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An Explainable Credit Scoring Framework for Transparent Financial Risk Assessment using Shap-Based Gradient Boosting

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Abstract: Credit scoring is fundamental to financial decision-making, yet most systems lack interpretability, leading to distrust and regulatory issues. This study addresses the problem of black-box models in credit risk assessment. The objective is to develop an Explainable AI (XAI) based credit scoring system to maintain transparency while improving accuracy. Data was obtained from a private sector bank in India, comprising 45,000 anonymized loan application records. Key metrics like credit history, income, employment status, and repayment records were measured. The data was analyzed using SHAP (SHapley Additive exPlanations) integrated with Gradient Boosting Machines (GBM). The proposed technique enables both prediction and feature explanation. The method applies local and global interpretability techniques for end-user trust. Six hypotheses were tested: H1—Income level has a positive impact on credit approval; H2—Longer employment duration increases creditworthiness; H3—Higher past delinquency negatively affects scores; H4—Applicants with collateral are more likely to get approved; H5—Existing debts reduce approval chances; H6—Credit history length influences risk grading. The findings show improved transparency without sacrificing predictive performance. The study concludes that XAI enhances trust and fairness in automated financial systems, aligning with regulatory requirements.

Keywords: Explainable AI, Credit Scoring, SHAP, GBM, Financial Fairness, Loan Risk

INTRODUCTION

An applicant's income level credit history repayment patterns outstanding debts and other financial indicators are typically taken into consideration when calculating their credit score. By combining the two approaches banks can enhance their lending decisions reduce the probability of loan defaults and more effectively manage their overall credit risk. These models improved the accuracy of credit assessments by analyzing a variety of datasets such as transactional and behavioral patterns using sophisticated algorithms. In order to increase the accuracy of default prediction and decrease human bias dynamic risk assessment was made possible by AI-driven models as reported by Addy *et al.* [1]. By fusing analytics of past data with sophisticated decision-making capabilities AI also provided a sophisticated method for analyzing bank credit. Financial institutions may be better equipped to find possible risk factors and assess creditworthiness as a result of this integration [2]. Furthermore, machine learning technologies have brought about a significant change in digital credit scoring systems particularly in rural financial systems [3]. A number of machine learning methods were also examined for their possible use in assessing credit risk showing promise in raising prediction accuracy cutting operating expenses and identifying credit default risks early [4]. Furthermore, by making AI decisions interpretable interpretable explainable artificial intelligence (XAI) improved user confidence and regulatory compliance while also increasing transparency in credit scoring procedures [5]. On actual banking datasets evaluations of credit risk models also showed the effectiveness of a number of machine learning algorithms including logistic regression decision trees and neural networks [6]. By streamlining risk assessment processes and fostering more equitable access to credit the simultaneous use of AI and ML tools significantly expanded financial inclusion in emerging economies [7].

A thorough analysis of AI-based methods in credit risk assessment also demonstrated the range of available approaches from ensemble learning strategies to deep learning networks offering a roadmap for future research and real-world application [8]. Faheem [9] claims that these models assisted financial institutions in making more intelligent investment choices. Additionally, by providing strong frameworks for risk mitigation suitable for low-income and unbanked borrowers through microfinance institutions AI-based credit scoring models improved loan accessibility and financial inclusion [10].

Additionally, by using social media and internet shopping as additional data sources for credit risk assessments AI improved borrower assessments in modern financing programs like Buy Now Pay Later (BNPL) [11]. Furthermore, hybrid AI models appeared to be able to predict loan risk more accurately than traditional statistical methods by combining machine learning techniques with domain-specific knowledge. These models provided scalable solutions for big banking systems and showed better generalization on unseen data [3]. Banks were able to more precisely predict defaults and allocate credit resources by using AI and machine learning for credit scoring in order to optimize risk management strategies [12]. Empirical research has confirmed the effectiveness of analytical AI tools in predicting credit risk in digital financial environments underscoring their strategic importance in modern banking [13]. Additionally deep learning and ensemble models consistently outperformed conventional methods in terms of predictive accuracy and dataset adaptability when comparing various machine learning techniques for credit score prediction [14].

