### Importing libraries and modules

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

### Loading the dataset

```
df=pd.read csv('/content/winequality-red.csv')
df.head(10)
   fixed acidity volatile acidity citric acid residual sugar
chlorides
             7.4
                               0.70
                                             0.00
                                                               1.9
0.076
             7.8
                                                               2.6
                               0.88
                                             0.00
0.098
             7.8
                               0.76
                                             0.04
                                                               2.3
2
0.092
            11.2
                               0.28
                                             0.56
                                                               1.9
0.075
             7.4
                               0.70
                                             0.00
                                                               1.9
0.076
                                             0.00
             7.4
                               0.66
                                                               1.8
0.075
             7.9
                               0.60
                                             0.06
                                                               1.6
6
0.069
             7.3
                                                               1.2
                               0.65
                                             0.00
0.065
             7.8
                               0.58
                                             0.02
                                                               2.0
0.073
             7.5
                               0.50
                                             0.36
                                                               6.1
0.071
   free sulfur dioxide total sulfur dioxide density
                                                                sulphates
                                                           рΗ
0
                   11.0
                                          34.0
                                                 0.9978 3.51
                                                                     0.56
                   25.0
                                          67.0
                                                 0.9968 3.20
                                                                     0.68
1
2
                   15.0
                                          54.0
                                                 0.9970 3.26
                                                                     0.65
                   17.0
3
                                          60.0
                                                                     0.58
                                                 0.9980 3.16
                   11.0
                                          34.0
                                                 0.9978 3.51
                                                                     0.56
5
                   13.0
                                                                     0.56
                                          40.0
                                                 0.9978 3.51
```

```
6
                   15.0
                                          59.0
                                                 0.9964 3.30
                                                                     0.46
7
                                                                     0.47
                   15.0
                                          21.0
                                                 0.9946 3.39
                   9.0
8
                                          18.0
                                                 0.9968 3.36
                                                                     0.57
9
                   17.0
                                         102.0
                                                 0.9978 3.35
                                                                     0.80
            quality
   alcohol
0
       9.4
1
       9.8
                   5
2
                   5
       9.8
                   6
3
       9.8
                   5
4
       9.4
5
                   5
       9.4
                   5
6
       9.4
                  7
7
      10.0
8
       9.5
                  7
9
                   5
      10.5
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
                                             float64
 0
                            1599 non-null
                            1599 non-null
                                             float64
 1
     volatile acidity
 2
     citric acid
                            1599 non-null
                                             float64
 3
     residual sugar
                            1599 non-null
                                             float64
4
                            1599 non-null
                                             float64
     chlorides
 5
     free sulfur dioxide
                            1599 non-null
                                             float64
 6
     total sulfur dioxide
                            1599 non-null
                                             float64
 7
                            1599 non-null
                                             float64
     density
 8
     рН
                            1599 non-null
                                             float64
 9
     sulphates
                                             float64
                            1599 non-null
10
     alcohol
                            1599 non-null
                                             float64
 11
     quality
                            1599 non-null
                                             int64
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
df.shape
(1599, 12)
df.describe()
       fixed acidity
                      volatile acidity citric acid
                                                       residual sugar \
         1599.000000
                            1599.000000
                                         1599,000000
                                                          1599.000000
count
```

mean std min 25% 50% 75% max	8.319637 1.741096 4.600006 7.100006 7.900006 9.200006	0       0.         0       0.         0       0.         0       0.         0       0.	179060 6 120000 6 390000 6 520000 6	0.270976 0.194801 0.000000 0.090000 0.260000 0.420000	2.538806 1.409928 0.900000 1.900000 2.200000 2.600000
	chlorides	free sulfur	dioxide tot	tal sulfur d	ioxide
density count 15 1599.000	\ 599.000000	1599	.000000	1599.0	900000
mean 0.996747	0.087467	15	5.874922	46.4	467792
std 0.001887 min 0.990070 25% 0.995600 50% 0.996750	0.047065	10.460157		32.895324	
	0.012000	1.000000		6.000000	
	0.070000	7.000000		22.000000	
	0.079000	14.000000		38.000000	
75% 0.997835	0.090000	21.000000		62.000000	
max 1.003690	0.611000	72	2.000000	289.0	900000
count 15 mean std min 25% 50% 75% max	pH 599.000000 3.311113 0.154386 2.740000 3.210000 3.310000 3.400000 4.010000	sulphates 1599.000000 0.658149 0.169507 0.330000 0.550000 0.620000 0.730000 2.000000	alcohol 1599.000000 10.422983 1.065668 8.400000 9.500000 10.200000 11.100000	1599.00000 5.63602 0.80750 3.00000 5.00000 6.00000	90 23 59 90 90 90

# **Data Preprocessing**

## Checking for Null values

```
df.isnull().sum()

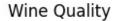
fixed acidity     0
volatile acidity     0
citric acid     0
residual sugar     0
chlorides     0
free sulfur dioxide     0
```

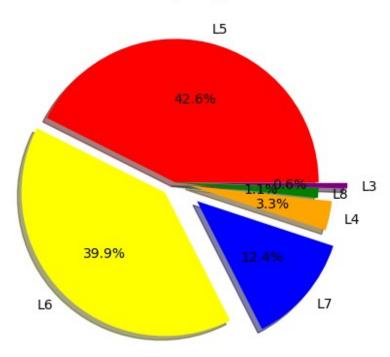
```
total sulfur dioxide 0
density 0
pH 0
sulphates 0
alcohol 0
quality 0
dtype: int64
```

#### Visualizations

Univariate Analysis - 1 (Pie Chart)

```
df['quality'].unique()
array([5, 6, 7, 4, 8, 3])
df['quality'].value_counts()
5
     681
6
     638
7
     199
      53
4
8
      18
3
      10
Name: quality, dtype: int64
plt.pie(df['quality'].value_counts(),
[0,0.1,0.2,0.1,0,0.2],labels=['L5','L6','L7','L4','L8','L3'],autopct='
%1.1f%
%', shadow=True, colors=['red', 'yellow', 'blue', 'orange', 'green', 'purple'
])
plt.title('Wine Quality')
plt.show()
```





#### Univariate Analysis -2 (distplot)

sns.distplot(df['residual sugar'])
plt.show()

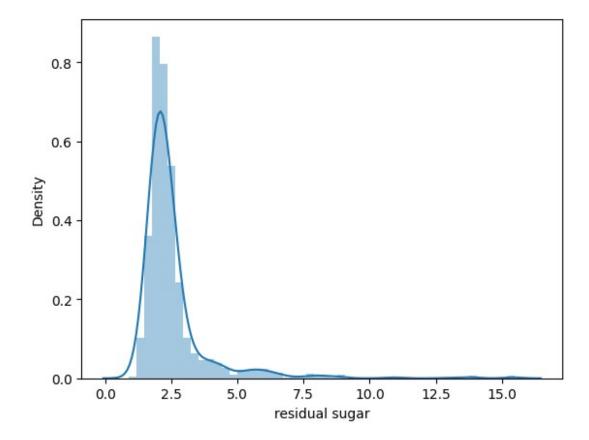
<ipython-input-791-3ebe262dcd43>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df['residual sugar'])



sns.distplot(df['free sulfur dioxide'])
plt.show()

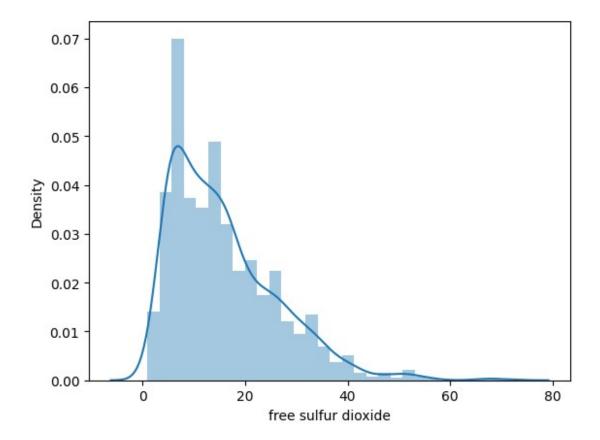
<ipython-input-792-12e549d3d17b>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df['free sulfur dioxide'])



sns.distplot(df['total sulfur dioxide'])
plt.show()

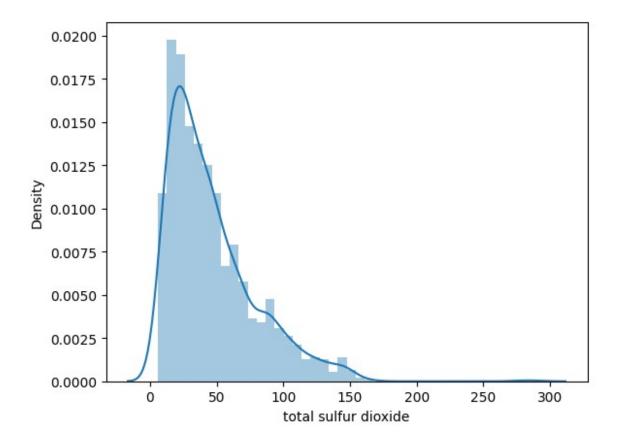
<ipython-input-793-f2f9a4b197ba>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

