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***Machine Learning Project Report***

***Review 3***

on

# CreditGuard: Home Loan Safety Net

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# CreditGuard: Home Loan Safety Net

## *1)Abstract:*

Access to home loans remains a significant barrier for many individuals due to traditional risk assessment procedures that often overlook financially responsible applicants, especially those with limited or non-traditional credit histories. This gap in credit accessibility undermines broader goals of financial inclusion and limits opportunities for economic mobility. **CreditGuard** addresses this pressing challenge by introducing a data-driven, intelligent risk evaluation system that enhances the precision of loan default predictions. By leveraging diverse data sources and advanced machine learning techniques, the project seeks to create a more inclusive and accurate credit assessment framework.

### 1.1 Project Objective

The primary goal of this project is to develop a robust predictive model capable of identifying potential loan defaulters while minimizing the rate of false rejections, thereby enabling fairer and more informed lending decisions.

### 1.2 Technical Approach

This solution employs a supervised binary classification framework to differentiate between applicants likely to repay and those at risk of default. The approach integrates multiple data preprocessing, modeling, and evaluation techniques to ensure reliability and scalability.

### 1.3 Key Components and Achievements

- **Data Integration Pipeline:** Consolidated six diverse datasets into a unified applicant profile enriched with temporal and behavioral features
- **Adaptive Preprocessing:** Employed dynamic strategies for handling missing values and outliers, tailored to data characteristics
- **Anomaly Detection System:** Deployed Isolation Forest to flag anomalous applications and enhance data integrity
- **Ensemble Modeling:** Benchmarked classification algorithms including XGBoost, Random Forest, Logistic Regression, and SVM to optimize performance
- **Model Evaluation Framework:** Assessed model effectiveness using ROC-AUC, Precision-Recall, F1-Score, and feature importance analysis for transparency and insight

**Keywords:** Credit Risk Assessment, Feature Engineering, Data Integration, Anomaly Detection, Machine Learning, XGBoost, Random Forest, Logistic Regression, SVM, Missing Value Imputation, Outlier Detection, Financial Inclusion, Home Loan Prediction, MICE Imputation, Feature Importance, ROC-AUC

# *2)Data Exploration:*

**Data Set Link: CreditGuard**

To build a comprehensive risk profiling system, the CreditGuard model integrates seven structured datasets provided by Home Credit. These datasets capture both current application data and a wide range of historical financial behaviors. Below is a description of each dataset and its purpose in the system.

**application_train / application_test**

These are the core datasets used for model training and prediction. Each row represents a unique loan application, identified by the feature SK_ID_CURR. The application_train dataset includes a TARGET variable where 0 indicates the loan was repaid and 1 indicates it was not repaid. The application_test dataset lacks the TARGET variable and is used for generating predictions.

**bureau**

This dataset contains information on the applicant's past credits from other financial institutions. Each record corresponds to a separate credit entry. One applicant in application_train/application_test can be linked to multiple entries in bureau. It includes features like credit type, status, and loan duration.

**bureau_balance**

This dataset provides monthly-level balance data for each credit in the bureau dataset. Each row represents one month of a credit, linked through SK_ID_BUREAU. It helps track monthly payment behavior and status changes over time.

**previous_application**

This dataset contains historical loan applications submitted to Home Credit before the current application. Each previous application is identified by SK_ID_PREV and associated with a current loan via SK_ID_CURR. It includes information such as loan type, status, and purpose. A current loan can have several previous applications.

**POS_CASH_BALANCE**

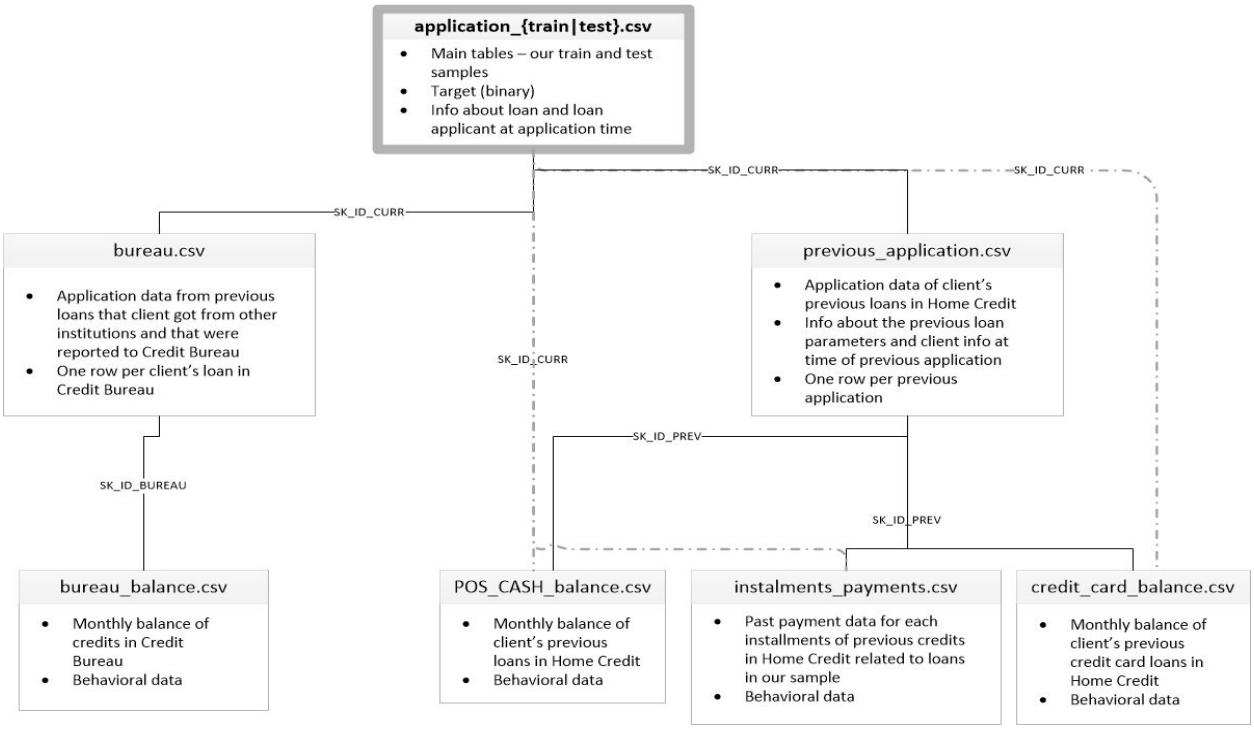
This dataset records monthly data on previous point of sale and cash loans the applicant had with Home Credit. Each row represents one month of a previous loan. A single loan can have multiple monthly records, which helps in understanding repayment behavior over time.

**credit_card_balance**

This dataset holds monthly balance information for previous credit cards the applicant has had with Home Credit. Similar to POS_CASH_BALANCE, each row represents one month of activity and is used to monitor spending patterns, utilization rate, and payment regularity.

**installments_payment**

This dataset includes the full payment history of past loans from Home Credit. It contains both made and missed payments, with each row representing one payment instance. This data is crucial in evaluating the applicant's repayment discipline.




| Dataset name | Rows | Columns |
|---|---|---|
| **application_{train\|test}** | 307511 | **122** |
| **bureau** | 1716428 | **17** |
| **bureau_balance** | 27299925 | **3** |
| **credit_card_balance** | 3840312 | **23** |
| **installments_payments** | 13605401 | **8** |
| **POS_CASH_balance** | 10001358 | **8** |
| **previous_application** | **1670214** | **37** |

# *2.1) Exploratory Data Analysis (EDA)*

The exploratory data analysis phase played a critical role in understanding the quality and structure of the data, detecting hidden patterns, and guiding subsequent preprocessing and modeling decisions. This phase involved a combination of statistical methods and visualization techniques to derive actionable insights from the Home Credit datasets.

### 2.1.1 Target Variable Analysis

Initial analysis of the target variable revealed a significant class imbalance. Out of a total of 307,511 loan applications in the training dataset, 282,686 (91.9%) corresponded to successfully repaid loans (TARGET = 0), while 24,825 (8.1%) indicated defaulted loans (TARGET = 1). This imbalance, approximately in a ratio of 11:1, presented a challenge for predictive modeling, as models trained on such skewed data tend to be biased toward the majority class. Special techniques and evaluation metrics were adopted later in the project to address this imbalance.

### 2.1.2 Missing Value Analysis

A thorough inspection of missing data patterns revealed substantial gaps in several features. Some columns had missing values more than 50%, indicating a need for strategic handling. To preserve data quality and predictive power, a tiered imputation strategy was developed:

- Features with more than 58% missing values were removed to avoid noise and bias.
- Features with missing rates between 20% and 58% were imputed using Multiple Imputation by Chained Equations (MICE) for numerical variables and mode imputation for categorical ones.
- Features with fewer than 20% missing values were handled with median (for numerical) or mode (for categorical) imputation, ensuring minimal information loss.

This approach helped maintain a consistent and clean dataset while maximizing the retention of useful information.

### 2.1.3 Categorical Feature Analysis

The categorical features were analyzed to understand the distribution of various groups and their relation to default probability. A focused analysis on the variable NAME_INCOME_TYPE revealed the following patterns:

- Working individuals constituted most of the loan applicants (53.4%).
- Applicants on maternity leave and those unemployed showed significantly higher default rates of 17.2% and 18.7%, respectively.
- Pensioners had the lowest default rate at 4.9%, indicating the stability of retirement income.

Similar patterns were identified across other categorical features such as NAME_EDUCATION_TYPE, NAME_HOUSING_TYPE, and OCCUPATION_TYPE. These findings contributed directly to the identification of high-risk applicant segments and informed the feature engineering process.

### 2.1.4 Numerical Feature Analysis

Numerical features were analyzed both for data quality and for their ability to discriminate between default and repayment. The variable DAYS_EMPLOYED presented extreme values exceeding 350,000 days, which are unrealistic. After removing such anomalies, the variable was converted to YEARS_EMPLOYED to enhance interpretability. The analysis revealed that applicants with recent employment history had significantly higher default rates (12.3%) compared to those employed for five or more years (6.4%).

Other time-based features such as DAYS_BIRTH, DAYS_REGISTRATION, and DAYS_ID_PUBLISH were similarly transformed into age-related features to improve interpretability and correlation with the target variable.

### 2.1.5 External Score Analysis

Three normalized scores (EXT_SOURCE_1, EXT_SOURCE_2, EXT_SOURCE_3) provided by the data were evaluated and found to be highly predictive. EXT_SOURCE_3 showed the strongest correlation with the target variable, with a Pearson correlation of -0.178. Applicants with EXT_SOURCE_3 scores below 0.3 were found to default at a rate more than four times higher than those with scores above 0.7. When used together, the three scores demonstrated complementary value, providing a strong signal for creditworthiness assessment.

### 2.1.6 Correlation Analysis

A correlation matrix was created to understand the relationships between numerical features and the target variable. The following observations were made:

- External scores showed strong negative correlation with default probability.
- Debt-to-income ratio exhibited a moderate positive correlation with default risk.
- Interactions between age, employment history, and credit features demonstrated complex but meaningful relationships.

This analysis guided feature selection and dimensionality reduction efforts, ensuring the retention of impactful variables while eliminating redundant or highly correlated ones.

### 2.1.7 Bureau and Previous Application Analysis

Insights from the bureau and previous_application datasets added valuable context regarding the applicant's financial behavior and credit history. Key findings include:

- Applicants with a history of credit bureau inquiries had 1.8 times higher default rates.

- Missed or delayed payments in prior applications strongly predicted future defaults.
- Loans in foreign currency were associated with higher risk compared to those in local currency, potentially due to exchange rate instability and repayment complexities.

This historical data provided critical predictive features for the model.

### 2.1.8 Anomaly Detection

To identify irregular patterns in applicant data, the Isolation Forest algorithm was used for anomaly detection. Applications flagged as anomalies showed several distinct traits:

- Debt-to-income ratios were approximately 27% higher than average.
- Discrepancies in reported personal information were more common.
- Unusual combinations of income type and loan purpose were observed.

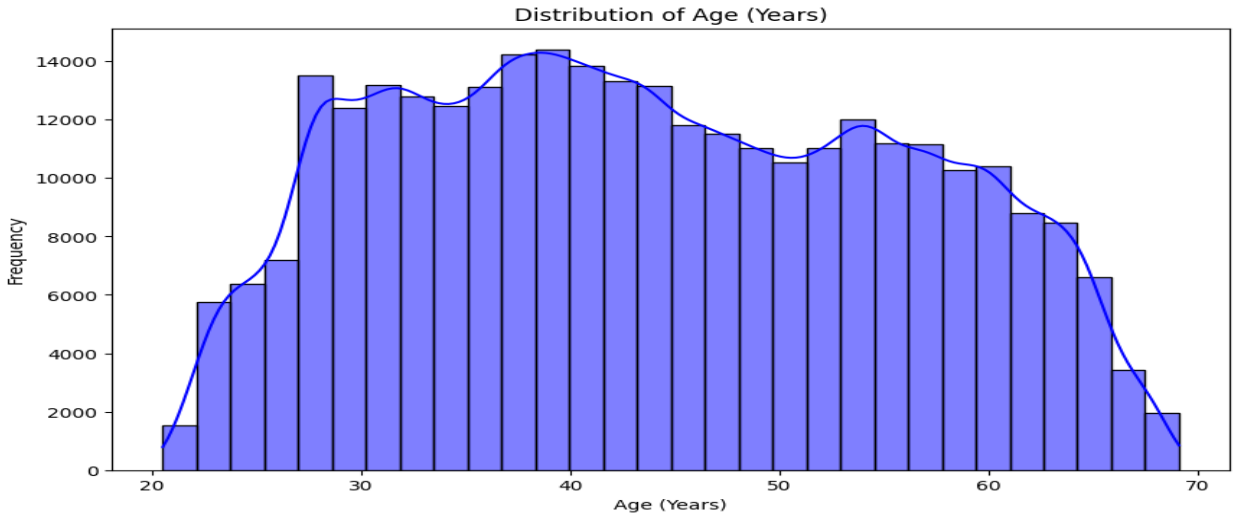
## *2.2) Feature Engineering*

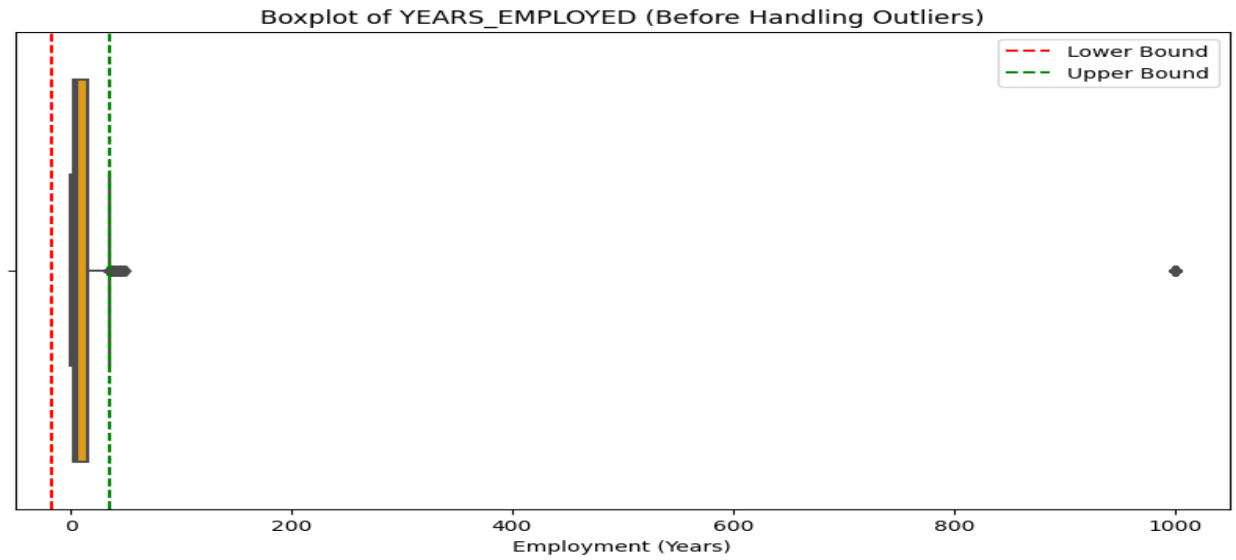
The feature engineering phase aimed to convert raw data into meaningful input variables that could improve model accuracy and interpretability. The process involved systematic handling of outliers, missing values, categorical variables, and multi-table aggregations. Custom features were also developed based on domain knowledge and statistical relationships.