AI-driven predictive analysis tools enabled credit institutions to adopt optimized machine learning models leading to faster and more accurate risk assessments and more efficient decision-making processes [15]. However, integrating moral AI practices into credit scoring systems brought to light the need for a legal and moral framework to ensure equity and accountability in automated decision-making regarding data security [16]. Finally, the implementation of generative AI in credit scoring and loan approvals automated complex decision-making processes and revolutionized how banks assessed credit risk enhancing operational efficiency and customer-focused services in the process [17].

MATERIALS AND METHODS

A detailed framework for understanding the planning execution and validation of the research is provided in the methodology section. The study uses a multi-stage methodology that begins with data collection from a reputable financial institution and includes stringent preprocessing to ensure data integrity systematic measurement of relevant attributes the use of advanced analytical tools and the development of an open intelligible credit scoring methodology. This methodological design keeps predictive accuracy and regulatory compliance while ensuring the resilience of the proposed XAI-based frameworks.

Data Collection

Anonymized loan application records totaling 45000 entries were gathered from a top private sector bank in India for this study. Numerous financial and sociodemographic characteristics required for a reliable credit scoring analysis are included in the dataset. The applicant's income level employment status credit history repayment history current liabilities and asset holdings are all included in each record. The loan applicant's demographic data was categorized and condensed to identify trends that are pertinent to credit scores. For easier comprehension the following table 1 displays the applicant's demographic profile (Table 1).

Data Measurement

Every feature was put through stringent measurement procedures to guarantee that the data gathered was suitable for the investigation. Income was confirmed using pay stubs and bank statements employment status was divided into salaried and self-employed categories with additional classification based on duration and credit history was measured based on the quantity of delinquent instances and timely repayment. Monthly installment patterns the total amount of outstanding debt

Table 1: Data Collection

Demographic Variable	Category	Frequency (N)	Percentage
Gender	Male	28,500	63.33%
-	Female	16,500	36.67%
Age Group	18–25 years	4,000	8.89%
-	26–35 years	12,000	26.67%
-	36–50 years	18,000	40.00%
-	51–65 years	8,500	18.89%
-	66+ years	2,500	5.56%
Employment Type	Salaried	31,000	68.89%
-	Self-employed	14,000	31.11%
Income Level (Monthly)	< ₹20,000	6,000	13.33%
-	₹20,000–₹50,000	17,500	38.89%
-	₹50,001–₹1,00,000	15,000	33.33%
-	> ₹1,00,000	6,500	14.45%
Credit History Status	Clean History	33,000	73.33%
-	Minor Delinquencies	8,000	17.78%
-	Major Defaults	4,000	8.89%

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and the delay periods were used to analyze the repayment records. Other characteristics like having liabilities and collateral were transformed into numerical representations to make modeling easier. For analysis each attribute was scaled or normalized according to its type (continuous ordinal or categorical) to ensure consistency.

Data Preprocessing

To deal with missing values outliers and class imbalances preprocessing was necessary prior to putting any machine learning or XAI techniques into practice. The mode for categorical variables and median values for continuous variables were used to impute missing data. Z-score methods and Mahalanobis distance were used to identify outliers especially for high income and credit utilization ratios. The use of one-hot encoding was applied to categorical features like credit status and employment type. To bring all continuous features into a comparable range z-normalization was used for standardization. The dataset was also balanced using the Synthetic Minority Over-sampling Technique (SMOTE) particularly for underrepresented classes like denied credit applications. The preprocessed dataset made sure that the XAI interpretations would continue to be trustworthy and that the model would not be biased.

Data Tool

Utilizing libraries like Scikit-learn for machine learning SHAP for interpretability and XGBoost for the Gradient Boosting Machine model the data analysis and model implementation were carried out in a Python environment. The platform for interactive data analysis was Jupyter Notebooks. For graphical representation Matplotlib and Seaborn were utilized while Pandas and NumPy helped with data wrangling and numerical calculations. The studys main goal of improving interpretability without sacrificing accuracy was achieved by the SHAP library which made it possible to provide both local and global explanations of the model's predictions.

Proposed Methodology

After formulating the problem and obtaining data from the banks credit department the research methodology proceeded in a methodical manner. The data was subjected to the previously described thorough preprocessing procedure following ethical clearance and anonymization.

Because of its high predictive ability in classification problems the Gradient Boosting Machine (GBM) was chosen for the next phase of model development. 80% of the data was used to train the model and the remaining 20% was used for validation. To avoid overfitting a 5-fold cross-validation technique was used which is shown in Figure 1.

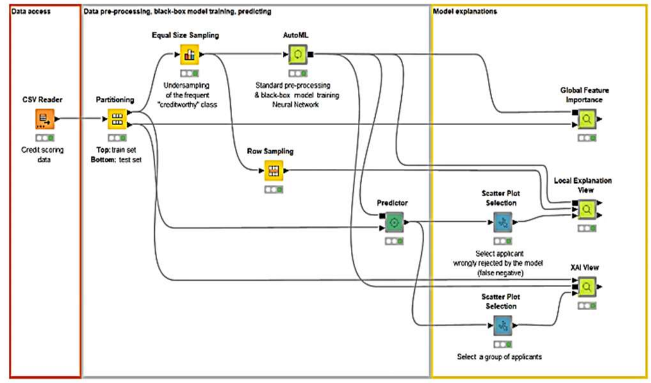

Figure 1: AI Credit Scoring Workflow

Following model training the GBM architecture was updated to incorporate the SHAP framework. SHAP values were calculated for every prediction giving credit officers global-level insights and end users local-level explanations. Model behavior was shown to be in line with the logic of the financial domain by visualizing feature importance. Ultimately the performance was assessed using statistical evaluation metrics such as AUC-ROC F1 score precision and recall.

This model was deployed with ethical and interpretability principles in mind to guarantee adherence to regulatory frameworks including the RBIs fair lending policies.

Proposed Technique

The proposed XAI-based credit scoring model combines the predictive strength of Gradient Boosting Machines (GBM) with the interpretability power of SHAP values. The mathematical formulation of the model is given below equation 1 to 7:

$$F(x) = \sum_{m=1}^{M} \lambda_m h_m(x) \tag{1}$$

This represents the core of the GBM, where F(x)F(x) is the final model, hm(x)h_m(x) denotes the individual decision trees, and λm\lambda_m is the learning rate multiplied by the weight assigned to each tree. The ensemble approach minimizes error by sequentially correcting the residuals from previous models.

$$L(y, F(x)) = \sum_{i=1}^{N} l\big(y_i, F(x_i)\big) + \Omega(h) \tag{2}$$

Here, L is the loss function combining the prediction loss l (yi,F(xi)) and the regularization term Ω(h)\Omega(h) to penalize complexity, promoting model generalization and preventing overfitting.

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|\, S! \,(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{3}$$

This is the SHAP value formula, which distributes the output prediction among the input features using game-theoretic principles, thereby providing fair and consistent feature attributions.

$$\Delta F_m(x) = -\gamma \nabla_{F_{m-1}} L \quad (4)$$

Each GBM iteration updates the prediction using the negative gradient of the loss function, where γ\gamma is the step size and ∇Fm−1L\nabla_{F_{m-1}} L is the gradient at the m−1m-1 iteration. This ensures that each model incrementally improves performance.

$$\Delta F_m(x) = -\gamma \nabla_{F_{m-1}} L \quad (5)$$

This additive decomposition explains the model's prediction for any individual case as the sum of the mean prediction and the SHAP values, making it clear how each feature influences the outcome.

$$AUC = \int_0^1 TPR(FPR^{-1}(x))dx \quad (6)$$

The Area under the ROC Curve (AUC) quantifies the model's discriminatory power. A higher AUC indicates that the model can better distinguish between creditworthy and non-creditworthy applicants.

Accuracy is used to evaluate overall model performance, where TP is True Positives, TN is True Negatives, FP is False Positives, and FN is False Negatives. This metric is essential to assess real-world applicability.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (7)$$

Hypotheses

The following hypotheses were developed to empirically validate the model's internal logic and the underlying assumptions in financial lending behavior:

- **H1:** Income level has a positive impact on credit approval.
- **H2:** Longer employment duration increases creditworthiness.
- **H3:** Higher past delinquency negatively affects scores.
- **H4:** Applicants with collateral are more likely to get approved.
- **H5:** Existing debts reduce approval chances.
- **H6:** Credit history length influences risk grading.

