Assesment Report

on

"Predict Loan Default"

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

in

B-Tech(CSE-AI)

By

Shobhit Tripathi (202401100300237)

Under the supervision of

Mr. Abhishek Shukla

KIET Group of Institutions, Ghaziabad

Affiliated to

Dr. A.P.J. Abdul Kalam Technical University, Lucknow

(Formerly UPTU)

18 April, 2025

Introduction

The goal of this project is to predict whether a borrower will default on a loan using historical financial data, credit scores, and other relevant borrower attributes. Loan defaults represent a significant challenge for financial institutions, often leading to substantial financial losses. Accurately identifying high-risk borrowers before issuing a loan can help minimize this risk and improve overall portfolio health. This classification problem is well-suited for machine learning, where patterns in past data can be used to forecast future defaults. By building a predictive model, we aim to assist lenders in making more informed and data-driven decisions, ultimately enhancing the reliability and security of the lending process.

Methodology

To solve the loan default prediction problem, we followed a structured machine learning pipeline. We began by cleaning and preprocessing the dataset, including handling missing values, encoding categorical variables, and converting binary responses into numerical format. After preparing the data, we performed exploratory data analysis (EDA) to understand feature distributions and correlations. The dataset was then split into training and testing sets, and a Random Forest Classifier was chosen for its robustness and ability to handle both numerical and categorical features. The model was trained on the processed data and evaluated using metrics such as accuracy, classification report, and ROC AUC score. Additionally, we analyzed feature importance to identify which variables contributed most to the prediction of loan defaults. This end-to-end approach ensures a reliable and interpretable model for classifying borrower risk.

CODE

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

import gc


from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import classification_report, roc_auc_score, roc_curve


# Show plots inline

%matplotlib inline


# Load the dataset (adjust path as needed)

data = pd.read_csv('1. Predict Loan Default.csv', nrows=10000)


# Strip whitespace from column names

data.columns = data.columns.str.strip()


# Check target and column names

print("Columns:", data.columns.tolist())


# Target variable

target_column = 'Default'


# Fill missing values

data.ffill(inplace=True)
```

```python
# Convert binary 'Yes'/'No' columns to 1/0
binary_cols = ['HasMortgage', 'HasDependents', 'HasCoSigner']
for col in binary_cols:
    if col in data.columns:
        data[col] = data[col].map({'Yes': 1, 'No': 0})

# Encode categorical variables
categorical_cols = ['LoanPurpose', 'Education', 'EmploymentType', 'MaritalStatus']
for col in categorical_cols:
    if col in data.columns:
        top_categories = data[col].value_counts().nlargest(4).index
        data[col] = data[col].where(data[col].isin(top_categories), 'Other')
        data = pd.get_dummies(data, columns=[col], drop_first=True)

# Drop LoanID if present
if 'LoanID' in data.columns:
    data.drop('LoanID', axis=1, inplace=True)

# Ensure all columns are numeric
non_numeric_cols = data.select_dtypes(include=['object']).columns
if len(non_numeric_cols) > 0:
    print("Warning: Non-numeric columns present:", non_numeric_cols.tolist())

# Downcast numeric columns to save memory
for col in data.select_dtypes(include=['float64', 'int64']).columns:
    data[col] = pd.to_numeric(data[col], downcast='float')

gc.collect()
```

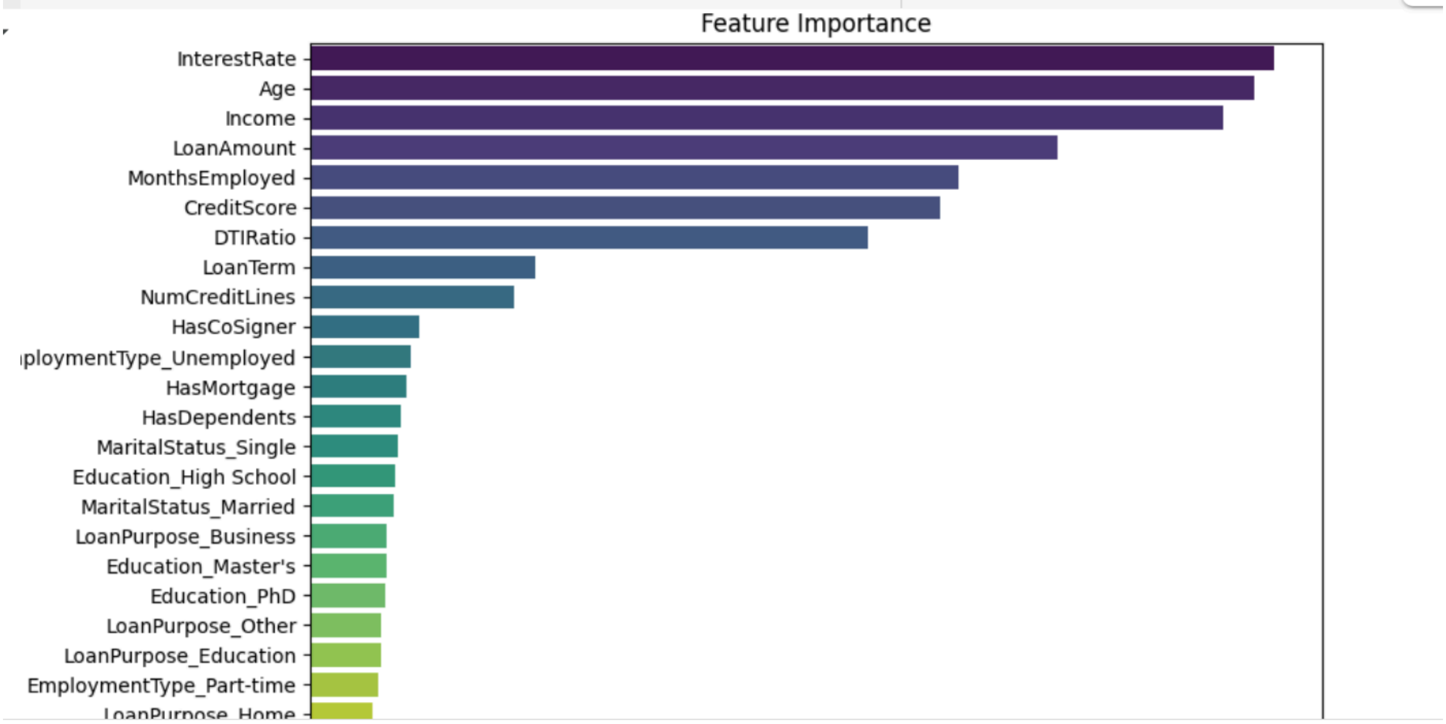
```python
# Split data
X = data.drop(target_column, axis=1)
y = data[target_column]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train model
model = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=42)
model.fit(X_train, y_train)

# Evaluate
y_pred = model.predict(X_test)
y_proba = model.predict_proba(X_test)[:, 1]

print("✅ Classification Report:")
print(classification_report(y_test, y_pred))
print("✅ ROC AUC Score:", roc_auc_score(y_test, y_proba))

# ==========================
# 📊 VISUALIZATIONS
# ==========================

# Feature importance
plt.figure(figsize=(10, 6))
importances = model.feature_importances_
indices = np.argsort(importances)[::-1]
features = X.columns[indices]
sns.barplot(x=importances[indices], y=features, palette='viridis')
plt.title('Feature Importance')
plt.xlabel('Importance')
```

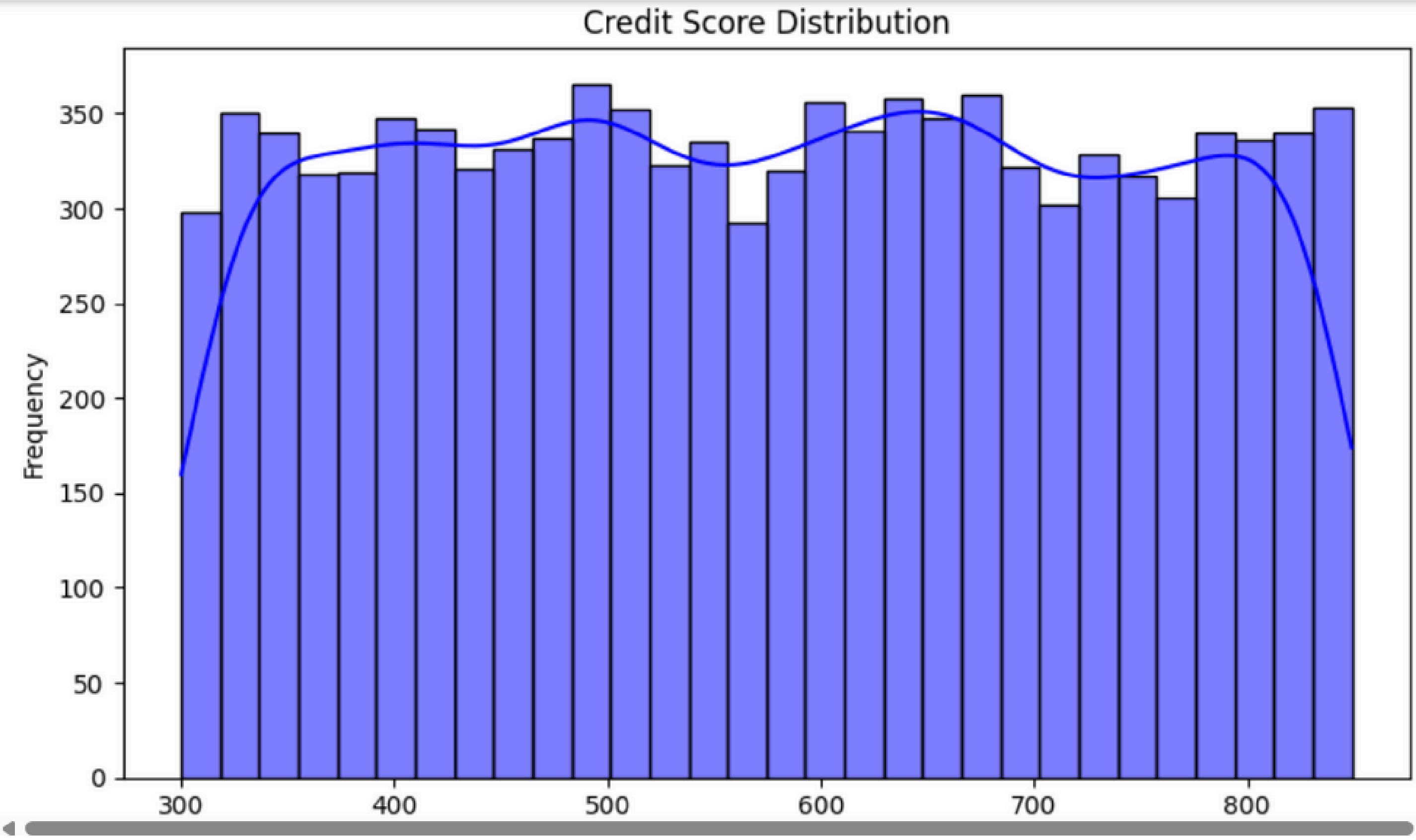
```python
plt.ylabel('Features')

plt.tight_layout()

plt.show()


# Credit Score distribution

if 'CreditScore' in data.columns:

    plt.figure(figsize=(8, 5))

    sns.histplot(data['CreditScore'], kde=True, bins=30, color='blue')

    plt.title('Credit Score Distribution')

    plt.xlabel('Credit Score')

    plt.ylabel('Frequency')

    plt.tight_layout()

    plt.show()


# Correlation heatmap

plt.figure(figsize=(12, 8))

sns.heatmap(data.corr(), annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)

plt.title("Correlation Heatmap")

plt.tight_layout()

plt.show()


# ROC Curve

fpr, tpr, _ = roc_curve(y_test, y_proba)

plt.figure(figsize=(8, 6))

plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc_score(y_test, y_proba)))

plt.plot([0, 1], [0, 1], 'k--')

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')
```

```
plt.title('ROC Curve')

plt.legend()

plt.grid(True)

plt.tight_layout()

plt.show()
```

Output

```
['LoanID', 'Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTerm', 'DTIRatio', 'Education', 'EmploymentType'
sification Report:
       precision    recall  f1-score   support

 0.0       0.88      1.00      0.94      1762
 1.0       1.00      0.00      0.01       238

racy                           0.88      2000
 avg       0.94      0.50      0.47      2000
 avg       0.90      0.88      0.83      2000

AUC Score: 0.733007277826
-input-12-8e4d351572c8>:84: FutureWarning:

`palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

rplot(x=importances[indices], y=features, palette='viridis')
```




Credit Score Distribution
Frequency
0
50
100
150
200
250
300
350
300
400
500
600
700
800

Credits

1.Google Colab for its environment to run code and generate output.