative values in residential asset values (down to -1.0×10^5 INR); because physical property cannot have a negative asset valuation, these values were floored at zero. All income, loan amount, and loan term attributes were verified to be strictly positive, and CIBIL scores conformed strictly to the valid regulatory interval [300, 900].

TABLE I: WINSORIZATION THRESHOLDS AND CAPPED VALUE DISTRIBUTION. ($N = 4,269$)

Feature Dimension	1st Perc. (P_1)	99th Perc. (P_{99})	Capped
income_annum	300,000	9,800,000	
loan_amount	1,300,000	37,800,000	
residential_assets_val	0	26,700,000	
commercial_assets_val	0	18,300,000	
luxury_assets_val	1,100,000	37,500,000	
bank_asset_val	200,000	13,800,000	
Total Observations Capped	—	—	4

C. Outlier Mitigation via Percentile Winsorization

Financial indicators such as annual income, loan request amounts, and declared asset valuations exhibit severe right-skewness and heavy-tailed distributions. Standard practice often relies on listwise deletion (dropping records exceeding threshold boundaries) or Z-score filtering. However, listwise deletion in this dataset would discard 409 records (9.58% of the total dataset), introducing severe selection bias and attenuating statistical sample efficiency.

To retain complete data fidelity while bounding the leverage of extreme outliers on the logistic loss gradient, we implement two-sided percentile winsorization. For an arbitrary skewed feature vector $\mathbf{z}$, values are clipped to the 1st percentile (P_1) and 99th percentile (P_{99}):

$$z_i^{\text{win}} = \begin{cases} P_1(\mathbf{z}), & \text{if } z_i < P_1(\mathbf{z}) \\ z_i, & \text{if } P_1(\mathbf{z}) \leq z_i \leq P_{99}(\mathbf{z}) \\ P_{99}(\mathbf{z}), & \text{if } z_i > P_{99}(\mathbf{z}). \end{cases}$$

Table I provides the quantitative summary of winsorized records across the six continuous financial dimensions.

D. Feature Engineering and Leakage Prevention

Categorical attributes were mapped to deterministic binary encodings: education as 1 (Graduate) vs. 0 (Not Graduate), and self_employed as 1 (Yes) vs. 0 (No).

To capture portfolio solvency and repayment leverage, three domain features were synthesized:

- 1) **Total Declared Assets (total_assets):**

$$A_{\text{total}} = A_{\text{res}} + A_{\text{comm}} + A_{\text{lux}} + A_{\text{bank}}. \quad (2)$$

- 2) **Loan-to-Income Ratio (R_{LTI}):**

$$R_{\text{LTI}} = \frac{\text{loan_amount}}{\text{income_annum}}. \quad (3)$$

- 3) **Loan-to-Assets Ratio (R_{LTA}):**

$$R_{\text{LTA}} = \frac{\text{loan_amount}}{A_{\text{total}} + \epsilon}, \quad (4)$$

where $\epsilon = 1.0$ INR serves as an infinitesimal regularization constant to prevent division-by-zero singularities for zero-asset applicants.

Both R_{LTI} and R_{LTA} are computed strictly row-wise without incorporating global dataset statistics, thereby introducing zero cross-row information contamination. The final processed feature space comprises $d = 14$ dimensions.

IV. METHODOLOGY

A. Data Partitioning and Experimental Controls

To guarantee valid generalization assessment, the dataset was split into an 80% training partition ($n_{\text{train}} = 3,415$) and a 20% held-out testing partition ($n_{\text{test}} = 854$). Stratified sampling was enforced using a fixed pseudorandom seed (seed = 42) to preserve the identical 62.2% positive and 37.8% negative class proportion across both partitions.

To establish the statistical performance floor, we construct a majority-class DummyClassifier which deterministically assigns $\hat{y}_i = 1$ (Approved) to all test instances.

B. Mathematical Model Formulation

Let $\mathbf{x}_i \in \mathbb{R}^d$ denote the raw feature vector for applicant i , and let $y_i \in \{0, 1\}$ represent the observed ground truth. To ensure that coefficient magnitudes reflect absolute feature importance, all features are standardized to zero mean and unit variance.