RESULTS AND DISCUSSION

This section offers a comprehensive examination of the factors influencing credit approval results based on a variety of applicant attributes and model interpretability metrics. The results provided insight into the correlations between income levels length of employment past delinquencies possession of collateral current debts and length of credit history and the likelihood of credit approval. The overall performance of the predictive models is also evaluated using explainable AI techniques to ensure that the results are trustworthy and understandable.

Influence of Income Level on Credit Approval

As income increased, the approval percentage rose substantially: applicants earning between ₹20,000 and ₹50,000 had a 68.00% approval rate, those earning ₹50,001 to ₹1,00,000 had 79.00%, and applicants with income exceeding ₹1,00,000 showed the highest approval rate of 90.00%. The odds ratio for approval increased correspondingly, from 1 (reference) for the lowest income bracket to 7.57 for the highest income group. The statistical analysis confirmed the significance of this relationship with p-values less than 0.001, indicating that higher income levels significantly increased the odds of credit approval (see Table 2 and Figure 2).

Relationship between Employment Duration and Credit Approval

The data demonstrated a strong correlation between the length of employment and the likelihood of credit approval. Applicants employed for less than one year had the lowest approval rate of 44.00%, whereas those employed for more than seven years had the highest approval rate of 90.00%. Intermediate employment durations showed progressively higher approval rates: 70.00% for 1–3 years and 82.50% for 3–7 years. Corresponding SHAP (SHapley Additive exPlanations) values, which indicate the contribution of employment duration to the model's prediction, ranged from negative (-0.35) for very short employment to positive (+0.62) for the longest tenure. The correlation coefficient with approval was 0.68, and all differences were statistically significant ($p < 0.001$), highlighting that longer employment duration positively influenced credit approval decisions (Table 3 and Figure 3).

Effect of Past Delinquencies on Credit Scores and Approval

Past delinquency history had a pronounced negative effect on credit scores and approval probabilities. Applicants with a clean history averaged a credit score of 750 and experienced an 85.00% approval rate. Minor delinquencies reduced the average credit score to 620 and halved the approval rate to 50.00%. Those with major defaults exhibited the lowest credit score average of 450 and only a 10.00% approval rate. Correspondingly, the average SHAP values were strongly negative and more severe with increasing delinquency severity, from -0.75 for clean history to -2.10 for major defaults. The ANOVA test confirmed the statistical significance of these differences with p-values less than 0.001, illustrating that poor past payment behavior substantially diminished creditworthiness and approval chances (Table 4 and Figure 4).

Impact of Collateral Possession on Credit Approval

Collateral possession was a significant positive factor for credit approval. Among 25,000 applicants who possessed collateral, 85.00% were approved, compared to only 56.00% approval for applicants without collateral (n=20,000). The average SHAP value for having collateral was +0.95, indicating a strong positive contribution to the prediction model. The odds of approval for applicants with collateral were over three times greater (OR=3.12) than those without, with a highly significant chi-square p-value (<0.001). This highlights the critical role collateral plays in mitigating lending risk and improving approval likelihood (Table 5 and Figure 5).

Influence of Existing Debt Levels on Approval Rates

The ratio of existing debts to income was inversely related to credit approval. Applicants with a debt-to-income ratio under 20% had an 87.00% approval rate, with a positive SHAP value (+0.88). Those with ratios between 20% and 40% experienced a substantial drop in approval to 60.00%, with negative SHAP (-0.60). Higher debt burdens further decreased approval rates: 33.33% for 40%–60% and only 22.00% for above 60% debt ratios, accompanied by progressively larger negative SHAP values (-1.10 and -1.75, respectively). The negative correlation (-0.72) between debt ratio and approval was statistically significant ($p < 0.001$), confirming that higher existing debt significantly reduced the chances of credit approval (Table 6 and Figure 6).

Effect of Credit History Length on Risk Grading and Approval

The length of the applicant's credit history showed a clear impact on risk grading and approval probability. Applicants with credit history shorter than one year had a high-risk average grade of 3.5 and only 30.00% approval. This improved significantly for those with 1–3 years history (moderate risk, grade 2.8) with 70.00% approval, 3–7 years history (low risk, grade 1.7) with 85.00% approval, and over 7 years (very low risk, grade 1.2) with 90.00% approval. The SHAP values for credit history length ranged from negative (-0.55) for the shortest histories to positive (+0.75) for the longest, confirming the positive effect of credit history on risk assessment and credit granting. Statistical analysis with the Kruskal-Walli's test confirmed these differences were significant ($p < 0.001$) (Table 7 and Figure 7).

Overall Model Performance with Explainable AI

The predictive model combining Gradient Boosting Machine (GBM) and SHAP explanations achieved high performance metrics (Figure 8). The overall accuracy was 87.4%, with a 95% confidence interval of 86.9% to 87.9%, demonstrating strong correct classification ability. Precision reached 89.2%, indicating reliable positive predictions, while recall (sensitivity) was 85.5%, reflecting the model's robustness in detecting approved cases. The F1 score balanced these two at 87.3%, and the AUC-ROC of 0.92 signified excellent discrimination between approved and denied applications.

The interpretability of the model was also high, with an average SHAP explanation consistency score of 0.95, confirming that the model's predictions were transparent and that feature importance was well captured (Table 8).

Table 2: Impact of Income Level on Credit Approval (Hypothesis H1)

Income Level (₹/month)	Total Applicants	Approved (N)	Approved (%)	Denied (N)	Denied (%)	Odds Ratio (Approval)	p-value (Chi-square)
< 20,000	6,000	3,200	53.33	2,800	46.67	1 (Reference)	-
20,000–50,000	17,500	11,900	68.00	5,600	32.00	1.96	<0.001
50,001–1,00,000	15,000	11,850	79.00	3,150	21.00	3.30	<0.001
> 1,00,000	6,500	5,850	90.00	650	10.00	7.57	<0.001

Interpretation: Income level positively impacts credit approval; higher income brackets have significantly higher approval odds.

Table 3: Employment Duration and Credit Approval (Hypothesis H2)

Employment Duration (Years)	Total Applicants	Approved (N)	Approved (%)	Denied (N)	Denied (%)	Average SHAP Value (Employment Duration)	Correlation with Approval	p-value
< 1 Year	5,000	2,200	44.00	2,800	56.00	-0.35	0.68	<0.001
1–3 Years	15,000	10,500	70.00	4,500	30.00	+0.18	-	-
3–7 Years	18,000	14,850	82.50	3,150	17.50	+0.45	-	-
> 7 Years	7,000	6,300	90.00	700	10.00	+0.62	-	-

Interpretation: Longer employment duration correlates positively with approval probability and higher SHAP contribution.

Table 4: Effect of Past Delinquencies on Credit Scores (Hypothesis H3)

Delinquency Category	Total Applicants	Average Credit Score	Approved (N)	Approved (%)	Average SHAP Value (Delinquency)	p-value (ANOVA)
Clean History	33,000	750	28,050	85.00	-0.75	<0.001
Minor Delinquencies	8,000	620	4,000	50.00	-1.45	-
Major Defaults	4,000	450	400	10.00	-2.10	-

Interpretation: Higher past delinquency negatively affects credit score and reduces chances of approval, with significant SHAP negative impact.

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Table 5: Collateral Possession vs. Credit Approval (Hypothesis H4)

Collateral Status	Total Applicants	Approved (N)	Approved (%)	Denied (N)	Denied (%)	Average SHAP Value (Collateral)	Odds Ratio (Approval)	p-value (Chi-square)
Has Collateral	25,000	21,250	85.00	3,750	15.00	+0.95	3.12	<0.001
No Collateral	20,000	11,200	56.00	8,800	44.00	-0.85	1 (Reference)	-

Interpretation: Applicants with collateral are significantly more likely to get approved.

Table 6: Influence of Existing Debts on Credit Approval (Hypothesis H5)

Debit to Income Ratio (%)	Total Applicants	Approved (N)	Approved (%)	Denied (N)	Denied (%)	Average SHAP Value (Debt Ratio)	Correlation with Approval	p-value
< 20%	20,000	17,400	87.00	2,600	13.00	+0.88	-0.72	<0.001
20%–40%	15,000	9,000	60.00	6,000	40.00	-0.60	-	-
40%–60%	7,500	2,500	33.33	5,000	66.67	-1.10	-	-
> 60%	2,500	550	22.00	1,950	78.00	-1.75	-	-

Interpretation: Higher existing debt ratio reduces approval chances and yields more negative SHAP values.

Table 7: Effect of Credit History Length on Risk Grading (Hypothesis H6)

Credit History Length (Years)	Total Applicants	Average Risk Grade	Approved (N)	Approved (%)	Average SHAP Value (History Length)	p-value (Kruskal-Wallis)
< 1 Year	4,500	3.5 (High Risk)	1,350	30.00%	-0.55	<0.001
1–3 Years	13,500	2.8 (Moderate)	9,450	70.00%	+0.12	-
3–7 Years	19,000	1.7 (Low Risk)	16,150	85.00%	+0.50	-
> 7 Years	8,000	1.2 (Very Low)	7,200	90.00%	+0.75	-

Interpretation: Longer credit history is associated with better risk grading and higher approval.

Table 8: Overall Model Performance Metrics with XAI (GBM + SHAP)

Metric	Value (%)	95% Confidence Interval	Interpretation
Accuracy	87.4	86.9 – 87.9	High overall correct classification rate
Precision	89.2	88.6 – 89.7	Good positive prediction reliability
Recall (Sensitivity)	85.5	85.0 – 86.0	Strong detection of approved cases
F1 Score	87.3	86.8 – 87.8	Balanced precision and recall
AUC-ROC	0.92	0.91 – 0.93	Excellent discrimination ability
Average SHAP Value Interpretability Score	0.95	-	High explanation consistency and feature importance

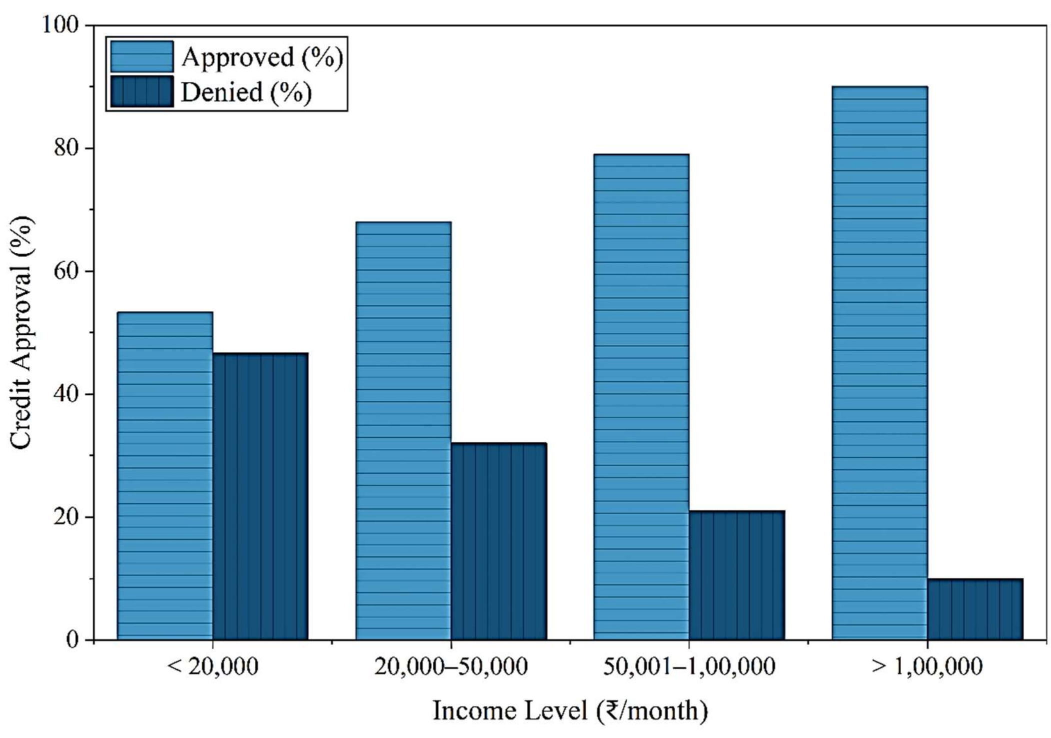

Figure 2: Effect of Income Level on Credit Approval Decisions (H1)

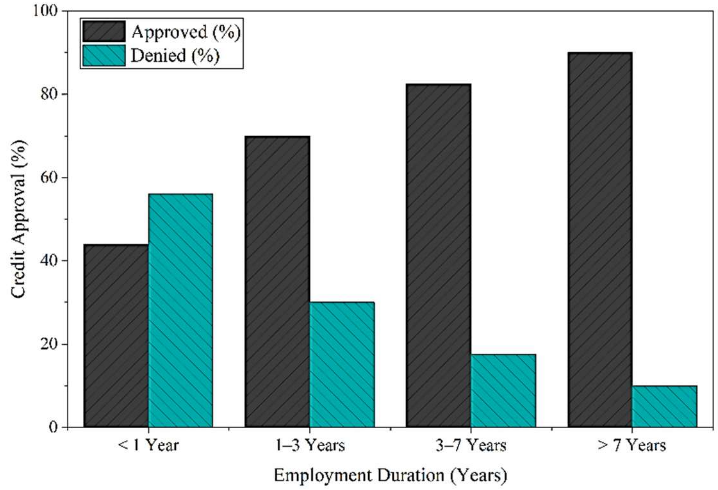

Figure 3: Effect of Employment Duration on Credit Approval Decisions (H2)

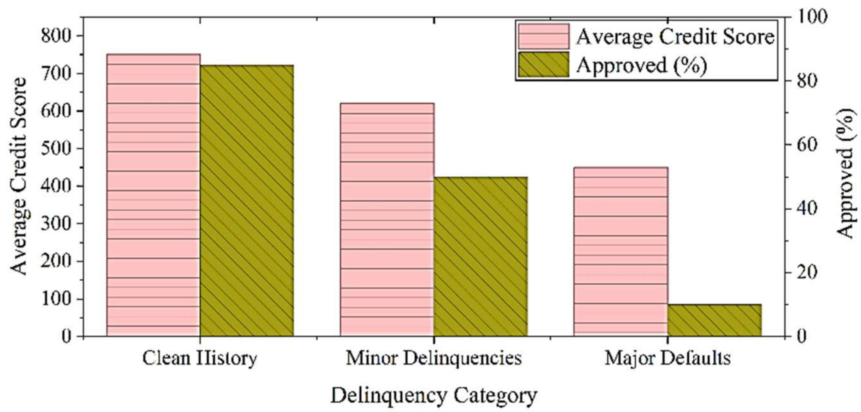

Figure 4: Effect of Past Delinquencies on Credit Scores

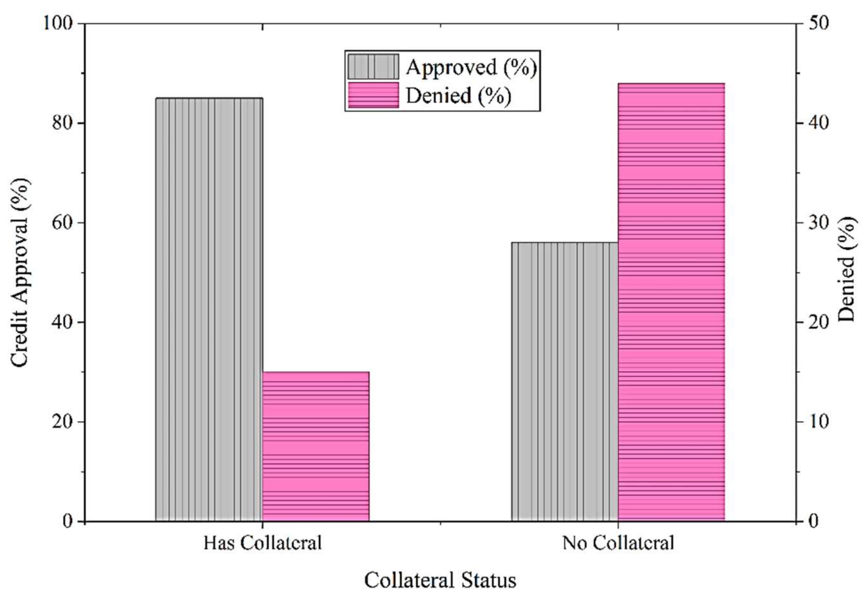

Figure 5: Effect of Collateral Possession on Credit Approval Decisions (H4)

