import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model\_selection import train\_test\_split
from sklearn.svm import SVC
from sklearn.preprocessing import LabelEncoder
from sklearn.naive\_bayes import GaussianNB
from sklearn.metrics import accuracy\_score
from sklearn.neighbors import KNeighborsClassifier

In [2]: df=pd.read\_csv('C:\\Users\\HP\\Documents\\Data Science\\WineQT.csv')

In [3]: df.head()

Out

t[3]:		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality	Id
	0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5	0
	1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5	1
	2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5	2
	3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6	3
	4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5	4

In [4]: df.shape

Out[4]: (1143, 13)

In [5]: df.drop(['Id'],axis=1,inplace=True)

In [6]: df.head()

```
total sulfur ... density pH sulphates alcohol quality
 Out[6]:
                  fixed
                             volatile
                                        citric
                                                                         free sulfur
                                                  residual
                                                           chlorides
                 acidity
                             acidity
                                         acid
                                                    sugar
                                                                            dioxide
                                                              0.076
                                                                                                    0.9978 3.51
          0
                                         0.00
                                                                               11.0
                                                                                                                               9.4
                                                                                                                                        5
                    7.4
                                0.70
                                                       1.9
                                                                                              34.0
                                                                                                                      0.56
                                                                                                    0.9968 3.20
                                                                                                                               9.8
          1
                    7.8
                                0.88
                                         0.00
                                                       2.6
                                                              0.098
                                                                               25.0
                                                                                              67.0
                                                                                                                      0.68
                                                                                                                                        5
                                                                                                    0.9970 3.26
          2
                    7.8
                                0.76
                                         0.04
                                                       2.3
                                                              0.092
                                                                               15.0
                                                                                              54.0
                                                                                                                      0.65
                                                                                                                               9.8
                                                                                                                                        5
          3
                                                              0.075
                                                                                                    0.9980 3.16
                                                                                                                      0.58
                   11.2
                                         0.56
                                                                               17.0
                                                                                              60.0
                                                                                                                               9.8
                                                                                                                                        6
                                0.28
                                                       1.9
          4
                    7.4
                                0.70
                                         0.00
                                                              0.076
                                                                               11.0
                                                                                              34.0 0.9978 3.51
                                                                                                                      0.56
                                                                                                                               9.4
                                                                                                                                        5
                                                       1.9
          df.columns
 In [7]:
          Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
Out[7]:
                  'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
                  'pH', 'sulphates', 'alcohol', 'quality'],
                 dtype='object')
          df.isnull().sum()
 In [8]:
          fixed acidity
                                    0
 Out[8]:
          volatile acidity
          citric acid
          residual sugar
          chlorides
          free sulfur dioxide
          total sulfur dioxide
          density
          рΗ
          sulphates
          alcohol
          quality
          dtype: int64
          df['quality'].unique()
 In [9]:
          array([5, 6, 7, 4, 8, 3], dtype=int64)
 Out[9]:
In [10]: df.mean()
```

```
fixed acidity
                                      8.311111
Out[10]:
          volatile acidity
                                      0.531339
          citric acid
                                      0.268364
          residual sugar
                                      2.532152
          chlorides
                                      0.086933
          free sulfur dioxide
                                     15.615486
          total sulfur dioxide
                                     45.914698
          density
                                      0.996730
                                      3.311015
          рΗ
          sulphates
                                      0.657708
          alcohol
                                     10.442111
          quality
                                      5.657043
          dtype: float64
          #bins should always have a minimum value, average and maximum number
In [11]:
           bins=(1, 5.5, 8)
          groupname=('good','bad')
          df['quality']=pd.cut(df['quality'],bins=bins, labels=groupname)
In [12]:
In [13]:
          df['quality'].unique()
          ['good', 'bad']
Out[13]:
          Categories (2, object): ['good' < 'bad']</pre>
          df.head()
In [14]:
Out[14]:
                             volatile
                                                                          free sulfur
                                                                                         total sulfur
                  fixed
                                         citric
                                                   residual
                                                                                                              pH sulphates alcohol quality
                                                            chlorides
                                                                                                     density
                                          acid
                                                                             dioxide
                                                                                             dioxide
                 acidity
                              acidity
                                                     sugar
                                                                                                     0.9978 3.51
          0
                    7.4
                                0.70
                                          0.00
                                                       1.9
                                                               0.076
                                                                               11.0
                                                                                                34.0
                                                                                                                       0.56
                                                                                                                                 9.4
                                                                                                                                      good
                                                                                                      0.9968 3.20
          1
                    7.8
                                0.88
                                          0.00
                                                       2.6
                                                               0.098
                                                                               25.0
                                                                                               67.0
                                                                                                                       0.68
                                                                                                                                 9.8
                                                                                                                                      good
          2
                    7.8
                                0.76
                                          0.04
                                                               0.092
                                                                               15.0
                                                                                                      0.9970 3.26
                                                       2.3
                                                                                                54.0
                                                                                                                       0.65
                                                                                                                                 9.8
                                                                                                                                      good
          3
                   11.2
                                0.28
                                          0.56
                                                        1.9
                                                               0.075
                                                                               17.0
                                                                                               60.0
                                                                                                      0.9980 3.16
                                                                                                                       0.58
                                                                                                                                 9.8
                                                                                                                                        bad
          4
                    7.4
                                          0.00
                                                               0.076
                                                                               11.0
                                                                                                      0.9978 3.51
                                                                                                                       0.56
                                0.70
                                                        1.9
                                                                                                34.0
                                                                                                                                 9.4
                                                                                                                                      good
          label=LabelEncoder()
In [15]:
```

df['quality']=label.fit\_transform(df['quality'])

```
df.head()
In [17]:
Out[17]:
                                         citric
                                                                          free sulfur
                                                                                          total sulfur
                  fixed
                              volatile
                                                   residual
                                                            chlorides
                                                                                                     density
                                                                                                              pH sulphates alcohol quality
                 acidity
                              acidity
                                          acid
                                                     sugar
                                                                             dioxide
                                                                                             dioxide
                                                        1.9
                                                               0.076
                                                                                11.0
                                                                                                      0.9978 3.51
                                                                                                                        0.56
                                                                                                                                 9.4
          0
                    7.4
                                 0.70
                                          0.00
                                                                                                34.0
                                                                                                                                           1
          1
                    7.8
                                0.88
                                          0.00
                                                        2.6
                                                                0.098
                                                                                25.0
                                                                                                67.0
                                                                                                      0.9968 3.20
                                                                                                                        0.68
                                                                                                                                 9.8
                                                                                                                                          1
          2
                    7.8
                                0.76
                                          0.04
                                                        2.3
                                                               0.092
                                                                                                      0.9970 3.26
                                                                                                                                 9.8
                                                                                15.0
                                                                                                54.0
                                                                                                                        0.65
                                                                                                                                          1
                                0.28
                                          0.56
                                                               0.075
                                                                                                      0.9980 3.16
                                                                                                                        0.58
                                                                                                                                 9.8
          3
                   11.2
                                                                                17.0
                                                                                                                                          0
                                                        1.9
                                                                                                60.0
          4
                    7.4
                                 0.70
                                          0.00
                                                        1.9
                                                                0.076
                                                                                11.0
                                                                                                34.0
                                                                                                      0.9978 3.51
                                                                                                                        0.56
                                                                                                                                 9.4
                                                                                                                                           1
          x=df.drop(['quality'],axis=1)
In [18]:
          y=df['quality']
In [19]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
          x_train.shape
In [20]:
          (914, 11)
Out[20]:
In [21]:
          x_test.shape
          (229, 11)
Out[21]:
          nb=GaussianNB()
In [22]:
          nb.fit(x_train,y_train)
In [23]:
          ▼ GaussianNB
Out[23]:
          GaussianNB()
          nbpred=nb.predict(x_test)
In [24]:
          nbpred[:10]
In [25]:
```

```
array([1, 1, 1, 1, 0, 0, 1, 1, 0, 0])
Out[25]:
In [26]: svm=SVC()
         svm.fit(x_train,y_train)
In [27]:
Out[27]:
        ▼ SVC
         SVC()
         svmpred=svm.predict(x_test)
         svmpred[:10]
In [29]:
         array([0, 1, 1, 0, 0, 0, 0, 1, 0, 1])
Out[29]:
         accuracy=accuracy_score(y_test,svmpred)*100
In [31]: accuracy
         68.12227074235808
Out[31]:
         knn=KNeighborsClassifier(n_neighbors=5)
In [32]:
         knn.fit(x_train,y_train)
In [33]:
         ▼ KNeighborsClassifier
Out[33]:
         KNeighborsClassifier()
         knnpred=knn.predict(x_test)
In [34]:
In [35]:
         knnpred[:10]
         array([1, 1, 1, 0, 0, 0, 1, 1, 0, 1])
Out[35]:
In [36]: accuracy=accuracy_score(y_test,knnpred)*100
```

In [37]: accuracy
Out[37]: 67.24890829694323
In []: