CREDIT RISK LOAN

Application of Machine Learning for Credit Risk Prediction in Consumer Loans

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OUTLINE

- Project Overview

- Exploratory Data Analysis (EDA)

- Machine Learning Modelling

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PROJECT OVERVIEW

Link Full Code on GitHub

Background

Credit risk is one of the most important things that can affect the **stability and profitability** of a financial institution. If the loan is not paid as agreed, the institution can suffer a huge loss. Therefore, it is important for financial institutions to be able to **recognize and manage credit risk** well, especially during **uncertain economic conditions**.

Traditional approaches to assessing creditworthiness, such as **fixed rule-based** credit scores, tend to lack the flexibility to handle the complexity of various customer data. It also tends to be difficult to recognize **hidden patterns** or **early signs** indicating **default risk**. Therefore, a more **modern and flexible approach** is needed to support a **more accurate credit scoring** process.

Machine learning provides a modern approach that enables **in-depth data analysis** by utilizing large amounts of **historical data**. These algorithms can detect **patterns in customer behavior**, estimate the **probability of default**, and improve **decision-making accuracy**. By building reliable **predictive models**, financial institutions can **reduce exposure** to **credit risk** and **strengthen loan management** systems.

Problem Statement 1

A 12,29% of the total 460 thousand customers are still in default, indicating a high level of credit risk in the loan portfolio.

Goal 2

The objective of this project is to reduce the number of customer defaults by improving the accuracy of credit risk assessment using machine learning models.

Objective 3

Develop machine learning models to identify potentially defaulting customers, analyze factors that affect credit-worthiness, and evaluate model performance using relevant metrics.

Business Metrics 4

The objective of this project is to reduce the number of customer defaults by improving the accuracy of credit risk assessment using machine learning models.

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EXPLORATORY DATA ANALYSIS

EDA

Link Full Code on GitHub

Dataset Overview

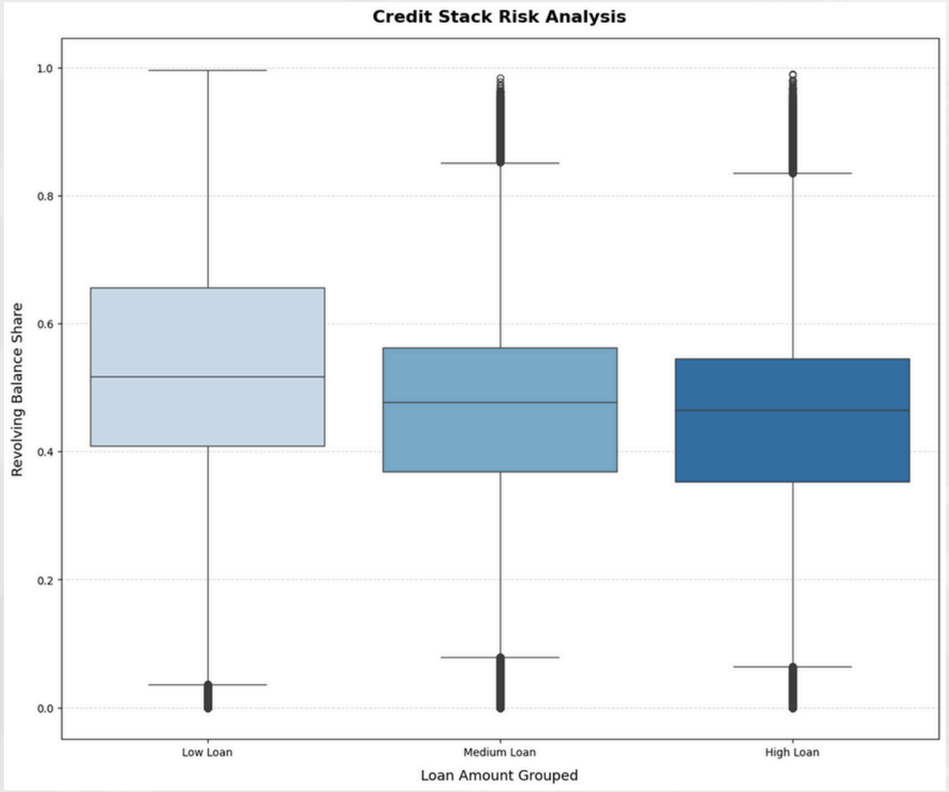
There are 466.285 rows and 70 columns

Target : 1 target variable

Features : 69 features

Link Full Code on GitHub

Credit Stack Risk Analysis



The analysis shows that the **larger the loan amount**, generally the **smaller the proportion of revolving debt** (RBS) in the borrower's total debt. This indicates that **borrowers with large loans** tend to have a **more controlled debt structure** and **rely less on consumptive debt facilities** such as credit cards.

While the **average RBS decreases as loan size increases**, there is a group of **borrowers with large loans** whose **RBS remains high**. This is an **indication of high risk**, as these borrowers are not only **carrying large loans**, but also have a **high reliance on short-term, high-interest debt**, which could be a sign of **liquidity stress** or **financial distress**.

On the other side, **borrowers with small loans show a wide variety of RBS**, so it is important **not to immediately assume that they are risk-free**. Therefore, a **thorough evaluation of their debt structure is still needed**.

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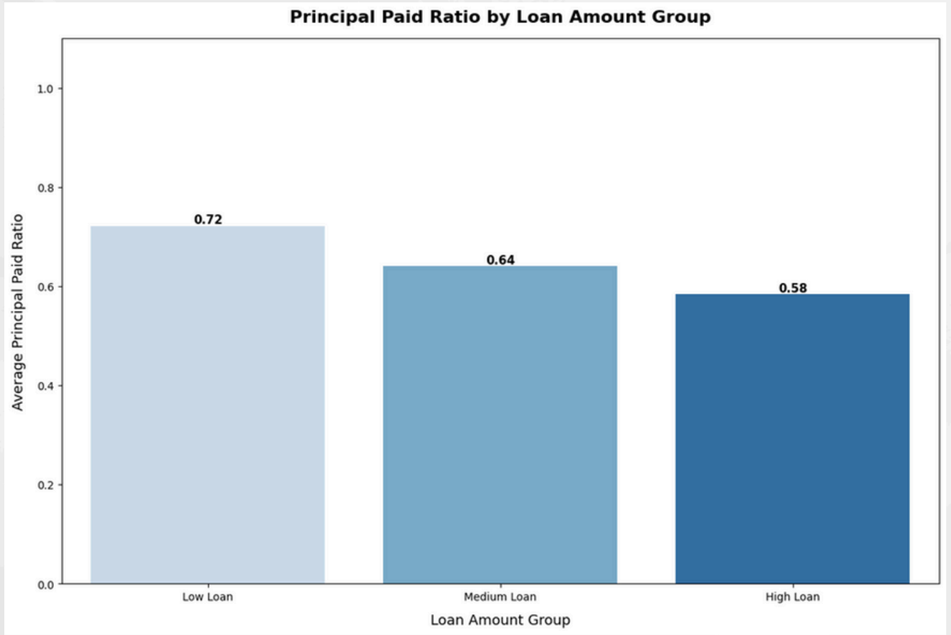
Principal Paid Ratio



The analysis shows that there is a decreasing trend in repayment progress as the loan amount increases. The **Low Loan** group had the **highest average principal repayment of 0,72**, followed by the **Medium Loan group with a ratio of 0,64**, and the **High Loan group recorded the lowest ratio of 0,58. This indicates that the larger the loan amount, the slower the repayment progress.**

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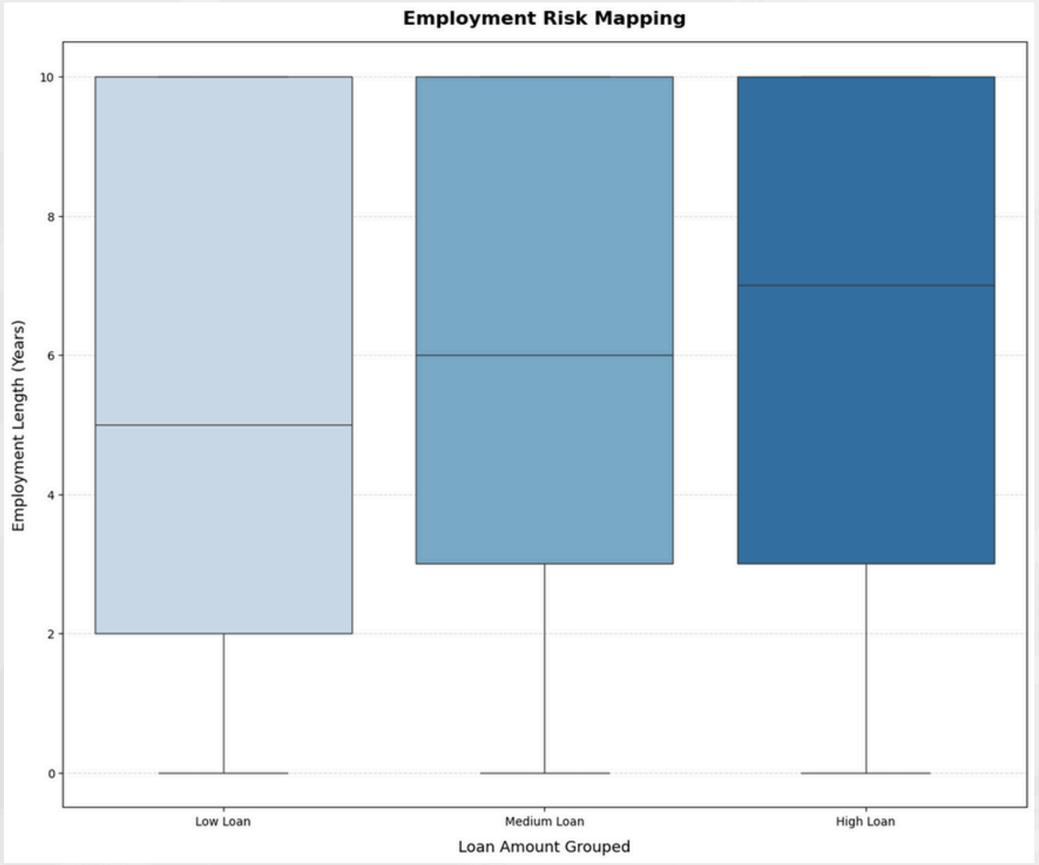
Employment Risk Mapping



The analysis shows that borrowers with larger loan amounts (High Loan) tend to have longer tenure. This is reflected in the **higher median length of employment compared to the medium and low loan groups.** This trend indicates that, **in general, borrowers with large loans have a better level of employment stability**, which can be a **positive signal in evaluating creditworthiness.**

Although the large loan group appears to be generally stable, there are still **individuals in this category who have a low length of employment, even zero years. This condition is of particular concern** because **large loans granted to individuals with low employment stability** have the **potential to increase the risk of default.**

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MACHINE LEARNING MODELLING

Link Full Code on GitHub

Data Preprocessing Workflow

1 Raw Data

The original dataset contains **466.285 rows and 70 columns of data**.

2 Check Duplicated Values

There is no duplicated data in the dataset.

3 Drop Missing Values

Delete columns that have entirely **unique values, are empty, have constant values, are redundant, or do not provide relevant information**.

4 Feature Engineering

Creating new columns, transforming the values of some columns, and **adjusting data types** to suit analysis and modeling needs.

5 Filling Missing Values

Fill the **missing values** in some columns using the **median value**, considering that the **median is more robust to outliers** than **the average**.

6 Pre-processing

Splitting the data into training and testing sets, **categorical feature transformation** with Label Encoding and One-Hot Encoding, **numerical feature standardization, relevant feature selection**, and **handling class imbalance** with oversampling techniques using SMOTE.

Modeling Workflow

1

Modeling without Hyperparameter Tuning

Running 5 machine learning algorithms, which are **Logistic Regression**, Extra Trees **Classifier**, **Random Forest**, **AdaBoost**, and **XGBoost**

2

Tuning Hyperparameter

Perform **hyperparameter tuning** using **cross-validation** of the **one best performing algorithm** to optimize the modeling results.

3

Tuned Model Comparison Model Evaluation

Perform a thorough in-person evaluation of the **selected model based on the best performance**.

Base Model Comparison

Model	Accuracy	AUC	Recall	Precision	F1-Score
Logistic Regression	82,60%	82,90%	89,80%	94,20%	91,90%
Extra Trees Classifier	91,50%	83,00%	97,10%	93,40%	95,20%
Random Forest	91,80%	83,80%	97,30%	93,60%	95,40%
AdaBoost	85,30%	82,10%	88,90%	94,00%	91,40%
XGBoost	92,40%	84,10%	98,10%	93,40%	95,70%

Of the **five algorithms used**, **XGBoost was chosen** because it **showed the highest accuracy of 92,4%**.

In addition, the **Recall value** of the model used is also high, which is an **important aspect in the context of credit risk**, given that **misclassifying a bad loan** as a good loan can lead to a **significant risk of loss**.

Link Full Code on GitHub

Hyperparameter Tuning

Model	Accuracy	AUC	Recall	Precision	F1-Score
Base XGBoost	92,40%	84,10%	98,10%	93,40%	95,70%
Tuned XGBoost	92,60%	84,20%	98,50%	93,40%	95,90%

Hyperparameter tuning improved model performance, although the improvement was **not significant**.

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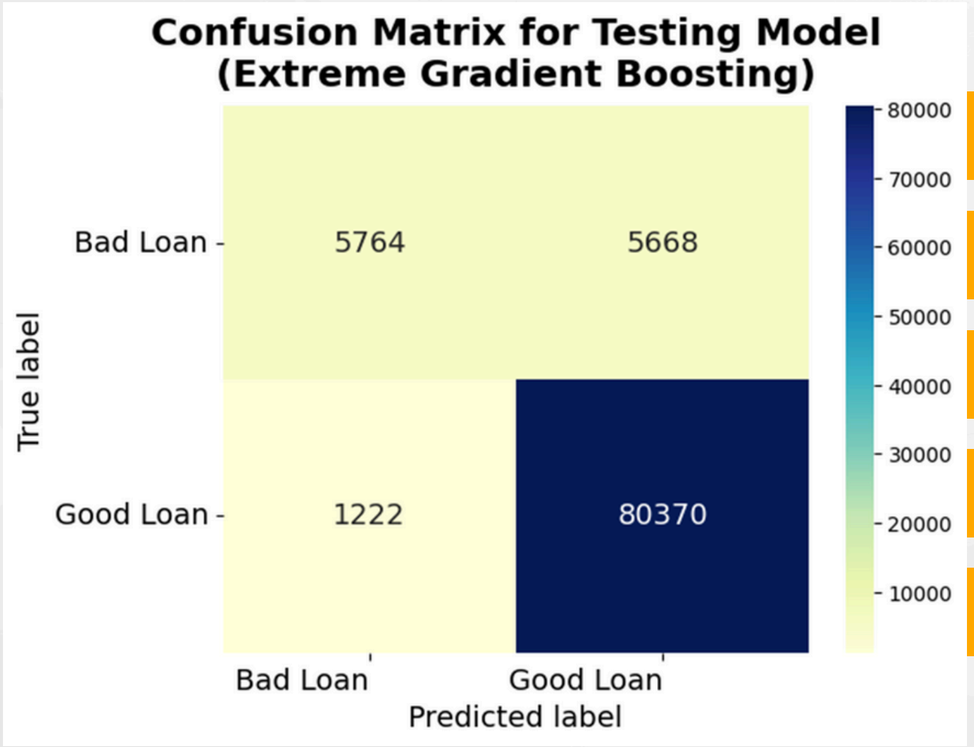
Model Evaluation



Accuracy : 92,6%

AUC : 84,2%

Recall : 98,5%

Precision : 93,4%

F1-Score : 95,9%

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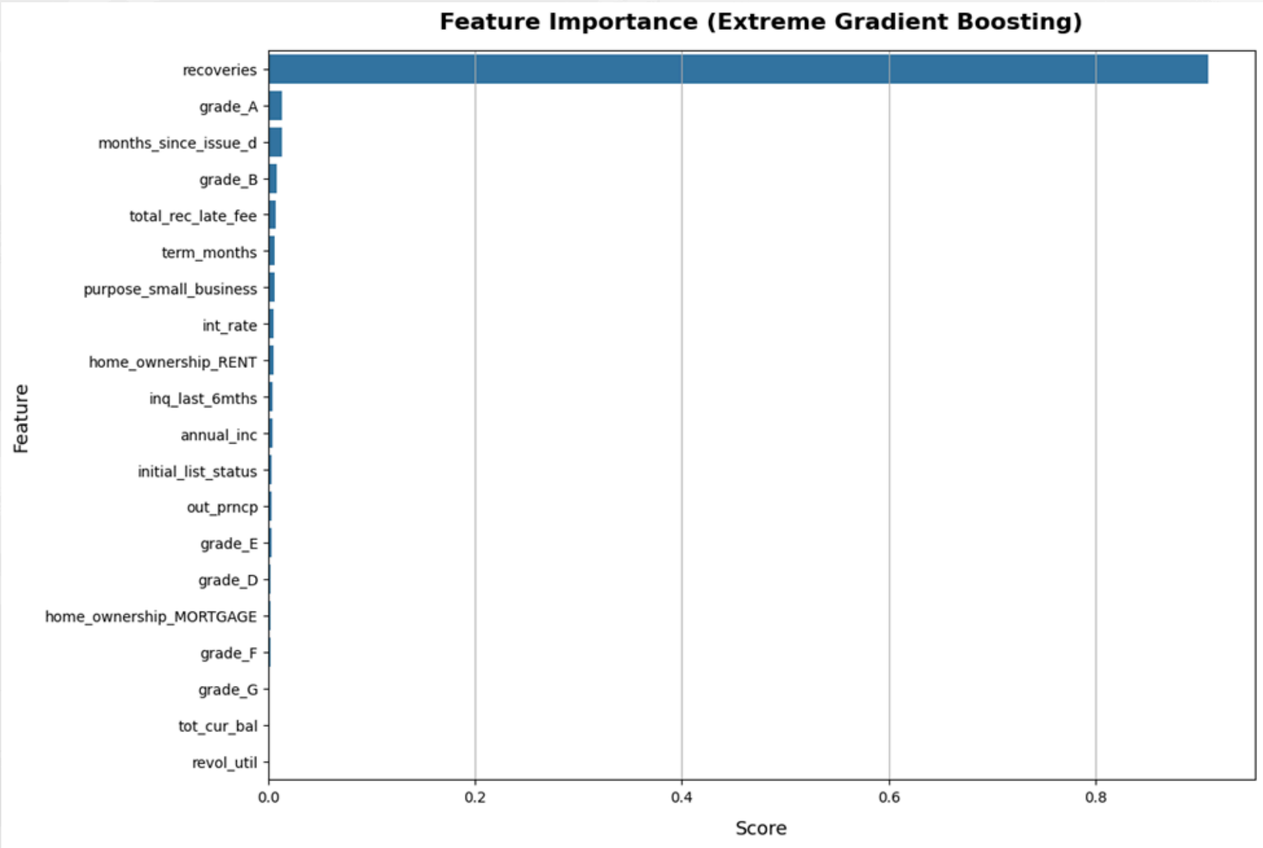
RECOMMENDATION

How Model Interpret the Data



Based on the **classification modeling results**, a number of **features** are obtained that have a **significant influence** on the **borrower's loan status**. From all available features, the **most influential features** were selected to support the **interpretation of results** and **business decision-making**. The **top five features** selected based on **their importance in predicting loan status are recoveries, grade, months_since_issue_d, total_rec_late_fee**, and **term**.

Link Full Code on GitHub

Business Recomendation

Recoveries

Recoveries provide an overview of the amount of funds recovered from non-performing loans. To **minimize potential losses due to bad debts**, companies need to build a **responsive and integrated collection system**. Therefore, it is recommended that companies **identify the characteristics of borrowers** who tend to be cooperative in the recovery process and **focus collection efforts more intensively on these groups**.

Grade

The grade assigned by the financial institution reflects the risk level of the borrower based on an internal system assessment. To strengthen risk control, **companies should adjust loan terms based on this grade**. Borrowers with low grades (e.g. A or B) can be given more competitive interest rates, while borrowers with high grades (e.g. F or G) should be charged higher interest rates or even rejected if they do not meet additional requirements such as collateral or guarantees. **This strategy will help balance the profit potential and default risk**.

Business Recomendation

months_since_issue_d

New loans generally do not show a consistent payment pattern, which **increases the level of uncertainty of default risk**. Therefore, companies need to implement a **strict monitoring system for loans less than six months old**. This enables **quick decisions** to be made if there are **indications of delays or violations**, such as through sending **early warnings** or providing **financial education sessions** to borrowers.

total_rec_late_fee

The higher the late fees paid by borrowers, the greater the risk they exhibit. This information can be utilized by companies to assess subsequent creditworthiness and **categorize borrowers into appropriate risk categories. For active loans, borrowers with a history of repeated delinquency should be given special attention**, such as through **sending automated alerts, providing financial counseling**, or **limiting future loan ceilings**.

Business Recomendation

term

Term, whether 36 months or 60 months, has a **direct impact on the level of credit risk**. Loans with **longer tenors tend to have a higher probability of default** due to the **increased uncertainty of economic conditions** over a longer period of time. Therefore, companies are advised to provide **incentives**, such as **lower interest rates**, to borrowers who choose **short tenors**. Meanwhile, **for loans with long tenors**, additional verification processes need to be carried out, such as assessment of **employment history**, **income stability**, and the borrower's **ability to meet long-term payment obligations**.

THANK YOU

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