# Machine Learning – Assignment 4

CS 5710 (CRN 22002)

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## Question 1:

- Import the pandas libraries. Read the csv file containing the data sets and display the basic statistical descriptions of the dataset.

```
[109] from google.colab import drive
      drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_remount=True).
```

```
[110] import pandas as pd
      import matplotlib.pyplot as plt
```

```
#read the csv file and assign it to a variable
dataset = pd.read_csv('/content/gdrive/My Drive/data.csv')
df = pd.DataFrame(dataset)

#display the basic statistical description of the data
df.describe()
```

| | Duration | Pulse | Maxpulse | Calories |
|---|---|---|---|---|
| count | 169.000000 | 169.000000 | 169.000000 | 164.000000 |
| mean | 63.846154 | 107.461538 | 134.047337 | 375.790244 |
| std | 42.299949 | 14.510259 | 16.450434 | 266.379919 |
| min | 15.000000 | 80.000000 | 100.000000 | 50.300000 |
| 25% | 45.000000 | 100.000000 | 124.000000 | 250.925000 |
| 50% | 60.000000 | 105.000000 | 131.000000 | 318.600000 |
| 75% | 60.000000 | 111.000000 | 141.000000 | 387.600000 |
| max | 300.000000 | 159.000000 | 184.000000 | 1860.400000 |

- Get the rows that has null values in any of their column values, copy their indexes into a list. Here we are storing the indexes just to see how our data looks after updating the null values. Update all the null values with the respective mean value. Now using the row indexes we can see how the rows look after updating.

```
#find the rows that has null values
nullVal = pd.DataFrame(df[df.isna().any(axis=1)])
print("Rows that has null values:")
print(nullVal)

#store the rows indexes in a list
nullValInx = list(nullVal.index.values)

#replace the null values with the respective mean value of the column
df = df.fillna(round(df.mean(),1))

#display the updated rowa]s
upd_val = pd.DataFrame(df,index=nullValInx)
print("\nRows that had null values, after update:")
upd_val
```

```
Rows that has null values:
     Duration  Pulse  Maxpulse  Calories
17         45     90       112       NaN
27         60    103       132       NaN
91         45    107       137       NaN
118        60    105       125       NaN
141        60     97       127       NaN

Rows that had null values, after update:
```

| | Duration | Pulse | Maxpulse | Calories |
|---|---|---|---|---|
| **17** | 45 | 90 | 112 | 375.8 |
| **27** | 60 | 103 | 132 | 375.8 |
| **91** | 45 | 107 | 137 | 375.8 |
| **118** | 60 | 105 | 125 | 375.8 |
| **141** | 60 | 97 | 127 | 375.8 |

- Here two columns, Pulse and Calories are selected and their respective max value, min value, count and mean are aggregated and displayed

```
[113] #aggregated data of coulmns, Pulse and Calories
      df.agg({'Pulse' : ['max', 'min', 'count', 'mean'], 'Calories' : ['max', 'min', 'count', 'mean']})
```

| | Pulse | Calories |
|---|---|---|
| **max** | 159.000000 | 1860.400000 |
| **min** | 80.000000 | 50.300000 |
| **count** | 169.000000 | 169.000000 |
| **mean** | 107.461538 | 375.790533 |

- Here we are displaying the rows whose Calories column values are between 500 and 1000. This is done in two steps. First we are filtering values greater than 500 and store it. Then filter the resulted data with values less than 1000.

```
#to filter values between 500 and 1000 calories
df_great_500 = df[df['Calories']>=500] #filter rows with calories above 500
df_filter = df_great_500[df_great_500["Calories"]<=1000] #from the above result, filter the rows with calories below 1000
df_filter
```

| | Duration | Pulse | Maxpulse | Calories |
|---|---|---|---|---|
| **51** | 80 | 123 | 146 | 643.1 |
| **62** | 160 | 109 | 135 | 853.0 |
| **65** | 180 | 90 | 130 | 800.4 |
| **66** | 150 | 105 | 135 | 873.4 |
| **67** | 150 | 107 | 130 | 816.0 |
| **72** | 90 | 100 | 127 | 700.0 |
| **73** | 150 | 97 | 127 | 953.2 |
| **75** | 90 | 98 | 125 | 563.2 |
| **78** | 120 | 100 | 130 | 500.4 |
| **83** | 120 | 100 | 130 | 500.0 |
| **90** | 180 | 101 | 127 | 600.1 |
| **99** | 90 | 93 | 124 | 604.1 |
| **101** | 90 | 90 | 110 | 500.0 |
| **102** | 90 | 90 | 100 | 500.0 |
| **103** | 90 | 90 | 100 | 500.4 |
| **106** | 180 | 90 | 120 | 800.3 |
| **108** | 90 | 90 | 120 | 500.3 |

