About the Dataset

CodeAlpha ML Project 1

Credit Score Classification

> Name:**SAYAB GULFARAZ**

> Intern - ID: **CA/S1/1492**

Objective:

- Build models that predict credit scores (categorized as "Good", "Standard", or "Poor") using historical credit data.
- Enhance credit risk assessment methodologies, allowing lenders to make more informed decisions.

Dataset:

- Train Data: 100,000 rows with various financial and personal features, such as: o Age, Occupation, Annual Income, Monthly Salary, Credit Card count, Loan details, and Payment Behavior.
- Test Data: 50,000 rows for evaluating the model performance.

Data Preprocessing:

- Missing Values: Addressed by imputing means for numerical columns and encoding categorical variables (e.g., month and occupation).
- Feature Engineering: Transforming categorical features (e.g., occupation, payment behavior) into numerical values and scaling numerical features (e.g., income, debt).
- Handling Outliers: Dealing with outliers like unrealistic ages (e.g., '-500') and cleaning unnecessary values.

Modeling:

- • Two machine learning models were trained: o Extreme Gradient Boosting (XGBClassifier): Achieved an accuracy of around 70.6%. o Light Gradient Boosting Machine (LGBMClassifier): Performed better, with an accuracy of 72.9% and a lower log loss (0.59 vs. 0.64 for XGB).

Evaluation:

• Confusion Matrix: Analyzed model performance in predicting "Good", "Standard", and "Poor" scores. • ROC Curves: Evaluated how well the models distinguish between different classes. • Accuracy & Log Loss: LightGBM showed superior performance, making it the best-suited model for this task.

Deployment:

• The trained LGBM model is applied to the test dataset to predict credit scores. • The predicted scores are added to the test data and saved for further analysis.

Visualization:

• Count plots and correlation heatmaps were used to visualize relationships between different features and credit scores, helping to better understand the dataset

Dataset Size

1. train.csv - 100000 rows
2. test.csv - 50000 rows

Columns

- ID: Unique identifier for each record in the dataset.

- Customer_ID: Unique identifier for each customer.
- Month: The month for which the financial data is recorded.
- Name: Name of the individual.
- Age: Age of the individual.
- SSN: Social Security Number, a unique identifier for individuals in the U.S.
- Occupation: The occupation or profession of the individual.
- Annual_Income: Annual income of the individual.
- Monthly_Inhand_Salary: Net monthly salary after deductions.
- Num_Bank_Accounts: Number of bank accounts held by the individual.
- Num_Credit_Card: Number of credit cards owned by the individual.
- Interest_Rate: Interest rate associated with financial transactions.
- Num_of_Loan: Number of loans the individual has.
- Type_of_Loan: The type of loan(s) the individual has.
- Delay_from_due_date: Delay in payments from the due date.
- Num_of_Delayed_Payment: Number of delayed payments.
- Changed_Credit_Limit: Whether there has been a change in credit limit.
- Num_Credit_Inquiries: Number of credit inquiries made.
- Credit_Mix: The mix of different types of credit.
- Outstanding_Debt: Amount of outstanding debt.
- Credit_Utilization_Ratio: Ratio of credit used to the total credit available.
- Credit_History_Age: Age of credit history.
- Payment_of_Min_Amount: Payment behavior regarding the minimum amount due.
- Total_EMI_per_month: Total Equated Monthly Installment (EMI) payments.
- Amount_invested_monthly: Amount invested by the individual monthly.
- Payment_Behaviour: Behavior related to payment patterns.
- Monthly_Balance: Monthly balance in the account.
- Credit_Score: The credit score assigned to the individual based on various factors.

Data Pre-Processing

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score,classification_report,confusion_matrix
```

```
df = pd.read_csv("train.csv",low_memory=False)
```

```
df.head()
```

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Credit_M
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3	...	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3	...	Goo
2	0x1604	CUS_0xd40	March	Aaron Maashoh	-500	821-00-0265	Scientist	19114.12	NaN	3	...	Goo
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3	...	Goo
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3	...	Goo

5 rows × 28 columns

```
print('Train Data Size : ',df.shape)
```

```
Train Data Size :  (23557, 28)
```

```
df.columns
```

```
Index(['ID', 'Customer_ID', 'Month', 'Name', 'Age', 'SSN', 'Occupation',
       'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
       'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan', 'Type_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Limit',
       'Num_Credit_Inquiries', 'Credit_Mix', 'Outstanding_Debt',
       'Credit_Utilization_Ratio', 'Credit_History_Age',
       'Payment_of_Min_Amount', 'Total_EMI_per_month',
       'Amount_invested_monthly', 'Payment_Behaviour', 'Monthly_Balance',
       'Credit_Score'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23557 entries, 0 to 23556
Data columns (total 28 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   ID                        23557 non-null  object
 1   Customer_ID               23557 non-null  object
 2   Month                     23557 non-null  object
 3   Name                      21208 non-null  object
 4   Age                       23557 non-null  object
 5   SSN                       23557 non-null  object
 6   Occupation                23557 non-null  object
 7   Annual_Income             23557 non-null  object
 8   Monthly_Inhand_Salary     20024 non-null  float64
 9   Num_Bank_Accounts         23557 non-null  int64
 10  Num_Credit_Card           23557 non-null  int64
 11  Interest_Rate             23557 non-null  int64
 12  Num_of_Loan               23557 non-null  object
 13  Type_of_Loan              20949 non-null  object
 14  Delay_from_due_date       23557 non-null  int64
 15  Num_of_Delayed_Payment    21894 non-null  object
 16  Changed_Credit_Limit      23557 non-null  object
 17  Num_Credit_Inquiries      23091 non-null  float64
 18  Credit_Mix                23557 non-null  object
 19  Outstanding_Debt          23557 non-null  object
 20  Credit_Utilization_Ratio  23557 non-null  float64
 21  Credit_History_Age        21356 non-null  object
 22  Payment_of_Min_Amount     23556 non-null  object
 23  Total_EMI_per_month       23556 non-null  float64
 24  Amount_invested_monthly   22516 non-null  object
 25  Payment_Behaviour         23556 non-null  object
 26  Monthly_Balance           23259 non-null  object
 27  Credit_Score              23556 non-null  object
dtypes: float64(4), int64(4), object(20)
memory usage: 5.0+ MB
```

```
df.isnull().sum()
```

```
ID                          0
Customer_ID                 0
Month                       0
Name                     2349
Age                         0
SSN                         0
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary    3533
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
Type_of_Loan             2608
Delay_from_due_date         0
Num_of_Delayed_Payment   1663
Changed_Credit_Limit        0
Num_Credit_Inquiries      466
Credit_Mix                  0
Outstanding_Debt            0
Credit_Utilization_Ratio    0
Credit_History_Age       2201
Payment_of_Min_Amount       1
Total_EMI_per_month         1
Amount_invested_monthly  1041
Payment_Behaviour           1
Monthly_Balance           298
Credit_Score                1
dtype: int64
```

Dataset consists of missing values.

```
# Drop unnecessary columns
df.drop(["ID","Customer_ID","Name","SSN","Type_of_Loan"],axis=1,inplace=True)
```

```
df.isnull().sum()
```

```
Month                       0
Age                         0
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary    3533
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
Delay_from_due_date         0
Num_of_Delayed_Payment   1663
Changed_Credit_Limit        0
Num_Credit_Inquiries      466
Credit_Mix                  0
Outstanding_Debt            0
Credit_Utilization_Ratio    0
Credit_History_Age       2201
Payment_of_Min_Amount       1
Total_EMI_per_month         1
Amount_invested_monthly  1041
Payment_Behaviour           1
Monthly_Balance           298
Credit_Score                1
dtype: int64
```

There are still features that comprise of missing values. The categorical features must be converted to numerical in order to fill missing data

```
## Finding the numerical and categorical columns
cat_cols = [feature for feature in df.columns if df[feature].dtypes == 'O']
num_cols = [feature for feature in df.columns if feature not in cat_cols]
```

```
## Finding the unique values in each of the categorical feature columns
for feature in cat_cols:
    print(f"{feature}:")
    print(f"Number of unique values in the {feature}: {df[feature].nunique()}")
    print(f"Unique values: {df[feature].unique()}")
    print('\n')
```

```
 '22 Years and 9 Months' '22 Years and 10 Months' '23 Years and 1 Months'
 '22 Years and 2 Months' '15 Years and 4 Months' '15 Years and 5 Months'
 '15 Years and 6 Months' '15 Years and 7 Months' '15 Years and 8 Months'
 '15 Years and 9 Months' '15 Years and 10 Months' '15 Years and 11 Months'
 '2 Years and 3 Months' '2 Years and 4 Months' '2 Years and 5 Months'
 '2 Years and 6 Months' '2 Years and 7 Months' '2 Years and 8 Months'
 '2 Years and 9 Months' '2 Years and 10 Months' '2 Years and 0 Months'
 '16 Years and 2 Months' '16 Years and 3 Months' '22 Years and 8 Months'
 '9 Years and 5 Months' '9 Years and 7 Months' '9 Years and 8 Months'
 '9 Years and 9 Months' '11 Years and 11 Months' '12 Years and 0 Months'
 '12 Years and 1 Months' '24 Years and 2 Months' '16 Years and 0 Months'
 '16 Years and 1 Months' '14 Years and 7 Months' '25 Years and 4 Months'
 '15 Years and 3 Months' '7 Years and 1 Months' '7 Years and 2 Months'
 '7 Years and 3 Months' '7 Years and 4 Months' '7 Years and 5 Months'
 '23 Years and 7 Months' '23 Years and 8 Months' '23 Years and 9 Months'
 '30 Years and 1 Months' '29 Years and 10 Months' '9 Years and 10 Months'
 '9 Years and 11 Months' '10 Years and 0 Months' '2 Years and 2 Months'
 '23 Years and 10 Months' '23 Years and 11 Months' '24 Years and 0 Months'
 '24 Years and 1 Months' '6 Years and 4 Months' '0 Years and 1 Months'
 '0 Years and 2 Months' '0 Years and 3 Months' '0 Years and 7 Months'
 '3 Years and 8 Months' '32 Years and 7 Months' '3 Years and 7 Months'
 '3 Years and 9 Months' '3 Years and 10 Months' '0 Years and 11 Months'
 '1 Years and 0 Months' '1 Years and 1 Months' '4 Years and 4 Months'
 '3 Years and 11 Months' '4 Years and 0 Months' '4 Years and 1 Months'
 '4 Years and 2 Months' '4 Years and 3 Months' '2 Years and 1 Months'
 '4 Years and 11 Month']


Payment_of_Min_Amount:
Number of unique values in the Payment_of_Min_Amount: 3
Unique values: ['No' 'NM' 'Yes' nan]


Amount_invested_monthly:
Number of unique values in the Amount_invested_monthly: 21469
Unique values: ['80.41529543900253' '118.28022162236736' '81.699521264648' ...
 '26.043795006084828' '182.10660460740283' '55.55475710191636']


Payment_Behaviour:
Number of unique values in the Payment_Behaviour: 7
Unique values: ['High_spent_Small_value_payments' 'Low_spent_Large_value_payments'
 'Low_spent_Medium_value_payments' 'Low_spent_Small_value_payments'
 'High_spent_Medium_value_payments' '!@9#%8'
 'High_spent_Large_value_payments' nan]


Monthly_Balance:
Number of unique values in the Monthly_Balance: 23259
Unique values: ['312.49408867943663' '284.62916249607184' '331.2098628537912' ...
 '317.67419532677604' '191.61138572545798' '298.1632332309445']


Credit_Score:
Number of unique values in the Credit_Score: 3
Unique values: ['Good' 'Standard' 'Poor' nan]
```

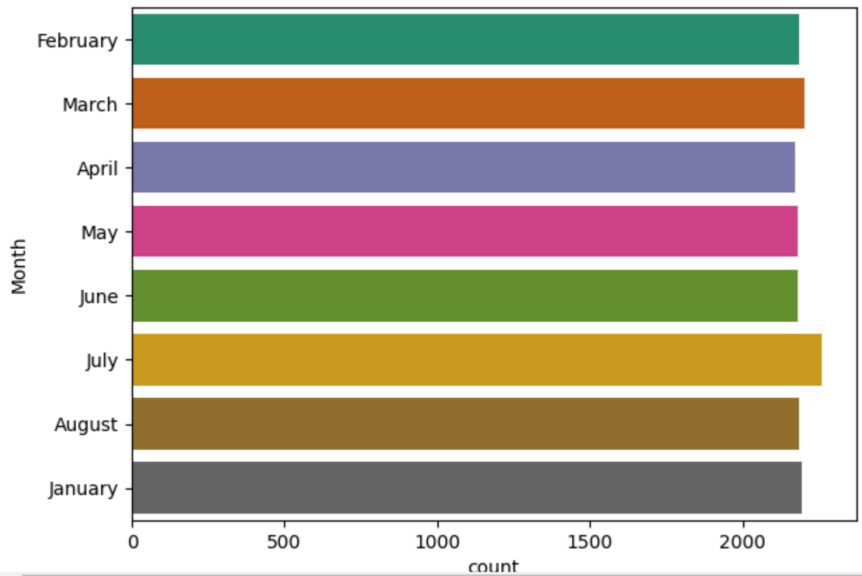
```
df.drop(df[df["Occupation"]=='_______'].index,inplace=True)
df.drop(df[df["Credit_Mix"]=='_'].index,inplace=True)
```

Data Encoding (Categorical ---> Numerical)

```
df["Month"].value_counts()
```

```
July        2257
March       2203
January     2192
February    2185
August      2184
May         2179
June        2179
April       2169
Name: Month, dtype: int64
```

```
plt.figure(figsize=(7,5))
sns.countplot(y="Month",data=df,palette="Dark2")
plt.show()
```

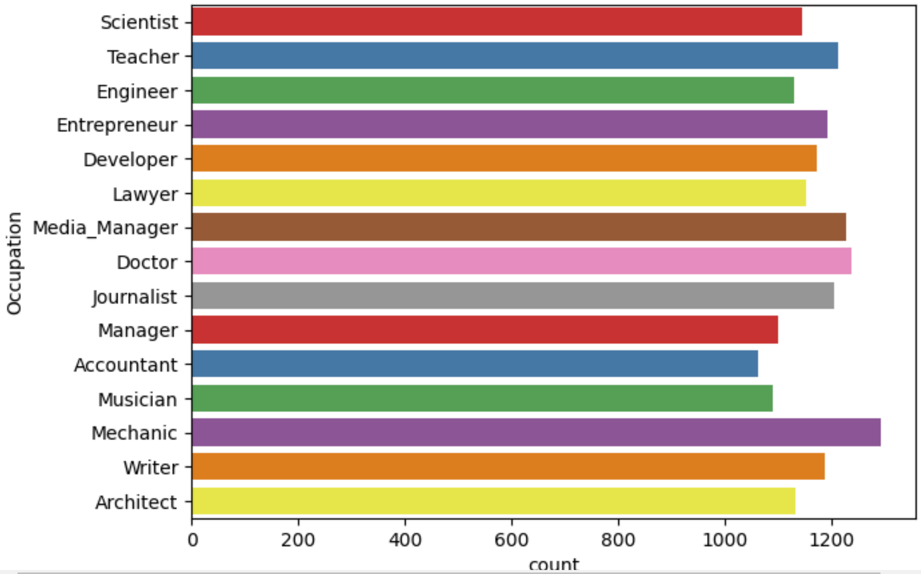



```
month_mapping = {
   'January': 1,
    'February': 2,
    'March': 3,
    "April":4,
    "May":5,
    "June":6,
    "July":7,
    "August":8}
df['Month'] = df['Month'].replace(month_mapping)
```

```
df["Occupation"].value_counts()
```

```
Mechanic         1293
Doctor           1238
Media_Manager    1229
Teacher          1213
Journalist       1205
Entrepreneur     1194
Writer           1187
Developer        1172
Lawyer           1154
Scientist        1146
Architect        1133
Engineer         1130
Manager          1101
Musician         1090
Accountant       1063
Name: Occupation, dtype: int64
```

```
plt.figure(figsize=(7,5))
sns.countplot(y="Occupation",data=df,palette="Set1")
plt.show()
```

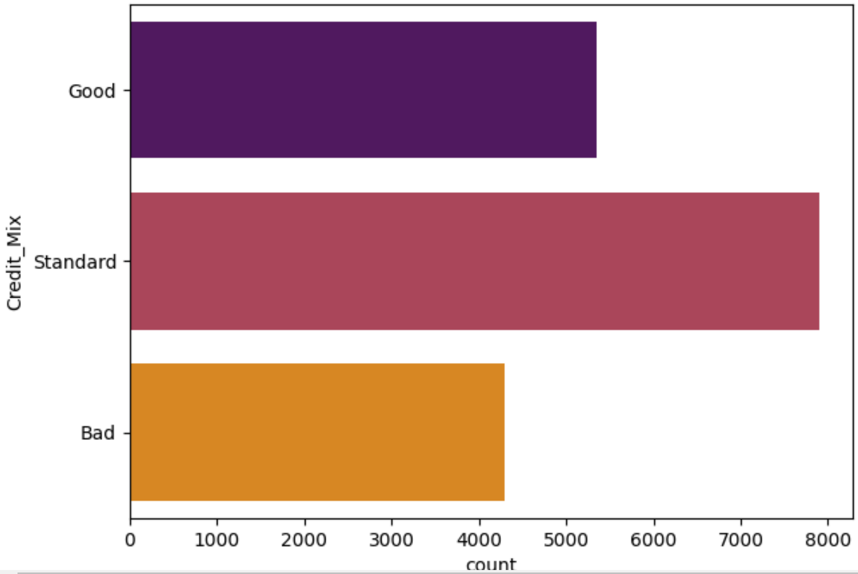



```
occupation_mapping = {
    'Lawyer': 1,
    'Architect': 2,
    'Engineer': 3,
    'Scientist': 4,
    'Mechanic': 5,
    'Accountant': 6,
    'Developer': 7,
    'Media_Manager': 8,
    'Teacher': 9,
    'Entrepreneur': 10,
    'Doctor': 11,
    'Journalist': 12,
    'Manager': 13,
    'Musician': 14,
    'Writer': 15
}

df['Occupation'] = df['Occupation'].replace(occupation_mapping)
```

```
df["Credit_Mix"].value_counts()
```

```
Standard    7895
Good        5354
Bad         4299
Name: Credit_Mix, dtype: int64
```

```
plt.figure(figsize=(7,5))
sns.countplot(y="Credit_Mix",data=df,palette="inferno")
plt.show()
```

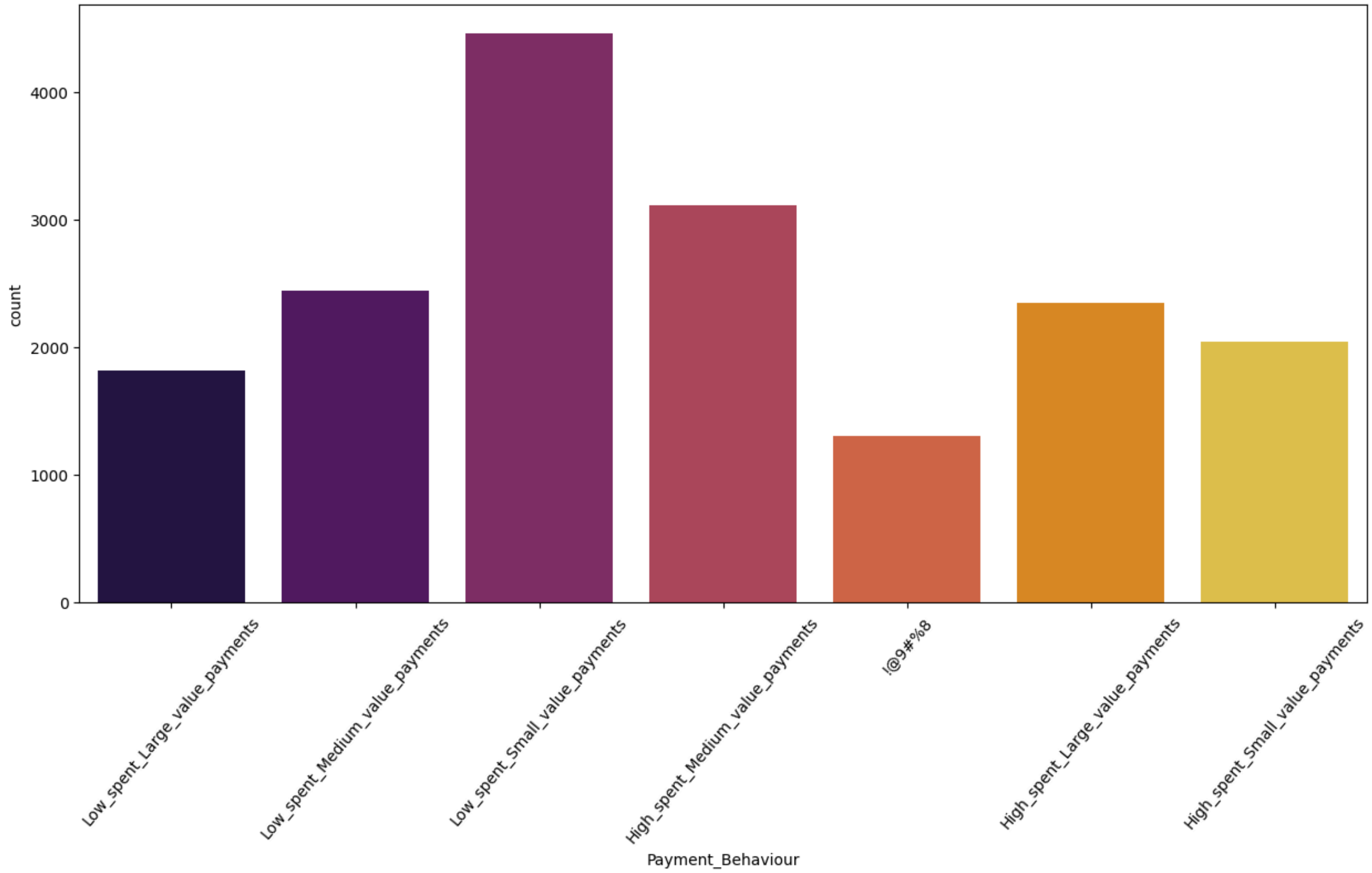



```
credit_map={"Good":1,"Standard":2,"Bad":3}
df['Credit_Mix'] = df['Credit_Mix'].replace(credit_map)
```

```
df["Payment_Behaviour"].value_counts()
```

```
Low_spent_Small_value_payments      4463
High_spent_Medium_value_payments    3116
Low_spent_Medium_value_payments     2445
High_spent_Large_value_payments     2350
High_spent_Small_value_payments     2050
Low_spent_Large_value_payments      1817
!@9#%8                              1306
Name: Payment_Behaviour, dtype: int64
```

```
plt.figure(figsize=(15,7))
sns.countplot(x="Payment_Behaviour",data=df,palette="inferno")
plt.xticks(rotation=50)
plt.show()
```



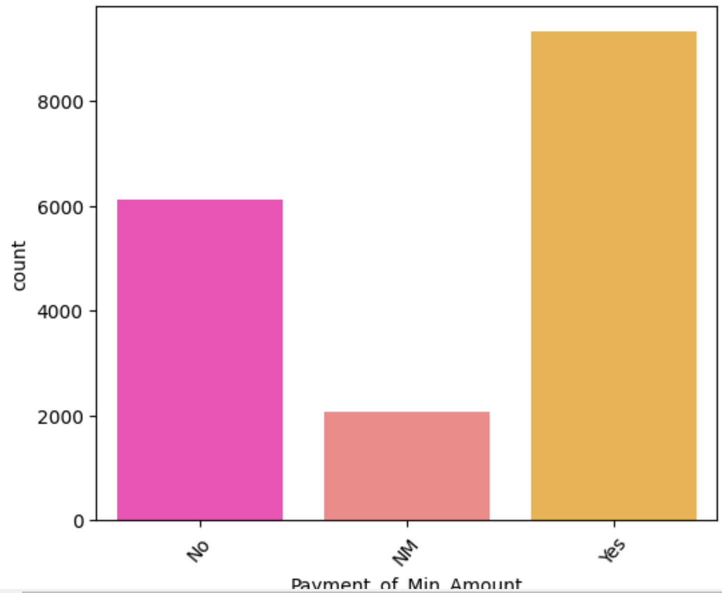

```
df['Payment_Behaviour']= df['Payment_Behaviour'].replace("!@9#%8",np.nan)
```

```
category_mapping = {
    'Low_spent_Small_value_payments':1,
    'High_spent_Medium_value_payments':2,
    'Low_spent_Medium_value_payments': 3,
    'High_spent_Large_value_payments': 4,
    'High_spent_Small_value_payments': 5,
    'Low_spent_Large_value_payments': 6
}
df['Payment_Behaviour'] = df['Payment_Behaviour'].replace(category_mapping)
```

```
df["Payment_of_Min_Amount"].value_counts()
```

```
Yes    9336
No     6126
NM     2085
Name: Payment_of_Min_Amount, dtype: int64
```

```
plt.figure(figsize=(6,5))
sns.countplot(x="Payment_of_Min_Amount",data=df,palette="spring")
plt.xticks(rotation=50)
plt.show()
```

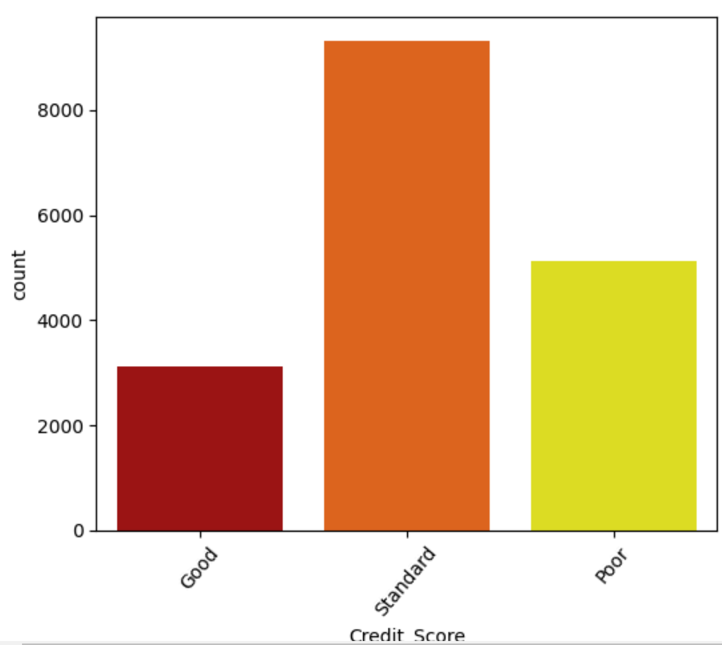



```
pay_map={"Yes":1,"No":2,"NM":3}
df['Payment_of_Min_Amount'] = df['Payment_of_Min_Amount'].replace(pay_map)
```

```
df["Credit_Score"].value_counts()
```

```
Standard    9310
Poor        5127
Good        3110
Name: Credit_Score, dtype: int64
```

```
plt.figure(figsize=(6,5))
sns.countplot(x="Credit_Score",data=df,palette="hot")
plt.xticks(rotation=50)
plt.show()
```




```
score_map={"Standard":0,"Poor":1,"Good":2}
df['Credit_Score'] = df['Credit_Score'].replace(score_map)
```

Handling Missing Data

```
df.isnull().sum()
```

```
Month                          0
Age                            0
Occupation                     0
Annual_Income                  0
Monthly_Inhand_Salary       2628
Num_Bank_Accounts              0
Num_Credit_Card                0
Interest_Rate                  0
Num_of_Loan                    0
Delay_from_due_date            0
Num_of_Delayed_Payment      1246
Changed_Credit_Limit           0
Num_Credit_Inquiries         359
Credit_Mix                     0
Outstanding_Debt               0
Credit_Utilization_Ratio       0
Credit_History_Age          1628
Payment_of_Min_Amount          1
Total_EMI_per_month            1
Amount_invested_monthly      763
Payment_Behaviour           1307
Monthly_Balance              217
Credit_Score                   1
dtype: int64
```

```
mean_salary = df["Monthly_Inhand_Salary"].mean()
df["Monthly_Inhand_Salary"].fillna(mean_salary, inplace=True)
```

```
df["Num_of_Delayed_Payment"] = pd.to_numeric(df["Num_of_Delayed_Payment"], errors="coerce")
n_mean=df["Num_of_Delayed_Payment"].mean()
df["Num_of_Delayed_Payment"].fillna(n_mean, inplace=True)
```

```
in_mean=df["Num_Credit_Inquiries"].mean()
df["Num_Credit_Inquiries"].fillna(in_mean, inplace=True)
```

```
df['Credit_History_Age'] = df['Credit_History_Age'].str.extract(r'(\d+)')
```

```
df["Credit_History_Age"] = pd.to_numeric(df["Credit_History_Age"], errors="coerce")
credit_mean=df["Credit_History_Age"].mean()
df["Credit_History_Age"].fillna(credit_mean, inplace=True)
```

```
df["Amount_invested_monthly"] = pd.to_numeric(df["Amount_invested_monthly"], errors="coerce")
invest_mean=df["Amount_invested_monthly"].mean()
df["Amount_invested_monthly"].fillna(invest_mean, inplace=True)
```

```
df.dropna(subset=["Payment_Behaviour"], inplace=True)
```

```
df["Monthly_Balance"] = pd.to_numeric(df["Monthly_Balance"], errors="coerce")
month_mean=df["Monthly_Balance"].mean()
df["Monthly_Balance"].fillna(month_mean, inplace=True)
```

```
df.isnull().sum()
```

```
Month                       0
Age                         0
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary       0
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
Delay_from_due_date         0
Num_of_Delayed_Payment      0
Changed_Credit_Limit        0
Num_Credit_Inquiries        0
Credit_Mix                  0
Outstanding_Debt            0
Credit_Utilization_Ratio    0
Credit_History_Age          0
Payment_of_Min_Amount       0
Total_EMI_per_month         0
Amount_invested_monthly     0
```

```
Payment_Behaviour           0
Monthly_Balance             0
Credit_Score                0
dtype: int64
```

All missing values have been handled

```
df["Annual_Income"] = pd.to_numeric(df["Annual_Income"], errors="coerce")
an_mean=df["Annual_Income"].mean()
df["Annual_Income"].fillna(an_mean, inplace=True)
```

```
df['Outstanding_Debt'] = pd.to_numeric(df['Outstanding_Debt'].str.replace(r'[^0-9.]', '', regex=True), errors='coerce')
```

```
df['Changed_Credit_Limit'] = df['Changed_Credit_Limit'].replace('_',np.nan)  # Replace '_' with 0
df["Changed_Credit_Limit"] = pd.to_numeric(df["Changed_Credit_Limit"], errors="coerce")
c_mean=df["Changed_Credit_Limit"].mean()
df["Changed_Credit_Limit"].fillna(c_mean, inplace=True)
```

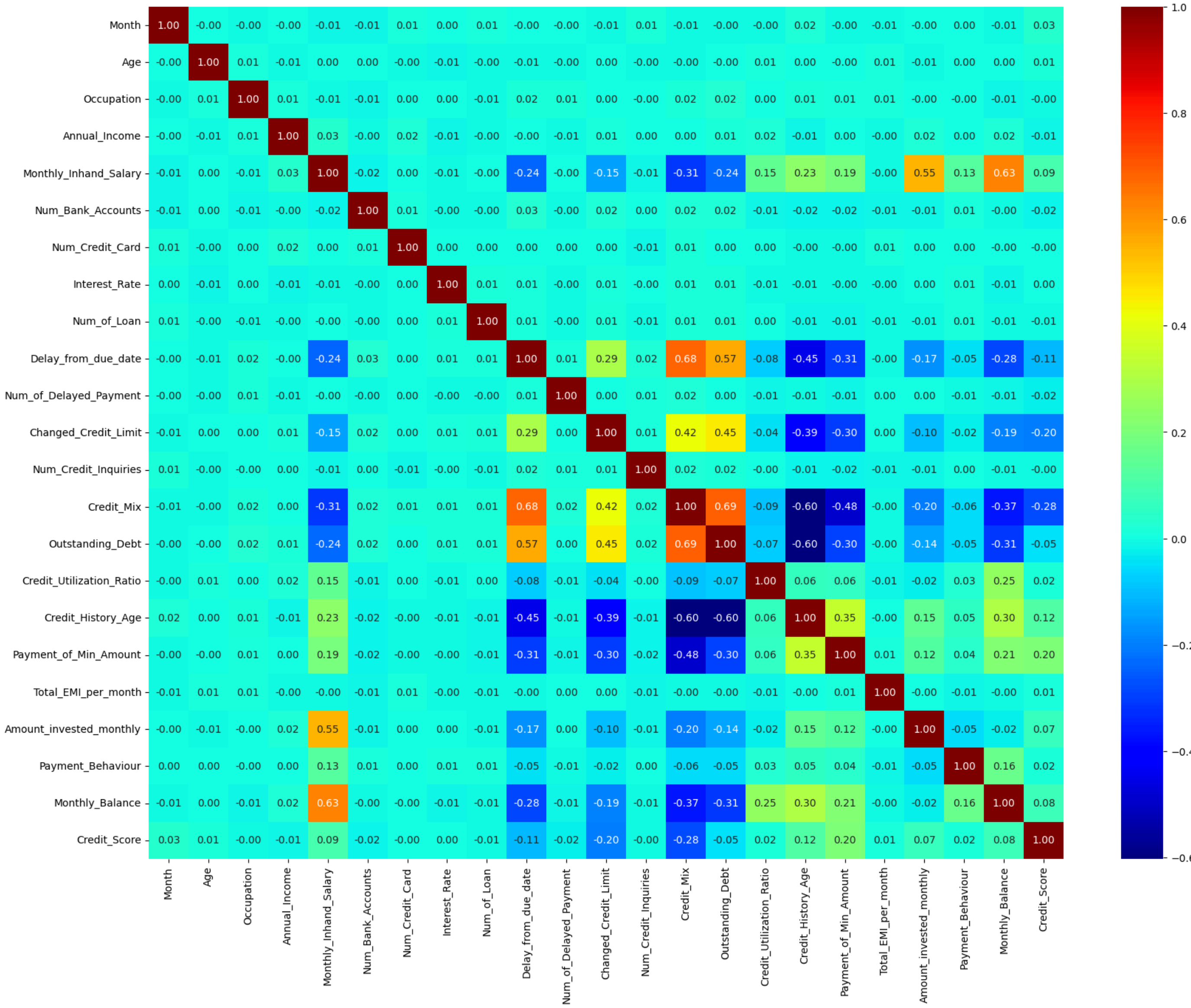
```
df['Age'] = df['Age'].replace('-500',np.nan)
df["Age"] = pd.to_numeric(df["Age"], errors="coerce")
age_mean=df["Age"].mean()
df["Age"].fillna(age_mean, inplace=True)
```

```
df["Num_of_Loan"] = pd.to_numeric(df["Num_of_Loan"], errors="coerce")
num_mean=df["Num_of_Loan"].mean()
df["Num_of_Loan"].fillna(num_mean, inplace=True)
```

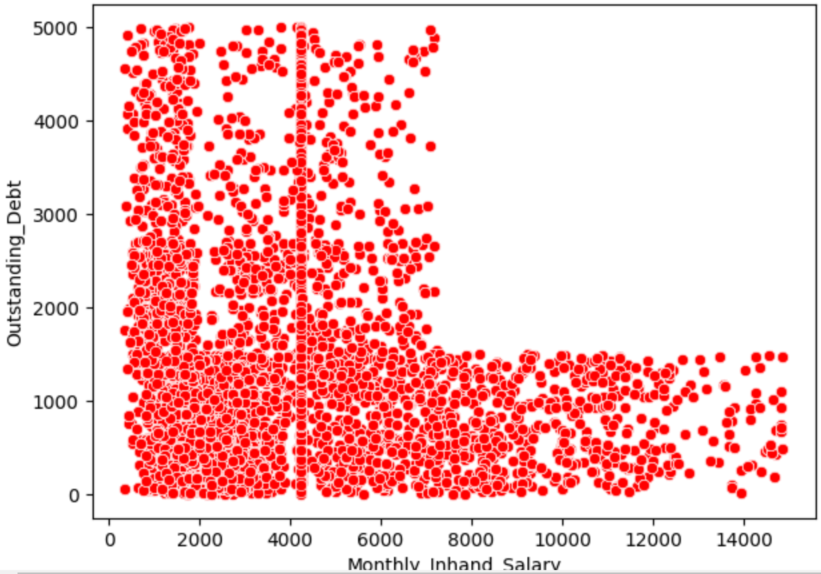
```
df['Delay_from_due_date'] = df['Delay_from_due_date'].abs()
```

Data Visualization

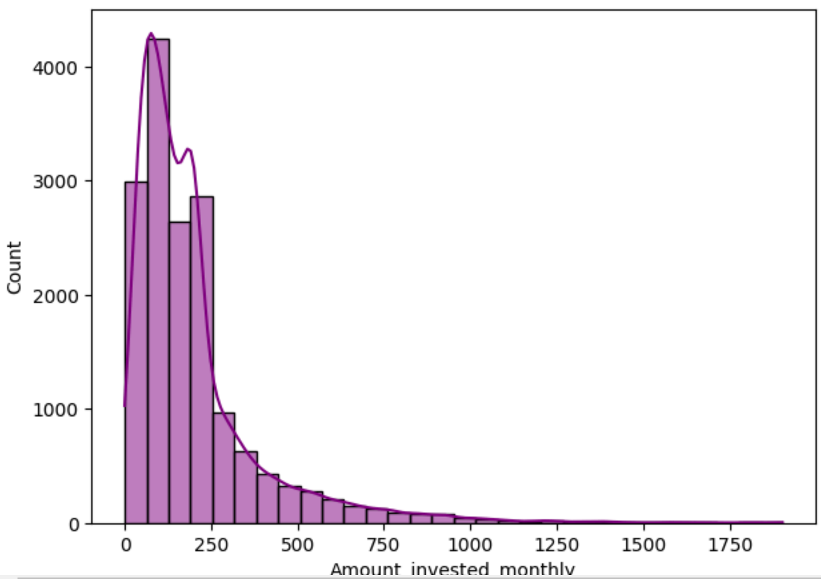
```
cr=df.corr()
plt.figure(figsize=(20,15))
sns.heatmap(cr,annot=True,fmt=".2f",cmap="jet")
plt.show()
```



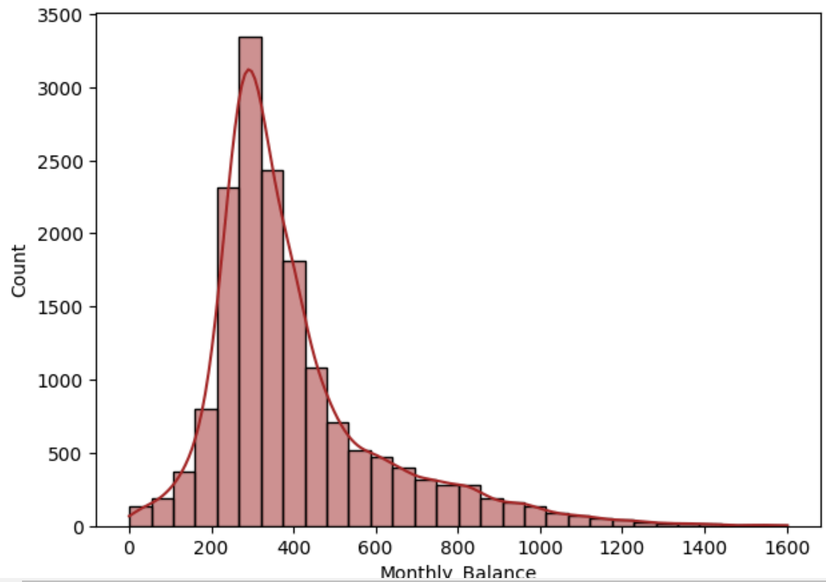
```
plt.figure(figsize=(7,5))
sns.scatterplot(data=df, x="Monthly_Inhand_Salary", y="Outstanding_Debt",color="red")
plt.show()
```



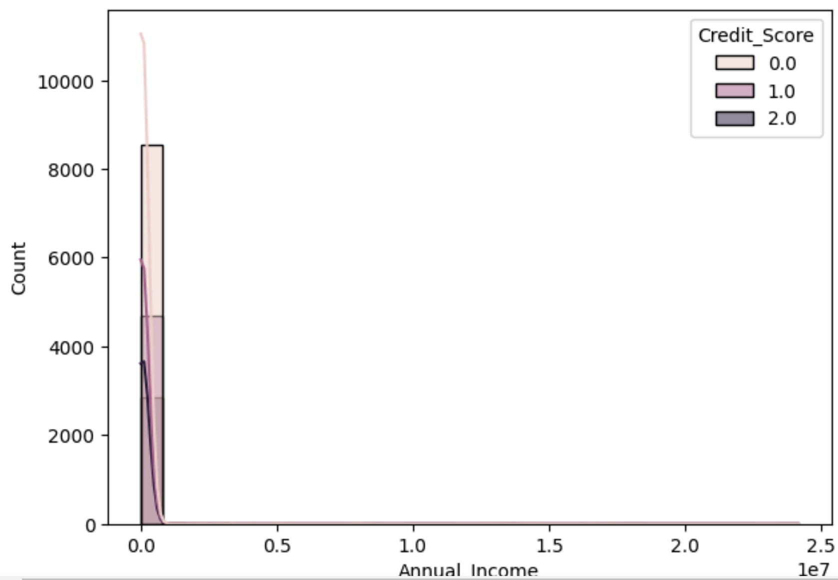

```
plt.figure(figsize=(7,5))
sns.histplot(data=df, x="Amount_invested_monthly", kde=True,bins=30,color="purple")
plt.show()
```




```
plt.figure(figsize=(7,5))
sns.histplot(data=df, x="Monthly_Balance", kde=True,bins=30,color="brown")
plt.show()
```




```
plt.figure(figsize=(7,5))
sns.histplot(data=df, x="Annual_Income", kde=True,bins=30,hue="Credit_Score")
plt.show()
```



Data Scaling

```
columns_to_scale = ['Age', 'Annual_Income', 'Monthly_Inhand_Salary', 'Outstanding_Debt','Credit_Utilization_Ratio', 'Credit_History_Age', 'T
                    'Amount_invested_monthly', 'Monthly_Balance']

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()


df[columns_to_scale] = scaler.fit_transform(df[columns_to_scale])
```

```
x=df.drop("Credit_Score",axis=1)
y=df["Credit_Score"]
```

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_state=42)
```

Model Training

We will be training the dataset on 2 different models:

1. Extreme Gradient Boosting Classifier
2. Light Gradient Boosting Machine

```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report,log_loss
from sklearn.metrics import roc_curve, auc
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
```

Extreme Gradient Boosting Classifier

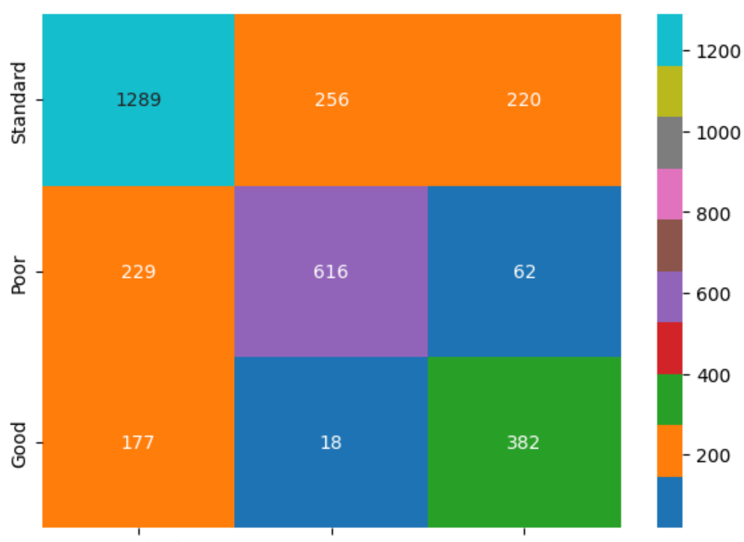
```
xgb_classifier = XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100,eval_metric='logloss', objective='binary:logistic', booster=
xgb_classifier.fit(xtrain, ytrain)
```

```
XGBClassifier
XGBClassifier(base_score=None, booster='gbtree', callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=0.1, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=3,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=100,
              n_jobs=None, num_parallel_tree=None, objective='multi:softprob', ...)
```

```
pred=xgb_classifier.predict(xtest)
xgb_ac=accuracy_score(ytest,pred)
print("XGB Accuracy Score :",xgb_ac)
```

```
XGB Accuracy Score : 0.7039088950446292
```

```
cf_mat=confusion_matrix(ytest, pred)
label_name=["Standard","Poor","Good"]
plt.figure(figsize=(7,5))

sns.heatmap(cf_mat,annot=True,fmt="d",xticklabels=label_name,yticklabels=label_name,cmap="tab10")
plt.show()
```



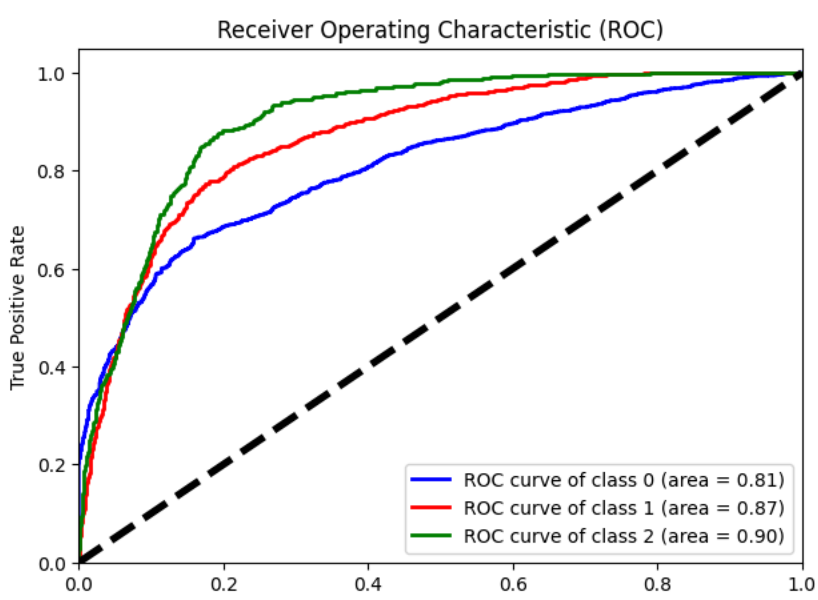

```
print(classification_report(ytest,pred,target_names=label_name))
```

```
              precision    recall  f1-score   support

    Standard       0.76      0.73      0.75      1765
        Poor       0.69      0.68      0.69       907
        Good       0.58      0.66      0.62       577

    accuracy                           0.70      3249
   macro avg       0.68      0.69      0.68      3249
weighted avg       0.71      0.70      0.71      3249
```

```
x_loss=xgb_classifier.predict_proba(xtest)
logloss = log_loss(ytest,x_loss)
print("Log Loss:", logloss)
```

```
Log Loss: 0.653367544600754
```

```
from sklearn.metrics import roc_curve, auc

fpr = dict()
tpr = dict()
roc_auc = dict()

n_classes = 3  # Number of classes

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(ytest,x_loss[:, i], pos_label=i)
    roc_auc[i] = auc(fpr[i], tpr[i])


plt.figure(figsize=(7,5))
colors = ['blue', 'red', 'green']
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,label='ROC curve of class {0} (area = {1:0.2f})'.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], color='black', linestyle='--',lw=4)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```



LightGBM (Light Gradient Boosting Machine)

```
lgb_classifier = LGBMClassifier(boosting_type='gbdt', num_leaves=31,max_depth=-1,learning_rate=0.1,
                                n_estimators=100,

                                random_state=42,
                                objective='multiclass',  # Multi-class objective
                                metric='multi_logloss')
```

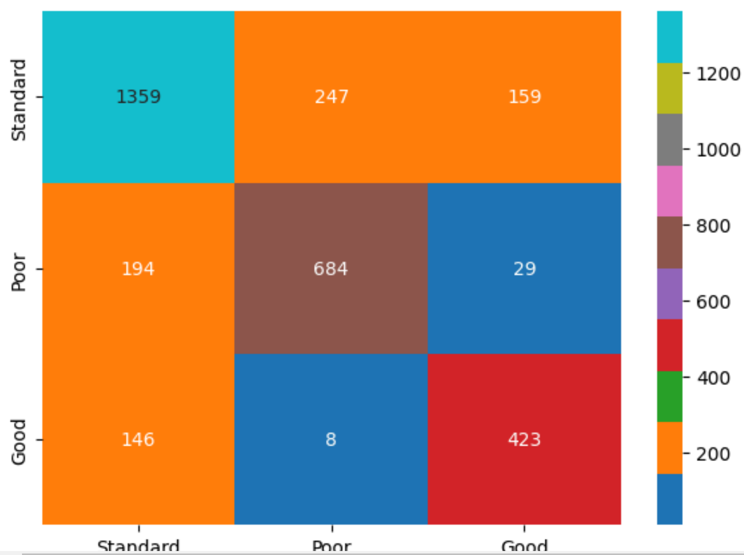
```
lgb_classifier.fit(xtrain, ytrain, eval_set=[(xtest, ytest)])
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.001307 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3168
[LightGBM] [Info] Number of data points in the train set: 12992, number of used features: 22
[LightGBM] [Info] Start training from score -0.639793
[LightGBM] [Info] Start training from score -1.219382
[LightGBM] [Info] Start training from score -1.730555
▾ LGBMClassifier
LGBMClassifier(metric='multi_logloss', objective='multiclass', random_state=42)
```

```
pred0=lgb_classifier.predict(xtest)
acc0=accuracy_score(ytest,pred0)
print("accuracy score :",acc0)
```

```
accuracy score : 0.7590027700831025
```

```
cf_mat=confusion_matrix(ytest, pred0)
label_name=["Standard","Poor","Good"]
plt.figure(figsize=(7,5))
sns.heatmap(cf_mat,annot=True,fmt="d",xticklabels=label_name,yticklabels=label_name,cmap="tab10")
plt.show()
```



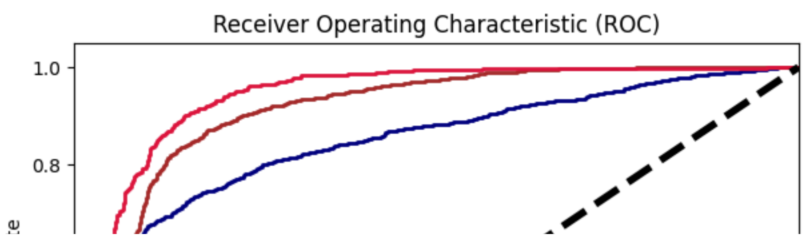

```
print(classification_report(ytest,pred0,target_names=label_name))
```

```
              precision    recall  f1-score   support

    Standard       0.80      0.77      0.78      1765
        Poor       0.73      0.75      0.74       907
        Good       0.69      0.73      0.71       577

    accuracy                           0.76      3249
   macro avg       0.74      0.75      0.75      3249
weighted avg       0.76      0.76      0.76      3249
```

```
lgb=lgb_classifier.predict_proba(xtest)
logloss2 = log_loss(ytest,lgb)
print("Log Loss:", logloss2)
```

```
Log Loss: 0.5606430088757401
```

```
from sklearn.metrics import roc_curve, auc

fpr = dict()
tpr = dict()
roc_auc = dict()

n_classes = 3  # Number of classes

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(ytest,lgb[:, i], pos_label=i)
    roc_auc[i] = auc(fpr[i], tpr[i])


plt.figure(figsize=(7,5))
colors = ['navy', 'brown', 'crimson']
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,label='ROC curve of class {0} (area = {1:0.2f})'.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], color='black', linestyle='--',lw=4)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```



Model Testin

CREDIT SCORE MODEL

CODEALPHA ML Internship Project 1

Name: **SAYAB GULFARAZ**

Intern-ID: **CA/S1/1492**

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler

# Load the test data
df_test = pd.read_csv("test.csv")

# Preprocess the test data
# Drop unnecessary columns
df_test.drop(["ID","Customer_ID","Name","SSN","Type_of_Loan"],axis=1,inplace=True)

# Encode categorical features
month_mapping = {
   'January': 1,
    'February': 2,
    'March': 3,
    "April":4,
    "May":5,
    "June":6,
    "July":7,
    "August":8,
    "September":9,
    "October":10,
    "November":11,
    "December":12}
df_test['Month'] = df_test['Month'].replace(month_mapping)
#df_test['Month'] = df_test['Month'].astype('int')


df_test.drop(df_test[df_test["Occupation"]=='_______'].index,inplace=True)
df_test.drop(df_test[df_test["Credit_Mix"]=='_'].index,inplace=True)


#df_test['Occupation'] = df_test['Occupation'].astype('int')
occupation_mapping = {
    'Lawyer': 1,
    'Architect': 2,
    'Engineer': 3,
    'Scientist': 4,
    'Mechanic': 5,
    'Accountant': 6,
    'Developer': 7,
    'Media_Manager': 8,
    'Teacher': 9,
    'Entrepreneur': 10,
    'Doctor': 11,
    'Journalist': 12,
    'Manager': 13,
    'Musician': 14,
    'Writer': 15,
    'Scientist': 16
}
df_test['Occupation'] = df_test['Occupation'].replace(occupation_mapping)

#df_test['Credit_Mix'] = df_test['Credit_Mix'].astype('int')
credit_map={"Good":1,"Standard":2,"Bad":3}
df_test['Credit_Mix'] = df_test['Credit_Mix'].replace(credit_map)

df_test['Payment_Behaviour']= df_test['Payment_Behaviour'].replace("!@9#%8",np.nan)
category_mapping = {
    'Low_spent_Small_value_payments':1,
    'High_spent_Medium_value_payments':2,
    'Low_spent_Medium_value_payments': 3,
    'High_spent_Large_value_payments': 4,
    'High_spent_Small_value_payments': 5,
    'Low_spent_Large_value_payments': 6
}
df_test['Payment_Behaviour'] = df_test['Payment_Behaviour'].replace(category_mapping)
```

```
pay_map={"Yes":1,"No":2,"NM":3}
df_test['Payment_of_Min_Amount'] = df_test['Payment_of_Min_Amount'].replace(pay_map)



# Handle missing values
mean_salary = df_test["Monthly_Inhand_Salary"].mean()
df_test["Monthly_Inhand_Salary"].fillna(mean_salary, inplace=True)
df_test["Num_of_Delayed_Payment"] = pd.to_numeric(df_test["Num_of_Delayed_Payment"], errors="coerce")
n_mean=df_test["Num_of_Delayed_Payment"].mean()
df_test["Num_of_Delayed_Payment"].fillna(n_mean, inplace=True)
in_mean=df_test["Num_Credit_Inquiries"].mean()
df_test["Num_Credit_Inquiries"].fillna(in_mean, inplace=True)
df_test['Credit_History_Age'] = df_test['Credit_History_Age'].str.extract(r'(\d+)')
df_test["Credit_History_Age"] = pd.to_numeric(df_test["Credit_History_Age"], errors="coerce")
credit_mean=df_test["Credit_History_Age"].mean()
df_test["Credit_History_Age"].fillna(credit_mean, inplace=True)
df_test["Amount_invested_monthly"] = pd.to_numeric(df_test["Amount_invested_monthly"], errors="coerce")
invest_mean=df_test["Amount_invested_monthly"].mean()
df_test["Amount_invested_monthly"].fillna(invest_mean, inplace=True)
df_test.dropna(subset=["Payment_Behaviour"], inplace=True)
df_test["Monthly_Balance"] = pd.to_numeric(df_test["Monthly_Balance"], errors="coerce")
month_mean=df_test["Monthly_Balance"].mean()
df_test["Monthly_Balance"].fillna(month_mean, inplace=True)


df_test["Annual_Income"] = pd.to_numeric(df_test["Annual_Income"], errors="coerce")
an_mean=df_test["Annual_Income"].mean()
df_test["Annual_Income"].fillna(an_mean, inplace=True)
df_test['Outstanding_Debt'] = pd.to_numeric(df_test['Outstanding_Debt'].str.replace(r'[^0-9.]', '', regex=True), errors='coerce')
df_test['Changed_Credit_Limit'] = df_test['Changed_Credit_Limit'].replace('_',np.nan)  # Replace '_' with 0
df_test["Changed_Credit_Limit"] = pd.to_numeric(df_test["Changed_Credit_Limit"], errors="coerce")
c_mean=df_test["Changed_Credit_Limit"].mean()
df_test["Changed_Credit_Limit"].fillna(c_mean, inplace=True)
df_test['Age'] = df_test['Age'].replace('-500',np.nan)
df_test["Age"] = pd.to_numeric(df_test["Age"], errors="coerce")
age_mean=df_test["Age"].mean()
df_test["Age"].fillna(age_mean, inplace=True)
df_test["Num_of_Loan"] = pd.to_numeric(df_test["Num_of_Loan"], errors="coerce")
num_mean=df_test["Num_of_Loan"].mean()
df_test["Num_of_Loan"].fillna(num_mean, inplace=True)
df_test['Delay_from_due_date'] = df_test['Delay_from_due_date'].abs()


# Scale numerical features
columns_to_scale = ['Age', 'Annual_Income', 'Monthly_Inhand_Salary', 'Outstanding_Debt',
                   'Credit_Utilization_Ratio', 'Credit_History_Age', 'Total_EMI_per_month',
                   'Amount_invested_monthly', 'Monthly_Balance']
scaler = StandardScaler()
df_test[columns_to_scale] = scaler.fit_transform(df_test[columns_to_scale])

# Separate features and target
X_test = df_test.copy()



from lightgbm import LGBMClassifier
import joblib

# Load the trained LightGBM model
lgb_classifier = LGBMClassifier(
    boosting_type='gbdt',
    num_leaves=31,
    max_depth=-1,
    learning_rate=0.1,
    n_estimators=100,
    random_state=42,
    objective='multiclass',
    metric='multi_logloss'
)


# Load the saved model from the specified path
model_path = '/content/lgb_model.pkl'
lgb_classifier = joblib.load(model_path)


# Make predictions on the test set
predicted_credit_scores = lgb_classifier.predict(X_test)


# Print the first 100 predicted credit scores in the form of an array
print("Predicted Credit Scores:")
print("[", end="")

for i in range(min(100, len(predicted_credit_scores))):
    if i > 0:
        print(", ", end="")
```

```
    print(predicted_credit_scores[i], end="")

    # Add line break after every 10 scores
    if (i + 1) % 10 == 0:
        print("\n", end="")

print("]")
```

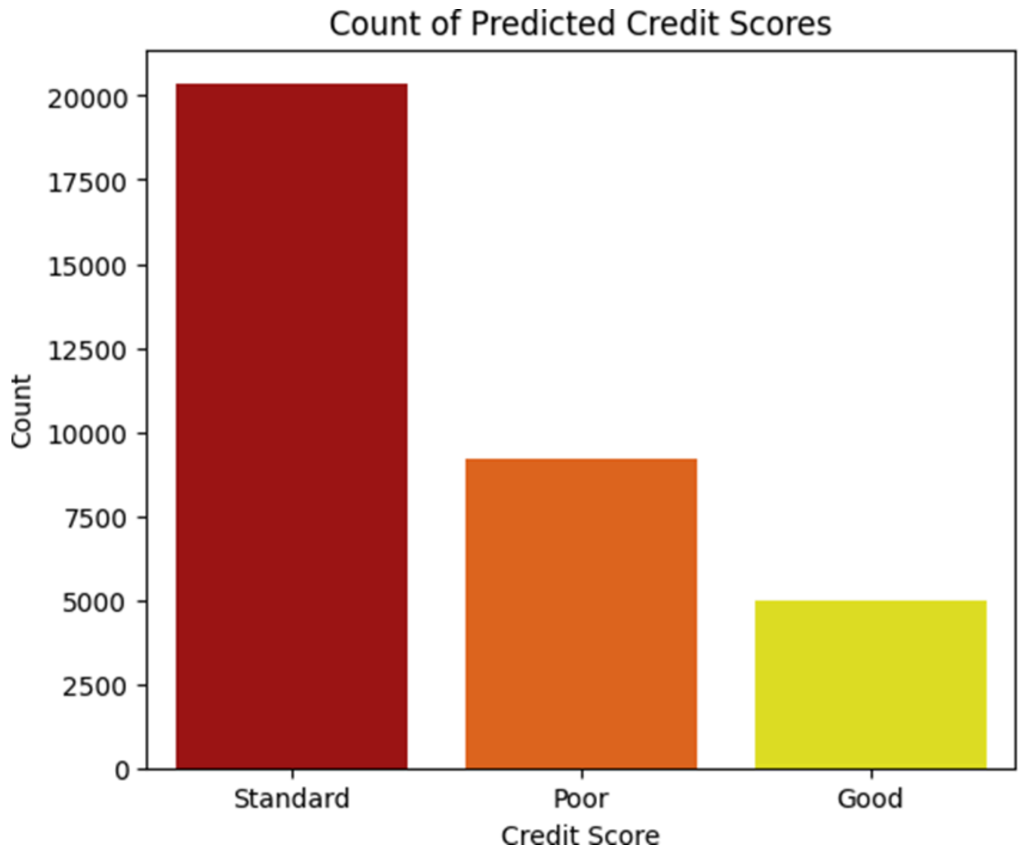
```
Predicted Credit Scores:
[0.0, 0.0, 0.0, 0.0, 2.0, 0.0, 0.0, 0.0, 2.0, 0.0
, 0.0, 0.0, 0.0, 0.0, 0.0, 2.0, 2.0, 2.0, 2.0, 2.0
, 2.0, 2.0, 1.0, 1.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0
, 0.0, 0.0, 2.0, 0.0, 0.0, 0.0, 1.0, 1.0, 0.0, 0.0
, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2.0, 2.0, 2.0
, 1.0, 1.0, 1.0, 0.0, 0.0, 0.0, 1.0, 1.0, 1.0, 2.0
, 2.0, 2.0, 0.0, 0.0, 0.0, 0.0, 1.0, 1.0, 1.0, 0.0
, 0.0, 0.0, 0.0, 1.0, 1.0, 1.0, 1.0, 0.0, 0.0, 0.0
, 0.0, 0.0, 1.0, 1.0, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0
, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0, 1.0
]
```

```
# Add the predicted credit scores to the test data
df_test["Credit_Score"] = predicted_credit_scores

# Save the updated test data to the same CSV file
df_test.to_csv("test.csv", index=False)

print("Predicted Credit Scores added to test.csv")
```

```
Predicted Credit Scores added to test.csv
```

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	W
1	Month	Age	Occupatio	Annual_In	Monthly_I	Num_Bank	Num_Cred	Interest_R	Num_of_L	Delay_fror	Num_of_D	Changed_(	Num_Cred	Credit_Mix	Outstandir	Credit_Util	Credit_Hist	Payment_(	Total_EMI_per_	Amount_invest	Payment_Beha	Credit_Score
2	9	-0.14056	16	-0.11279	-0.80938	3	4	3	4	3	7	11.27	2022	1	-0.53269	0.538351	0.441874	2	-0.169330331	0.218586386	1	0
3	10	-0.13906	16	-0.11279	-0.80938	3	4	3	4	3	9	13.27	4	1	-0.53269	0.151383	0.441874	2	-0.169330331	-0.926354538	2	0
4	11	-0.13906	16	-0.11279	-0.80938	3	4	3	4	1	4	12.27	4	1	-0.53269	0.299881	0.001651	2	-0.169330331	-0.251829352	3	0
5	12	-2.13E-17	16	-0.11279	-0.00016	3	4	3	4	4	5	11.27	4	1	-0.53269	0.029545	0.567991	2	-0.169330331	-0.832615219	2	0
6	10	-0.13306	9	-0.10078	-0.3924	2	4	6	1	3	3	5.42	5	1	-0.71056	-0.42331	1.072459	2	-0.172835206	0.298318686	6	2
7	9	-0.12256	3	-0.01805	-0.00016	1	5	8	3	8	1942	7.1	3	1	-0.10482	0.577356	-0.06259	2	-0.146835152	1.074514535	3	0
8	10	-0.12256	3	-0.01805	2.75235	1	5	8	3	6	3	2.1	3	1	-0.10482	0.666624	-0.06259	2	-0.146835152	1.373079141	6	0
9	11	-0.12256	3	-0.01805	2.75235	1	5	8	1381	8	5	7.1	5	1	-0.10482	-0.08998	-0.06259	2	-0.146835152	3.435558238	3	0
10	12	-0.12256	3	-0.01805	2.75235	1	5	8	3	8	6	7.1	5	1	-0.10482	0.279386	0.001651	2	-0.146835152	1.653452442	2	2
11	9	-0.09255	10	-0.10395	-0.53865	2	5	4	1	5	6	1.99	4	1	-0.68675	1.389052	-0.18871	2	-0.173108767	-0.672857323	2	0
12	11	-0.09255	10	-0.10395	-0.53865	2	5	4	1	5	6	1.99	4	1	-0.68675	0.889461	-0.06259	2	-0.173108767	-0.019558983	3	0
13	12	-0.09255	10	3.041312	-0.53865	2	5	4	1	6	6	1.99	7	1	-0.68675	0.645767	-0.06259	2	-0.173108767	0.204170608	1	0
14	10	-0.14206	7	-0.10024	-0.45587	7	5	5	0	5	18	2.58	5	2	-0.41651	-0.12276	1.576926	1	-0.174979263	-0.436897723	2	0
15	11	-0.14206	7	-0.10024	-0.45587	7	5	5	-100	5	15	2.58	5	2	-0.41651	0.811251	0.001651	1	-0.174979263	-0.792803763	2	0
16	12	-0.14206	7	-0.10024	-0.45587	7	5	5	0	5	18	2.58	5	2	-0.41651	-0.53104	1.576926	1	-0.174979263	-0.077445398	1	0
17	9	-0.12856	1	-0.07093	0.621815	4	5	8	0	8	7	14.14	4	1	-0.75988	1.146024	1.703043	2	-0.174979263	-0.741954674	4	2
18	10	-0.12706	1	-0.07093	0.621815	4	5	8	0	9	31.27265	10.14	4	1	-0.75988	1.163843	1.703043	2	-0.174979263	-0.187923124	5	2
19	12	-0.12706	1	-0.07093	0.621815	4	5	8	0	8	7	10.14	1552	1	-0.75988	-0.61229	1.703043	2	-0.174979263	-0.344200364	4	2
20	9	-0.12406	1	-0.0271	2.16184	0	1	8	2	0	31.27265	9.34	4	1	-0.93001	-0.75906	0.001651	2	-0.071148171	0.684624143	2	2
21	10	-0.12406	1	-0.0271	2.16184	0	1	8	2	0	31.27265	9.34	4	1	-0.93001	-0.24542	1.576926	2	-0.071148171	4.0998329	6	2
22	11	-0.12406	1	-0.0271	2.16184	0	1	8	2	0	1	9.34	4	1	-0.93001	-1.21592	1.576926	3	-0.071148171	5.031770399	3	2
23	12	-0.12406	1	-0.0271	-0.00016	0	1	8	2	0	0	10.34	4	1	-0.93001	0.466955	1.576926	3	-0.071148171	1.91705186	3	2
24	10	-0.13006	8	-0.10136	-0.00016	8	7	15	3	30	17	17.13	9	2	0.243335	1.191674	-0.44094	1	-0.166948447	-0.439804559	5	1
25	11	-0.12856	8	-0.10136	-0.53912	8	7	15	3	29	15	17.13	9	2	0.243335	0.693373	-0.44094	3	-0.166948447	-0.773827318	2	1
26	12	-0.12856	8	-0.10136	-0.53912	8	7	15	3	30	14	17.13	9	2	0.243335	0.48327	-0.44094	3	-0.166948447	-0.510147292	2	1
27	9	-0.13906	11	-0.03968	1.9469	2	5	7	3	11	12	8.24	8	1	-0.03996	1.796473	0.441874	3	-0.149125439	0.095320948	4	0
28	10	-0.13906	11	-0.03968	1.9469	2	5	7	3	11	9	10.37048	8	1	-0.03996	-0.60732	0.441874	2	-0.149125439	3.83845421	3	0
29	11	1.19606	11	-0.03968	-0.00016	2	5	7	3	11	8	8.24	8	1	-0.03996	-0.64303	0.441874	2	-0.149125439	1.233491855	6	0
30	10	-0.10756	12	-0.10343	-0.46552	1	6	12	2	2	3	5.76	5	1	-0.8699	0.30814	1.072459	2	-0.169667481	-0.458351102	2	0
31	12	-0.10756	12	-0.10343	-0.00016	1	6	12	2	1	0	5.76	5	1	-0.8699	1.570474	1.072459	2	-0.169667481	-0.921923932	4	0
32	9	-2.13E-17	9	-0.10161	-0.42312	5	5	20	3	16	19	11	8	2	-0.08232	-0.84085	0.063524	1	-0.167571757	0.402506295	1	0
33	12	-2.13E-17	9	-0.10161	-0.42312	5	5	20	3	16	20	11	8	2	-0.08232	1.234141	0.001651	1	-0.167571757	-0.491980214	2	0
34	9	-0.12556	3	-0.05969	1.061079	3	6	1	2	4	2	3.51	3	1	-0.41087	0.731023	0.001651	2	-0.159576621	-0.626382624	4	2
35	12	-0.12556	3	-0.05969	-0.00016	3	6	1766	2	5	2	3.51	5	1	-0.41087	1.678047	0.946342	2	-0.159576621	0.903264287	5	0
36	9	-0.12106	10	-0.08585	0.201784	6	4	14	3	10	8	5.54	7	2	-1.0801	0.239323	1.072459	1	-0.16080512	0.712954598	6	0
37	10	-0.12106	10	-0.08585	0.201784	6	4	14	3	10	10	5.54	7	2	-1.0801	0.341156	1.072459	1	-0.16080512	-0.267277889	3	0
38	9	-0.11656	13	-0.12075	-1.25817	6	5	32	7	24	9	8.86	9	2	1.023104	1.214409	-1.19764	1	-0.170814695	0.000321741	5	1
39	12	-2.13E-17	13	-0.12075	-1.25817	6	5	32	7	23	31.27265	8.86	9	2	1.023104	-0.52476	-1.19764	1	-0.170814695	-0.808116909	1	1
40	9	-0.11956	10	-0.10788	-0.60623	8	7	14	5	12	31.27265	7.83	5	2	-0.57742	-1.23262	-0.06259	1	-0.163433137	-0.93757727	4	0
41	10	-0.11956	10	-0.10788	-0.60623	8	7	14	5	16	14	7.83	7	2	-0.57742	1.244397	-0.06259	1	-0.163433137	-0.477416178	3	0
42	12	-0.11956	10	-0.10788	-0.60623	8	7	14	5	16	15	1.83	7	2	-0.57742	1.214487	0.063524	1	-0.163433137	-0.290055762	3	0
43	9	-0.12856	16	-0.10296	-0.42534	6	6	3097	2	8	14	6.28	1	2	-0.52554	0.961036	-0.18871	1	-0.169835534	-0.916746864	4	0
44	10	-0.12856	16	-0.10296	-0.42534	163	6	7	2	8	31.27265	6.28	1	2	-0.52554	-1.01117	-0.18871	3	-0.169835534	-0.147277301	6	0
45	10	-0.14356	6	2.22E-17	-0.00016	6	7	16	0	16	11	9.13	4	2	-0.11035	0.465682	1.324692	3	-0.174979263	-0.378220067	4	0
46	11	-0.14356	6	-0.05709	1.172754	6	7	16	0	18	31.27265	16.13	30.0921	2	-0.11035	1.018075	1.450809	1	-0.174979263	1.640981121	1	0
47	9	-0.10605	9	-0.10273	-0.49146	6	7	17	6	9	1150	9.22	10	2	-0.12186	-0.66897	-1.44988	1	-0.146303275	0.244807759	1	0
48	12	-0.10605	9	-0.10273	-0.49146	6	7	17	6	11	31.27265	9.22	10	2	-0.12186	-1.74312	0.001651	1	-0.146303275	-0.734741252	4	0
49	10	-0.13456	14	-0.0527	1.123905	6	6	12	0	18	8	17.92	1	2	-1.14242	0.040097	1.072459	3	-0.103213461	2.676395935	6	2
50	11	-0.13456	14	-0.0527	1.123905	6	6	12	0	18	6	10.92	3	2	-1.14242	0.811724	1.198575	1	-0.103213461	-0.191464675	2	2

```
# Create a count plot with custom x-tick labels
import matplotlib.pyplot as plt import seaborn as sns

plt.figure(figsize=(6, 5))
sns.countplot(x=predicted_credit_scores, data=df_test, palette="hot") plt.title('Count of Predicted Credit Scores')
plt.xlabel('Credit Score') plt.ylabel('Count')
plt.xticks(ticks=[0, 1, 2], labels=['Standard', 'Poor', 'Good']) plt.show()
```



Start coding or generate with AI.