WineQuality Data Prediction

April 19, 2025

Importing the dependencies

[1]:
```
import pandas as pd
```

[2]:
```
import numpy as np
```

[3]:
```
import matplotlib.pyplot as plt
```

[4]:
```
import seaborn as sns
```

[5]:
```
from sklearn.model_selection import train_test_split
```

[6]:
```
from sklearn.ensemble import RandomForestClassifier
```

[7]:
```
from sklearn.metrics import accuracy_score
```

Data Collection

[8]:
```
wine_dataset=pd.read_csv('winequality-red.csv')
```

[9]:
```
wine_dataset.head()
```

[9]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol  quality
0      9.4        5
1      9.8        5
```

```
2      9.8        5
3      9.8        6
4      9.4        5
```

[10]:
```
wine_dataset.shape
```

[10]:
```
(1599, 12)
```

[11]:
```
wine_dataset.isnull().sum()
```

[11]:
```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

[12]:
```
wine_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

[13]:
```
wine_dataset.describe()
```

[13]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    1599.000000       1599.000000  1599.000000     1599.000000
mean        8.319637          0.527821     0.270976        2.538806
std         1.741096          0.179060     0.194801        1.409928
min         4.600000          0.120000     0.000000        0.900000
25%         7.100000          0.390000     0.090000        1.900000
50%         7.900000          0.520000     0.260000        2.200000
75%         9.200000          0.640000     0.420000        2.600000
max        15.900000          1.580000     1.000000       15.500000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  1599.000000          1599.000000           1599.000000  1599.000000
mean      0.087467            15.874922             46.467792     0.996747
std       0.047065            10.460157             32.895324     0.001887
min       0.012000             1.000000              6.000000     0.990070
25%       0.070000             7.000000             22.000000     0.995600
50%       0.079000            14.000000             38.000000     0.996750
75%       0.090000            21.000000             62.000000     0.997835
max       0.611000            72.000000            289.000000     1.003690

                pH    sulphates      alcohol      quality
count  1599.000000  1599.000000  1599.000000  1599.000000
mean      3.311113     0.658149    10.422983     5.636023
std       0.154386     0.169507     1.065668     0.807569
min       2.740000     0.330000     8.400000     3.000000
25%       3.210000     0.550000     9.500000     5.000000
50%       3.310000     0.620000    10.200000     6.000000
75%       3.400000     0.730000    11.100000     6.000000
max       4.010000     2.000000    14.900000     8.000000
```

[14]:
```python
wine_dataset.groupby('quality').mean()
```

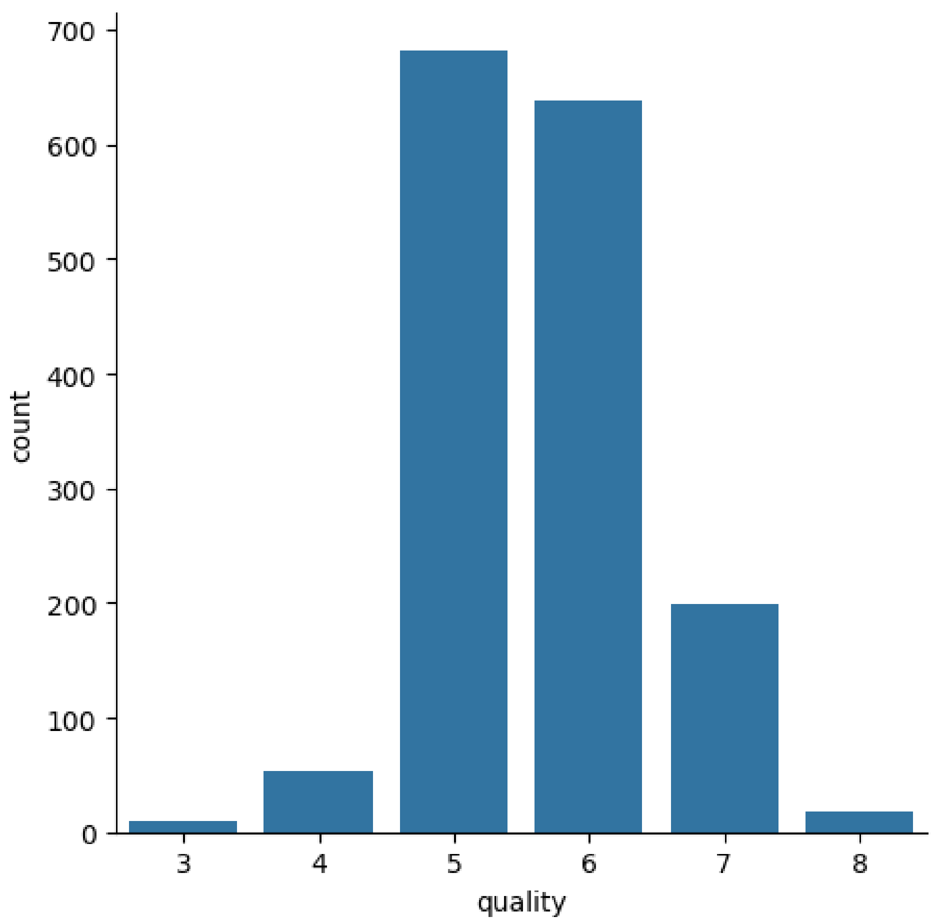
[14]:
```
         fixed acidity  volatile acidity  citric acid  residual sugar  \
quality
3             8.360000          0.884500     0.171000        2.635000
4             7.779245          0.693962     0.174151        2.694340
5             8.167254          0.577041     0.243686        2.528855
6             8.347179          0.497484     0.273824        2.477194
7             8.872362          0.403920     0.375176        2.720603
8             8.566667          0.423333     0.391111        2.577778

         chlorides  free sulfur dioxide  total sulfur dioxide   density  \
quality
3         0.122500            11.000000             24.900000  0.997464
4         0.090679            12.264151             36.245283  0.996542
5         0.092736            16.983847             56.513950  0.997104
6         0.084956            15.711599             40.869906  0.996615
```

```
7          0.076588            14.045226            35.020101  0.996104
8          0.068444            13.277778            33.444444  0.995212

                pH  sulphates    alcohol
quality
3         3.398000   0.570000   9.955000
4         3.381509   0.596415  10.265094
5         3.304949   0.620969   9.899706
6         3.318072   0.675329  10.629519
7         3.290754   0.741256  11.465913
8         3.267222   0.767778  12.094444
```

Visualization

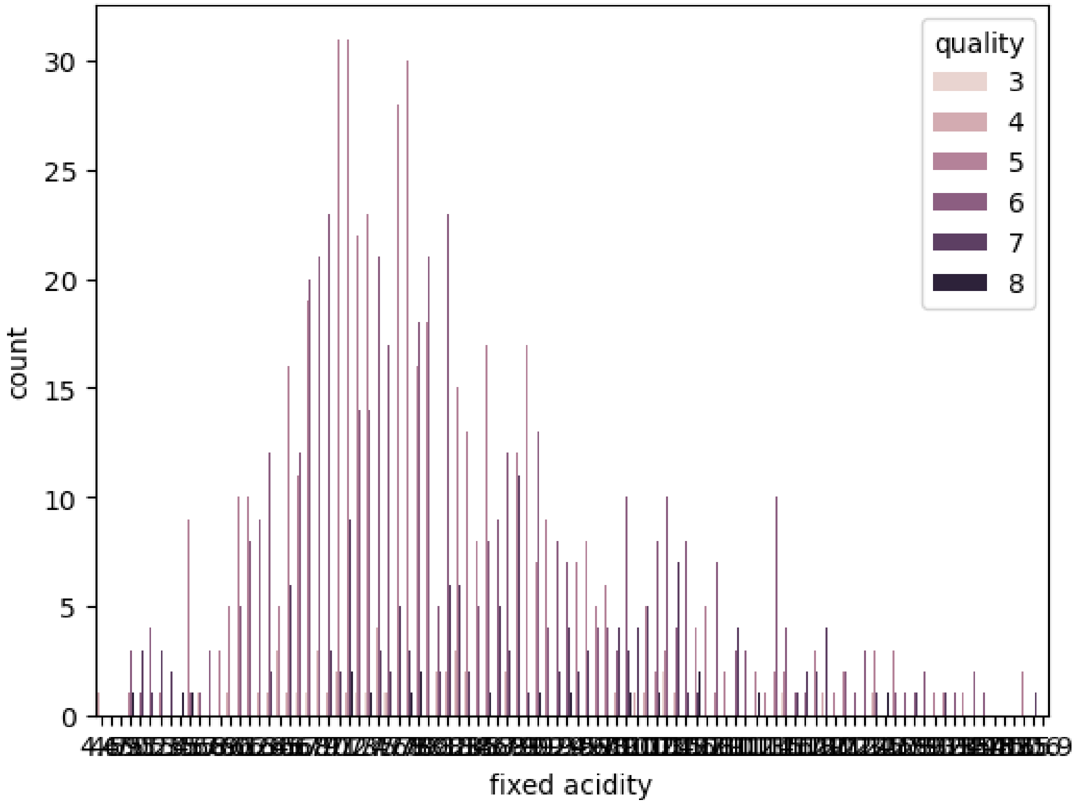
[15]:
```
sns.catplot(x='quality',data=wine_dataset,kind='count')
```

[15]: <seaborn.axisgrid.FacetGrid at 0x23ec4576810>



[16]:
```
sns.countplot(x='fixed acidity',hue='quality',data=wine_dataset)
```

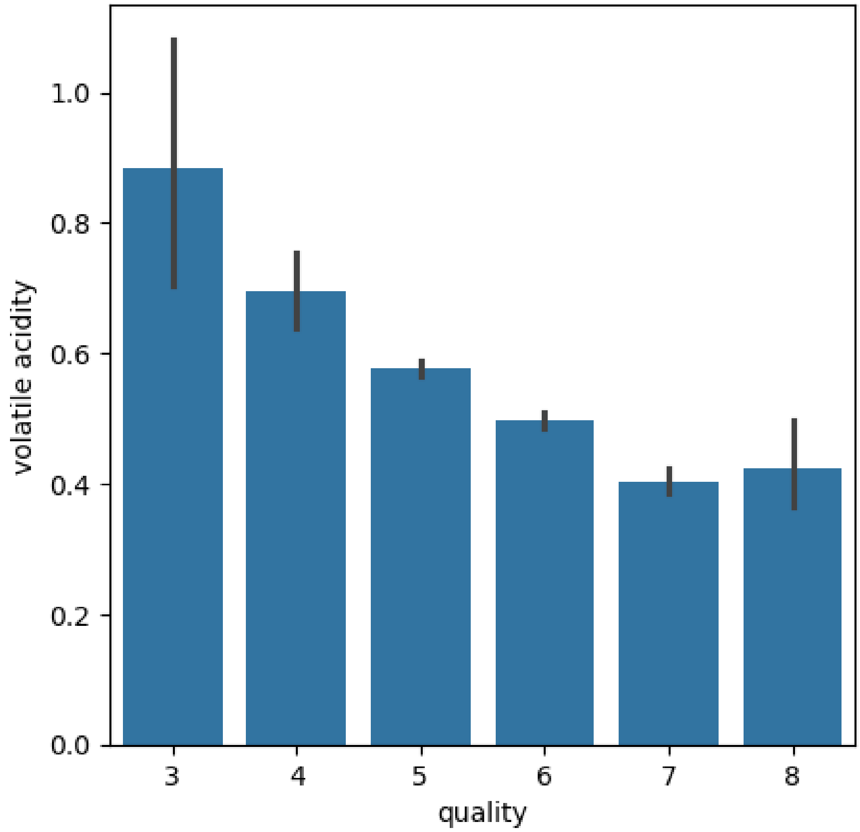
[16]: <Axes: xlabel='fixed acidity', ylabel='count'>



Volatile acidity vs quality

[17]:
```
plot=plt.figure(figsize=(5,5))
sns.barplot(x='quality',y='volatile acidity',data=wine_dataset)
```

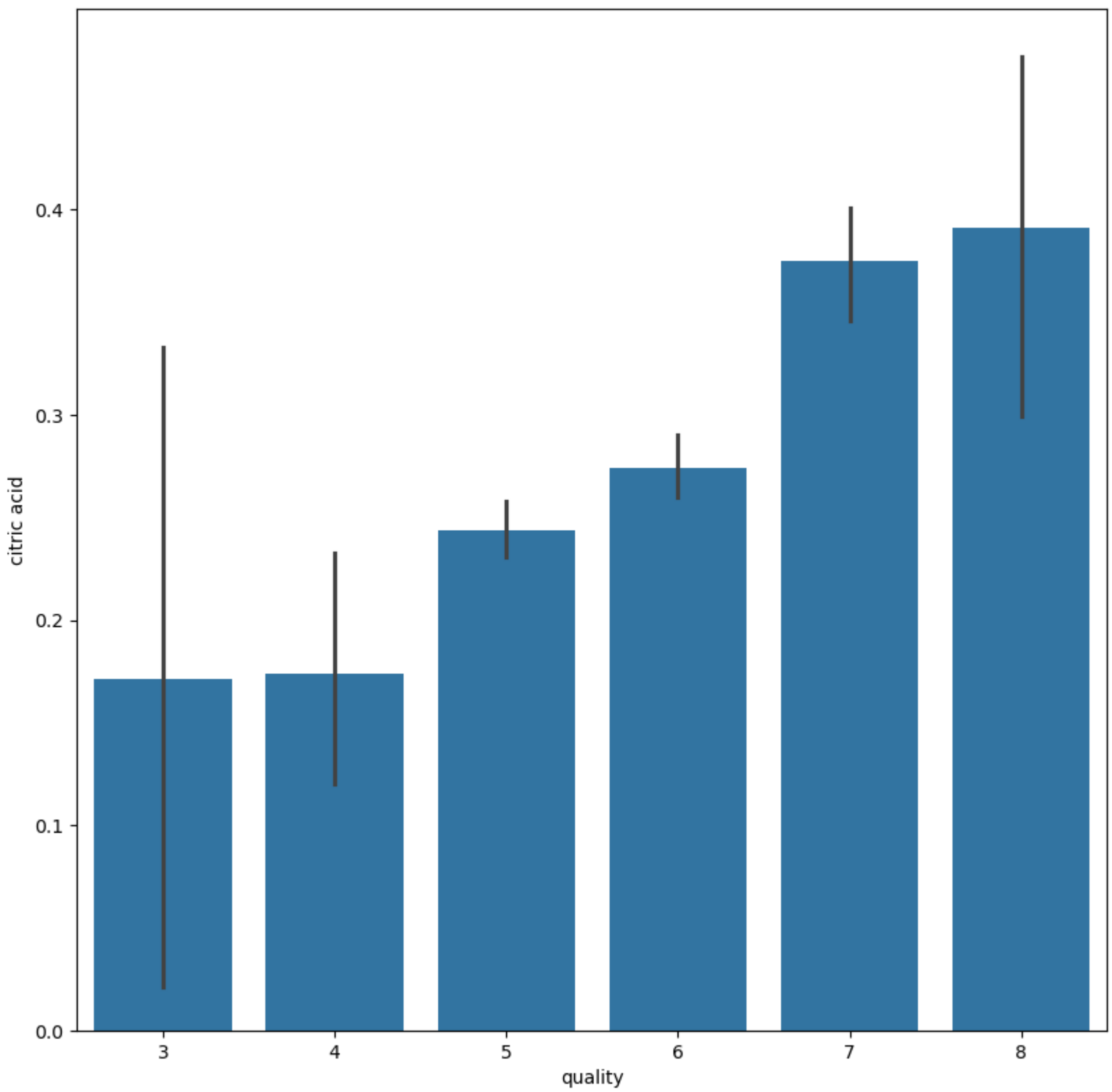
[17]: <Axes: xlabel='quality', ylabel='volatile acidity'>



volatile acidity and quality are inversely proportional to each other

[19]:
```
plot=plt.figure(figsize=(10,10))
sns.barplot(x='quality',y='citric acid',data=wine_dataset)
```

[19]: <Axes: xlabel='quality', ylabel='citric acid'>



Citric acid is directly proportional to the quality

[21]:
```
correlation=wine_dataset.corr()
```

[22]:
```
print(correlation)
```

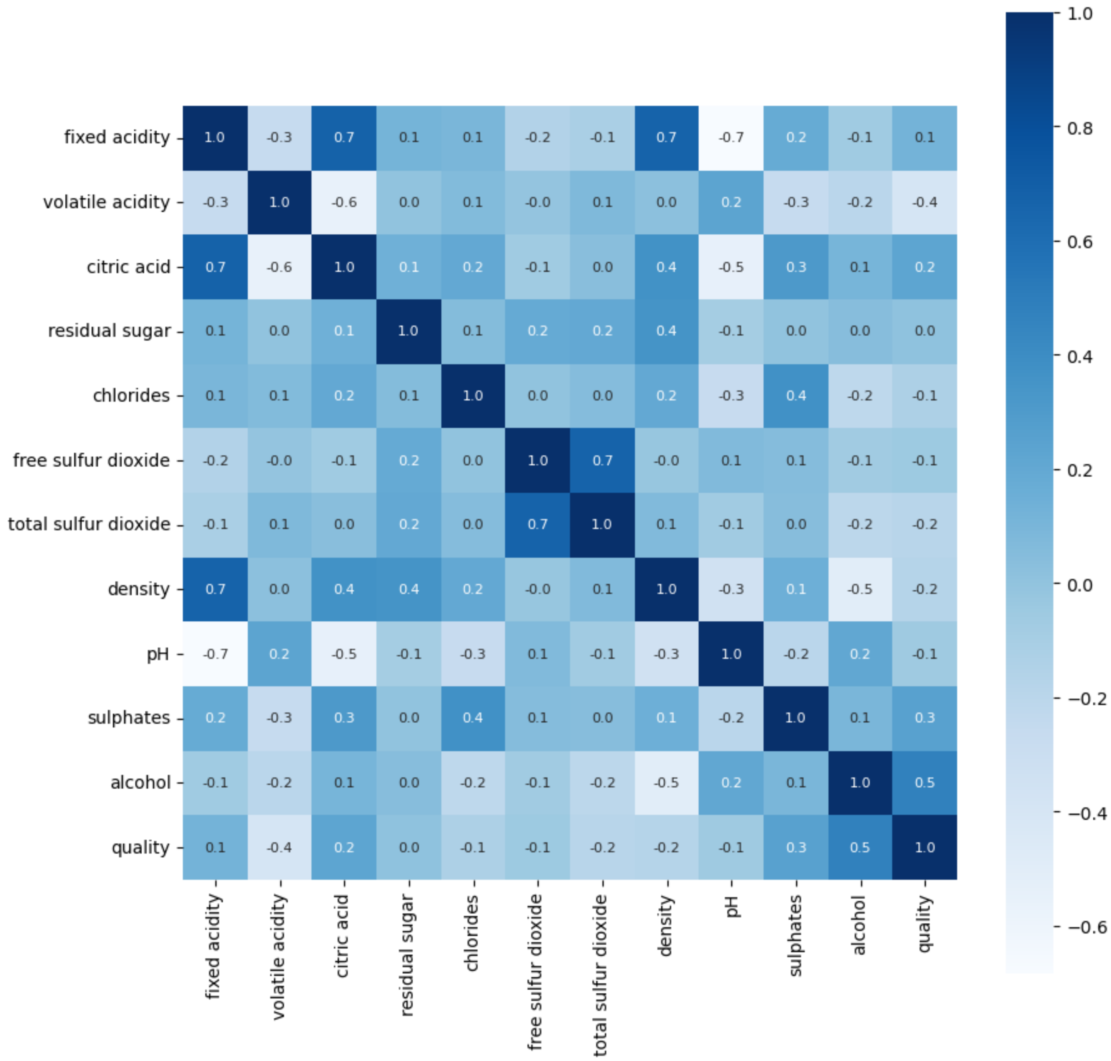
```
                      fixed acidity  volatile acidity  citric acid  \
fixed acidity              1.000000         -0.256131     0.671703
volatile acidity          -0.256131          1.000000    -0.552496
citric acid                0.671703         -0.552496     1.000000
residual sugar             0.114777          0.001918     0.143577
chlorides                  0.093705          0.061298     0.203823
free sulfur dioxide       -0.153794         -0.010504    -0.060978
total sulfur dioxide      -0.113181          0.076470     0.035533
```

```
density                    0.668047          0.022026     0.364947
pH                        -0.682978          0.234937    -0.541904
sulphates                  0.183006         -0.260987     0.312770
alcohol                   -0.061668         -0.202288     0.109903
quality                    0.124052         -0.390558     0.226373

                      residual sugar  chlorides  free sulfur dioxide  \
fixed acidity               0.114777   0.093705            -0.153794
volatile acidity            0.001918   0.061298            -0.010504
citric acid                 0.143577   0.203823            -0.060978
residual sugar              1.000000   0.055610             0.187049
chlorides                   0.055610   1.000000             0.005562
free sulfur dioxide         0.187049   0.005562             1.000000
total sulfur dioxide        0.203028   0.047400             0.667666
density                     0.355283   0.200632            -0.021946
pH                         -0.085652  -0.265026             0.070377
sulphates                   0.005527   0.371260             0.051658
