Importing required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix,accuracy_score
from sklearn.linear_model import LogisticRegression

import warnings
```

Importing and displaying dataset

```
titanic_data = pd.read_csv("Titanic-Dataset.csv")
```

```
titanic_data
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

```
titanic_data.size
```

```
10692
```

```
titanic_data.shape
```

```
(891, 12)
```

```
titanic_data.head(3)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S

```
titanic_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

```
titanic_data.columns
```

```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

```
titanic_data.isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
# Dropping the column "Cabin"
titanic_data = titanic_data.drop(columns='Cabin', axis=1)
```

```
titanic_data.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
# Replacing missing values of "Age" and "Fare" with mean values
titanic_data["Age"].fillna(titanic_data["Age"].mean(),inplace=True)
titanic_data["Fare"].fillna(titanic_data["Fare"].mean(),inplace=True)
```

```
titanic_data.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	13.002015	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	22.000000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	29.699118	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	35.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
titanic_data.isnull().sum()
```

```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       2
dtype: int64
```

```
# Now working using "Embarked" column
print(titanic_data['Embarked'].mode())
titanic_data["Embarked"].fillna(titanic_data["Embarked"].mode()[0], inplace=True)
```

```
0    S
Name: Embarked, dtype: object
```

```
titanic_data.isnull().sum()
```

```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

Exploratory Data analysis

```
titanic_data.describe()
```

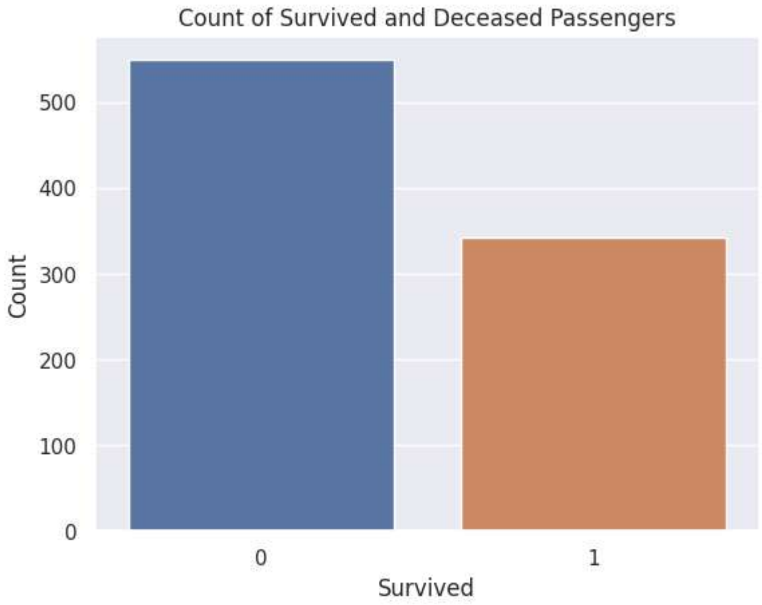
	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	13.002015	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	22.000000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	29.699118	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	35.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
titanic_data["Survived"].value_counts()
```

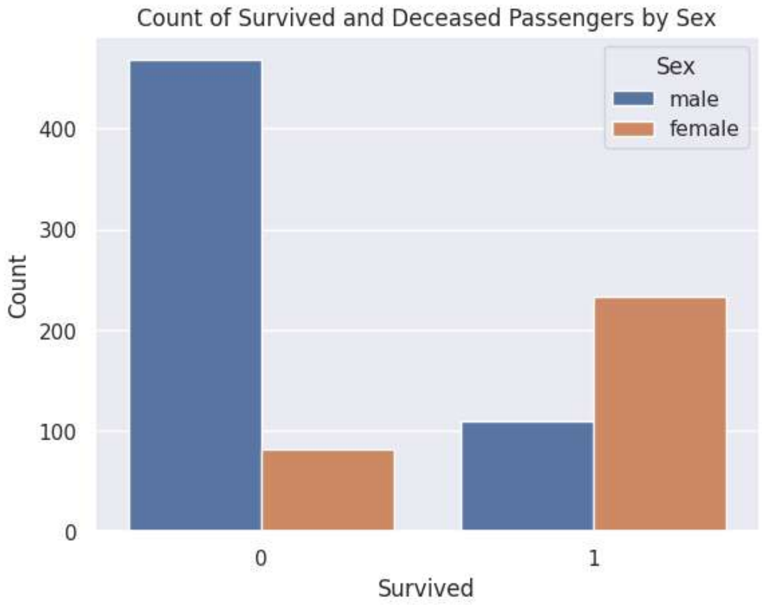
```
0    549
1    342
Name: Survived, dtype: int64
```

Data visuliazation

```
# prompt:

sns.countplot(x="Survived", data=titanic_data)
plt.xlabel("Survived")
plt.ylabel("Count")
plt.title("Count of Survived and Deceased Passengers")
plt.show()
```

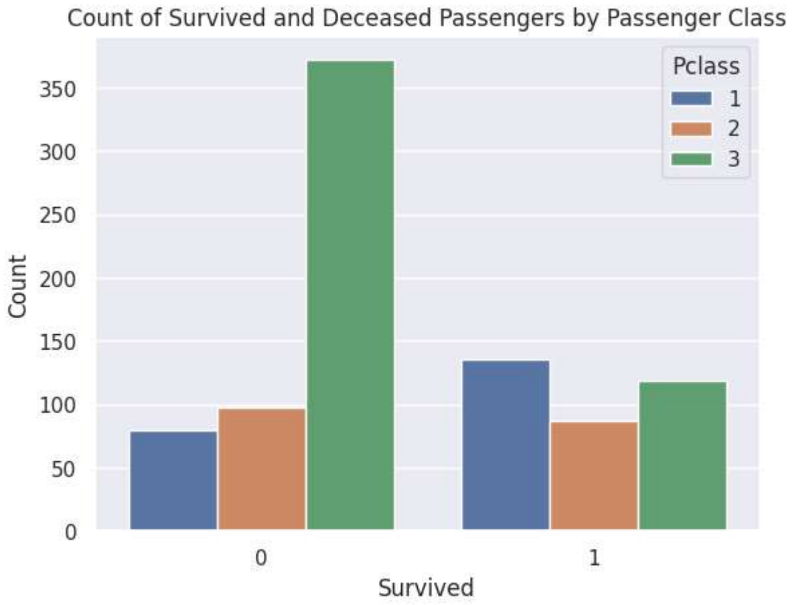


```
# prompt:

sns.countplot(x="Survived", hue="Sex", data=titanic_data)
plt.xlabel("Survived")
plt.ylabel("Count")
plt.title("Count of Survived and Deceased Passengers by Sex")
plt.show()
```

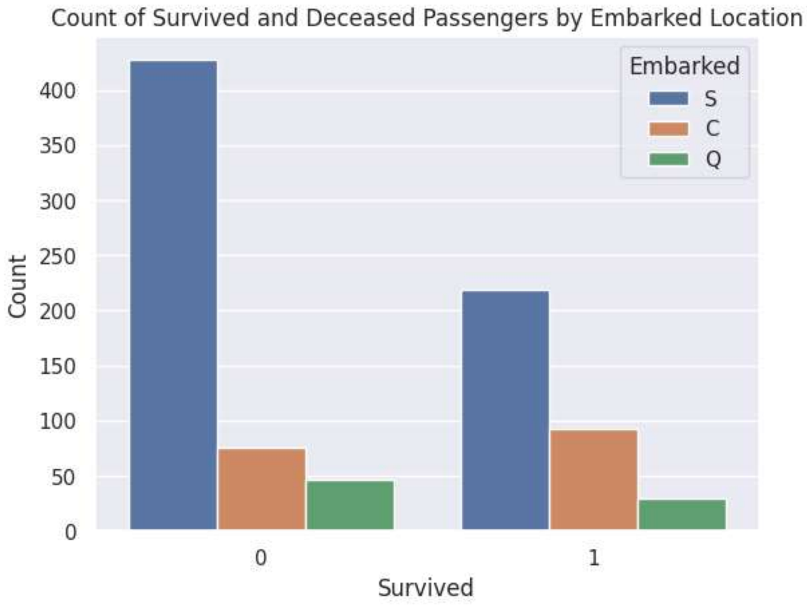


```
# prompt:
```

```
# prompt:

sns.countplot(x="Survived", hue="Pclass", data=titanic_data)
plt.xlabel("Survived")
plt.ylabel("Count")
plt.title("Count of Survived and Deceased Passengers by Passenger Class")
plt.show()
```



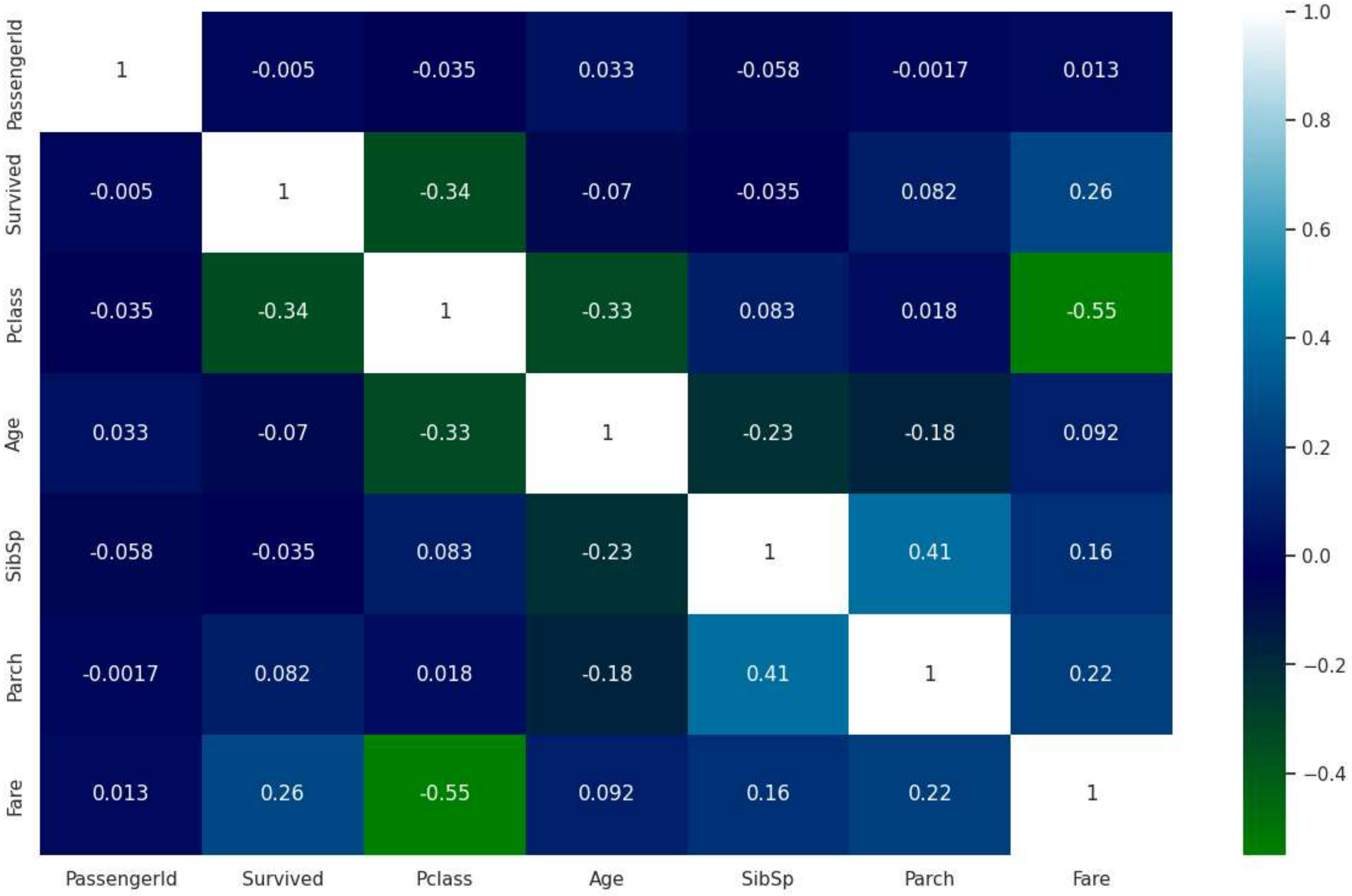
```
# prompt:

sns.countplot(x="Survived", hue="Embarked", data=titanic_data)
plt.xlabel("Survived")
plt.ylabel("Count")
plt.title("Count of Survived and Deceased Passengers by Embarked Location")
plt.show()
```



Checking correlation using heatmap

```
corr = titanic_data.corr()
plt.figure(figsize=(15, 9))
sns.heatmap(corr, annot=True, cmap='ocean')
```

```
<ipython-input-46-aeb4f38af05d>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version
  corr = titanic_data.corr()
<Axes: >
```



```
## Dropping unnecessary columns
titanic_data = titanic_data.drop(columns=['Name','Ticket'])
titanic_data.head()
```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	male	22.0	1	0	7.2500	S
1	2	1	1	female	38.0	1	0	71.2833	C
2	3	1	3	female	26.0	0	0	7.9250	S
3	4	1	1	female	35.0	1	0	53.1000	S
4	5	0	3	male	35.0	0	0	8.0500	S

```
# Encoding the categorical values to numerical values
titanic_data["Sex"].value_counts()
```

```
male      577
female    314
Name: Sex, dtype: int64
```

```
titanic_data["Sex"] = titanic_data["Sex"].astype('category')
titanic_data["Sex"] = titanic_data["Sex"].cat.codes
titanic_data["Sex"].value_counts()
```

```
1    577
0    314
Name: Sex, dtype: int64
```

```
titanic_data["Embarked"].value_counts()
```

```
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```

```
titanic_data["Embarked"] = titanic_data["Embarked"].astype('category')
titanic_data["Embarked"] = titanic_data["Embarked"].cat.codes
titanic_data["Embarked"].value_counts()
```

```
2    646
0    168
1     77
Name: Embarked, dtype: int64
```

Splitting the data into train and test sets

```
x = titanic_data.drop(columns=['PassengerId',"Survived"],axis=1)
y = titanic_data['Survived']
```

```
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state=46,test_size=0.3)
```

```
print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(623, 7) (268, 7) (623,) (268,)
```

Training a model

```
model = LogisticRegression()
titanic_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Sex          891 non-null    int8   
 4   Age          891 non-null    float64
 5   SibSp        891 non-null    int64  
 6   Parch        891 non-null    int64  
 7   Fare         891 non-null    float64
 8   Embarked     891 non-null    int8   
dtypes: float64(2), int64(5), int8(2)
memory usage: 50.6 KB
```

```
titanic_data.astype({'Age':'int', 'Fare':'int'}).dtypes
```

```
PassengerId    int64
Survived       int64
Pclass         int64
Sex             int8
Age            int64
SibSp          int64
Parch          int64
Fare           int64
Embarked        int8
dtype: object
```

```
# prompt:

model.fit(x_train,y_train)
```

```
LogisticRegression()
```

```
▾ LogisticRegression
LogisticRegression()
```

Accuracy,confusion_matrix and Classification_report

```
x_train_pred = model.predict(x_train)
```

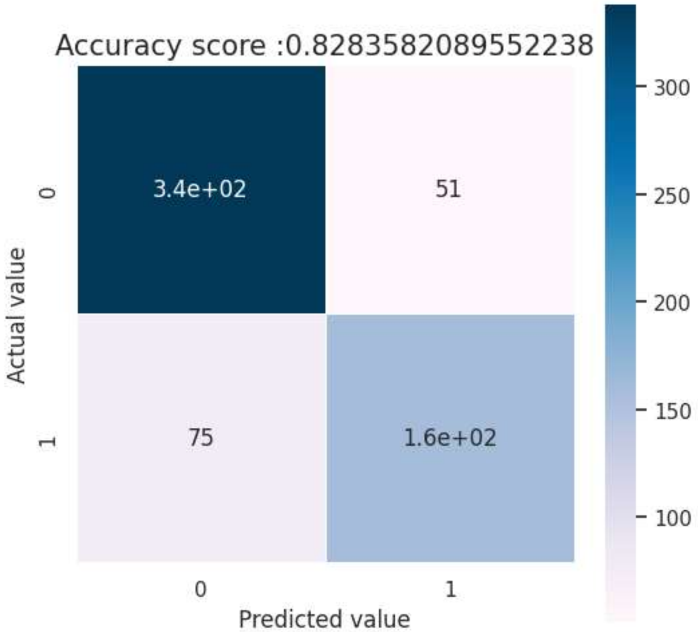
```
training_data_accuracy = accuracy_score(y_train, x_train_pred)
print('Accuracy_score_of_training_data : ', training_data_accuracy)
```

```
Accuracy_score_of_training_data :  0.797752808988764
```

```
x_test_pred = model.predict(x_test)
training_data_accuracy = accuracy_score(y_test, x_test_pred)
print('Accuracy_score_of_training_data : ', training_data_accuracy)
```

```
Accuracy_score_of_training_data :  0.8283582089552238
```

```
cm = confusion_matrix(y_train,Y_pred)
plt.figure(figsize=(6,6))
sns.heatmap(data=cm, linewidths=.5, annot=True, square=True, cmap='PuBu')
plt.xlabel("Predicted value")
plt.ylabel("Actual value")
all_sample_title = 'Accuracy score :{0}'.format(model.score(x_test,y_test))
plt.title(all_sample_title,size=15)
plt.savefig("three.png")
```



```
y_pred = model.predict(x_test)
Y_pred = model.predict(x_train)
print("Classification report - \n",classification_report(y_test,y_pred))
```

```
Classification report -
               precision    recall  f1-score   support

           0       0.83      0.89      0.86       160
           1       0.82      0.73      0.77       108

    accuracy                           0.83       268
   macro avg       0.83      0.81      0.82       268
weighted avg       0.83      0.83      0.83       268
```

```
print("\nClassification report- \n",classification_report(y_train,Y_pred))
```

```
Classification report-
               precision    recall  f1-score   support

           0       0.82      0.87      0.84       389
           1       0.76      0.68      0.72       234
```

```
    accuracy                           0.80       623
   macro avg       0.79      0.77      0.78       623
weighted avg       0.80      0.80      0.80       623
```