In [ ]:
```
# import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# import scalers
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import Normalizer

# import feature selection
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature_selection import chi2
from sklearn.feature_selection import f_classif
from sklearn.feature_selection import mutual_info_classif
from sklearn.feature_selection import mutual_info_regression
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import SelectPercentile
from sklearn.feature_selection import SelectFromModel
from sklearn.feature_selection import RFE

# import classificators
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

# import regressors
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor

# import metrics
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import confusion_matrix

# import library for unalanced data

# Synthetic Minority Oversampling Technique (SMOTE)
from imblearn.over_sampling import SMOTE
# K-Nearest Neighbor OveRsampling (KNNOR)
from knnor import data_augment
# SMOTE + Tomek
from imblearn.combine import SMOTETomek
# SMOTE + ENN
from imblearn.combine import SMOTEENN
# random over sampler
```

```
from imblearn.over_sampling import RandomOverSampler

# import system
import os
import sys
```

Deal with unbalanced data

https://www.analyticsvidhya.com/blog/2020/10/overcoming-class-imbalance-using-smote-techniques/

K-Nearest Neighbor OveRsampling approach: https://www.sciencedirect.com/science/article/pii/S156849462

Online learning:

https://www.sciencedirect.com/topics/physics-and-astronomy/weight-vector

In [ ]:
```
models_classific = {
    'LogisticRegression': LogisticRegression(),
    'SVC': SVC(),
    'DecisionTreeClassifier': DecisionTreeClassifier(),
    'RandomForestClassifier': RandomForestClassifier(),
}
```

In [ ]:
```
def get_data(PATH,file_name):
    try:
        df = pd.read_excel(PATH+file_name, header=1)
        # fill empty space with _
        csv_filename = file_name.replace(" ","_")
        df.to_csv(PATH+csv_filename[:-5]+".csv", index=False)
        df = pd.read_csv(PATH+csv_filename[:-5]+".csv")
        return df
    except:
        print("Error: file not found")
        sys.exit(1)
```

In [ ]:
```
df = get_data("../data/","default of credit card clients.xls")
df.head()
```

Out[ ]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY
0	1	20000	2	2	1	24	2	2	-1	
1	2	120000	2	2	2	26	-1	2	0	
2	3	90000	2	2	2	34	0	0	0	
3	4	50000	2	2	1	37	0	0	0	
4	5	50000	1	2	1	57	-1	0	-1	

5 rows × 25 columns

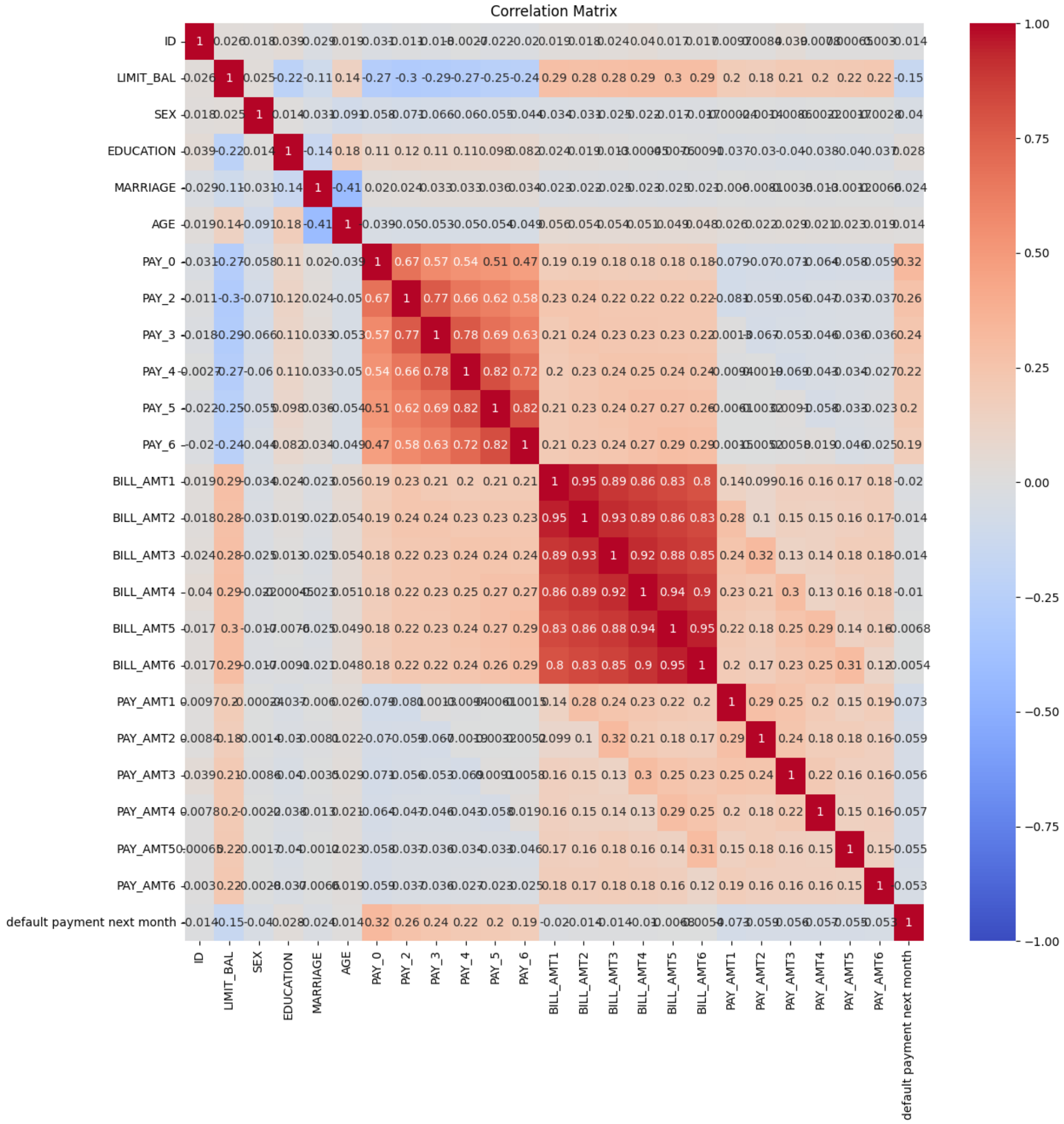
In [ ]:
```
# make function looks nicer
def data_summary(df, interactive=False):
    """
    Prints a summary of the given DataFrame.

    Parameters:
    df (pd.DataFrame): The DataFrame to summarize.
    interactive (bool): If True, pauses after each summary part and clear

    Returns:
    dict: A dictionary containing various summary information of the Data
    """
    hashtable = {
        "Data shape": df.shape,
        "Data columns": df.columns.to_list(),
        "Data types": df.dtypes.to_dict(),
        "Data describe": df.describe().to_string(),
        "Data null count": df.isnull().sum().to_dict(),
        "Data Count": df.count().to_dict()
    }

    for key, value in hashtable.items():
        print(f"{key}:\n{value}\n")
        if interactive:
            input("Press Enter to continue...")
            os.system('cls' if os.name == 'nt' else 'clear')

    return None
```

In [ ]:
```
# check if the data is clean enough
def check_data(df):
    return df.isnull().sum()

# check if the the range of each column, not include the first row
def check_range(df):
    for col in df.columns:
        print(col, df[col].unique())
```

In [ ]:
```
# check the correlation between each column
corr = df.corr()
plt.figure(figsize=(14, 14))
```

```
plt.title('Correlation Matrix')
sns.heatmap(corr, annot=True, vmin=-1, vmax=1, cmap='coolwarm')
```

Out[ ]: <AxesSubplot:title={'center':'Correlation Matrix'}>



In [ ]:
```
# write a function about one-hot encoding
def one_hot_encoding(df, col_list):
    df = df.copy()
    for col in col_list:
        dummies = pd.get_dummies(df[col], prefix=col[:4])
        df = pd.concat([df, dummies], axis=1)
        df = df.drop(col, axis=1)
    return df
```

In [ ]:
```
def pre_processing_class(df,scaler):
    # remove uncessary columns
    df = df.drop(['ID'], axis=1)
    # One-hot encoding
    col_list = ["EDUCATION", "MARRIAGE"]
    df = one_hot_encoding(df, col_list)
    # scale the data
    X = df.drop(['default payment next month'], axis=1)
    X = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
```

```
    y = df['default payment next month']
    return X,y
```

Task1: Build a classification model that predicts whether or not a customer will default on their next payment

In [ ]:
```
# scaler name
scaler_standard = StandardScaler()
scaler_min_max = MinMaxScaler()
scaler_robust = RobustScaler()
scaler_norm = Normalizer()
X, y = pre_processing_class(df, scaler_standard)
```

In [ ]:
```
def train_test_split_class(X,y,random_state=33,test_size=0.2,oversample=F
    # split the data
    if cross_val:
        pass
        # do something
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=t

    if oversample:
        X_train_oversample, y_train_oversample = oversampler.fit_resample
    else:
        X_train_oversample, y_train_oversample = [],[]
    return X_train, X_test, y_train, y_test,X_train_oversample, y_train_o
```