alcohol                     0.042075  -0.221141            -0.069408
quality                     0.013732  -0.128907            -0.050656

                      total sulfur dioxide   density        pH  sulphates  \
fixed acidity                    -0.113181  0.668047 -0.682978   0.183006
volatile acidity                  0.076470  0.022026  0.234937  -0.260987
citric acid                       0.035533  0.364947 -0.541904   0.312770
residual sugar                    0.203028  0.355283 -0.085652   0.005527
chlorides                         0.047400  0.200632 -0.265026   0.371260
free sulfur dioxide               0.667666 -0.021946  0.070377   0.051658
total sulfur dioxide              1.000000  0.071269 -0.066495   0.042947
density                           0.071269  1.000000 -0.341699   0.148506
pH                               -0.066495 -0.341699  1.000000  -0.196648
sulphates                         0.042947  0.148506 -0.196648   1.000000
alcohol                          -0.205654 -0.496180  0.205633   0.093595
quality                          -0.185100 -0.174919 -0.057731   0.251397

                       alcohol   quality
fixed acidity        -0.061668  0.124052
volatile acidity     -0.202288 -0.390558
citric acid           0.109903  0.226373
residual sugar        0.042075  0.013732
chlorides            -0.221141 -0.128907
free sulfur dioxide  -0.069408 -0.050656
total sulfur dioxide -0.205654 -0.185100
density              -0.496180 -0.174919
pH                    0.205633 -0.057731
sulphates             0.093595  0.251397
alcohol               1.000000  0.476166
quality               0.476166  1.000000
```

Constructing heat map to understand the correlation between the columns

[24]:
```python
plt.figure(figsize=(10,10))
sns.heatmap(correlation,cbar=True,square=True,fmt='.1f',annot=True,annot_kws={'size':8},cmap='Blues')
```

[24]: <Axes: >



Data preprocessing

[25]:
```python
X=wine_dataset.drop(['quality'],axis=1)
```

[27]:
```python
print(X)
```

```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0               7.4             0.700         0.00             1.9      0.076
```

```
1               7.8             0.880         0.00              2.6       0.098
2               7.8             0.760         0.04              2.3       0.092
3              11.2             0.280         0.56              1.9       0.075
4               7.4             0.700         0.00              1.9       0.076
…             …               …          …             …          …
1594            6.2             0.600         0.08              2.0       0.090
1595            5.9             0.550         0.10              2.2       0.062
1596            6.3             0.510         0.13              2.3       0.076
1597            5.9             0.645         0.12              2.0       0.075
1598            6.0             0.310         0.47              3.6       0.067

      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                    11.0                  34.0  0.99780  3.51       0.56
1                    25.0                  67.0  0.99680  3.20       0.68
2                    15.0                  54.0  0.99700  3.26       0.65
3                    17.0                  60.0  0.99800  3.16       0.58
4                    11.0                  34.0  0.99780  3.51       0.56
…                    …                   …       …     …         …
1594                 32.0                  44.0  0.99490  3.45       0.58
1595                 39.0                  51.0  0.99512  3.52       0.76
1596                 29.0                  40.0  0.99574  3.42       0.75
1597                 32.0                  44.0  0.99547  3.57       0.71
1598                 18.0                  42.0  0.99549  3.39       0.66

      alcohol
0         9.4
1         9.8
2         9.8
3         9.8
4         9.4
…       …
1594     10.5
1595     11.2
1596     11.0
1597     10.2
1598     11.0

[1599 rows x 11 columns]
```

Label binarisation

[31]:
```python
Y=wine_dataset['quality'].apply(lambda y_value: 1 if y_value>=7 else 0)
```

[32]:
```python
print(Y)
```

```
0       0
1       0
2       0
3       0
```

```
4       0
       ..
1594    0
1595    0
1596    0
1597    0
1598    0
Name: quality, Length: 1599, dtype: int64
```

Spliting the data into training and test data

[33]:
```
train_x,test_x,train_y,test_y=train_test_split(X,Y,test_size=0.
↪2,stratify=Y,random_state=2)
```

[34]:
```
print(X.shape,train_x.shape,train_y.shape,test_x.shape,test_y.shape)
```

```
(1599, 11) (1279, 11) (1279,) (320, 11) (320,)
```

Model Training using RandomForest Classifier Model

[35]:
```
model=RandomForestClassifier()
```

[36]:
```
model.fit(train_x,train_y)
```

[36]:
```
RandomForestClassifier()
```

[37]:
```
train_x_prediction=model.predict(train_x)
```

[38]:
```
train_x_accuracy=accuracy_score(train_x_prediction,train_y)
```

[39]:
```
print(train_x_accuracy)
```

```
1.0
```

[40]:
```
test_x_prediction=model.predict(test_x)
```

[41]:
```
test_x_accuracy=accuracy_score(test_x_prediction,test_y)
```

[42]:
```
print(test_x_accuracy)
```

```
0.9375
```

[45]:
```
X_new=test_x.iloc[2]
```

[47]:
```
nparray=np.asarray(X_new)
```

[48]:
```
reshaped=nparray.reshape(1,-1)
```

[49]:
```
X_new_df=pd.DataFrame(reshaped,columns=train_x.columns)
```

[50]:
```
prediction=model.predict(X_new_df)
```

[51]:
```
print(prediction)
```

```
[0]
```

[52]:
```
print(test_y.iloc[2])
```

```
0
```

[60]:
```
input_data=(7.5,0.5,0.36,6.1,0.071,17.0,102.0,0.9978,3.35,0.8,10.5)
```

[61]:
```
nparray=np.asarray(input_data)
```

[62]:
```
reshaped=nparray.reshape(1,-1)
```

[63]:
```
input_data_df=pd.DataFrame(reshaped,columns=train_x.columns)
```

[64]:
```
prediction=model.predict(input_data_df)
```

[65]:
```
print(prediction)
```

```
[0]
```

[66]:
```
if (prediction[0]==1):
    print('Good Quality Wine')
else:
    print('Bad Quality Wine')
```

```
Bad Quality Wine
```

[ ]:
```
```