```
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.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
```

wine\_dataset = pd.read\_csv('\_/content/winequality-red.csv')
wine\_dataset

⊋		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality
	0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
	1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8	5
	2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8	5
	3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8	6
	4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
	1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5
	1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6
	1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	6
	1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5
	1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6

1599 rows × 12 columns

wine\_dataset.shape

(1599, 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

wine\_dataset

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	5
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	

wine\_dataset.isnull().sum()

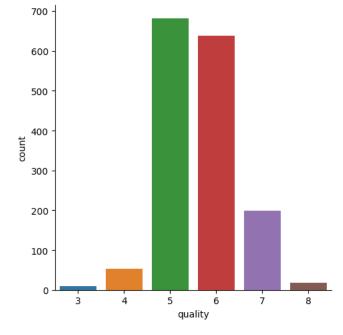
fixed acidity 0 volatile acidity 0 citric acid residual sugar 0 chlorides 0 free sulfur dioxide 0 total sulfur dioxide density 0 0 sulphates 0 alcohol 0 quality dtype: int64

wine\_dataset.describe()

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density
count	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
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.001887
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996750
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997835
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690

sns.catplot(x = 'quality', data = wine\_dataset, kind = 'count')

<seaborn.axisgrid.FacetGrid at 0x78b479bf53f0>



# seperating the data and label

X = wine\_dataset.drop('quality' , axis =1)

```
Y = wine_dataset['quality']
print(X)
           fixed acidity volatile acidity citric acid residual sugar chlorides \
                                                   0.00
                                                                             0.076
     0
                     7.4
                                     0.700
                                                                    1.9
                     7.8
                                     0.880
                                                   0.00
                                                                    2.6
                                                                             0.098
     2
                     7.8
                                     0.760
                                                   0.04
                                                                    2.3
                                                                             0.092
                                     0.280
                    11.2
                                                   0.56
                                                                    1.9
                                                                             0.075
     3
     4
                     7.4
                                     0.700
                                                   0.00
                                                                    1.9
                                                                             0.076
                                     0.600
                                                   0.08
                                                                    2.0
                                                                             0.090
     1594
                     6.2
     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
                                                34.0 0.99780 3.51
                          11.0
                                                                          0.56
     1
                          25.0
                                                67.0 0.99680 3.20
                                                                          0.68
                          15.0
                                                54.0 0.99700
                                                                          0.65
                                                60.0 0.99800 3.16
                          17.0
                                                                          0.58
                          11.0
     4
                                                34.0 0.99780 3.51
                                                                          0.56
     1594
                          32.0
                                                44.0 0.99490 3.45
                                                                          0.58
                                                51.0 0.99512
     1595
                          39.0
                                                               3.52
                                                                          0.76
     1596
                          29.0
                                                40.0 0.99574
                                                                          0.75
                                                               3.42
     1597
                          32.0
                                                44.0 0.99547 3.57
                                                                          0.71
     1598
                                                42.0 0.99549 3.39
                          18.0
                                                                          0.66
           alcohol
     0
               9.4
               9.8
     1
     2
               9.8
               9.8
               9.4
     1594
              10.5
     1595
              11.2
     1596
              11.0
     1597
              10.2
     1598
             11.0
     [1599 rows x 11 columns]
print(Y)
     0
             5
             5
     1
             5
     2
     3
             6
             5
     1594
            5
     1595
     1596
             6
     1597
     1598
     Name: quality, Length: 1599, dtype: int64
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state = 2)
print(X.shape, X_train.shape, X_test.shape)
     (1599, 11) (1279, 11) (320, 11)
model = RandomForestClassifier()
model.fit(X_train, Y_train)
     ▼ RandomForestClassifier
     RandomForestClassifier()
X_train_prediction = model.predict(X_train)
train_data_accuracy = accuracy_score(X_train_prediction, Y_train)
```