Red Wine Quality Prediction Project

```
import pandas as pd
In [1]:
          import numpy as np
          import matplotlib.pyplot as plt
          %matplotlib inline
          import seaborn as sns
          from sklearn.feature selection import SelectKBest, f classif
          from sklearn.preprocessing import StandardScaler
          from sklearn.model selection import train test split,GridSearchCV
          from sklearn.metrics import accuracy score, classification report, confusion matrix, roc au
          from sklearn.svm import SVC
          from sklearn.ensemble import AdaBoostClassifier,RandomForestClassifier
          from sklearn.neighbors import KNeighborsClassifier
          import pickle
          import warnings
          warnings.filterwarnings('ignore')
          df=pd.read csv('winequality-red.csv')
In [2]:
          df.head()
Out[2]:
                                                             free
                                                                      total
                      volatile
               fixed
                              citric
                                     residual
                                              chlorides
                                                           sulfur
                                                                     sulfur
                                                                            density
                                                                                      pH sulphates alcohol quality
             acidity
                      acidity
                               acid
                                       sugar
                                                          dioxide
                                                                    dioxide
          0
                7.4
                         0.70
                               0.00
                                                  0.076
                                                                             0.9978
                                                                                     3.51
                                                                                                                  5
                                          1.9
                                                             11.0
                                                                       34.0
                                                                                               0.56
                                                                                                         9.4
                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
                                                                             0.9970
                                                                                    3.26
                                                                                                         9.8
                                                                                                                   5
                                                                       54.0
                                                                                               0.65
          3
                11.2
                         0.28
                               0.56
                                                  0.075
                                                             17.0
                                                                       60.0
                                                                             0.9980
                                                                                     3.16
                                                                                               0.58
                                                                                                                   6
                                          1.9
                                                                                                         9.8
                                                                                                                   5
          4
                7.4
                         0.70
                               0.00
                                          1.9
                                                  0.076
                                                             11.0
                                                                             0.9978
                                                                                               0.56
                                                                                                         9.4
          df.tail()
In [3]:
Out[3]:
                                                              free
                                                                      total
                        volatile
                  fixed
                                citric
                                       residual
                                                chlorides
                                                            sulfur
                                                                     sulfur
                                                                            density
                                                                                      pH sulphates alcohol quality
                acidity
                         acidity
                                 acid
                                         sugar
                                                           dioxide
                                                                   dioxide
          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
                          0.550
                                 0.10
                                                    0.062
                                                              39.0
                                                                                   3.52
                    5.9
                                            2.2
                                                                      51.0
                                                                            0.99512
                                                                                               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
                          0.645
                                  0.12
                                                    0.075
                                                              32.0
                                                                            0.99547
                                                                                               0.71
                                                                                                        10.2
                                                                                                                   5
          1598
                    6.0
                          0.310
                                 0.47
                                            3.6
                                                    0.067
                                                              18.0
                                                                            0.99549
                                                                                               0.66
                                                                                                        11.0
                                                                                                                   6
In [4]:
          df.head(14)
```

Out[4]: free total volatile fixed citric residual chlorides sulfur sulfur density pH sulphates alcohol quality acidity acidity acid sugar dioxide dioxide 0 7.4 0.700 0.00 1.9 0.076 11.0 34.0 0.9978 3.51 0.56 9.4 5

1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
5	7.4	0.660	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4	5
6	7.9	0.600	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4	5
7	7.3	0.650	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0	7
8	7.8	0.580	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5	7
9	7.5	0.500	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5	5
10	6.7	0.580	0.08	1.8	0.097	15.0	65.0	0.9959	3.28	0.54	9.2	5
11	7.5	0.500	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5	5
12	5.6	0.615	0.00	1.6	0.089	16.0	59.0	0.9943	3.58	0.52	9.9	5
13	7.8	0.610	0.29	1.6	0.114	9.0	29.0	0.9974	3.26	1.56	9.1	5

Labels:

- 1 fixed acidity: most acids involved with wine
- 2 volatile acidity: -The amount acetic acid in wine at too high can lead to unpleasant taste
- 3 Citric acid: citric acid can add freshnees and flavor to wines found in very small quantities
- 4 residual sugar: wine after the alcoholic fermentation finishes. It's measured in grams per liter
- 5 chlorides: Amount of sallt in wine
- 6 free sulfur dioxide: free sulfur dioxide is a key factor in winemaking, It's important to monitor and manage free SO2 levels to ensure wine quality and longevity.
- 7 total sulfur dioxide: Winemakers carefully monitor and manage SO2 levels to maintain wine quality and safety.
- 8 density: density of water is close to that of water depending on the percent of alcohol and sugar content
- 9 pH: decribes how acidic and basic wine is
- 10 sulphates : a wine addictive which can contribute to sulfur dioxide gas(so2) 11 alcohol : Alcohol Present

Target:

Quality: Since Quality of wine is base don features and scores between 0 -10

Exploratory Data Analysis(EDA)

```
Shows Shape of the Dataset
       #checking null values
In [6]:
       df.isna().sum()
                               0
       fixed acidity
Out[6]:
       volatile acidity
                              0
       citric acid
       residual sugar
       chlorides
       free sulfur dioxide
                             0
       total sulfur dioxide
                              0
       density
                              0
       Нq
                              0
                              0
       sulphates
       alcohol
                              0
                               0
       quality
       dtype: int64
       There are no null values present in our Dataset
In [7]:
       df.info()
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 1599 entries, 0 to 1598
       Data columns (total 12 columns):
        # Column
                                Non-Null Count Dtype
       --- ----
                                 _____
           fixed acidity
                              1599 non-null float64
        0
        1 volatile acidity
                                1599 non-null float64
```

1599 non-null float64 1599 non-null float64

1599 non-null float64

1599 non-null float64

1599 non-null float64 1599 non-null float64

1599 non-null float64

1599 non-null int64

5 free sulfur dioxide 1599 non-null float64 6 total sulfur dioxide 1599 non-null float64

dtypes: float64(11), int64(1)
memory usage: 150.0 KB

2 citric acid

chlorides

density

9 sulphates10 alcohol

11 quality

residual sugar

In [8]: df.describe()

3

4

7

Hq 8

df.shape

(1599, 12)

In [5]:

Out[5]:

Out[8]:

	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

SO using the Describe method i can see that mean, standard value, minimum, maximum and Inter Quantile values of our Data set So As per my observations

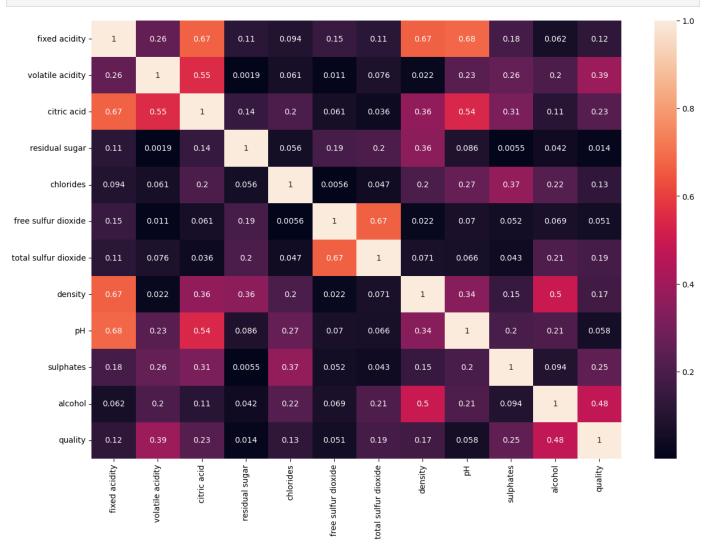
- 1. There is a gap between 75% of residual sugar and maximum residual sugar
- 2. There is a gap betweeen 75% and max value of free sulfur dioxide
- 3. There is a gap between 75% and max values of total sulfur dioxide

All These tells us that there is an Outlier present in our dataset which needs to be taken care of for better model accuracy

```
In [9]: corr = df.corr().abs()
```

Now, will check the multicolinearity between columns

```
In [10]: plt.figure(figsize=(15,10))
    sns.heatmap(corr,annot=True)
    plt.show()
```

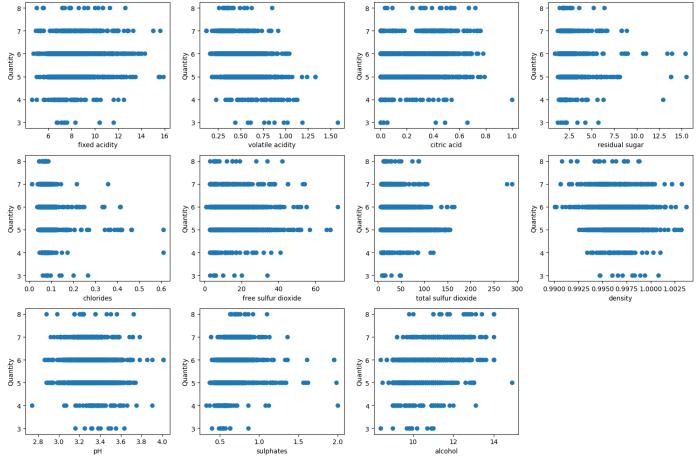


```
In [11]: # Seperating the labels as x and target as y
x = df.drop('quality',axis = 1)
y = df.quality
```

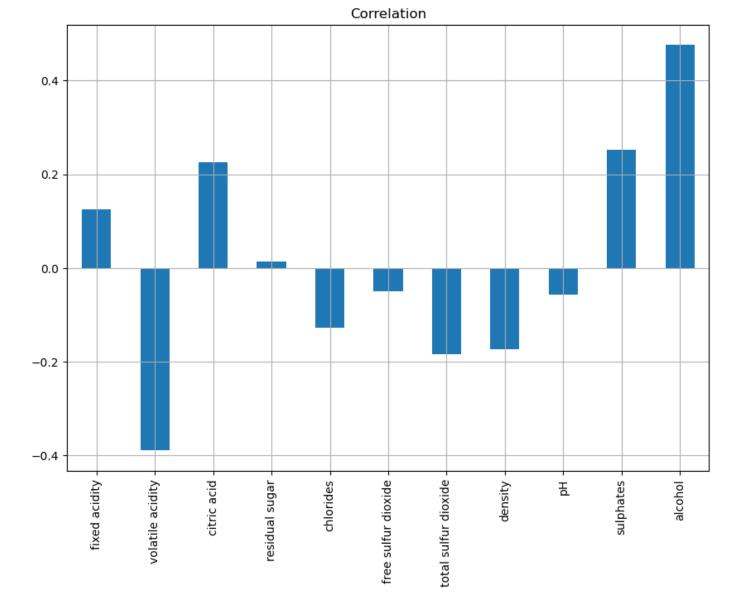
```
In [12]: plt.figure(figsize=(15,10))

plotnumber = 1

for column in x:
    if plotnumber <= 12:
        ax = plt.subplot(3,4,plotnumber)
        plt.scatter(x[column],y)
        plt.xlabel(column,fontsize=10)
        plt.ylabel('Quantity',fontsize=10)
        plotnumber +=1
plt.tight_layout()</pre>
```



In [13]: #Checking the realtionship between labels and target using scatterplot
 x.corrwith(y).plot(kind = 'bar',grid = True, figsize = (10,7), title = 'Correlation')
 plt.show()



```
In [14]: best_feature = SelectKBest(score_func = f_classif, k =11)
    fit = best_feature.fit(x,y)

In [15]: bst_scores = pd.DataFrame(fit.scores_)
    bst_column = pd.DataFrame(x.columns)

In [16]: feature_score = pd.concat([bst_column,bst_scores], axis =1)
    feature_score.columns = ['feature Name', 'Scores']
    feature_score.nlargest(11, 'Scores')
```

ut[16]:		feature Name	Scores
	10	alcohol	115.854797
	1	volatile acidity	60.913993
	6	total sulfur dioxide	25.478510
	9	sulphates	22.273376
	2	citric acid	19.690664
	7	density	13.396357
	0	fixed acidity	6.283081
	4	chlorides	6.035639

```
3
                               1.053374
                 residual sugar
          df['quality'].value counts()
In [17]:
               681
Out[17]:
               638
         7
               199
         4
                53
         8
                18
          3
                10
         Name: quality, dtype: int64
          #Converting the data into categories i.e quality of range above and equal to 7 will be g
In [18]:
          df['quality'] = [1 if x>=7 else 0 for x in df.quality]
In [19]:
          df['quality'].value counts()
               1382
Out[19]:
                217
         Name: quality, dtype: int64
          df.head()
In [20]:
Out[20]:
                                                        free
                                                                total
              fixed
                    volatile citric residual
                                           chlorides
                                                                      density
                                                      sulfur
                                                               sulfur
                                                                              pH sulphates alcohol quality
             acidity
                     acidity
                             acid
                                     sugar
                                                     dioxide
                                                              dioxide
         0
                7.4
                       0.70
                             0.00
                                       1.9
                                              0.076
                                                        11.0
                                                                 34.0
                                                                      0.9978 3.51
                                                                                       0.56
                                                                                                9.4
                                                                                                        0
                7.8
                       0.88
                             0.00
                                              0.098
                                                        25.0
                                                                 67.0
                                                                      0.9968 3.20
                                                                                                9.8
                                                                                                        0
                                       2.6
                                                                                       0.68
         2
                7.8
                       0.76
                             0.04
                                       2.3
                                              0.092
                                                        15.0
                                                                 54.0
                                                                      0.9970 3.26
                                                                                       0.65
                                                                                                9.8
                                                                                                        0
         3
               11.2
                       0.28
                             0.56
                                       1.9
                                              0.075
                                                        17.0
                                                                 60.0
                                                                       0.9980
                                                                            3.16
                                                                                       0.58
                                                                                                9.8
                                                                                                        0
          4
                7.4
                       0.70
                                              0.076
                                                                      0.9978 3.51
                                                                                                        0
                             0.00
                                       1.9
                                                        11.0
                                                                 34.0
                                                                                       0.56
                                                                                                9.4
In [21]:
         x fe = df.drop('quality', axis = 1)
          y la = df.quality
          scaler = StandardScaler()
In [22]:
          x scaled = scaler.fit transform(x fe)
          x scaled
         array([[-0.52835961, 0.96187667, -1.39147228, ..., 1.28864292,
Out[22]:
                  -0.57920652, -0.96024611],
                  [-0.29854743, 1.96744245, -1.39147228, ..., -0.7199333,
                    0.1289504 , -0.58477711],
                  [-0.29854743, 1.29706527, -1.18607043, ..., -0.33117661,
                  -0.04808883, -0.58477711],
                  [-1.1603431, -0.09955388, -0.72391627, ..., 0.70550789,
                    0.54204194, 0.54162988],
                  [-1.39015528, 0.65462046, -0.77526673, ..., 1.6773996,
                    0.30598963, -0.20930812],
                  [-1.33270223, -1.21684919, 1.02199944, ..., 0.51112954,
                    0.01092425, 0.54162988]])
```

4.754233

4.341764

5

8

free sulfur dioxide

рН

-Train Test Split

```
In [23]: x_train,x_test,y_train,y_test = train_test_split(x_scaled, y_la, test_size = 0.20, rando
```

-Creating The Function for training and testing score so that we can get the result just by calling the function

```
In [24]:

def score(clas, x_train, x_test, y_train, y_test, train = True):
    if train:
        y_pred = clas.predict(x_train)
        print('\n -----Train Result -----\n')
        print('Accuracy Score:', accuracy_score(y_train,y_pred))
        print('\n ----- Classification Report -----\n', classification_report(y_train,y_pred))

elif train == False:
        pred = clas.predict(x_test)
        print('\n ----- Test Result -----\n')
        print('Accuracy_Score:', accuracy_score(y_test,pred))
        print('\n ----- Classification Report ----- \n', classification_report(y_test,pred))
        print('\n ----- Confusion Matrix -----\n', confusion_matrix(y_test,pred))
```

-Model Instantiating

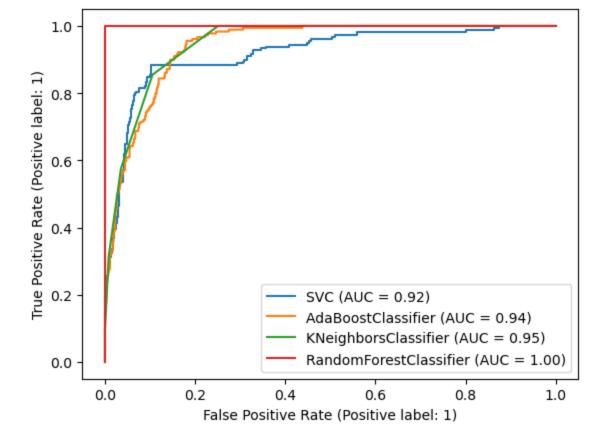
```
In [25]: svc = SVC()
    ada = AdaBoostClassifier()
    knn = KNeighborsClassifier()
    rfc = RandomForestClassifier()
```

-Training of the Models

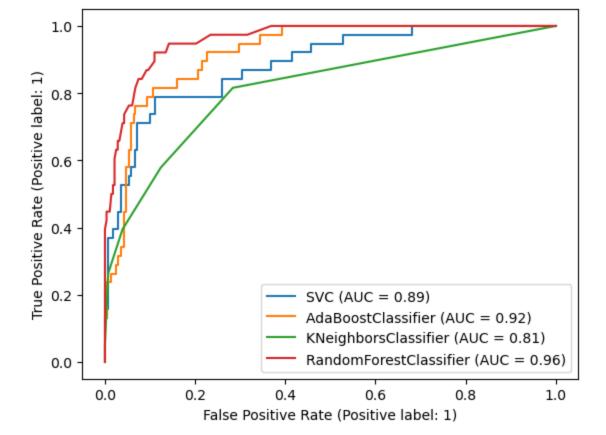
```
In [26]: svc.fit(x_train, y_train)
    ada.fit(x_train, y_train)
    knn.fit(x_train, y_train)
    rfc.fit(x_train, y_train)
    print('Training of all Models')
```

Training of all Models

-Ploting roc_auc_curve for training



```
In [30]:
         #Traning score of each model
         print(svc.score(x train,y train))
         print(ada.score(x train,y train))
        print(knn.score(x train,y train))
        0.8928850664581705
        0.9061767005473026
        0.910086004691165
         #Plotting roc auc curve for testing model
In [31]:
         disp = plot roc curve(svc, x test, y test)
        plot_roc_curve(ada,x_test,y_test,ax =disp.ax_)
         plot_roc_curve(knn,x_test,y_test,ax =disp.ax_)
         plot_roc_curve(rfc,x_test,y_test,ax =disp.ax_)
         plt.legend(prop ={'size' :10}, loc = 'lower right')
         plt.show()
```



```
print(svc.score(x test,y test))
In [32]:
         print(ada.score(x test,y test))
         print(knn.score(x_test,y_test))
        print(rfc.score(x test,y test))
        0.9125
        0.896875
        0.89375
        0.928125
         # Training score, Testing Score, Classification Report, Confusion matrix of RandomForest
In [33]:
         rfc.fit(x train, y train)
         score(rfc, x train, x test, y train, y test, train = True)
         score(rfc, x train, x test, y train, y test, train = False)
         ----Train Result ----
        Accuracy Score: 1.0
         ---- Classification Report ----
                        precision
                                     recall f1-score
                                                         support
                    0
                            1.00
                                      1.00
                                                1.00
                                                           1100
                            1.00
                                      1.00
                                                1.00
                                                           179
                                                1.00
                                                           1279
            accuracy
                            1.00
                                      1.00
                                                1.00
                                                           1279
           macro avg
                            1.00
                                      1.00
                                                1.00
                                                           1279
        weighted avg
         ---- COnfusion Matrix ----
          [[1100
                  0]
             0 179]]
```

---- Test Result ----

Accuracy Score: 0.928125

```
precision recall f1-score support
                         0.94 0.99 0.96
0.83 0.50 0.62
                                                        282
                                                         38
                                                     320
                                             0.93
           accuracy
        macro avg 0.88 0.74 0.79 weighted avg 0.92 0.93 0.92
                                                        320
                                                       320
         ---- Confusion Matrix ----
         [[278 4]
         [ 19 19]]
In [34]: rfc.get_params().keys()
        dict keys(['bootstrap', 'ccp alpha', 'class weight', 'criterion', 'max depth', 'max feat
Out[34]:
        ures', 'max leaf nodes', 'max samples', 'min impurity decrease', 'min samples leaf', 'mi
        n samples split', 'min weight fraction leaf', 'n estimators', 'n jobs', 'oob score', 'ra
        ndom state', 'verbose', 'warm start'])
In [35]: # Hyperparameter Tuning
        param = {
            'n estimators': range(1, 15),
            'criterion': ['gini', 'entropy'],
            'max_depth': range(2, 10),
            'max features': range(0, 12),
            'max leaf nodes': range(2, 4)
In [36]: grid = GridSearchCV(rfc,param grid = param)
        grid.fit(x train, y train)
        print('Best Params =', grid.best params )
        Best Params = {'criterion': 'gini', 'max depth': 3, 'max features': 5, 'max leaf nodes':
        3, 'n estimators': 4}
In [37]: rfc = RandomForestClassifier(criterion = 'gini', max depth = 7, max features =11, max leaf
In [41]: rfc.fit(x_train,y train)
        score(rfc,x train,x test,y train,y test,train = True)
        score(rfc,x train,x test,y train,y test,train = False)
         ----Train Result ----
        Accuracy Score: 0.8866301798279906
         ---- Classification Report ----
                      precision recall f1-score support
                         0.90 0.98
                                            0.94
                                                      1100
                         0.70
                                   0.34
                                             0.45
                                                       179
                                             0.89
                                                      1279
            accuracy
                         0.80 0.66
0.87 0.89
                                             0.69 1279
0.87 1279
           macro avg
        weighted avg
         ---- COnfusion Matrix -----
         [[1074 26]
         [ 119 60]]
         ---- Test Result ----
```

---- Classification Report ----

0.80 0.61

0.90

0.88

```
---- Confusion Matrix ---- [[278 4] [ 29 9]]
```

macro avg

weighted avg

```
In [42]: #USing Pickle Method
filename = 'winequality.ipynb'
pickle.dump(rfc,open(filename, 'wb'))
```

0.65

0.87

320

320