In [ ]:
```
def train_models(name,model, X_train, y_train):
    model.fit(X_train, y_train)
    print(name + ' trained.')
    print('Training accuracy: {:.2f}%'.format(accuracy_score(y_train, mod

def evaluate_models(name,model, X_test, y_test):

    # accuracy
    print(name + ' Accuracy: {:.2f}%'.format(model.score(X_test, y_test)

    # ROC AUC
    if name != 'SVC':
        print(name + ' ROC AUC: {:.2f}%'.format(roc_auc_score(y_test, mod

    # confusion matrix
    y_pred = model.predict(X_test)
    cm = confusion_matrix(y_test, y_pred)
    recall = cm[1][1] / (cm[1][1] + cm[1][0])
    precision = cm[1][1] / (cm[1][1] + cm[0][1])
    specificity = cm[0][0] / (cm[0][0] + cm[0][1])
    print(name + ' Recall: {:.2f}%'.format(recall * 100))
    print(name + ' Precision: {:.2f}%'.format(precision * 100))
    print(name + ' Specificity: {:.2f}%'.format(specificity * 100))

    # confusion matrix report
    print(name + ' Confusion Matrix Report: \n', classification_report(y_

    if name != 'SVC':
        # ROC curve
        fpr, tpr, _ = roc_curve(y_test, model.predict_proba(X_test)[:,1])
```

```
        plt.figure(figsize=(8, 6))
        plt.plot(fpr, tpr, label=name)
        plt.plot([0, 1], [0, 1], color='black', linestyle='--')
        plt.xlabel('False Positive Rate (Fall-Out)')
        plt.ylabel('True Positive Rate (Recall)')
        plt.title('ROC Curve')
        plt.legend()
        plt.show()

# test overfitting
def cross_validation(name,model, X, y):
    scores = cross_val_score(model, X, y, cv=5)
    print(name + ' Cross Validation Accuracy: {:.2f}%'.format(scores.mean
```

In [ ]:

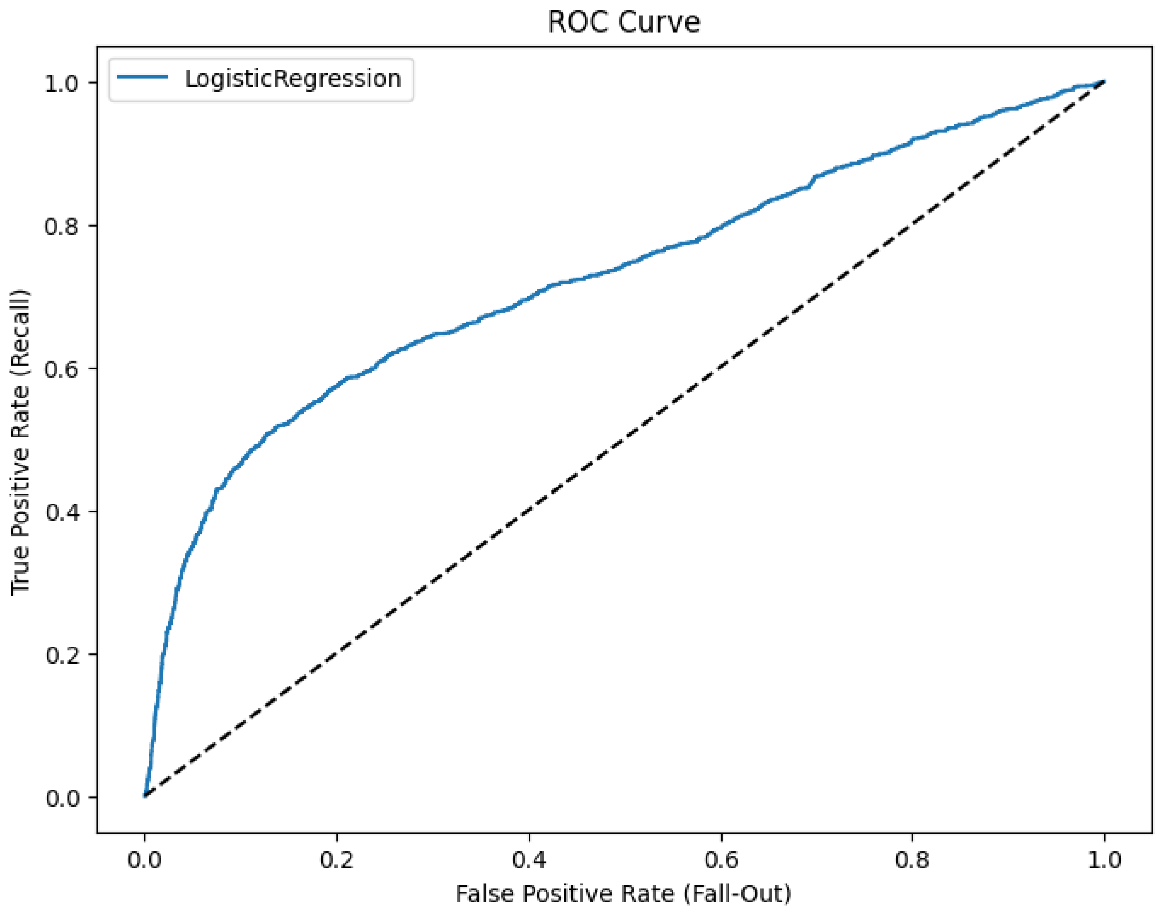
```
def model_start(model_name,X_train,y_train,X,y,X_test,y_test):
    train_models(model_name,models_classific[model_name], X_train, y_trai
    evaluate_models(model_name,models_classific[model_name], X_test, y_te
    cross_validation(model_name,models_classific[model_name], X, y)

def train_different_sampler(X,y,modelname,random_state=33):

    sampler = {
        'SMOTE': SMOTE(random_state=random_state),
        'SMOTETomek': SMOTETomek(random_state=random_state),
        'SMOTEENN': SMOTEENN(random_state=random_state),
        'RandomOverSampler': RandomOverSampler(random_state=random_state)
        # 'Knnor': data_augment.KNNOR()
    }

    print("-----------------------------")

    print("Training without oversampling")
    X_train, X_test, y_train, y_test, X_train_oversample, y_train_oversam
    model_start(modelname,X_train,y_train,X,y,X_test,y_test)

    print("-----------------------------")

    print("Oversampler Using Different Sampler")

    print("-----------------------------")

    for name, sampler in sampler.items():
        print("OverSampling with " + name)
        X_train, X_test, y_train, y_test, X_train_oversample, y_train_ove
        # model_name,X_train,y_train,X,y,X_test,y_test
        model_start(modelname,X_train_oversample,y_train_oversample,X,y,X
        print("-----------------------------")
```

Logistic Regression

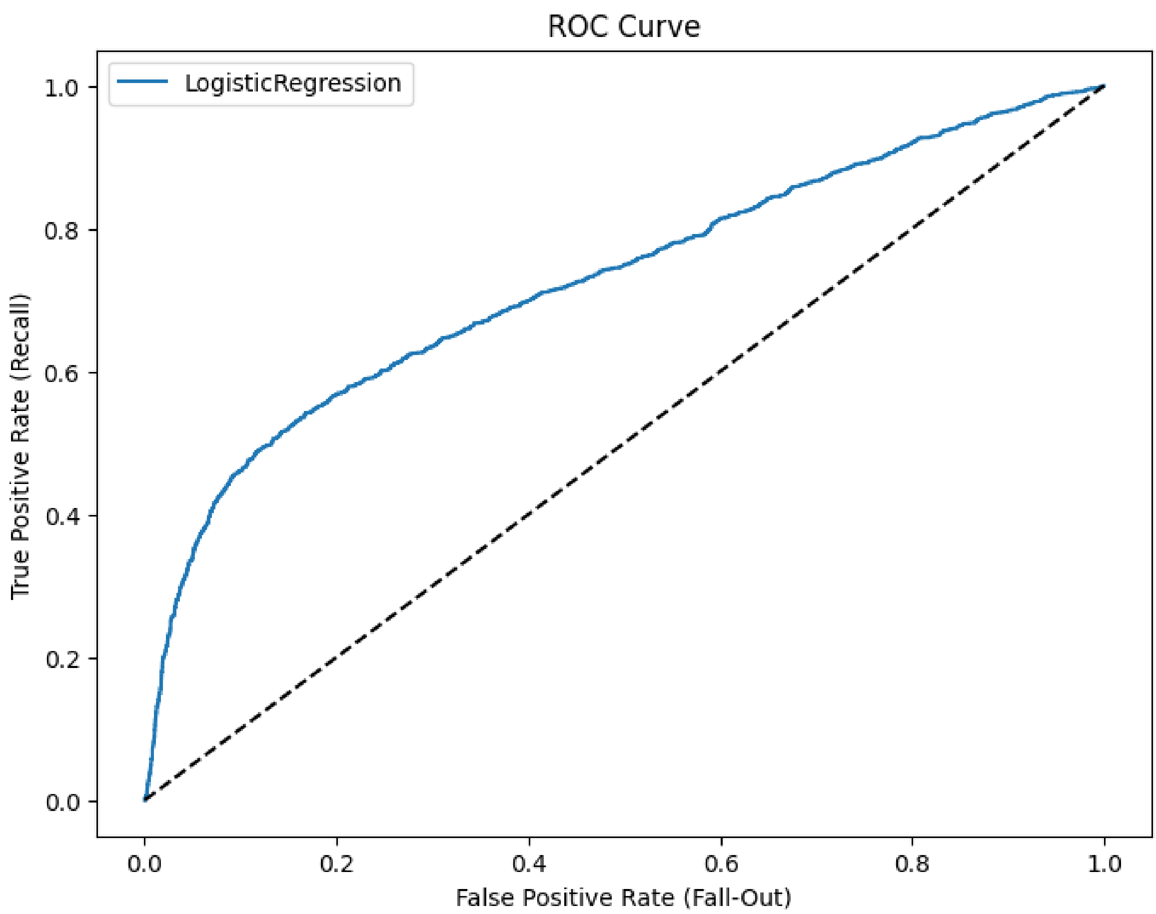
In [ ]:

```
train_different_sampler(X,y,'LogisticRegression')
```

