WINE QUALITY PREDICTION

Objective:

To predict whether a wine sample is good or not.

Importing the Dependencies

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

The Dataset

```
In [3]:
         wine_dataset=pd.read_csv(r'C:\Users\HP\Downloads\archive (3)\winequality-red.csv')
In [4]:
         wine_dataset.shape
         (1599, 12)
Out[4]:
In [5]:
         wine_dataset.head()
                fixed
                           volatile
                                      citric
                                               residual
                                                                      free sulfur
                                                                                    total sulfur
                                                       chlorides
                                                                                               density
                                                                                                        pH sulphates alcohol quality
               acidity
```

	aciuity	aciuity	aciu	Suyai		dioxide	uloxide					
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

Looking for null values

```
In [6]: wine dataset.isnull().sum()
        fixed acidity
Out[6]:
        volatile acidity
                                  0
                                  0
        citric acid
        residual sugar
                                  0
        chlorides
                                  0
                                  0
        free sulfur dioxide
        total sulfur dioxide
                                  0
        density
                                  0
                                  0
        рΗ
        sulphates
                                  0
        alcohol
                                  0
        quality
                                  0
        dtype: int64
        This dataset has no null values
```

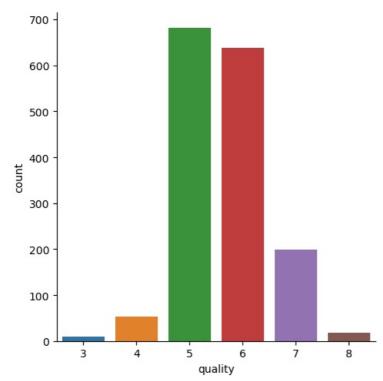
Statistical insights of the dataset

```
In [7]: wine_dataset.describe()
```

Out[7]:		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates
	count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000
	mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792	0.996747	3.311113	0.658149
	std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.001887	0.154386	0.169507
	min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070	2.740000	0.330000
	25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600	3.210000	0.550000
	50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996750	3.310000	0.620000
	75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997835	3.400000	0.730000
	max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690	4.010000	2.000000
4											

Number of values for each quality

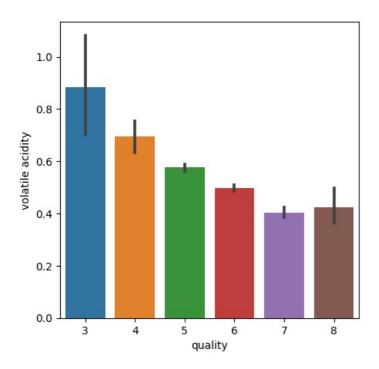
```
sns.catplot(x='quality',data=wine_dataset,kind='count')
         <seaborn.axisgrid.FacetGrid at 0x1eb9fa28950>
Out[10]:
```



Volatile Acidity vs Quality

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

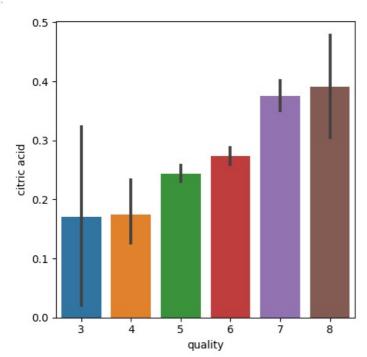
<Axes: xlabel='quality', ylabel='volatile acidity'>



Citric Acid vs Quality

```
In [12]: plot=plt.figure(figsize=(5,5))
sns.barplot(x='quality',y='citric acid',data=wine_dataset)
```

Out[12]: <Axes: xlabel='quality', ylabel='citric acid'>



Correlation:

1.Positive Correlation

2. Negative Correlation

```
In [13]:
              correlation=wine dataset.corr()
              plt.figure(figsize=(10,10))
In [17]:
              sns.heatmap(correlation,cbar=True,square=True,fmt='.1f',annot=True,annot kws={'size':8},cmap='Reds')
Out[17]:
                                                                                                                                                                            1.0
                                                                                                                                                                          - 0.8
                       fixed acidity -
                                                     -0.3
                                                                                            -0.2
                                                                                                     -0.1
                                                                                                                        -0.7
                                                                                                                                           -0.1
                    volatile acidity -
                                                               -0.6
                                                                                                                                  -0.3
                                                                                                                                           -0.2
                                                                                                                                                     -0.4
                                                                                                                                                                          - 0.6
                          citric acid -
                                                     -0.6
                                                                                                                        -0.5
                     residual sugar -
                                                                                                                        -0.1
                                                                                                                                                                          - 0.4
                           chlorides -
                                                                                  1.0
                                                                                                                        -0.3
                                                                                                                                           -0.2
                                                                                                                                                     -0.1
               free sulfur dioxide -
                                                               -0.1
                                                                                                                                                     -0.1
                                                                                                                                                                          - 0.2
               total sulfur dioxide -
                                                                                                                        -0.1
                                                                                                                                           -0.2
                                                                                                                                                     -0.2
                                                                                                                                                                          - 0.0
                             density -
                                                                                                                        -0.3
                                                                                                                                           -0.5
                                                                                                                                                     -0.2
                                           -0.7
                                                               -0.5
                                                                         -0.1
                                                                                                               -0.3
                                                                                                                                                     -0.1
                                                                                                                                                                            -0.2
                          sulphates -
                                                     -0.3
                                                                                                                        -0.2
                              alcohol -
                                            -0.1
                                                     -0.2
                                                                                  -0.2
                                                                                            -0.1
                                                                                                     -0.2
                                                                                                               -0.5
                                                                                                                                                                            -0.4
                              quality
                                                                                                                         -0.1
                                            fixed acidity
                                                               citric acid
                                                                                  chlorides
                                                                                                                                            alcohol
                                                                                           free sulfur dioxide
                                                                                                               density
                                                                                                                                  sulphates
                                                     volatile acidity
                                                                                                     total sulfur dioxide
                                                                        residual sugar
                                                                                                                         핂
                                                                                                                                                                          - -0.6
```

Seperating the data and the label

```
In [18]: X=wine_dataset.drop('quality',axis=1)
In [19]: 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
                7.8
                                 0.760
                                                                            0.092
2
                                                0.04
                                                                  2.3
3
                                 0.280
                                                                            0.075
               11.2
                                                0.56
                                                                  1.9
4
                7.4
                                 0.700
                                                0.00
                                                                  1.9
                                                                            0.076
                                 0.600
                                                                  2.0
                                                                            0.090
1594
                6.2
                                                0.08
1595
                5.9
                                 0.550
                                                0.10
                                                                  2.2
                                                                            0.062
1596
                6.3
                                 0.510
                                                0.13
                                                                  2.3
                                                                            0.076
1597
                                 0.645
                                                                            0.075
                5.9
                                                0.12
                                                                  2.0
1598
                6.0
                                 0.310
                                                0.47
                                                                  3.6
                                                                            0.067
      free sulfur dioxide
                           total sulfur dioxide
                                                                   sulphates
                                                   density
                                                             3.51
0
                                             34.0
                                                  0.99780
                                                                        0.56
                      11.0
                      25.0
                                             67.0
                                                   0.99680
                                                             3.20
                                                                        0.68
1
2
                      15.0
                                             54.0
                                                   0.99700
                                                             3.26
                                                                        0.65
3
                                                  0.99800
                      17.0
                                             60.0
                                                             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
                                                                        0.75
1596
                      29.0
                                             40.0
                                                   0.99574
                                                             3 42
1597
                      32.0
                                             44.0
                                                  0.99547
                                                             3.57
                                                                        0.71
1598
                                             42.0 0.99549
                                                                        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 Binarization

```
In [20]: Y=wine_dataset['quality'].apply(lambda Y_value:1 if Y_value>=7 else 0)
In [21]: print(Y)
         0
                 0
                  0
         1
         2
                 0
         3
                 0
         4
                 0
         1594
                 0
         1595
                 0
         1596
         1597
         1598
         Name: quality, Length: 1599, dtype: int64
```

Splitting Training data and Test data

Model Training

Random Forest Classifier

```
In [24]: model=RandomForestClassifier()
In [25]: model.fit(X_train,Y_train)
```

```
Out[25]: RandomForestClassifier
RandomForestClassifier()
```

Model Evaluation

Accuracy Score

Accuracy on test data

Building a predictive system

```
In [29]: input_data=(7.8,0.58,0.02,2.0,0.073,9.0,18.0,0.9968,3.36,0.57,9.5)
```

Changing the input data to a numpy array

```
In [30]: input_data_as_numpy_array=np.asarray(input_data)
```

Reshaping the data as we are predicting the label for only one instance

```
In [31]: input_data_reshaped=input_data_as_numpy_array.reshape(1,-1)
```

The prediction

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