

An Assessment Report

on

"Problem Statement"

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

in

CSEAI

By

Tanmay Kesharwani (202401100300261)

Under the supervision of

"MR. ABHISHEK SHUKLA"

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Introduction

In the modern financial ecosystem, lending institutions face significant risks when providing loans to individuals. One of the critical challenges is predicting whether a borrower is likely to default on a loan. Accurately identifying such risks not only safeguards financial institutions but also contributes to the health of the economy.

This project focuses on building a machine learning model that predicts loan default using various borrower-related features like income, credit score, employment status, loan purpose, and more.

Methodology

Our approach followed these major steps:

1. Data Exploration

- Dataset includes borrower data such as CreditScore, Income, LoanAmount, etc.
- The target variable is Default (1 for default, 0 for no default).

2. Data Preprocessing

- Missing Values: Dropped for simplicity.
- Encoding: Label Encoding was applied to categorical variables.
- Splitting: Dataset split into 80% training and 20% testing sets.

3. Model Selection

 Chose Random Forest Classifier due to its efficiency on tabular datasets and ability to handle both linear and nonlinear relationships.

4. Evaluation Metrics

Accuracy, Precision, and Recall were used to evaluate performance.

5. Confusion Matrix

• Used a heatmap to visualize true positives, false positives, true negatives, and false negatives.

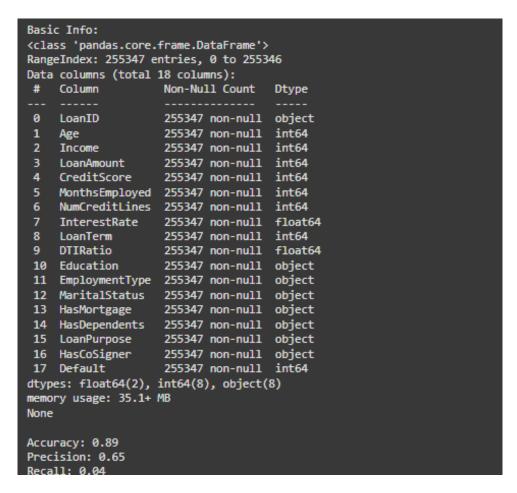
Code

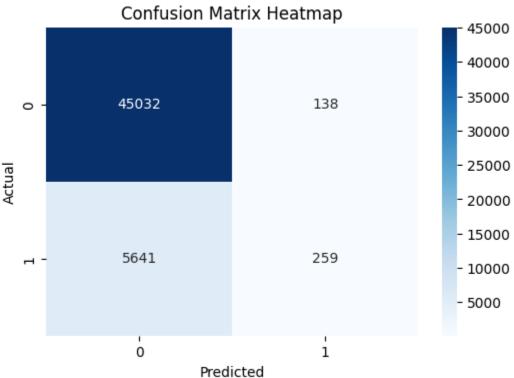
```
from google.colab import files
uploaded = files.upload()
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score
# 1. Load dataset
df = pd.read_csv("Predict Loan Default.csv")
print("First 5 rows:\n", df.head())
# 2. Data Info
print("\nBasic Info:")
print(df.info())
# 3. Handle missing values (drop or fill)
df = df.dropna() # for simplicity
# 4. Encode categorical variables (if any)
le = LabelEncoder()
for col in df.select_dtypes(include=['object']).columns:
  df[col] = le.fit_transform(df[col])
# 5. Separate features and target
```

```
X = df.drop('Default', axis=1) # replace 'Loan_Default' with actual column name if different
y = df['Default']
# 6. Split data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
#7. Train a classifier
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
# 8. Predict and Evaluate
y_pred = model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
print(f"\nAccuracy: {acc:.2f}")
print(f"Precision: {prec:.2f}")
print(f"Recall: {rec:.2f}")
# 9. Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
# 10. Heatmap
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

Output

| First 5 rows: | | | | | | | | |
|---------------|--|-----|------------|-------------|-------------|-------------|------|---|
| | LoanID | Age | Income | LoanAmount | CreditScore | MonthsEmplo | oyed | \ |
| 0 | I38PQUQS96 | 56 | 85994 | 50587 | 520 | | 80 | |
| 1 | HPSK72WA7R | 69 | 50432 | 124440 | 458 | | 15 | |
| 2 | C10Z6DPJ8Y | 46 | 84208 | 129188 | 451 | | 26 | |
| 3 | V2KKSFM3UN | 32 | 31713 | 44799 | 743 | | 0 | |
| 4 | EY08JDHTZP | 60 | 20437 | 9139 | 633 | | 8 | |
| | | | | | | | | |
| | NumCreditLin | es | InterestRa | ate LoanTer | m DTIRatio | Education | \ | |
| 0 | | 4 | 15 | .23 3 | 6 0.44 | Bachelor's | | |
| 1 | | 1 | 4 | .81 6 | 0.68 | Master's | | |
| 2 | | 3 | 21 | .17 2 | 4 0.31 | Master's | | |
| 3 | | 3 | 7 | .07 2 | 4 0.23 | High School | | |
| 4 | | 4 | 6 | .51 4 | 8 0.73 | Bachelor's | | |
| | | | | | | | | |
| | EmploymentType MaritalStatus HasMortgage HasDependents LoanPurpo | | | | ose | \ | | |
| 0 | Full-tim | e | Divorce | ed Y | 'es | Yes Ot | ther | |
| 1 | Full-tim | e | Marri | ed | No | No Ot | ther | |
| 2 | Unemploye | d | Divorce | ed Y | 'es | Yes A | Auto | |
| 3 | Full-tim | e | Marri | ed | No | No Busir | ness | |
| 4 | Unemploye | d | Divorce | ed | No | Yes A | Auto | |
| | | | | | | | | |
| | HasCoSigner Default | | | | | | | |
| 0 | Yes | | 0 | | | | | |
| 1 | Yes | | 0 | | | | | |
| 2 | No | | 1 | | | | | |
| 3 | No | | 0 | | | | | |
| 4 | No | | 0 | | | | | |





References / Credits

- Dataset Source: Provided for academic use (uploaded by project author).
- Libraries Used: pandas, numpy, matplotlib, seaborn, sklearn