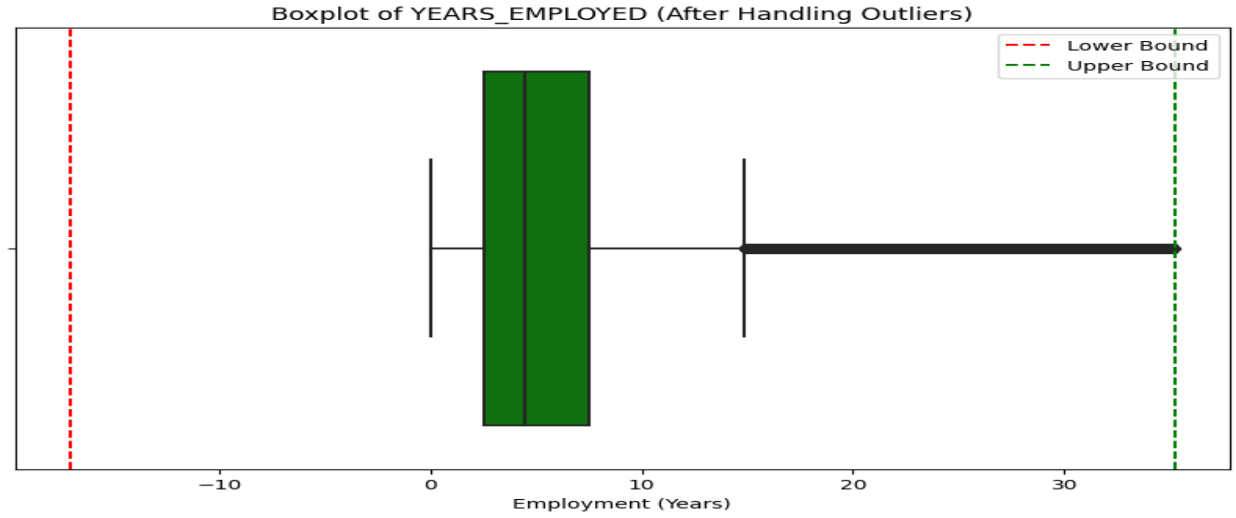
### 2.2.1 Key Steps

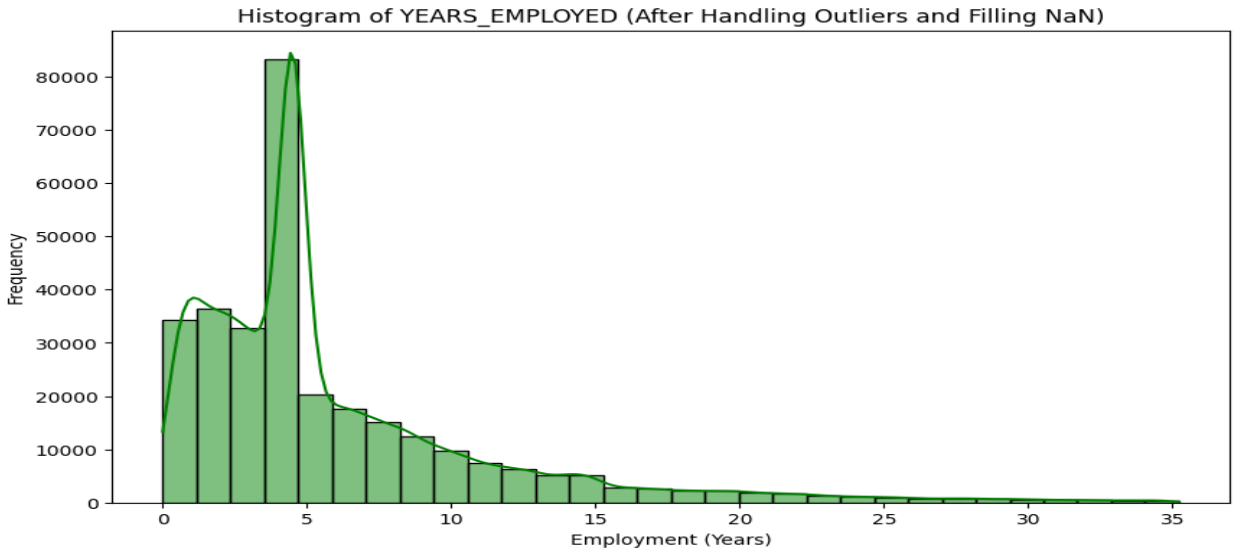
1. **Outlier Handling**

Outliers were identified in key numerical variables using the interquartile range (IQR) method. Any value lying beyond 1.5 times the IQR was considered an outlier and replaced with the median value of the respective feature. Variables such as YEARS_EMPLOYED and YEARS_REGISTRATION were adjusted accordingly. Boxplots and histograms were used to visualize and validate the corrections.




Boxplot of YEARS_EMPLOYED (Before Handling Outliers)
Lower Bound
Upper Bound
0
200
400
600
800
1000
Employment (Years)


Boxplot of YEARS_EMPLOYED (After Handling Outliers)
Lower Bound
Upper Bound
−10
0
10
20
30
Employment (Years)


Histogram of YEARS_EMPLOYED (After Handling Outliers and Filling NaN)
Frequency
80000
70000
60000
50000
40000
30000
20000
10000
0
0
5
10
15
20
25
30
35
Employment (Years)

2. **Categorical Encoding**

   Label encoding was applied to categorical variables such as OCCUPATION_TYPE, CODE_GENDER, and NAME_EDUCATION_TYPE. This transformation allowed the integration of these variables into machine learning models while preserving ordinal relationships where applicable.

3. **Missing Value Imputation**

   A tiered imputation strategy was adopted based on the extent of missingness:

- For features with less than or equal to 20% missing values:
  - Numerical features were imputed using the median.
  - Categorical features were imputed using the mode.
- For features with 20% to 58% missing values:
  - Numerical features were imputed using IterativeImputer with ten nearest features.
  - Categorical features continued to use mode imputation.

4. **Derived Features**

   Several new features were derived to improve model interpretability and performance. These included:

- AGE_YEARS, derived from DAYS_BIRTH
- YEARS_EMPLOYED, derived from DAYS_EMPLOYED
- YEARS_REGISTRATION, derived from DAYS_REGISTRATION

   These transformations improved the human readability of time-based features and helped identify default risk trends across different age and employment segments.

5. **Redundant Column Removal**

   Columns with more than 80% identical values were removed to avoid noise and redundancy. For example, the TARGET column was temporarily excluded during preprocessing steps to avoid data leakage.

### 2.2.2 Automated Feature Engineering via Relational Aggregation

To extract more meaningful features from the auxiliary datasets, a manual aggregation strategy was applied using relational joins. Six external datasets were incorporated: bureau, bureau_balance, previous_application, POS_CASH_balance, installments_payments, and credit_card_balance.

**Aggregation Strategy**

**Bureau and Bureau Balance**

Derived the feature STATUS_DELAYED by counting the total number of months a client was overdue (STATUS codes '1' to '5') in the bureau_balance dataset. Created CREDIT_STATUS, a categorical variable indicating whether a bureau record was "Completed", "Delayed", or "X" (no status). Aggregated key numeric variables such as AMT_CREDIT_SUM using sum operations per SK_ID_CURR.

**Previous Applications**

Calculated mean and maximum values for features like AMT_CREDIT, AMT_ANNUITY, and DAYS_DECISION to capture credit behavior trends.

**POS/CASH Balance**

Aggregated variables such as CNT_INSTALMENT_FUTURE using mean and sum, and SK_DPD using max to evaluate delayed installment patterns.

**Installments Payments**

Summed AMT_INSTALMENT and AMT_PAYMENT per applicant to estimate prior payment consistency.

**Credit Card Balance**

Computed average AMT_BALANCE and maximum AMT_CREDIT_LIMIT_ACTUAL for each applicant, helping assess financial exposure.

Merging Strategy

All aggregated datasets were merged into the main application_data dataframe using SK_ID_CURR as the common key. This resulted in a final dataset with 171 consolidated features.

Post-Aggregation Refinement

After merging, missing values in the engineered features were addressed using:

- Median imputation for numerical columns
- Mode imputation for categorical columns

StandardScaler was applied to scale numerical values prior to clustering and modeling steps.

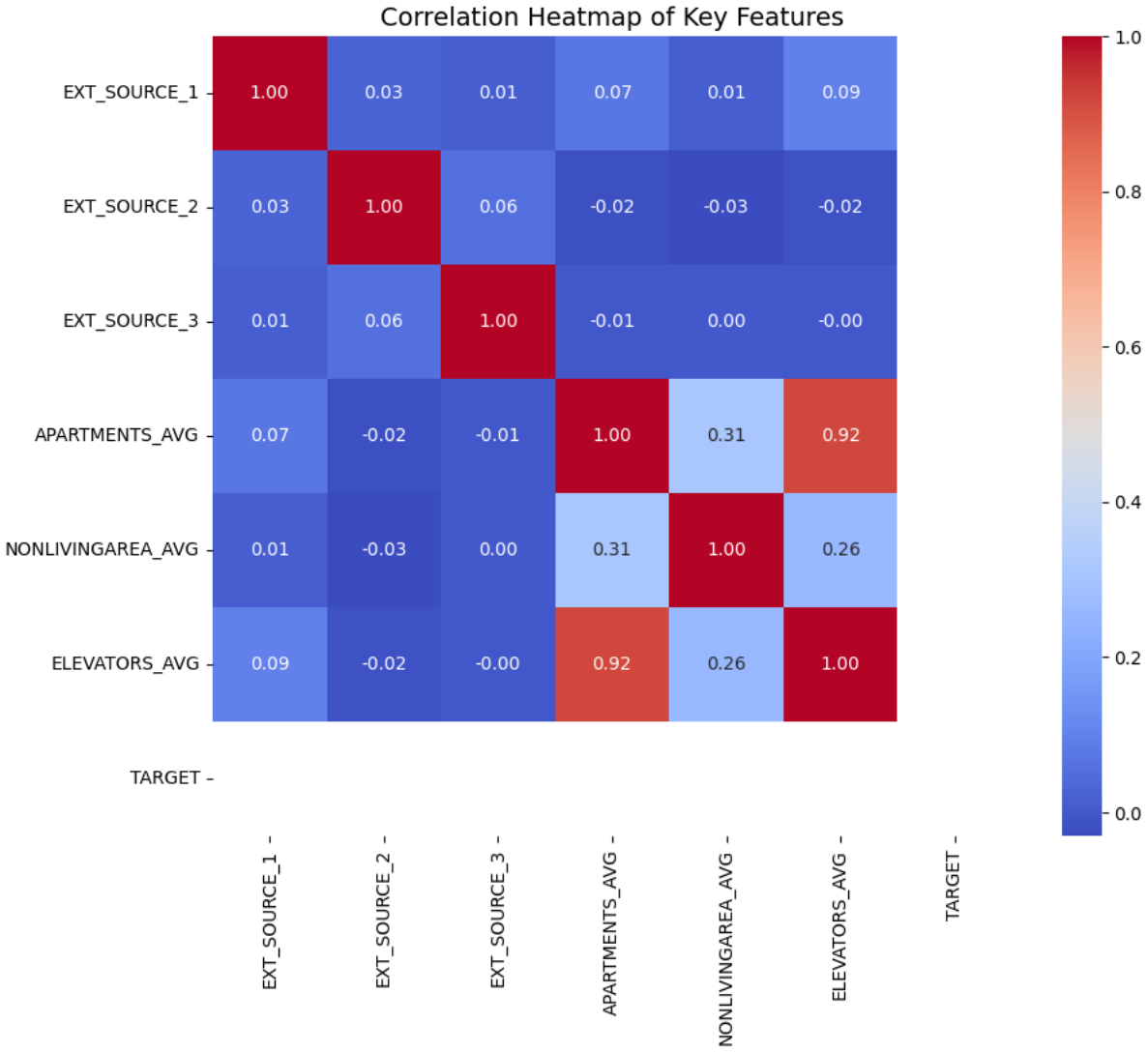
# *3) Visualization & Data Preprocessing*

**Google Colab Link: -** Google Collab

## 3.1 Visualization

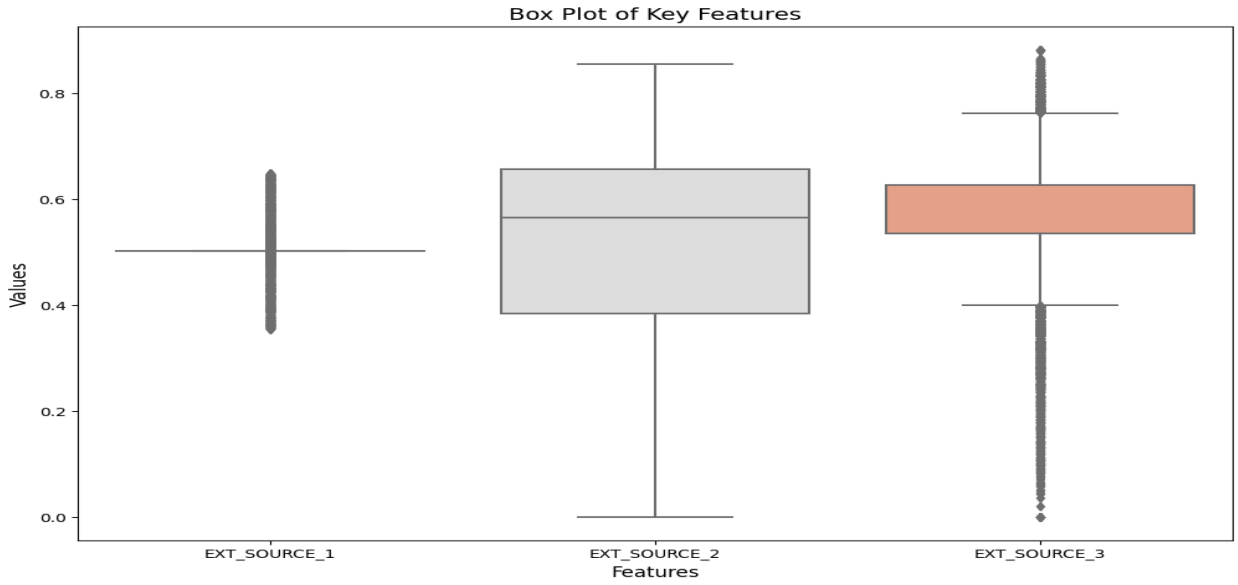
Data visualization was conducted to identify patterns, detect anomalies, and understand relationships within the dataset (final_data.csv). The use of appropriate plots enabled clear insights, which informed the preprocessing and modeling strategies.

**Correlation Matrix Heatmap** was used to examine linear relationships between numerical features. This heatmap provided a visual overview of pairwise correlation coefficients, helping to identify strongly related variables that may impact model interpretability.

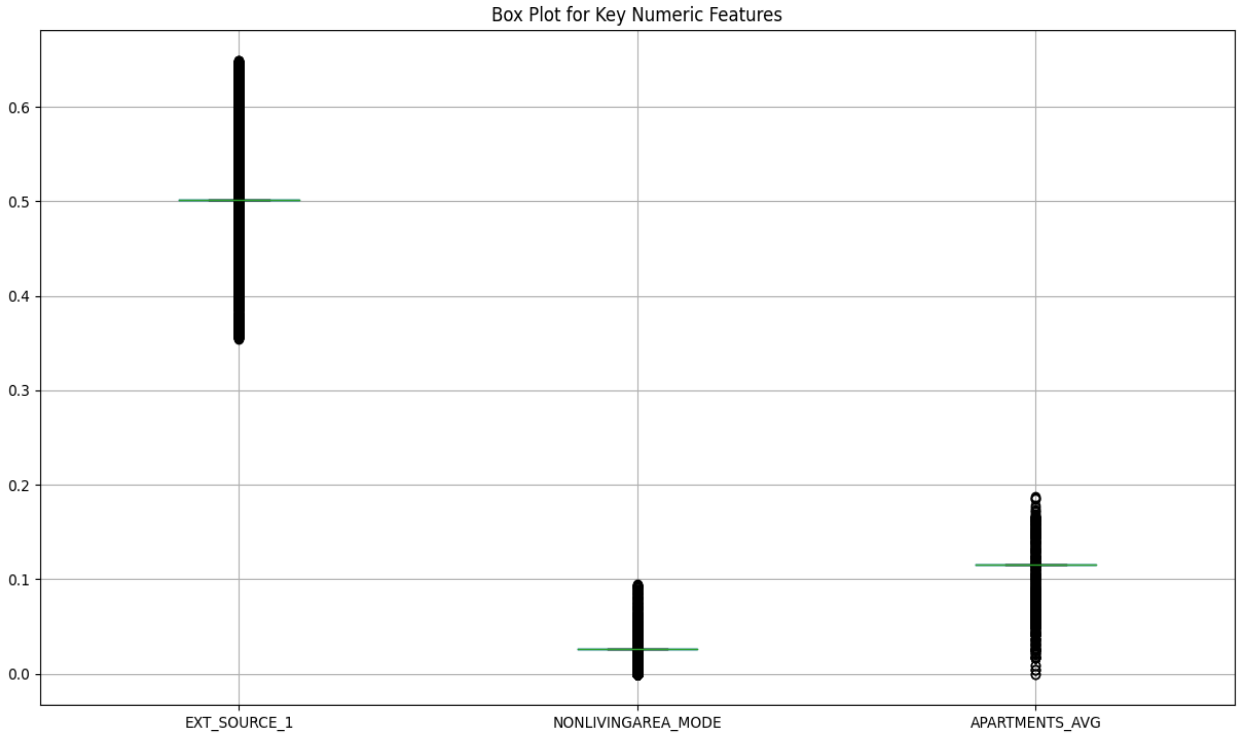


**Correlation Matrix of Numerical Features**

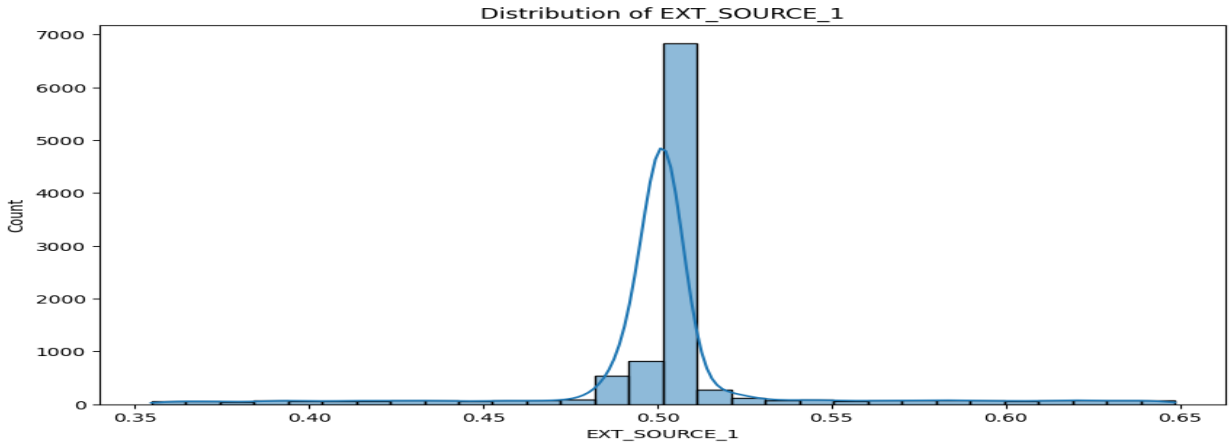
**Box Plots** were employed to detect outliers and examine the spread of key numerical features such as YEARS_EMPLOYED and AGE_YEARS. These plots highlighted central tendency, data dispersion, and extreme values that required adjustment.



