Loan Approval Prediction - Model Development

Step 1: Import Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import classification_report, accuracy_score, precision_score, recall_score, f1_sco
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.preprocessing import StandardScaler
from imblearn.under_sampling import RandomUnderSampler
```

Step 2: Import Cleaned Loan Dataset

In [2]:
```
df = pd.read_csv(r'prosperLoanDataCleaned.csv')
df.head()
```

Out[2]:

	Term	MonthsOfEmployementExperience	IsHomeowner	OpenCreditLines	TotalInquiries	AvailableBankcardCredit	DebtTo
0	36	2.000000	1	4.000000	3	1500.000000	
1	36	96.071582	0	9.260164	1	11210.225447	
2	36	19.000000	0	2.000000	5	2580.000000	
3	36	1.000000	0	7.000000	4	3626.000000	
4	36	121.000000	1	9.000000	1	178.000000	

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55106 entries, 0 to 55105
Data columns (total 17 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Term                          55106 non-null  int64  
 1   MonthsOfEmployementExperience 55106 non-null  float64
 2   IsHomeowner                   55106 non-null  int64  
 3   OpenCreditLines               55106 non-null  float64
 4   TotalInquiries                55106 non-null  int64  
 5   AvailableBankcardCredit       55106 non-null  float64
 6   DebtToIncomeRatio             55106 non-null  float64
 7   IncomeVerifiable              55106 non-null  int64  
 8   StatedMonthlyIncome           55106 non-null  float64
 9   LoanNumber                    55106 non-null  int64  
 10  LoanAmount                    55106 non-null  int64  
 11  MonthlyInstallment            55106 non-null  float64
 12  InterestRate                  55106 non-null  float64
 13  IsEmployed                    55106 non-null  int64  
 14  AverageCreditScore            55106 non-null  int64  
 15  AnyDelinquencies              55106 non-null  int64  
 16  GoodLoan                      55106 non-null  int64  
dtypes: float64(7), int64(10)
memory usage: 7.1 MB
```

Step 3: Data Pre-processing

In [4]:
```python
df = df.drop(['LoanNumber'], axis=1)
categorical = ['Term','IsHomeowner','IsEmployed','AnyDelinquencies','IncomeVerifiable']
numerical = ['LoanAmount','InterestRate','MonthlyInstallment','MonthsOfEmployementExperience','AverageCr
             ,'OpenCreditLines','TotalInquiries','AvailableBankcardCredit','DebtToIncomeRatio','StatedMo
```

Handling Outliers

In [5]:
```python
df[numerical].skew()
```

Out[5]:
```
LoanAmount                        1.646822
InterestRate                      0.115913
MonthlyInstallment                1.953124
MonthsOfEmployementExperience     1.834853
AverageCreditScore               -1.351894
OpenCreditLines                   1.131160
TotalInquiries                    6.574083
AvailableBankcardCredit           7.593415
DebtToIncomeRatio                12.416432
StatedMonthlyIncome              44.534218
dtype: float64
```

In [6]:
```python
Q1 = df[numerical].quantile(0.25)
Q3 = df[numerical].quantile(0.75)
IQR = Q3 - Q1

# Calculate median
median = df[numerical].median()

# Identify outliers
outliers_lower = (df[numerical] < (Q1 - 1.5 * IQR))
outliers_upper = (df[numerical] > (Q3 + 1.5 * IQR))

# Replace outliers with median
df[numerical] = df[numerical].mask(outliers_lower, median, axis=1)
df[numerical] = df[numerical].mask(outliers_upper, median, axis=1)
```

In [7]:
```python
df[numerical].skew()
```

Out[7]:
```
LoanAmount                    1.106712
InterestRate                  0.115913
MonthlyInstallment            0.980513
MonthsOfEmployementExperience 0.856838
AverageCreditScore           -0.158725
OpenCreditLines               0.453486
TotalInquiries                1.077752
AvailableBankcardCredit       1.292952
DebtToIncomeRatio             0.428901
StatedMonthlyIncome           0.591492
dtype: float64
```

Step 4: Prepare Data for Model Training

Shuffle the Rows of a DataFrame

In [8]:
```
df = df.sample(frac=1, random_state=42)
df
```

Out[8]:

	Term	MonthsOfEmployementExperience	IsHomeowner	OpenCreditLines	TotalInquiries	AvailableBankcardCredit	De
2098	36	60.000000	1	8.000000	5	362.000000	
43905	36	9.000000	0	5.000000	9	0.000000	
46310	36	96.071582	0	9.260164	1	11210.225447	
53388	36	63.000000	1	6.000000	5	1913.000000	
32128	36	11.000000	1	9.000000	8	138.000000	
...	...	...	...	...	...	...	
44732	36	49.000000	1	4.000000	5	7046.000000	
54343	36	22.000000	0	2.000000	6	0.000000	
38158	36	87.000000	0	6.000000	13	491.000000	
860	36	18.000000	1	8.000000	14	7252.000000	
15795	36	16.000000	0	6.000000	2	4368.500000	

55106 rows × 16 columns

Separate the Input Features (X) from the Target Variable (y).

In [9]:
```
X = df.drop(columns=['GoodLoan'])
y = df['GoodLoan']
```

Standardize Numerical Features using Feature Scaling.

In [10]:
```
Standard_Scaler = StandardScaler()
X[numerical] = Standard_Scaler.fit_transform(X[numerical])

print("Scaled Features (x):")
print(X.head())

print("\nTarget Variable (y):")
print(y.head())
```

```
Scaled Features (x):
       Term  MonthsOfEmployementExperience  IsHomeowner  OpenCreditLines  \
2098     36                      -0.124567            1        -0.023026
43905    36                      -1.124880            0        -0.762092
46310    36                       0.582939            0         0.287422
53388    36                      -0.065725            1        -0.515737
32128    36                      -1.085652            1         0.223329

       TotalInquiries  AvailableBankcardCredit  DebtToIncomeRatio  \
2098        -0.114880                -0.875305           2.405529
43905        0.820833                -0.934278           2.680542
46310       -1.050592                 0.891976          -0.436274
53388       -0.114880                -0.622632           1.488818
32128        0.586905                -0.911796           0.534950

       IncomeVerifiable  StatedMonthlyIncome  LoanAmount  MonthlyInstallment  \
2098                  1             2.068814   -0.939101           -1.510281
43905                 1            -1.551569   -1.204407           -1.168564
46310                 1            -1.522892   -0.275839           -0.085855
53388                 1            -0.524802   -0.408491           -0.274842
32128                 0            -1.911839   -0.673796           -0.693528

       InterestRate  IsEmployed  AverageCreditScore  AnyDelinquencies
2098       1.200108           1           -0.268925                 0
43905      1.817964           1           -0.858709                 0
46310      1.079491           1            0.025967                 1
53388      0.848102           1           -1.153601                 0
32128     -0.301455           1           -2.038278                 0

Target Variable (y):
2098     1
43905    0
46310    0
53388    0
32128    1
Name: GoodLoan, dtype: int64
```

Split the Data into Train Test and Validation Sets.

In [11]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.25, random_state=42)
```

Perform Feature Selection

In [12]:
```
# Instantiate SelectKBest with ANOVA F-value as the score function
k_best_selector = SelectKBest(score_func=f_classif, k=12)  # Select top 12 features

# Fit SelectKBest to training data
X_train_selected = k_best_selector.fit_transform(X_train, y_train)

# Print the names of the selected features
selected_feature_indices = k_best_selector.get_support(indices=True)
selected_feature_names = X.columns[selected_feature_indices]
print("Selected Features:")
for feature in selected_feature_names:
    print(feature)

X_train = X_train[selected_feature_names]
X_val = X_val[selected_feature_names]
X_test = X_test[selected_feature_names]
```

```
Selected Features:
Term
IsHomeowner
OpenCreditLines
TotalInquiries
AvailableBankcardCredit
DebtToIncomeRatio
IncomeVerifiable
StatedMonthlyIncome
MonthlyInstallment
InterestRate
AverageCreditScore
AnyDelinquencies
```

Step 6: Model Building

Subset Selection

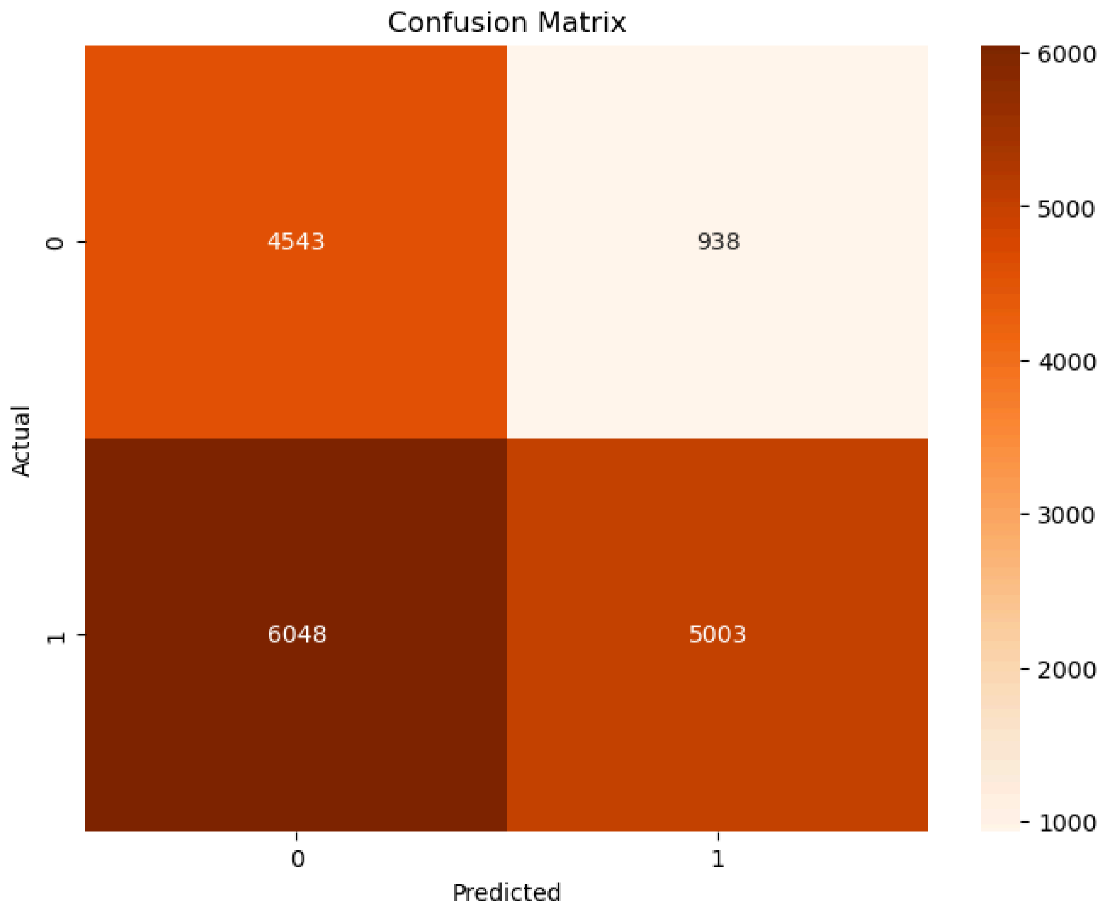
In [13]:
```
def forward_stepwise_selection(model, X_train, X_test, y_train, y_test):
    remaining_features = list(X_train.columns)
    selected_features = []
    prev_score = 0
    while True:
        best_score = 0
        for feature in remaining_features:
            model.fit(X_train[selected_features + [feature]], y_train)
            y_pred = model.predict(X_test[selected_features + [feature]])
            #score = f1_score(y_test, y_pred, average='weighted')
            fpr, tpr, _ = roc_curve(y_test, y_pred)
            score = auc(fpr, tpr)
            #score = accuracy_score(y_test, y_pred)
            if score > best_score:
                best_score = score
                best_feature = feature
        if best_score > prev_score:
            prev_score = best_score
            selected_features.append(best_feature)
            remaining_features.remove(best_feature)
        else:
            break
    return selected_features
```

Logistic Regression

In [14]:
```
LR = LogisticRegression(max_iter=1000,class_weight={0:3, 1:1}, random_state=42)

# Best Subset Selection
# best_subset_LR = forward_stepwise_selection(LR,X_train, X_val, y_train, y_val)
# print("\nSelected Features:", best_subset_LR)

# Hyper-parameter Tuning
# param_grid = {
#     'C': [0.001, 0.01, 0.1, 1, 10, 100]
# }
# grid_search = GridSearchCV(LR, param_grid, cv=5, scoring='roc_auc')
# grid_search.fit(X_train[best_subset_LR], y_train)
# best_params_LR = grid_search.best_params_
# print("\nBest Parameters:", best_params_LR)

best_subset_LR = ['InterestRate', 'Term', 'TotalInquiries', 'StatedMonthlyIncome', 'AnyDelinquencies',
                'DebtToIncomeRatio', 'IsHomeowner', 'AverageCreditScore', 'MonthlyInstallment', 'IncomeV
print("\nSelected Features:", best_subset_LR)
best_params_LR =  {'C': 1}
print("\nBest Parameters:", best_params_LR)

# Model with best parameters
LR = LogisticRegression(**best_params_LR,max_iter=1000,class_weight={0:3, 1:1}, random_state=42)
```

```
# Perform cross-validation
cv_scores = cross_val_score(LR, X_train[best_subset_LR], y_train, cv=5)

# Print cross-validation scores
print("\nCross-validation scores:", cv_scores)

# Calculate mean validation accuracy
validation_acc_LR = np.mean(cv_scores)
print("\nValidation accuracy:", np.mean(validation_acc_LR))

# Fit the model with selected features
LR.fit(X_train[best_subset_LR], y_train)

# Calculate training accuracy
y_pred = LR.predict(X_train[best_subset_LR])
train_acc_LR = accuracy_score(y_train, y_pred)
print("Training accuracy:", train_acc_LR)

# Calculate testing accuracy
y_pred = LR.predict(X_test[best_subset_LR])
test_acc_LR = accuracy_score(y_test, y_pred)
print("Testing accuracy:", test_acc_LR)

# Calculate precision, recall, and F1 score
precision_LR = precision_score(y_test, y_pred, average='weighted')
recall_LR = recall_score(y_test, y_pred, average='weighted')
f1_LR = f1_score(y_test, y_pred, average='weighted')

# Build a classification report
classification_rep_LR = classification_report(y_test, y_pred)

# Plot a confusion matrix
confusion_matrix_LR = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix_LR, annot=True, fmt='d', cmap='Oranges')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Print the classification report
print("Classification Report:\n", classification_rep_LR)
print("Precision:", precision_LR)
print("Recall:", recall_LR)
print("F1 Score:", f1_LR)

print("\nThe accuracy of the Logistic Regression Model is:", round(test_acc_LR*100,2),"% .")

fpr_LR, tpr_LR, _ = roc_curve(y_test, y_pred)
auc_LR = auc(fpr_LR, tpr_LR)

print("\nThe ROC-AUC Score of the Logistic Regression Model is:",auc_LR,".")
```

```
Selected Features: ['InterestRate', 'Term', 'TotalInquiries', 'StatedMonthlyIncome', 'AnyDelinquencies',
'DebtToIncomeRatio', 'IsHomeowner', 'AverageCreditScore', 'MonthlyInstallment', 'IncomeVerifiable']

Best Parameters: {'C': 1}

Cross-validation scores: [0.57034221 0.57673695 0.57414449 0.57569997 0.57639129]

Validation accuracy: 0.5746629796059454
Training accuracy: 0.5752160387141376
Testing accuracy: 0.577425598838616
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.43      0.83      0.57      5481
           1       0.84      0.45      0.59     11051

    accuracy                           0.58     16532
   macro avg       0.64      0.64      0.58     16532
weighted avg       0.71      0.58      0.58     16532

Precision: 0.7051338751472839
Recall: 0.577425598838616
F1 Score: 0.5810628014428235

The accuracy of the Logistic Regression Model is: 57.74 % .

The ROC-AUC Score of the Logistic Regression Model is: 0.6407912785179315 .
```

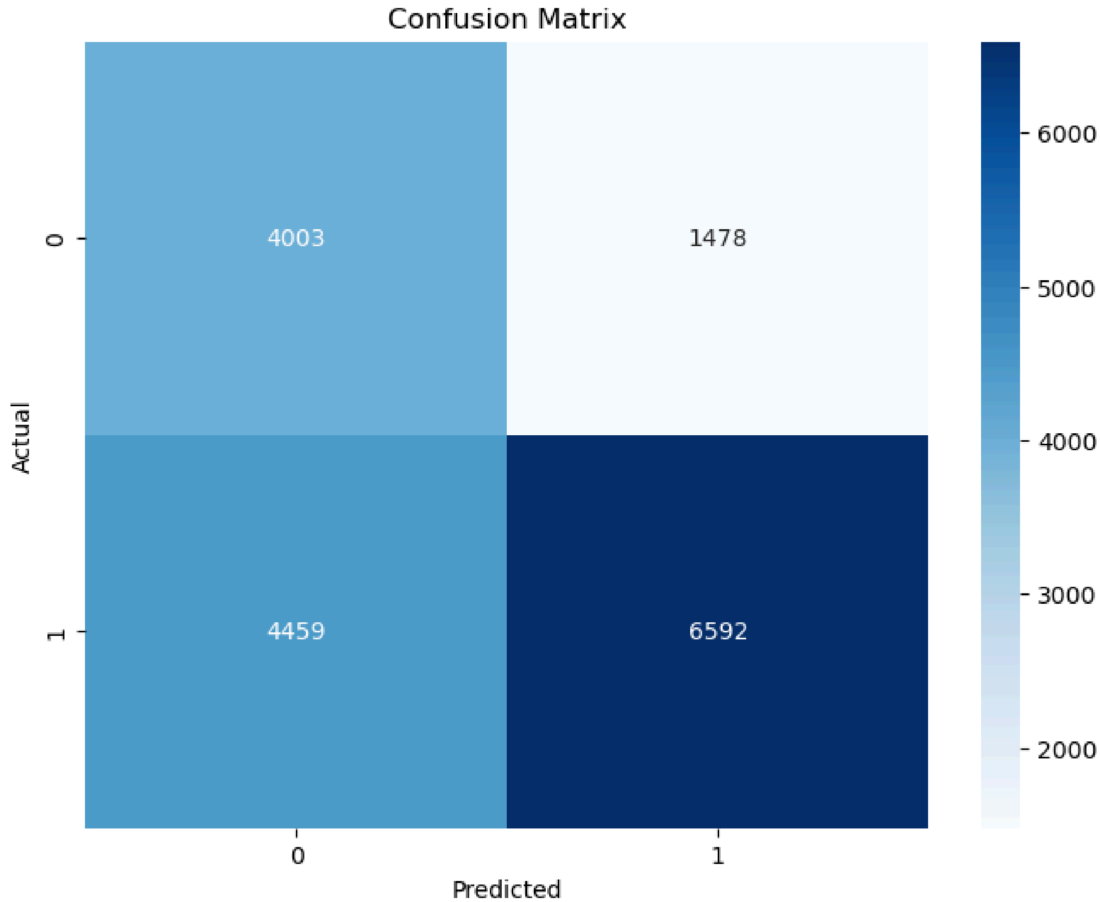
Extreme Gradient Boosting (XGBoost)

In [15]:

```
weight=len(y_train[y_train == 0]) / len(y_train[y_train == 1])
XGB = XGBClassifier(random_state=42,scale_pos_weight=weight)

# Best Subset Selection
# best_subset_XGB = forward_stepwise_selection(XGB,X_train, X_val, y_train, y_val)

# Hyper-parameter Tuning
# param_grid = {
#     'n_estimators': [100, 200, 300],  # Number of boosting rounds
#     'learning_rate': [0.05, 0.1, 0.2],  # Step size shrinkage used in update to prevent overfitting
#     'max_depth': [3, 4, 5],  # Maximum depth of a tree, deeper trees can model more complex relationsh
# }

# grid_search = GridSearchCV(XGB, param_grid, cv=5, scoring='roc_auc')
# grid_search.fit(X_train[best_subset_XGB], y_train)
# best_params_XGB = grid_search.best_params_
```

```
# print("\nSelected Features:", best_subset_XGB)
# print("\nBest Parameters:", best_params_XGB)

best_subset_XGB = ['InterestRate', 'MonthlyInstallment', 'AverageCreditScore', 'Term', 'AnyDelinquencies
'IsHomeowner', 'DebtToIncomeRatio', 'StatedMonthlyIncome', 'OpenCreditLines']
print("\nSelected Features:", best_subset_XGB)

best_params_XGB = {'learning_rate': 0.1, 'max_depth': 4, 'n_estimators': 100}
print("\nBest Parameters:", best_params_XGB)

# Model with best parameters
XGB = XGBClassifier(**best_params_XGB,random_state=42,scale_pos_weight=weight)

# Perform cross-validation
cv_scores = cross_val_score(XGB, X_train[best_subset_XGB], y_train, cv=5)

# Print cross-validation scores
print("\nCross-validation scores:", cv_scores)

# Calculate mean validation accuracy
validation_acc_XGB = np.mean(cv_scores)
print("\nValidation accuracy:", np.mean(validation_acc_XGB))

# Fit the model with selected features
XGB.fit(X_train[best_subset_XGB], y_train)

# Calculate training accuracy
y_pred = XGB.predict(X_train[best_subset_XGB])
train_acc_XGB = accuracy_score(y_train, y_pred)
print("Training accuracy:", train_acc_XGB)

# Calculate testing accuracy
y_pred = XGB.predict(X_test[best_subset_XGB])
test_acc_XGB = accuracy_score(y_test, y_pred)
print("Testing accuracy:", test_acc_XGB)

# Calculate precision, recall, and F1 score
precision_XGB = precision_score(y_test, y_pred, average='weighted')
recall_XGB = recall_score(y_test, y_pred, average='weighted')
f1_XGB = f1_score(y_test, y_pred, average='weighted')

# Build a classification report
classification_rep_XGB = classification_report(y_test, y_pred)

# Plot a confusion matrix
confusion_matrix_XGB = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix_XGB, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Print the classification report
print("Classification Report:\n", classification_rep_XGB)
print("Precision:", precision_XGB)
print("Recall:", recall_XGB)
print("F1 Score:", f1_XGB)

print("\nThe accuracy of the Extreme Gradient Boosting Model is:", round(test_acc_XGB*100,2),"% .")

fpr_XGB, tpr_XGB, _ = roc_curve(y_test, y_pred)
auc_XGB = auc(fpr_XGB, tpr_XGB)

print("\nThe ROC-AUC Score of the Extreme Gradient Boosting (XGBoost) is:",auc_XGB,".")
```

```
Selected Features: ['InterestRate', 'MonthlyInstallment', 'AverageCreditScore', 'Term', 'AnyDelinquencie
s', 'IsHomeowner', 'DebtToIncomeRatio', 'StatedMonthlyIncome', 'OpenCreditLines']

Best Parameters: {'learning_rate': 0.1, 'max_depth': 4, 'n_estimators': 100}

Cross-validation scores: [0.63480816 0.64379537 0.6389561  0.63878327 0.64362254]

Validation accuracy: 0.6399930867611475
Training accuracy: 0.652886277220878
Testing accuracy: 0.6408782966368255
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.47      0.73      0.57      5481
           1       0.82      0.60      0.69     11051

    accuracy                           0.64     16532
   macro avg       0.64      0.66      0.63     16532
weighted avg       0.70      0.64      0.65     16532

Precision: 0.7028706412690978
Recall: 0.6408782966368256
F1 Score: 0.6512743583745236

The accuracy of the Extreme Gradient Boosting Model is: 64.09 % .

The ROC-AUC Score of the Extreme Gradient Boosting (XGBoost) is: 0.6634241410232973 .
```

Under Sampling the Dataset to handle the Imbalance in Data

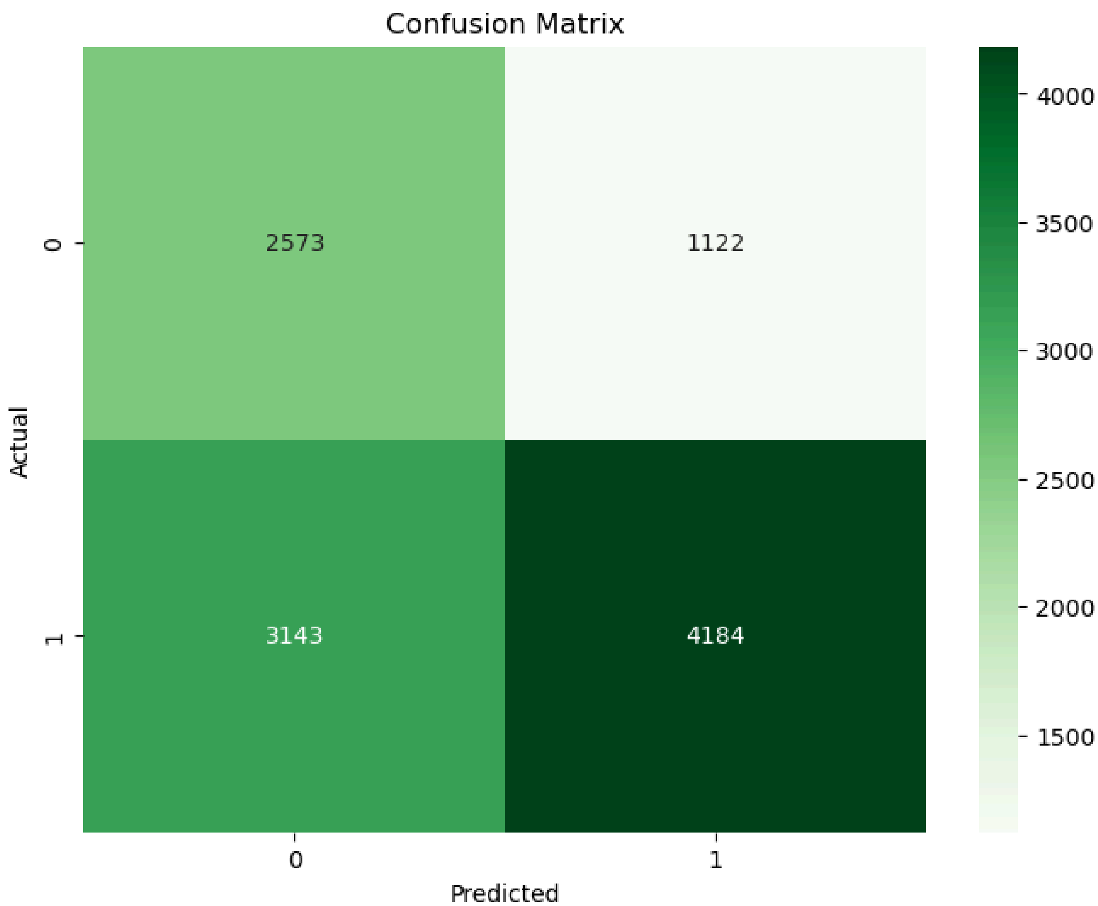
In [16]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.25, random_state=42)


undersampler = RandomUnderSampler(random_state=42)
X_train, y_train = undersampler.fit_resample(X_train, y_train)
```

K - Nearest Neighbour (KNN)

In [17]:
```
KNN = KNeighborsClassifier()

# Best Subset Selection
# best_subset_KNN = forward_stepwise_selection(KNN,X_train, X_val, y_train, y_val)
# print("\nSelected Features:", best_subset_KNN)

# Hyper-parameter Tuning
# param_grid = {
#     'n_neighbors': [3, 5, 7, 9, 11],  # Different values of k
#     'weights': ['uniform', 'distance'],  # Weighting scheme
#     'metric': ['euclidean', 'manhattan']  # Distance metric
# }
# grid_search = GridSearchCV(KNN, param_grid, cv=5, scoring='roc_auc')
# grid_search.fit(X_train[best_subset_KNN], y_train)
# best_params_KNN = grid_search.best_params_
# print("\nBest Parameters:", best_params_KNN)

best_subset_KNN = ['MonthlyInstallment', 'LoanAmount', 'Term', 'AverageCreditScore', 'AnyDelinquencies',
print("\nSelected Features:", best_subset_KNN)
best_params_KNN = {'metric': 'manhattan', 'n_neighbors': 11, 'weights': 'uniform'}
print("\nBest Parameters:", best_params_KNN)

# Model with best parameters
KNN = KNeighborsClassifier(**best_params_KNN)

# Perform cross-validation
cv_scores = cross_val_score(KNN, X_train[best_subset_KNN], y_train, cv=5)

# Print cross-validation scores
print("\nCross-validation scores:", cv_scores)

# Calculate mean validation accuracy
validation_acc_KNN = np.mean(cv_scores)
print("\nValidation accuracy:", np.mean(validation_acc_KNN))

# Fit the model with selected features
KNN.fit(X_train[best_subset_KNN], y_train)

# Calculate training accuracy
y_pred = KNN.predict(X_train[best_subset_KNN])
train_acc_KNN = accuracy_score(y_train, y_pred)
print("Training accuracy:", train_acc_KNN)

# Calculate testing accuracy
y_pred = KNN.predict(X_test[best_subset_KNN])
test_acc_KNN = accuracy_score(y_test, y_pred)
print("Testing accuracy:", test_acc_KNN)

# Calculate precision, recall, and F1 score
precision_KNN = precision_score(y_test, y_pred, average='weighted')
recall_KNN = recall_score(y_test, y_pred, average='weighted')
f1_KNN = f1_score(y_test, y_pred, average='weighted')

# Build a classification report
classification_rep_KNN = classification_report(y_test, y_pred)

# Plot a confusion matrix
confusion_matrix_KNN = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(confusion_matrix_KNN, annot=True, fmt='d', cmap='Greens')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Print the classification report
print("Classification Report:\n", classification_rep_KNN)
print("Precision:", precision_KNN)
print("Recall:", recall_KNN)
print("F1 Score:", f1_KNN)

print("\nThe accuracy of the K - Nearest Neighbour Model is:", round(test_acc_KNN*100,2),"% .")

fpr_KNN, tpr_KNN, _ = roc_curve(y_test, y_pred)
auc_KNN = auc(fpr_KNN, tpr_KNN)

print("\nThe ROC-AUC Score of the K - Nearest Neighbour Model is:",auc_KNN,".")
```

```
Selected Features: ['MonthlyInstallment', 'LoanAmount', 'Term', 'AverageCreditScore', 'AnyDelinquencie
s', 'InterestRate']

Best Parameters: {'metric': 'manhattan', 'n_neighbors': 11, 'weights': 'uniform'}

Cross-validation scores: [0.61836969 0.63467279 0.62962113 0.61859931 0.63206247]

Validation accuracy: 0.6266650774958114
Training accuracy: 0.6920180031229908
Testing accuracy: 0.6130466340047178
```



```
Classification Report:
              precision    recall  f1-score   support

           0       0.45      0.70      0.55      3695
           1       0.79      0.57      0.66      7327

    accuracy                           0.61     11022
   macro avg       0.62      0.63      0.60     11022
weighted avg       0.68      0.61      0.62     11022

Precision: 0.6750960859798549
Recall: 0.6130466340047178
F1 Score: 0.6236435188070928

The accuracy of the K - Nearest Neighbour Model is: 61.3 % .

The ROC-AUC Score of the K - Nearest Neighbour Model is: 0.6336925191697419 .
```

Multilayer Perceptron (MLP) Classifier

In [18]:
```
MLP = MLPClassifier(random_state=42, max_iter=1000)

# Best Subset Selection
# best_subset_MLP = forward_stepwise_selection(MLP,X_train, X_val, y_train, y_val)
best_subset_MLP = ['InterestRate', 'MonthlyInstallment', 'LoanAmount', 'TotalInquiries',
                   'StatedMonthlyIncome', 'AnyDelinquencies', 'AverageCreditScore']
print("\nSelected Features:", best_subset_MLP)


# Hyper-parameter Tuning
# param_grid = {
#     'hidden_layer_sizes': [(50,), (100,), (50, 50), (100, 50)],  # Different architectures for hidden
#     'activation': ['relu', 'tanh'],  # Activation functions
#     'alpha': [0.0001, 0.001, 0.01],  # L2 regularization parameter
# }
# grid_search = GridSearchCV(MLP, param_grid, cv=5, scoring='roc_auc')
# grid_search.fit(X_train[best_subset_MLP], y_train)
# best_params_MLP = grid_search.best_params_
best_params_MLP = {'activation': 'relu', 'alpha': 0.01, 'hidden_layer_sizes': (50,)}
print("\nBest Parameters:", best_params_MLP)

# Model with best parameters
MLP = MLPClassifier(**best_params_MLP,random_state=42, max_iter=1000)

# Perform cross-validation
cv_scores = cross_val_score(MLP, X_train[best_subset_MLP], y_train, cv=5)

# Print cross-validation scores
print("\nCross-validation scores:", cv_scores)

# Calculate mean validation accuracy
validation_acc_MLP = np.mean(cv_scores)
print("\nValidation accuracy:", np.mean(validation_acc_MLP))

# Fit the model with selected features
MLP.fit(X_train[best_subset_MLP], y_train)

# Calculate training accuracy
y_pred = MLP.predict(X_train[best_subset_MLP])
train_acc_MLP = accuracy_score(y_train, y_pred)
print("Training accuracy:", train_acc_MLP)

# Calculate testing accuracy
y_pred = MLP.predict(X_test[best_subset_MLP])
test_acc_MLP = accuracy_score(y_test, y_pred)
print("Testing accuracy:", test_acc_MLP)

# Calculate precision, recall, and F1 score
precision_MLP = precision_score(y_test, y_pred, average='weighted')
```

```
recall_MLP = recall_score(y_test, y_pred, average='weighted')
f1_MLP = f1_score(y_test, y_pred, average='weighted')

# Build a classification report
classification_rep_MLP = classification_report(y_test, y_pred)

# Plot a confusion matrix
confusion_matrix_MLP = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix_MLP, annot=True, fmt='d', cmap='Purples')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Print the classification report
print("Classification Report:\n", classification_rep_MLP)
print("Precision:", precision_MLP)
print("Recall:", recall_MLP)
print("F1 Score:", f1_MLP)

print("\nThe accuracy of the Multilayer Perceptron (MLP) Classifier Model is:", round(test_acc_MLP*100,2

fpr_MLP, tpr_MLP, _ = roc_curve(y_test, y_pred)
auc_MLP = auc(fpr_MLP, tpr_MLP)

print("\nThe ROC-AUC Score of the Multilayer Perceptron (MLP) Classifier Model is:",auc_MLP,".")
```

```
Selected Features: ['InterestRate', 'MonthlyInstallment', 'LoanAmount', 'TotalInquiries', 'StatedMonthly
Income', 'AnyDelinquencies', 'AverageCreditScore']
```

```
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
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C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
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C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
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C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
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C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
C:\Users\parka\anaconda3.1\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (1000) reached and the optimization hasn't converged yet.
  warnings.warn(
```
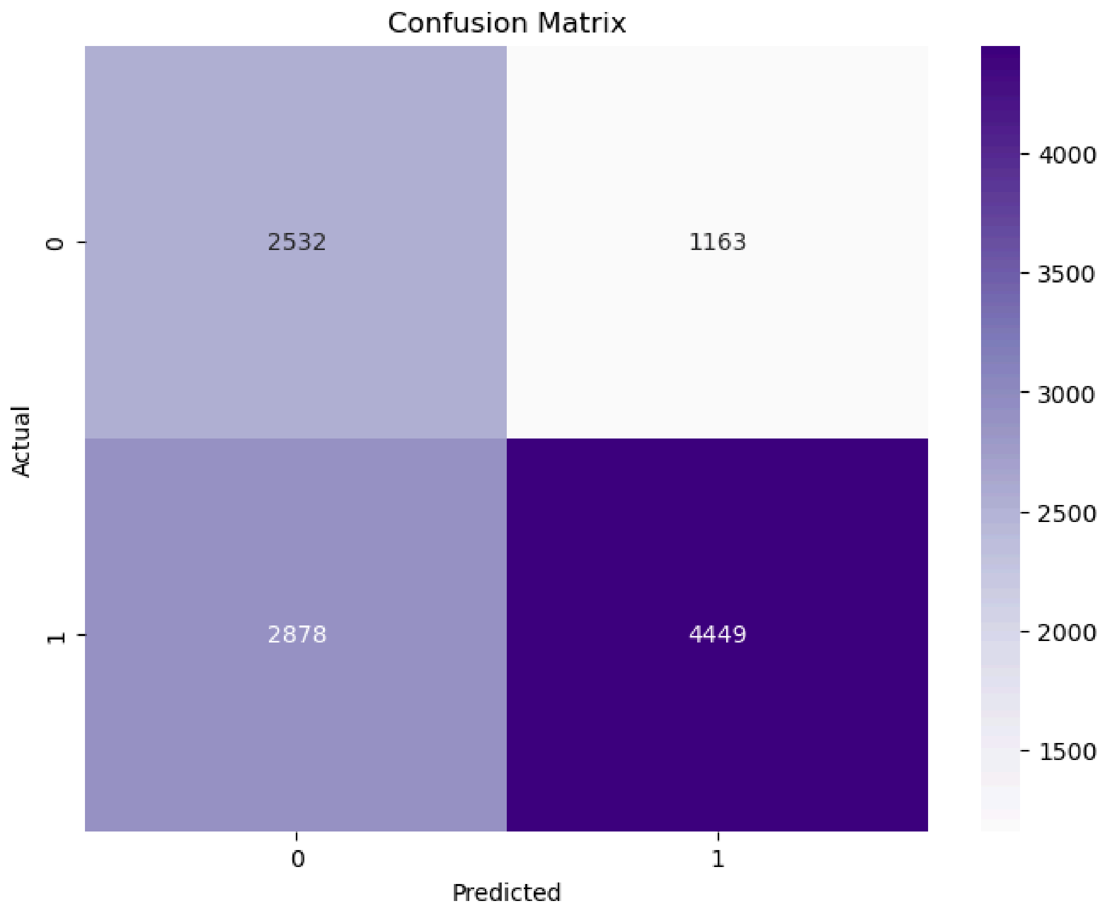

```
Best Parameters: {'activation': 'relu', 'alpha': 0.01, 'hidden_layer_sizes': (50,)}

Cross-validation scores: [0.64707233 0.65487945 0.64225029 0.64913892 0.65502986]

Validation accuracy: 0.6496741689946086
Training accuracy: 0.662579222926426
Testing accuracy: 0.6333696243875885
```



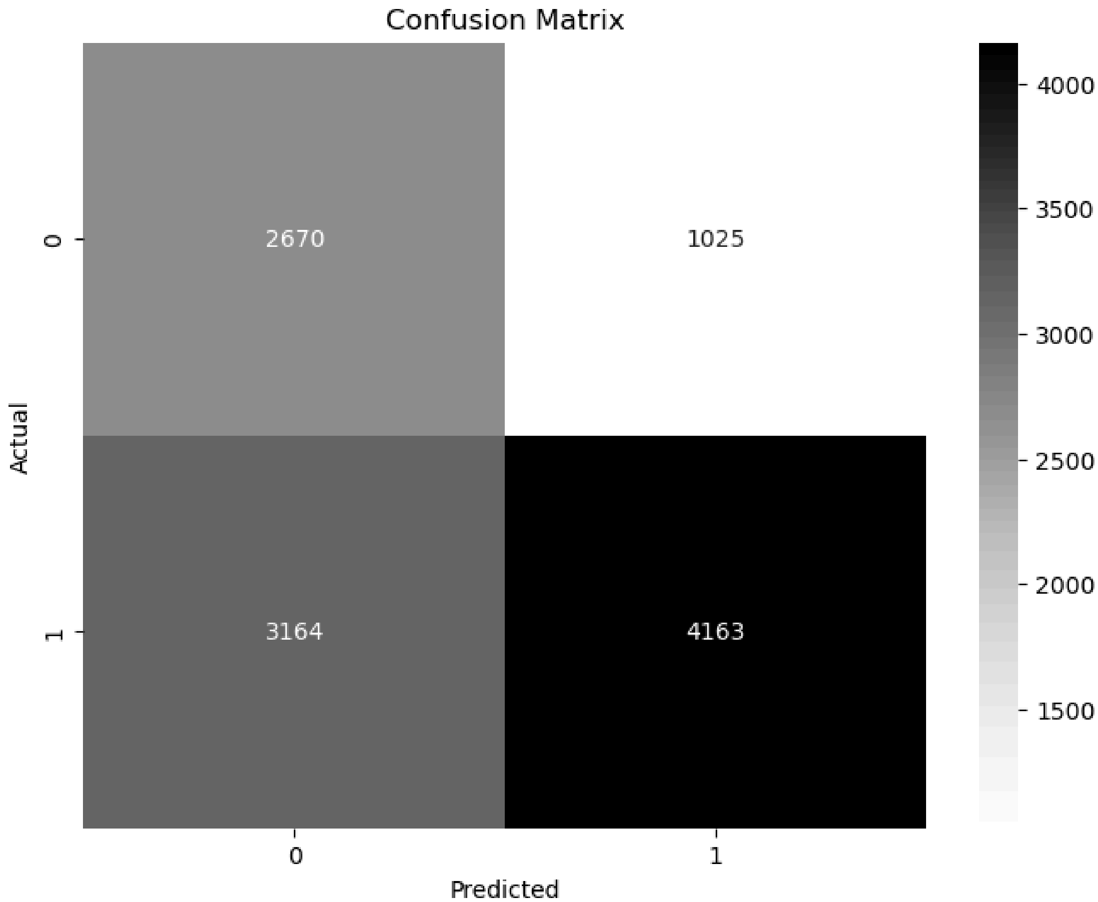

```
Classification Report:
              precision    recall  f1-score   support

           0       0.47      0.69      0.56      3695
           1       0.79      0.61      0.69      7327

    accuracy                           0.63     11022
   macro avg       0.63      0.65      0.62     11022
weighted avg       0.68      0.63      0.64     11022

Precision: 0.6838990016433403
Recall: 0.6333696243875885
F1 Score: 0.6436009997482628

The accuracy of the Multilayer Perceptron (MLP) Classifier Model is: 63.34 % .

The ROC-AUC Score of the Multilayer Perceptron (MLP) Classifier Model is: 0.6462282809258506 .
```

Support Vector Machine (SVM)

In [19]:
```
SVM = SVC(random_state=42)

# Best Subset Selection
# best_subset_SVM = forward_stepwise_selection(SVM,X_train, X_val, y_train, y_val)
best_subset_SVM = ['InterestRate', 'MonthlyInstallment', 'TotalInquiries', 'AvailableBankcardCredit',
 'AverageCreditScore', 'StatedMonthlyIncome', 'LoanAmount', 'AnyDelinquencies', 'IsHomeowner', 'IncomeVe
print("\nSelected Features:", best_subset_SVM)

# Hyper-parameter Tuning
# param_grid = {
#     'C': [0.1, 1, 10, 100],              # Regularization parameter
#     'kernel': ['linear', 'rbf', 'poly'],# Kernel type
#     'gamma': ['scale', 'auto'],         # Kernel coefficient for RBF and poly kernels
#     'degree': [2, 3, 4],                # Degree for poly kernel
#     'coef0': [0.0, 0.1, 0.5]            # Independent term in poly and sigmoid kernels
# }
```

```
# random_search = RandomizedSearchCV(SVM, param_grid, cv=5, scoring='roc_auc')
# random_search.fit(X_train[best_subset_SVM], y_train)
# best_params_SVM = random_search.best_params_
best_params_SVM = {'kernel': 'rbf', 'gamma': 'auto', 'degree': 3, 'coef0': 0.0, 'C': 1}
print("\nBest Parameters:", best_params_SVM)

# Model with best parameters
SVM = SVC(**best_params_SVM)

# Perform cross-validation
cv_scores = cross_val_score(SVM, X_train[best_subset_SVM], y_train, cv=5)

# Print cross-validation scores
print("\nCross-validation scores:", cv_scores)

# Calculate mean validation accuracy
validation_acc_SVM = np.mean(cv_scores)
print("\nValidation accuracy:", np.mean(validation_acc_SVM))

# Fit the model with selected features
SVM.fit(X_train[best_subset_SVM], y_train)

# Calculate training accuracy
y_pred = SVM.predict(X_train[best_subset_SVM])
train_acc_SVM = accuracy_score(y_train, y_pred)
print("Training accuracy:", train_acc_SVM)

# Calculate testing accuracy
y_pred = SVM.predict(X_test[best_subset_SVM])
test_acc_SVM = accuracy_score(y_test, y_pred)
print("Testing accuracy:", test_acc_SVM)

# Calculate precision, recall, and F1 score
precision_SVM = precision_score(y_test, y_pred, average='weighted')
recall_SVM = recall_score(y_test, y_pred, average='weighted')
f1_SVM = f1_score(y_test, y_pred, average='weighted')

# Build a classification report
classification_rep_SVM = classification_report(y_test, y_pred)

# Plot a confusion matrix
confusion_matrix_SVM = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix_SVM, annot=True, fmt='d', cmap='Greys')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Print the classification report
print("Classification Report:\n", classification_rep_SVM)
print("Precision:", precision_SVM)
print("Recall:", recall_SVM)
print("F1 Score:", f1_SVM)

print("\nThe accuracy of the Support Vector Machine Model is:", round(test_acc_SVM*100,2),"% .")

fpr_SVM, tpr_SVM, _ = roc_curve(y_test, y_pred)
auc_SVM = auc(fpr_SVM, tpr_SVM)

print("\nThe ROC-AUC Score of the Support Vector Machine Model is:",auc_SVM,".")
```

```
Selected Features: ['InterestRate', 'MonthlyInstallment', 'TotalInquiries', 'AvailableBankcardCredit',
'AverageCreditScore', 'StatedMonthlyIncome', 'LoanAmount', 'AnyDelinquencies', 'IsHomeowner', 'IncomeVer
ifiable']

Best Parameters: {'kernel': 'rbf', 'gamma': 'auto', 'degree': 3, 'coef0': 0.0, 'C': 1}

Cross-validation scores: [0.65258324 0.65350172 0.652124   0.64546498 0.64813964]

Validation accuracy: 0.650362715942214
Training accuracy: 0.6634058969413061
Testing accuracy: 0.6199419343131918
```



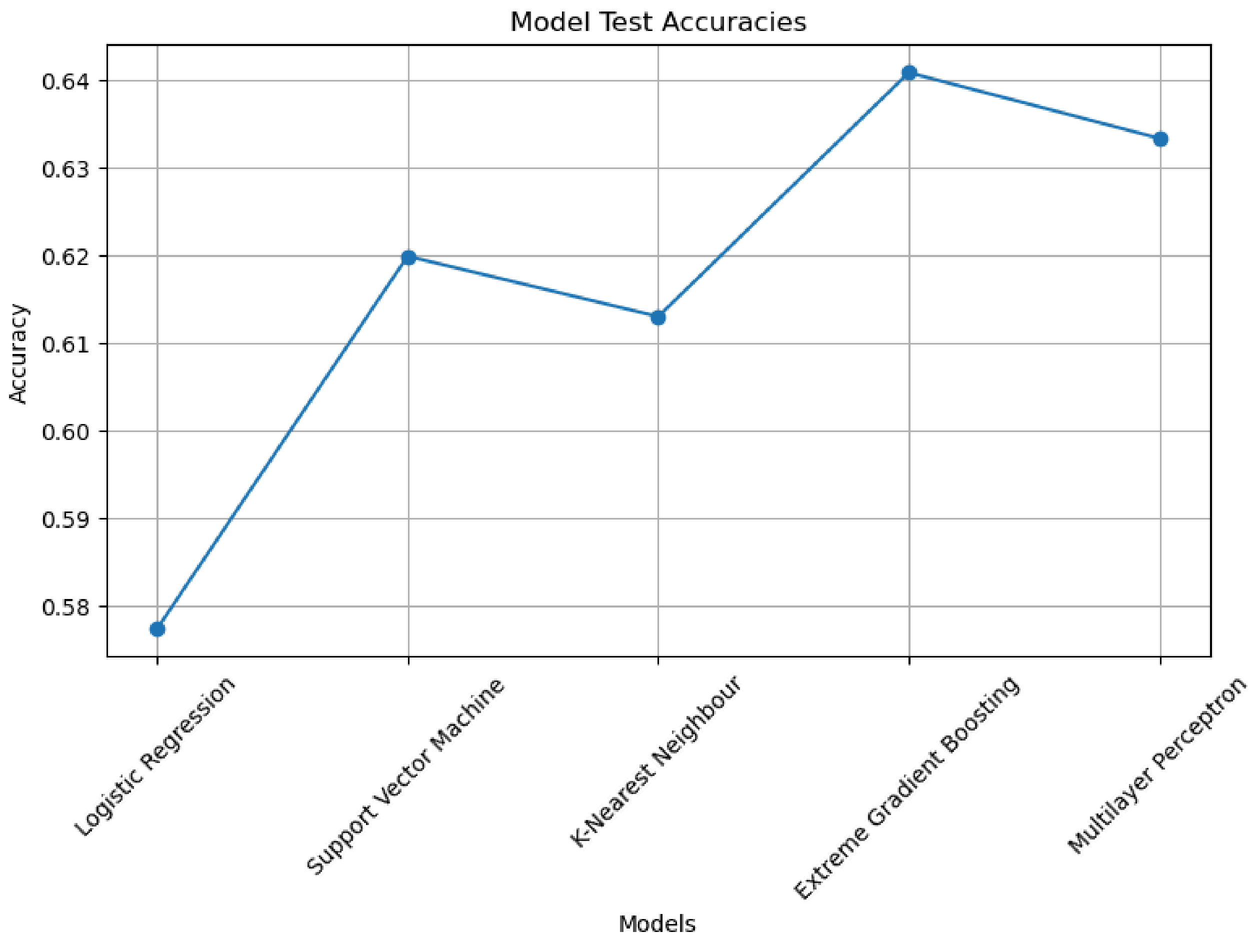

```
Classification Report:
              precision    recall  f1-score   support

           0       0.46      0.72      0.56      3695
           1       0.80      0.57      0.67      7327

    accuracy                           0.62     11022
   macro avg       0.63      0.65      0.61     11022
weighted avg       0.69      0.62      0.63     11022

Precision: 0.6868495709927309
Recall: 0.6199419343131918
F1 Score: 0.6301194637007504

The accuracy of the Support Vector Machine Model is: 61.99 % .

The ROC-AUC Score of the Support Vector Machine Model is: 0.6453853090862888 .
```

Step 7: Model Comparison

In [20]:

```
models = ['Logistic Regression', 'Support Vector Machine', 'K-Nearest Neighbour', 'Extreme Gradient Boos
accuracies = [test_acc_LR, test_acc_SVM ,test_acc_KNN, test_acc_XGB, test_acc_MLP]  # Example accuracies

plt.figure(figsize=(8, 6))
plt.plot(models, accuracies, marker='o')
```

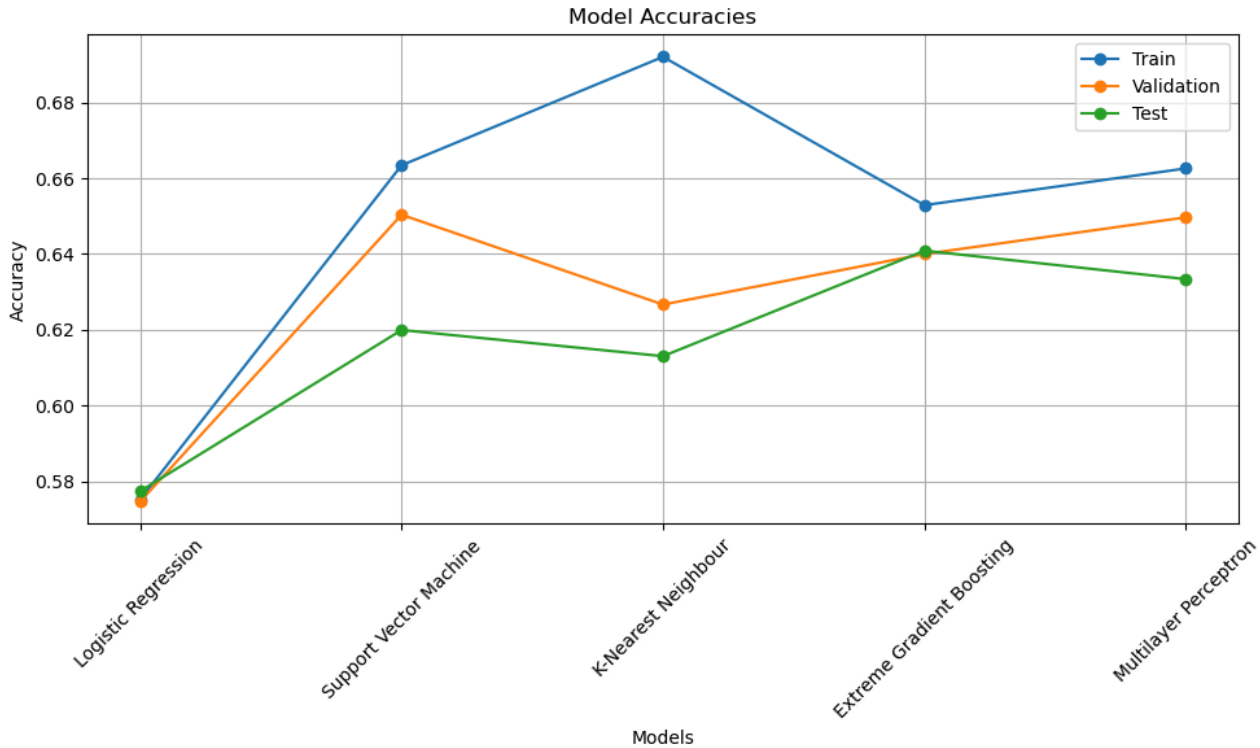
```
plt.title('Model Test Accuracies')
plt.xlabel('Models')
plt.ylabel('Accuracy')

plt.grid(True)
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.tight_layout()  # Adjust layout to prevent cropping of labels
plt.show()
```



In [21]:

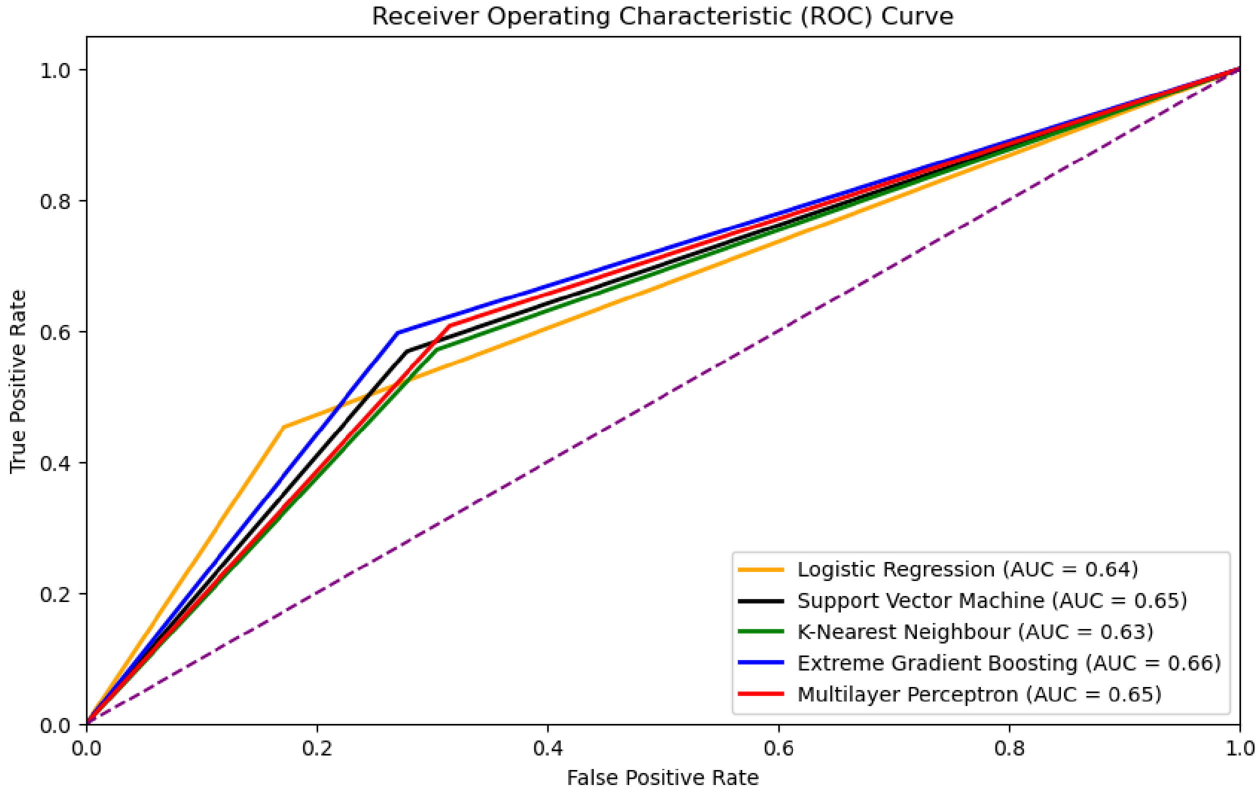
```
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Support Vector Machine', 'K-Nearest Neighbour', 'Extreme Gradient Boos

train_accuracies = [train_acc_LR, train_acc_SVM, train_acc_KNN, train_acc_XGB, train_acc_MLP]
validation_accuracies = [validation_acc_LR, validation_acc_SVM, validation_acc_KNN, validation_acc_XGB,
test_accuracies = [test_acc_LR, test_acc_SVM, test_acc_KNN, test_acc_XGB, test_acc_MLP]
f1_scores = [f1_LR,f1_SVM,f1_KNN,f1_XGB,f1_MLP]

plt.figure(figsize=(10, 6))

# Plot train accuracies
plt.plot(models, train_accuracies, marker='o', label='Train')

# Plot validation accuracies
plt.plot(models, validation_accuracies, marker='o', label='Validation')

# Plot test accuracies
plt.plot(models, test_accuracies, marker='o', label='Test')

plt.title('Model Accuracies')
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.grid(True)
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
```

```
plt.legend()  # Show legend
plt.tight_layout()  # Adjust layout to prevent cropping of labels
plt.show()
```



In [22]:

```
plt.figure(figsize=(10, 6))
plt.plot(fpr_LR, tpr_LR, color='orange', lw=2, label=f'Logistic Regression (AUC = {auc_LR:.2f})')
plt.plot(fpr_SVM, tpr_SVM, color='black', lw=2, label=f'Support Vector Machine (AUC = {auc_SVM:.2f})')
plt.plot(fpr_KNN, tpr_KNN, color='green', lw=2, label=f'K-Nearest Neighbour (AUC = {auc_KNN:.2f})')
plt.plot(fpr_XGB, tpr_XGB, color='blue', lw=2, label=f'Extreme Gradient Boosting (AUC = {auc_XGB:.2f})')
plt.plot(fpr_MLP, tpr_MLP, color='red', lw=2, label=f'Multilayer Perceptron (AUC = {auc_MLP:.2f})')
plt.plot([0, 1], [0, 1], color='purple', linestyle='--')
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) Curve')
plt.legend(loc='lower right')
plt.show()
```



In [24]:

```
roc_auc_scores = [auc_LR,auc_SVM,auc_KNN,auc_XGB,auc_MLP]
df_table = pd.DataFrame({
    'Model': models,
    'Train Accuracy': train_accuracies,
    'Validation Accuracy': validation_accuracies,
    'Test Accuracy': test_accuracies,
    'ROC-AUC Score': roc_auc_scores,
     'F1-Score': f1_scores
})

# Print the DataFrame
df_table
```

Out[24]:

	Model	Train Accuracy	Validation Accuracy	Test Accuracy	ROC-AUC Score	F1-Score
0	Logistic Regression	0.575216	0.574663	0.577426	0.640791	0.581063
1	Support Vector Machine	0.663406	0.650363	0.619942	0.645385	0.630119
2	K-Nearest Neighbour	0.692018	0.626665	0.613047	0.633693	0.623644
3	Extreme Gradient Boosting	0.652886	0.639993	0.640878	0.663424	0.651274
4	Multilayer Perceptron	0.662579	0.649674	0.633370	0.646228	0.643601

In [ ]:

In [ ]: