

1.Download the dataset 2.Load the dataset

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

```
data=pd.read_csv("abalone.csv",encoding='ISO-8859-1')
data.head()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7	8.5

```
data.describe()
```

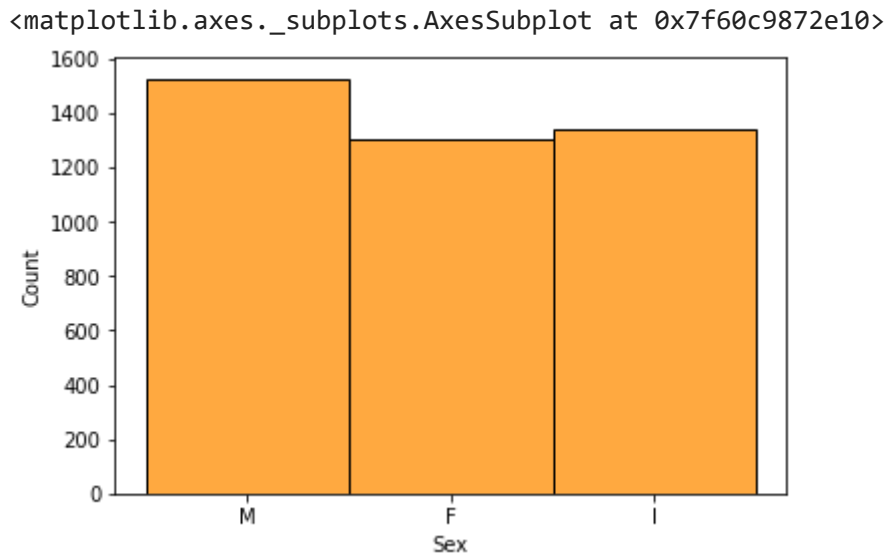
	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000

```
data.dtypes
```

```
Sex           object
Length        float64
Diameter      float64
Height        float64
Whole weight  float64
Shucked weight float64
Viscera weight float64
Shell weight  float64
Rings         int64
Age           float64
dtype: object
```

3.Perform Below Visualizations Univariate Analysis ,Bi - Variate Analysis,Multi - Variate Analysis

```
#univariate analysis "Histogram"
sns.histplot(data["Sex"],color='darkorange')
```



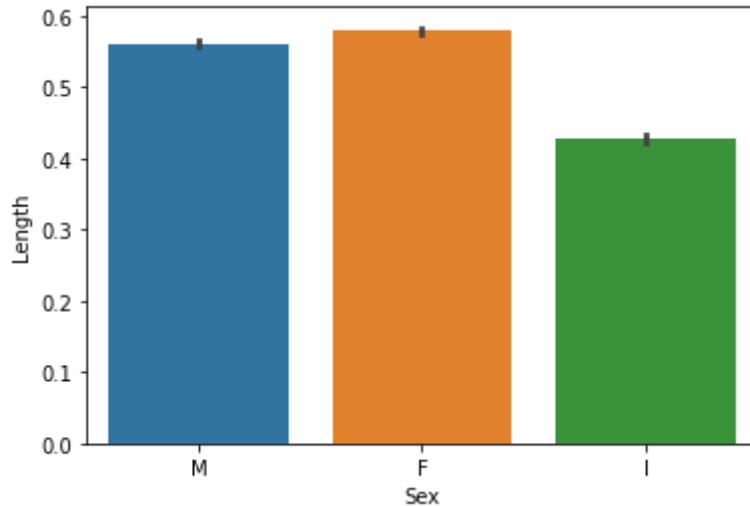
```
#univariate analysis "Countplot"
sns.countplot(data['Sex'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f60c8d39c50>
```



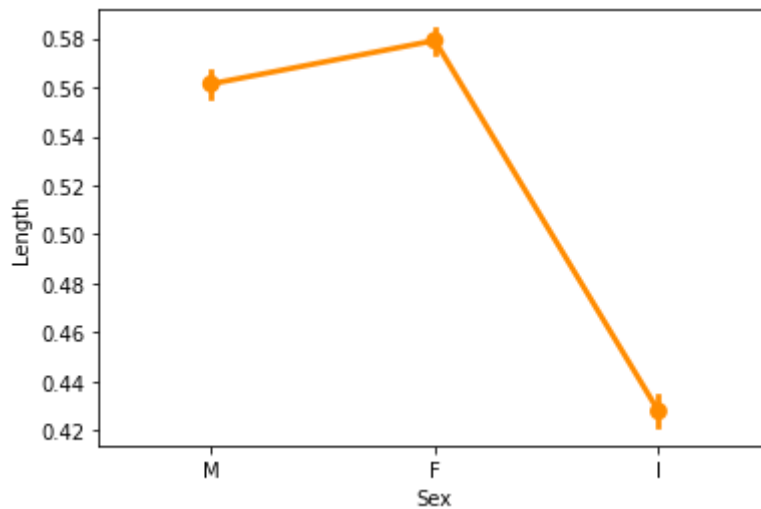
```
#bivariate analysis"Barplot"
sns.barplot(x='Sex',y='Length',data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f60c886f190>
```



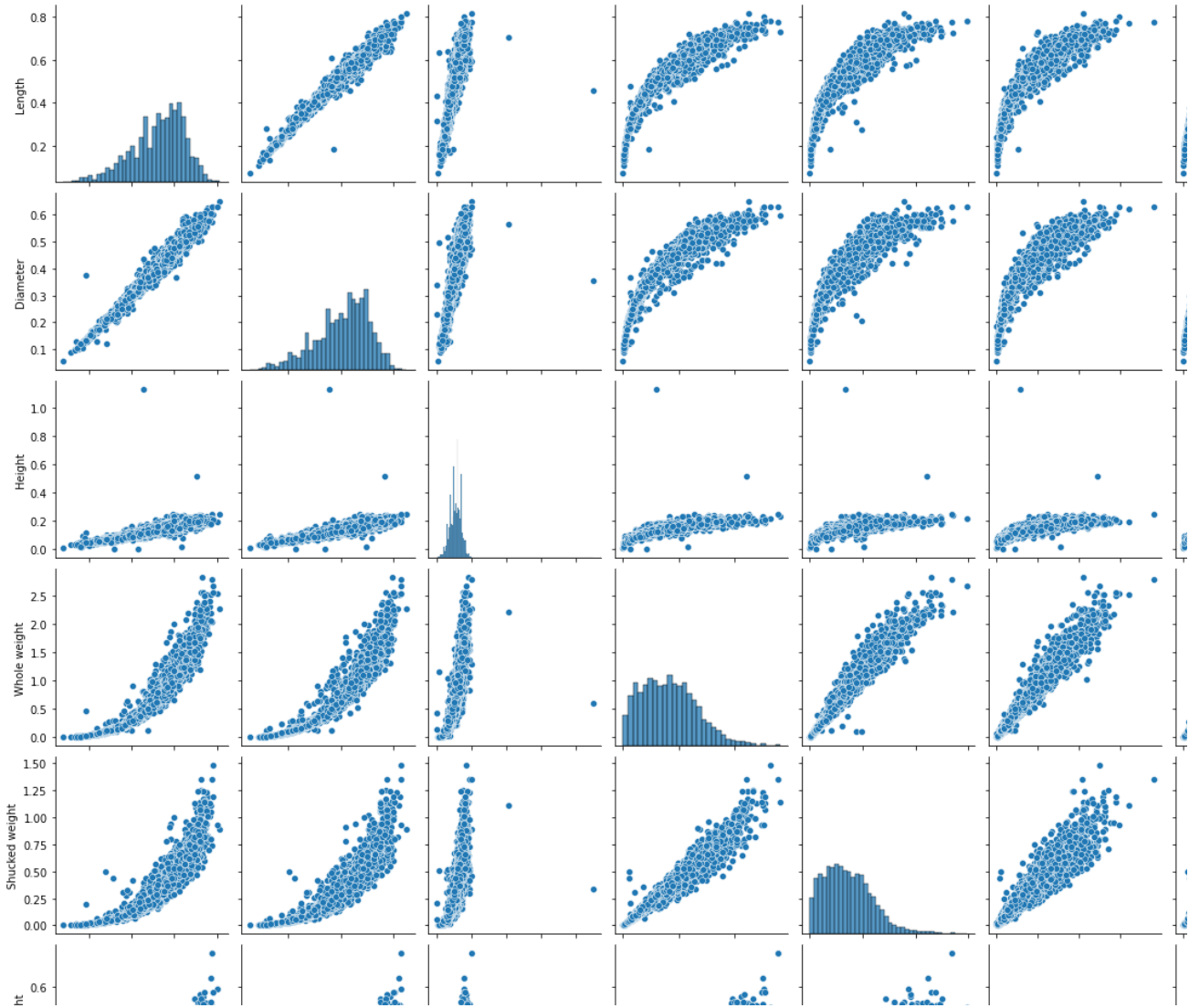
```
#bivariate analysis"Pointplot"
sns.pointplot(x='Sex',y='Length',data=data,color='darkorange')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f60c880f7d0>
```



```
#Multivariate analysis"Pairplot"
sns.pairplot(data)
```

<seaborn.axisgrid.PairGrid at 0x7f60c875f590>



4. Perform descriptive statistics on the dataset.



Descriptive statistics of the data set accessed.
data.describe().T

	count	mean	std	min	25%	50%	75%	max
Length	4177.0	0.523992	0.120093	0.0750	0.4500	0.5450	0.615	0.8150
Diameter	4177.0	0.407881	0.099240	0.0550	0.3500	0.4250	0.480	0.6500
Height	4177.0	0.139516	0.041827	0.0000	0.1150	0.1400	0.165	1.1300
Whole weight	4177.0	0.828742	0.490389	0.0020	0.4415	0.7995	1.153	2.8255
Shucked weight	4177.0	0.359367	0.221963	0.0010	0.1860	0.3360	0.502	1.4880
Viscera weight	4177.0	0.180594	0.109614	0.0005	0.0935	0.1710	0.253	0.7600
Shell weight	4177.0	0.238831	0.139203	0.0015	0.1300	0.2340	0.329	1.0050
Rings	4177.0	9.933684	3.224169	1.0000	8.0000	9.0000	11.000	29.0000
Age	4177.0	11.433684	3.224169	2.5000	9.5000	10.5000	12.500	30.5000

```
data.isnull().any().any()
```

```
False
```

```
data.isnull().any()
```

```
Sex           False
Length        False
Diameter      False
Height        False
Whole weight  False
Shucked weight False
Viscera weight False
Shell weight  False
Rings         False
Age           False
dtype: bool
```

```
df2=data.dropna(how='all')
```

5.Handle the Missing values

```
df2.isnull().sum().sum()
```

```
0
```

This dataset does not contain any missing value

```
missing_values=data.isnull().sum()
missing_values[missing_values>0]/len(data)*100
```

```
Series([], dtype: float64)
```

6.Find the outliers and replace the outliers

```
sns.boxplot(data['Age'],data=data)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f60c3a83bd0>
```



```
for x in ['Age']:
    q75,q25 = np.percentile(data.loc[:,x],[75,25])
    intr_qr = q75-q25
```

```
max = q75+(1.5*intr_qr)
min = q25-(1.5*intr_qr)
```

```
data.loc[data[x] < min,x] = np.nan
data.loc[data[x] > max,x] = np.nan
```

Age

```
data.isnull().sum()
```

```
Sex          0
Length       0
Diameter     0
Height       0
Whole weight 0
Shucked weight
Viscera weight
Shell weight 0
Rings        0
Age          278
dtype: int64
```

7.Check for Categorical columns and perform encoding.

```
df2.Sex.value_counts()
```

```
M    1528
I    1342
F    1307
Name: Sex, dtype: int64
```

```
from sklearn.preprocessing import LabelEncoder
```

```
le= LabelEncoder()
```

```
df2.Sex = le.fit_transform(df2.Sex)
df2.head()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings	Age
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15	16.5
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7	8.5
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9	10.5

```
df2.describe()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
mean	1.052909	0.523992	0.407881	0.139516	0.828742	0.359367
std	0.822240	0.120093	0.099240	0.041827	0.490389	0.221963
min	0.000000	0.075000	0.055000	0.000000	0.002000	0.001000
25%	0.000000	0.450000	0.350000	0.115000	0.441500	0.186000
50%	1.000000	0.545000	0.425000	0.140000	0.799500	0.336000
75%	2.000000	0.615000	0.480000	0.165000	1.153000	0.502000

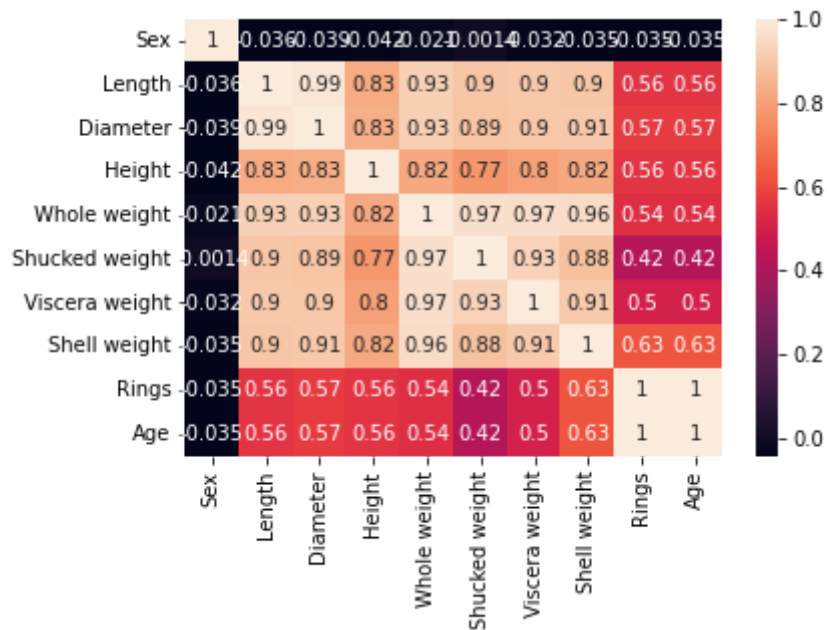
```
df2.corr()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight
Sex	1.000000	-0.036066	-0.038874	-0.042077	-0.021391	-0.001373	-0.032067	-0.032067
Length	-0.036066	1.000000	0.986812	0.827554	0.925261	0.897914	0.903018	0.897914
Diameter	-0.038874	0.986812	1.000000	0.833684	0.925452	0.893162	0.899724	0.893162
Height	-0.042077	0.827554	0.833684	1.000000	0.819221	0.774972	0.798319	0.819221
Whole weight	-0.021391	0.925261	0.925452	0.819221	1.000000	0.969405	0.966375	0.969405
Shucked weight	-0.001373	0.897914	0.893162	0.774972	0.969405	1.000000	0.931961	0.897914
Viscera weight	-0.032067	0.903018	0.899724	0.798319	0.966375	0.931961	1.000000	0.903018
Shell weight	-0.032067	0.897914	0.893162	0.819221	0.969405	0.897914	0.903018	1.000000

```
import seaborn as sns
```

```
sns.heatmap(df2.corr(),annot = True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f60c3c17450>
```



```
df2.head()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings	Age
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15	16.5
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7	8.5
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9	10.5
3	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10	11.5
4	1	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7	8.5

```
X = df2.drop(columns = ['Rings'], axis = 1)
X.head()
```


	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Age
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5

```
y = df2.Rings
y.head()
```

```
0    15
1     7
2     9
3    10
4     7
Name: Rings, dtype: int64
```

```
from sklearn.preprocessing import MinMaxScaler
```

```
scale = MinMaxScaler()
```

```
x_scaled = pd.DataFrame(scale.fit_transform(X), columns = X.columns)
```

```
x_scaled.head()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Age
0	1.0	0.513514	0.521008	0.084071	0.181335	0.150303	0.132324	0.147982	0.500000
1	1.0	0.371622	0.352941	0.079646	0.079157	0.066241	0.063199	0.068261	0.214286
2	0.0	0.614865	0.613445	0.119469	0.239065	0.171822	0.185648	0.207773	0.285714
3	1.0	0.493243	0.521008	0.110619	0.182044	0.144250	0.149440	0.152965	0.321429
4	0.5	0.344595	0.336134	0.070796	0.071897	0.059516	0.051350	0.053313	0.214286

10. Split the data into training and testing

```
# train test split
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x_scaled,y,test_size=0.2,random_state = 1)
x_test.shape

(836, 9)
```

11. Build the Model,12. Train the Model

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
```

```
model.fit(x_train,y_train)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: ConvergenceWarning:
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
LogisticRegression()
```

```
test_pred= model.predict(x_test)
test_pred
```

```
array([ 9,  9,  7,  9, 13,  6,  9,  9, 11,  8, 10,  6,  9, 10,  7,  9, 11,
        11, 10,  9,  9, 11,  7, 11,  9,  9, 11, 13, 10, 10, 10,  9,  9,  8,
         7,  7, 10, 11,  9, 10,  9, 11, 11, 10,  8,  8, 10,  9, 10,  9, 10,
         9, 10,  6, 11,  9,  9,  7,  8,  7,  8,  9, 11,  9,  8,  8, 10, 10,
         9,  8,  9,  9,  7,  9,  8,  7, 11, 10,  9,  9,  8,  8,  9,  8, 11,
         8, 11,  7, 11,  9, 10,  8,  8,  9,  7,  9,  9, 10,  6, 13,  8, 10,
         7,  8, 11,  8, 13,  9, 11,  9,  7, 10,  9,  7,  7, 10,  8,  7, 10,
         9,  9,  7,  7, 10,  8,  9, 10, 10,  8,  9,  8,  7,  8,  8, 10,  7,
        11, 11,  8,  9,  7,  9,  9, 11,  8,  9, 10, 11,  9,  9, 10,  7,  9,
        10,  9,  9, 10, 10,  9, 11,  9, 10, 10,  6,  8,  7, 11,  9,  9, 13,
         7, 11, 11,  8,  8, 10, 11, 11,  7,  8,  9,  9,  9,  7,  7, 10, 12,
         9, 10, 11,  6,  8,  6, 11,  8, 11,  8,  5,  7,  9,  5,  8, 11,  9,
         8,  8,  8,  8,  9,  7, 10,  8,  9,  8,  8,  8, 10,  9, 10,  8, 13,
         8, 10, 10,  8, 11,  9, 11, 10,  9,  9,  9, 10, 10,  8,  6, 10, 10,
        10,  9, 11,  9,  9,  9,  7,  9, 10,  7,  8, 10,  9, 11, 11, 11,  6,
        12, 10, 13,  7, 10, 10, 11,  8,  9,  8,  9, 11,  9,  9, 11,  9, 12,
        11,  9, 11, 13,  7,  9, 10, 11,  9,  8, 10,  7,  7,  8,  6,  7,  7,
         9,  8,  8, 10,  9,  8, 10,  7,  9, 11,  9, 11,  8,  8,  9, 11,  9,
        13,  8,  8,  9,  8, 10,  9,  7,  7, 13, 11, 11,  9,  5,  9, 11, 10,
         9, 13, 10,  8, 10,  9, 11, 10,  8, 10,  7,  8,  9,  9,  5, 11, 11,
         7,  7, 11, 11,  9, 13, 13,  9, 11,  9,  9,  6, 11,  8,  6,  9,  8,
        10, 11,  9,  9,  6, 10,  8,  8, 10,  6,  8, 11,  7,  9, 10, 10, 10,
         9,  9,  8, 11,  8,  6, 11,  7,  7, 13, 11,  7,  8, 11,  8,  9,  7,
        10, 10,  8,  9,  7, 10, 10, 11, 11,  8,  7,  9, 10, 11,  7, 10, 13,
         9, 11,  9, 10,  9,  9, 12,  7,  9,  9,  8,  8,  8,  9, 11,  8, 13,
         5,  6, 10,  9,  9, 10,  8, 11,  8,  8, 10, 12,  8,  8,  9, 11,  8,
         8,  9, 10,  8, 10, 11,  8,  8, 11,  9,  5,  7,  8, 11,  9,  8, 11,
```

```

10, 10, 7, 9, 11, 9, 11, 10, 12, 10, 9, 10, 9, 6, 8, 9, 9,
8, 11, 11, 5, 7, 7, 10, 10, 7, 8, 7, 9, 9, 10, 8, 9, 8,
7, 6, 7, 7, 10, 9, 8, 11, 6, 9, 8, 11, 11, 9, 9, 10, 11,
9, 9, 13, 7, 6, 8, 7, 11, 9, 8, 8, 11, 9, 10, 8, 11, 9,
5, 10, 13, 11, 10, 9, 11, 10, 11, 13, 11, 7, 7, 11, 11, 9, 9,
7, 10, 8, 9, 9, 10, 9, 11, 9, 11, 10, 10, 8, 10, 8, 8, 9,
8, 8, 9, 8, 10, 13, 10, 11, 8, 10, 7, 9, 9, 11, 10, 8, 11,
8, 10, 9, 9, 10, 5, 13, 11, 8, 9, 5, 11, 8, 13, 8, 9, 8,
6, 9, 10, 5, 9, 9, 8, 10, 10, 8, 10, 11, 10, 11, 11, 9, 9,
9, 7, 11, 7, 7, 9, 9, 8, 9, 11, 7, 9, 11, 10, 8, 9, 8,
7, 7, 9, 9, 10, 9, 7, 10, 7, 8, 9, 9, 6, 10, 8, 8, 10,
7, 11, 8, 7, 13, 9, 11, 10, 8, 13, 8, 9, 11, 7, 9, 9, 8,
9, 9, 9, 9, 7, 6, 6, 9, 11, 6, 7, 10, 11, 8, 9, 8, 13,
7, 9, 9, 8, 7, 7, 10, 7, 8, 10, 9, 11, 10, 11, 9, 9, 7,
8, 9, 6, 10, 8, 7, 11, 10, 10, 10, 11, 7, 7, 7, 9, 8, 11,
10, 10, 8, 13, 9, 8, 9, 12, 10, 9, 11, 11, 11, 9, 13, 8, 9,
11, 9, 8, 9, 10, 13, 9, 11, 8, 9, 8, 11, 9, 11, 10, 9, 10,
7, 8, 7, 10, 9, 7, 10, 8, 7, 7, 9, 6, 7, 7, 8, 9, 9,
7, 9, 8, 8, 11, 9, 7, 9, 10, 10, 8, 7, 8, 8, 8, 11, 10,
10, 9, 10, 11, 11, 11, 8, 10, 9, 10, 11, 10, 8, 11, 10, 6, 7,
9, 10, 10, 10, 13, 8, 7, 9, 10, 10, 9, 7, 8, 10, 6, 9, 9,
9, 8, 7, 9, 11, 11, 7, 10, 11, 6, 9, 9, 8, 7, 10, 9, 11,
9, 10, 9])

```

y_test

```

17      10
1131     8
299     9
1338    10
2383    16
...
1787     8
3075    11
2766     8
1410    10
2529     8

```

Name: Rings, Length: 836, dtype: int64

```

train_pred = model.predict(x_train)
train_pred

```

```

array([9, 6, 8, ..., 7, 9, 6])

```

13. Test the Model

```

# testing on a random value

```

14. Measure the performance using Metrics.

```

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_curve

```

```
accuracy_score(y_test,test_pred)
```

```
0.2631578947368421
```

```
accuracy_score(y_train,train_pred)
```

```
0.30859024244238253
```

```
confusion_matrix(y_test,test_pred)
```

```
array([[ 0,  0,  0,  1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  2,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  4,  6,  1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  3, 11,  6,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  1,  8, 28, 16,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  4, 25, 43,  8,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0, 17, 44, 45,  1,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0, 10, 35, 70, 16,  1,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  1, 10, 10, 65, 48,  9,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  1,  5, 22, 41, 22,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  5,  2,  8, 28, 20,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  2,  0,  0, 12, 25,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  4, 20,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0, 17,  0,  4,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  6,  1,  3,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  5,  2,  5,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  6,  1,  3,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  6,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  3,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  2,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  2,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0]])
```

```
pd.crosstab(y_test,test_pred)
```

col_0 5 6 7 8 9 10 11 12 13

Rings

2	1	0	0	0	0	0	0	0	0
3	2	0	0	0	0	0	0	0	0
4	4	6	1	0	0	0	0	0	0
5	3	11	6	0	0	0	0	0	0
6	1	8	28	16	0	0	0	0	0
7	0	4	25	43	8	0	0	0	0
8	0	0	17	44	45	1	0	0	0
9	0	0	10	35	70	16	1	0	0
10	0	1	10	10	65	48	9	0	0
11	0	0	1	5	22	41	22	0	0
12	0	0	5	2	8	28	20	0	0
13	0	0	2	0	0	12	25	0	0
14	0	0	0	0	0	4	20	0	0
15	0	0	0	0	0	0	17	0	4
16	0	0	0	0	0	0	6	1	3
17	0	0	0	0	0	0	5	2	5
18	0	0	0	0	0	0	6	1	3
19	0	0	0	0	0	0	0	1	6
20	0	0	0	0	0	0	0	1	3
21	0	0	0	0	0	0	0	1	2
22	0	0	0	0	0	0	0	0	1
23	0	0	0	0	0	0	0	0	2

```
print(classification_report(y_test,test_pred))
```

	precision	recall	f1-score	support
2	0.00	0.00	0.00	1
3	0.00	0.00	0.00	2
4	0.00	0.00	0.00	11
5	0.27	0.15	0.19	20
6	0.27	0.15	0.19	53
7	0.24	0.31	0.27	80
8	0.28	0.41	0.34	107
9	0.32	0.53	0.40	132
10	0.32	0.34	0.33	143
11	0.17	0.24	0.20	91
12	0.00	0.00	0.00	63

13	0.00	0.00	0.00	39
14	0.00	0.00	0.00	24
15	0.00	0.00	0.00	21
16	0.00	0.00	0.00	10
17	0.00	0.00	0.00	12
18	0.00	0.00	0.00	10
19	0.00	0.00	0.00	7
20	0.00	0.00	0.00	4
21	0.00	0.00	0.00	3
22	0.00	0.00	0.00	1
23	0.00	0.00	0.00	2
accuracy				0.26 836
macro avg	0.09	0.10	0.09	836
weighted avg	0.21	0.26	0.23	836

```

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Undefined
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Undefined
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Undefined
_warn_prf(average, modifier, msg_start, len(result))

```

8.Split the data into dependent and independent variables

```
from sklearn.datasets import load_iris
```

```
from sklearn import preprocessing
data = load_iris()
```

```

# separate the independent and dependent variables
X_data = data.data
target = data.target
print("Dependent variable")
print(X_data)
print("Independent variable")
print(target)

```

```

Dependent variable
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]
 [5.4 3.7 1.5 0.2]
 [4.8 3.4 1.6 0.2]
 [4.8 3.  1.4 0.1]
 [4.3 3.  1.1 0.1]
 [5.8 4.  1.2 0.2]

```

```
[5.7 4.4 1.5 0.4]
[5.4 3.9 1.3 0.4]
[5.1 3.5 1.4 0.3]
[5.7 3.8 1.7 0.3]
[5.1 3.8 1.5 0.3]
[5.4 3.4 1.7 0.2]
[5.1 3.7 1.5 0.4]
[4.6 3.6 1. 0.2]
[5.1 3.3 1.7 0.5]
[4.8 3.4 1.9 0.2]
[5. 3. 1.6 0.2]
[5. 3.4 1.6 0.4]
[5.2 3.5 1.5 0.2]
[5.2 3.4 1.4 0.2]
[4.7 3.2 1.6 0.2]
[4.8 3.1 1.6 0.2]
[5.4 3.4 1.5 0.4]
[5.2 4.1 1.5 0.1]
[5.5 4.2 1.4 0.2]
[4.9 3.1 1.5 0.2]
[5. 3.2 1.2 0.2]
[5.5 3.5 1.3 0.2]
[4.9 3.6 1.4 0.1]
[4.4 3. 1.3 0.2]
[5.1 3.4 1.5 0.2]
[5. 3.5 1.3 0.3]
[4.5 2.3 1.3 0.3]
[4.4 3.2 1.3 0.2]
[5. 3.5 1.6 0.6]
[5.1 3.8 1.9 0.4]
[4.8 3. 1.4 0.3]
[5.1 3.8 1.6 0.2]
[4.6 3.2 1.4 0.2]
[5.3 3.7 1.5 0.2]
[5. 3.3 1.4 0.2]
[7. 3.2 4.7 1.4]
[6.4 3.2 4.5 1.5]
[6.9 3.1 4.9 1.5]
[5.5 2.3 4. 1.3]
[6.5 2.8 4.6 1.5]
[5.7 2.8 4.5 1.3]
```

9. Scale the independent variable

```
# scale of independent variables
standard = preprocessing.scale(target)
print(standard)
```

```
[-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 0. 0. 0. 0.
0. 0. 0. 0. 0. 0.]
```

0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487
1.22474487	1.22474487	1.22474487	1.22474487	1.22474487	1.22474487]

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