Assignment 3 : IBM-Project-9130-1658982501

Problem Statement: Abalone Age Prediction

Description :

Predicting the age of abalone from physical measurements. The age of abalone is determined by cutting the shell through the cone, staining it, and counting the number of rings through a microscope -- a boring and time-consuming task. Other measurements, which are easier to obtain, are used to predict age. Further information, such as weather patterns and location (hence food availability) may be required to solve the problem.

Importing Modules

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

1. Dataset has been downloaded

```
from google.colab import files


uploaded = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving abalone.csv to abalone.csv
```

2. Load the dataset into the tool

```
data=pd.read_csv("abalone.csv")
data.head()
```

```
  Sex  Length  Diameter  Height  Whole weight  Shucked weight  Viscera 
weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245  
0.1010   
1   M   0.350     0.265   0.090        0.2255          0.0995  
0.0485   
2   F   0.530     0.420   0.135        0.6770          0.2565  
0.1415   
3   M   0.440     0.365   0.125        0.5160          0.2155  
0.1140   
4   I   0.330     0.255   0.080        0.2050          0.0895  
0.0395   

   Shell weight  Rings  
0         0.150     15  
```

```
1          0.070      7
2          0.210      9
3          0.155     10
4          0.055      7
```

Let's know the shape of the data

```
data.shape
```

```
(4177, 9)
```

One additional task is that, we have to add the "Age" column using "Rings" data. We just have to add '1.5' to the ring data

```
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()
```

```
  Sex  Length  Diameter  Height  Whole_weight  Shucked_weight
Viscera_weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245
0.1010
1   M   0.350     0.265   0.090        0.2255          0.0995
0.0485
2   F   0.530     0.420   0.135        0.6770          0.2565
0.1415
3   M   0.440     0.365   0.125        0.5160          0.2155
0.1140
4   I   0.330     0.255   0.080        0.2050          0.0895
0.0395

   Shell_weight   Age
0         0.150  16.5
1         0.070   8.5
2         0.210  10.5
3         0.155  11.5
4         0.055   8.5
```

3. Perform Below Visualizations.

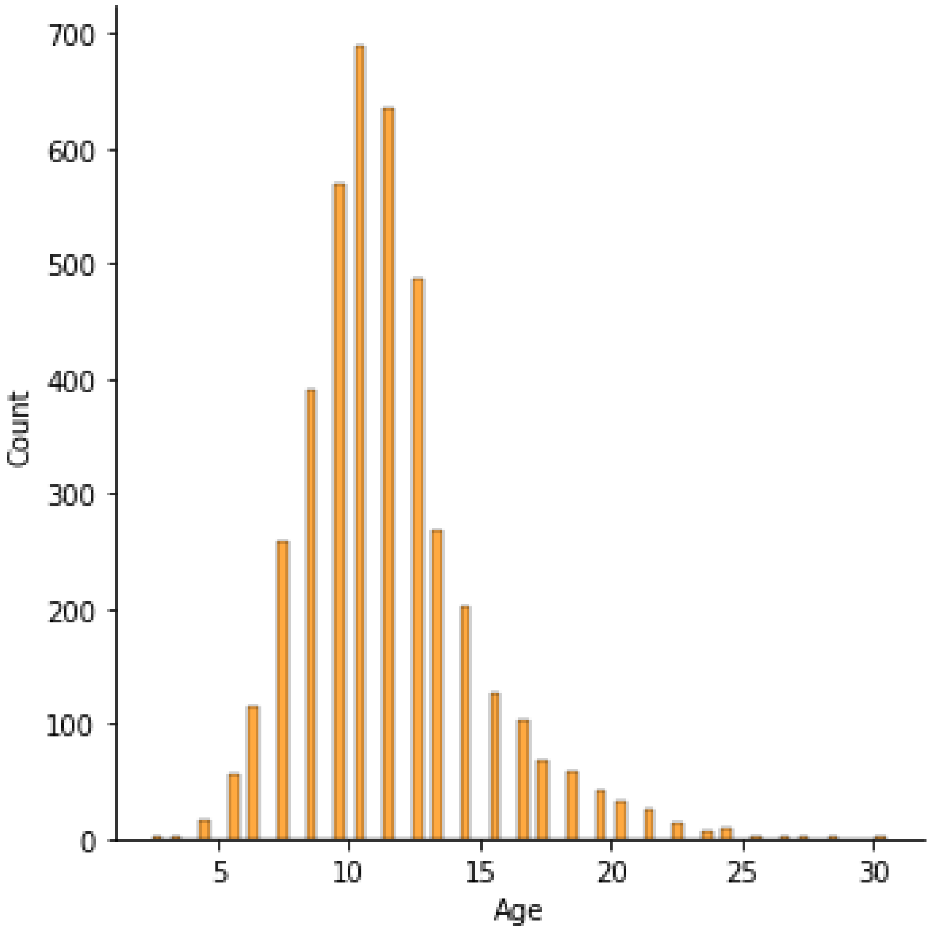
(i) Univariate Analysis

The term univariate analysis refers to the analysis of one variable. You can remember this because the prefix “uni” means “one.” There are three common ways to perform univariate analysis on one variable: 1. Summary statistics – Measures the center and spread of values.

Histogram

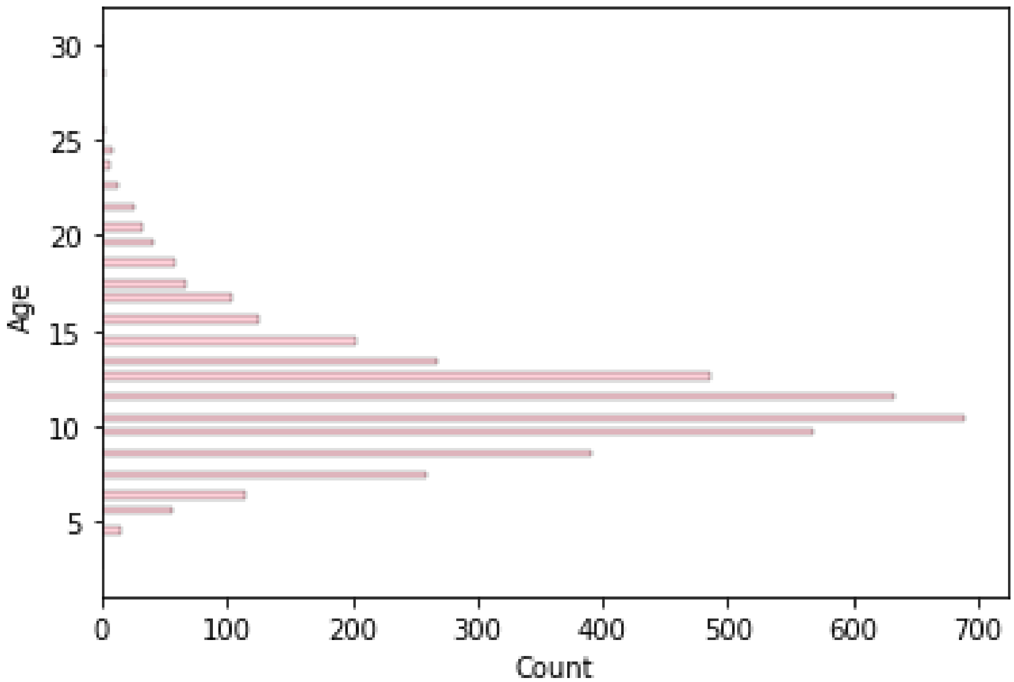
```
sns.displot(data["Age"], color='darkorange')
```

```
<seaborn.axisgrid.FacetGrid at 0x7f0fd4a65f10>
```



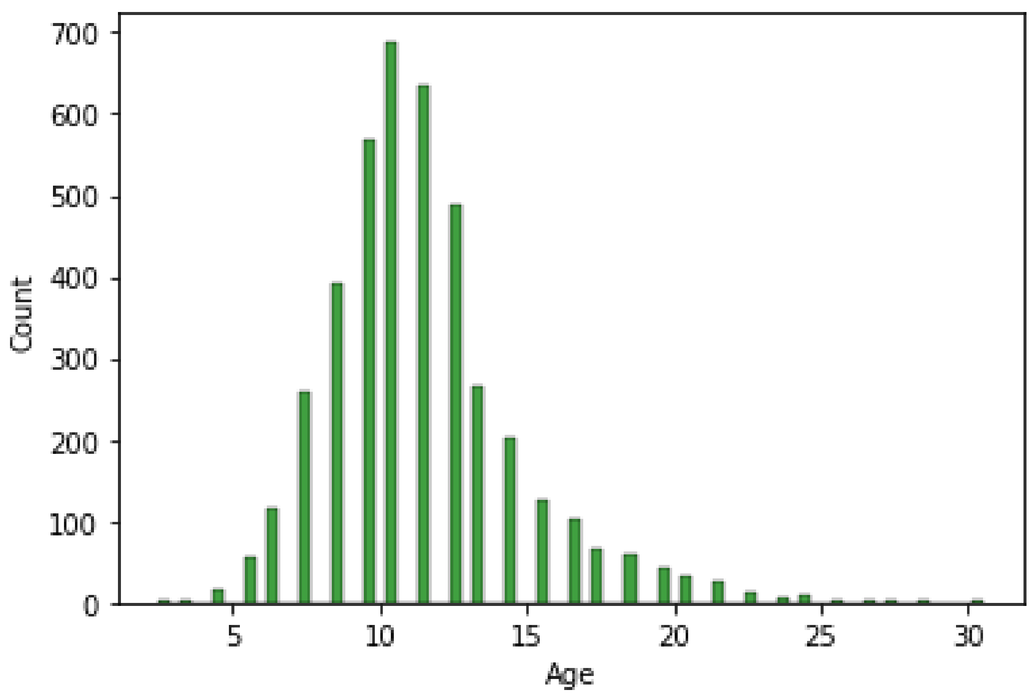

```
sns.histplot(y=data.Age,color='pink')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fc838ac10>
```




```
sns.histplot(x=data.Age,color='green')
```

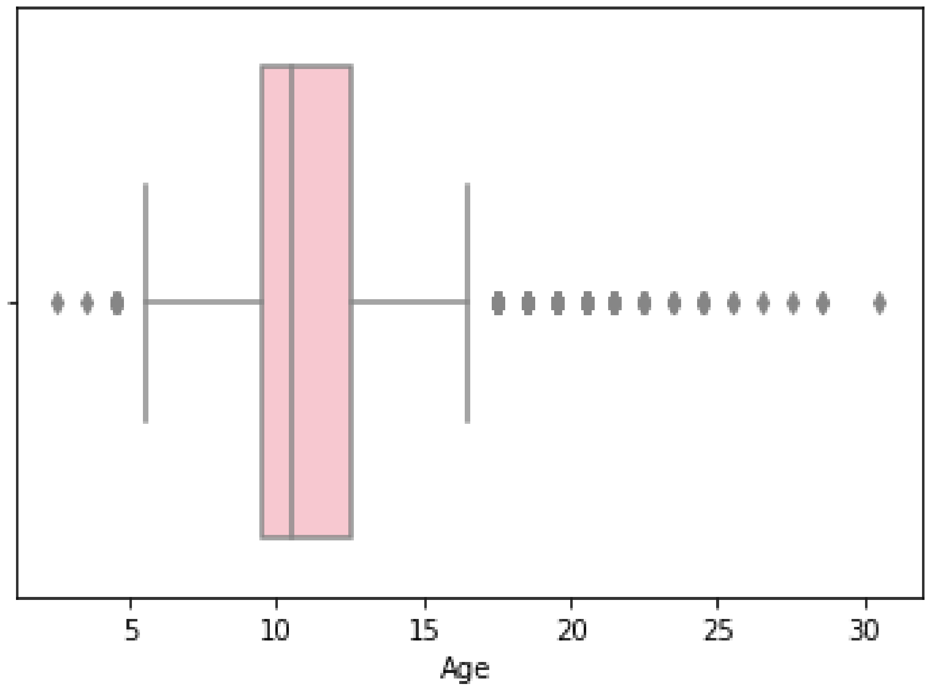
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fc539b090>
```



Boxplot

```
sns.boxplot(x=data.Age,color='pink')
```

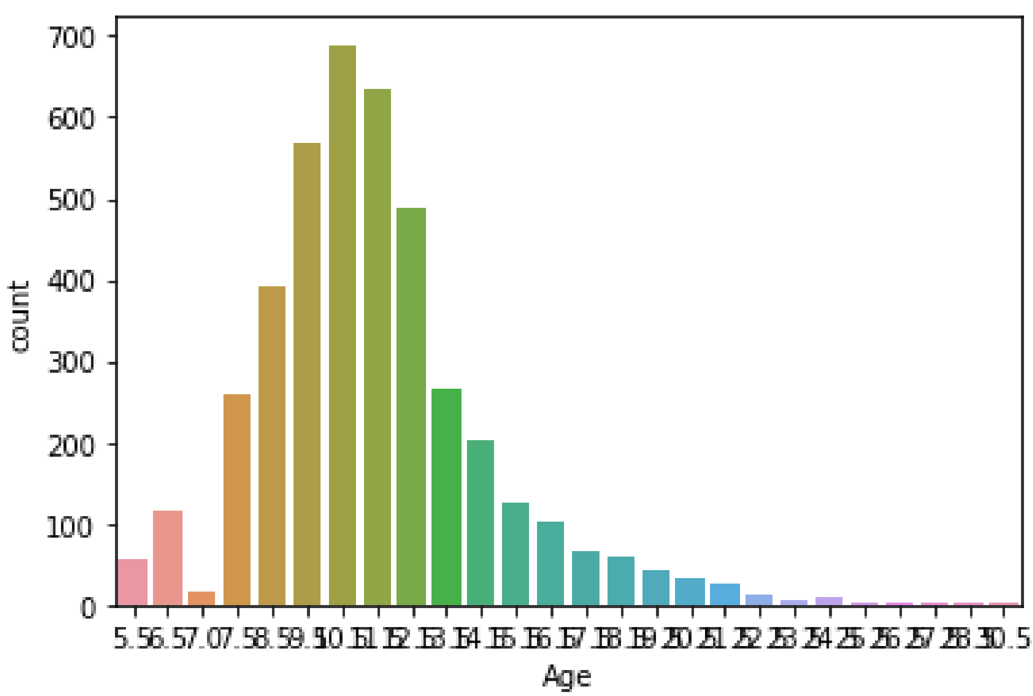
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fc515fe10>
```



Countplot

```
sns.countplot(x=data.Age)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fbf258d90>
```



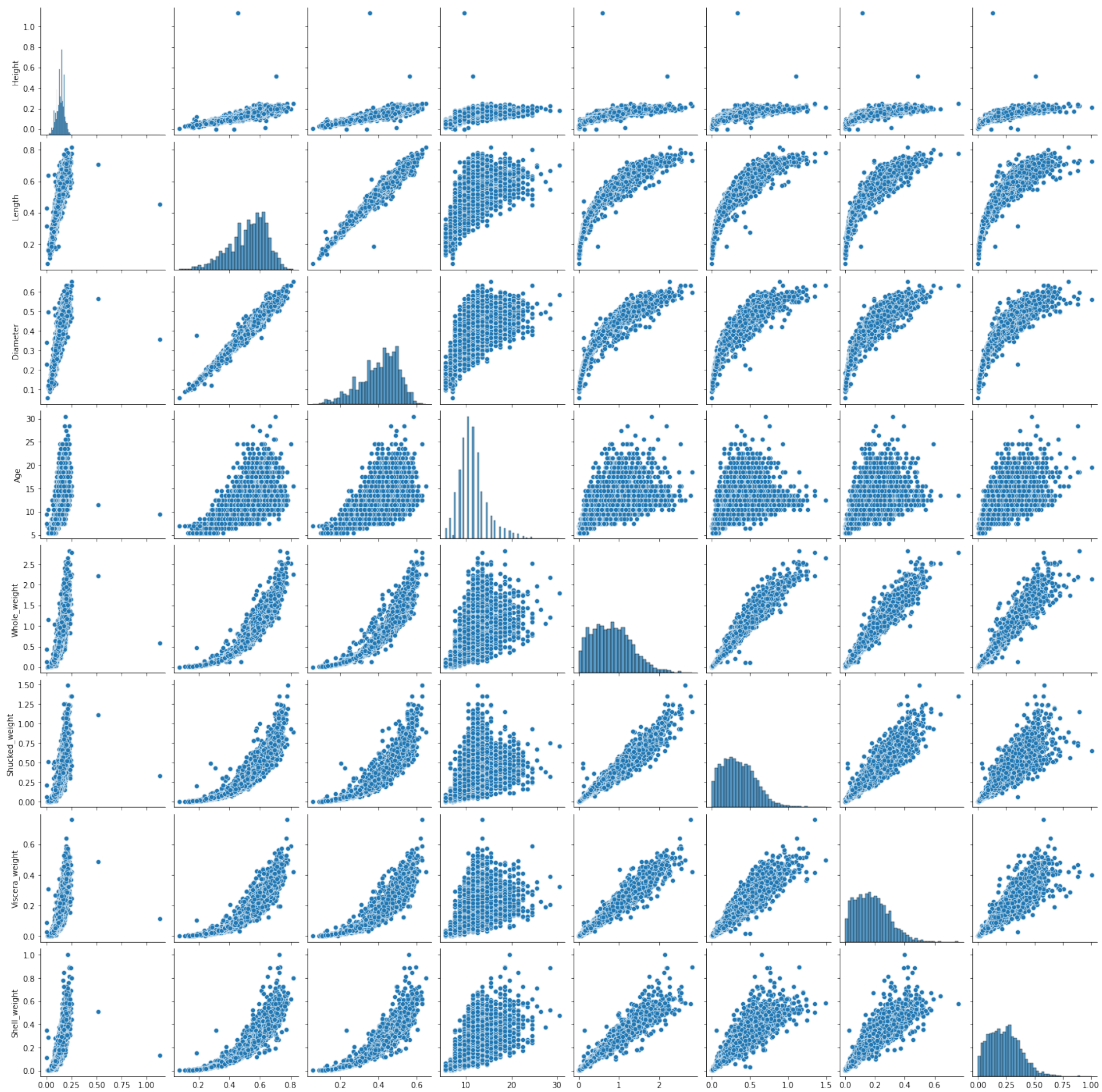
(iii) Multi-Variate Analysis

Multivariate analysis is based in observation and analysis of more than one statistical outcome variable at a time. In design and analysis, the technique is used to perform trade studies across multiple dimensions while taking into account the effects of all variables on the responses of interest.

Pairplot

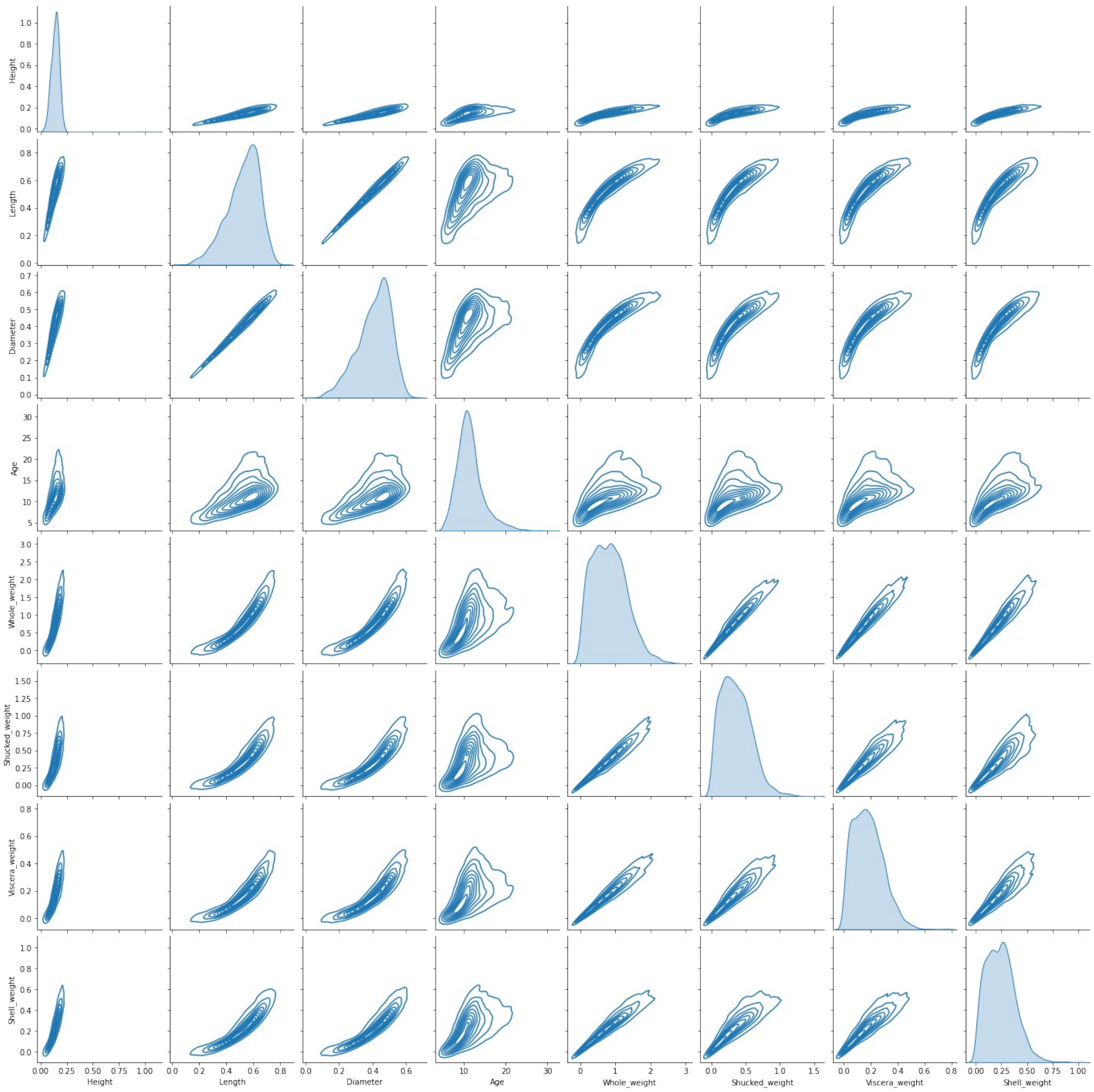
```
sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","Shucked_weight","Viscera_weight","Shell_weight"]])
```

```
<seaborn.axisgrid.PairGrid at 0x7f0fbf93ae50>
```



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

```
<seaborn.axisgrid.PairGrid at 0x7f0fb9239a90>
```

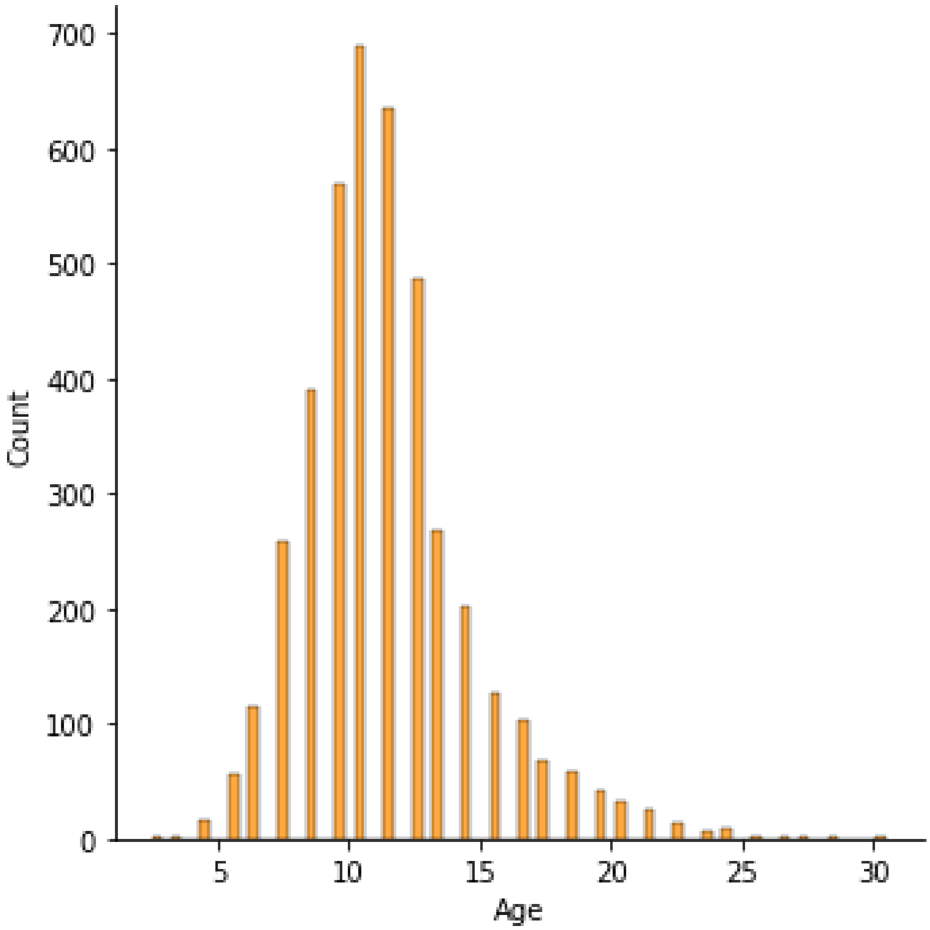


(ii) Bi-Variate Analysis

Image result for bivariate analysis in python It is a methodical statistical technique applied to a pair of variables (features/ attributes) of data to determine the empirical relationship between them. In order words, it is meant to determine any concurrent relations (usually over and above a simple correlation analysis).

```
sns.displot(data["Age"], color='darkorange')
```

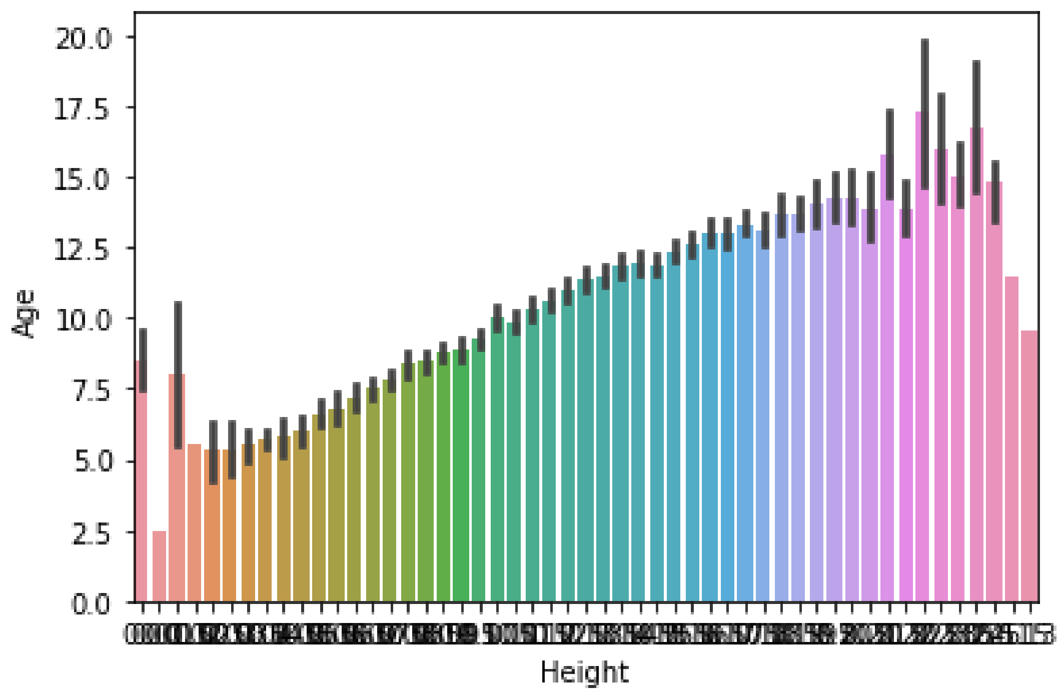
<seaborn.axisgrid.FacetGrid at 0x7f0fbf43da90>



Barplot

```
sns.barplot(x=data.Height,y=data.Age)
```

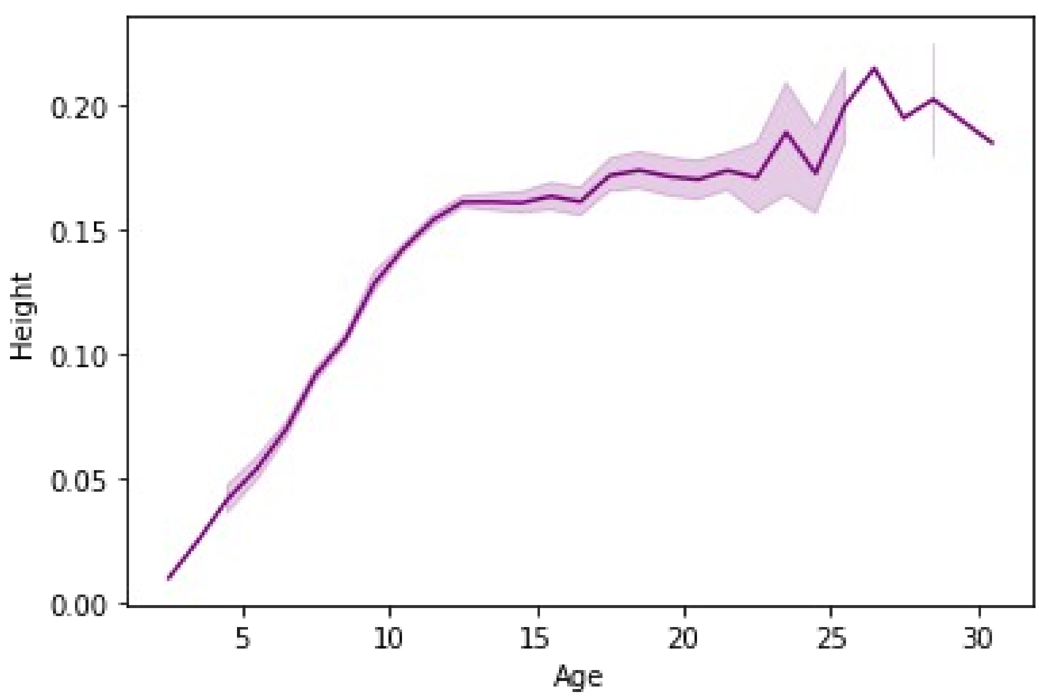
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fb96a0990>



Linearplot

```
sns.lineplot(x=data.Age,y=data.Height, color='purple')
```

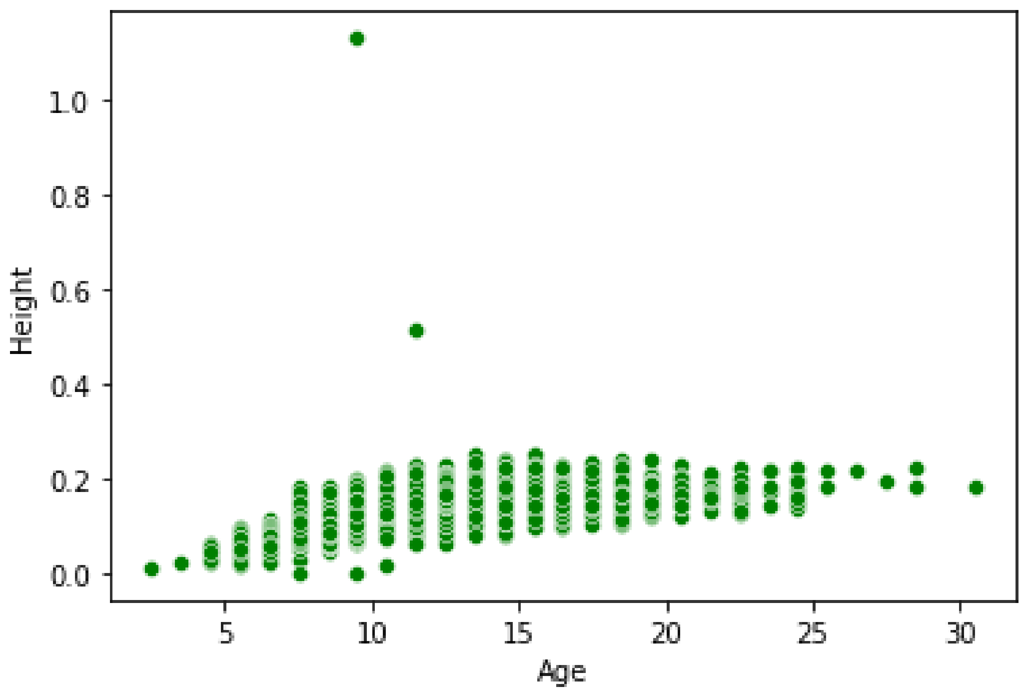
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fb945af90>
```



Scatterplot

```
sns.scatterplot(x=data.Age,y=data.Height,color='green')
```

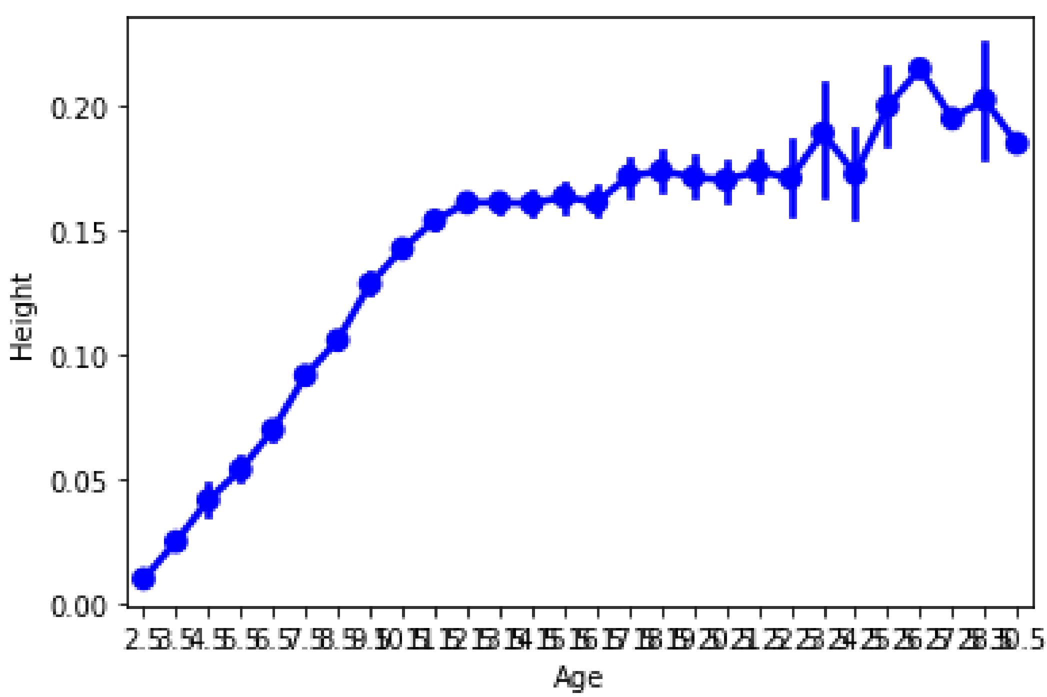
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fb944d690>



Pointplot

```
sns.pointplot(x=data.Age, y=data.Height, color="blue")
```

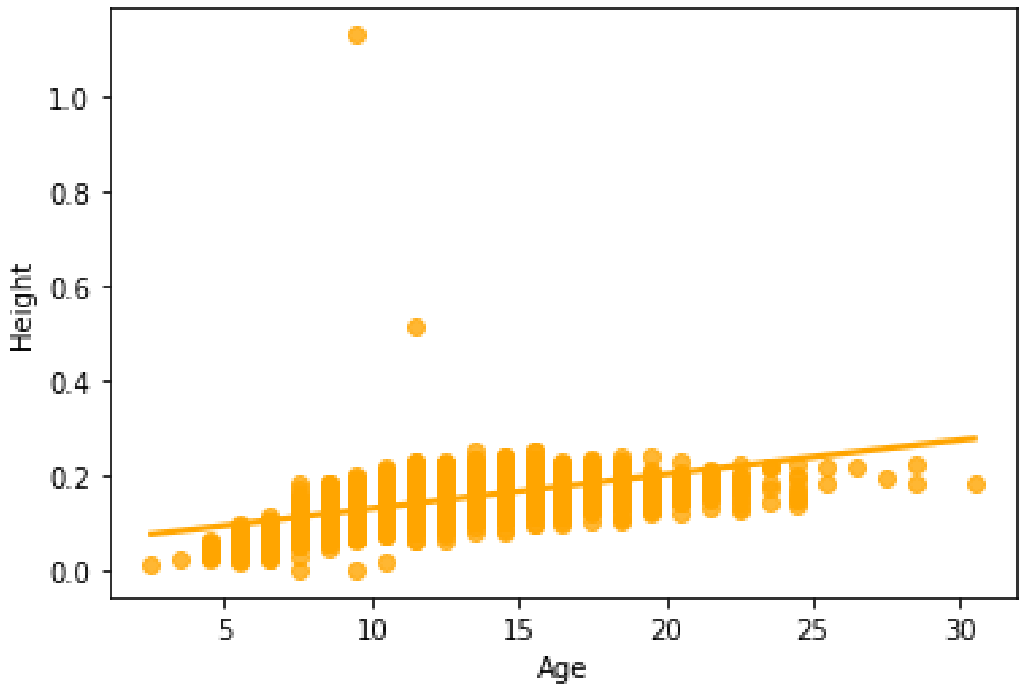
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fbacbaf10>



Regplot

```
sns.regplot(x=data.Age,y=data.Height,color='orange')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fbabcf750>
```



4. Perform descriptive statistics on the dataset

```
data.describe(include='all')
```

	Sex	Length	Diameter	Height	Whole_weight	\
count	4177	4177.000000	4177.000000	4177.000000	4177.000000	
unique	3	NaN	NaN	NaN	NaN	
top	M	NaN	NaN	NaN	NaN	
freq	1528	NaN	NaN	NaN	NaN	
mean	NaN	0.523992	0.407881	0.139516	0.828742	
std	NaN	0.120093	0.099240	0.041827	0.490389	
min	NaN	0.075000	0.055000	0.000000	0.002000	
25%	NaN	0.450000	0.350000	0.115000	0.441500	
50%	NaN	0.545000	0.425000	0.140000	0.799500	
75%	NaN	0.615000	0.480000	0.165000	1.153000	
max	NaN	0.815000	0.650000	1.130000	2.825500	

	Shucked_weight	Viscera_weight	Shell_weight	Age
count	4177.000000	4177.000000	4177.000000	4177.000000
unique	NaN	NaN	NaN	NaN
top	NaN	NaN	NaN	NaN
freq	NaN	NaN	NaN	NaN
mean	0.359367	0.180594	0.238831	11.433684
std	0.221963	0.109614	0.139203	3.224169
min	0.001000	0.000500	0.001500	2.500000

```
25%            0.186000        0.093500      0.130000     9.500000
50%            0.336000        0.171000      0.234000    10.500000
75%            0.502000        0.253000      0.329000    12.500000
max            1.488000        0.760000      1.005000    30.500000
```

5. Check for Missing values and deal with them

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

```
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

```
outliers=data.quantile(q=(0.25,0.75))
outliers
```

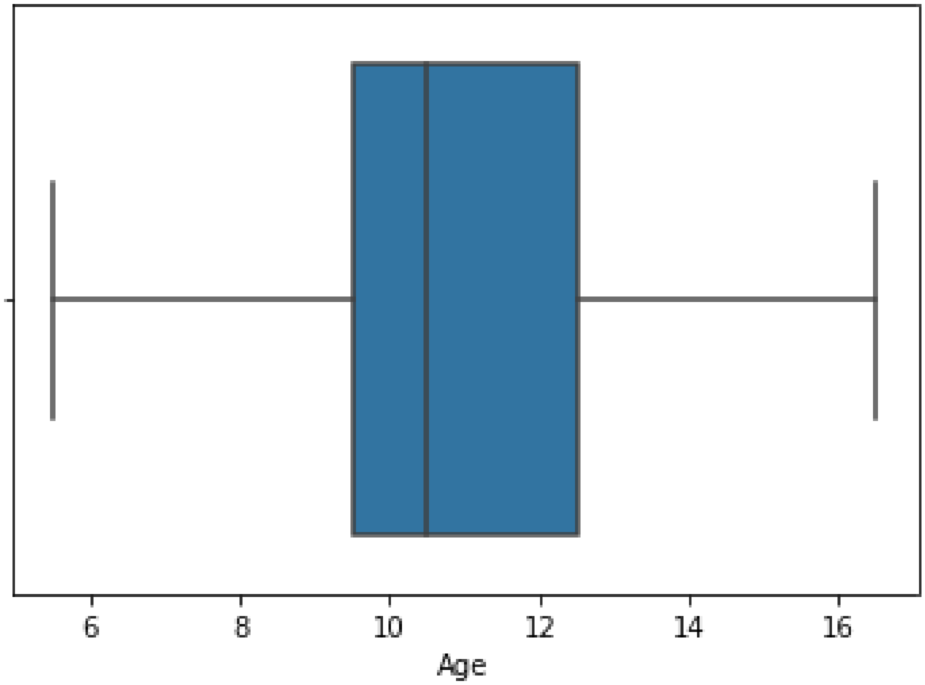
```
      Length  Diameter  Height  Whole_weight  Shucked_weight
Viscera_weight  \
0.25   0.450      0.35   0.115        0.4415           0.186
0.0935
0.75   0.615      0.48   0.165        1.1530           0.502
0.2530

      Shell_weight   Age
0.25         0.130   9.5
0.75         0.329  12.5
```

```
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)
```

```
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
```

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fb93bef10>
```



7. Check for Categorical columns and perform encoding

```
data.head()
```

```
  Sex  Length  Diameter  Height  Whole_weight  Shucked_weight  
Viscera_weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245  
0.1010   
1   M   0.350     0.265   0.090        0.2255          0.0995  
0.0485   
2   F   0.530     0.420   0.135        0.6770          0.2565  
0.1415   
3   M   0.440     0.365   0.125        0.5160          0.2155  
0.1140   
4   I   0.330     0.255   0.080        0.2050          0.0895  
0.0395   

   Shell_weight   Age  
0         0.150  16.5  
1         0.070   8.5  
2         0.210  10.5  
3         0.155  11.5  
4         0.055   8.5  
```

```
from sklearn.preprocessing import LabelEncoder

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

data.head()
```

```
   Sex  Length  Diameter  Height  Whole_weight  Shucked_weight  \
0    2   0.455     0.365   0.095        0.5140          0.2245
1    2   0.350     0.265   0.090        0.2255          0.0995
2    0   0.530     0.420   0.135        0.6770          0.2565
3    2   0.440     0.365   0.125        0.5160          0.2155
4    1   0.330     0.255   0.080        0.2050          0.0895

   Viscera_weight  Shell_weight   Age
0          0.1010         0.150  16.5
1          0.0485         0.070   8.5
2          0.1415         0.210  10.5
3          0.1140         0.155  11.5
4          0.0395         0.055   8.5
```

8. Split the data into dependent and independent variables

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

```
0    2
1    2
2    0
3    2
4    1
Name: Sex, dtype: int64
```

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

```
   Length  Diameter  Height  Whole_weight  Shucked_weight
Viscera_weight  \
0   0.455     0.365   0.095        0.5140          0.2245
0.1010
1   0.350     0.265   0.090        0.2255          0.0995
0.0485
2   0.530     0.420   0.135        0.6770          0.2565
0.1415
3   0.440     0.365   0.125        0.5160          0.2155
0.1140
4   0.330     0.255   0.080        0.2050          0.0895
0.0395

   Shell_weight   Age
0         0.150  16.5
```

```
1         0.070   8.5
2         0.210  10.5
3         0.155  11.5
4         0.055   8.5
```

9. Scale the independent variables

```
from sklearn.preprocessing import scale
X_Scaled = pd.DataFrame(scale(x), columns=x.columns)
X_Scaled.head()
```

```
     Length  Diameter    Height  Whole_weight  Shucked_weight  
Viscera_weight  \
0 -0.574558 -0.432149 -1.064424     -0.641898       -0.607685       -
0.726212
1 -1.448986 -1.439929 -1.183978     -1.230277       -1.170910       -
1.205221
2  0.050033  0.122130 -0.107991     -0.309469       -0.463500       -
0.356690
3 -0.699476 -0.432149 -0.347099     -0.637819       -0.648238       -
0.607600
4 -1.615544 -1.540707 -1.423087     -1.272086       -1.215968       -
1.287337

   Shell_weight       Age
0     -0.638217  1.577830
1     -1.212987 -0.919022
2     -0.207139 -0.294809
3     -0.602294  0.017298
4     -1.320757 -0.919022
```

10. Split the data into training and testing

```
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)
```

```
X_Train.shape,X_Test.shape
```

```
((3341, 8), (836, 8))
```

```
Y_Train.shape,Y_Test.shape
```

```
((3341,), (836,))
```

```
X_Train.head()
```

```
        Length  Diameter    Height  Whole_weight  Shucked_weight  \
3141 -2.864726 -2.750043 -1.423087     -1.622870       -1.553902   
3521 -2.573250 -2.598876 -2.020857     -1.606554       -1.551650   
883   1.132658  1.230689  0.728888      1.145672        1.041436   
3627  1.590691  1.180300  1.446213      2.164373        2.661269   
2106  0.591345  0.474853  0.370226      0.432887        0.255175   
```

```
      Viscera_weight  Shell_weight       Age
3141       -1.583867     -1.644065 -1.543234
3521       -1.565619     -1.626104 -1.387181
883         0.286552      1.538726  1.577830
3627        2.330326      1.377072  0.017298
2106        0.272866      0.906479  1.265723
```

```
X_Test.head()
```

```
        Length  Diameter    Height  Whole_weight  Shucked_weight  \
668   0.216591  0.172519  0.370226      0.181016       -0.368878
1580 -0.199803 -0.079426 -0.466653     -0.433875       -0.443224
3784  0.799543  0.726798  0.370226      0.870348        0.755318
463  -2.531611 -2.447709 -2.020857     -1.579022       -1.522362
2615  1.007740  0.928354  0.848442      1.390405        1.415417

      Viscera_weight  Shell_weight       Age
668         0.569396      0.690940  0.953617
1580       -0.343004     -0.325685 -0.606915
3784        1.764639      0.565209  0.329404
463        -1.538247     -1.572219 -1.543234
2615        1.778325      0.996287  0.641511
```

```
Y_Train.head()
```

```
3141    1
3521    1
883     2
3627    2
2106    2
Name: Sex, dtype: int64
```

```
Y_Test.head()
```

```
668     2
1580    1
3784    2
463     1
2615    2
Name: Sex, dtype: int64
```

11. Build the Model

```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=10,criterion='entropy')
```

```
model.fit(X_Train,Y_Train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

```
y_predict = model.predict(X_Test)
```

```
y_predict_train = model.predict(X_Train)
```

12. Train the Model

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

print('Training accuracy: ',accuracy_score(Y_Train,y_predict_train))

Training accuracy:  0.9817419934151451
```

13.Test the Model

```
print('Testing accuracy: ',accuracy_score(Y_Test,y_predict))

Testing accuracy:  0.5466507177033493
```

14. Measure the performance using Metrics

```
pd.crosstab(Y_Test,y_predict)

col_0    0    1    2
Sex
0      122   33   94
1       29  221   41
2      125   57  114

print(classification_report(Y_Test,y_predict))

              precision    recall  f1-score   support

           0       0.44      0.49      0.46       249
           1       0.71      0.76      0.73       291
           2       0.46      0.39      0.42       296

    accuracy                           0.55       836
   macro avg       0.54      0.54      0.54       836
weighted avg       0.54      0.55      0.54       836
```