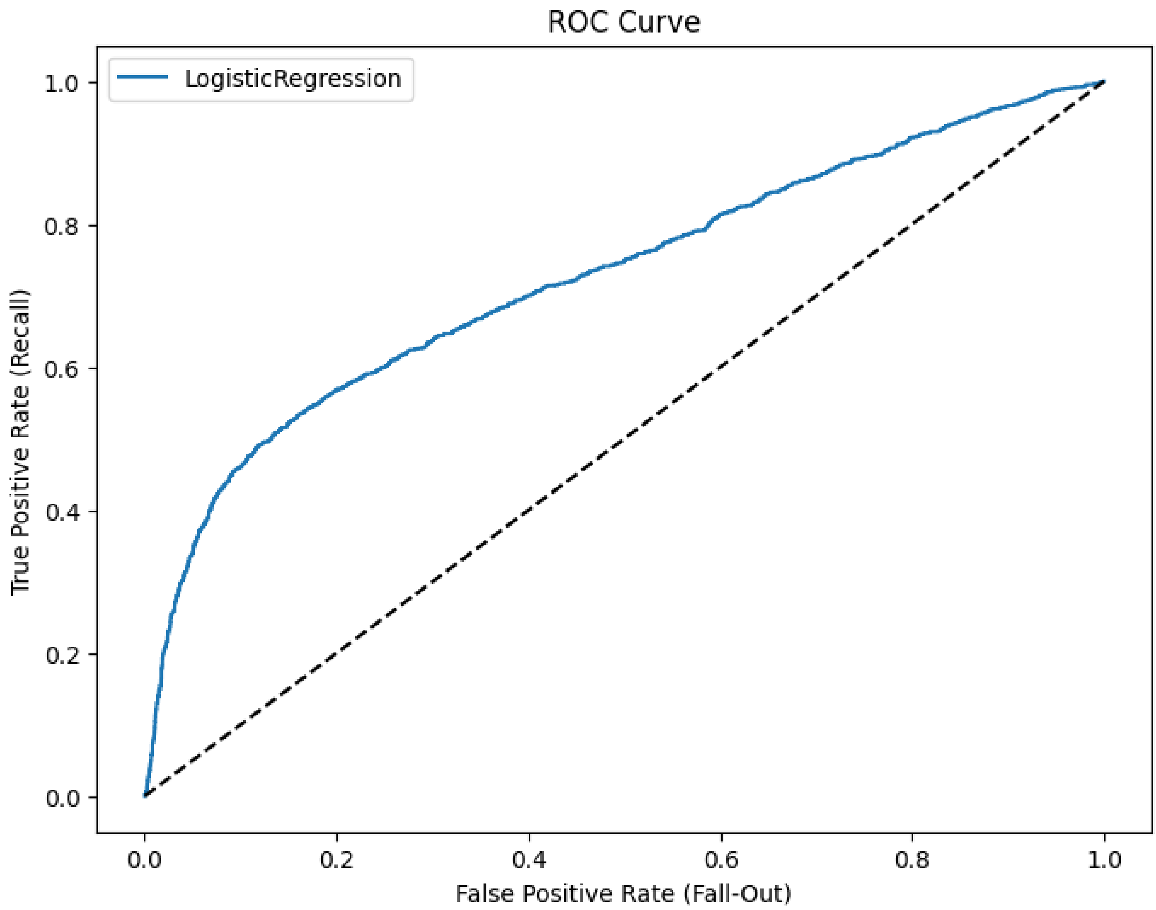
```
-----------------------------
Training without oversampling
LogisticRegression trained.
Training accuracy: 81.11%
LogisticRegression Accuracy: 81.22%
LogisticRegression ROC AUC: 72.42%
LogisticRegression Recall: 23.68%
LogisticRegression Precision: 72.62%
LogisticRegression Specificity: 97.48%
LogisticRegression Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.82      0.97      0.89      4678
           1       0.73      0.24      0.36      1322

    accuracy                           0.81      6000
   macro avg       0.77      0.61      0.62      6000
weighted avg       0.80      0.81      0.77      6000
```



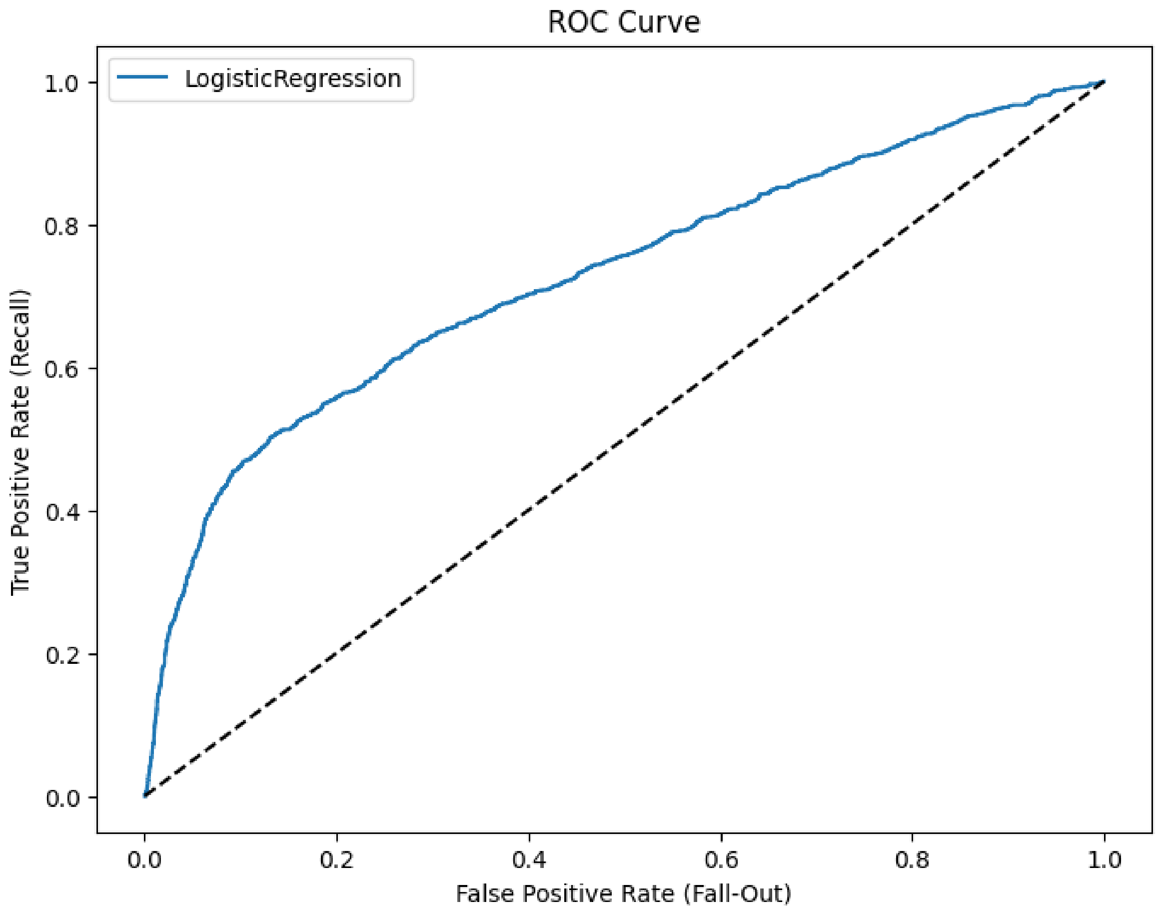
```
LogisticRegression Cross Validation Accuracy: 81.03%
-----------------------------
Oversampler Using Different Sampler
-----------------------------
OverSampling with SMOTE
LogisticRegression trained.
Training accuracy: 67.59%
LogisticRegression Accuracy: 66.88%
LogisticRegression ROC AUC: 72.62%
LogisticRegression Recall: 65.36%
LogisticRegression Precision: 36.11%
LogisticRegression Specificity: 67.32%
LogisticRegression Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.87      0.67      0.76      4678
           1       0.36      0.65      0.47      1322

    accuracy                           0.67      6000
   macro avg       0.62      0.66      0.61      6000
weighted avg       0.76      0.67      0.70      6000
```



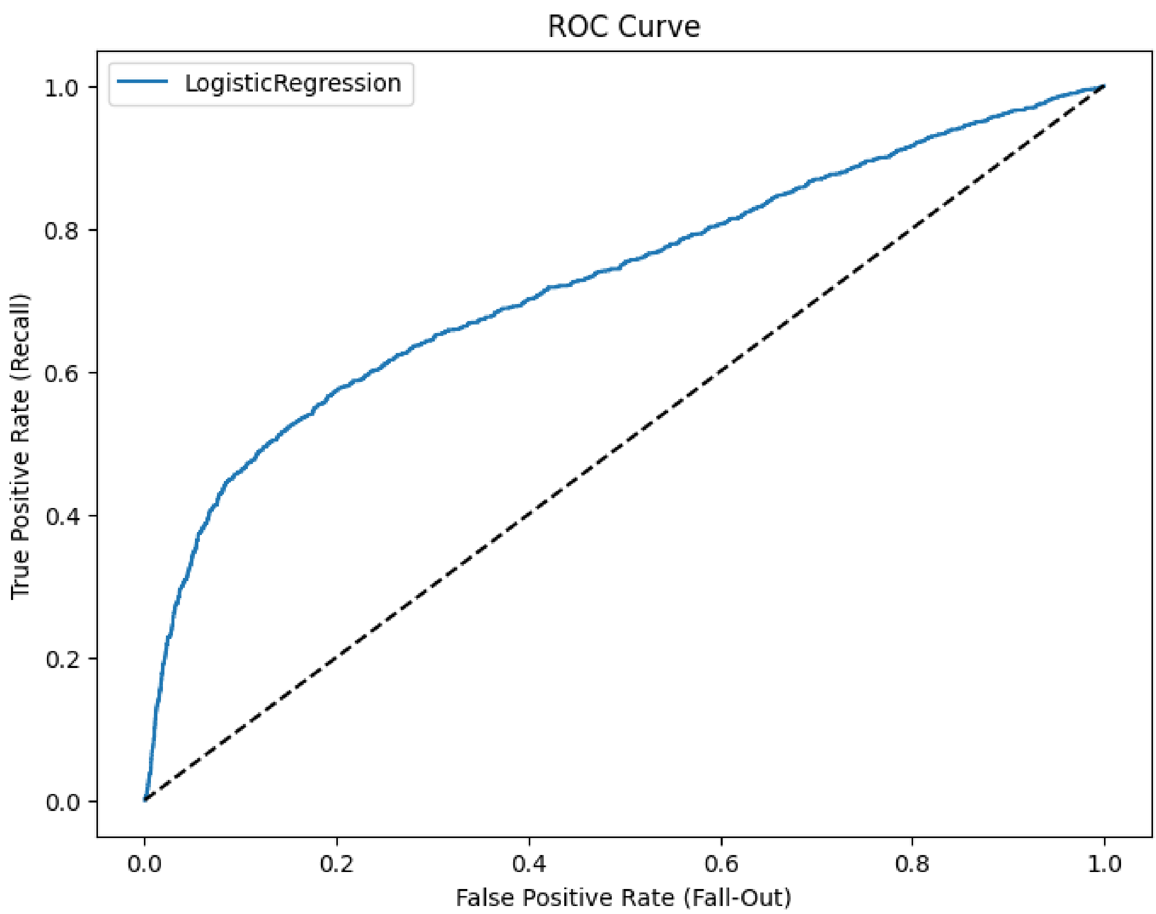
```
LogisticRegression Cross Validation Accuracy: 81.03%
-----------------------------
OverSampling with SMOTETomek
LogisticRegression trained.
Training accuracy: 68.05%
LogisticRegression Accuracy: 67.00%
LogisticRegression ROC AUC: 72.63%
LogisticRegression Recall: 65.28%
LogisticRegression Precision: 36.20%
LogisticRegression Specificity: 67.49%
LogisticRegression Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.87      0.67      0.76      4678
           1       0.36      0.65      0.47      1322

    accuracy                           0.67      6000
   macro avg       0.62      0.66      0.61      6000
weighted avg       0.76      0.67      0.70      6000
```



```
LogisticRegression Cross Validation Accuracy: 81.03%
-----------------------------
OverSampling with SMOTEENN
LogisticRegression trained.
Training accuracy: 71.31%
LogisticRegression Accuracy: 55.00%
LogisticRegression ROC AUC: 72.63%
LogisticRegression Recall: 75.95%
LogisticRegression Precision: 29.65%
LogisticRegression Specificity: 49.08%
LogisticRegression Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.88      0.49      0.63      4678
           1       0.30      0.76      0.43      1322

    accuracy                           0.55      6000
   macro avg       0.59      0.63      0.53      6000
weighted avg       0.75      0.55      0.58      6000
```



```
LogisticRegression Cross Validation Accuracy: 81.03%
-----------------------------
OverSampling with RandomOverSampler
LogisticRegression trained.
Training accuracy: 67.17%
LogisticRegression Accuracy: 67.53%
LogisticRegression ROC AUC: 72.65%
LogisticRegression Recall: 65.81%
LogisticRegression Precision: 36.77%
LogisticRegression Specificity: 68.02%
LogisticRegression Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.88      0.68      0.77      4678
           1       0.37      0.66      0.47      1322

    accuracy                           0.68      6000
   macro avg       0.62      0.67      0.62      6000
weighted avg       0.76      0.68      0.70      6000
```




```
LogisticRegression Cross Validation Accuracy: 81.03%
-----------------------------
```

SVM

In [ ]:
```
train_different_sampler(X,y,'SVC')
```

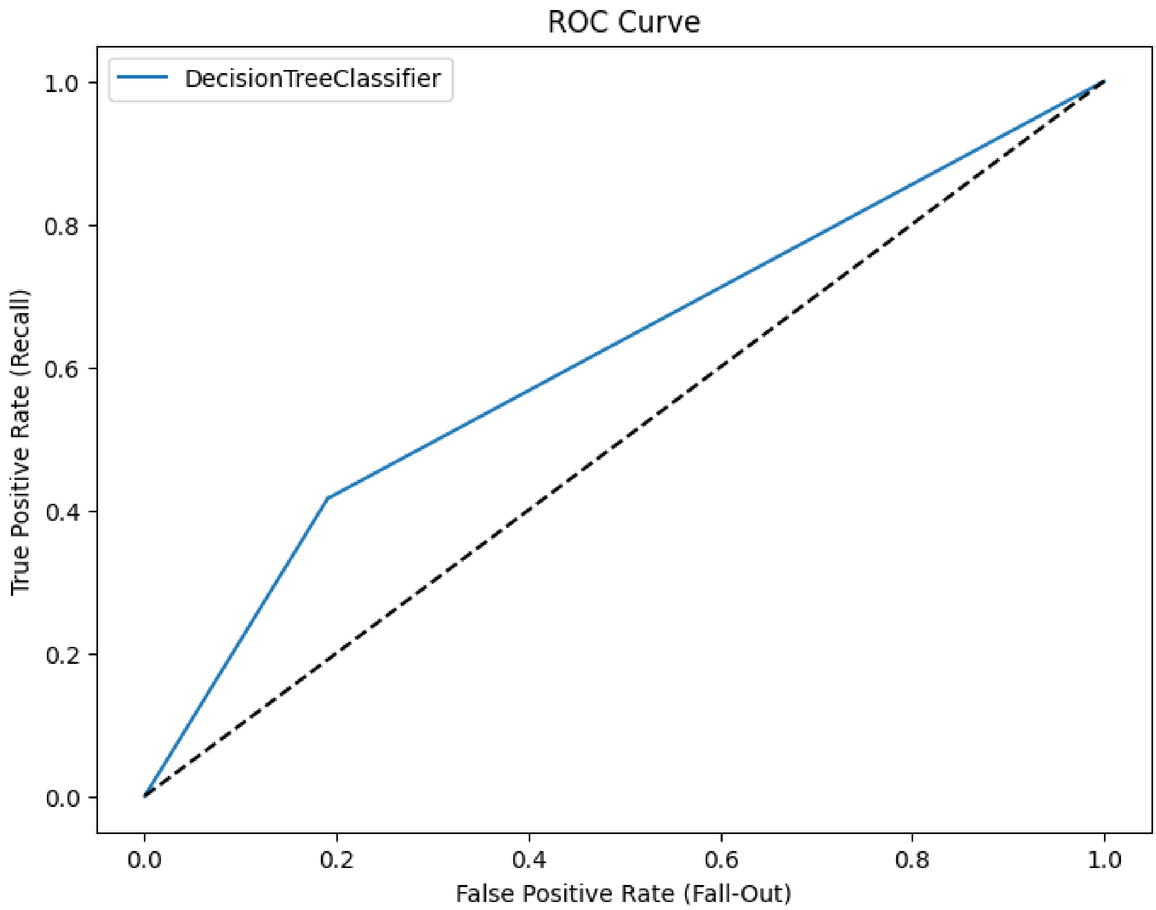
```
-----------------------------
Training without oversampling
SVC trained.
Training accuracy: 82.43%
SVC Accuracy: 82.27%
SVC Recall: 32.83%
SVC Precision: 71.15%
SVC Specificity: 96.24%
SVC Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.84      0.96      0.89      4678
           1       0.71      0.33      0.45      1322

    accuracy                           0.82      6000
   macro avg       0.77      0.65      0.67      6000
weighted avg       0.81      0.82      0.80      6000

SVC Cross Validation Accuracy: 81.95%
-----------------------------
Oversampler Using Different Sampler
-----------------------------
OverSampling with SMOTE
SVC trained.
Training accuracy: 72.77%
SVC Accuracy: 77.45%
SVC Recall: 57.41%
SVC Precision: 49.00%
SVC Specificity: 83.11%
SVC Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.87      0.83      0.85      4678
           1       0.49      0.57      0.53      1322

    accuracy                           0.77      6000
   macro avg       0.68      0.70      0.69      6000
weighted avg       0.79      0.77      0.78      6000

SVC Cross Validation Accuracy: 81.95%
-----------------------------
OverSampling with SMOTETomek
SVC trained.
Training accuracy: 73.36%
SVC Accuracy: 77.40%
SVC Recall: 57.49%
SVC Precision: 48.91%
SVC Specificity: 83.03%
SVC Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.87      0.83      0.85      4678
           1       0.49      0.57      0.53      1322

    accuracy                           0.77      6000
   macro avg       0.68      0.70      0.69      6000
weighted avg       0.79      0.77      0.78      6000

SVC Cross Validation Accuracy: 81.95%
-----------------------------
```

```
OverSampling with SMOTEENN
SVC trained.
Training accuracy: 83.50%
SVC Accuracy: 66.22%
SVC Recall: 72.09%
SVC Precision: 36.50%
SVC Specificity: 64.56%
SVC Confusion Matrix Report:
              precision    recall  f1-score   support

           0       0.89      0.65      0.75      4678
           1       0.36      0.72      0.48      1322

    accuracy                           0.66      6000
   macro avg       0.63      0.68      0.62      6000
weighted avg       0.78      0.66      0.69      6000

SVC Cross Validation Accuracy: 81.95%
-----------------------------
OverSampling with RandomOverSampler
SVC trained.
Training accuracy: 72.63%
SVC Accuracy: 77.28%
SVC Recall: 58.47%
SVC Precision: 48.71%
SVC Specificity: 82.60%
SVC Confusion Matrix Report:
              precision    recall  f1-score   support

           0       0.88      0.83      0.85      4678
           1       0.49      0.58      0.53      1322

    accuracy                           0.77      6000
   macro avg       0.68      0.71      0.69      6000
weighted avg       0.79      0.77      0.78      6000

SVC Cross Validation Accuracy: 81.95%
-----------------------------
```

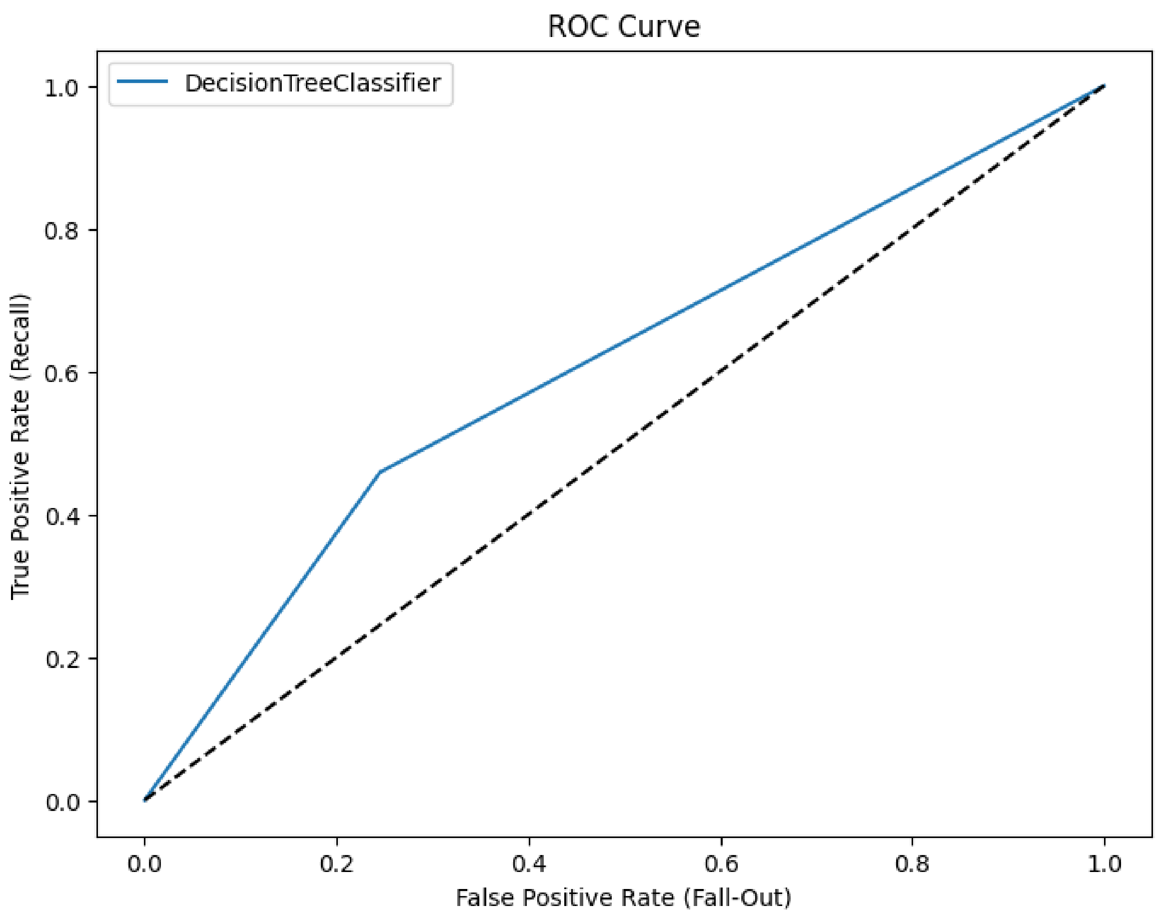
Random Forest model

In [ ]:
```
train_different_sampler(X,y,'DecisionTreeClassifier')
```

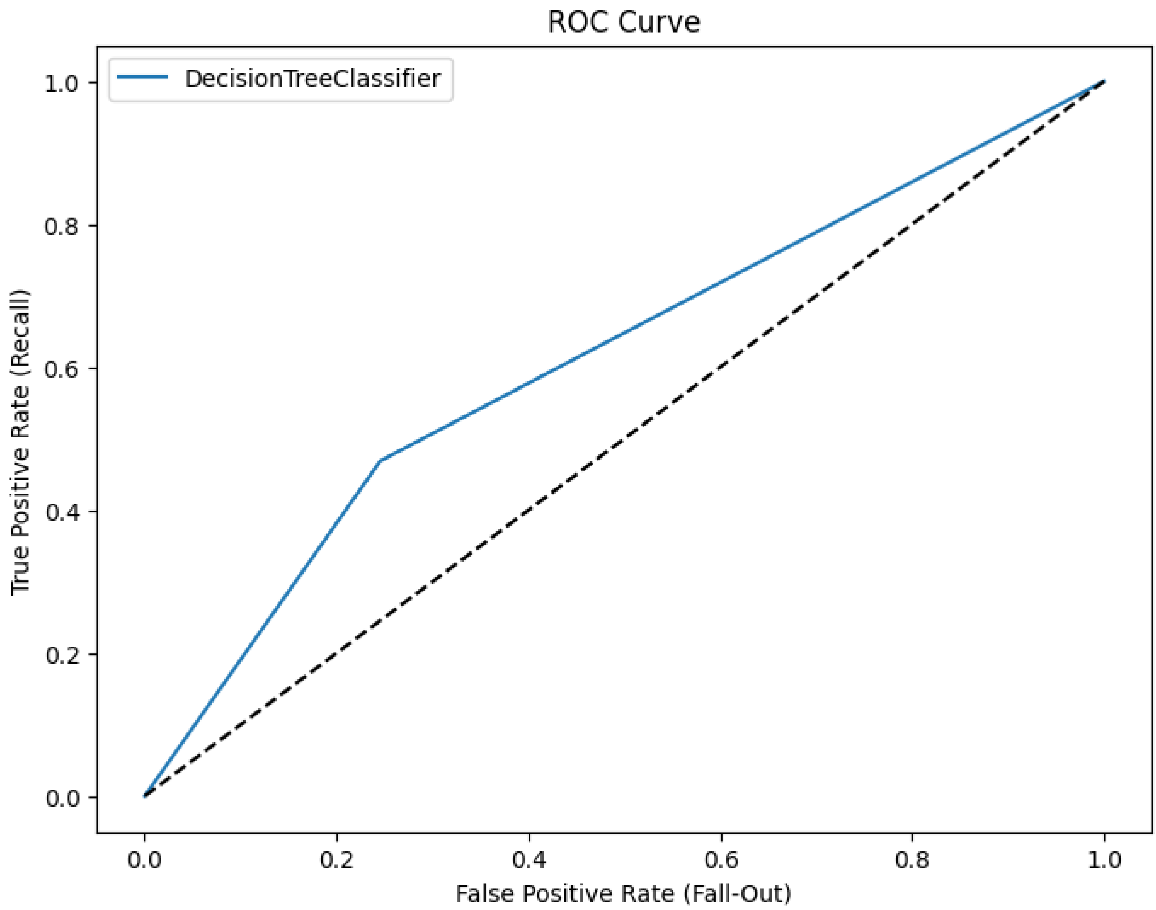
```
-----------------------------
Training without oversampling
DecisionTreeClassifier trained.
Training accuracy: 99.93%
DecisionTreeClassifier Accuracy: 72.25%
DecisionTreeClassifier ROC AUC: 61.27%
DecisionTreeClassifier Recall: 41.75%
DecisionTreeClassifier Precision: 38.15%
DecisionTreeClassifier Specificity: 80.87%
DecisionTreeClassifier Confusion Matrix Report:
              precision    recall  f1-score   support

           0       0.83      0.81      0.82      4678
           1       0.38      0.42      0.40      1322

    accuracy                           0.72      6000
   macro avg       0.61      0.61      0.61      6000
weighted avg       0.73      0.72      0.73      6000
```



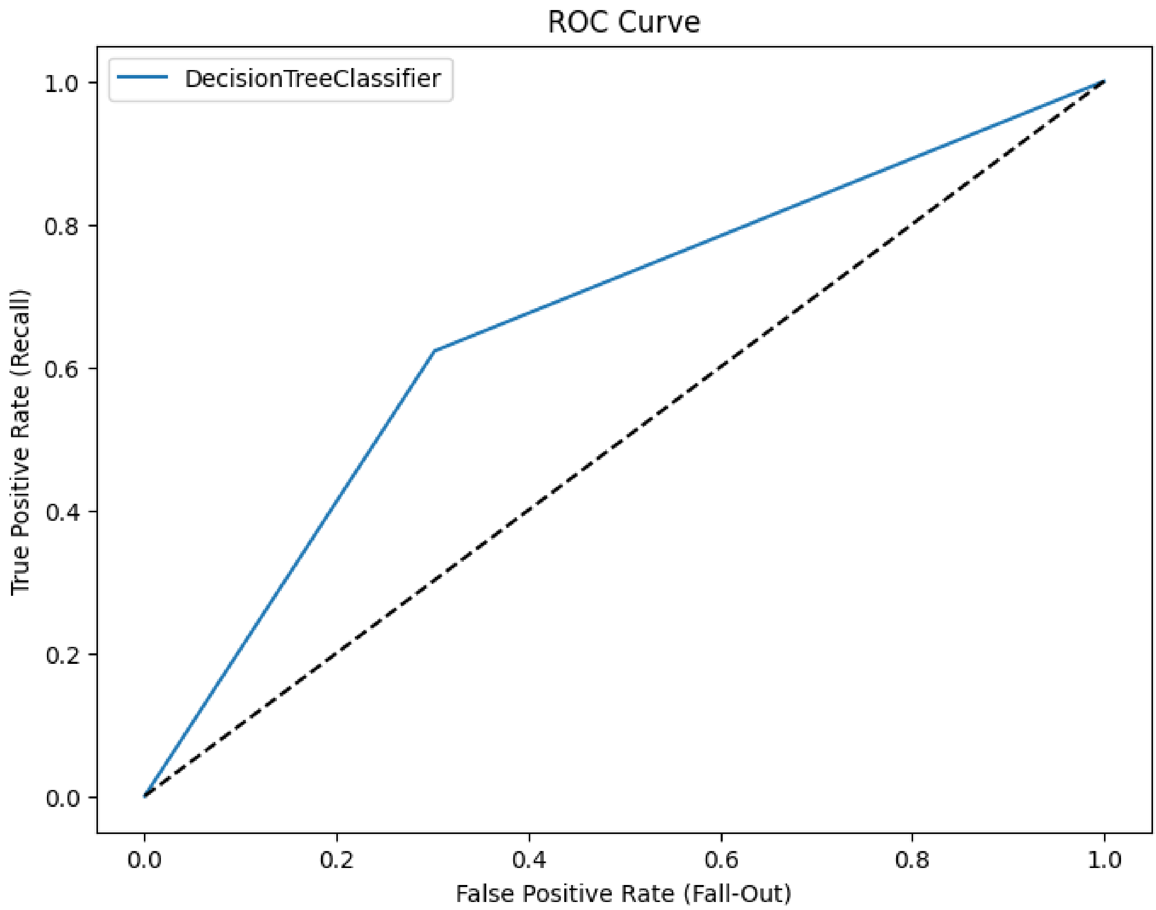
```
DecisionTreeClassifier Cross Validation Accuracy: 72.19%
-----------------------------
Oversampler Using Different Sampler
-----------------------------
OverSampling with SMOTE
DecisionTreeClassifier trained.
Training accuracy: 99.96%
DecisionTreeClassifier Accuracy: 68.93%
DecisionTreeClassifier ROC AUC: 60.68%
DecisionTreeClassifier Recall: 45.99%
DecisionTreeClassifier Precision: 34.58%
DecisionTreeClassifier Specificity: 75.42%
DecisionTreeClassifier Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.83      0.75      0.79      4678
           1       0.35      0.46      0.39      1322

    accuracy                           0.69      6000
   macro avg       0.59      0.61      0.59      6000
weighted avg       0.72      0.69      0.70      6000
```



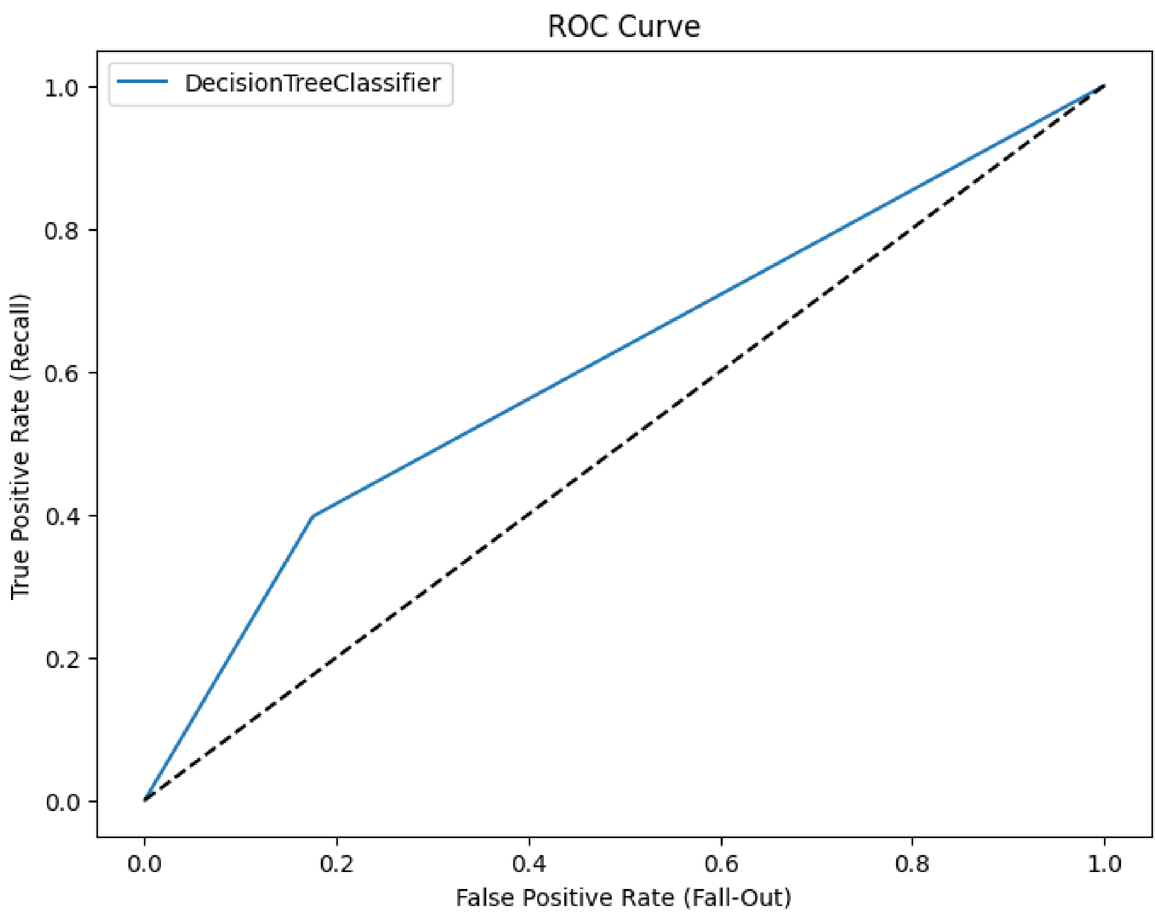
```
DecisionTreeClassifier Cross Validation Accuracy: 72.31%
-----------------------------
OverSampling with SMOTETomek
DecisionTreeClassifier trained.
Training accuracy: 99.96%
DecisionTreeClassifier Accuracy: 69.15%
DecisionTreeClassifier ROC AUC: 61.16%
DecisionTreeClassifier Recall: 46.90%
DecisionTreeClassifier Precision: 35.05%
DecisionTreeClassifier Specificity: 75.44%
DecisionTreeClassifier Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.83      0.75      0.79      4678
           1       0.35      0.47      0.40      1322

    accuracy                           0.69      6000
   macro avg       0.59      0.61      0.60      6000
weighted avg       0.73      0.69      0.71      6000
```



```
DecisionTreeClassifier Cross Validation Accuracy: 72.29%
-----------------------------
OverSampling with SMOTEENN
DecisionTreeClassifier trained.
Training accuracy: 100.00%
DecisionTreeClassifier Accuracy: 68.13%
DecisionTreeClassifier ROC AUC: 66.02%
DecisionTreeClassifier Recall: 62.25%
DecisionTreeClassifier Precision: 36.81%
DecisionTreeClassifier Specificity: 69.79%
DecisionTreeClassifier Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.87      0.70      0.77      4678
           1       0.37      0.62      0.46      1322

    accuracy                           0.68      6000
   macro avg       0.62      0.66      0.62      6000
weighted avg       0.76      0.68      0.71      6000
```



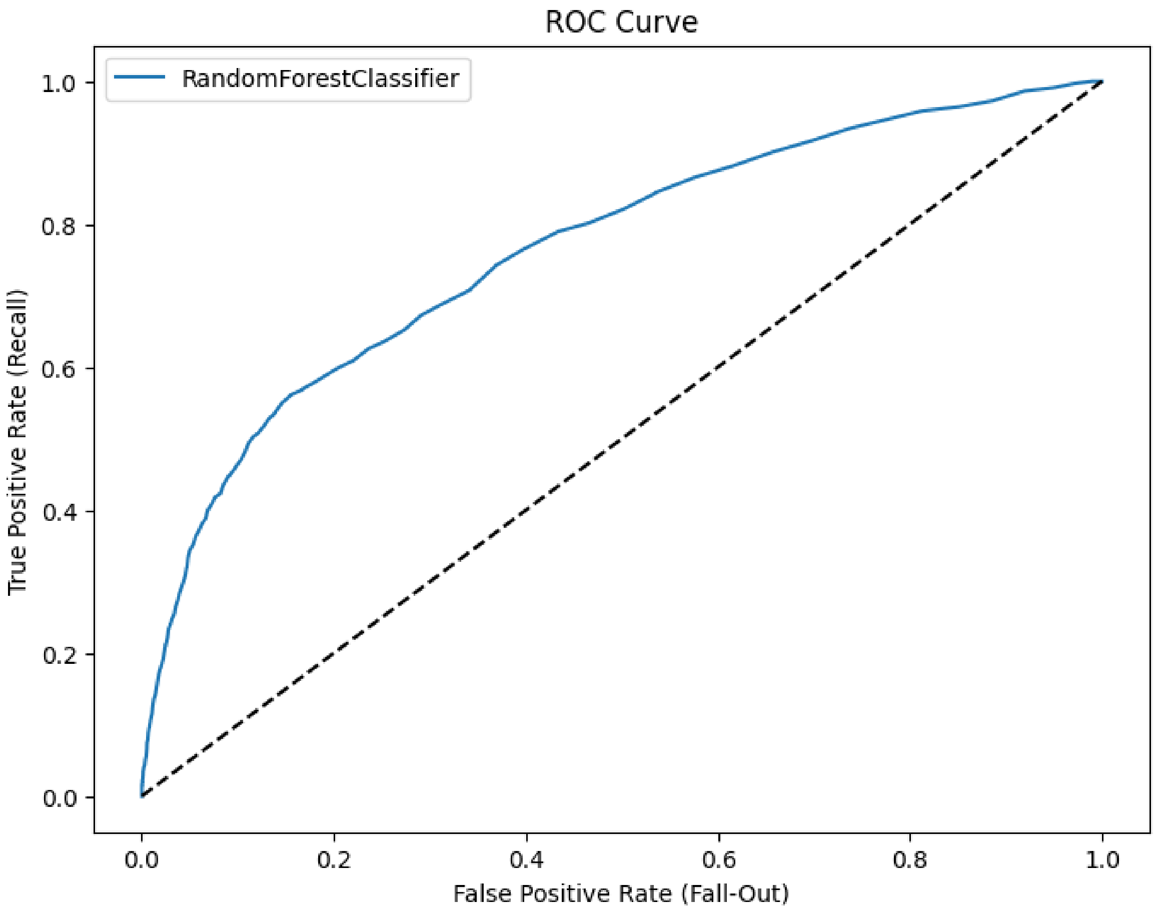
```
DecisionTreeClassifier Cross Validation Accuracy: 72.43%
-----------------------------
OverSampling with RandomOverSampler
DecisionTreeClassifier trained.
Training accuracy: 99.95%
DecisionTreeClassifier Accuracy: 73.05%
DecisionTreeClassifier ROC AUC: 61.09%
DecisionTreeClassifier Recall: 39.71%
DecisionTreeClassifier Precision: 39.03%
DecisionTreeClassifier Specificity: 82.47%
DecisionTreeClassifier Confusion Matrix Report:
              precision    recall  f1-score   support

           0       0.83      0.82      0.83      4678
           1       0.39      0.40      0.39      1322

    accuracy                           0.73      6000
   macro avg       0.61      0.61      0.61      6000
weighted avg       0.73      0.73      0.73      6000
```



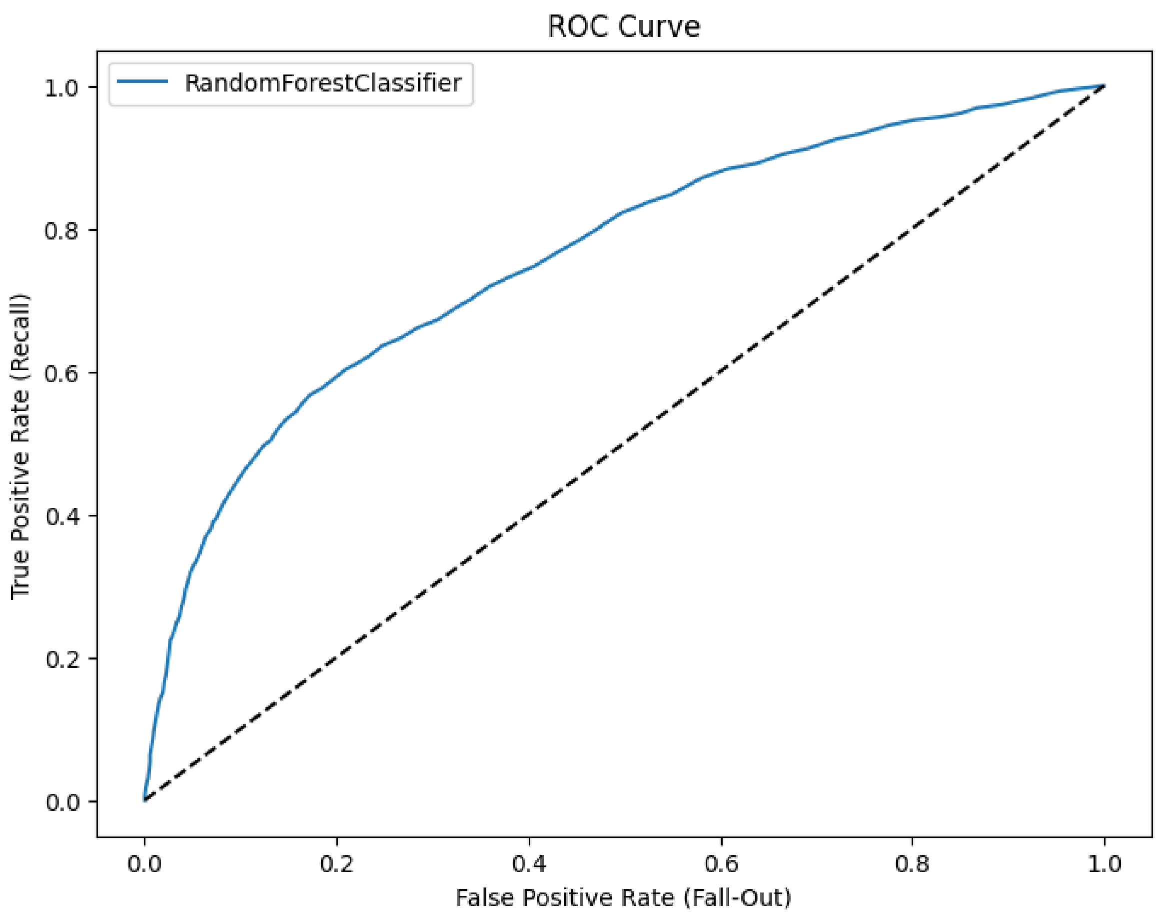

```
DecisionTreeClassifier Cross Validation Accuracy: 72.28%
-----------------------------
```

In [ ]:
```
train_different_sampler(X,y,'RandomForestClassifier')
```

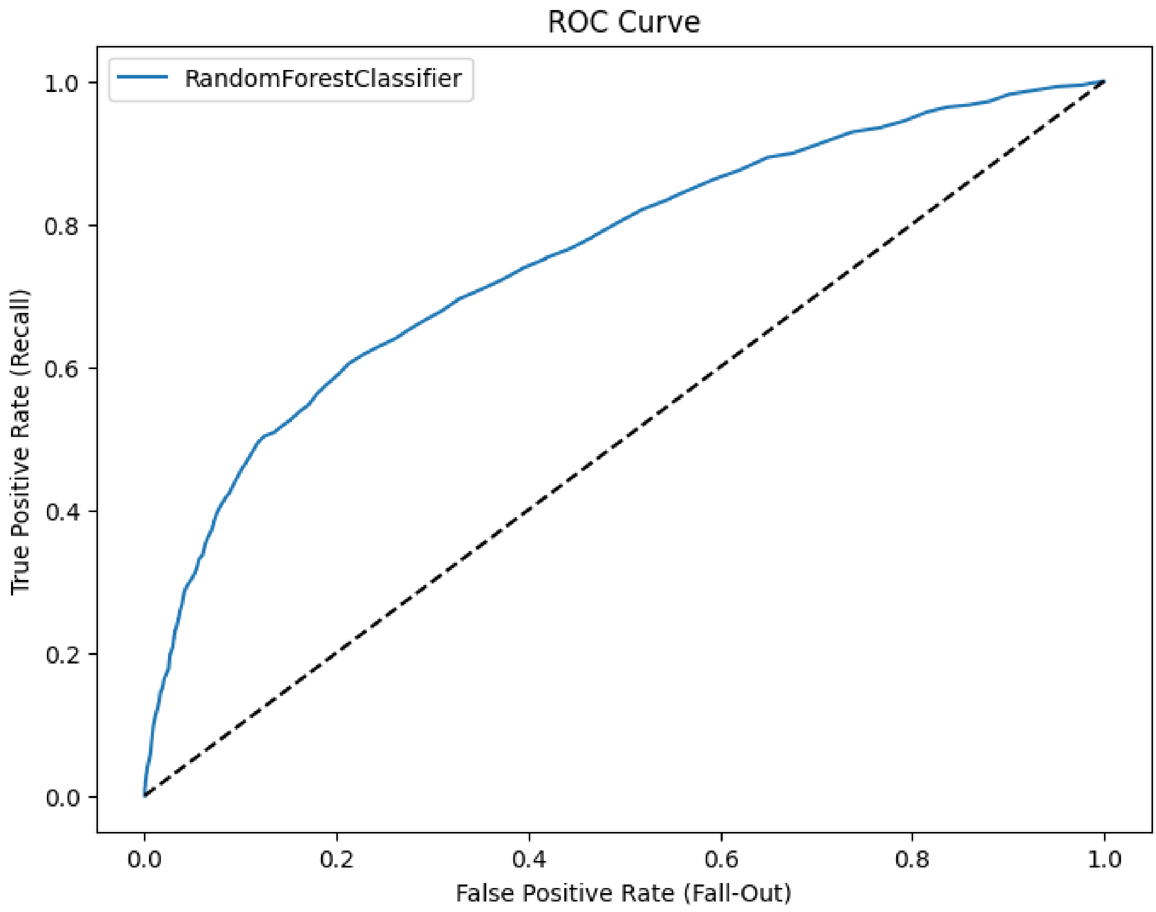
```
-----------------------------
Training without oversampling
RandomForestClassifier trained.
Training accuracy: 99.93%
RandomForestClassifier Accuracy: 81.60%
RandomForestClassifier ROC AUC: 76.43%
RandomForestClassifier Recall: 36.38%
RandomForestClassifier Precision: 64.65%
RandomForestClassifier Specificity: 94.38%
RandomForestClassifier Confusion Matrix Report:
              precision    recall  f1-score   support

           0       0.84      0.94      0.89      4678
           1       0.65      0.36      0.47      1322

    accuracy                           0.82      6000
   macro avg       0.74      0.65      0.68      6000
weighted avg       0.80      0.82      0.80      6000
```



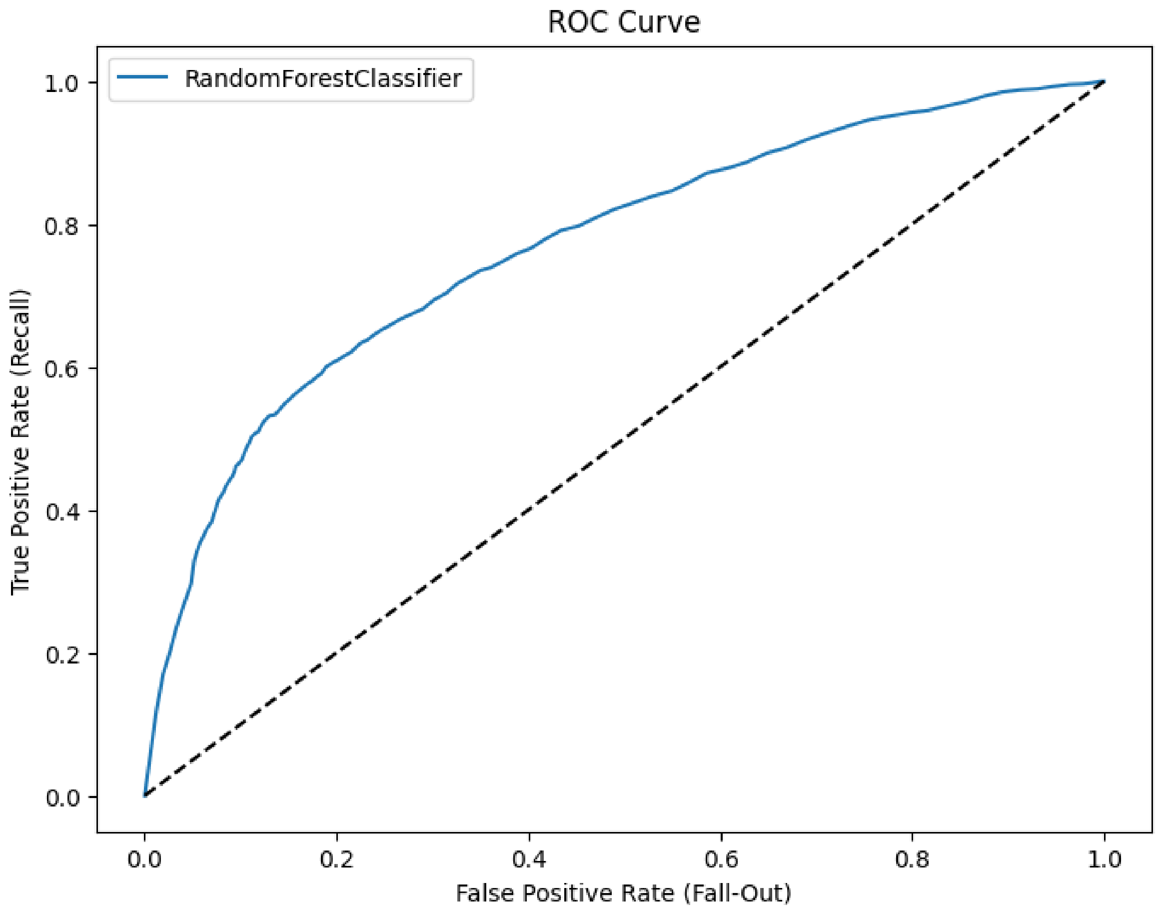
```
RandomForestClassifier Cross Validation Accuracy: 81.51%
-----------------------------
Oversampler Using Different Sampler
-----------------------------
OverSampling with SMOTE
RandomForestClassifier trained.
Training accuracy: 99.96%
RandomForestClassifier Accuracy: 79.77%
RandomForestClassifier ROC AUC: 75.85%
RandomForestClassifier Recall: 47.28%
RandomForestClassifier Precision: 54.73%
RandomForestClassifier Specificity: 88.95%
RandomForestClassifier Confusion Matrix Report:
               precision    recall  f1-score   support

           0       0.86      0.89      0.87      4678
           1       0.55      0.47      0.51      1322

    accuracy                           0.80      6000
   macro avg       0.70      0.68      0.69      6000
weighted avg       0.79      0.80      0.79      6000
```



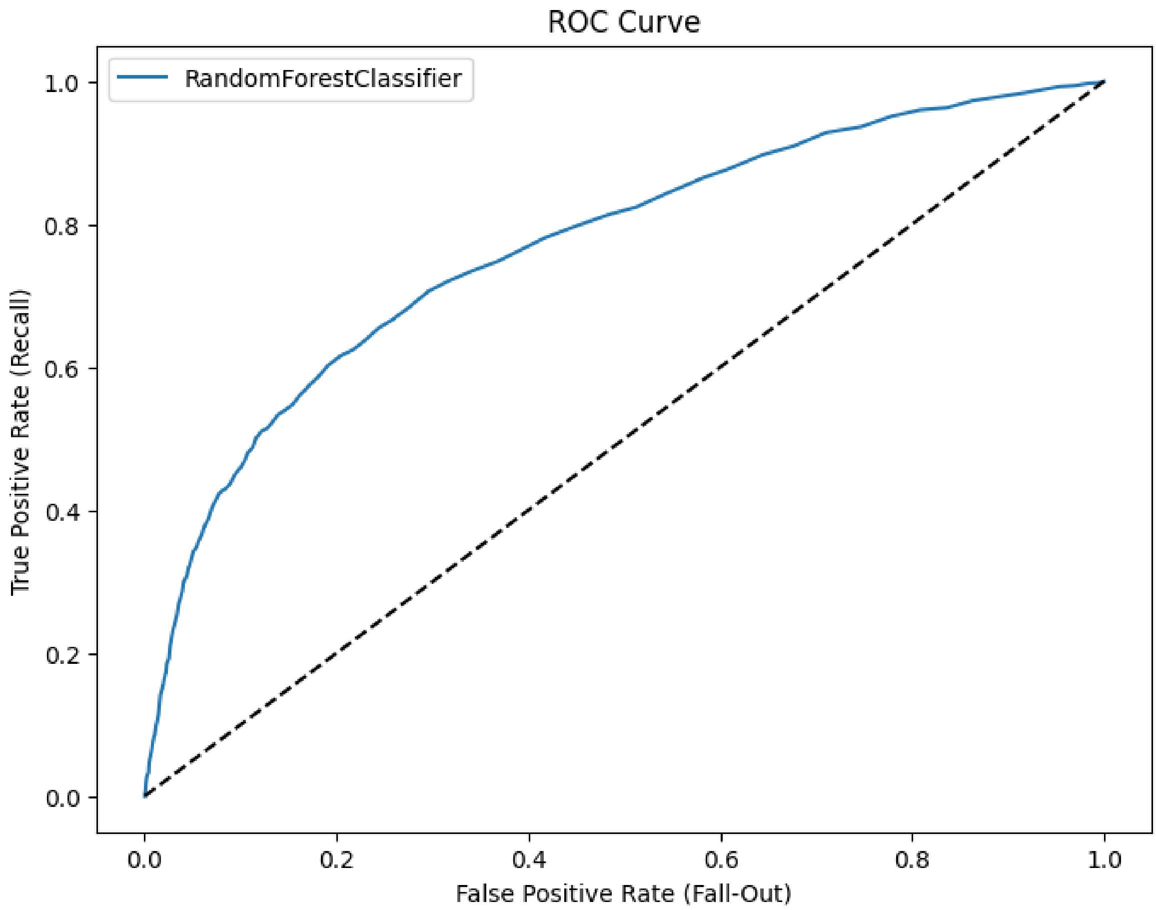
```
RandomForestClassifier Cross Validation Accuracy: 81.36%
-----------------------------
OverSampling with SMOTETomek
RandomForestClassifier trained.
Training accuracy: 99.96%
RandomForestClassifier Accuracy: 79.90%
RandomForestClassifier ROC AUC: 75.38%
RandomForestClassifier Recall: 47.43%
RandomForestClassifier Precision: 55.10%
RandomForestClassifier Specificity: 89.08%
RandomForestClassifier Confusion Matrix Report:
              precision    recall  f1-score   support

           0       0.86      0.89      0.87      4678
           1       0.55      0.47      0.51      1322

    accuracy                           0.80      6000
   macro avg       0.70      0.68      0.69      6000
weighted avg       0.79      0.80      0.79      6000
```



```
RandomForestClassifier Cross Validation Accuracy: 81.50%
-----------------------------
OverSampling with SMOTEENN
RandomForestClassifier trained.
Training accuracy: 100.00%
RandomForestClassifier Accuracy: 75.27%
RandomForestClassifier ROC AUC: 76.77%
RandomForestClassifier Recall: 61.57%
RandomForestClassifier Precision: 45.47%
RandomForestClassifier Specificity: 79.14%
RandomForestClassifier Confusion Matrix Report:
              precision    recall  f1-score   support

           0       0.88      0.79      0.83      4678
           1       0.45      0.62      0.52      1322

    accuracy                           0.75      6000
   macro avg       0.67      0.70      0.68      6000
weighted avg       0.79      0.75      0.76      6000
```



```
RandomForestClassifier Cross Validation Accuracy: 81.49%
-----------------------------
OverSampling with RandomOverSampler
RandomForestClassifier trained.
Training accuracy: 99.95%
RandomForestClassifier Accuracy: 80.88%
RandomForestClassifier ROC AUC: 76.80%
RandomForestClassifier Recall: 42.97%
RandomForestClassifier Precision: 59.11%
RandomForestClassifier Specificity: 91.60%
RandomForestClassifier Confusion Matrix Report:
              precision    recall  f1-score   support

           0       0.85      0.92      0.88      4678
           1       0.59      0.43      0.50      1322

    accuracy                           0.81      6000
   macro avg       0.72      0.67      0.69      6000
weighted avg       0.79      0.81      0.80      6000
```




```
RandomForestClassifier Cross Validation Accuracy: 81.59%
-----------------------------
```

Build a regression model that predicts a customer's limit balance if they were a new customer to the bank with only X0, X2-5 available to you as data.

In [ ]:
```
def pre_processing_regre(df,scaler):
    # remove uncessary columns
    df = df.drop(['ID'], axis=1)
```

```
    # One-hot encoding
    col_list = ["EDUCATION", "MARRIAGE"]
    df = one_hot_encoding(df, col_list)
    # scale the data
    X = df.drop(['LIMIT_BAL'], axis=1)
    X = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
    y = df['LIMIT_BAL']
    return X,y

X, y = pre_processing_regre(df, scaler_standard)
```

In [ ]:
```
models_regre = {
    'LinearRegression': LinearRegression(),
    'SVR': SVR(),
    'DecisionTreeRegressor': DecisionTreeRegressor(),
    'RandomForestRegressor': RandomForestRegressor(),
}
```

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

def train_models(name,model, X_train, y_train):
    model.fit(X_train, y_train)
    print(name + ' trained.')

def evaluate_models(name,model, X_test, y_test):
    print(name + ' Accuracy: {:.2f}%'.format(model.score(X_test, y_test)
```

Linear Regression

In [ ]:
```
train_models("linear_regression",models_regre["LinearRegression"], X_trai
evaluate_models("linear_regression",models_regre["LinearRegression"], X_t
```

```
linear_regression trained.
linear_regression Accuracy: 36.10%
```

Random Forest

In [ ]:
```
train_models("SVR",models_regre["SVR"], X_train, y_train)
evaluate_models("SVR",models_regre["SVR"], X_test, y_test)
```

```
SVR trained.
SVR Accuracy: -4.24%
```

In [ ]:
```
train_models("DecisionTreeRegressor",models_regre["DecisionTreeRegressor"
evaluate_models("DecisionTreeRegressor",models_regre["DecisionTreeRegress
```

```
DecisionTreeRegressor trained.
DecisionTreeRegressor Accuracy: -6.16%
```

In [ ]:
```
train_models("RandomForestRegressor",models_regre["RandomForestRegressor"
evaluate_models("RandomForestRegressor",models_regre["RandomForestRegress
```

```
RandomForestRegressor trained.
RandomForestRegressor Accuracy: 46.90%
```

ANN model

In [ ]: