In [ ]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from imblearn.over_sampling import SMOTE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import recall_score,precision_score,accuracy_score,roc_curve,auc,f1_score
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import GaussianNB
```

In [ ]:
```python
df=pd.read_csv("/content/BankChurners.csv")
df.head()
```

Out[128]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Category	Montl
0	768805383	Existing Customer	45	M	3	High School	Married	$60K-80K$	Blue	
1	818770008	Existing Customer	49	F	5	Graduate	Single	Less than $40K	Blue	
2	713982108	Existing Customer	51	M	3	Graduate	Married	$80K-120K$	Blue	
3	769911858	Existing Customer	40	F	4	High School	Unknown	Less than $40K	Blue	
4	709106358	Existing Customer	40	M	3	Uneducated	Married	$60K-80K$	Blue	

5 rows × 23 columns

In [ ]:
```
df.drop(['CLIENTNUM','Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Educat
```

EDA

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 20 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Attrition_Flag            10127 non-null  object 
 1   Customer_Age              10127 non-null  int64  
 2   Gender                    10127 non-null  object 
 3   Dependent_count           10127 non-null  int64  
 4   Education_Level           10127 non-null  object 
 5   Marital_Status            10127 non-null  object 
 6   Income_Category           10127 non-null  object 
 7   Card_Category             10127 non-null  object 
 8   Months_on_book            10127 non-null  int64  
 9   Total_Relationship_Count  10127 non-null  int64  
 10  Months_Inactive_12_mon    10127 non-null  int64  
 11  Contacts_Count_12_mon     10127 non-null  int64  
 12  Credit_Limit              10127 non-null  float64
 13  Total_Revolving_Bal       10127 non-null  int64  
 14  Avg_Open_To_Buy           10127 non-null  float64
 15  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 16  Total_Trans_Amt           10127 non-null  int64  
 17  Total_Trans_Ct            10127 non-null  int64  
 18  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 19  Avg_Utilization_Ratio     10127 non-null  float64
dtypes: float64(5), int64(9), object(6)
memory usage: 1.5+ MB
```

In [ ]:
```
df['Attrition_Flag'].value_counts()
```

Out[131]:
```
Existing Customer    8500
Attrited Customer    1627
Name: Attrition_Flag, dtype: int64
```

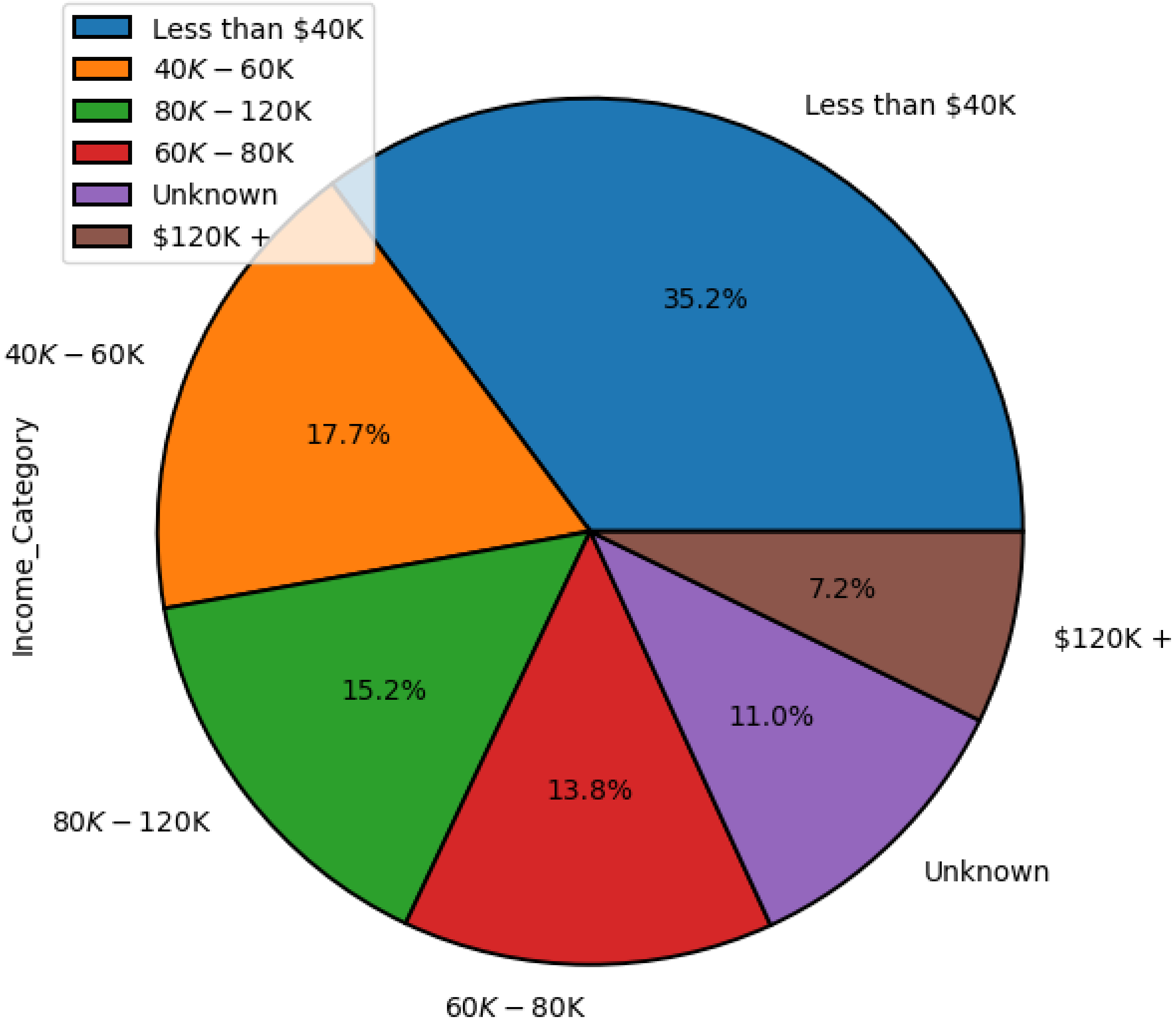
In [ ]:
```
df.describe()
```

Out[132]:

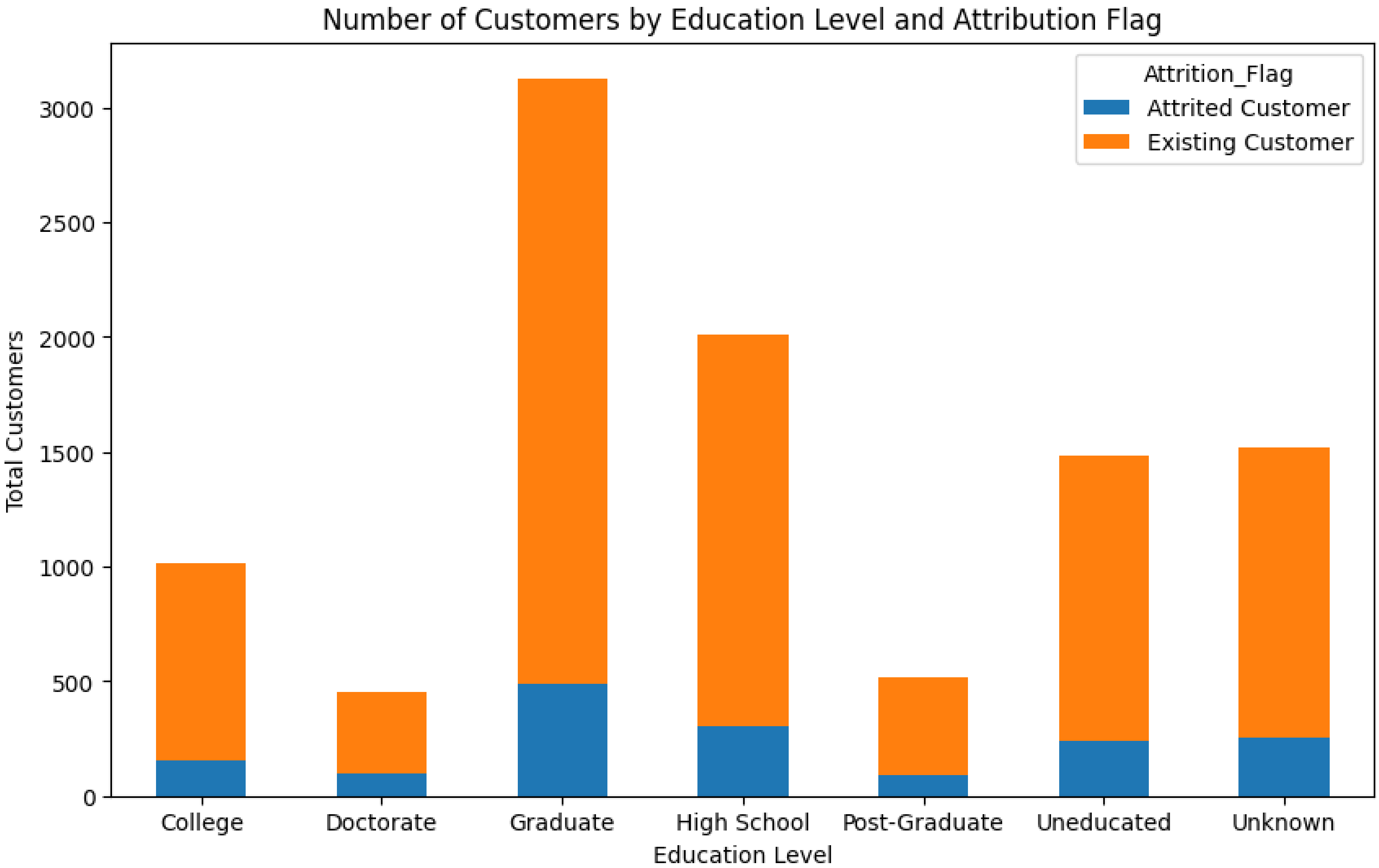
	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	Contacts_Count_12_mon	Credit_Li
count	10127.000000	10127.000000	10127.000000	10127.000000	10127.000000	10127.000000	10127.000(
mean	46.325960	2.346203	35.928409	3.812580	2.341167	2.455317	8631.953(
std	8.016814	1.298908	7.986416	1.554408	1.010622	1.106225	9088.776(
min	26.000000	0.000000	13.000000	1.000000	0.000000	0.000000	1438.300(
25%	41.000000	1.000000	31.000000	3.000000	2.000000	2.000000	2555.000(
50%	46.000000	2.000000	36.000000	4.000000	2.000000	2.000000	4549.000(
75%	52.000000	3.000000	40.000000	5.000000	3.000000	3.000000	11067.500(
max	73.000000	5.000000	56.000000	6.000000	6.000000	6.000000	34516.000(

Data Visualization

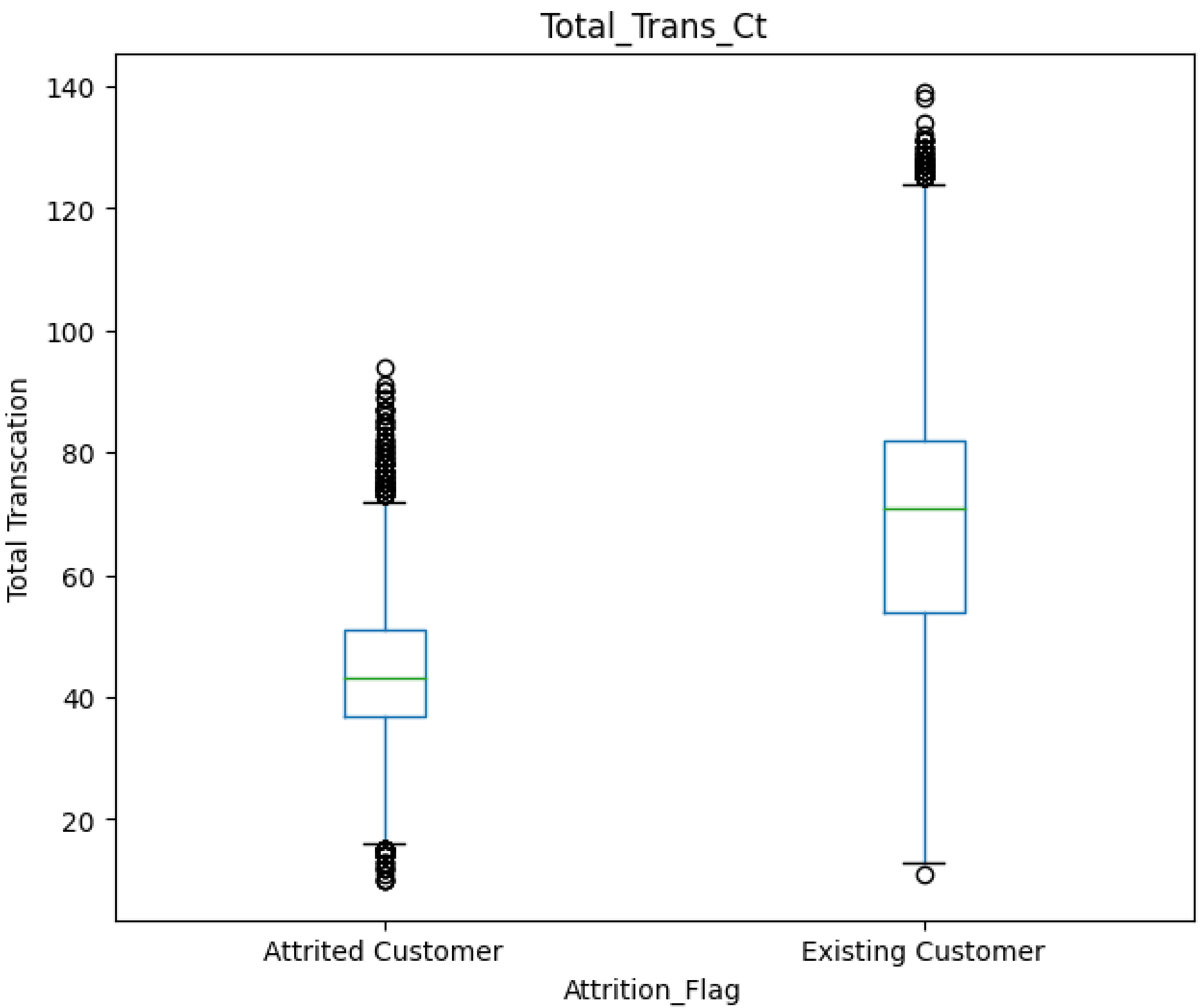
In [ ]:
```
df.Income_Category.value_counts().plot(kind="pie",figsize=(7,8),wedgeprops = {"edgecolor" : "black",'linewidth':1.4,'a
plt.legend(loc = 'upper left')
plt.show()
```


Less than $40K
40K − 60K
80K − 120K
60K − 80K
Unknown
$120K +
Less than $40K
35.2%
40K − 60K
17.7%
Income_Category
15.2%
13.8%
11.0%
7.2%
$120K +
80K − 120K
Unknown
60K − 80K

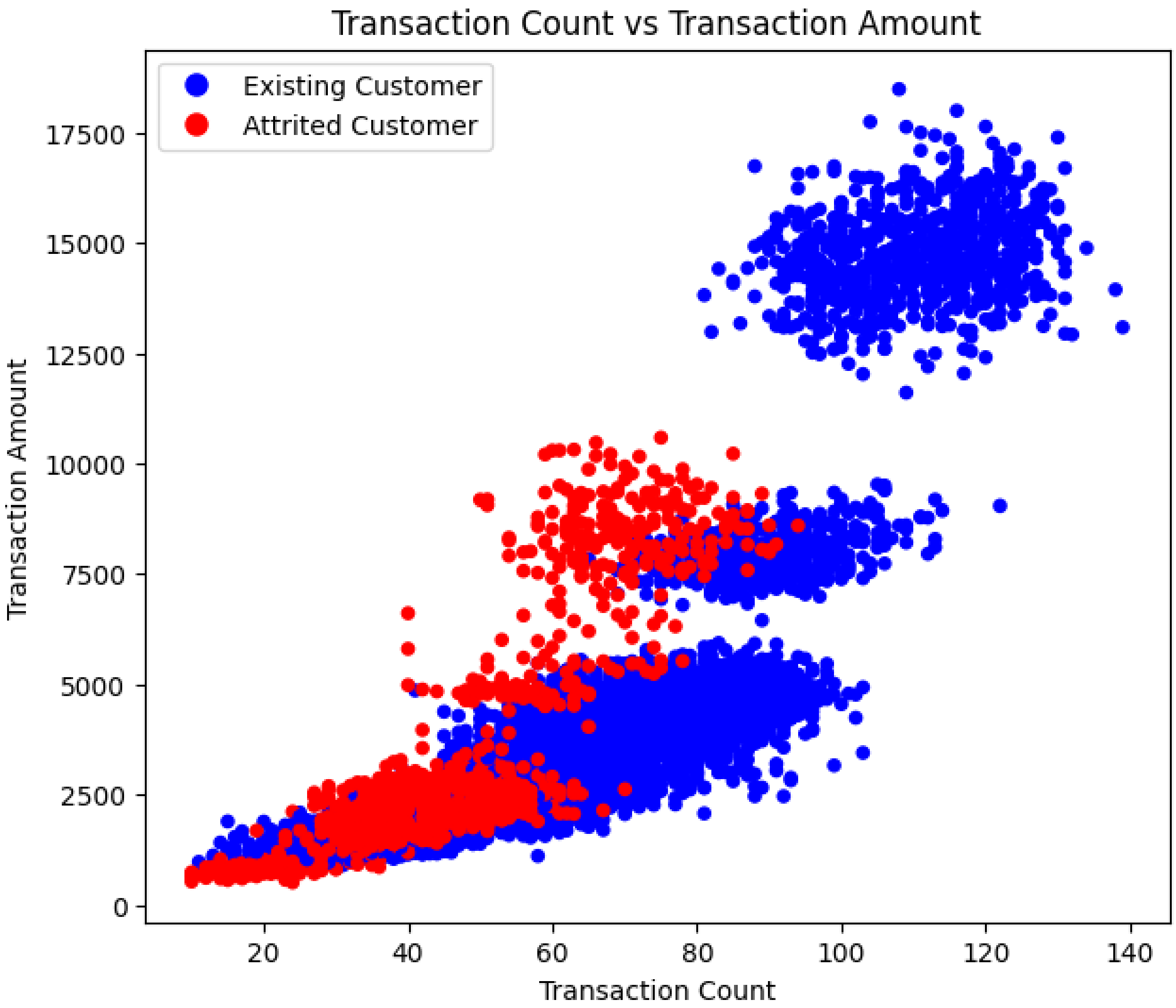
In [ ]:
```
df.groupby(['Education_Level', 'Attrition_Flag']).size().unstack().plot(kind="bar",rot=0,figsize=(10,6),stacked=True)
plt.xlabel('Education Level')
plt.ylabel('Total Customers')
plt.title('Number of Customers by Education Level and Attribution Flag')
plt.show()
```



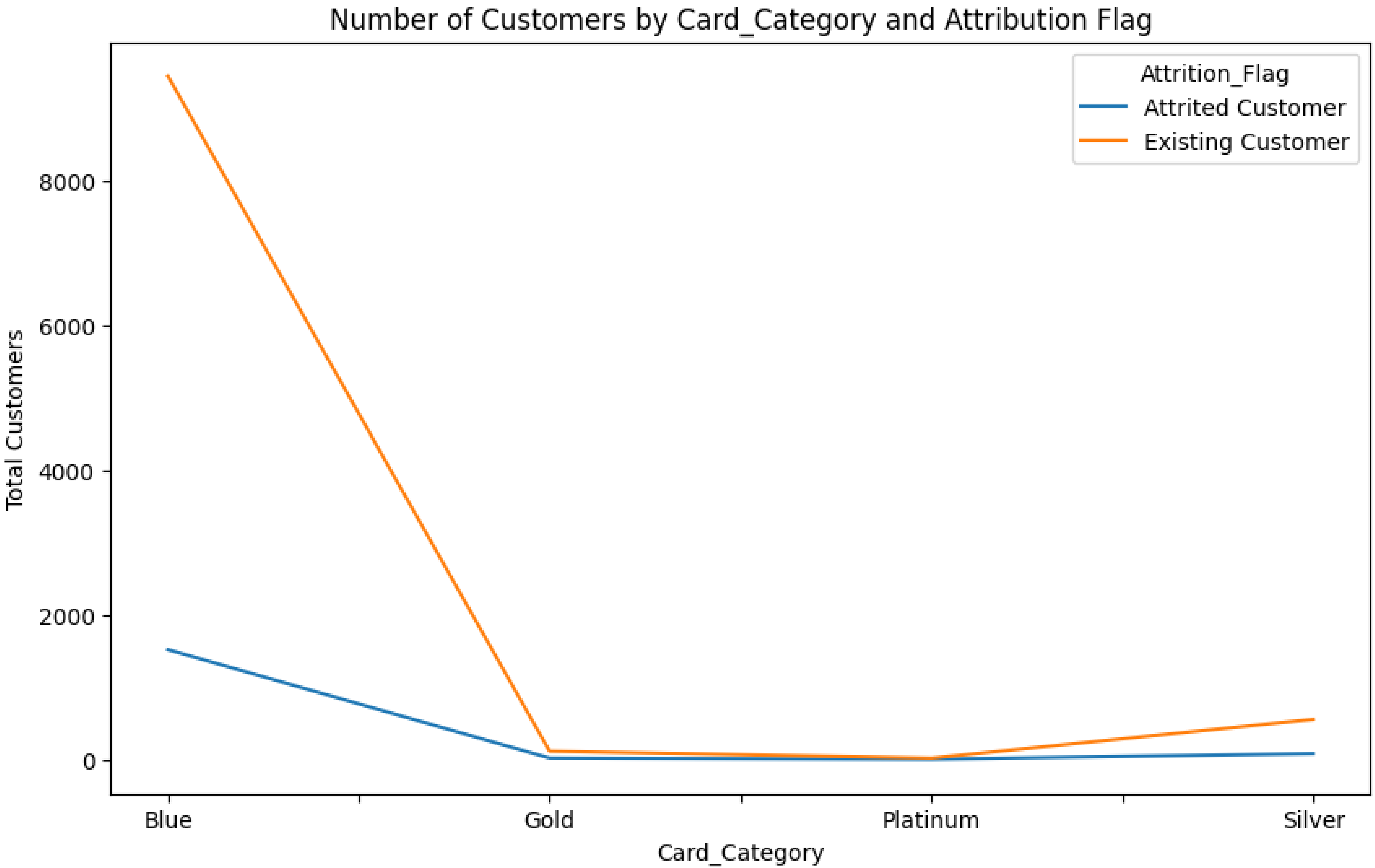
In [ ]:
```
df.boxplot(column='Total_Trans_Ct', by='Attrition_Flag',figsize=(7,6),grid=False,rot=0)
plt.ylabel("Total Transcation")
plt.suptitle("")
plt.show()
```



In [ ]:
```
colors = ['red' if flag == 'Attrited Customer' else 'blue' for flag in df['Attrition_Flag']]
df.plot.scatter('Total_Trans_Ct','Total_Trans_Amt',c=colors,figsize=(7,6))
legend_elements = [plt.Line2D([0], [0], marker='o', color='w', label='Existing Customer', markerfacecolor='blue', mark
                   plt.Line2D([0], [0], marker='o', color='w', label='Attrited Customer', markerfacecolor='red', marke
plt.legend(handles=legend_elements)
plt.title('Transaction Count vs Transaction Amount')
plt.xlabel('Transaction Count')
plt.ylabel('Transaction Amount')
plt.show()
```


Transaction Count vs Transaction Amount
Existing Customer
Attrited Customer
Transaction Amount
Transaction Count
0
2500
5000
7500
10000
12500
15000
17500
20
40
60
80
100
120
140

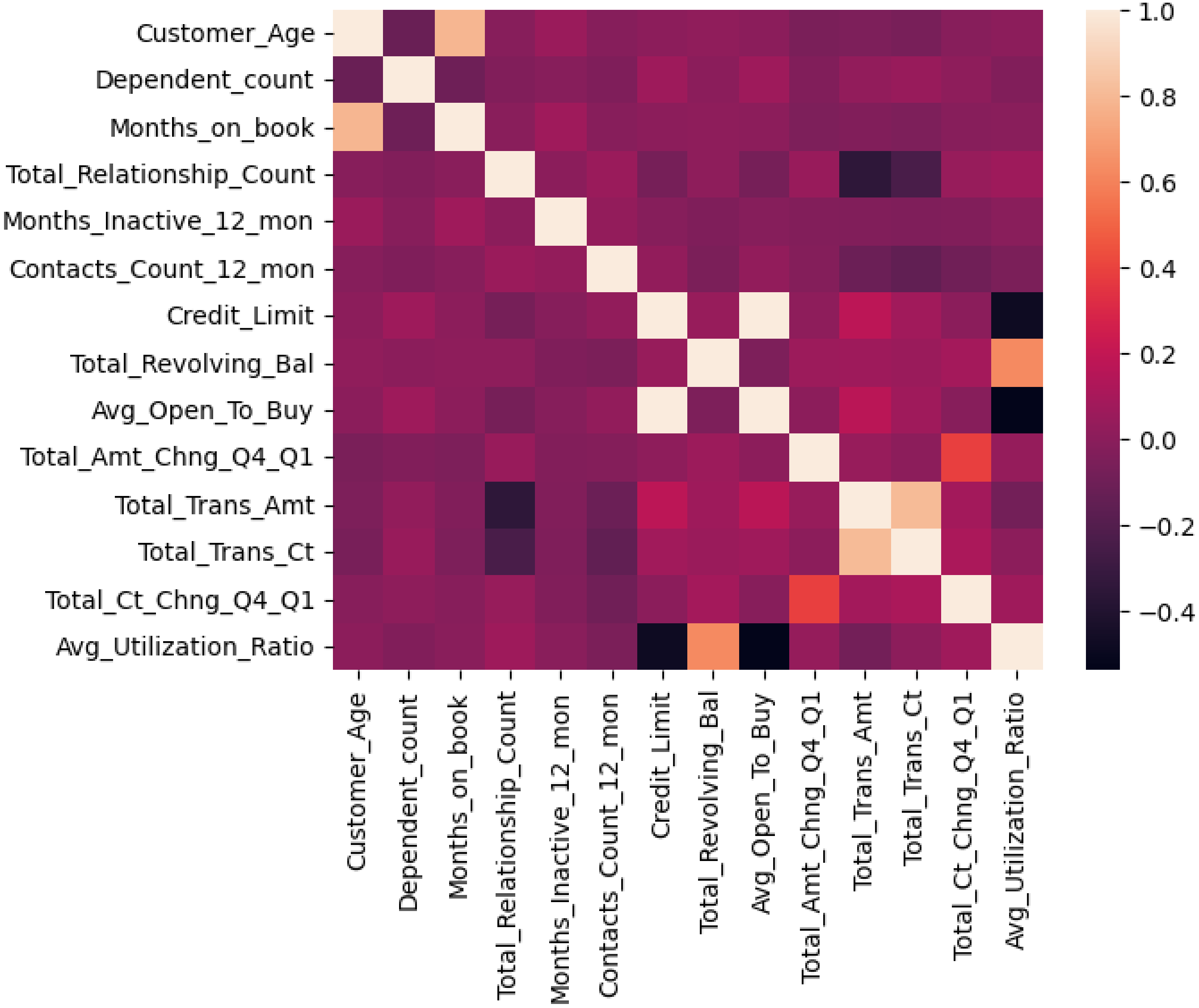
In [ ]:
```
df.groupby(['Card_Category', 'Attrition_Flag']).size().unstack().plot(rot=0,figsize=(10,6),stacked=True)
plt.xlabel('Card_Category')
plt.ylabel('Total Customers')
plt.title('Number of Customers by Card_Category and Attribution Flag')
plt.show()
```



In [ ]:
```
sns.heatmap(df.corr())
```

```
<ipython-input-138-aa4f4450a243>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr())
```

Out[138]:
```
<Axes: >
```


Customer_Age
Dependent_count
Months_on_book
Total_Relationship_Count
Months_Inactive_12_mon
Contacts_Count_12_mon
Credit_Limit
Total_Revolving_Bal
Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1
Total_Trans_Amt
Total_Trans_Ct
Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Data Preprocessing for Machine Learning

In [ ]:
```
df.head()
```

Out[140]:

	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Category	Months_on_book
0	Existing Customer	45	M	3	High School	Married	$60K-$80K	Blue	39
1	Existing Customer	49	F	5	Graduate	Single	Less than $40K	Blue	44
2	Existing Customer	51	M	3	Graduate	Married	$80K-$120K	Blue	36
3	Existing Customer	40	F	4	High School	Unknown	Less than $40K	Blue	34
4	Existing Customer	40	M	3	Uneducated	Married	$60K-$80K	Blue	21

In [ ]:
```
le=LabelEncoder()
df.Attrition_Flag=le.fit_transform(df.Attrition_Flag)
df.Education_Level=le.fit_transform(df.Education_Level)
df.Income_Category=le.fit_transform(df.Income_Category)
```

In [ ]:
```
mapCard = {"Blue":0, "Silver":1, "Gold":2, "Platinum":3}
df["Card_Category"] = df["Card_Category"].map(mapCard)
```

In [ ]:
```
gender=pd.get_dummies(df.Gender,prefix='Gender')
marital_status=pd.get_dummies(df.Marital_Status,prefix='Martial_status')
```

In [ ]:
```
df=pd.concat([df, gender,marital_status], axis=1)
df.drop(['Gender','Marital_Status'],axis=1,inplace=True)
```

In [ ]:
```
df.head()
```

Out[102]:

	Attrition_Flag	Customer_Age	Dependent_count	Education_Level	Income_Category	Card_Category	Months_on_book	Total_Relationship_Count
0	1	45	3	3	2	0	39	5
1	1	49	5	2	4	0	44	6
2	1	51	3	2	3	0	36	4
3	1	40	4	3	4	0	34	3
4	1	40	3	5	2	0	21	5

5 rows × 24 columns

In [ ]:
```
X=df.iloc[:,1:].values
y=df.iloc[:,0].values
```

In [ ]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=.75,random_state=10)
```

In [ ]:
```
sc=MinMaxScaler(feature_range=(0,1))
X_train_sc = sc.fit_transform(X_train)
X_test_sc = sc.transform(X_test)
```

In [ ]:
```
smt = SMOTE(sampling_strategy=0.8)
X_train_sc_sm, y_train_sm = smt.fit_resample(X_train_sc, y_train)
```

In [ ]:
```
df1=pd.DataFrame(y_train)
df2=pd.DataFrame(y_train_sm)
```

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

Out[151]:
```
1    2118
0     413
dtype: int64
```

In [ ]:
```
df2.value_counts()
```

Out[152]:
```
1    2118
0    1694
dtype: int64
```

Machine Learning Algorithm

##KNeighborsClassifier

In [ ]:
```
knn=KNeighborsClassifier()
```

In [ ]:
```
param_grid = {'n_neighbors': [3, 5, 7, 9, 11], 'weights': ['uniform', 'distance']}


grid_search = GridSearchCV(knn, param_grid=param_grid, cv=5)

grid_search.fit(X_train_sc_sm,y_train_sm)

print(grid_search.best_params_)
```

```
{'n_neighbors': 3, 'weights': 'distance'}
```

In [ ]:
```
model1=KNeighborsClassifier(n_neighbors=3,weights='distance')
model1.fit(X_train_sc_sm,y_train_sm) #trained model
```

Out[222]:
```
KNeighborsClassifier(n_neighbors=3, weights='distance')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:
```
pred_train_model=model1.predict(X_train_sc_sm)
pred_test_model=model1.predict(X_test_sc)
```

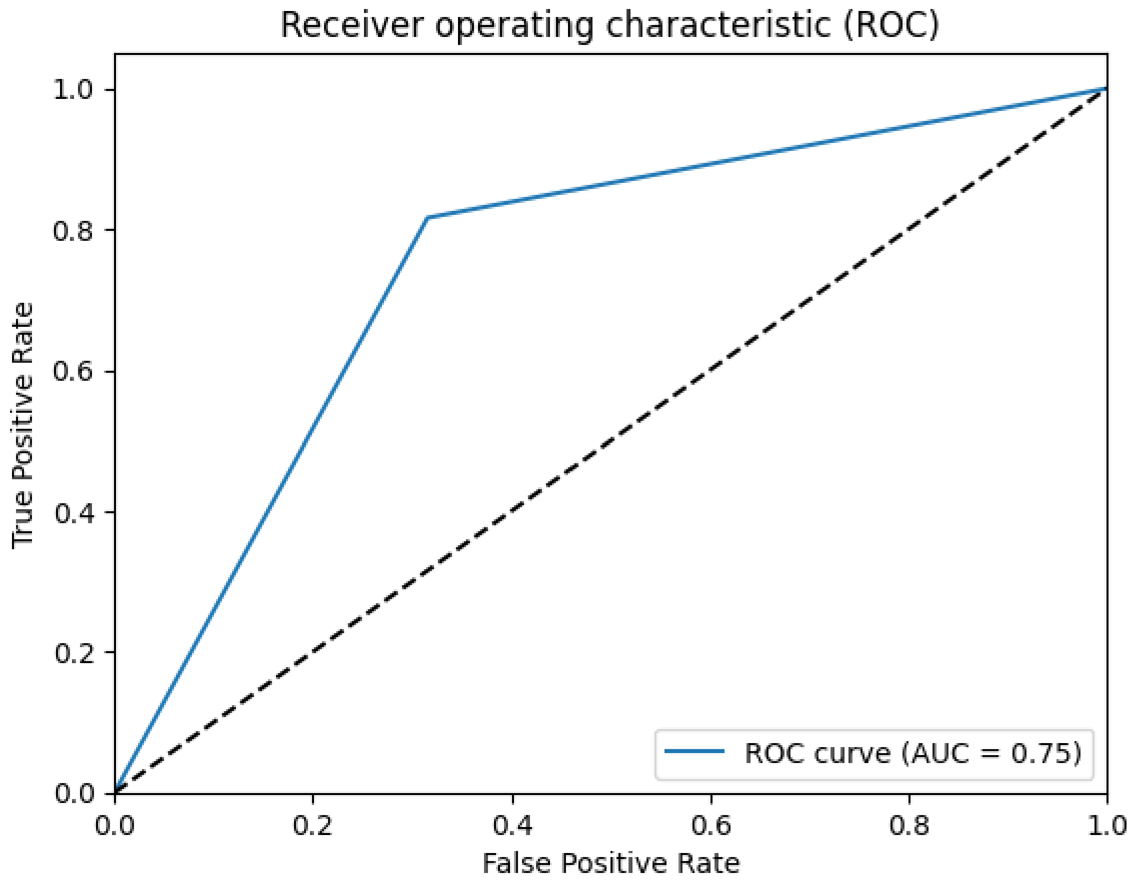
In [ ]:
```
print("Accuracy Score: ",accuracy_score(y_test,pred_test_model))
print("F-1 Score: ",f1_score(y_test, pred_test_model))
print("\n--------------------------Roc Curve--------------------------------\n")
fpr, tpr, thresholds = roc_curve(y_test, pred_test_model)

roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```

```
Accuracy Score:  0.7950236966824644
F-1 Score:  0.8699574041593584

--------------------------Roc Curve--------------------------------
```



##Logistics Regression

In [ ]:
```
logr=LogisticRegression(max_iter=1000) #untrained model
```

In [ ]:
```
param_grid = {'C': [0.1, 0.5, 1, 5, 10], 'penalty': ['l1', 'l2'], 'solver': ['liblinear', 'saga']}

grid_search = GridSearchCV(logr, param_grid=param_grid, cv=5)

grid_search.fit(X_train_sc_sm,y_train_sm)

print(grid_search.best_params_)
```

```
{'C': 5, 'penalty': 'l2', 'solver': 'liblinear'}
```

In [ ]:
```
model2=LogisticRegression(C=5,penalty='l2',solver='liblinear')
model2.fit(X_train_sc_sm,y_train_sm)
```

Out[227]:
```
LogisticRegression(C=5, solver='liblinear')
```

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In [ ]:
```
pred_train_model=model2.predict(X_train_sc_sm)
pred_test_model=model2.predict(X_test_sc)
```

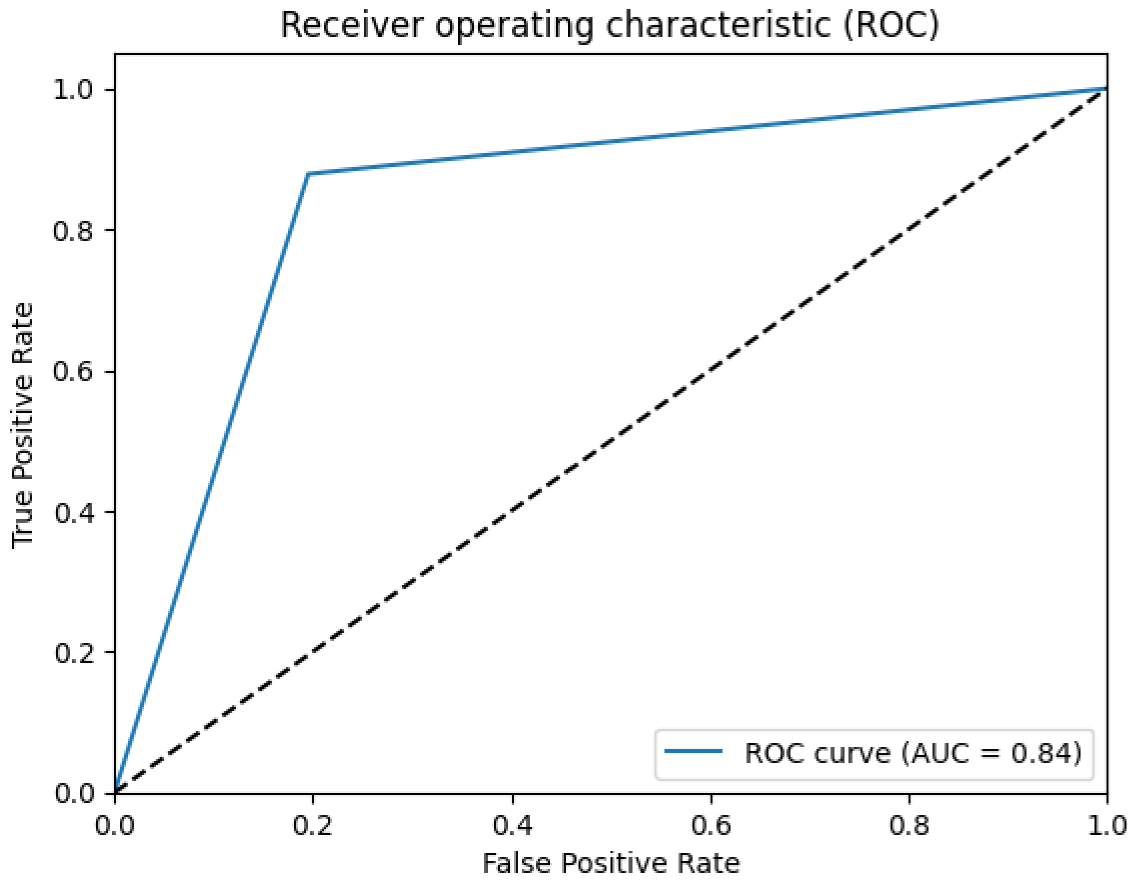
In [ ]:
```
print("Accuracy Score: ",accuracy_score(y_test,pred_test_model))
print("F-1 Score: ",f1_score(y_test, pred_test_model))
print("\n--------------------------Roc Curve--------------------------------\n")
fpr, tpr, thresholds = roc_curve(y_test, pred_test_model)

roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```

```
Accuracy Score:  0.866640337019484
F-1 Score:  0.9171370143149284

---------------------------Roc Curve--------------------------------
```



Decision Tree

In [ ]:
```
dt=DecisionTreeClassifier() #untrained model
```

In [ ]:
```
param_grid = {'max_depth': [3, 5, 7, 9,], 'criterion': ['gini', 'entropy'], 'min_samples_split': [2, 5, 10]}


grid_search = GridSearchCV(dt, param_grid=param_grid, cv=5)

grid_search.fit(X_train_sc_sm,y_train_sm)

print(grid_search.best_params_)
```

```
{'criterion': 'gini', 'max_depth': 9, 'min_samples_split': 2}
```

In [ ]:
```
model3=DecisionTreeClassifier(criterion='entropy',max_depth=9,min_samples_split=5)
model3.fit(X_train_sc_sm,y_train_sm)
```

Out[232]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=9, min_samples_split=5)
```

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In [ ]:
```
pred_train_model=model3.predict(X_train_sc_sm)
pred_test_model=model3.predict(X_test_sc)
```

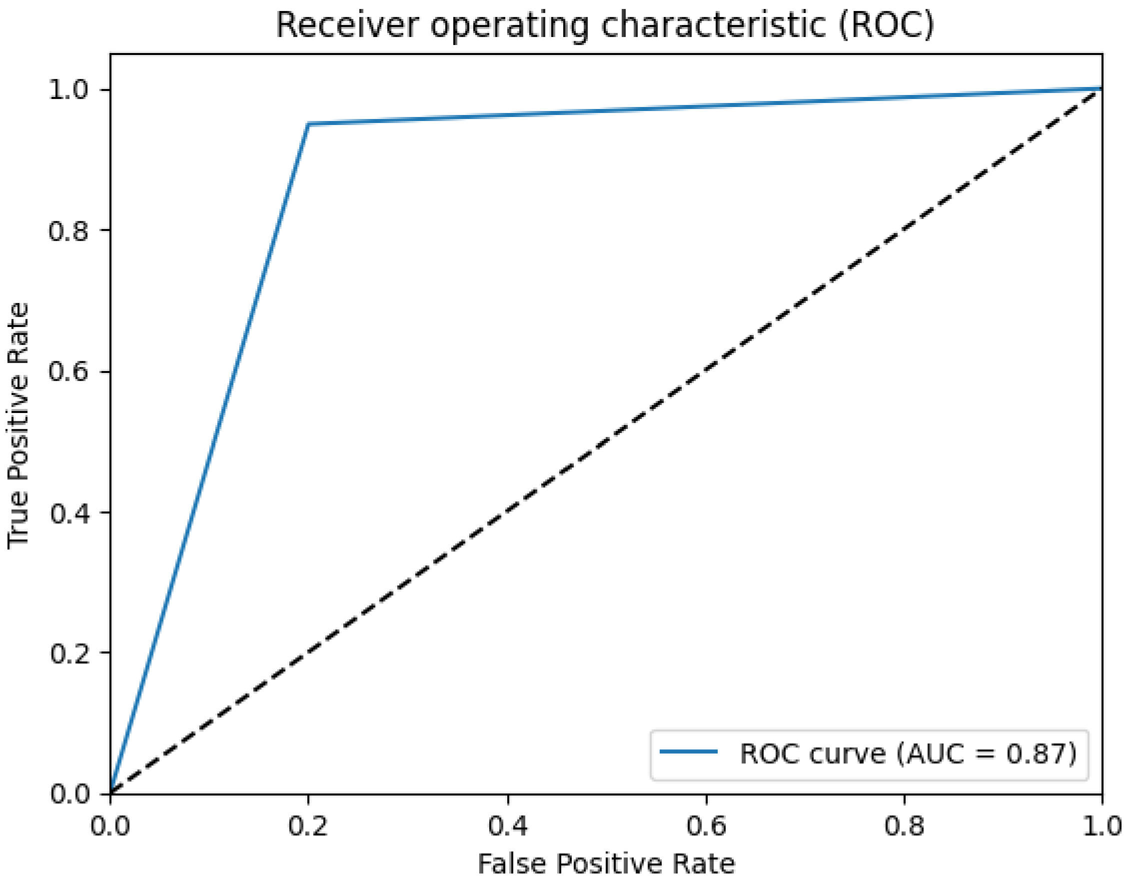
In [ ]:
```
print("Accuracy Score: ",accuracy_score(y_test,pred_test_model))
print("F-1 Score: ",f1_score(y_test, pred_test_model))
print("\n---------------------------Roc Curve--------------------------------\n")
fpr, tpr, thresholds = roc_curve(y_test, pred_test_model)

roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```

```
Accuracy Score:  0.9254870984728805
F-1 Score:  0.9553768527278461

---------------------------Roc Curve--------------------------------
```



Naive Bayes

In [ ]:
```
nb = GaussianNB() #untrained model
```

In [ ]:
```
param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5]}

grid_search = GridSearchCV(nb, param_grid=param_grid, cv=5)

grid_search.fit(X_train_sc_sm,y_train_sm)

print(grid_search.best_params_)
```

```
{'var_smoothing': 1e-05}
```

In [ ]:
```
model4=GaussianNB(var_smoothing=1e-9)
model4.fit(X_train_sc_sm,y_train_sm)
```

Out[237]:
```
GaussianNB()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:
```
pred_train_model=model4.predict(X_train_sc_sm)
pred_test_model=model4.predict(X_test_sc)
```

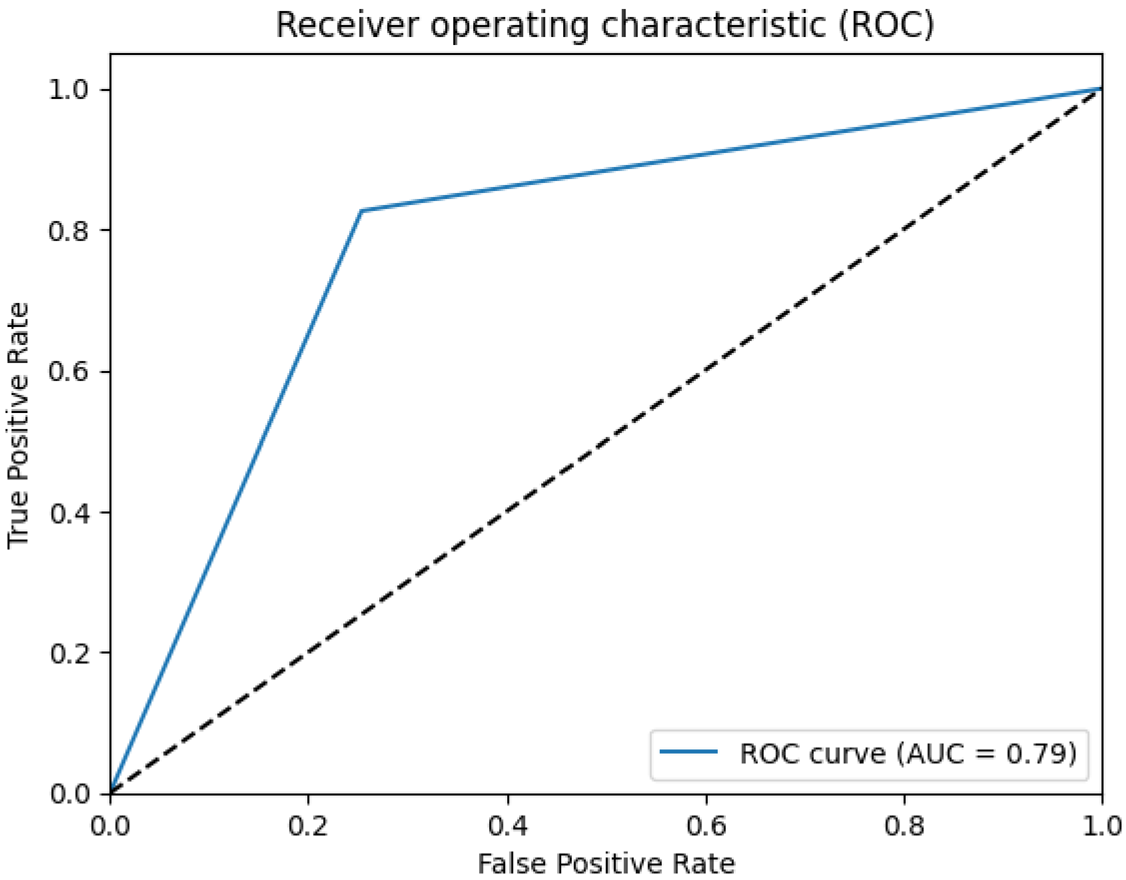
In [ ]:
```
print("Accuracy Score: ",accuracy_score(y_test,pred_test_model))
print("F-1 Score: ",f1_score(y_test, pred_test_model))
print("\n---------------------------Roc Curve--------------------------------\n")
fpr, tpr, thresholds = roc_curve(y_test, pred_test_model)

roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```

```
Accuracy Score:  0.8131911532385466
F-1 Score:  0.8813644344118384

---------------------------Roc Curve--------------------------------
```


Receiver operating characteristic (ROC)
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.79)
0.0
0.2
0.4
0.6
0.8
1.0

In [ ]: