```
In [55]:
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.model_selection import train_test_split
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.svm import SVC
         from sklearn import svm
         from sklearn.metrics import confusion_matrix,classification_report
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.naive_bayes import GaussianNB
         from sklearn.preprocessing import StandardScaler,LabelEncoder
         from sklearn.metrics import accuracy_score
         from sklearn.ensemble import VotingClassifier
```

## In [3]: wine=pd.read\_csv('C:\\Users\\LENOVO\\Documents\\wine.csv')

# In [4]: # view the first 10 of our dataset wine.head(10)

#### Out[4]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
5	7.4	0.66	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4
6	7.9	0.60	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4
7	7.3	0.65	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0
8	7.8	0.58	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5
9	7.5	0.50	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5
4											N .

In [5]: # the last 5 from our dataset
wine.tail()

## Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcoh
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11

In [6]: wine.shape

Out[6]: (1599, 12)

In [7]: #statistical decription of the dataset
wine.describe()

# Out[7]:

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

In [8]: wine.isnull()

Out[8]:

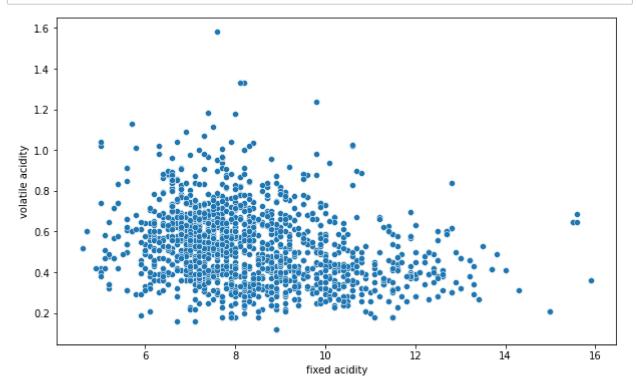
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcol
0	False	False	False	False	False	False	False	False	False	False	Fa
1	False	False	False	False	False	False	False	False	False	False	Fa
2	False	False	False	False	False	False	False	False	False	False	Fa
3	False	False	False	False	False	False	False	False	False	False	Fa
4	False	False	False	False	False	False	False	False	False	False	Fa
1594	False	False	False	False	False	False	False	False	False	False	Fa
1595	False	False	False	False	False	False	False	False	False	False	Fa
1596	False	False	False	False	False	False	False	False	False	False	Fa
1597	False	False	False	False	False	False	False	False	False	False	Fa
1598	False	False	False	False	False	False	False	False	False	False	Fa

1599 rows × 12 columns

```
In [10]: | wine.nunique
Out[10]: <bound method DataFrame.nunique of</pre>
                                                       fixed acidity volatile acidity citri
          c acid residual sugar chlorides \
          0
                            7.4
                                             0.700
                                                             0.00
                                                                                         0.076
                                                                                1.9
          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
                                                             0.00
                                                                                         0.076
                                             0.700
                                                                               1.9
                                                              . . .
                                                                                . . .
          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
                            5.9
                                                                                2.0
                                                                                         0.075
          1597
                                             0.645
                                                             0.12
          1598
                            6.0
                                             0.310
                                                             0.47
                                                                                3.6
                                                                                         0.067
                 free sulfur dioxide
                                       total sulfur dioxide density
                                                                                sulphates \
                                                                            рΗ
          0
                                 11.0
                                                          34.0
                                                                0.99780
                                                                          3.51
                                                                                      0.56
          1
                                 25.0
                                                                                      0.68
                                                          67.0
                                                                0.99680
                                                                          3.20
          2
                                 15.0
                                                          54.0
                                                                0.99700
                                                                          3.26
                                                                                      0.65
          3
                                 17.0
                                                          60.0
                                                                0.99800
                                                                                      0.58
                                                                          3.16
          4
                                 11.0
                                                                0.99780
                                                                          3.51
                                                                                      0.56
                                                          34.0
                                  . . .
                                                                                       . . .
                                                           . . .
          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
                                                                          3.57
                                                                                      0.71
                                                                0.99547
          1598
                                 18.0
                                                         42.0
                                                                0.99549
                                                                                      0.66
                                                                          3.39
                          quality
                 alcohol
          0
                     9.4
                                 5
                                 5
                     9.8
          1
          2
                     9.8
                                 5
          3
                     9.8
                                 6
          4
                     9.4
                                 5
                     . . .
          1594
                    10.5
                                 5
                    11.2
                                 6
          1595
                                 6
          1596
                    11.0
          1597
                    10.2
                                 5
          1598
                    11.0
                                 6
          [1599 rows x 12 columns]>
```

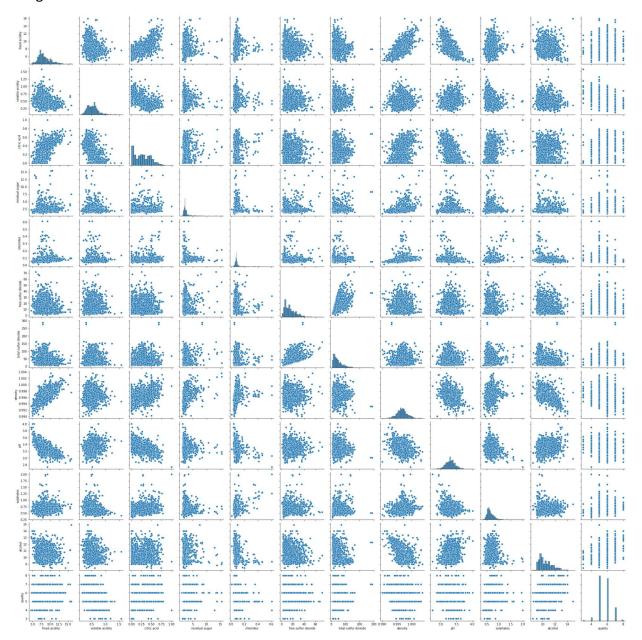
```
In [11]: wine['quality'].value_counts()
Out[11]: 5    681
        6    638
        7    199
        4    53
        8    18
        3    10
        Name: quality, dtype: int64
```

```
In [12]: plt.figure(figsize=(10,6))
sns.scatterplot(x=wine['fixed acidity'],y=wine['volatile acidity']);
```



In [13]: plt.figure(figsize=(10,6))
 sns.pairplot(wine);

<Figure size 720x432 with 0 Axes>



```
In [14]: # Preprocessing the dataset
    bins=(1, 6.5, 8)
    group_name=['good','bad']
    wine['quality']= pd.cut(wine['quality'],bins=bins,labels=group_name)

In [15]: wine['quality'].unique()

Out[15]: ['good', 'bad']
    Categories (2, object): ['good' < 'bad']

In [19]: wine[:10]</pre>
```

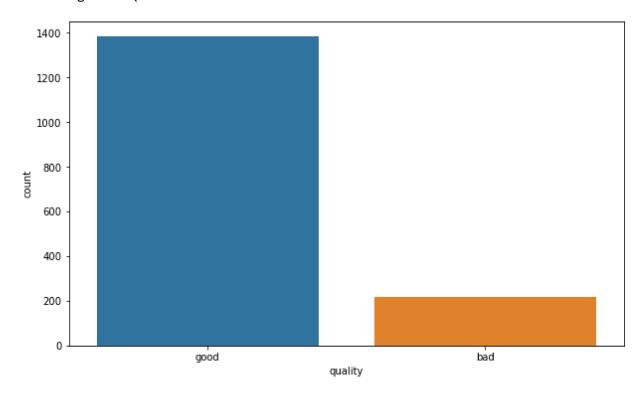
Out[19]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
5	7.4	0.66	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4
6	7.9	0.60	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4
7	7.3	0.65	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0
8	7.8	0.58	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5
9	7.5	0.50	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5
4											<b></b>

```
In [16]: plt.figure(figsize=(10,6))
    sns.countplot(wine['quality']);
```

C:\Users\LENOVO\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureWa rning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments with out an explicit keyword will result in an error or misinterpretation.

warnings.warn(



```
In [26]: label_quality=LabelEncoder()
In [28]: wine['quality'] = label_quality.fit_transform(wine['quality'])
```

In [29]: wine[:10]

Out[29]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	
5	7.4	0.66	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4	
6	7.9	0.60	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4	
7	7.3	0.65	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0	
8	7.8	0.58	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5	
9	7.5	0.50	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5	

In [31]: wine['quality'].value\_counts()

Out[31]: 1 1382 0 217

Name: quality, dtype: int64

In [32]: x=wine.drop(['quality'],axis=1)

In [33]: x

#### Out[33]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcoh
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11

1599 rows × 11 columns

```
In [34]: y=wine['quality']
In [36]: y
Out[36]: 0
                  1
         1
                  1
         2
                  1
         3
                  1
         4
                  1
         1594
                  1
         1595
                  1
         1596
                  1
         1597
                  1
         1598
         Name: quality, Length: 1599, dtype: int32
In [37]: # training , testing and spliting the dataset
         x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=45
```

```
In [40]: # applying standard scaler to get optimizer result
        sc = StandardScaler()
        x_train = sc.fit_transform(x_train)
        x test= sc.transform(x test)
In [41]: x_train
Out[41]: array([[-1.09852129, 1.50992721, -1.38824517, ..., 1.14517889,
                -0.8026406 , 1.10997762],
               [-1.09852129, 0.6327804, -0.30279894, ..., 1.79318941,
                 0.02216045, -0.59560931],
               [1.33427414, 1.70799262, 0.52420772, ..., -0.99325583,
                -0.8026406 , -0.50085448],
               [-0.75097909, 0.18005946, -0.71630226, ..., 0.17316311,
                -0.39024008, -1.16413829],
               [0.29164752, -0.046301, 0.36914398, ..., -0.34524531,
                -0.27241136, -0.8798738 ],
               [1.21842673, -1.51764404, 1.0927748, ..., 0.10836206,
                 1.25936202, 0.44669381]])
In [42]: #USING DECISION TREE CLASSIFIER ALGORITHM
        dtc=DecisionTreeClassifier(random state=45)
In [43]: |dtc.fit(x_train,y_train)
Out[43]: DecisionTreeClassifier(random state=45)
In [44]: dtc pred= dtc.predict(x test)
In [48]: dtc pred[:30]
1, 1, 0, 1, 1, 0, 1, 1])
In [58]: # to determine the accuracy of the model
        accuracy_score(y_test,dtc_pred)*100
Out[58]: 86.0
In [50]: #USING RANDOM FOREST CLASSIFIER ALGORITHM
        rfc=RandomForestClassifier(n estimators=200)
In [51]: rfc.fit(x_train,y_train)
Out[51]: RandomForestClassifier(n_estimators=200)
In [52]: rfc_pred = rfc.predict(x_test)
```

```
In [53]: rfc_pred[:30]
1, 1, 1, 1, 0, 1, 1])
In [57]: | # to determine the accuracy of the model
        accuracy_score(y_test,rfc_pred)*100
Out[57]: 89.5
In [59]: |#USING KNEAREST NIEGHBOR ALGORITHM
        knn=KNeighborsClassifier(n_neighbors=5)
In [60]: knn.fit(x train,y train)
Out[60]: KNeighborsClassifier()
In [61]: knn pred= knn.predict(x test)
In [63]: knn_pred[:30]
Out[63]: array([1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1,
               1, 1, 1, 1, 0, 1, 1])
In [64]: # to determine the accuracy of the model
        accuracy_score(y_test,rfc_pred)*100
Out[64]: 89.5
In [66]: |nb=GaussianNB()
In [67]: |nb.fit(x_train,y_train)
Out[67]: GaussianNB()
In [68]: | nb pred=nb.predict(x test)
In [70]: | nb pred[:30]
Out[70]: array([1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1,
               1, 1, 1, 1, 0, 1, 1])
In [71]: # to determine the accuracy of the model
        accuracy_score(y_test,nb_pred)*100
Out[71]: 82.0
In [74]: # USING VOTING ENSEMBLE TO DECIDE THE BEST MODEL
        estimators=[('Decision',dtc), ('Random',rfc),('KNeighbors',knn),('Gaussian',nb)]
In [75]: VC= VotingClassifier(estimators=estimators,voting='hard')
```

```
In [76]: VC.fit(x train,y train)
Out[76]: VotingClassifier(estimators=[('Decision',
                                    DecisionTreeClassifier(random state=45)),
                                    ('Random',
                                    RandomForestClassifier(n_estimators=200)),
                                    ('KNeighbors', KNeighborsClassifier()),
                                    ('Gaussian', GaussianNB())])
In [77]: vc pred=VC.predict(x test)
In [78]: vc_pred[:30]
Out[78]: array([1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1,
               1, 1, 1, 1, 0, 1, 1])
In [79]: # to determine the accuracy of the model
        accuracy_score(y_test,vc_pred)*100
Out[79]: 88.0
In [80]: #USING BAGGING ENSEMBLE
        from sklearn.ensemble import BaggingClassifier
In [81]: BC= BaggingClassifier(base estimator=dtc,n estimators=10)
In [82]: BC.fit(x train,y train)
Out[82]: BaggingClassifier(base_estimator=DecisionTreeClassifier(random state=45))
In [83]: bc pred=BC.predict(x test)
In [84]: bc pred[:30]
1, 1, 1, 1, 1, 0, 1, 1])
In [85]: # to determine the accuracy of the model
        accuracy_score(y_test,bc_pred)*100
Out[85]: 87.5
In [86]: # USING STACKING ENSEMBLE
        from sklearn.ensemble import StackingClassifier
In [87]: SR= StackingClassifier(estimators=estimators, final estimator=dtc)
```

```
In [88]: | SR.fit(x_train,y_train)
Out[88]: StackingClassifier(estimators=[('Decision',
                                     DecisionTreeClassifier(random_state=45)),
                                     ('Random',
                                     RandomForestClassifier(n_estimators=200)),
                                     ('KNeighbors', KNeighborsClassifier()),
                                     ('Gaussian', GaussianNB())],
                          final estimator=DecisionTreeClassifier(random state=45))
In [89]: | sr_pred=SR.predict(x_test)
In [90]: sr_pred[:30]
1, 1, 1, 1, 0, 1, 1])
In [91]: # to determine the accuracy of the model
        accuracy_score(y_test,sr_pred)*100
Out[91]: 87.5
In [92]: # USING VOTING ENSEMBLE TO DECIDE THE BEST MODEL
        from sklearn.ensemble import VotingClassifier
In [93]: | estimators=[('Voting',VC), ('Bagging',BC),('Stacking',SR)]
In [94]: VC= VotingClassifier(estimators=estimators,voting='hard')
```

```
In [95]: VC.fit(x_train,y_train)
Out[95]: VotingClassifier(estimators=[('Voting',
                                      VotingClassifier(estimators=[('Decision',
                                                                  DecisionTreeClassif
         ier(random_state=45)),
                                                                 ('Random',
                                                                  RandomForestClassif
         ier(n estimators=200)),
                                                                 ('KNeighbors',
                                                                  KNeighborsClassifie
         r()),
                                                                 ('Gaussian',
                                                                  GaussianNB())])),
                                     ('Bagging',
                                      BaggingClassifier(base_estimator=DecisionTreeClas
         sifier(random_state=45))),
                                     ('Stacking',
                                      StackingClassifier(estimators=[('Decision',
                                                                    DecisionTreeClass
         ifier(random_state=45)),
                                                                   ('Random',
                                                                    RandomForestClass
         ifier(n estimators=200)),
                                                                   ('KNeighbors',
                                                                    KNeighborsClassif
         ier()),
                                                                   ('Gaussian',
                                                                    GaussianNB())],
                                                        final_estimator=DecisionTreeCl
         assifier(random state=45)))])
In [96]:
         final pred=VC.predict(x test)
In [97]: final pred[:30]
1, 1, 1, 1, 0, 1, 1])
In [98]: # to determine the accuracy of the model
         accuracy_score(y_test,final_pred)*100
Out[98]: 88.75
         # pickle to save model
In [100]:
         import pickle
In [101]: with open('wine.plk','wb') as f:
             pickle.dump(wine, f, protocol=pickle.HIGHEST_PROTOCOL)
 In [ ]:
```