Detecting Parkinsons Disease using Machine Learning ASSIGNMENT - 3

Date	4th October 2022
Team ID	PNT2022TMID27836
Student Name	Prabhakaran M (311519104044)
Domain Name	Healthcare
Project Name	Detecting Parkinsons Disease using Machine Learning
Maximum Marks	2 Marks

1.)IMPORT THE REQUIRED LIBRARIES

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

2.)DOWNLOAD AND UPLOAD THE DATASET

```
In [2]: df = pd.read_csv('abalone.csv')
df.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 0.0395 7
```

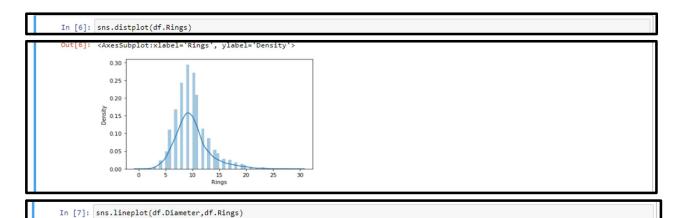
3.)HANDLE MISSING VALUES AND DEAL WITH THEM

4.) PERFORM THE DESCRIPTIVE STATISTICS ON THE DATASET

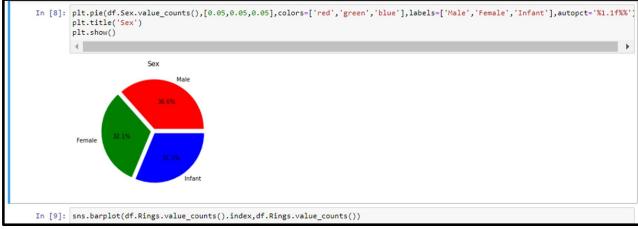
:]:		Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
	count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
	mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	9.933684
	std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
	min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	1.000000
	25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	8.000000
	50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	9.000000
	75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	11.000000
	max	0.815000	0.650000	1.130000	2.825500	1,488000	0.760000	1.005000	29.000000
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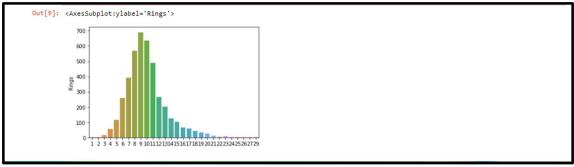
5.) PERFORM VARIOUS VISUALISATIONS

a.) UNIVARIANTE ANALYSIS

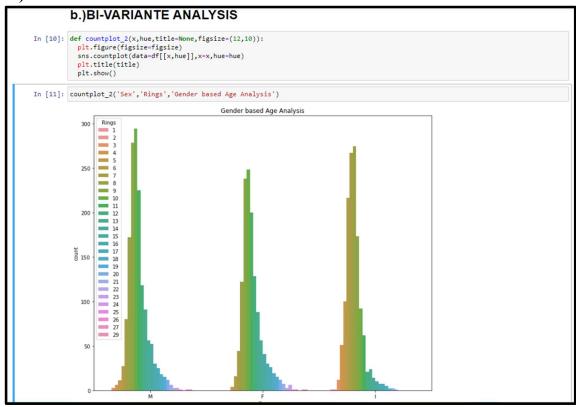




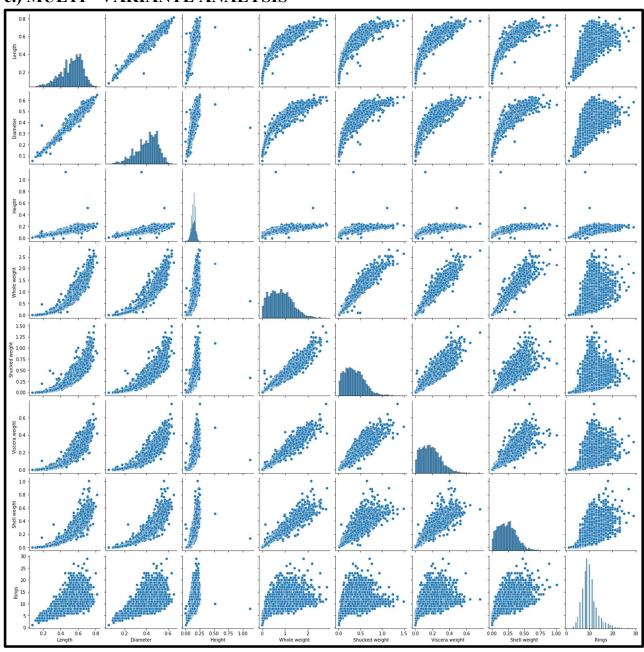




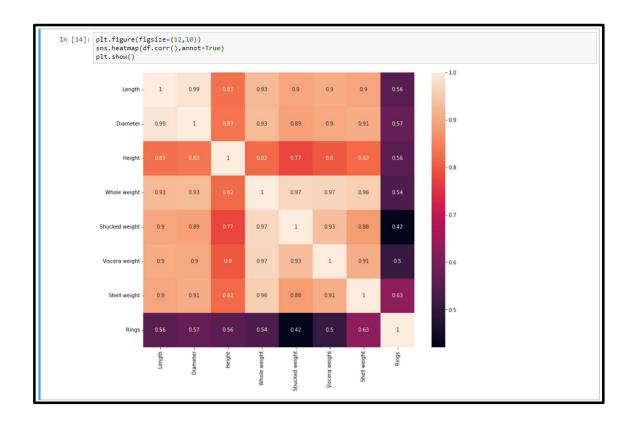
b.) BI - VARIANTE ANALYSIS



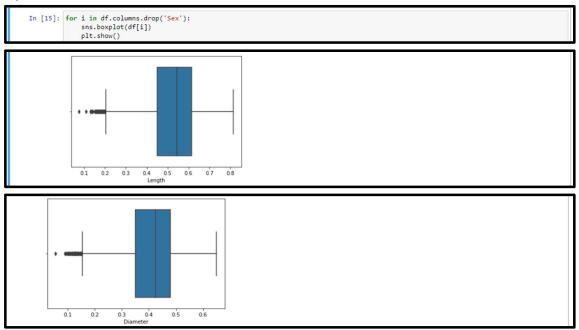
c.) MULTI - VARIANTE ANALYSIS



	df.corr()								
ut[13]:		Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
	Length	1.000000	0.986812	0.827554	0.925261	0.897914	0.903018	0.897706	0.556720
	Diameter	0.986812	1.000000	0.833684	0.925452	0.893162	0.899724	0.905330	0.574660
	Height	0.827554	0.833684	1.000000	0.819221	0.774972	0.798319	0.817338	0.557467
	Whole weight	0.925261	0.925452	0.819221	1.000000	0.969405	0.966375	0.955355	0.540390
	Shucked weight	0.897914	0.893162	0.774972	0.969405	1.000000	0.931961	0.882617	0.420884
	Viscera weight	0.903018	0.899724	0.798319	0.966375	0.931961	1.000000	0.907656	0.503819
	Shell weight	0.897706	0.905330	0.817338	0.955355	0.882617	0.907656	1.000000	0.627574
	Rings	0.556720	0.574660	0.557467	0.540390	0.420884	0.503819	0.627574	1.000000

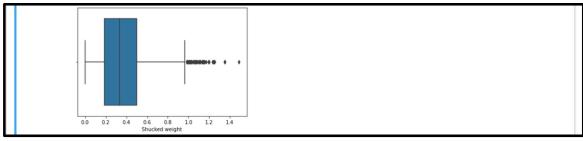


6.) FIND AND REPLACE THE OUTLIERS



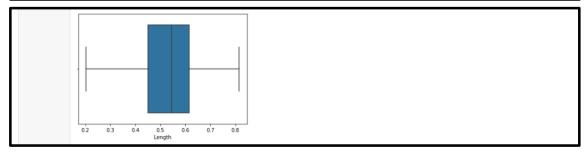


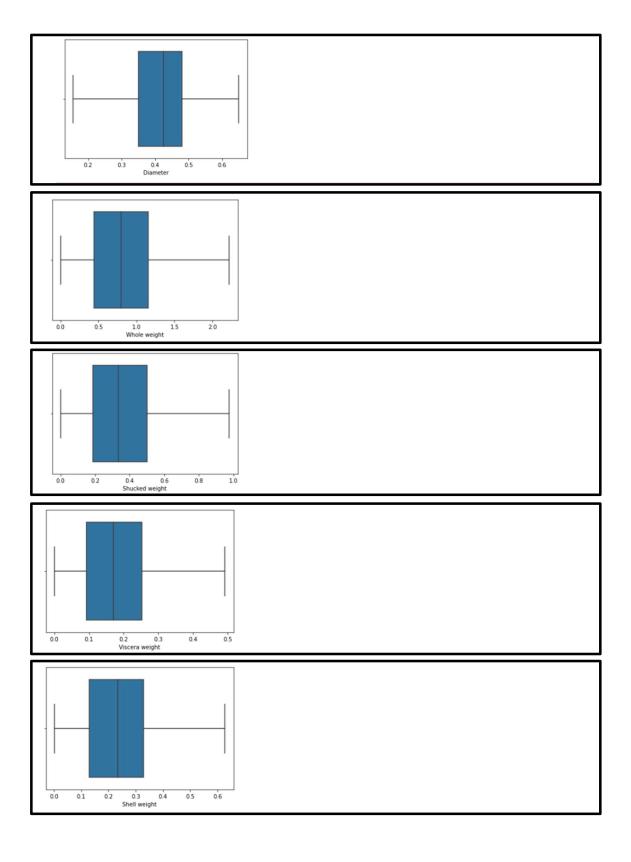


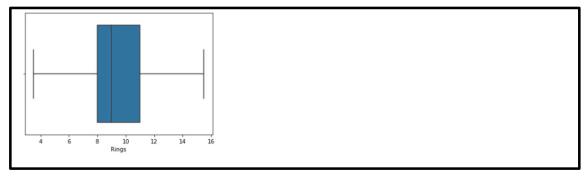


```
In [16]:
    for i in df.columns.drop('Sex'):
        Q1 = df[i].quantile(0.25)
        Q3 = df[i].quantile(0.75)
        IQR = Q3-Q1
        upper_limit = Q3 + (1.5*IQR)
        lower_limit = Q1 - (1.5*IQR)
        df[i] = np.where(df[i])=upper_limit,Q3 + (1.5*IQR),df[i])
        df[i] = np.where(df[i]<=lower_limit,Q1 - (1.5*IQR),df[i])

In [17]:
    for i in df.columns.drop('Sex'):
        sns.boxplot(df[i])
        plt.show()</pre>
```



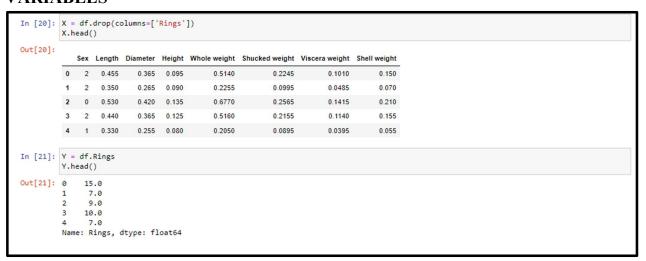




7.) CHECK FOR CATEGORICAL COLUMNS AND ENCODE THEM

	= La	belEnco			mport LabelE	ncoder			
: df	.head	I()	-						
:	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15.0
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7.0
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9.0
	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10.0
3	-								

8.)SPLIT DATA INTO DEPENDENT AND INDEPENDENT VARIABLES



9.) SCALE THE INDEPENDENT VARIABLES

	sca X_s	le =	MinMaxS	caler() ataFrame		port MinMaxS	caler rm(X),columns:	=X.columns)		
[22]:		Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	
	0	1.0	0.412245	0.424242	0.275	0.230813	0.229231	0.204372	0.237220	
	1	1.0	0.240816	0.222222	0.250	0.100755	0.101026	0.097611	0.109425	
	2	0.0	0.534694	0.535354	0.475	0.304294	0.262051	0.286731	0.333067	
	3	1.0	0.387755	0.424242	0.425	0.231714	0.220000	0.230808	0.245208	
	4	0.5	0.208163	0.202020	0.200	0.091514	0.090769	0.079309	0.085463	

10.) SPLIT THE DATA INTO TRAINING AND TESTING

```
In [23]: 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)
```

11.) BUILD THE MODEL

```
In [24]: from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

12.) TRAIN THE MODEL

```
In [25]: model.fit(x_train,y_train)
Out[25]: LinearRegression()
```

13.) TEST THE MODEL

```
In [26]: y_predict = model.predict(x_test)
In [27]: pd.DataFrame({"Actual":y_test,"Predicted":y_predict.round(0)})
Out[27]:
             Actual Predicted
        668 13.0 13.0
        1580 8.0
                      9.0
        3784 11.0 10.0
         463
             5.0
                      5.0
        2615 12.0 10.0
        575 11.0 10.0
        3231
              12.0
                      9.0
        1084 7.0 9.0
         290 15.5
                      12.0
        2713 4.0 6.0
        836 rows × 2 columns
```

14.) MEASURE THE PERFORMANCE USING METRICS

```
In [28]: from sklearn import metrics metrics.r2_score(y_test,y_predict)

Out[28]: 0.58432381444787
```