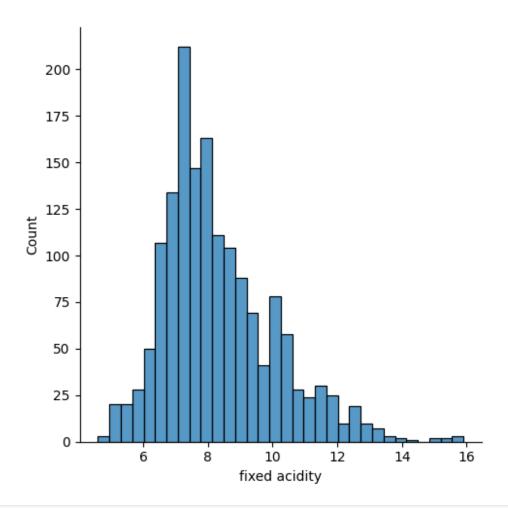
sns.distplot(df['total sulfur dioxide'])



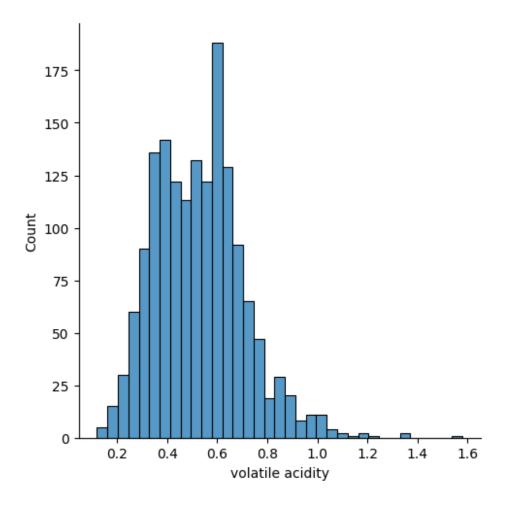
Univariate Analysis -3 (displot)

sns.displot(df['fixed acidity'])

<seaborn.axisgrid.FacetGrid at 0x7c543fb7e7a0>



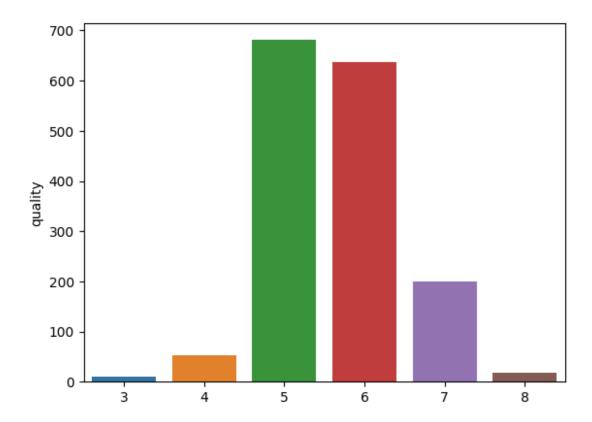
sns.displot(df['volatile acidity'])
<seaborn.axisgrid.FacetGrid at 0x7c543fb7cdf0>



#### Univariate Analysis - 4 (Barplot)

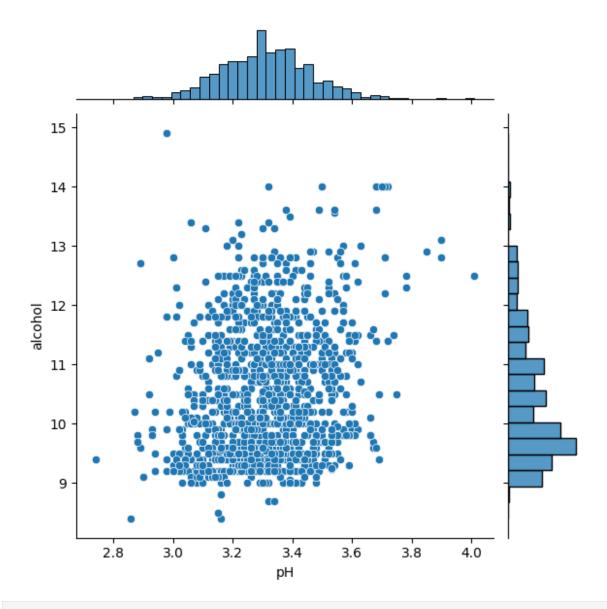
sns.barplot(x=df['quality'].value\_counts().index,y=df['quality'].value
\_counts())

<Axes: ylabel='quality'>

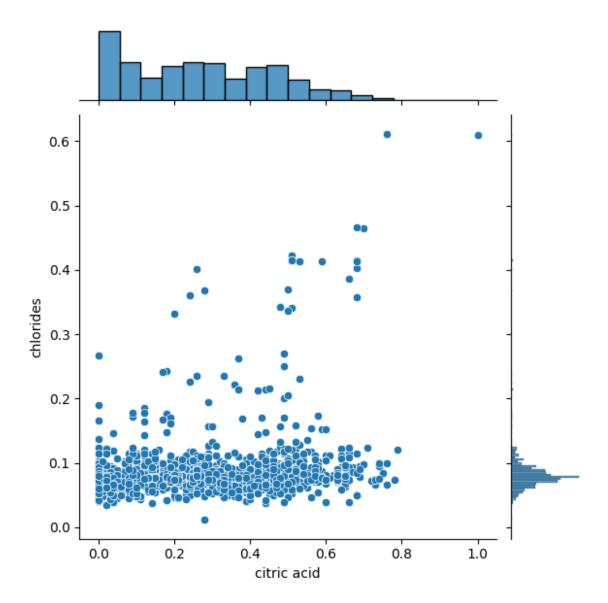


#### Bivariate Analysis - 1 (jointplot)

```
sns.jointplot(x = df['pH'], y = df['alcohol'], data = df)
plt.show()
```



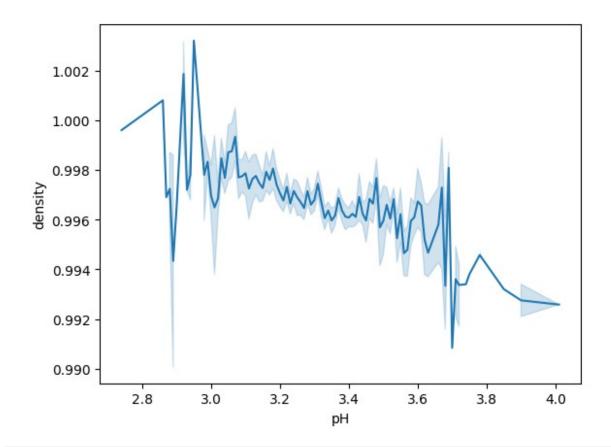
sns.jointplot(x = df['citric acid'], y = df['chlorides'], data = df)
plt.show()



Bivariate analysis - 2 (lineplot)

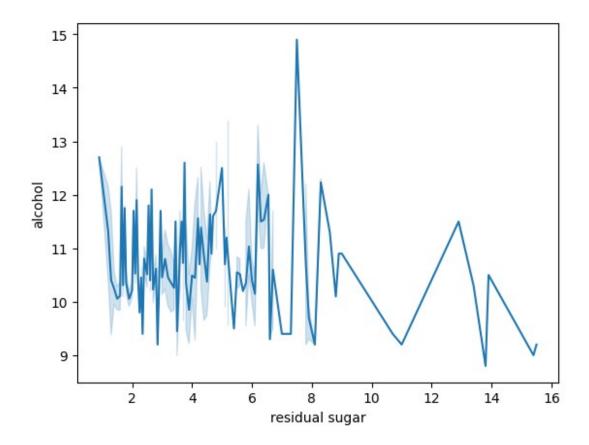
sns.lineplot(x=df['pH'],y=df['density'])

<Axes: xlabel='pH', ylabel='density'>



sns.lineplot(x=df['residual sugar'],y=df['alcohol'])

<Axes: xlabel='residual sugar', ylabel='alcohol'>

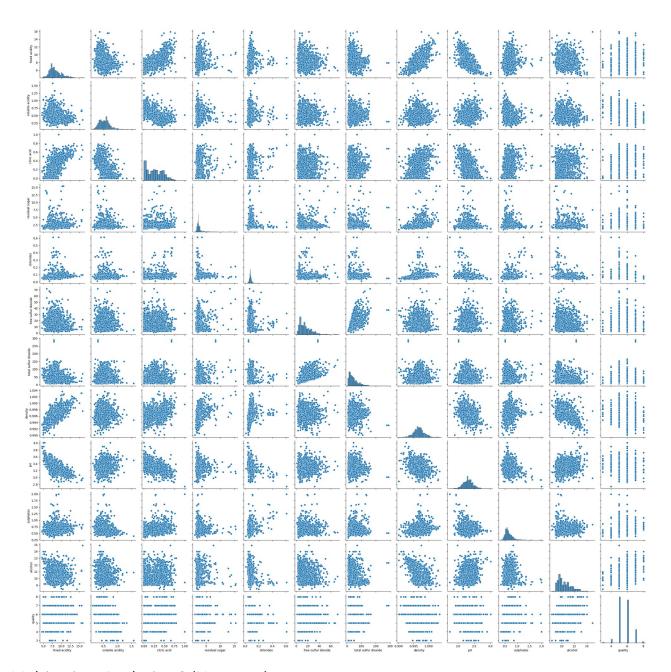


#### Multivariate Analysis - 1 (pairplot)

```
plt.figure(figsize=(20,20))
sns.pairplot(df)
```

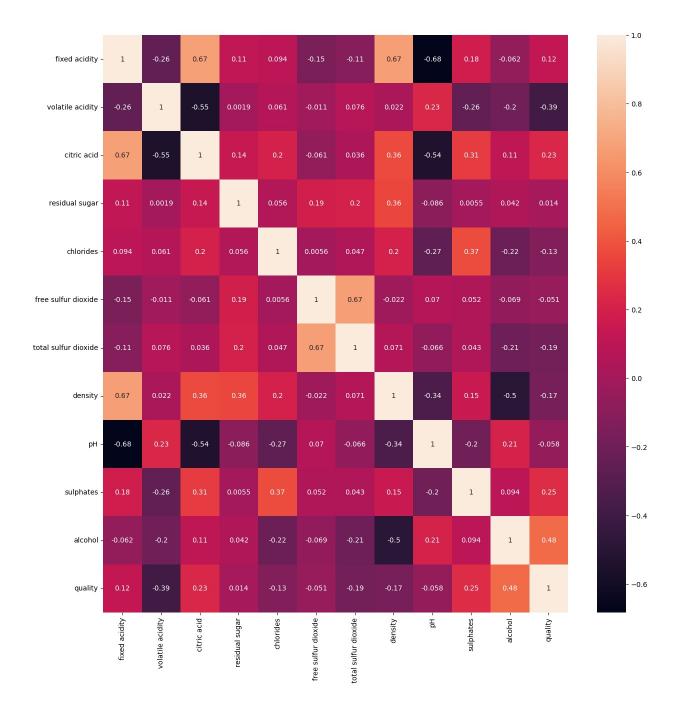
<seaborn.axisgrid.PairGrid at 0x7c543f4b0af0>

<Figure size 2000x2000 with 0 Axes>



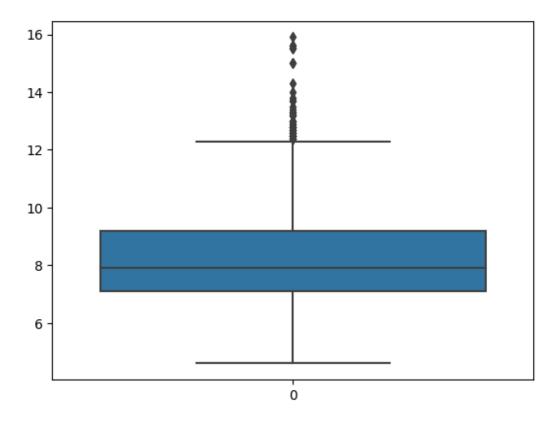
#### Multivariate Analysis - 2 (Heatmap)

```
plt.figure(figsize=(15,15))
sns.heatmap(df.corr(),annot=True)
```

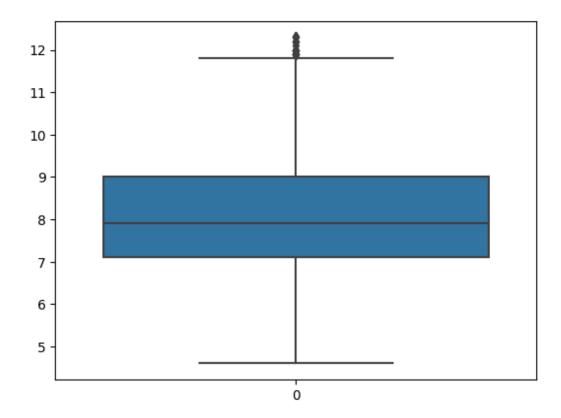


## Outlier Detection and Replacement

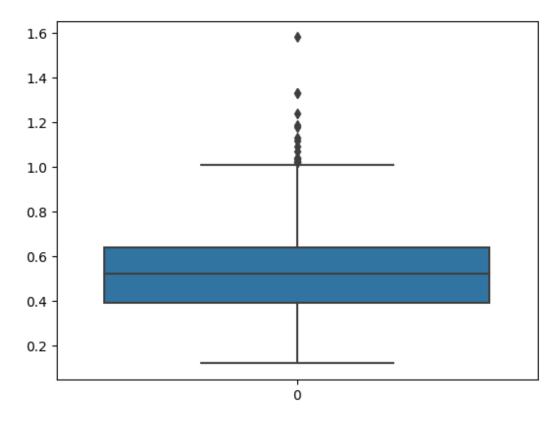
sns.boxplot(df['fixed acidity'])



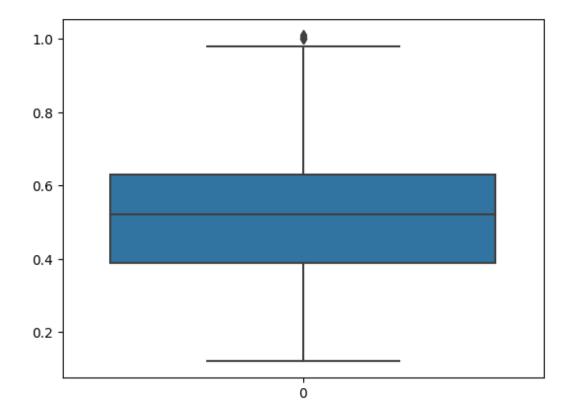
```
q1=df['fixed acidity'].quantile(0.25)
q3=df['fixed acidity'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['fixed acidity'] = np.where((df['fixed acidity']>upper_limit) |
(df['fixed acidity']<lower_limit),df['fixed acidity'])
sns.boxplot(df['fixed acidity'])</pre>
<Axes: >
```



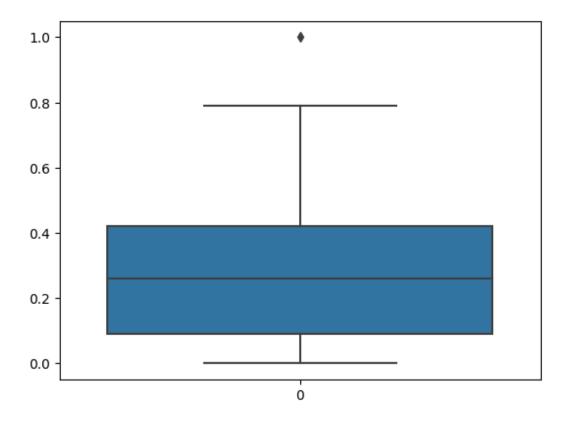
```
sns.boxplot(df['volatile acidity'])
<Axes: >
```



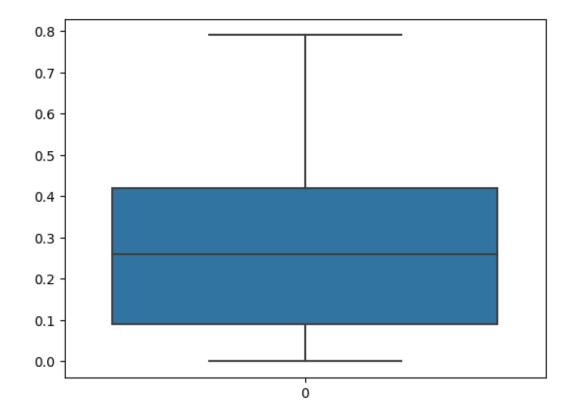
```
q1=df['volatile acidity'].quantile(0.25)
q3=df['volatile acidity'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['volatile acidity'] = np.where((df['volatile acidity']>upper_limit)
| (df['volatile acidity']<lower_limit),df['volatile acidity'].median(),df['volatile acidity'])
sns.boxplot(df['volatile acidity'])
</pre>
<Axes: >
```



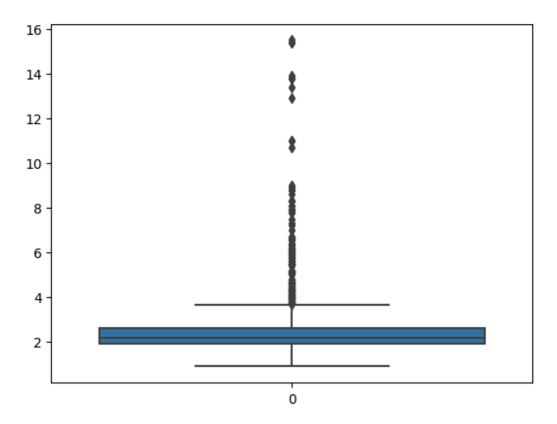
sns.boxplot(df['citric acid'])



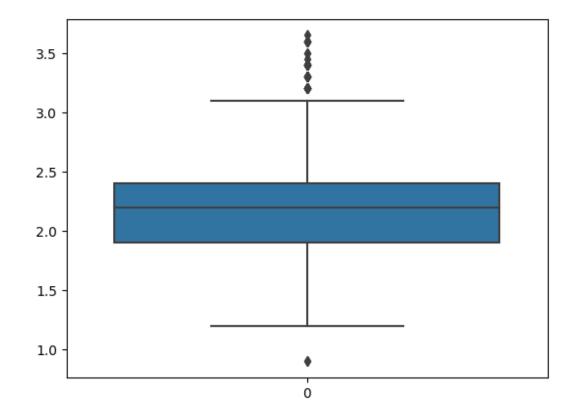
```
q1=df['citric acid'].quantile(0.25)
q3=df['citric acid'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['citric acid'] = np.where((df['citric acid']>upper_limit) |
(df['citric acid']<lower_limit),df['citric acid'].median(),df['citric acid'])
sns.boxplot(df['citric acid'])
</pre>
<Axes: >
```



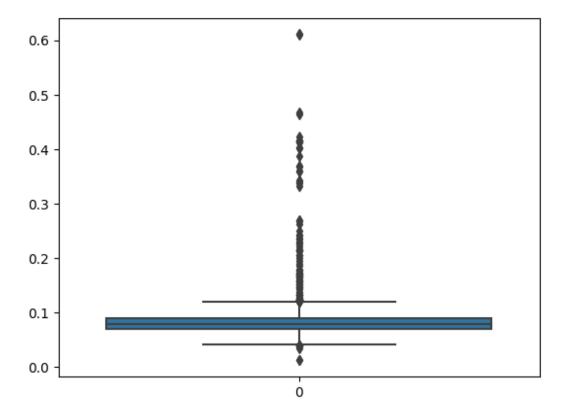
sns.boxplot(df['residual sugar'])



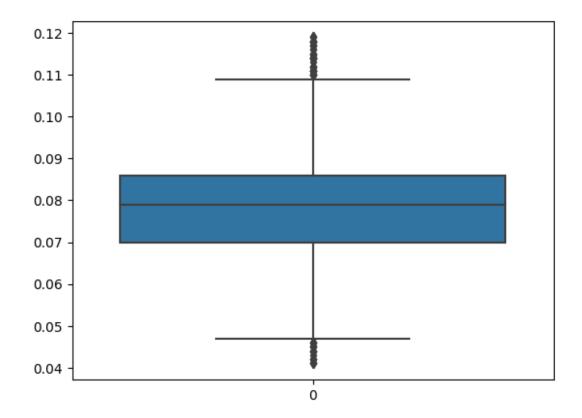
```
q1=df['residual sugar'].quantile(0.25)
q3=df['residual sugar'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['residual sugar'] = np.where((df['residual sugar']>upper_limit) |
(df['residual sugar']<lower_limit),df['residual
sugar'].median(),df['residual sugar'])
sns.boxplot(df['residual sugar'])
</pre>
```



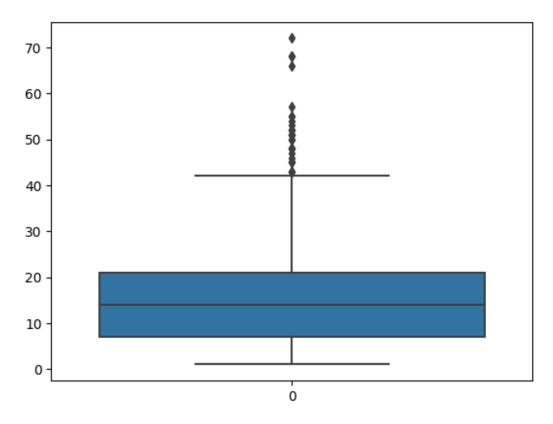
sns.boxplot(df['chlorides'])



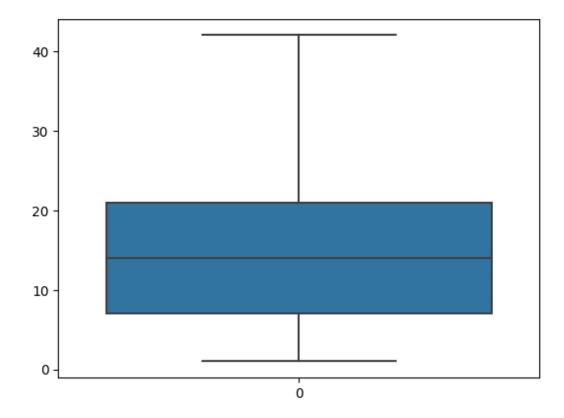
```
q1=df['chlorides'].quantile(0.25)
q3=df['chlorides'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['chlorides'] = np.where((df['chlorides']>upper_limit) |
(df['chlorides']<lower_limit),df['chlorides'].median(),df['chlorides'])
sns.boxplot(df['chlorides'])</pre>
<Axes: >
```



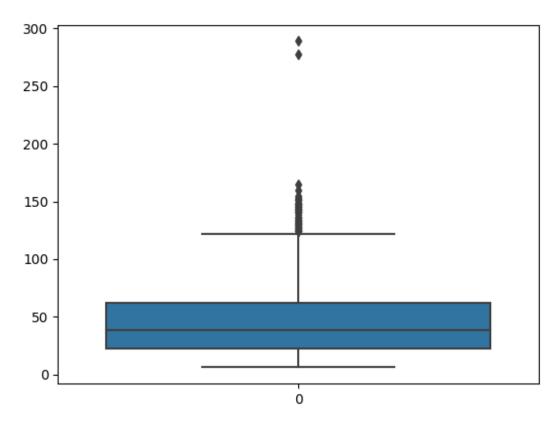
sns.boxplot(df['free sulfur dioxide'])
<Axes: >



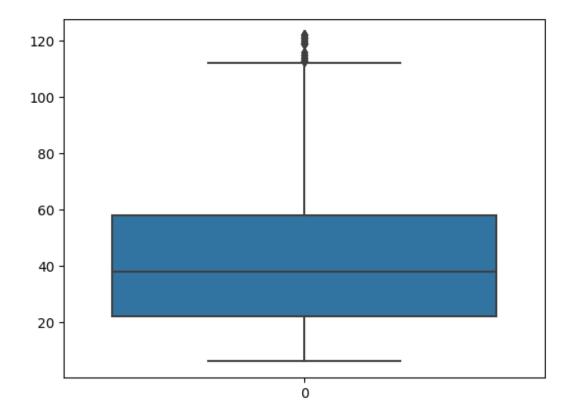
```
q1=df['free sulfur dioxide'].quantile(0.25)
q3=df['free sulfur dioxide'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['free sulfur dioxide'] = np.where((df['free sulfur dioxide']>upper_limit) | (df['free sulfur dioxide']lower_limit),df['free sulfur dioxide'].median(),df['free sulfur dioxide'])
sns.boxplot(df['free sulfur dioxide'])
```



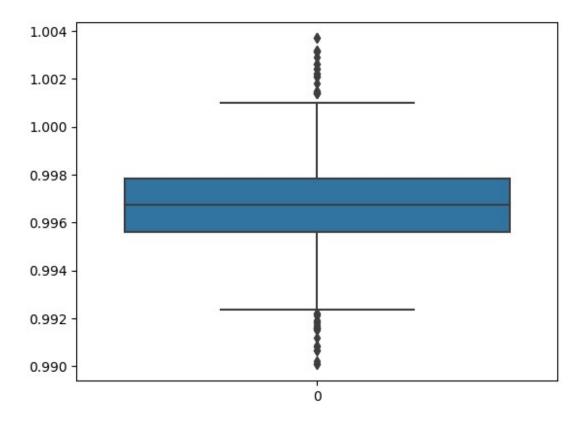
```
sns.boxplot(df['total sulfur dioxide'])
<Axes: >
```



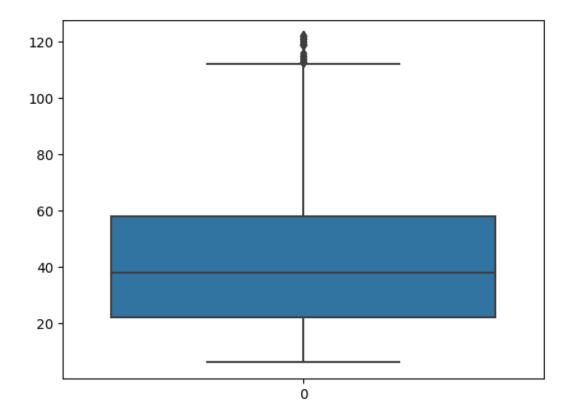
```
ql=df['total sulfur dioxide'].quantile(0.25)
q3=df['total sulfur dioxide'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['total sulfur dioxide'] = np.where((df['total sulfur dioxide']>upper_limit) | (df['total sulfur dioxide']<lower_limit),df['total sulfur dioxide'].median(),df['total sulfur dioxide'])
sns.boxplot(df['total sulfur dioxide'])</pre>
```



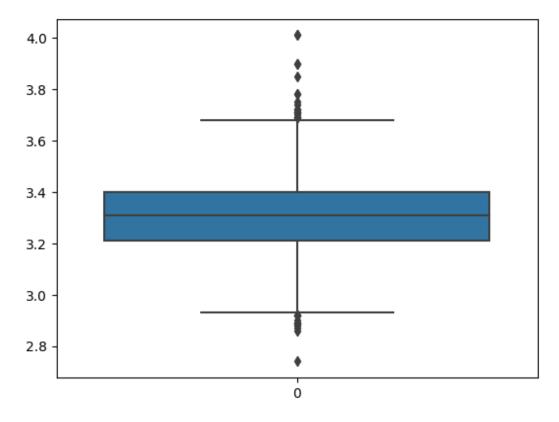
sns.boxplot(df['density'])



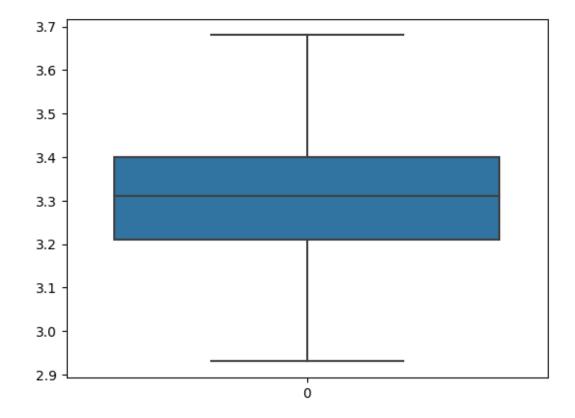
```
q1=df['density'].quantile(0.25)
q3=df['density'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['density'] = np.where((df['density']>upper_limit) |
(df['density']<lower_limit),df['density'].median(),df['density'])
sns.boxplot(df['total sulfur dioxide'])
</pre>
<Axes: >
```



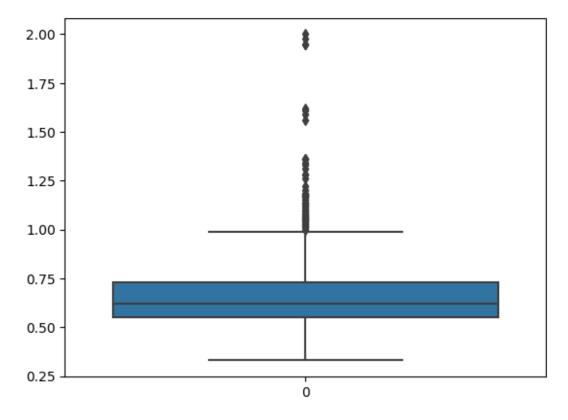
sns.boxplot(df['pH'])



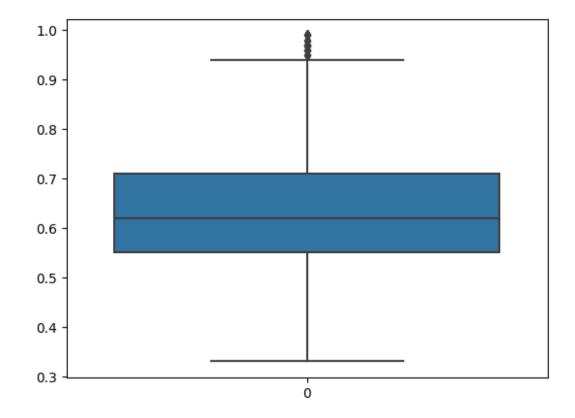
```
q1=df['pH'].quantile(0.25)
q3=df['pH'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['pH'] = np.where((df['pH']>upper_limit) |
(df['pH']<lower_limit),df['pH'].median(),df['pH'])
sns.boxplot(df['pH'])</pre>
<Axes: >
```



sns.boxplot(df['sulphates'])

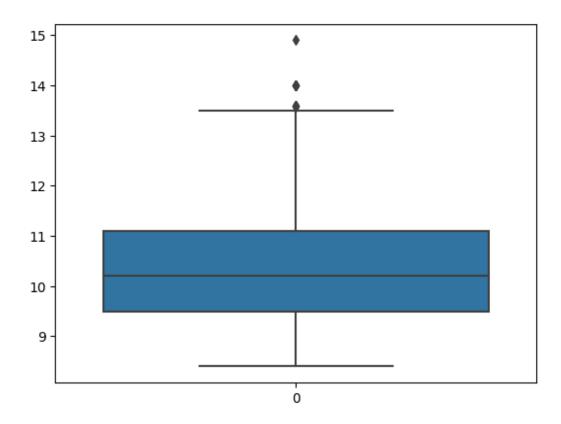


```
q1=df['sulphates'].quantile(0.25)
q3=df['sulphates'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['sulphates'] = np.where((df['sulphates']>upper_limit) |
(df['sulphates']<lower_limit),df['sulphates'].median(),df['sulphates'])
sns.boxplot(df['sulphates'])</pre>
<Axes: >
```

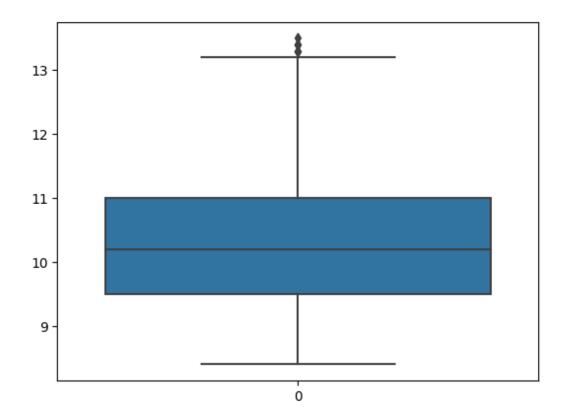


sns.boxplot(df['alcohol'])

<Axes: >

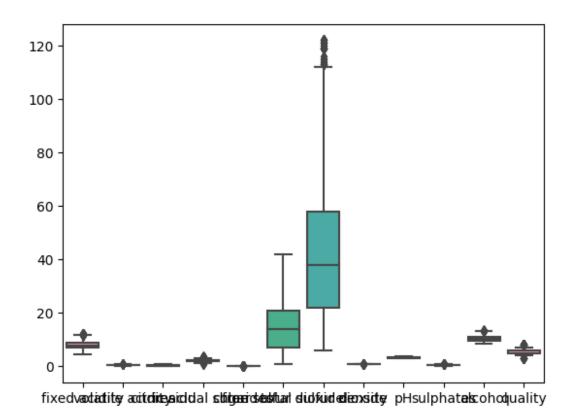


```
q1=df['alcohol'].quantile(0.25)
q3=df['alcohol'].quantile(0.75)
IQR = q3-q1
upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
df['alcohol'] = np.where((df['alcohol']>upper_limit) |
(df['alcohol']<lower_limit),df['alcohol'].median(),df['alcohol'])
sns.boxplot(df['alcohol'])
</pre>
<Axes: >
```



sns.boxplot(df)

<Axes: >



# Splitting the data into features and target

<pre>X=df.drop(columns=['quality'],axis=1) X.head(10)</pre>							
		volatile acidity	citric acid	residual sugar			
chlorides	-	0.70	0.00	1.9			
0 0.076	7.4	0.70	0.00	1.9			
1	7.8	0.88	0.00	2.6			
0.098	7.0	0100	0.00	210			
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		0.00	0.00	1.0			
5	7.4	0.66	0.00	1.8			
0.075 6	7.9	0.60	0.06	1.6			
0.069	7.9	0.00	0.00	1.0			
7	7.3	0.65	0.00	1.2			
0.065	,	0.05	0.00				
8	7.8	0.58	0.02	2.0			
0.073							
9	7.5	0.50	0.36	2.2			

```
0.071
   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
                  11.0
                                         34.0
                                                0.9978 3.51
                                                                    0.56
5
                  13.0
                                         40.0
                                                0.9978 3.51
                                                                    0.56
6
                  15.0
                                         59.0
                                                0.9964 3.30
                                                                    0.46
7
                  15.0
                                         21.0
                                                0.9946 3.39
                                                                    0.47
                   9.0
                                         18.0
                                                0.9968 3.36
                                                                    0.57
8
9
                  17.0
                                        102.0
                                                 0.9978 3.35
                                                                    0.80
   alcohol
0
       9.4
       9.8
1
2
       9.8
3
       9.8
4
       9.4
5
       9.4
6
       9.4
7
      10.0
8
       9.5
      10.5
y=df['quality']
y.head(10)
     5
0
     5
1
2
     5
     6
3
     5
4
     5
5
     5
6
7
     7
8
     7
Name: quality, dtype: int64
```

#### Balancing the dataset

```
from imblearn.over sampling import SMOTE
sm = SMOTE(sampling_strategy='minority', random_state=42)
X resampled, Y resampled = sm.fit resample(X,y)
X resampled.head()
   fixed acidity volatile acidity citric acid residual sugar
chlorides \
             7.4
                               0.70
                                            0.00
                                                              1.9
0.076
                                                              2.6
                               0.88
                                            0.00
1
             7.8
0.098
             7.8
                               0.76
                                            0.04
                                                              2.3
2
0.092
            11.2
                               0.28
                                            0.56
                                                              1.9
0.075
             7.4
                               0.70
                                            0.00
                                                              1.9
4
0.076
   free sulfur dioxide total sulfur dioxide density pH
                                                               sulphates
/
0
                  11.0
                                         34.0
                                                 0.9978 3.51
                                                                    0.56
                  25.0
                                                0.9968 3.20
                                                                    0.68
1
                                         67.0
2
                  15.0
                                                0.9970 3.26
                                                                    0.65
                                         54.0
                  17.0
                                                                    0.58
3
                                         60.0
                                                0.9980 3.16
                  11.0
                                         34.0
                                                0.9978 3.51
                                                                    0.56
   alcohol
0
       9.4
       9.8
1
2
       9.8
3
       9.8
4
       9.4
```

### Scaling the data

```
from sklearn.preprocessing import StandardScaler
scale=StandardScaler()

X_scaled=pd.DataFrame(scale.fit_transform(X_resampled),columns=X_resampled.columns)
X_scaled.head(10)
```

fixed a		latile acidity	citric aci	d residual s	ugar
0 -0.5	•	0.836418	-1.20152	3 -0.62	1499 -
0.256246 1 -0.2	280978	1.915642	-1.20152	3 1.02	0535
1.484148 2 -0.2	200070	1.196159			
1.009495					
3 2.0 0.335355	969129	-1.681771	1.60542	1 -0.62	1499 -
4 -0.5	557461	0.836418	-1.20152	3 -0.62	1499 -
0.256246 5 -0.5	557461	0.596591	-1.20152	3 -0.85	6075 -
0.335355 6 -0.2	011057	0.236849	-0.90077	9 -1.32	5228 -
0.810008					
7 -0.0 1.126444	526582	0.536634	-1.20152	3 -2.26	3533 -
8 -0.2	280978	0.116936	-1.10127	5 -0.38	6923 -
0.493573 9 -0.4	488340	-0.362719	0.60294	0.08	2230 -
0.651791					
		de total sulfu	ur dioxide	density	рН
sulphates 0	-0.2730	94	-0.109066	0.512630 1.2	25184 -
0.469038 1	1.2868	76	1 187198 -	0.099961 -0.9	69023
0.577948					
2 0.316202	0.1726	12	0.6/6548	0.022557 -0.5	44338
3 0.294540	0.3954	65	0.912233	0.635149 -1.2	52147 -
4	-0.2730	94	-0.109066	0.512630 1.2	25184 -
0.469038 5	-0.0502	41	0.126618	0.512630 1.2	25184 -
0.469038	0.1726			0.344998 -0.2	
6 1.341527					
7 1.254278	0.1726	12	-0.619716 -	1.447662 0.3	75813 -
8	-0.4959	46	-0.737558 -	0.099961 0.1	63471 -
0.381789 9	0.3954	65	2.562023	0.512630 0.0	92690
1.624935					
alcoho <sup>-</sup>					
0 -0.907428 1 -0.487303					
2 -0.487303					

```
3 -0.487303
4 -0.907428
5 -0.907428
6 -0.907428
7 -0.277241
8 -0.802397
9 0.247916
```

#### Train-Test-Split for Model - 1

```
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test =
    train_test_split(X_scaled,Y_resampled,test_size=0.2,random_state=42)

X_train.shape
(1816, 11)

X_test.shape
(454, 11)

Y_train.shape
(1816,)

Y_test.shape
(454,)
```

## Model Training - 1 (Linear Regression)

```
from sklearn.linear_model import LinearRegression
LinReg=LinearRegression()
LinReg.fit(X_train,Y_train)
LinearRegression()

Y_pred_1=LinReg.predict(X_test)
Y_pred_1
array([5.02726067, 4.09327914, 3.79222271, 5.7697455, 4.95621419, 4.8764308, 6.7669688, 5.18800074, 5.1286554, 3.27335691, 6.05434038, 3.81316565, 3.55631923, 5.86933722, 3.75363426, 3.73563697, 3.80419401, 5.29750095, 5.39782959, 6.27465925, 4.7976689, 6.5291879, 3.90050452, 4.97788385, 4.177395, 5.56906896, 3.70738333, 4.65386128, 3.7464695, 4.14824489, 4.51757566, 4.43666482, 3.81562677, 4.51079308, 3.88368174, 3.86106089, 6.03815831, 4.06684654, 3.61120231, 3.92721958,
```

```
5.41459307, 3.81674754, 3.8164644 , 4.87630756, 4.3384424
4.73061212, 5.67852234, 4.72985685, 4.55603596, 3.92405506,
3.97830868, 3.61524614, 3.60008007, 3.75180924, 6.6971253,
5.83104316, 6.55932802, 5.68590963, 6.79684662, 5.13319146,
5.46668465, 5.12630187, 4.42514098, 4.78776279, 5.43738783,
6.85901268, 4.51079308, 4.74550129, 5.54649335, 6.16065682,
3.59461948, 5.81685712, 5.62216515, 3.83692923, 3.69687779,
4.82304888, 4.05667905, 3.58448767, 3.63528992, 4.66393196,
5.73889251, 3.72510798, 4.19389034, 4.09114426, 3.68533006,
5.19550969, 4.69196058, 3.87548034, 3.78295838, 6.10899617,
5.87228031, 3.8798717 , 3.98242027, 4.02749154, 4.69377462,
3.60319833, 3.44475546, 4.98805155, 4.77405897, 3.55552211,
3.53287027, 5.14635516, 4.75351337, 5.80816376, 3.86411723,
6.00914029, 4.75396939, 5.94496939, 5.20872152, 4.80636412,
3.92228059, 5.28507298, 3.70934417, 4.22319824, 4.98088433,
3.90198056, 6.32907061, 5.43646407, 5.12951664, 4.79871411,
6.27409071, 4.03847709, 3.90840519, 3.6871529 , 3.34742
4.41692165, 4.60211259, 3.81580456, 4.52230042, 4.88575474,
3.89672496, 6.3729031 , 4.73501902, 6.19658263, 3.90282362,
4.91823954, 3.87651855, 4.78010581, 5.66562563, 4.85313993,
4.7409428 , 6.85575175 , 3.76218288 , 5.34894889 , 4.0224938 ,
5.91012637, 3.79441941, 3.86867602, 4.20022974, 3.65578812,
5.08471643, 4.84400533, 3.6374376 , 4.42360726, 5.58996291,
3.90588293, 7.04906305, 6.14317544, 3.91354081, 4.92498657,
3.85815981, 3.63954782, 3.90824917, 6.28717498, 4.77613682,
6.09006275, 3.99257813, 5.45567049, 4.09419189, 4.14807601,
6.20877588, 5.21735984, 5.861678 , 5.5474441 , 3.96629375,
4.80034684, 3.63814892, 4.85275761, 4.74743157, 6.05887431,
3.81417697, 4.72764543, 4.05998048, 3.82717898, 5.14252653,
4.57021613, 6.81124042, 5.56809399, 5.89930521, 3.96756721,
5.41903066, 3.94129817, 6.21709314, 3.95006075, 4.03519643,
6.45992919, 6.2459964 , 4.14882513, 3.70811563, 5.49520864,
3.78314396, 6.81865121, 3.82582756, 3.77085697, 4.97857596,
4.97853531, 4.66506403, 6.90657299, 4.29380961, 5.12883364,
4.08346398, 6.52640756, 5.43542177, 4.72288735, 4.62812284,
4.07219149, 4.58267084, 6.019496 , 5.07218453, 6.31971191,
5.36374679, 3.6385272 , 4.48751974, 5.47408305, 3.81985096,
5.27556177, 5.3616683 , 4.80582684, 4.9217133 , 5.37640882,
3.38480937, 6.83221322, 4.9058687 , 4.18822673, 6.03647384,
6.60452465, 5.53483373, 6.74654199, 6.84858904, 4.61358551,
4.62007622, 3.85553402, 5.34257688, 4.78058369, 4.18192818,
5.54759001, 4.89337402, 3.75256894, 3.81306442, 4.90212683,
3.61204068, 6.6706726 , 3.86291923, 3.80406208, 7.03822381,
4.86761056, 4.93017755, 4.72288735, 4.67763742, 5.46411233,
3.91157347, 5.38491541, 4.25921808, 4.80077285, 5.11187913,
4.26302103, 6.20982069, 3.69384176, 3.7243979 , 4.03894484,
4.01525162, 4.67230338, 6.88642707, 3.9260423 , 5.34276246,
3.59895294, 4.0428277 , 3.89866803, 5.1286554 , 5.58614029,
5.60194323, 4.05787009, 5.31690733, 4.02591086, 5.68828458,
```

```
6.60612818, 5.02410545, 6.83606978, 5.08176092, 6.83226998,
       5.05603013, 3.77348732, 4.57250334, 3.83674248, 3.77821226,
       4.37529801, 4.08359094, 6.14366791, 6.02729905, 4.07613711,
                , 3.91257032, 4.99162091, 3.74984923, 4.89118298,
       4.707273
       3.53987846, 5.7623143 , 4.15816367, 5.50287224, 3.66553435,
       5.29063841, 3.64085282, 5.58614029, 5.05262274, 3.7419973
       3.87738943, 3.95771349, 5.2199185 , 3.82186852, 5.47315613,
       5.50550025, 4.70813192, 5.60232414, 3.73979037, 4.61600927,
       5.92755423, 5.04300382, 3.49088059, 4.96472934, 5.58864868,
       4.84828639, 3.78560675, 6.55790797, 4.60340474, 3.57485049,
       4.96645787, 6.28302371, 4.44606253, 5.23251427, 3.86933165,
       5.18453078, 5.12268573, 6.09150201, 3.553885 , 4.14082978,
       3.32906056, 4.36492319, 4.99472362, 5.87042867, 4.28820362,
       3.66818259, 3.98061781, 4.4853977 , 4.9444642 , 3.70739311,
       4.95821719, 4.6501794 , 3.87257097, 5.40416232, 3.77124548,
       4.00803117, 3.79257172, 5.88733168, 3.82607971, 3.75460604,
       7.47227245, 5.54705234, 5.49520864, 3.84176809, 6.78104942,
       6.7908776 , 5.90430697 , 4.99689697 , 3.71346863 , 5.98826607 ,
       4.95992187, 5.50755632, 6.00266836, 5.20991425, 5.99698667,
       4.67930774, 5.17977542, 4.64039337, 4.0808636 , 6.67752977,
       4.02087523, 3.96866858, 3.98846811, 6.02884356, 6.41287872,
       4.02548464, 4.02883501, 5.29993228, 5.63219382, 4.22952486,
       4.8762535 , 4.50401913 , 6.25162955 , 6.51924451 , 3.48206464 ,
       4.30923736, 6.16226474, 4.03257773, 6.31183543, 5.64000449,
       5.21392511, 5.46298792, 6.48811376, 3.64208819, 4.22048689,
       4.72176406, 3.86306898, 5.16189063, 5.03787134, 6.46214881,
       3.93439481, 5.26393663, 3.99831768, 5.1377641 , 3.695829
       4.40677869, 5.80576394, 5.42878736, 4.28022108, 3.89077479,
                                         , 5.4978573 , 3.70859059,
       5.64303116, 3.78560675, 5.784532
       4.72197402, 4.18020017, 5.58233651, 6.26057536, 3.27980893,
       6.00914029, 4.99253595, 4.0269963 , 5.76060322, 5.47315613,
       4.00724435, 3.63349804, 4.29890616, 5.05115735, 3.56334557,
       4.75403951, 4.12066649, 5.38719776, 3.91354081, 6.17216038,
       5.07218453, 4.53387021, 3.46440905, 4.18175253])
Y pred 1 train=LinReq.predict(X train)
Y pred 1 train
array([5.36140723, 4.88567986, 5.38440789, ..., 4.83099135,
5.80418812,
       4.2617047 ])
Quality=pd.DataFrame({'Actual quality:':Y test,'Predicted
quality':Y_pred_1})
Quality
      Actual quality: Predicted quality
188
                    5
                                5.027261
2083
                    3
                                4.093279
                    3
1675
                                3.792223
```

```
1089
                      7
                                   5.769745
                                   4.956214
1378
                      6
                                   6.172160
1580
                      6
1047
                      5
                                   5.072185
892
                      6
                                   4.533870
                      3
1674
                                   3.464409
8
                      7
                                   4.181753
[454 rows x 2 columns]
```

### Evaluation of Model-1

```
from sklearn import metrics

print("Testing Accuracy : ",metrics.r2_score(Y_test,Y_pred_1))
print("Training Accuracy : ",metrics.r2_score(Y_train,Y_pred_1_train))
print("Mean Squared Error :
   ",metrics.mean_squared_error(Y_test,Y_pred_1))
print("Root Mean Squared Error :
   ",np.sqrt(metrics.mean_squared_error(Y_test,Y_pred_1)))

Testing Accuracy : 0.5196342611962517
Training Accuracy : 0.530025681114703
Mean Squared Error : 0.9026562488758573
Root Mean Squared Error : 0.9500822326913904
```

### Testing Model-1 with random values

<pre>df.head()</pre>								
fixed a	cidity vo	latile ac:	idity (	citric	acid	residu	al su	ıgar
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	11 0		0.00		0 50			1 0
3	11.2		0.28		0.56			1.9
0.075 4	7.4		0.70		0.00			1.9
0.076	7.4		0.70		0.00			1.9
0.070								
free su	ılfur dioxi	de total	sulfur	dioxid	le dei	nsity	рΗ	sulphates
\						_	•	•
0	11	. 0		34.	0 0	. 9978	3.51	0.56
1	25	0		67	0 0	0000	2 20	0.60
1	25	. ⊍		67.	0 0	. 9968	3.20	0.68

```
2
                  15.0
                                         54.0
                                                0.9970 3.26
                                                                   0.65
                                                                   0.58
3
                  17.0
                                         60.0
                                                0.9980 3.16
                  11.0
                                         34.0
                                                0.9978 3.51
                                                                   0.56
   alcohol
            quality
0
       9.4
                  5
1
       9.8
                  5
2
       9.8
3
       9.8
                  6
                  5
       9.4
LinReg.predict([[7.2,0.54,0.02,1.14,0.074,7,31,0.9946,3.48,0.67,9.25]]
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439:
UserWarning: X does not have valid feature names, but LinearRegression
was fitted with feature names
 warnings.warn(
array([10.71390243])
LinReq.predict([[8.9,0.23,0.03,1.5,0.062,5,28,0.9918,3.14,0.51,9.44]])
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439:
UserWarning: X does not have valid feature names, but LinearRegression
was fitted with feature names
 warnings.warn(
array([9.86629743])
```

# Train - Test split for Model - 2

```
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test =
    train_test_split(X_scaled,Y_resampled,test_size=0.2,random_state=42)

X_train.shape, X_test.shape

((1816, 11), (454, 11))

Y_train.shape, Y_test.shape

((1816,), (454,))
```

### Model Training -2 (Logistic Regression)

```
from sklearn.linear model import LogisticRegression
LogReg=LogisticRegression(multi class='ovr')
LogReg.fit(X train,Y train)
LogisticRegression(multi class='ovr')
Y pred 2=LogReg.predict(X test)
Y pred 2
array([5, 3, 3, 6, 5, 5, 6, 5, 6, 3, 6, 3, 3, 6, 3, 3, 6, 6, 6, 6, 6,
6,
       3, 5, 3, 6, 3, 5, 3, 3, 5, 5, 3, 6, 3, 3, 6, 3, 3, 6, 3, 3,
5,
       3, 6, 5, 5, 5, 3, 3, 3, 3, 5, 5, 6, 6, 6, 5, 6, 6, 5, 6, 6,
6,
       6, 5, 6, 6, 3, 7, 6, 3, 3, 5, 3, 3, 5, 6, 3, 3, 3, 6, 5,
3,
       3, 6, 6, 3, 3, 3, 5, 3, 3, 5, 6, 3, 5, 5, 6, 3, 6, 5, 5, 6,
5,
       3, 6, 3, 3, 6, 3, 6, 6, 5, 6, 6, 3, 3, 3, 3, 3, 5, 3, 5, 3,
7,
       5, 6, 3, 5, 3, 5, 3, 5, 6, 3, 6, 4, 5, 3, 3, 5, 6, 3, 3,
5,
       6, 3, 6, 6, 3, 6, 3, 3, 6, 5, 5, 3, 5, 5, 3, 6, 5, 5, 5,
5,
      3, 5, 3, 6, 3, 5, 3, 3, 6, 3, 6, 6, 6, 6, 3, 6, 3, 6, 3, 6, 6,
3,
       3, 6, 3, 6, 5, 3, 5, 6, 5, 7, 3, 6, 3, 6, 5, 6, 3, 5, 5, 5, 6,
6,
       6, 3, 5, 6, 3, 5, 5, 3, 6, 6, 3, 7, 3, 5, 6, 6, 5, 6, 6, 6, 5,
3,
       5, 5, 5, 5, 5, 3, 3, 5, 3, 6, 3, 3, 6, 5, 5, 6, 5, 5, 3, 6, 3,
5,
       5, 3, 6, 3, 3, 5, 3, 6, 3, 6, 3, 3, 6, 6, 6, 6, 3, 6, 6,
6,
       5, 6, 5, 6, 5, 3, 5, 3, 3, 5, 3, 5, 6, 3, 5, 5, 5, 3, 6, 3, 6,
3,
       6, 3, 5, 3, 6, 5, 3, 3, 5, 5, 3, 6, 5, 5, 5, 3, 6, 6, 5, 3, 6,
5,
       6, 3, 6, 3, 3, 6, 6, 5, 5, 3, 5, 6, 6, 3, 5, 3, 5, 6, 5, 5, 3,
3,
       5, 5, 3, 5, 5, 3, 5, 3, 3, 5, 3, 3, 7, 5, 6, 3, 7, 6, 5, 5,
3,
       6, 5, 6, 5, 5, 6, 3, 6, 6, 3, 6, 3, 3, 3, 6, 6, 3, 3, 5, 5, 3,
5,
       3, 7, 6, 3, 5, 6, 5, 6, 5, 5, 5, 6, 3, 5, 5, 3, 5, 5, 6, 3, 5,
```

```
3,
       6, 3, 5, 6, 6, 5, 3, 5, 3, 5, 5, 5, 6, 6, 3, 6, 5, 3, 6,
6,
       3, 3, 5, 6, 3, 5, 3, 6, 3, 6, 6, 3, 3, 3])
Y pred 2 train=LogReg.predict(X train)
Y pred 2 train
array([5, 3, 6, ..., 6, 6, 5])
Quality 2=pd.DataFrame({'Actual quality:':Y test,'Predicted
quality :Y_pred_2})
Quality 2
      Actual quality: Predicted quality
188
                                        3
                    3
2083
                    3
                                        3
1675
                    7
                                        6
1089
1378
                    6
                                        5
1580
                    6
                                        6
                    5
                                        6
1047
                                        3
                    6
892
1674
                    3
                                        3
                                        3
8
[454 rows x 2 columns]
```

#### Evaluation of Model-2

```
from sklearn.metrics import accuracy score, confusion matrix,
classification report
print("Testing Accuracy : ",accuracy_score(Y_test,Y_pred_2))
print("Training Accuracy : ",accuracy_score(Y_train,Y_pred_2_train))
Testing Accuracy: 0.6453744493392071
Training Accuracy: 0.6618942731277533
confusion_matrix(Y_test,Y_pred_2)
array([[136,
               0,
                    0,
                          0,
                               0,
                                    0],
               0,
                    4,
                          3,
                                    0],
       [ 1,
                               0,
        27,
                   83,
                         29,
                                    0],
               1,
                               1,
                               3,
                   44,
                         71,
                                    0],
       [ 12,
               0,
               0,
                    3,
                         27,
          1,
                               3,
                                    0],
          0,
               0,
                    0,
                        5,
                               0,
                                    011)
pd.crosstab(Y test,Y pred 2)
```

```
col 0
           3 4
                  5
                      6 7
quality
3
         136
              0
                  0
                      0
                         0
4
                  4
                      3
                         0
           1
              0
5
                    29
          27
             1
                 83
                         1
6
          12
             0
                 44
                     71
                         3
7
                  3
                         3
           1
              0
                     27
8
           0
              0
                  0
                      5
                         0
print(classification_report(Y_test,Y_pred_2))
              precision
                            recall f1-score
                                               support
           3
                   0.77
                              1.00
                                        0.87
                                                   136
           4
                   0.00
                              0.00
                                        0.00
                                                     8
           5
                              0.59
                   0.62
                                        0.60
                                                   141
           6
                   0.53
                              0.55
                                        0.54
                                                   130
           7
                   0.43
                              0.09
                                        0.15
                                                    34
           8
                   0.00
                              0.00
                                        0.00
                                                     5
                                        0.65
                                                   454
    accuracy
   macro avg
                   0.39
                              0.37
                                        0.36
                                                   454
                              0.65
                                        0.61
weighted avg
                   0.61
                                                   454
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
classification.py:1344: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero division` parameter to control this behavior.
  warn prf(average, modifier, msg start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/ classificatio
n.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
zero division` parameter to control this behavior.
  warn prf(average, modifier, msg start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/ classificatio
n.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
zero division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

### Testing Model-2 with random values

```
LogReg.predict([[8.7,0.5,0.03,1.1,0.08,9,31,0.9998,3.87,0.48,9.83]])

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439:
UserWarning: X does not have valid feature names, but
LogisticRegression was fitted with feature names
warnings.warn(
```

```
array([4])
LogReg.predict([[7.2,0.6,0.05,2.8,0.066,12,23,0.9774,3.29,0.29,9.47]])
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439:
UserWarning: X does not have valid feature names, but
LogisticRegression was fitted with feature names
  warnings.warn(
array([8])
```

### Train - Test split for Model-3

```
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test =
    train_test_split(X_resampled,Y_resampled,test_size=0.2,random_state=30)

X_train.shape, X_test.shape

((1816, 11), (454, 11))

Y_train.shape, Y_test.shape

((1816,), (454,))
```

### Model Training - 3 (Random Forest Classifier)

```
from sklearn.ensemble import RandomForestClassifier
RanFor = RandomForestClassifier(criterion='entropy')
RanFor.fit(X train,Y train)
RandomForestClassifier(criterion='entropy')
Y pred 3 = RanFor.predict(X test)
Y pred 3
array([5, 3, 6, 6, 3, 5, 3, 6, 5, 5, 5, 6, 3, 6, 6, 3, 3, 6, 5, 5, 5,
5,
       5, 6, 5, 6, 7, 3, 6, 5, 7, 7, 5, 5, 3, 5, 5, 6, 3, 3, 7, 3, 6,
3,
       7, 5, 6, 6, 7, 3, 3, 6, 6, 3, 3, 5, 3, 5, 5, 6, 3, 5, 6, 5,
6,
       5, 3, 6, 5, 3, 7, 3, 6, 5, 6, 5, 3, 6, 5, 3, 3, 6, 6, 6, 6, 3,
5,
       6, 6, 3, 3, 5, 5, 3, 3, 6, 6, 7, 5, 3, 3, 5, 5, 5, 5, 3, 6, 3, 6,
6,
       5, 6, 3, 3, 6, 8, 3, 6, 7, 3, 6, 3, 6, 6, 6, 5, 3, 5, 6, 5, 5,
3,
```

```
3, 6, 5, 3, 7, 3, 6, 3, 5, 5, 5, 7, 6, 5, 5, 6, 3, 3, 3, 6, 3,
3,
       3, 5, 6, 7, 5, 3, 6, 5, 5, 3, 5, 5, 6, 6, 3, 6, 3, 3, 5, 6, 3,
6,
       7, 5, 3, 6, 3, 5, 5, 3, 3, 7, 5, 6, 3, 6, 5, 5, 5, 5, 5, 3, 6,
3,
       6, 3, 3, 6, 5, 3, 5, 5, 6, 3, 3, 5, 6, 3, 6, 5, 3, 5, 6, 3, 5,
6,
       5, 5, 5, 3, 6, 6, 5, 5, 6, 5, 5, 5, 5, 6, 5, 5, 3, 3, 5, 5, 5,
6,
       3, 6, 3, 3, 5, 6, 6, 5, 3, 5, 7, 3, 6, 5, 3, 5, 6, 3, 3, 5, 3,
3,
       5, 6, 6, 5, 5, 7, 5, 6, 3, 6, 3, 3, 5, 3, 5, 3, 5, 3, 7, 6, 5,
3,
       5, 5, 6, 6, 5, 6, 6, 5, 6, 3, 3, 5, 3, 5, 6, 3, 5, 5, 5, 7,
3,
       3, 3, 3, 6, 6, 3, 6, 5, 3, 3, 5, 5, 6, 5, 5, 6, 6, 3, 3, 3,
6,
       3, 3, 6, 5, 5, 7, 3, 3, 6, 3, 6, 5, 3, 6, 3, 3, 6, 5, 6, 5, 5,
5,
       6, 6, 7, 6, 5, 5, 6, 3, 3, 5, 3, 6, 3, 5, 3, 3, 3, 3, 3, 6,
6,
       3, 6, 6, 6, 5, 5, 3, 6, 5, 6, 3, 3, 6, 6, 7, 7, 6, 5, 6, 3, 6,
5,
       3, 3, 7, 3, 6, 6, 7, 3, 5, 3, 5, 5, 6, 5, 5, 6, 6, 5, 5, 5, 3,
3,
       7, 5, 7, 6, 3, 5, 5, 3, 5, 3, 5, 3, 5, 5, 6, 5, 3, 3, 3,
3,
       3, 5, 3, 7, 3, 5, 6, 3, 3, 3, 6, 5, 5, 6])
Y pred 3 train = RanFor.predict(X train)
Y pred 3 train
array([5, 5, 3, ..., 6, 7, 3])
```

### Evaluation for Model-3

```
print("Testing Accuracy = ", accuracy_score(Y_test,Y_pred_3))
print("Training Accuracy = ",accuracy_score(Y_train,Y_pred_3_train))
Testing Accuracy = 0.801762114537445
Training Accuracy = 1.0
pd.crosstab(Y_test,Y_pred_3)
col 0
           3
quality
         151
                1
                     0
                         0
                            0
4
           2
                6
                     7
                         0
                            0
5
           1
              106
                    23
                         1
                            0
```

```
6
               29
                   90
                        7
7
           0
                3
                           1
                    6
                      17
8
           0
                0
                    1
                         2
                            0
print(classification report(Y test,Y pred 3))
              precision
                            recall f1-score
                                                support
           3
                   0.98
                              0.99
                                        0.99
                                                    152
           4
                   0.00
                              0.00
                                        0.00
                                                     15
           5
                   0.73
                              0.81
                                        0.77
                                                    131
           6
                   0.71
                              0.71
                                        0.71
                                                    126
           7
                   0.63
                              0.63
                                        0.63
                                                     27
           8
                                                      3
                   0.00
                              0.00
                                        0.00
                                        0.80
                                                    454
    accuracy
                   0.51
                              0.52
                                        0.52
                                                    454
   macro avg
                   0.77
                                        0.79
weighted avg
                              0.80
                                                    454
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
classification.py:1344: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/ classificatio
n.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero division` parameter to control this behavior.
  warn prf(average, modifier, msg start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/ classificatio
n.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero division` parameter to control this behavior.
  warn prf(average, modifier, msg start, len(result))
print(confusion matrix(Y test,Y pred 3))
[[151
        0
            1
                    0
                         0]
                7
                         01
    2
        0
            6
                    0
        0 106
               23
                    1
                         0]
    1
          29
               90
                    7
                         01
        0
    0
        0
            3
                6
                   17
                         1]
    0
        0
            0
                1
                    2
                         0]]
```

### Testing Model-3 with random values

```
RanFor.predict([[7.6,0.81,0.34,2.5,0.052,14,26,0.9936,3.45,0.59,10.23])
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439:
UserWarning: X does not have valid feature names, but
RandomForestClassifier was fitted with feature names
  warnings.warn(
array([6])
RanFor.predict([[6.5,0.75,0.29,1.3,0.074,21,29,0.9946,3.28,0.62,9.19]])
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439:
UserWarning: X does not have valid feature names, but
RandomForestClassifier was fitted with feature names
  warnings.warn(
array([3])
```