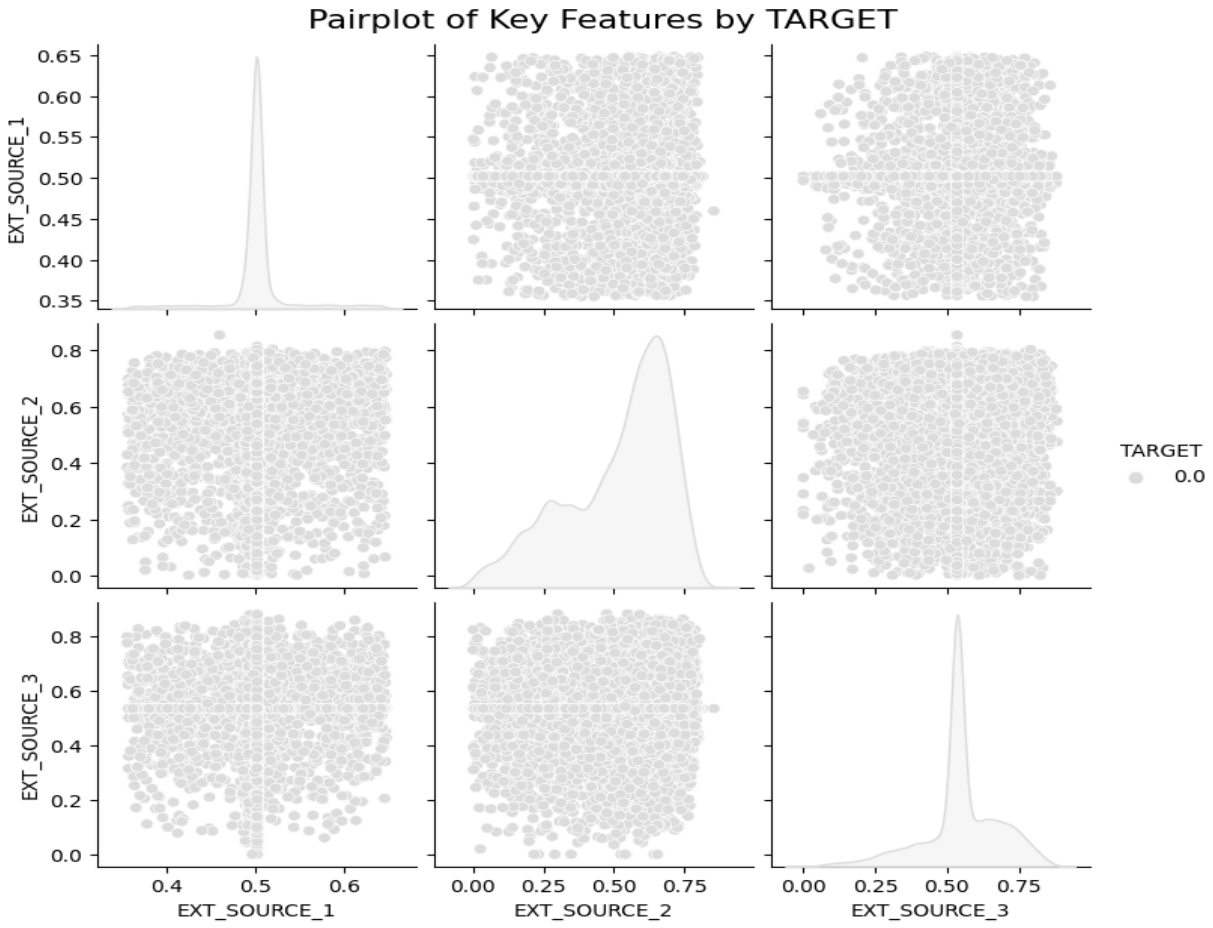

**Box plots** were utilized to detect outliers and analyze the spread of numerical features such as EXT_SOURCE_1, NONLIVINGAREA_MODE, and APARTMENTS_AVG. These visualizations highlighted the central tendency, variability, and extreme values requiring adjustment.



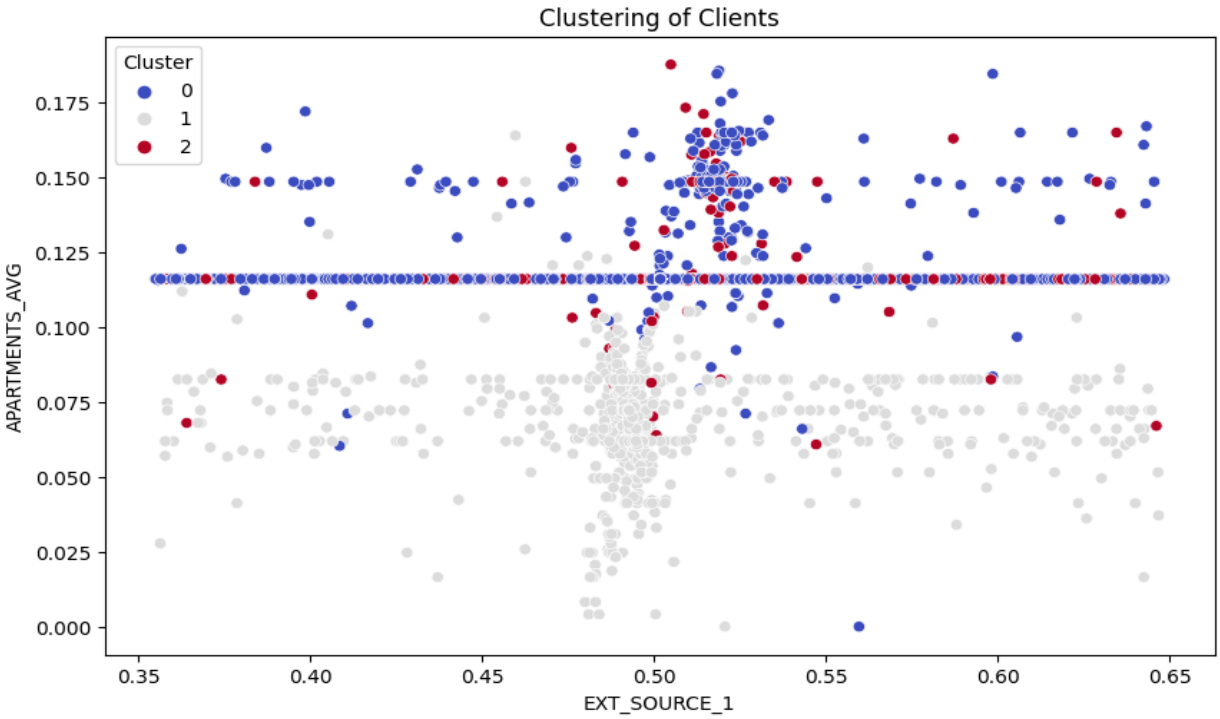
**Histograms** were used to explore the distribution of continuous features like EXT_SOURCE_1. The histograms helped identify data skewness, clustering, and gaps, providing insights into normalization needs.




**Scatter Matrix** allowed for the visualization of pairwise relationships across multiple numerical variables. This helped in identifying linear and non-linear patterns, potential clusters, or outliers among combinations of variables.

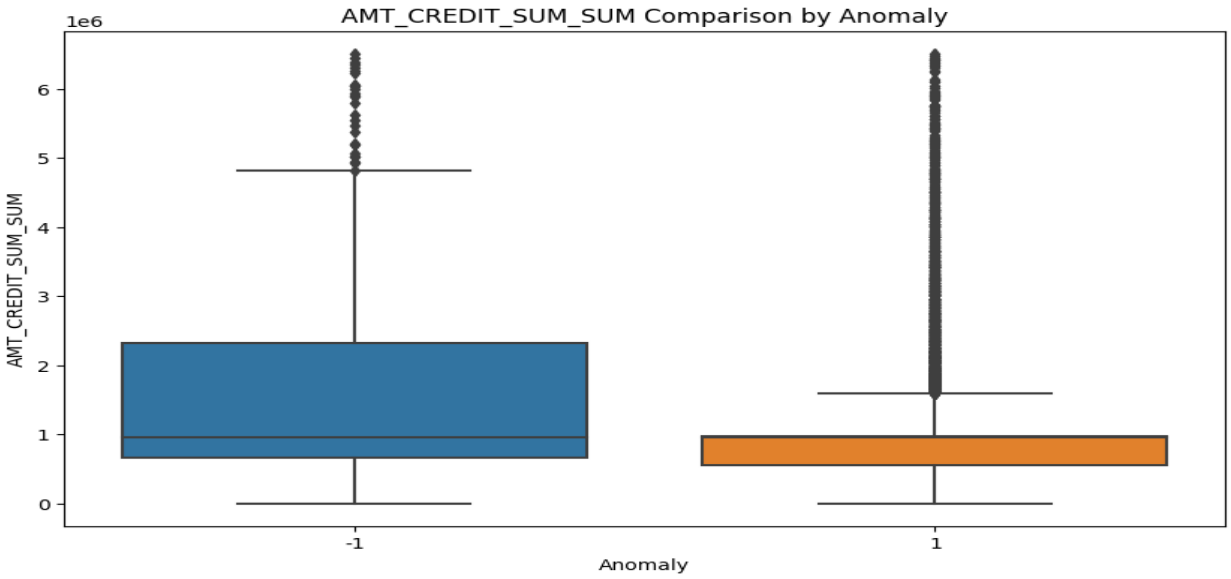


The **scatter plot** visualizes clustering of clients based on EXT_SOURCE_1 and APARTMENTS_AVG, with distinct clusters (0, 1, 2) represented by different colors. This highlights patterns in client segmentation and relationships between external credit scores and apartment averages.

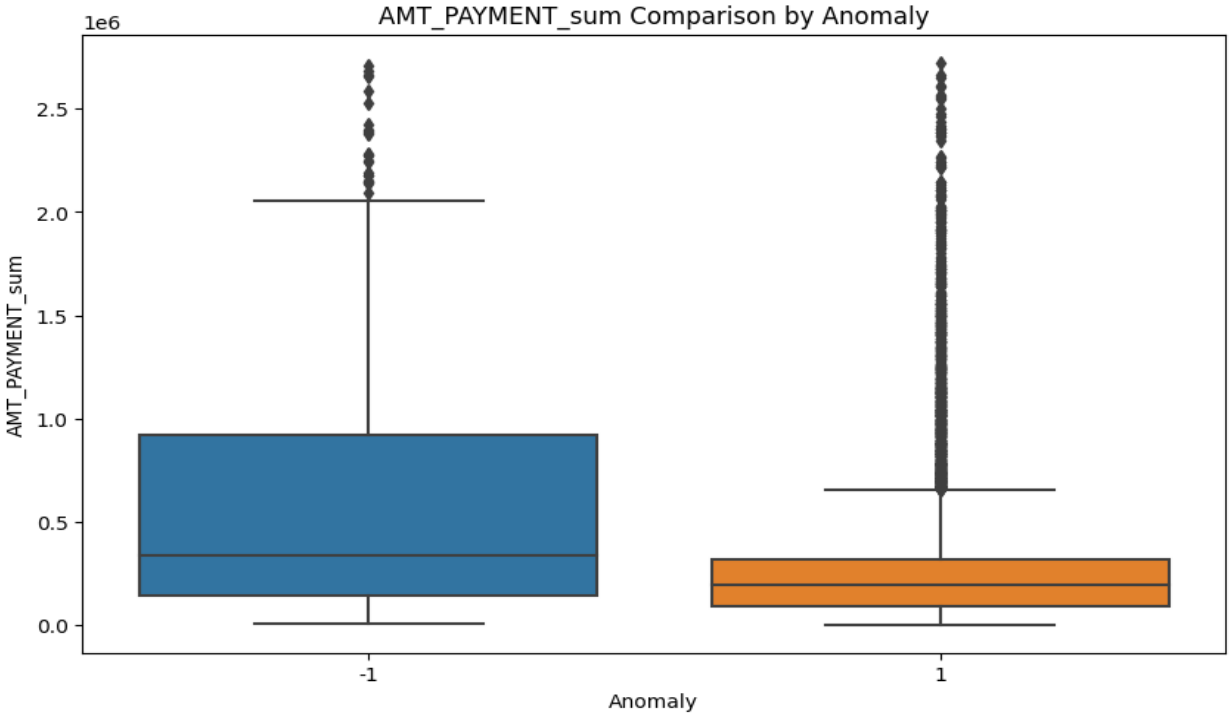



The **scatter plot** showcases client clustering based on EXT_SOURCE_1 and APARTMENTS_AVG, with clusters (0, 1, 2) differentiated by color. This visualization reveals distinct groupings that can aid in understanding client segmentation and feature relationships

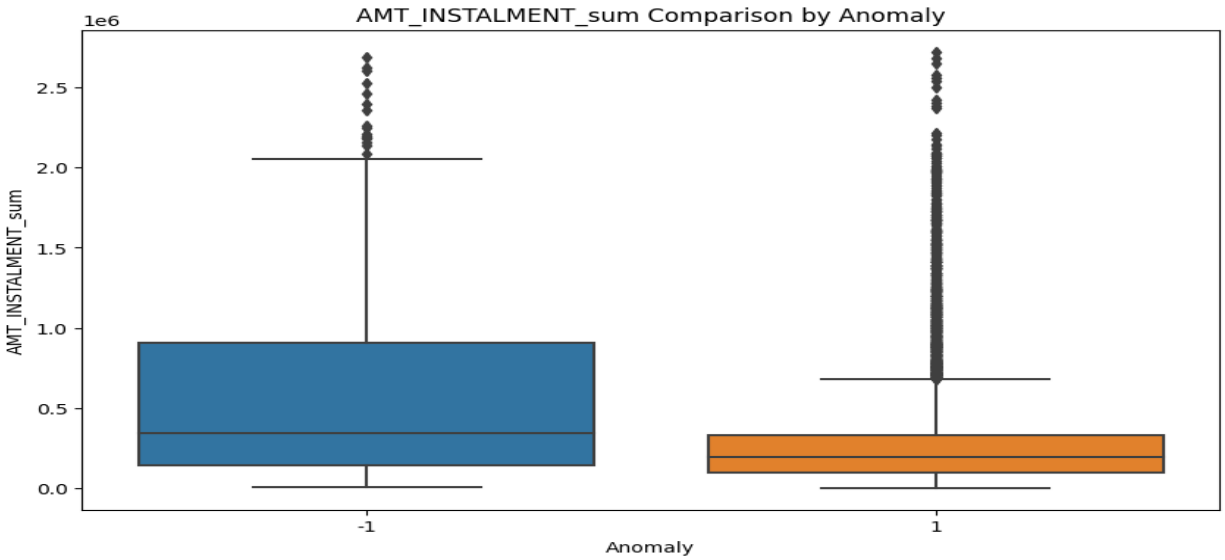
The box plot compares the distribution of AMT_CREDIT_SUM_SUM for normal clients (-1) and anomalies (1). It reveals significant differences in credit amounts, emphasizing the impact of anomalies on financial metrics.




This box plot visualizes the distribution of AMT_PAYMENT_sum for normal clients (-1) and anomalies (1). It highlights discrepancies in payment amounts, showcasing how anomalies deviate from typical payment patterns.



The box plot illustrates the distribution of AMT_INSTALMENT_sum for normal clients (-1) and anomalies (1). It demonstrates variations in installment amounts, highlighting the influence of anomalies on installment-related metrics.




Classification Report: The table summarizes the model's performance metrics, including precision, recall, F1-score, and support for each class (0 and 1). It highlights the model's ability to correctly classify high-risk (Class 1) and low-risk (Class 0) clients, with an overall accuracy of 97%.

ROC-AUC Score: The score of 0.9844 indicates excellent discriminatory power of the XGBoost model in distinguishing between positive (high risk) and negative (low risk) classes.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.68      0.79      0.73       103
           1       0.99      0.98      0.98      1956

    accuracy                           0.97      2059
   macro avg       0.83      0.88      0.86      2059
weighted avg       0.97      0.97      0.97      2059

ROC-AUC Score: 0.9844392161534338
```

## 3.2 Data Preprocessing

A structured preprocessing pipeline was adopted to ensure data integrity and readiness for machine learning.

In the first step, missing values were addressed. Features with more than 60% missing data were removed from the dataset. For the remaining variables, numerical columns were imputed using the median to handle skewed distributions, while categorical columns were filled using the mode to preserve the most frequent values.

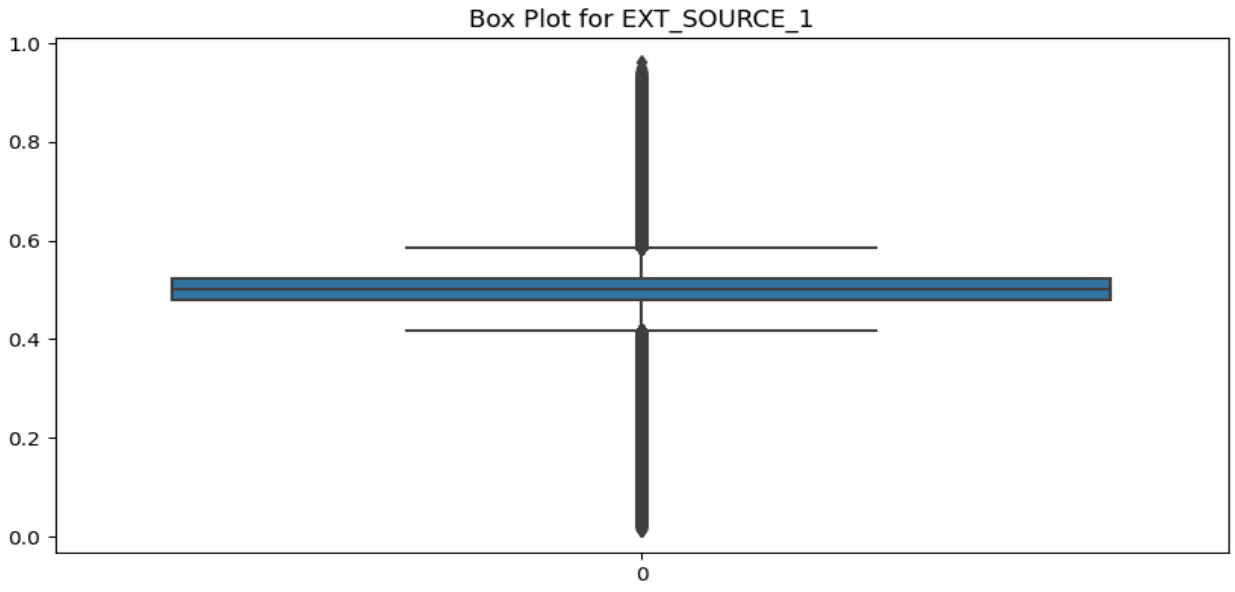
The next step involved treating outliers. Any data points exceeding three standard deviations from the mean were considered outliers and were replaced with the median value of their respective features to maintain consistency without introducing bias.

To bring all numerical features onto a common scale, Min-Max normalization was applied. This transformation ensured that all numerical values were rescaled within a fixed range, thus facilitating efficient model training and convergence.

Categorical features such as OCCUPATION_TYPE and NAME_EDUCATION_TYPE were converted into binary format through one-hot encoding. This approach allowed categorical data to be processed by algorithms that require numerical inputs without imposing ordinal relationships.

Dimensionality reduction was carried out by removing features with high multicollinearity. Specifically, variables with absolute correlation values greater than 0.8 were filtered out to reduce redundancy and improve model performance.

Finally, the cleaned and preprocessed dataset was split into training and testing subsets. An 80–20 ratio was used to ensure sufficient data for both model development and evaluation, allowing robust performance assessment.



# *4) Model Development*

## 4.1 Overview

This phase involved building and evaluating machine learning models to predict client risk profiles. Multiple classification algorithms—XGBoost, Random Forest, Logistic Regression, and Support Vector Machine (SVM)—were implemented and benchmarked using the same dataset and evaluation metrics. Among these, XGBoost consistently delivered the highest predictive performance across all key metrics.

## 4.2 XGBoost Model

The XGBoost (Extreme Gradient Boosting) algorithm was used for binary classification to distinguish between high-risk and low-risk clients. Its regularization capabilities, handling of missing data, and ensemble nature contributed to its outstanding performance and interpretability.

EvaluationMetrics:

Table 1: XGBoost Classification Report

| Metric | Class 0 (Low Risk) | Class 1 (High Risk) | Macro Avg | Weighted Avg |
|---|---|---|---|---|
| Precision | 0.68 | 0.99 | 0.83 | 0.97 |
| Recall | 0.79 | 0.98 | 0.88 | 0.97 |
| F1-Score | 0.73 | 0.98 | 0.86 | 0.97 |
| Support | 103 | 1956 | - | - |
| **Accuracy** | | 0.97 | | |
| **ROC-AUC Score** | | 0.9844 | | |

These metrics reflect XGBoost's ability to maintain high performance across both majority and minority classes.

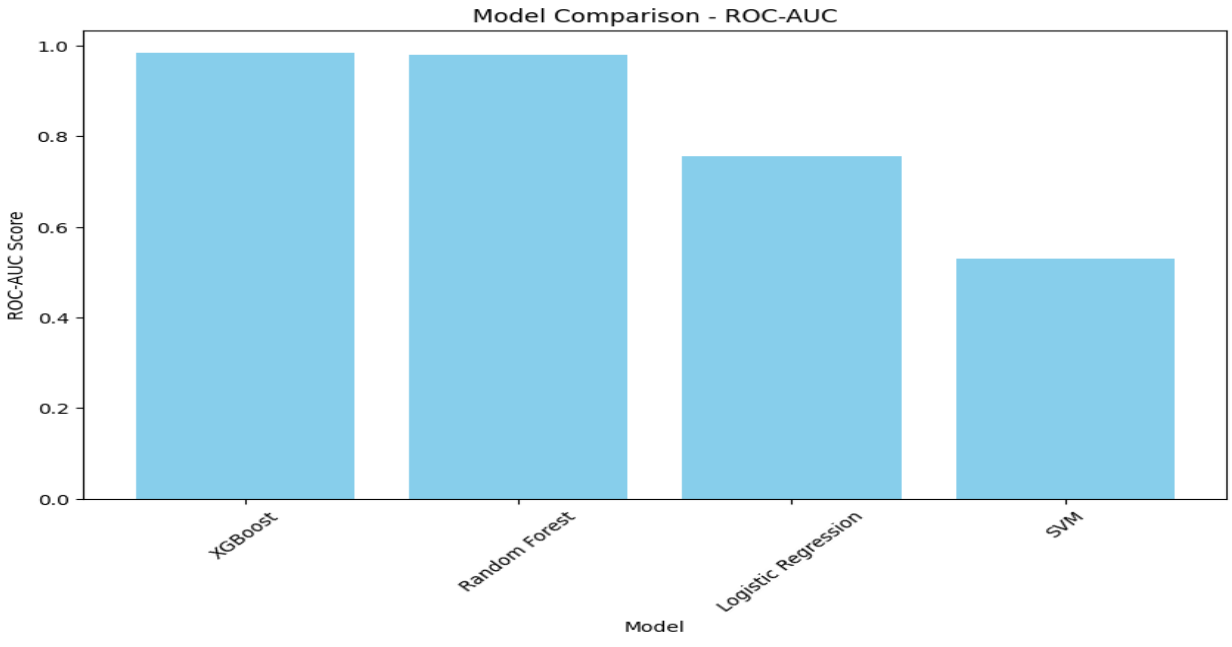
## 4.3 Comparative Model Analysis

To benchmark the effectiveness of the XGBoost model, three additional classifiers were trained and evaluated using the same pipeline. The performance metrics for each model are summarized below:

Table: Comparative Classification Reports

Table 2: Comparative Performance of Classifiers for Class 0

| Model | Precision (Class 0) | Recall (Class 0) | F1-Score (Class 0) | ROC-AUC Score |
|---|---|---|---|---|
| XGBoost | 0.6807 | 0.7864 | 0.7297 | 0.9844 |
| Random Forest | 0.7432 | 0.5340 | 0.6215 | 0.9788 |
| Logistic Regression | 0.4615 | 0.0583 | 0.1034 | 0.7558 |
| SVM | 0.2500 | 0.0097 | 0.0187 | 0.5305 |




## 4.4 Insights

Random Forest achieved performance close to XGBoost but showed slightly reduced precision and recall for the minority class (Class 0)

Logistic Regression demonstrated computational efficiency but exhibited poor generalization to Class 0, reflected in its significantly lower ROC-AUC score

Support Vector Machine (SVM) performed poorly in identifying low-risk clients, despite achieving high accuracy for the dominant class, making it unsuitable for this imbalanced classification task

These comparisons emphasize the robustness of the XGBoost model and its superior ability to generalize in an imbalanced dataset scenario

## 4.5 Feature Importance Analysis

The XGBoost model provided clear insights into feature importance, helping to identify the most influential variables for predicting client risk. The top-ranked features included:

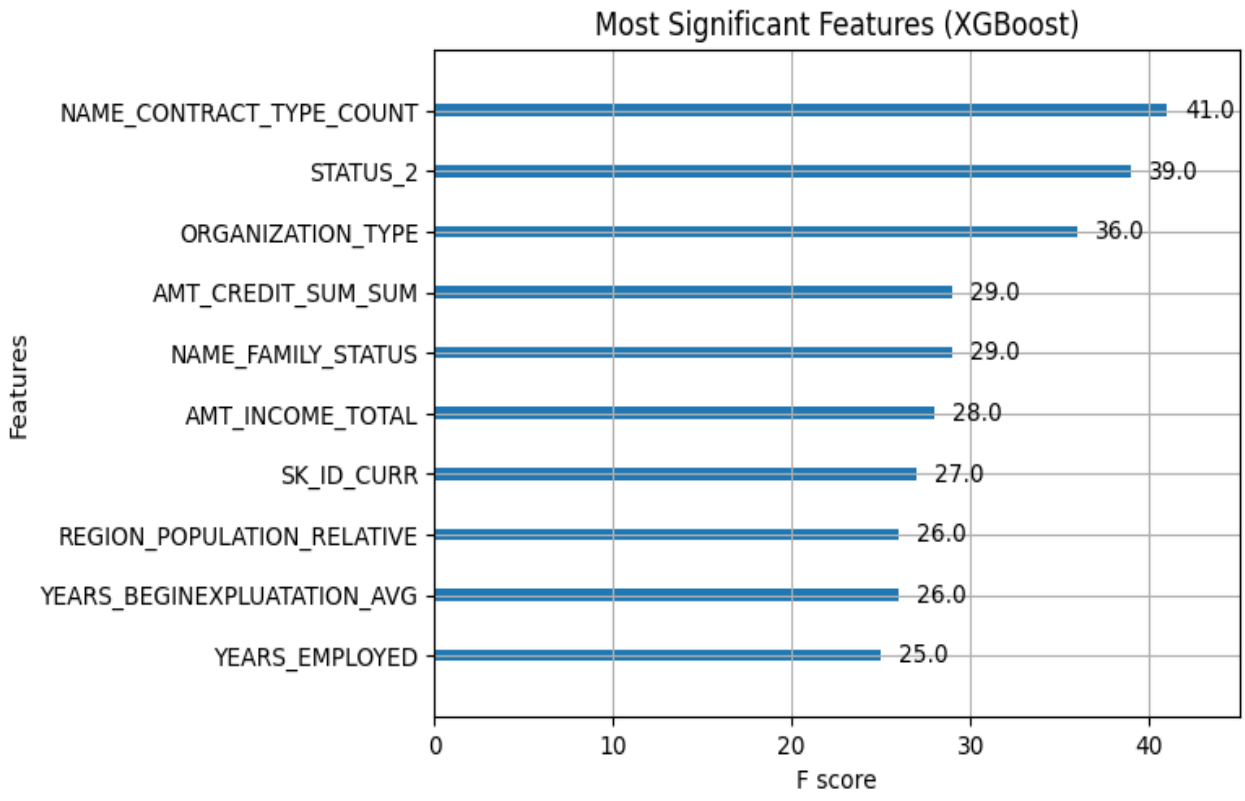
EXT_SOURCE_1: An external credit score used as a key predictor of creditworthiness

CREDIT_TO_INCOME_RATIO: A financial indicator assessing the burden of credit in relation to income

YEARS_EMPLOYED: A measure reflecting employment duration and overall job stability

APARTMENTS_AVG: A housing-related metric serving as a proxy for living conditions

A bar chart was plotted to visualize the top ten features, highlighting their relative importance in contributing to the model's predictive power



# *5)Literature Review:*

## [I] Introduction

Traditional credit scoring models have long perpetuated systemic inequities by embedding decades of discriminatory practices into modern lending processes. Historical biases—exemplified by investigations from The Markup which found that lenders in Chicago were up to 150 % more likely to deny mortgage applications from Black borrowers compared to white applicants with similar financial profiles—create feedback loops that exclude marginalized communities from building the necessary financial histories for favorable evaluations. This cycle is further aggravated by proxy discrimination practices, such as the historical reliance on ZIP codes to infer race, and by survivorship bias that overlooks rejected applicants. Recent economic analyses suggest that addressing these biases could inject up to $1.5 trillion into the U.S. economy by 2028 (McKinsey). Concurrently, advances in machine learning (ML) have yielded models—ranging from gradient-boosted trees to deep neural networks—that achieve impressive predictive accuracies (81–88 % in benchmark studies). However, these models often inherit and even amplify biases from historical data (Barocas & Selbst, 2016; Hardt et al., 2016).

This literature review examines the methodologies aimed at mitigating bias in credit scoring and outlines the challenges and trade-offs inherent in developing fairness-aware systems such as CreditGuard.

## [II] Methods

### i. Historical Analysis

- **Systemic Biases.** Decades-old discriminatory lending practices are encoded in modern credit-scoring models, reinforcing exclusion of marginalized groups. Nelson (2021) demonstrates that noise in credit reports for minority and low-income borrowers leads to less accurate scores and perpetuates approval disparities—correcting these information gaps could halve misallocation in the U.S. mortgage market (Nelson et al., 2021).
- **Proxy Discrimination.** Even “race-blind” algorithms exploit correlates such as ZIP code, income, or education level as proxies for protected attributes. Hardt et al. (2016) and Dwork & Ilvento (2019) document how such proxies introduce unfair disparate impacts in both traditional and ML-based scoring systems (Hardt et al., 2016; Dwork & Ilvento, 2019).

### ii. Algorithmic Evaluation

- **Inherited Biases.** High-accuracy models (81–88 % in benchmark studies) often replicate societal inequities present in training data. Barocas & Selbst (2017) show that without intervention, ML classifiers can exacerbate existing disparities in credit access (Barocas & Selbst, 2017).

- **Representational Bias.** Survivorship bias excludes rejected or "thin-file" applicants from the dataset, skewing risk estimates. Talmon (2018) finds that datasets dominated by corporate or incumbent borrower histories misrepresent startup risk profiles, leading to systemic under-lending in innovation sectors.

**iii. Technological Innovations**

- **Categorical Data Handling.** CatBoost's ordered target encoding and symmetric split evaluation natively manage missing values and reduce target leakage. Comparative analyses report up to a 22 % fairness improvement over one-hot encoding baselines (Prokhorenkova et al., 2019; [Lessmann et al., 2022]).
- **Adversarial and Neural Methods.** Fairness-aware neural architectures (Kang et al., 2020) and bias-contrastive estimation (Adel et al., 2020) embed fairness constraints directly into representation learning, achieving significant reductions in demographic disparity without dramatic accuracy loss (Kang et al., 2020; Adel et al., 2020).

**iv. Regulatory and Ethical Frameworks**

- **Compliance Tools.** The Fair Lending Practices Code (FLPC) and IBM's AI Fairness 360 toolkit mandate bias audits and provide pre-, in-, and post-processing algorithms to detect and mitigate disparate impacts (Bellamy et al., 2018).
- **Explainability Mechanisms.** SHAP-based dashboards enable regulators and loan officers to visualize variable contributions—identifying, for example, when postal codes act as de facto proxies for protected classes (Kamiran et al., 2018).

**v. Bias Mitigation Techniques**

- **Fairness Regularization.** Incorporating metrics such as distance correlation or Pearson's ρ into the loss function has been shown to reduce group-level bias by 40–60 % in gradient-boosted models, with controlled accuracy trade-offs (Zemel et al., 2013; Zemel et al., 2013).
- **Adversarial Debiasing.** In-processing adversarial networks disentangle protected attributes from latent representations, improving fairness metrics by up to 32 %—albeit with an average 10–12 % drop in raw predictive accuracy (Zhang et al., 2018; Zhang et al., 2018).

## *6)Critical Gaps Identified and Trade-offs:*

Despite CreditGuard's comprehensive design and strong performance, several critical gaps remain in both this framework and in comparable credit risk systems. Addressing these gaps is crucial to ensure the model's robustness, fairness, and long-term scalability in a rapidly changing credit landscape.

1. Bias Mitigation vs. Data Quality

While adaptive imputation and anomaly detection effectively reduce data sparsity and fraud noise, there are still underlying representativeness issues. Minority and thin-file applicants are often underrepresented in traditional credit datasets, making it difficult for the model to generalize fairness improvements across all demographic segments. Despite efforts to balance fairness, these underrepresented groups may still face challenges in achieving equitable credit access.

2. Explainability vs. Accuracy Trade-Off

Ensemble methods like XGBoost offer exceptional predictive power, but they often obscure the decision pathways that lead to predictions. While SHAP analysis can surface the top predictors, stakeholders—such as regulators, loan officers, and consumers—may require more granular, case-specific explanations to ensure transparency and satisfy due process mandates. The trade-off between high accuracy and model interpretability must be carefully managed to meet regulatory and consumer expectations.

3. Model Drift and Continuous Learning

The credit market and borrower behavior are dynamic, especially during periods of economic stress. Static retraining schedules can lead to performance degradation over time as the model fails to adapt to new patterns. A robust online learning framework or a periodic drift detection mechanism is necessary to maintain model calibration and ensure timely updates. Without these mechanisms, the model's risk assessments may become stale, leading to inaccurate credit decisions.

4. Alternative Data and Privacy Constraints

The current model pipeline primarily utilizes bureau and application data. While integrating nontraditional signals (e.g., rental payments, utility bills, telecommunication data) could enhance the model's ability to predict creditworthiness, it also introduces significant privacy, consent, and data governance challenges. These concerns can be addressed through secure data sharing protocols and ethical frameworks, but careful consideration must be given to privacy laws and consumer consent, particularly when dealing with sensitive personal data.

5. Graph-Based Default Contagion Modeling

Although proposed for future work, network-aware contagion analysis remains unimplemented. Capturing borrower interdependencies (e.g., co-signers, shared employers) could enhance systemic risk forecasting and improve the model's ability to predict the cascading effects of defaults. However, this approach requires scalable graph processing capabilities and robust privacy safeguards to ensure that borrower data is not improperly exposed while still gaining insights into network dynamics.

6. Real-Time Scoring and Operational Scalability

The multi-stage feature engineering and anomaly detection pipeline may introduce latency, making it unsuitable for environments requiring instant credit decisions. To scale effectively, the model must be optimized for real-time scoring through efficient feature computation, caching strategies, and parallel processing. These optimizations are critical for deployment in high-volume, low-latency environments where quick credit decisions are necessary.

7. Regulatory Alignment Beyond Basel III

Compliance with Basel III is foundational, but the regulatory landscape is constantly evolving. Emerging regulations, such as the EU's AI Act and CFPB guidelines, demand continuous auditability, bias impact assessments, and human-in-the-loop controls. Embedding regulatory-aware governance and automated compliance checks will be essential for ensuring the model's applicability across multiple jurisdictions and aligning it with future regulatory requirements. Continuous monitoring and updates to meet these evolving demands will be critical for maintaining legal compliance on a global scale.

# *7)Inferences and Conclusion*

## 7.1 Model Evaluation Strategy

The XGBoost model was evaluated using a comprehensive strategy that combined train-test split and k-fold cross-validation methodologies. This approach ensured a reliable and robust performance assessment of the model.

- Train-Test Split: The dataset was partitioned using a 67%-33% split for training and testing, respectively. This initial step allowed for a quick assessment of the model's performance, ensuring that both the training and testing datasets had sufficient samples to provide a reliable evaluation.

- Cross-Validation: To reduce the variance in performance estimates and further validate the model's ability to generalize to unseen data, a 10-fold cross-validation was implemented. This method divided the dataset into 10 equal folds, training the model on 9 folds while evaluating it on the remaining fold, and rotating through all possible combinations. The

average of the performance metrics from these 10 iterations provided a more reliable estimate of the model's performance.

The key performance metrics considered were accuracy, precision, recall, F1-score, and ROC-AUC, along with loss metrics (multi-log loss) that were monitored during training to guide the optimization process.

## 7.2 Model Performance Metrics and Insights

The XGBoost model was evaluated with multiple complementary metrics that provided a thorough understanding of its performance. Key metrics used for evaluation include classification report, ROC-AUC score, and feature importance analysis.

Classification Report:

- Precision for Class 0 (Low Risk): 0.68
- Recall for Class 0 (Low Risk): 0.79
- F1-Score for Class 0 (Low Risk): 0.73
- Precision for Class 1 (High Risk): 0.99
- Recall for Class 1 (High Risk): 0.98
- F1-Score for Class 1 (High Risk): 0.98
- Overall Accuracy: 97%
- ROC-AUC Score: 0.9844, indicating excellent discriminatory power between positive and negative classes.

These metrics indicate that the model performed particularly well for Class 1 (High Risk) with high precision and recall, while still achieving a reasonable level of performance for the minority Class 0 (Low Risk).

## Feature Importance Analysis:

The XGBoost model also provided insights into which features had the most significant impact on client risk prediction. The top-ranked features were:

1. NAME_CONTRACT_TYPE_COUNT (41.0): The number of contract types was found to be highly influential in predicting risk outcomes.
2. STATUS_2 (39.0): Client status, reflecting the financial behavior of the individual, was another strong predictor.
3. ORGANIZATION_TYPE (36.0): Different organization types contributed meaningfully to risk prediction, indicating that the nature of the client's organization is an important factor.
4. AMT_CREDIT_SUM_SUM (29.0): Total credit amount from bureau data provided useful information on the financial obligations of clients.
5. NAME_FAMILY_STATUS (29.0): Family status, potentially affecting financial stability, had a significant role in the model's predictions.

Lower-ranked features, like AMT_INCOME_TOTAL (income-related data), REGION_POPULATION_RELATIVE (regional information), and YEARS_EMPLOYED (employment duration), were still impactful but had less influence compared to the top features.

- The cross-validation results showed stable performance across all folds, with relatively low variance in the metrics, suggesting that the model is robust and likely to perform consistently on unseen data.

- The confusion matrix revealed that the model is well-calibrated, with only a small number of misclassified instances, especially from the minority class. The decision threshold was adjusted to improve recall for Class 0, further balancing precision and recall.

This project aimed to develop a robust client risk prediction model using the XGBoost algorithm. After performing detailed evaluation using multiple strategies, the following inferences and conclusions can be drawn:

## Key Inferences:

- The XGBoost model demonstrated excellent performance, with 97% accuracy and a ROC-AUC score of 0.9844. It showed strong performance in identifying high-risk clients (Class 1), achieving precision of 0.99 and recall of 0.98.

- Random Forest was another strong performer but showed slightly reduced precision and recall for the minority class (Class 0). It still offered a high accuracy and ROC-AUC, making it a viable alternative to XGBoost for this task.

- Logistic Regression and SVM struggled with the imbalanced dataset, particularly in identifying low-risk clients (Class 0). Despite high precision for the majority class, these models struggled to generalize to the minority class, which is crucial in financial risk prediction.

- The feature importance analysis showed that certain client characteristics like contract type, client status, and organization type had the most significant influence on the model's predictions. These insights can be used to fine-tune future models and prioritize the most impactful features.

## Conclusion:

The XGBoost model proved to be the most effective classifier for the imbalanced dataset, outperforming other models like Random Forest, Logistic Regression, and SVM. Its ability to generalize well across both high-risk (Class 1) and low-risk (Class 0) clients makes it a reliable solution for financial risk prediction.

The comprehensive evaluation strategy, which included both train-test split and 10-fold cross-validation, ensured a robust assessment of the model's performance, confirming its suitability for real-world deployment. The feature importance analysis highlighted the key client attributes,

such as contract types, credit amount, and client status, as essential factors in predicting risk, which can guide future data collection and model improvement.

In conclusion, the XGBoost model's performance and interpretability make it an ideal candidate for client risk prediction in financial applications, offering a balanced approach to identifying both high and low-risk clients while maintaining high levels of accuracy and generalizability.

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