- Here we are displaying the rows whose Calories column values are greater than 500 and Pulse column values are less than 100. This is done in two steps. First, we are filtering Calories values greater than 500 and store it. Then filter the resulted data with Pulse values less than 1000.

```
df_great_500 = df[df['Calories']>500]  #filter rows with calories above 500
df_pulse_100 = df_great_500[df_great_500["Pulse"]<100] #from the above result, filter the rows with pulse below 100
df_pulse_100
```

| | Duration | Pulse | Maxpulse | Calories |
|---|---|---|---|---|
| **65** | 180 | 90 | 130 | 800.4 |
| **70** | 150 | 97 | 129 | 1115.0 |
| **73** | 150 | 97 | 127 | 953.2 |
| **75** | 90 | 98 | 125 | 563.2 |
| **99** | 90 | 93 | 124 | 604.1 |
| **103** | 90 | 90 | 100 | 500.4 |
| **106** | 180 | 90 | 120 | 800.3 |
| **108** | 90 | 90 | 120 | 500.3 |

- Creating a new data frame containing the all the columns except Maxpulse

```
#create a new dataframe containg all columns except Maxpulse
df_modified = df[["Duration","Pulse","Calories"]]
df_modified
```

| | Duration | Pulse | Calories |
|---|---|---|---|
| **0** | 60 | 110 | 409.1 |
| **1** | 60 | 117 | 479.0 |
| **2** | 60 | 103 | 340.0 |
| **3** | 45 | 109 | 282.4 |
| **4** | 45 | 117 | 406.0 |
| **...** | ... | ... | ... |
| **164** | 60 | 105 | 290.8 |
| **165** | 60 | 110 | 300.0 |
| **166** | 60 | 115 | 310.2 |
| **167** | 75 | 120 | 320.4 |
| **168** | 75 | 125 | 330.4 |

169 rows × 3 columns

- Delete the Maxpulse column from the main data frame.

```
#delete the Maxpulse column from the main frame
del df["Maxpulse"]
df
```

| | Duration | Pulse | Calories |
|---|---|---|---|
| 0 | 60 | 110 | 409.1 |
| 1 | 60 | 117 | 479.0 |
| 2 | 60 | 103 | 340.0 |
| 3 | 45 | 109 | 282.4 |
| 4 | 45 | 117 | 406.0 |
| ... | ... | ... | ... |
| 164 | 60 | 105 | 290.8 |
| 165 | 60 | 110 | 300.0 |
| 166 | 60 | 115 | 310.2 |
| 167 | 75 | 120 | 320.4 |
| 168 | 75 | 125 | 330.4 |

169 rows × 3 columns

- Converting the datatype of Calories column from float to int.

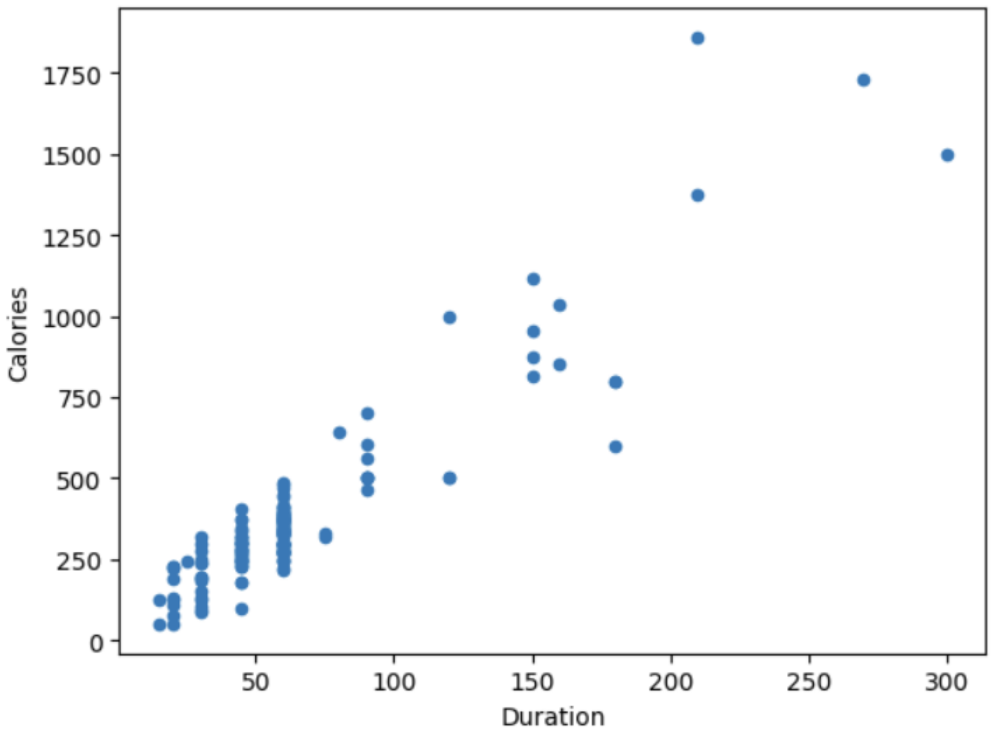
```
#convert the datatype of Calories column to int
df["Calories"] = df["Calories"].astype(int)
df
```

| | Duration | Pulse | Calories |
|---|---|---|---|
| 0 | 60 | 110 | 409 |
| 1 | 60 | 117 | 479 |
| 2 | 60 | 103 | 340 |
| 3 | 45 | 109 | 282 |
| 4 | 45 | 117 | 406 |
| ... | ... | ... | ... |
| 164 | 60 | 105 | 290 |
| 165 | 60 | 110 | 300 |
| 166 | 60 | 115 | 310 |
| 167 | 75 | 120 | 320 |
| 168 | 75 | 125 | 330 |

169 rows × 3 columns

- Creating a scatter plot for Duration and Calories.

```
#create a scatter plot for the columns, Duration and Calories
df.plot.scatter(x='Duration', y='Calories')
plt.show()
```




Question 2:

Import the libraries and read the titanic dataset

```
[1] from google.colab import drive
    drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

```
#import libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
[21] #read dataset
     titanic_df = pd.read_csv('/content/gdrive/My Drive/titanic_train.csv')
     titanic_df.head()
```

| | 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 |

Correlation Map of the given dataset

```
#correlation matrix of given data
titanic_df.corr()
```

| | PassengerId | Survived | Pclass | Age | SibSp | Parch | Fare |
|---|---|---|---|---|---|---|---|
| **PassengerId** | 1.000000 | -0.005007 | -0.035144 | 0.036847 | -0.057527 | -0.001652 | 0.012658 |
| **Survived** | -0.005007 | 1.000000 | -0.338481 | -0.077221 | -0.035322 | 0.081629 | 0.257307 |
| **Pclass** | -0.035144 | -0.338481 | 1.000000 | -0.369226 | 0.083081 | 0.018443 | -0.549500 |
| **Age** | 0.036847 | -0.077221 | -0.369226 | 1.000000 | -0.308247 | -0.189119 | 0.096067 |
| **SibSp** | -0.057527 | -0.035322 | 0.083081 | -0.308247 | 1.000000 | 0.414838 | 0.159651 |
| **Parch** | -0.001652 | 0.081629 | 0.018443 | -0.189119 | 0.414838 | 1.000000 | 0.216225 |
| **Fare** | 0.012658 | 0.257307 | -0.549500 | 0.096067 | 0.159651 | 0.216225 | 1.000000 |

Encode the values in Column from str to int to calculate the correlation value with the target column.

```
[73] #encode columns with type str to type int
     from sklearn.preprocessing import LabelEncoder

     #Since correlation cannot be calculated when the column values are str type, we encode them with numbers
     lb_make = LabelEncoder()
     titanic_df["Sex_Encoded"] = lb_make.fit_transform(titanic_df["Sex"])
     titanic_df["Sex_Encoded"].value_counts()

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

```
[72] #Calculate Correlation between Survived and Encoded values of Column Sex
     corr_Val = titanic_df["Survived"].corr(titanic_df["Sex_Encoded"])
     print("Correlation between Survived and Sex Coulumn:",corr_Val)

     Correlation between Survived and Sex Coulumn: -0.5433513806577555
```

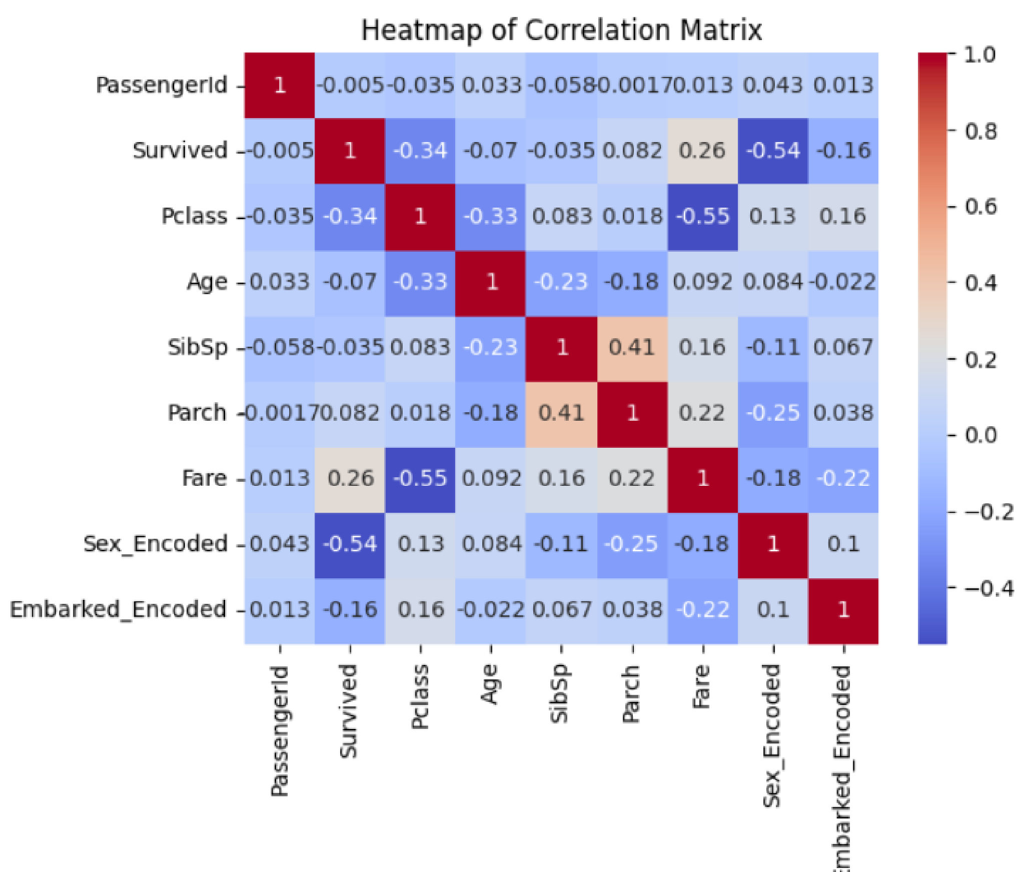
Correlation after adding the Encoded Column

```
titanic_df.corr()
```

| | PassengerId | Survived | Pclass | Age | SibSp | Parch | Fare | Sex_Encoded | Embarked_Encoded |
|---|---|---|---|---|---|---|---|---|---|
| **PassengerId** | 1.000000 | -0.005007 | -0.035144 | 0.033207 | -0.057527 | -0.001652 | 0.012658 | 0.042939 | 0.013083 |
| **Survived** | -0.005007 | 1.000000 | -0.338481 | -0.069809 | -0.035322 | 0.081629 | 0.257307 | -0.543351 | -0.163517 |
| **Pclass** | -0.035144 | -0.338481 | 1.000000 | -0.331339 | 0.083081 | 0.018443 | -0.549500 | 0.131900 | 0.157112 |
| **Age** | 0.033207 | -0.069809 | -0.331339 | 1.000000 | -0.232625 | -0.179191 | 0.091566 | 0.084153 | -0.022239 |
| **SibSp** | -0.057527 | -0.035322 | 0.083081 | -0.232625 | 1.000000 | 0.414838 | 0.159651 | -0.114631 | 0.066654 |
| **Parch** | -0.001652 | 0.081629 | 0.018443 | -0.179191 | 0.414838 | 1.000000 | 0.216225 | -0.245489 | 0.038322 |
| **Fare** | 0.012658 | 0.257307 | -0.549500 | 0.091566 | 0.159651 | 0.216225 | 1.000000 | -0.182333 | -0.221226 |
| **Sex_Encoded** | 0.042939 | -0.543351 | 0.131900 | 0.084153 | -0.114631 | -0.245489 | -0.182333 | 1.000000 | 0.104057 |
| **Embarked_Encoded** | 0.013083 | -0.163517 | 0.157112 | -0.022239 | 0.066654 | 0.038322 | -0.221226 | 0.104057 | 1.000000 |

HeatMap of Correlation

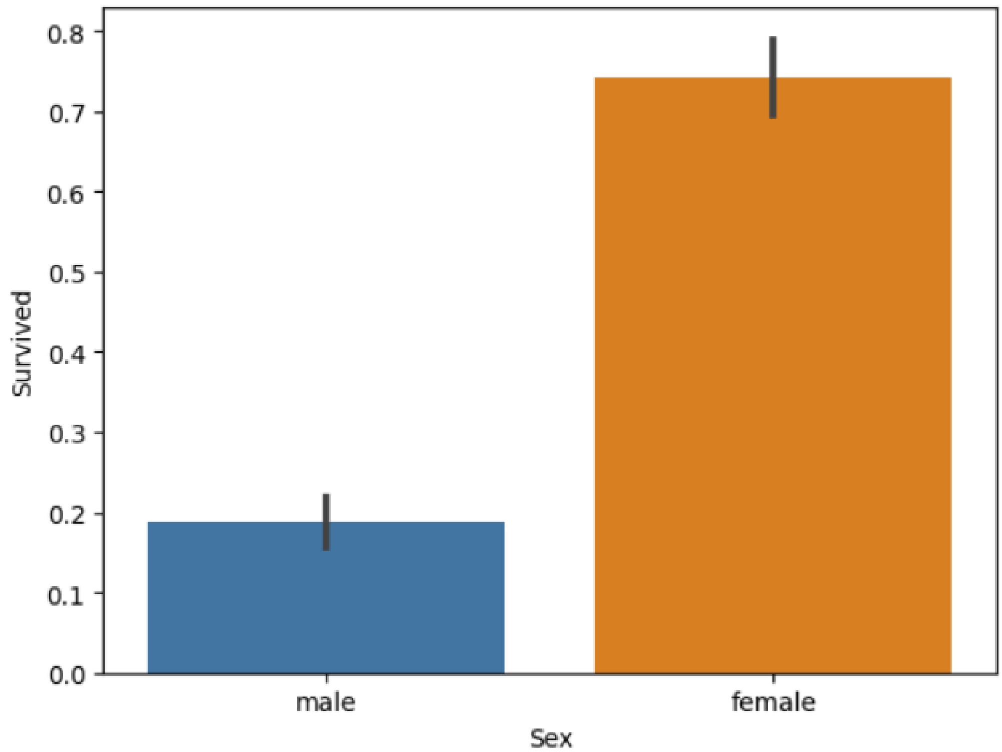
```
sns.heatmap(titanic_df.corr(), cmap='coolwarm', annot=True)
plt.title('Heatmap of Correlation Matrix')
plt.show()
```



Answer for a: As the survival rate of women in more compared to men, and more men died compared to women. Hence, we can keep this feature.

```
sns.barplot(x='Sex', y='Survived', data=titanic_df)
```

```
<Axes: xlabel='Sex', ylabel='Survived'>
```




```
[126] #Find how many men and women survived and died
      a = titanic_df[titanic_df['Survived'] == 0]
      m0 = a[a['Sex'] == "male"]
      f0 = a[a['Sex'] == "female"]
      print("No. of Male Died:",m0["Sex"].count())
      print("No. of Female Died:",f0["Sex"].count())

      a = titanic_df[titanic_df['Survived'] == 1]
      m1 = a[a['Sex'] == "male"]
      f1 = a[a['Sex'] == "female"]
      print("\nNo. of Male Survived:",m1["Sex"].count())
      print("No. of Female Survived:",f1["Sex"].count())
```

```
No. of Male Died: 468
No. of Female Died: 81

No. of Male Survived: 109
No. of Female Survived: 233
```

Find the null values and fill the required columns

```
[80] #Since model cannot be trained when the column values are str type, we encode them with type int
     lb_make = LabelEncoder()
     titanic_df["Embarked_Encoded"] = lb_make.fit_transform(titanic_df["Embarked"])
     titanic_df["Embarked_Encoded"].value_counts()
```

```
2    644
0    168
1     77
3      2
Name: Embarked_Encoded, dtype: int64
```

```
#checking for null values
titanic_df.isnull().any()
```

```
PassengerId         False
Survived            False
Pclass              False
Name                False
Sex                 False
Age                 False
SibSp               False
Parch               False
Ticket              False
Fare                False
Cabin                True
Embarked             True
Sex_Encoded         False
Embarked_Encoded    False
dtype: bool
```

```
[82] #filling null values with mean
     titanic_df['Age'] = titanic_df['Age'].fillna(titanic_df['Age'].mean())
```

```
#dropping Name, Ticket,Cabin and Passenger ID as they more unique values which might not be necessary
#Columns Sex and Embarked are also dropped as we have the encoded columns
X = titanic_df.drop(['Survived','Name','Sex','Ticket','Cabin','Embarked','PassengerId'], axis=1)
Y = titanic_df['Survived']

#splitting the dataset into training set and testing set
X_Train, X_Test, Y_Train, Y_Test = train_test_split(X, Y, test_size=0.25,random_state = 0)
```

```
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn import metrics
from sklearn.metrics import classification_report,confusion_matrix, accuracy_score

#instantiating the Naive Bayes model and fitting it with traning set
gnb = GaussianNB()
gnb.fit(X_Train,Y_Train)

# Predicting the Test set result
Y_Pred = gnb.predict(X_Test)

#evaluating the model
print("Gaussian Naive Bayers Accuracy is:",round(accuracy_score(Y_Test,Y_Pred) * 100,2))
print("\nClassification Report:\n\n",metrics.classification_report(Y_Test,Y_Pred,zero_division=0))
```

```
Gaussian Naive Bayers Accuracy is: 78.03

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.78      0.82       139
           1       0.68      0.77      0.73        84

    accuracy                           0.78       223
   macro avg       0.77      0.78      0.77       223
weighted avg       0.79      0.78      0.78       223
```


```
              precision    recall  f1-score   support

           0       0.85      0.78      0.82       139
           1       0.68      0.77      0.73        84

    accuracy                           0.78       223
   macro avg       0.77      0.78      0.77       223
weighted avg       0.79      0.78      0.78       223
```


Question 3:

To implement the Naïve Bayes method for the give dataset, glass.csv. Split the given dataset into training set and testing set. Train the model with the training data set. Predict the model for the test input and evaluate it.

[2]
```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

```
#import libraries
import numpy as np
import random as rnd
import pandas as pd

from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn import metrics

from sklearn.svm import SVC, LinearSVC
from sklearn.neighbors import KNeighborsClassifier
```

[7]
```python
# reading the dataset file
df = pd.read_csv('/content/gdrive/My Drive/glass.csv')

X = df.drop(['Type'], axis=1)
Y = df["Type"]

#splitting the dataset into training set and testing set
X_Train, X_Test, Y_Train, Y_Test = train_test_split(X, Y, test_size=0.25,random_state = 0)
```

```python
#instantiating the Naive Bayes model and fitting it with traning set
gnb = GaussianNB()
gnb.fit(X_Train,Y_Train)

# Predicting the Test set result
Y_Pred = gnb.predict(X_Test)

#evaluating the model
print("Gaussian Naive Bayers Accuracy is:",round(accuracy_score(Y_Test,Y_Pred) * 100,2))
print("\nClassification Report:\n\n",metrics.classification_report(Y_Test,Y_Pred,zero_division=0))
```

```
Gaussian Naive Bayers Accuracy is: 46.3

Classification Report:

              precision    recall  f1-score   support

           1       0.32      0.64      0.43        14
           2       0.45      0.21      0.29        24
           3       0.50      0.40      0.44         5
           5       0.00      0.00      0.00         2
           6       0.67      1.00      0.80         2
           7       1.00      1.00      1.00         7

    accuracy                           0.46        54
   macro avg       0.49      0.54      0.49        54
weighted avg       0.49      0.46      0.44        54
```

To implement the linear SVM method for the same dataset. Predicting the outputs for the test set and evaluating the model.

```
#instantiating the linear SVM model and fitting it with traning set
svc = SVC(kernel='linear')
svc.fit(X_Train, Y_Train)

# Predicting the Test set result
Y_pred = svc.predict(X_Test)

#evaluating the model
print("SVM accuracy is:", round(accuracy_score(Y_Test,Y_pred) * 100, 2))
print("\nClassification Report:\n\n",metrics.classification_report(Y_Test,Y_pred,zero_division=0))
```

```
SVM accuracy is: 55.56

Classification Report:

              precision    recall  f1-score   support

           1       0.43      0.86      0.57        14
           2       0.60      0.38      0.46        24
           3       0.00      0.00      0.00         5
           5       0.67      1.00      0.80         2
           6       0.00      0.00      0.00         2
           7       1.00      1.00      1.00         7

    accuracy                           0.56        54
   macro avg       0.45      0.54      0.47        54
weighted avg       0.53      0.56      0.51        54
```