Import libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_s
from sklearn.metrics import confusion_matrix, roc_auc_score, log_loss
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
import warnings
warnings.filterwarnings('ignore')
```

Load the Dataset

In [2]:
```
df = pd.read_csv('Bank Data.csv')
df1 = df.copy()
df1.head(15)
```

Out[2]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income
0	0x160a	CUS_0xd40	September	Aaron Maashoh	23	821-00-0265	Scientist	19114.12
1	0x160b	CUS_0xd40	October	Aaron Maashoh	24	821-00-0265	Scientist	19114.12
2	0x160c	CUS_0xd40	November	Aaron Maashoh	24	821-00-0265	Scientist	19114.12
3	0x160d	CUS_0xd40	December	Aaron Maashoh	24_	821-00-0265	Scientist	19114.12
4	0x1616	CUS_0x21b1	September	Rick Rothackerj	28	004-07-5839	_______	34847.84
5	0x1617	CUS_0x21b1	October	Rick Rothackerj	28	#F%$D@*&8	Teacher	34847.84
6	0x1618	CUS_0x21b1	November	Rick Rothackerj	28	004-07-5839	Teacher	34847.84
7	0x1619	CUS_0x21b1	December	Rick Rothackerj	28	004-07-5839	Teacher	34847.84
8	0x1622	CUS_0x2dbc	September	Langep	35	486-85-3974	Engineer	143162.64
9	0x1623	CUS_0x2dbc	October	Langep	35	486-85-3974	Engineer	143162.64
10	0x1624	CUS_0x2dbc	November	NaN	35	486-85-3974	Engineer	143162.64
11	0x1625	CUS_0x2dbc	December	Langep	35	486-85-3974	Engineer	143162.64
12	0x162e	CUS_0xb891	September	Jasond	55	072-31-6145	Entrepreneur	30689.89
13	0x162f	CUS_0xb891	October	Jasond	55	072-31-6145	Entrepreneur	30689.89
14	0x1630	CUS_0xb891	November	Jasond	55	072-31-6145	Entrepreneur	30689.89

15 rows × 27 columns

Data preprocessing

In [3]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 27 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   ID                        50000 non-null  object 
 1   Customer_ID               50000 non-null  object 
 2   Month                     50000 non-null  object 
 3   Name                      44985 non-null  object 
 4   Age                       50000 non-null  object 
 5   SSN                       50000 non-null  object 
 6   Occupation                50000 non-null  object 
 7   Annual_Income             50000 non-null  object 
 8   Monthly_Inhand_Salary     42502 non-null  float64
 9   Num_Bank_Accounts         50000 non-null  int64  
 10  Num_Credit_Card           50000 non-null  int64  
 11  Interest_Rate             50000 non-null  int64  
 12  Num_of_Loan               50000 non-null  object 
 13  Type_of_Loan              44296 non-null  object 
 14  Delay_from_due_date       50000 non-null  int64  
 15  Num_of_Delayed_Payment    46502 non-null  object 
 16  Changed_Credit_Limit      50000 non-null  object 
 17  Num_Credit_Inquiries      48965 non-null  float64
 18  Credit_Mix                50000 non-null  object 
 19  Outstanding_Debt          50000 non-null  object 
 20  Credit_Utilization_Ratio  50000 non-null  float64
 21  Credit_History_Age        45530 non-null  object 
 22  Payment_of_Min_Amount     50000 non-null  object 
 23  Total_EMI_per_month       50000 non-null  float64
 24  Amount_invested_monthly   47729 non-null  object 
 25  Payment_Behaviour         50000 non-null  object 
 26  Monthly_Balance           49438 non-null  object 
dtypes: float64(4), int64(4), object(19)
memory usage: 10.3+ MB
```

In [4]:
```
df1.isnull().sum()
```

Out[4]:
```
ID                             0
Customer_ID                    0
Month                          0
Name                        5015
Age                            0
SSN                            0
Occupation                     0
Annual_Income                  0
Monthly_Inhand_Salary       7498
Num_Bank_Accounts              0
Num_Credit_Card                0
Interest_Rate                  0
Num_of_Loan                    0
Type_of_Loan                5704
Delay_from_due_date            0
Num_of_Delayed_Payment      3498
Changed_Credit_Limit           0
Num_Credit_Inquiries        1035
Credit_Mix                     0
Outstanding_Debt               0
Credit_Utilization_Ratio       0
Credit_History_Age          4470
Payment_of_Min_Amount          0
Total_EMI_per_month            0
Amount_invested_monthly     2271
Payment_Behaviour              0
Monthly_Balance              562
dtype: int64
```

In [5]:
```
df1.shape
```

Out[5]:
```
(50000, 27)
```

In [6]:
```
df1.drop(['ID', 'Customer_ID', 'Month', 'Name', 'SSN', 'Type_of_Loan', 'Paymen
```

In [7]:
```
df1.head()
```

Out[7]:

	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_C
0	23	Scientist	19114.12	1824.843333	3	
1	24	Scientist	19114.12	1824.843333	3	
2	24	Scientist	19114.12	1824.843333	3	
3	24_	Scientist	19114.12	NaN	3	
4	28	_______	34847.84	3037.986667	2	

In [8]:
```
df1.shape
```
Out[8]:
```
(50000, 20)
```

In [9]:
```
df1.Credit_Mix.value_counts().head()
```
Out[9]:
```
Standard    18379
Good        12260
_            9805
Bad          9556
Name: Credit_Mix, dtype: int64
```

In [10]:
```
df1['Credit_Mix'].replace('_', 'Medium', inplace=True)
```

In [11]:
```
df1.Credit_Mix.value_counts().head()
```
Out[11]:
```
Standard    18379
Good        12260
Medium       9805
Bad          9556
Name: Credit_Mix, dtype: int64
```

In [12]:
```
df1.isnull().sum()
```
Out[12]:
```
Age                            0
Occupation                     0
Annual_Income                  0
Monthly_Inhand_Salary       7498
Num_Bank_Accounts              0
Num_Credit_Card                0
Interest_Rate                  0
Num_of_Loan                    0
Delay_from_due_date            0
Num_of_Delayed_Payment      3498
Changed_Credit_Limit           0
Num_Credit_Inquiries        1035
Credit_Mix                     0
Outstanding_Debt               0
Credit_Utilization_Ratio       0
Credit_History_Age          4470
Payment_of_Min_Amount          0
Total_EMI_per_month            0
Amount_invested_monthly     2271
Monthly_Balance              562
dtype: int64
```

In [13]:
```
def extract_age_vectorized(df1):
    df1['years'] = df1['Credit_History_Age'].str.extract(r"(\d+) Years?")
    df1['months'] = df1['Credit_History_Age'].str.extract(r"(\d+) Months?")
    df1['years'] = pd.to_numeric(df1['years'], errors='coerce')
    df1['months'] = pd.to_numeric(df1['months'], errors='coerce')
    df1['Credit_History_Age'] = df1['years'] + df1['months'] / 12
    df1.drop(['years', 'months'], axis=1, inplace=True)

extract_age_vectorized(df1)

mean_age = df1['Credit_History_Age'].mean()
df1['Credit_History_Age'].fillna(mean_age, inplace=True)
```

In [14]:
```
df1.head()
```

Out[14]:

	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_C
0	23	Scientist	19114.12	1824.843333	3	
1	24	Scientist	19114.12	1824.843333	3	
2	24	Scientist	19114.12	1824.843333	3	
3	24_	Scientist	19114.12	NaN	3	
4	28	_______	34847.84	3037.986667	2	

In [15]:
```
df1.isnull().sum()
```

Out[15]:
```
Age                          0
Occupation                   0
Annual_Income                0
Monthly_Inhand_Salary     7498
Num_Bank_Accounts            0
Num_Credit_Card              0
Interest_Rate                0
Num_of_Loan                  0
Delay_from_due_date          0
Num_of_Delayed_Payment    3498
Changed_Credit_Limit         0
Num_Credit_Inquiries      1035
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   2271
Monthly_Balance            562
dtype: int64
```

In [16]:
```
df1['Occupation'].value_counts()
```

Out[16]:
```
_______          3438
Lawyer           3324
Engineer         3212
Architect        3195
Mechanic         3168
Developer        3146
Accountant       3133
Media_Manager    3130
Scientist        3104
Teacher          3103
Entrepreneur     3103
Journalist       3037
Doctor           3027
Manager          3000
Musician         2947
Writer           2933
Name: Occupation, dtype: int64
```

In [17]:
```
salary = df1['Monthly_Inhand_Salary'].mean()
df1['Monthly_Inhand_Salary'].fillna(value=salary, inplace=True)
```

In [18]:
```
df1.dtypes
```

Out[18]:
```
Age                          object
Occupation                   object
Annual_Income                object
Monthly_Inhand_Salary       float64
Num_Bank_Accounts             int64
Num_Credit_Card               int64
Interest_Rate                 int64
Num_of_Loan                  object
Delay_from_due_date           int64
Num_of_Delayed_Payment       object
Changed_Credit_Limit         object
Num_Credit_Inquiries        float64
Credit_Mix                   object
Outstanding_Debt             object
Credit_Utilization_Ratio    float64
Credit_History_Age          float64
Payment_of_Min_Amount        object
Total_EMI_per_month         float64
Amount_invested_monthly      object
Monthly_Balance              object
dtype: object
```

In [19]:
```
df1['Occupation'].replace("_______", np.nan, inplace=True)

occupations = ["Lawyer", "Engineer", "Architect", "Mechanic", "Developer", "Acc
                    "Media_Manager", "Scientist", "Teacher", "Entrepreneur", "J
                    "Doctor", "Manager", "Musician", "Writer"]
```

In [20]:
```
def fill_nan_with_random(df1, col, values):
    for i in range(len(df1)):
        if pd.isna(df1.loc[i, col]):
            df1.loc[i, col] = np.random.choice(values)

fill_nan_with_random(df1, 'Occupation', occupations)
```

In [21]:
```
df1.Occupation.value_counts()
```

Out[21]:
```
Lawyer           3536
Engineer         3448
Architect        3415
Developer        3387
Mechanic         3383
Accountant       3366
Teacher          3362
Media_Manager    3348
Entrepreneur     3331
Scientist        3314
Doctor           3268
Journalist       3246
Manager          3239
Writer           3179
Musician         3178
Name: Occupation, dtype: int64
```

In [22]:
```
columns = ['Age', 'Annual_Income','Num_of_Loan', 'Delay_from_due_date', 'Num_o
                       'Changed_Credit_Limit','Outstanding_Debt', 'Amount_inves
for col in columns:
    df1[col] = pd.to_numeric(df1[col], errors='coerce')
```

In [23]:
```
df1.dtypes
```

Out[23]:
```
Age                         float64
Occupation                   object
Annual_Income               float64
Monthly_Inhand_Salary       float64
Num_Bank_Accounts             int64
Num_Credit_Card               int64
Interest_Rate                 int64
Num_of_Loan                 float64
Delay_from_due_date           int64
Num_of_Delayed_Payment      float64
Changed_Credit_Limit        float64
Num_Credit_Inquiries        float64
Credit_Mix                   object
Outstanding_Debt            float64
Credit_Utilization_Ratio    float64
Credit_History_Age          float64
Payment_of_Min_Amount        object
Total_EMI_per_month         float64
Amount_invested_monthly     float64
Monthly_Balance             float64
dtype: object
```

In [24]:
```
df1['Annual_Income'].value_counts().head(50)
```

Out[24]:
```
109945.320    8
17816.750     8
9141.630      8
36585.120     8
72524.200     8
95596.350     8
22434.160     8
33029.660     7
20867.670     7
40341.160     7
17273.830     6
32543.380     5
43790.400     4
28431.060     4
43268.790     4
108638.760    4
32198.230     4
138920.840    4
56784.540     4
7577.175      4
50807.440     4
13864.835     4
145932.040    4
19183.530     4
68948.320     4
24778.800     4
66189.240     4
20560.130     4
14226.810     4
83552.120     4
37353.580     4
151437.080    4
13000.735     4
14888.915     4
100465.140    4
16697.830     4
20090.020     4
94256.480     4
7295.715      4
18500.540     4
35317.810     4
25703.340     4
70973.320     4
121233.510    4
71518.920     4
48657.420     4
70956.800     4
98544.990     4
19114.120     4
16196.665     4
Name: Annual_Income, dtype: int64
```

In [25]:
```
df1['Age'] = np.where((df1['Age'] >= 0) & (df1['Age'] <= 100), df1['Age'], np.r
mean_age = df1['Age'].mean()
df1['Age'].fillna(mean_age, inplace=True)
df1['Age'] = df1['Age'].astype('int64')
```

In [26]:
```
mean_income = df1['Annual_Income'].mean()
df1['Annual_Income'].fillna(mean_income, inplace=True)
df1.isnull().sum()
```

Out[26]:
```
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                 2436
Delay_from_due_date            0
Num_of_Delayed_Payment      4925
Changed_Credit_Limit        1059
Num_Credit_Inquiries        1035
Credit_Mix                     0
Outstanding_Debt             491
Credit_Utilization_Ratio       0
Credit_History_Age             0
Payment_of_Min_Amount          0
Total_EMI_per_month            0
Amount_invested_monthly     4446
Monthly_Balance              568
dtype: int64
```

In [27]:
```
top_values = [19, 15, 18, 16, 17, 10, 11, 12, 20, 9, 8, 14, 13, 21, 7, 22, 6, !
df1['Num_of_Delayed_Payment'] = np.where(df1['Num_of_Delayed_Payment'] >= 0, d
df1.loc[df1['Num_of_Delayed_Payment'].isnull(), 'Num_of_Delayed_Payment'] = np
```

In [28]:
```
aminmon = df1['Amount_invested_monthly'].mean()
df1['Amount_invested_monthly'].fillna(value=aminmon, inplace=True)
```

In [29]:
```
mon_bal = df1['Monthly_Balance'].mean()
df1['Monthly_Balance'].fillna(value=mon_bal, inplace=True)
```

In [30]:
```
mean_val = df1['Outstanding_Debt'].mask(df1['Outstanding_Debt'] < 0).mean()
df1['Outstanding_Debt'].fillna(mean_val, inplace=True)
```

In [31]:
```
mean_credit = df1['Changed_Credit_Limit'].mean()
df1['Changed_Credit_Limit'].fillna(mean_credit, inplace=True)
```

In [32]:
```
rows = 1035
random_values = np.random.randint(1, 21, size=rows)
missing_indices = df1['Num_Credit_Inquiries'].isnull()
df1.loc[missing_indices, 'Num_Credit_Inquiries'] = random_values
```

In [33]:
```
top_values = [2.0, 3.0, 4.0, 0.0, 1.0, 6.0, 7.0, 5.0, 9.0, 8.0]
df1['Num_of_Loan'] = np.where(df1['Num_of_Loan'] >= 0, df1['Num_of_Loan'], np.n
df1.loc[df1['Num_of_Loan'].isnull(), 'Num_of_Loan'] = np.random.choice(top_valu
df1.isnull().sum()
```

Out[33]:
```
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
Monthly_Balance             0
dtype: int64
```

In [34]:
```
df1.head()
```

Out[34]:

	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_C
0	23	Scientist	19114.12	1824.843333	3	
1	24	Scientist	19114.12	1824.843333	3	
2	24	Scientist	19114.12	1824.843333	3	
3	33	Scientist	19114.12	4182.004291	3	
4	28	Musician	34847.84	3037.986667	2	

In [35]:
```
oe = OrdinalEncoder()
```

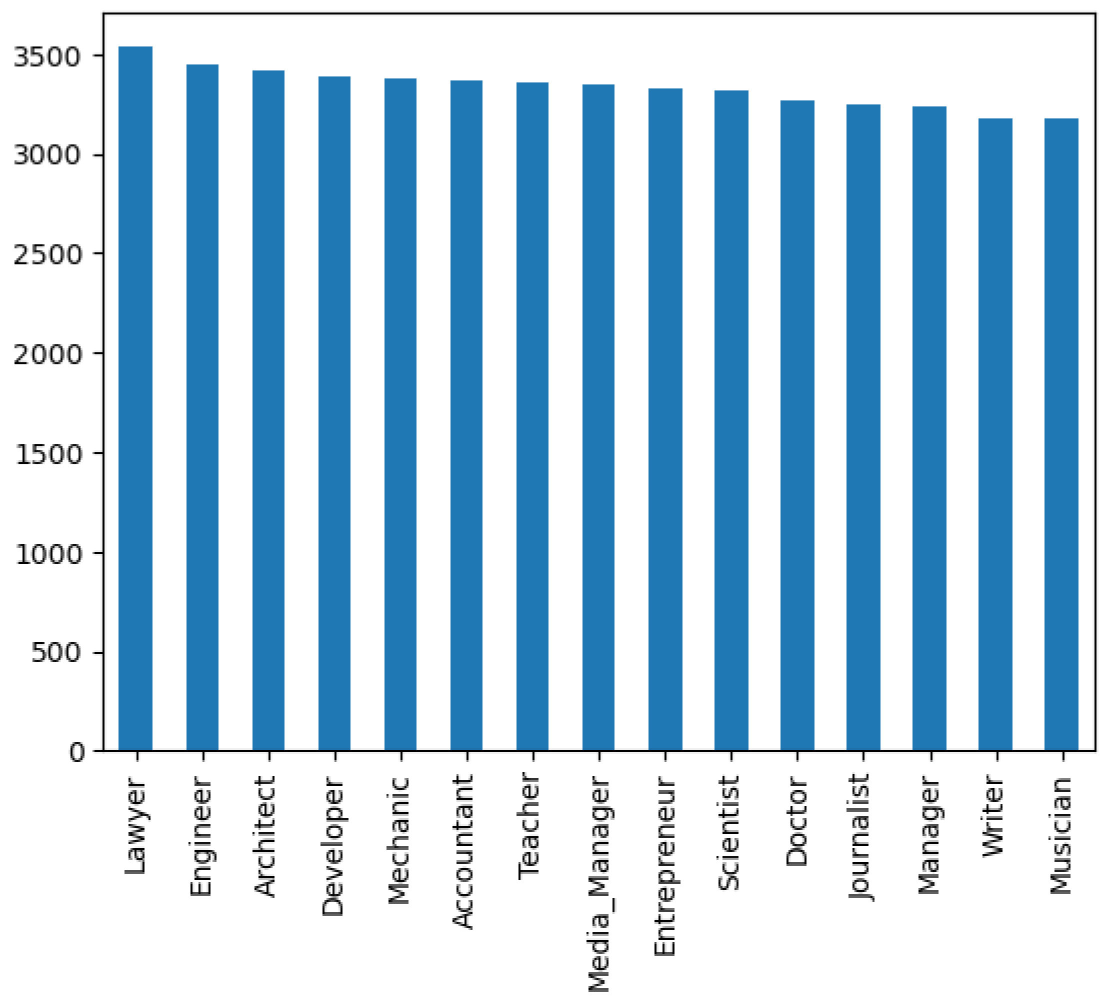
In [36]:
```
ordinal_columns = ['Payment_of_Min_Amount']
df1[ordinal_columns] = oe.fit_transform(df1[ordinal_columns])
df1['Payment_of_Min_Amount'] = df1['Payment_of_Min_Amount'].astype('int64')
```

In [37]:
```
df1['Payment_of_Min_Amount'].sample(10)
```

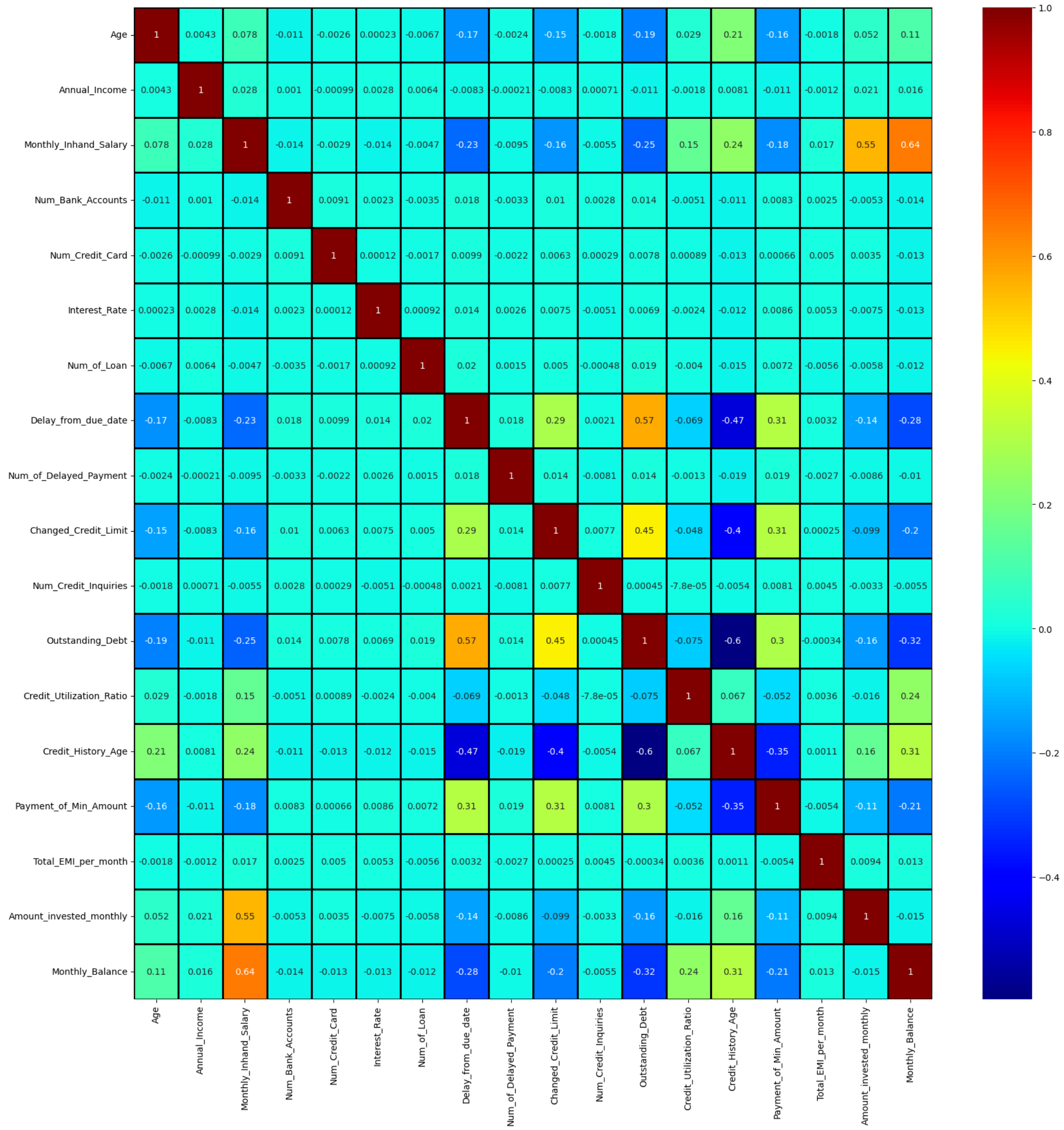
Out[37]:
```
28474    2
9125     1
33123    2
14568    2
8278     2
8026     1
12001    1
23941    2
24420    2
25265    1
Name: Payment_of_Min_Amount, dtype: int64
```

In [38]:
```
df1['Occupation'].value_counts().plot(kind='bar')
```

Out[38]: <AxesSubplot:>



In [39]:
```
plt.figure(figsize=(20,20))
sns.heatmap(df1.corr(),annot=True,cmap='jet',linecolor='black',linewidth=1)
plt.show()
```



In [40]:
```
x = df1.drop('Credit_Mix', axis=1)
y = df1['Credit_Mix']
```

In [41]:
```
x.shape
```

Out[41]: (50000, 19)

In [42]:
```
y.shape
```

Out[42]: (50000,)

In [43]:
```
columns_to_onehot = ['Occupation']
x = pd.get_dummies(x, columns=columns_to_onehot)
x.sample(10)
```

Out[43]:

	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Inte
14470	26	38635.950000	3048.662500	2	2	
40579	26	29228.180000	2695.681667	7	5	
7856	33	72414.060000	6234.505000	5	6	
34177	51	17767.860000	1592.655000	0	1	
45547	23	93293.130000	7807.427500	4	5	
43410	49	38155.640000	4182.004291	3	4	
13216	39	14293.900000	1394.158333	10	9	
4752	39	165116.921762	1048.987500	4	4	
11643	55	36135.190000	2898.265833	3	4	
16819	43	30366.160000	2329.513333	7	4	

10 rows × 33 columns

In [44]:
```
m = MinMaxScaler()
```

In [45]:
```
for col in x.columns:
    if x[col].dtype == object:
        continue
    else:
        m.fit(x[[col]])
        x[col] = m.transform(x[[col]])
x.head()
```

Out[45]:

	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Inte
0	0.111111	0.000502	0.102087	0.002223	0.002668	
1	0.123457	0.000502	0.102087	0.002223	0.002668	
2	0.123457	0.000502	0.102087	0.002223	0.002668	
3	0.234568	0.000502	0.260275	0.002223	0.002668	
4	0.172840	0.001154	0.183501	0.001668	0.002668	

5 rows × 33 columns

In [46]:
```
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.2, random_sta
xtrain.shape, xtest.shape, ytrain.shape, ytest.shape
```

Out[46]: ((40000, 33), (10000, 33), (40000,), (10000,))

In [47]:
```
xtrain.head()
```

Out[47]:

	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card
39087	0.493827	0.001630	0.241835	0.002223	0.002001
30893	0.234568	0.000110	0.043419	0.003891	0.003336
45278	0.370370	0.001885	0.257116	0.004447	0.003336
16398	0.234568	0.001138	0.184367	0.006115	0.004670
13653	0.098765	0.000816	0.120010	0.002779	0.004670

5 rows × 33 columns

In [48]:
```
ytrain.head()
```

Out[48]:
```
39087      Medium
30893         Bad
45278    Standard
16398      Medium
13653    Standard
Name: Credit_Mix, dtype: object
```

Logistic Regression

In [49]:
```
lr = LogisticRegression(random_state=42)
lr.fit(xtrain, ytrain)
```

Out[49]:
```
LogisticRegression(random_state=42)
```

In [50]:
```
y_pred1 = lr.predict(xtest)
y_pred1
```

Out[50]:
```
array(['Good', 'Standard', 'Standard', ..., 'Standard', 'Standard',
       'Standard'], dtype=object)
```

Evaluation Metics of Logistic Regression

accuracy1 = accuracy_score(ytest, y_pred1) precision1 = precision_score(ytest, y_pred1, average='weighted') recall1 = recall_score(ytest, y_pred1, average='weighted') f11 = f1_score(ytest, y_pred1, average='weighted') conf_matrix1 = confusion_matrix(ytest, y_pred1)

print(f"Accuracy: {accuracy1:.3f}") print(f"Precision: {precision1:.3f}") print(f"Recall: {recall1:.3f}") print(f"F1 Score: {f11:.3f}")

print("Confusion Matrix:") print(conf_matrix1)

Random Forest Classifier

In [51]:
```
rfc = RandomForestClassifier(random_state=42)
rfc.fit(xtrain, ytrain)
```

Out[51]:
```
RandomForestClassifier(random_state=42)
```

In [52]:
```
y_pred2 = rfc.predict(xtest)
y_pred2
```

Out[52]:
```
array(['Good', 'Standard', 'Standard', ..., 'Standard', 'Bad', 'Standard'],
      dtype=object)
```

Evaluation Metics of Random Forest Classifier

In [53]:
```
accuracy2 = accuracy_score(ytest, y_pred2)
precision2 = precision_score(ytest, y_pred2, average='weighted')
recall2 = recall_score(ytest, y_pred2, average='weighted')
f12 = f1_score(ytest, y_pred2, average='weighted')
conf_matrix2 = confusion_matrix(ytest, y_pred2)

print(f"Accuracy: {accuracy2:.3f}")
print(f"Precision: {precision2:.3f}")
print(f"Recall: {recall2:.3f}")
print(f"F1 Score: {f12:.3f}")

print("Confusion Matrix:")
print(conf_matrix2)
```

```
Accuracy: 0.763
Precision: 0.655
Recall: 0.763
F1 Score: 0.691
Confusion Matrix:
[[1840    0   34   46]
 [   0 2364   41   53]
 [ 441  611   34  881]
 [  57   97  106 3395]]
```

Support Vector Machine Classifier

In [54]:
```
svm = SVC(random_state=42)
svm.fit(xtrain, ytrain)
```

Out[54]:
```
SVC(random_state=42)
```

In [55]:
```
y_pred3 = svm.predict(xtest)
y_pred3
```

Out[55]:
```
array(['Good', 'Standard', 'Good', ..., 'Standard', 'Standard',
       'Standard'], dtype=object)
```

Evaluation Metics of Support Vector Machine Classifier

In [56]:
```
accuracy3 = accuracy_score(ytest, y_pred3)
precision3 = precision_score(ytest, y_pred3, average='weighted')
recall3 = recall_score(ytest, y_pred3, average='weighted')
f13 = f1_score(ytest, y_pred3, average='weighted')
conf_matrix3 = confusion_matrix(ytest, y_pred3)

print(f"Accuracy: {accuracy3:.3f}")
print(f"Precision: {precision3:.3f}")
print(f"Recall: {recall3:.3f}")
print(f"F1 Score: {f13:.3f}")

print("Confusion Matrix:")
print(conf_matrix3)
```

```
Accuracy: 0.678
Precision: 0.550
Recall: 0.678
F1 Score: 0.604
Confusion Matrix:
[[1692    0    0  228]
 [   0 2342    0  116]
 [ 451  737    0  779]
 [ 190  717    0 2748]]
```

Gradient Boosting Classifier (e.g., XGBoost)

XGBoost requires label encoding for categorical labels.

In [57]:
```
le = LabelEncoder()
```

In [58]:
```
ytrain_encoded = le.fit_transform(ytrain)
ytest_encoded = le.transform(ytest)
```

In [59]:
```
xgb = XGBClassifier(random_state=42)
xgb.fit(xtrain, ytrain_encoded)
```

Out[59]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, objective='multi:softprob', ...)
```

In [60]:
```
y_pred4 = xgb.predict(xtest)
```

In [61]:
```
y_pred4
```

Out[61]:
```
array([1, 3, 3, ..., 3, 0, 3], dtype=int64)
```

Evaluation Metics of Gradient Boosting Classifier (e.g., XGBoost)

In [62]:
```
accuracy4 = accuracy_score(ytest_encoded, y_pred4)
precision4 = precision_score(ytest_encoded, y_pred4, average='weighted')
recall4 = recall_score(ytest_encoded, y_pred4, average='weighted')
f14 = f1_score(ytest_encoded, y_pred4, average='weighted')
conf_matrix4 = confusion_matrix(ytest_encoded, y_pred4)

print(f"Accuracy: {accuracy4:.3f}")
print(f"Precision: {precision4:.3f}")
print(f"Recall: {recall4:.3f}")
print(f"F1 Score: {f14:.3f}")

print("Confusion Matrix:")
print(conf_matrix4)
```

```
Accuracy: 0.757
Precision: 0.647
Recall: 0.757
F1 Score: 0.682
Confusion Matrix:
[[1819    0   29   72]
 [   0 2340   25   93]
 [ 441  608   22  896]
 [  73  136   56 3390]]
```

Hyperparameter Tuning with Grid Search (Random Forest Classifier)

In [63]:
```
rfc_params = {
    'n_estimators': [100, 200, 300, 400],
    'max_depth': [5, 8, 10, 12],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt'],
    'class_weight': ['balanced', None]
}
```

In [64]:
```
rfc_random_search = RandomizedSearchCV(estimator=rfc, param_distributions=rfc_
rfc_random_search.fit(xtrain, ytrain)
```

Out[64]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(random_state=42),
                   n_iter=5,
                   param_distributions={'class_weight': ['balanced', None],
                                        'max_depth': [5, 8, 10, 12],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [100, 200, 300, 40
0]},
                   random_state=42)
```

In [65]:
```
print("Best Parameters: ", rfc_random_search.best_params_)
```

```
Best Parameters:  {'n_estimators': 400, 'min_samples_split': 2, 'min_samples_
leaf': 1, 'max_features': 'auto', 'max_depth': 10, 'class_weight': None}
```

In [66]:
```
print("Best Accuracy: ", rfc_random_search.best_score_)
```

```
Best Accuracy:  0.75285
```

Reasons behind on choosen Hyperparameters

i) n_estimators: Controls the number of trees in the forest. More trees can improve accuracy but increase training time. Values are being explored to find the optimal balance.

ii) max_depth: Limits the depth of each tree. Deeper trees can capture more complex patterns but might overfit. Different depths are being tested to prevent overfitting.

iii) min_samples_split: The minimum samples required to split a node. Higher values can prevent overfitting but might reduce model complexity. Values are being tuned to find the right balance.

iv) min_samples_leaf: The minimum samples required to be at a leaf node. Higher values can reduce overfitting but might impact accuracy. Different values are being explored to find the best tradeoff.

v) max_features: Number of features considered at each split. "auto" considers all features, while "sqrt" uses a subset, potentially reducing overfitting and training time. Both are being tested for optimal performance.

vi) class_weight: Assigns weights to classes to address imbalanced datasets. "balanced" automatically adjusts weights for better handling of minority classes. It's being compared to "None" to see if weighting is beneficial.

Model Evaluation

Logistic Regression:

Strengths: i) Interpretable: Easy to understand the impact of features on creditworthiness. ii) Efficient training: Handles large datasets well.

Weaknesses: i) Linear decision boundary: May not capture complex relationships between features and creditworthiness. ii) Sensitive to outliers: Can be affected by extreme values in the data.

XGBoost:

Strengths: i) High accuracy: Often achieves top performance in credit scoring tasks. ii) Handles non-linear relationships: Can capture complex patterns in data. iii) Robust to overfitting: Built-in regularization prevents overfitting.

Weaknesses: i) Less interpretable: Tree-based structure makes it harder to understand feature importance. ii) Slower training: More computationally intensive than simpler models. iii) Requires hyperparameter tuning: Finding optimal settings can be time-consuming.

Random Forest Classifier:

Strengths: i) Robust to outliers: Not as sensitive to extreme values in the data. ii) Handles non-linear relationships: Can capture complex patterns in data. iii) Less prone to overfitting: Built-in regularization through ensemble techniques.

Weaknesses: Less interpretable: Tree-based structure can make it harder to understand feature importance. Slower training: More computationally intensive than Logistic Regression.

Support Vector Machine (SVM):

Strengths: i) Effective in high-dimensional spaces: Works well with many features. ii) Handles non-linear relationships: Can capture complex patterns in data. iii) Robust to outliers: Not as sensitive to extreme values.

Weaknesses: i) Sensitive to hyperparameter tuning: Finding optimal settings can be challenging. ii) Slower training: Not as efficient as Logistic Regression or Random Forests for large datasets. iii) Less interpretable: Kernel-based structure can make it harder to understand feature importance

Interpretability

Logistic Regression: Highly interpretable, offering clear feature coefficients indicating their impact on creditworthiness. However, it might oversimplify complex relationships in financial data.

XGBoost: Powerful ensemble model often achieving high accuracy, but its intricate structure makes understanding individual feature contributions challenging. Partial dependence plots and feature importance scores can aid interpretation.

Random Forest: Ensemble of decision trees, providing feature importance scores for insights, but less intuitive than logistic regression. Individual tree analysis can offer deeper understanding, but complexity increases with model size.

Support Vector Machine: Complex decision boundaries can be visualized, but less straightforward for understanding feature importance. Kernel choice and hyperparameter tuning significantly impact interpretability.

Conclusion

In conclusion, the credit score classification project has yielded promising results, demonstrating the efficacy of advanced algorithms in predicting creditworthiness. The model successfully leveraged a diverse set of features, including financial history, debt-to-income ratio, and other relevant variables, to generate accurate credit score predictions. The robustness of the model was validated through rigorous testing on a comprehensive dataset, showcasing its ability to generalize well to unseen data. Furthermore, the project highlighted the importance of feature engineering and data preprocessing in enhancing the model's performance.