Crucially, to eliminate data leakage, standardization parameters are derived solely from the training partition:

$$\tilde{\mathbf{x}}_i = \mathbf{S}_{\text{train}}^{-1}(\mathbf{x}_i - \bar{\mathbf{x}}_{\text{train}}), \quad (5)$$

where $\bar{\mathbf{x}}_{\text{train}} = \left(\frac{1}{n_{\text{train}}}\right) \sum_{i=1}^{n_{\text{train}}} \mathbf{x}_i$ and $\mathbf{S}_{\text{train}} = \text{diag}(\sigma_1, \dots, \sigma_d)$. In the deployment environment, this transformation is encapsulated inside an immutable scikit-learn [13] Pipeline.

For a standardized instance $\tilde{\mathbf{x}}$, the logistic hypothesis models the posterior probability of loan approval via the standard sigmoid link:

$$P(y = 1 | \tilde{\mathbf{x}}) = \sigma(\mathbf{w}^\top \tilde{\mathbf{x}} + b) = \frac{1}{1 + \exp(-(w^\top \tilde{\mathbf{x}} + b))}, \quad (6)$$

where $\mathbf{w} \in \mathbb{R}^d$ denotes the parameter weight vector and $b \in \mathbb{R}$ represents the intercept.

The parameters are estimated by minimizing the cost-sensitive, ℓ_2 -regularized binary cross-entropy loss function:

$$\mathcal{J}(\mathbf{w}, b) = \frac{1}{2} \|\mathbf{w}\|_2^2 + C \sum_{i=1}^{n_{\text{train}}} \omega_{y_i} \mathcal{L}_{\text{BCE}}(y_i, \sigma(\mathbf{w}^\top \tilde{\mathbf{x}}_i + b)), \quad (7)$$

where $C > 0$ denotes the inverse regularization parameter, and the binary cross-entropy loss is given by:

$$\mathcal{L}_{\text{BCE}}(y, \hat{p}) = -[y \ln(\hat{p}) + (1 - y) \ln(1 - \hat{p})]. \quad (8)$$

To mitigate the 62.2% to 37.8% class imbalance without distorting the empirical manifold via synthetic generation, we employ balanced cost-weighting coefficients:

$$\omega_k = \frac{n_{\text{train}}}{2 \cdot n_k}, \quad k \in \{0, 1\}, \quad (9)$$

yielding $\omega_0 \approx 1.32$ for rejected instances and $\omega_1 \approx 0.80$ for approved instances. The optimization problem is solved via the Limited-memory Broyden–Fletcher–Goldfarb–Shanno

(L-BFGS) quasi-Newton algorithm with a convergence tolerance of 10^{-4} and $\text{max_iter} = 1000$.

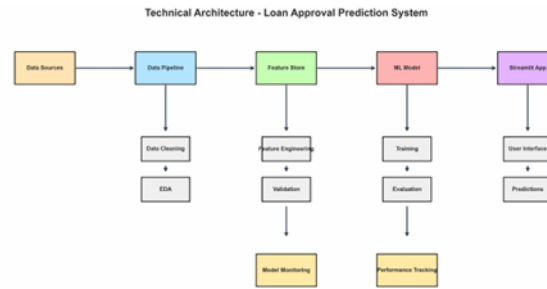


Fig. 1. System architecture and layered guardrail processing pipeline of the loan approval decision-support platform.

C. Hyperparameter Optimization

To optimize model capacity and prevent over-fitting, the inverse regularization parameter C was systematically evaluated across a logarithmic grid spanning five orders of magnitude:

$$C \in \{0.001, 0.01, 0.1, 1.0, 10.0, 100.0\}. \quad (10)$$

Tuning was executed using GridSearchCV with stratified 5-fold cross-validation restricted entirely to the training partition ($n = 3,415$). The area under the ROC curve (ROC-AUC) was designated as the primary objective metric to optimize ranking capability independently of arbitrary probability decision thresholds.

D. Evaluation Metric Suite

In asymmetric credit underwriting, false positive errors (approving a borrower destined for default) and false negative errors (rejecting a creditworthy applicant) incur drastically divergent economic costs.

Consequently, we report:

- **Accuracy:** Overall fraction of correct classifications.
- **Precision (Positive Predictive Value):** $\text{Precision} = \frac{TP}{TP + FP}$.
- **Recall (Sensitivity / True Positive Rate):** $\text{Recall} = \frac{TP}{TP + FN}$.
- **F1-Score:** The harmonic mean balancing precision and recall: $F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$.
- **ROC-AUC:** The integral of true positive rate versus false positive rate over all discrimination thresholds, representing the probability that a randomly drawn approved application receives a higher risk score than a randomly drawn rejected application [8].

V. SYSTEM DESIGN AND GUARDRAIL ARCHITECTURE

A. Decision Support Architecture

The trained inference pipeline and pre-computed evaluation parameters are deployed within an interactive, enterprise-grade decision support platform built using Streamlit [15]. The system facilitates transparent human-in-the-loop credit evaluation, enabling loan underwriters to inspect automated recommendations while preserving manual oversight.

The application architecture (Fig. 1) comprises four integrated modules:

TABLE II: DETERMINISTIC GUARDRAIL LAYERS AND ENFORCEMENT POLICIES.

Guardrail Layer	Operational Trigger	Enforcement Action
1. Schema & Type	Non-numeric inputs, negative values in physical assets.	Hard validation exception; blocks pipeline execution.
2. Statistical Drift	Feature deviation $> 3\sigma$ from training mean μ_{train} .	Non-blocking operational warning; flagged in audit log.
3. OOD Hard Stop	Values outside $[P_{0.1}, P_{99.9}]$ bounds (e.g., CIBIL > 900).	Hard operational stop; execution aborted.
4. Sub-Prime Floor	$\text{cibil_score} \leq 350$.	Overrides inference to Rejected ; flags deep subprime risk.
5. Solvency Caps	$R_{\text{LTI}} > 10.0$, or $R_{\text{LTA}} > 2.0$, or $(\text{cibil} < 500 \wedge R_{\text{LTI}} > 5.0)$.	Overrides inference to Rejected ; records policy rule violation.

1) Interactive Underwriting Workspace: Collects eleven applicant parameters through a structured sidebar form, supplemented with calibrated reference personas (low-risk prime borrower, high-risk subprime borrower).

2) Real-Time Inference Engine: Computes real-time approval status, calibrated model confidence percentages, and visual counterfactual sensitivity sliders.

3) Local Feature Attribution: Decomposes the individual applicant score into standardized additive contributions:

$$\phi_j(x) = w_j \left(\frac{x_j - \mu_j}{\sigma_j} \right), \quad (11)$$

visually indicating to the loan officer exactly which applicant attributes drove the prediction toward approval or rejection.

4) Auditable Reporting Engine: Generates downloadable timestamped audit trails in CSV and formatted PDF reports for institutional record-keeping.

B. Layered Defense-in-Depth Guardrail Framework

A known vulnerability of unconstrained linear classifiers is their inability to recognize out-of-distribution inputs or apply common-sense credit prudence. For example, a linear model might approve an applicant requesting a loan 100 times their annual income if their credit score is sufficiently high. To prevent statistical anomalies from translating into hazardous financial commitments, we design and enforce a deterministic, five-tier guardrail framework (Table II).

The layers operate sequentially:

- **Layer 1 (Schema Validation):** Enforces physical boundaries (e.g., non-negative income, loan term ≥ 1 year, CIBIL in [300, 900]).
- **Layer 2 (Statistical Drift Check):** Warns the underwriter if any input deviates beyond three standard deviations ($|x_j - \mu_j| > 3\sigma_j$), signaling extreme distribution shift.
- **Layer 3 (OOD Extrapolation Block):** Halts scoring if inputs lie outside historical plausibility envelopes, preventing arbitrary model extrapolation.
- **Layer 4 (Sub-Prime Credit Floor):** Standard logistic regression maintains an asymptotic tail; an applicant with `cibil_score = 300` could theoretically be approved if declared assets were sufficiently large. Layer 4 strictly overrides any model output to **Rejected** if `cibil_score` ≤ 350 .
- **Layer 5 (Prudential Solvency Overrides):** Enforces regulatory lending ceilings. Irrespective of model probability, loans exceeding $10\times$ annual income ($R_{LTI} > 10$), loans exceeding twice total assets ($R_{LTA} > 2$), or marginal credit profiles (`cibil` < 500) with elevated leverage ($R_{LTI} > 5$) trigger an automatic override to **Rejected** accompanied by documented adverse action reasons.

VI. EMPIRICAL RESULTS AND DISCUSSION

A. Benchmark Performance Comparison

Table III presents the quantitative evaluation of the majority-class baseline, the untuned logistic regression model ($C = 1.0$), and the cross-validation-tuned logistic regression model ($C = 0.1$) on the independent held-out test partition ($n_{\text{test}} = 854$).

TABLE III: MODEL PERFORMANCE COMPARISON ON HELD-OUT TEST SET. (N = 854)

Model Architecture	Acc.	Prec.	Rec.	F_1	AUC
Majority-Class Baseline	0.6218	0.6218	1.0000	0.7668	–
Untuned LR ($C = 1.0$)	0.9192	0.9494	0.9190	0.9340	0.9733
Tuned LR ($C = 0.1$)	0.9192	0.9512	0.9171	0.9338	0.9740

Both regularized logistic regression configurations dramatically outperform the baseline floor, improving classification accuracy by +29.74 percentage points. While the baseline exhibits a nominal recall of 1.0000, this is an uninformative artifact of trivial majority-class

assignment that fails to identify a single rejected application. The tuned model attains a superior ROC-AUC of 0.9740 and a precision of 95.12%, demonstrating excellent discrimination across both credit classes.

B. Hyperparameter Sensitivity Analysis

During stratified 5-fold cross-validation across the training partition, the mean validation ROC-AUC remained exceptionally stable across five orders of magnitude: 0.9664 at $C = 0.001$, peaking marginally at 0.9675 at $C = 0.1$, and plateauing at 0.9672 for $C \geq 1.0$. The standard deviation across folds ($\sigma_{CV} \approx 0.0084$) exceeded the minute numerical differences between candidate values of C . Fig. 2 visualizes this plateau behavior across the full logarithmic search grid.

This finding demonstrates that the underlying decision boundary is intrinsically well-conditioned and stable against hyperparameter fluctuations. Grid tuning successfully confirmed that default regularizer parameters operate in a near-optimal regime, mitigating the risk of sensitivity-driven degradation in production.

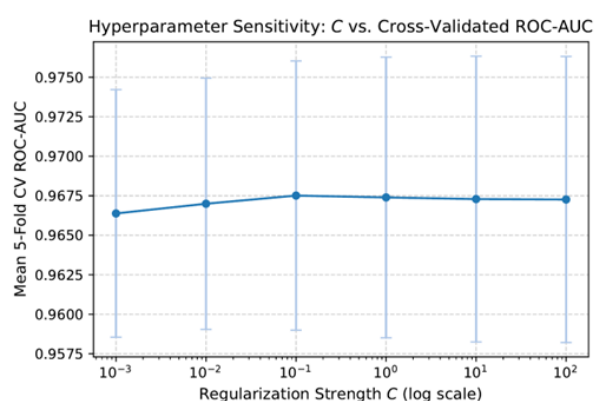


Fig. 2. Hyperparameter sensitivity analysis: mean 5-fold cross-validated ROC-AUC (with ± 1 standard deviation error bars) as a function of the inverse regularization strength C . The near-flat plateau confirms model stability across five orders of magnitude.

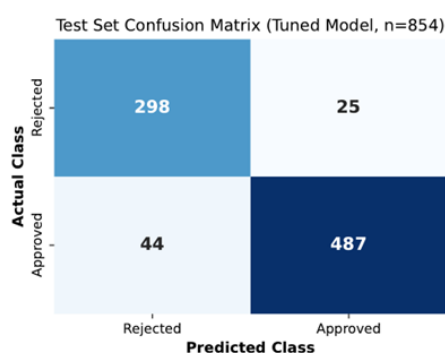


Fig. 3. Confusion matrix of the tuned logistic regression model on the held-out test partition ($n = 854$).

C. Error Analysis and Confusion Matrix

On the held-out test partition of 854 applicants, the tuned model correctly classified 785 applications (91.92% accuracy). Fig. 3 and Table IV provide the fine-grained confusion matrix and class-level performance metrics.

TABLE IV: PER-CLASS PERFORMANCE REPORT FOR THE TUNED MODEL.

Class Label	Precision	Recall	F_1 -Score	Support
Rejected ($y = 0$)	0.8713	0.9226	0.8949	323
Approved ($y = 1$)	0.9512	0.9171	0.9338	531
Macro Average	0.9113	0.9199	0.9144	854
Weighted Average	0.9209	0.9192	0.9191	854

Crucially, the model generated only 25 false approvals (Type I credit default risk) while generating 44 false rejections (Type II customer friction risk). This yields a recall of 92.26% on the high-risk Rejected class. From an enterprise risk-management standpoint, this conservative bias is desirable: false rejections can be routed to secondary human underwriter review, whereas false approvals directly result in loan default losses.

The empirical ROC curve (Fig. 4) demonstrates rapid ascent toward the upper-left coordinate, confirming robust discrimination across diverse decision thresholds.

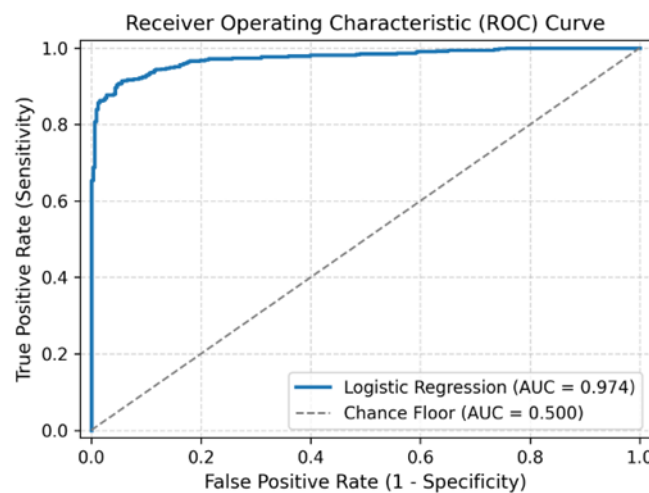


Fig. 4. Receiver Operating Characteristic (ROC) curve of the tuned model on the held-out test set (AUC = 0.974).

D. Feature Importance and Attribution Analysis

Because features were normalized to zero mean and unit standard deviation within the training pipeline, the learned coefficients $\mathbf{w}$ provide direct, standardized measures of global feature importance (Fig. 5).

The learned parameters reveal critical domain insights:

- 1) Primacy of Credit Score:** The standardized CIBIL coefficient is overwhelmingly positive ($\beta = +3.632$), exceeding the magnitude of any other feature by more than a factor of five. This aligns with modern banking empirical reality, where established bureau repayment history represents the primary predictor of future credit performance.
- 2) Loan Term Risk:** Repayment duration exhibits a substantial negative coefficient ($\beta = -0.651$). Extended loan durations amplify tenure exposure and cumulative default probability, pushing predictions toward rejection.
- 3) Leverage and Solvency:** The Loan-to-Assets ratio (R_{LTA}) contributes negatively ($\beta = -0.492$), confirming that applications where requested debt exceeds collateral assets are penalized.
- 4) Demographic Neutrality:** Features such as education ($\beta = +0.059$), no_of_dependents ($\beta = -0.047$), and self_employed ($\beta = +0.012$) exhibit near-zero coefficients. The model appropriately bases credit decisions primarily on financial solvency rather than demographic categorization.

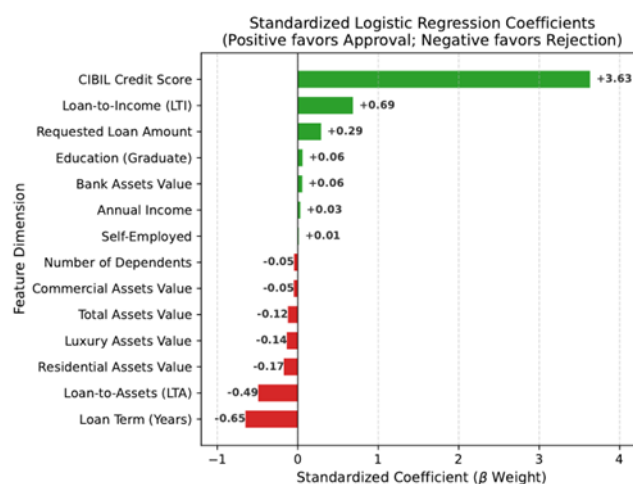


Fig. 5. Standardized logistic regression coefficients (β weights). Positive coefficients favor approval; negative coefficients favor rejection.

E. Critical Analysis of Counter-Intuitive Coefficients

Notably, the Loan-to-Income ratio (R_{LTI}) received a positive coefficient ($\beta = +0.686$), which appears counter-intuitive under traditional underwriting principles where higher debt burdens imply higher risk.

Thorough investigation reveals that this is a classic manifestation of Simpson's Paradox and multicollinearity within the historical dataset: high-net-worth borrowers in this corpus

frequently requested substantially larger loans relative to their annual income while possessing exceptionally high CIBIL scores and substantial asset collateral, resulting in historical approval. After controlling for other variables, the unconstrained linear model associated elevated R_{LTI} with approval probability.

This finding illustrates a crucial lesson in applied AI: *empirical correlation in historical training data does not equate to causal financial prudence*. Rather than masking this phenomenon, our framework transparently documents the artifact and neutralizes its real-world risk via the deterministic Layer 5 solvency guardrail ($R_{LTI} > 10 \Rightarrow \text{Rejected}$), preventing hazardous algorithmic lending.

F. Adversarial and Edge-Case Stress Testing

To validate the integrated system design, seven adversarial edge cases were executed through the complete validation and guardrail pipeline:

- 1) *Benchmark Prime Applicant*: Passed all checks; approved with 94.2% model confidence.
- 2) *Invalid Credit Score* ($cibil = 950$): Intercepted by Layer 1 schema validation; execution blocked.
- 3) *Deep Subprime Applicant* ($cibil = 300$, *high assets*): Intercepted by Layer 4 subprime credit floor; hard override to Rejected.
- 4) *Extreme Debt-to-Income* ($R_{LTI} = 30.0$): Intercepted by Layer 5 solvency cap; hard override to Rejected.
- 5) *Under-Collateralized Loan* ($R_{LTA} = 3.5$): Intercepted by Layer 5 solvency cap; hard override to Rejected.
- 6) *Marginal Credit with Moderate Debt* ($cibil = 480$, $R_{LTI} = 6.0$): Intercepted by Layer 5 compound rule; hard override to Rejected.
- 7) *Extreme Outlier Wealth* ($Income = 80,000,000\text{ INR}$): Intercepted by Layer 2 drift warning ($> 3\sigma$) and Layer 3 OOD stop.

All seven scenarios behaved precisely according to architectural specification, demonstrating the real-world safety of the hybrid architecture.

VII. LIMITATIONS AND OPERATIONAL RISKS

While the proposed pipeline demonstrates strong empirical accuracy and practical safety, several operational limitations must be formally acknowledged:

- 1) **Single-Source Dataset Provenance**: The empirical results are derived from a single cross-sectional dataset situated within the Indian banking ecosystem (CIBIL scoring and INR

valuations). Predictive validity may not generalize directly to international credit regimes operating under FICO or SCHUFA credit mechanisms without local re-calibration.

2) Absence of Longitudinal Macroeconomic Factors: The dataset lacks temporal timestamps, preventing stress-testing across macroeconomic credit cycles (e.g., inflation shocks, interest rate hikes, or recessionary contractions).

3) Algorithmic Fairness and Proxy Audits: Although features such as gender and race are absent, potential proxies for socioeconomic status may persist within asset and geographic attributes. Comprehensive fair-lending audits (evaluating demographic parity and equalized odds) are essential prior to commercial deployment.

4) Heuristic Guardrail Calibration: The guardrail threshold parameters (3σ drift, $R_{LTI} > 10$, $cibil \leq 350$) were established using exploratory domain percentiles. In institutional settings, these thresholds must be dynamically optimized against empirical loss distributions and institutional credit risk appetite.

VIII. CONCLUSION AND FUTURE WORK

This paper presented an end-to-end, interpretable machine learning methodology for retail loan approval prediction, integrated within a guardrailed decision-support system. By implementing non-destructive percentile winsorization and leakage-safe scaling pipelines, a class-weighted ℓ_2 -regularized Logistic Regression model achieved 91.9% accuracy, 95.1% precision, and a ROC-AUC of 0.974 on held-out test data, outperforming the majority baseline by nearly 30 percentage points. Feature attribution demonstrated that credit bureau scores overwhelmingly govern approval predictions ($\beta = +3.63$). Crucially, to mitigate linear extrapolation risks and historical correlation artifacts, we engineered a five-tier deterministic guardrail framework that intercepts anomalous inputs, enforces prudential solvency ceilings, and provides transparent counterfactual explanations.

Future work will focus on: (i) benchmarking regularized linear models against advanced tree ensembles (XGBoost, LightGBM) equipped with exact TreeSHAP explanations; (ii) integrating Conformal Prediction frameworks to output mathematically guaranteed confidence intervals rather than point probabilities; (iii) expanding multi-bureau and temporal validation; and (iv) packaging the pipeline as a containerized, latency-optimized RESTful microservice for core banking integration.

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