

EXCEL COLLEGE OF ENGINEERING(AUTONOMOUS)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING. WEB
PHISHING DETECTION (ASSIGNMENT 3)

DATE : 06-11-2022

PROBLEM : TO PERFORM ABALONE AGE PREDICTION

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OUTPUT :

SCREENSHOTS:

1.Download the dataset

2. Load the dataset into the tool

```
In [1]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

```
In [2]: data=pd.read_csv("abalone.csv")
data.head()
```

```
Out[2]:
```

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

We have to add the "Age" column using "Rings" data. We just have to add '1.5' to the ring data

```
In [3]: Age=1.5*data.Rings
data["Age"]=Age
data=data.rename(columns = {'Whole weight':'Whole_weight','Shucked weight': 'Shucked_weight','Viscera weight': 'Viscera_weight',
                             'Shell weight': 'Shell_weight'})
data=data.drop(columns=["Rings"],axis=1)
data.head()
```

```
Out[3]:
```

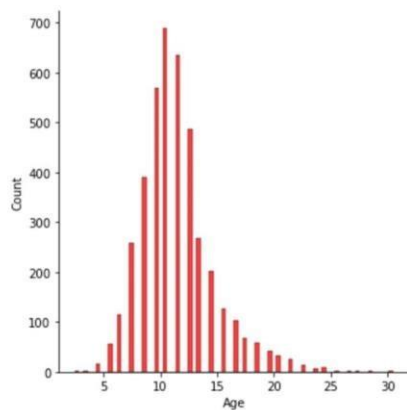
	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

3. Perform Below Visualizations

Univariate Analysis

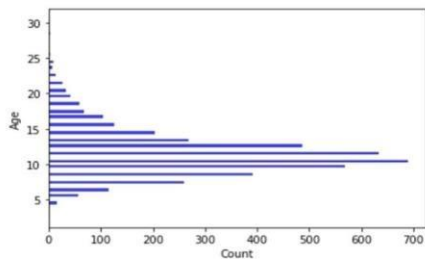
```
In [7]: sns.displot(data["Age"], color='red')
```

```
Out[7]: <seaborn.axisgrid.FacetGrid at 0x204e94d81f0>
```



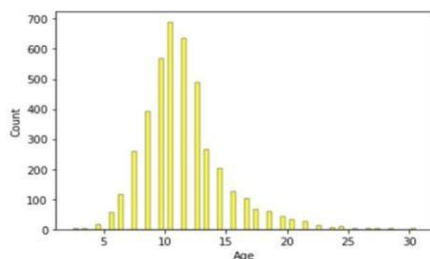
```
In [8]: sns.histplot(y=data.Age,color='blue')
```

```
Out[8]: <AxesSubplot:xlabel='Count', ylabel='Age'>
```



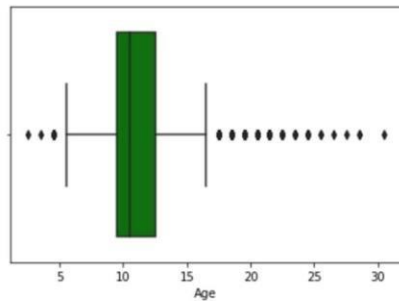
```
In [9]: sns.histplot(x=data.Age,color='yellow')
```

```
Out[9]: <AxesSubplot:xlabel='Age', ylabel='Count'>
```



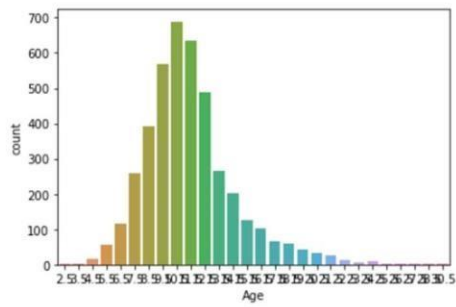
```
In [10]: sns.boxplot(x=data.Age,color='green')
```

```
Out[10]: <AxesSubplot:xlabel='Age'>
```



```
In [11]: sns.countplot(x=data.Age)
```

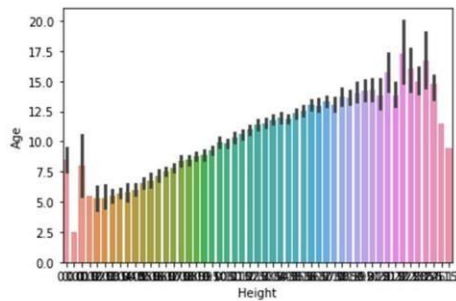
```
Out[11]: <AxesSubplot:xlabel='Age', ylabel='count'>
```



Bi-Variate Analysis

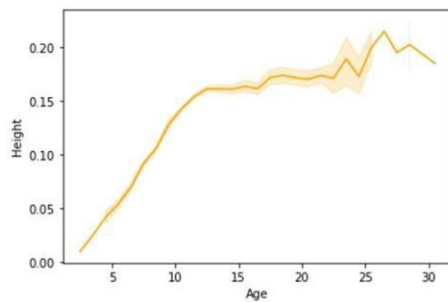
```
In [12]: sns.barplot(x=data.Height,y=data.Age)
```

```
Out[12]: <AxesSubplot:xlabel='Height', ylabel='Age'>
```



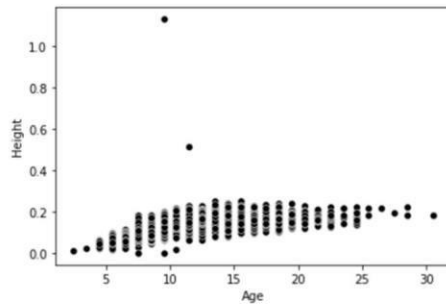
```
In [13]: sns.lineplot(x=data.Age,y=data.Height, color='orange')
```

```
Out[13]: <AxesSubplot:xlabel='Age', ylabel='Height'>
```



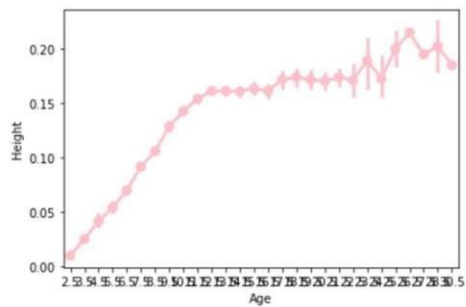
```
In [14]: sns.scatterplot(x=data.Age,y=data.Height,color='black')
```

```
Out[14]: <AxesSubplot:xlabel='Age', ylabel='Height'>
```



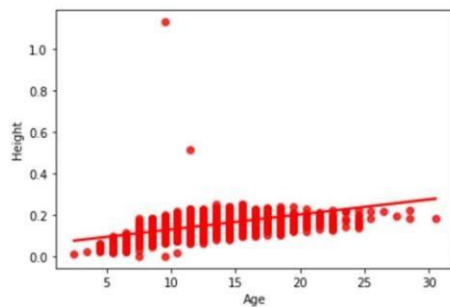
```
In [15]: sns.pointplot(x=data.Age, y=data.Height, color="pink")
```

```
Out[15]: <AxesSubplot:xlabel='Age', ylabel='Height'>
```



```
In [16]: sns.regplot(x=data.Age,y=data.Height,color='red')
```

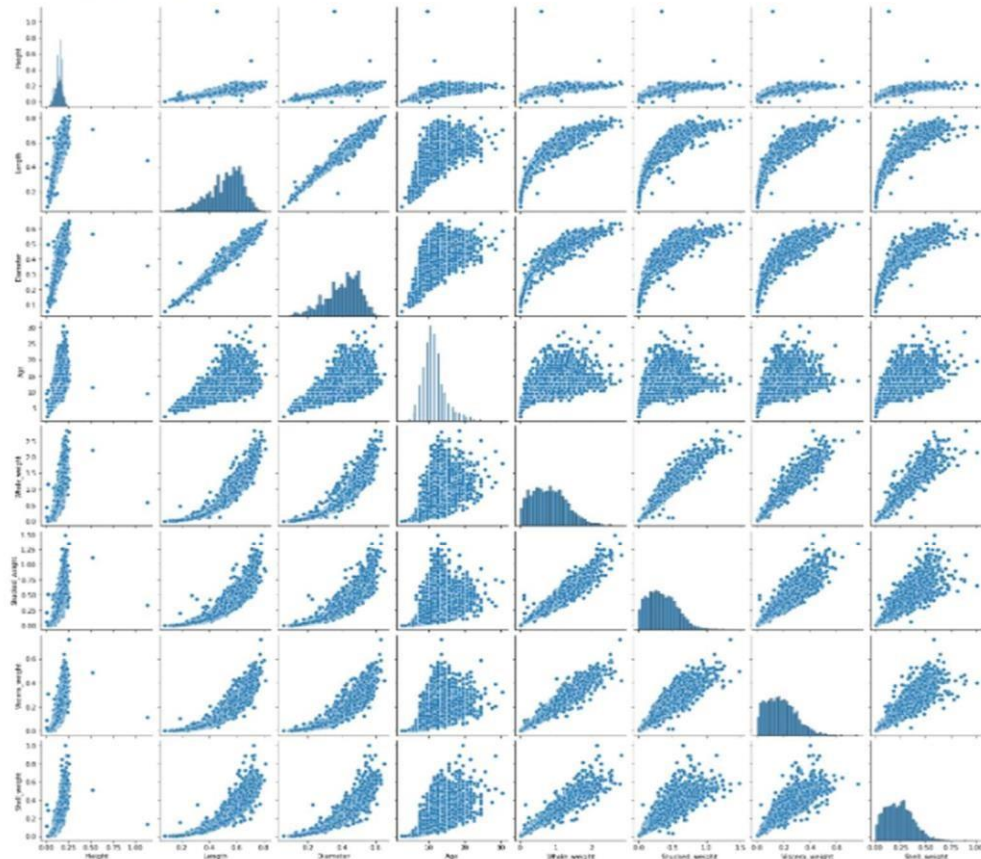
```
Out[16]: <AxesSubplot:xlabel='Age', ylabel='Height'>
```



Multi-Variate Analysis

```
In [17]: sns.pairplot(data=data[["Height", "Length", "Diameter", "Age", "Whole_weight", "Shucked_weight", "Viscera_weight", "Shell_weight"]])
```

```
Out[17]: <seaborn.axisgrid.PairGrid at 0x204eae550>
```



4. Perform descriptive statistics on the dataset

```
In [18]: data.describe(include='all')
```

```
Out[18]:
```

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
count	4177	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
unique	3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	M	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	1528	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	0.523992	0.407881	0.139516	0.826742	0.359367	0.180594	0.238831	11.433684
std	NaN	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
min	NaN	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	2.500000
25%	NaN	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	9.500000
50%	NaN	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	10.500000
75%	NaN	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	12.500000
max	NaN	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	30.500000

5. Check for Missing values and deal with them ¶

```
In [19]: data.isnull().sum()
```

```
Out[19]: Sex                0
Length                0
Diameter              0
Height               0
Whole_weight         0
Shucked_weight       0
Viscera_weight       0
Shell_weight         0
Age                  0
dtype: int64
```

6. Find the outliers and replace them outliers

```
In [20]: outliers=data.quantile(q=(0.25,0.75))
outliers
```

```
Out[20]:
```

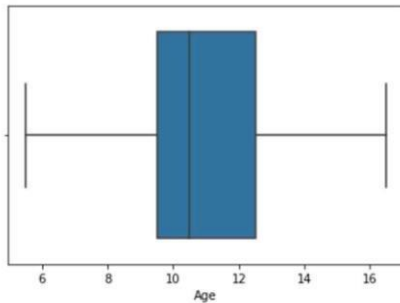
	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0.25	0.450	0.35	0.115	0.4415	0.186	0.0935	0.130	9.5
0.75	0.615	0.48	0.165	1.1530	0.502	0.2530	0.329	12.5

```
In [21]: a = data.Age.quantile(0.25)
b = data.Age.quantile(0.75)
c = b - a
lower_limit = a - 1.5 * c
data.median(numeric_only=True)
```

```
Out[21]: Length      0.5450
Diameter    0.4250
Height      0.1400
Whole_weight 0.7995
Shucked_weight 0.3360
Viscera_weight 0.1710
Shell_weight 0.2340
Age         10.5000
dtype: float64
```

```
In [22]: data['Age'] = np.where(data['Age'] < lower_limit, 7, data['Age'])
sns.boxplot(x=data.Age,showfliers = False)
```

```
Out[22]: <AxesSubplot:xlabel='Age'>
```



7. Check for Categorical columns and perform encoding

```
In [23]: data.head()
```

```
Out[23]:
```

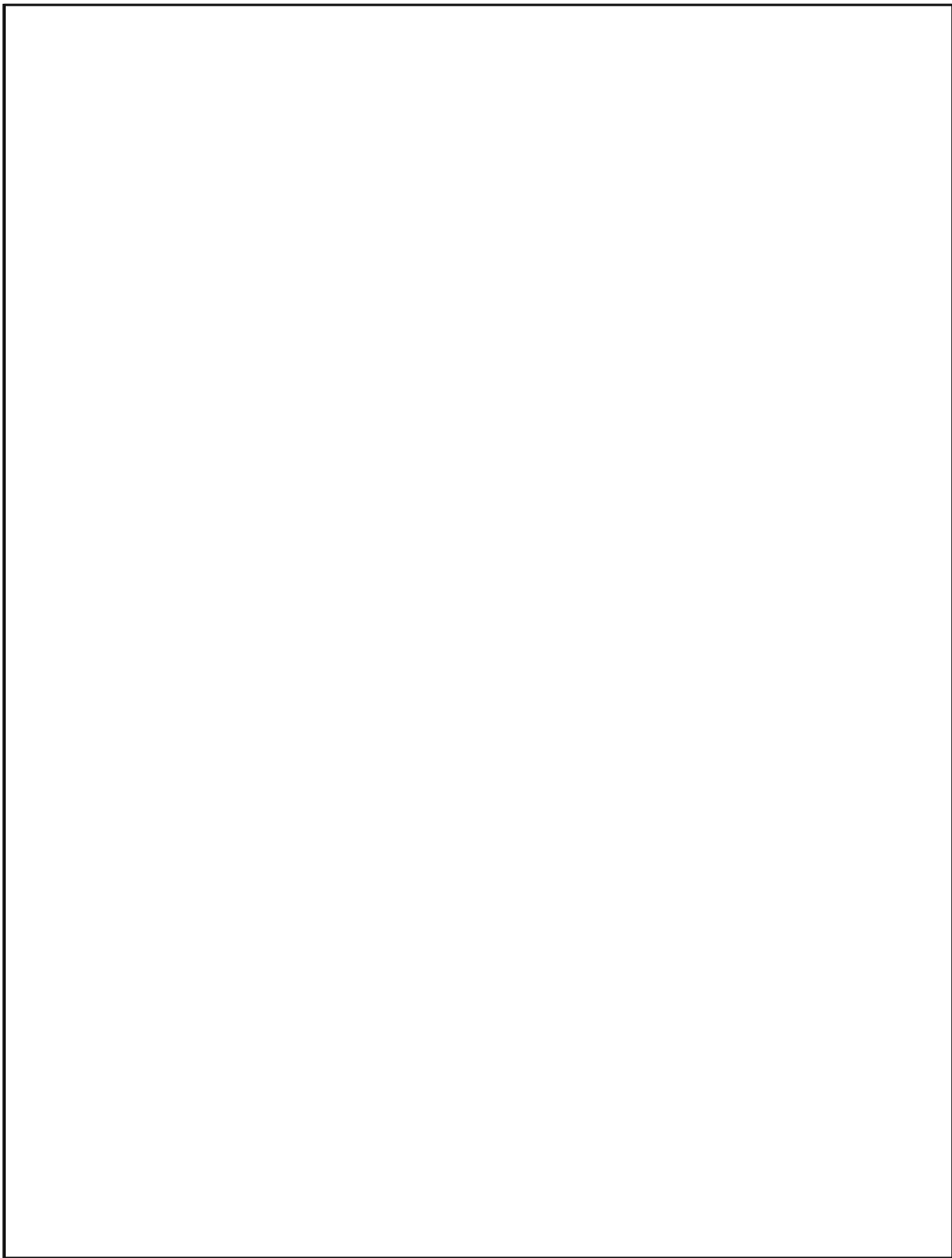
	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

```
In [24]: from sklearn.preprocessing import LabelEncoder
```

```
lab = LabelEncoder()
data.Sex = lab.fit_transform(data.Sex)
data.head()
```

```
Out[24]:
```

	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
4	1	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5



8. Split the data into dependent and independent variables

```
In [25]: y = data["Sex"]
y.head()
```

```
Out[25]: 0    2
         1    2
         2    0
         3    2
         4    1
         Name: Sex, dtype: int32
```

```
In [26]: x=data.drop(columns=["Sex"],axis=1)
x.head()
```

```
Out[26]:
```

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

9. Scale the independent variables

```
In [27]: from sklearn.preprocessing import scale
X_Scaled = pd.DataFrame(scale(x), columns=x.columns)
X_Scaled.head()
```

```
Out[27]:
```

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	-0.574558	-0.432149	-1.064424	-0.641898	-0.607685	-0.726212	-0.638217	1.577830
1	-1.448986	-1.439929	-1.183978	-1.230277	-1.170910	-1.205221	-1.212987	-0.919022
2	0.050033	0.122130	-0.107991	-0.309469	-0.463500	-0.356690	-0.207139	-0.294809
3	-0.699476	-0.432149	-0.347099	-0.637819	-0.648238	-0.607600	-0.602294	0.017298
4	-1.615544	-1.540707	-1.423087	-1.272086	-1.215968	-1.287337	-1.320757	-0.919022

10. Split the data into training and testing

```
In [28]: 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=0)
```

```
In [29]: X_Train.shape,X_Test.shape
```

```
Out[29]: ((3341, 8), (836, 8))
```

```
In [30]: Y_Train.shape,Y_Test.shape
```

```
Out[30]: ((3341,), (836,))
```

```
In [31]: X_Train.head()
```

```
Out[31]:
```

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
3141	-2.864726	-2.750043	-1.423087	-1.622870	-1.553902	-1.583867	-1.644065	-1.543234
3521	-2.573250	-2.598876	-2.020857	-1.606554	-1.551650	-1.565619	-1.626104	-1.387181
883	1.132658	1.230689	0.728888	1.145672	1.041436	0.286552	1.538726	1.577830
3627	1.590691	1.180300	1.446213	2.164373	2.661269	2.330326	1.377072	0.017298
2106	0.591345	0.474853	0.370226	0.432887	0.255175	0.272866	0.906479	1.265723

```
In [32]: X_Test.head()
```

```
Out[32]:
```

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
668	0.216591	0.172519	0.370226	0.181016	-0.368878	0.569396	0.690940	0.953617
1580	-0.199803	-0.079426	-0.466653	-0.433875	-0.443224	-0.343004	-0.325685	-0.606915
3784	0.799543	0.726798	0.370226	0.870348	0.755318	1.764639	0.565209	0.329404
463	-2.531611	-2.447709	-2.020857	-1.579022	-1.522362	-1.538247	-1.572219	-1.543234
2615	1.007740	0.928354	0.848442	1.390405	1.415417	1.778325	0.996287	0.641511

```
In [33]: Y_Train.head()
```

```
Out[33]: 3141    1
         3521    1
         883     2
         3627    2
         2106    2
         Name: Sex, dtype: int32
```



```
In [34]: Y_Test.head()
Out[34]: 668      2
         1580     1
         3784     2
         463      1
         2615     2
         Name: Sex, dtype: int32
```

11. Build the Model

```
In [35]: from sklearn.ensemble import RandomForestClassifier
         model = RandomForestClassifier(n_estimators=10,criterion='entropy')

In [36]: model.fit(X_Train,Y_Train)
Out[36]: RandomForestClassifier(criterion='entropy', n_estimators=10)

In [37]: y_predict = model.predict(X_Test)

In [38]: y_predict_train = model.predict(X_Train)
```

12. Train the Model

```
In [39]: from sklearn.metrics import accuracy_score,confusion_matrix,classification_report

In [40]: print('Training accuracy: ',accuracy_score(Y_Train,y_predict_train))
Training accuracy:  0.980544747081712
```

13. Test the Model

```
In [41]: print('Testing accuracy: ',accuracy_score(Y_Test,y_predict))
Testing accuracy:  0.5526315789473685
```

14. Measure the performance using Metrics

```
In [42]: pd.crosstab(Y_Test,y_predict)
```

```
Out[42]: col_0  0   1   2
         Sex
         ---
0  115   24  110
1   41  225   25
2  118   56  122
```

```
In [43]: print(classification_report(Y_Test,y_predict))
```

	precision	recall	f1-score	support
0	0.42	0.46	0.44	249
1	0.74	0.77	0.76	291
2	0.47	0.41	0.44	296
accuracy			0.55	836
macro avg	0.54	0.55	0.55	836
weighted avg	0.55	0.55	0.55	836

*****THANKING
YOU*****