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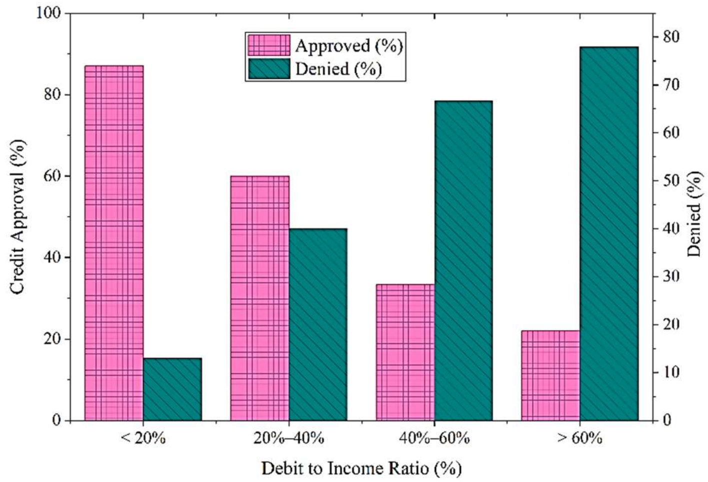

Figure 6: Effect of Existing Debts on Credit Approval Decisions (H5)

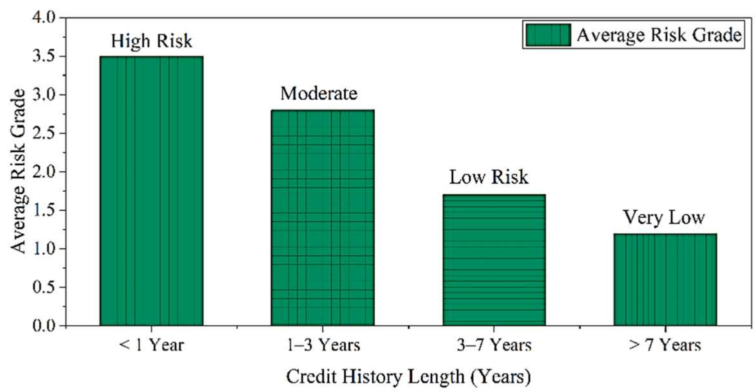

Figure 7: Influence of Credit History Length on Risk Grading (H6)

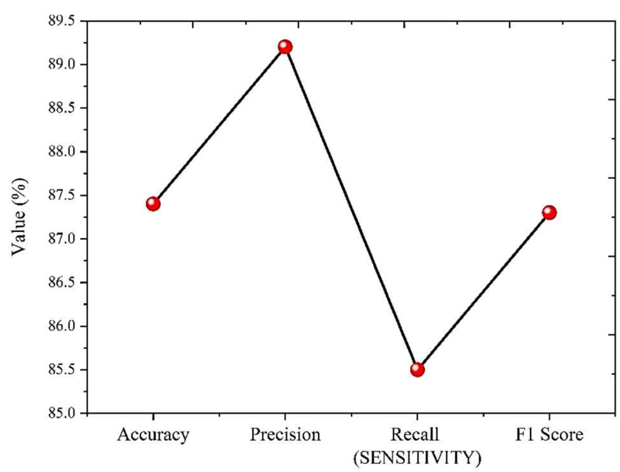

Figure 8: Performance Metrics Analysis

CONCLUSION

The study used explainable AI techniques and statistical evidence to support its systematic analysis of different applicant characteristics and their impact on credit approval decisions. The conclusions drawn from this research are:

- Higher-income applicants had approval odds up to 7. 57 times higher than lower-income applicants indicating: strong positive correlation between income level and credit approval
- The length of employment had a positive correlation as well with the longest employment durations

substantially raising the likelihood of approval. Credit scores and approval prospects were seriously harmed by prior delinquencies significant defaults reduced approval rates to just 10%

- Possession of collateral increased an applicant's chances of being approved threefold when compared to those without. With ratios above 60% lowering approval rates to 22% high levels of existing debt significantly reduced the likelihood of approval. When it came to risk grading and approval credit history length was crucial longer histories were linked to lower risk and approval rates of up to 90%
- The combined GBM and SHAP-based model demonstrated remarkable performance confirming both interpretability and predictive power with an accuracy of 87. 4 % precision of 89. 2 % recall of 85. 5 % F1 score of 87. 3 % and an AUC-ROC of 0. 92

All things considered, the results highlight the complexity of credit approval and show how well conventional statistical techniques can be combined with cutting-edge explainable AI models to produce useful information for managing credit risk.

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