ASSIGNMENT -3

Date	10 October 2022
Team ID	PNT2022TMID38667
Project Name	Project - Early Detection of Chronic Kidney Disease using Machine Learning
Maximum Marks	2 Marks

1. Download the dataset

	A	B	C	D	E	F	G	H	I
1	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
2	M	0.455	0.365	0.095	0.514	0.2245	0.101	0.15	15
3	M	0.35	0.265	0.09	0.2255	0.0995	0.0485	0.07	7
4	F	0.53	0.42	0.135	0.677	0.2565	0.1415	0.21	9
5	M	0.44	0.365	0.125	0.516	0.2155	0.114	0.155	10
6	I	0.33	0.255	0.08	0.205	0.0895	0.0395	0.055	7
7	I	0.425	0.3	0.095	0.3515	0.141	0.0775	0.12	8
8	F	0.53	0.415	0.15	0.7775	0.237	0.1415	0.33	20
9	F	0.545	0.425	0.125	0.768	0.294	0.1495	0.26	16
10	M	0.475	0.37	0.125	0.5095	0.2165	0.1125	0.165	9
11	F	0.55	0.44	0.15	0.8945	0.3145	0.151	0.32	19
12	F	0.525	0.38	0.14	0.6065	0.194	0.1475	0.21	14
13	M	0.43	0.35	0.11	0.406	0.1675	0.081	0.135	10
14	M	0.49	0.38	0.135	0.5415	0.2175	0.095	0.19	11
15	F	0.535	0.405	0.145	0.6845	0.2725	0.171	0.205	10
16	F	0.47	0.355	0.1	0.4755	0.1675	0.0805	0.185	10
17	M	0.5	0.4	0.13	0.6645	0.258	0.133	0.24	12
18	I	0.355	0.28	0.085	0.2905	0.095	0.0395	0.115	7
19	F	0.44	0.34	0.1	0.451	0.188	0.087	0.13	10
20	M	0.365	0.295	0.08	0.2555	0.097	0.043	0.1	7
21	M	0.45	0.32	0.1	0.381	0.1705	0.075	0.115	9
22	M	0.355	0.28	0.095	0.2455	0.0955	0.062	0.075	11
23	I	0.38	0.275	0.1	0.2255	0.08	0.049	0.085	10
24	F	0.565	0.44	0.155	0.9395	0.4275	0.214	0.27	12
25	F	0.55	0.415	0.135	0.7635	0.318	0.21	0.2	9
26	F	0.615	0.48	0.165	1.1615	0.513	0.301	0.305	10
27	F	0.56	0.44	0.14	0.9285	0.3825	0.188	0.3	11
28	F	0.58	0.45	0.185	0.9955	0.3945	0.272	0.285	11
29	M	0.59	0.445	0.14	0.931	0.356	0.234	0.28	12
30	M	0.605	0.475	0.18	0.9365	0.394	0.219	0.295	15
31	M	0.575	0.425	0.14	0.8635	0.393	0.227	0.2	11
32	M	0.58	0.47	0.165	0.9975	0.3935	0.242	0.33	10
33	F	0.68	0.56	0.165	1.639	0.6055	0.2805	0.46	15
34	M	0.665	0.525	0.165	1.338	0.5515	0.3575	0.35	18
35	F	0.68	0.55	0.175	1.798	0.815	0.3925	0.455	19
36	F	0.705	0.55	0.2	1.7095	0.633	0.4115	0.49	13
37	M	0.465	0.355	0.105	0.4795	0.227	0.124	0.125	8
38	F	0.54	0.475	0.155	1.217	0.5305	0.3075	0.34	16
39	F	0.45	0.355	0.105	0.5225	0.237	0.1165	0.145	8
40	F	0.575	0.445	0.135	0.883	0.381	0.2035	0.26	11
41	M	0.355	0.29	0.09	0.3275	0.134	0.086	0.09	9
42	F	0.45	0.335	0.105	0.425	0.1865	0.091	0.115	9

2.Load the dataset

In [3]:
```
##import required libraries

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

import warnings
warnings.filterwarnings("ignore")
```

In [6]:
```
## 2.Load the dataset
data = pd.read_csv('abalone.csv')
data.head()
```

Out[6]:

	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

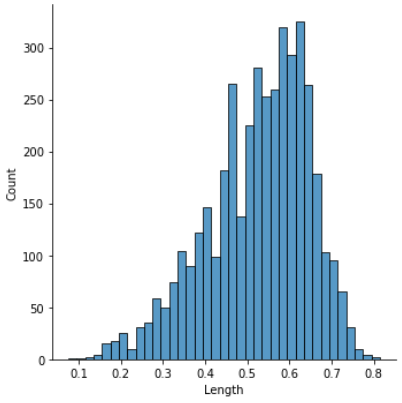
3. Perform Below Visualization

- Univariate Analysis

In [7]:
```
##3i.univariate analysis

df=pd.read_csv('abalone.csv')
df.head()
sns.displot(df.Length)
```

Out[7]:
```
<seaborn.axisgrid.FacetGrid at 0x25d097d4700>
```



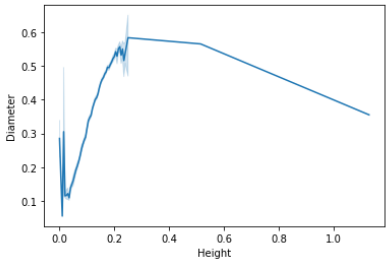
- Bi - Variate Analysis

Length

```
In [8]: ## 3ii.bivariate analysis

        df=pd.read_csv('abalone.csv')
        df.head()
        sns.lineplot(df.Height,df.Diameter)
```

```
Out[8]: <AxesSubplot:xlabel='Height', ylabel='Diameter'>
```

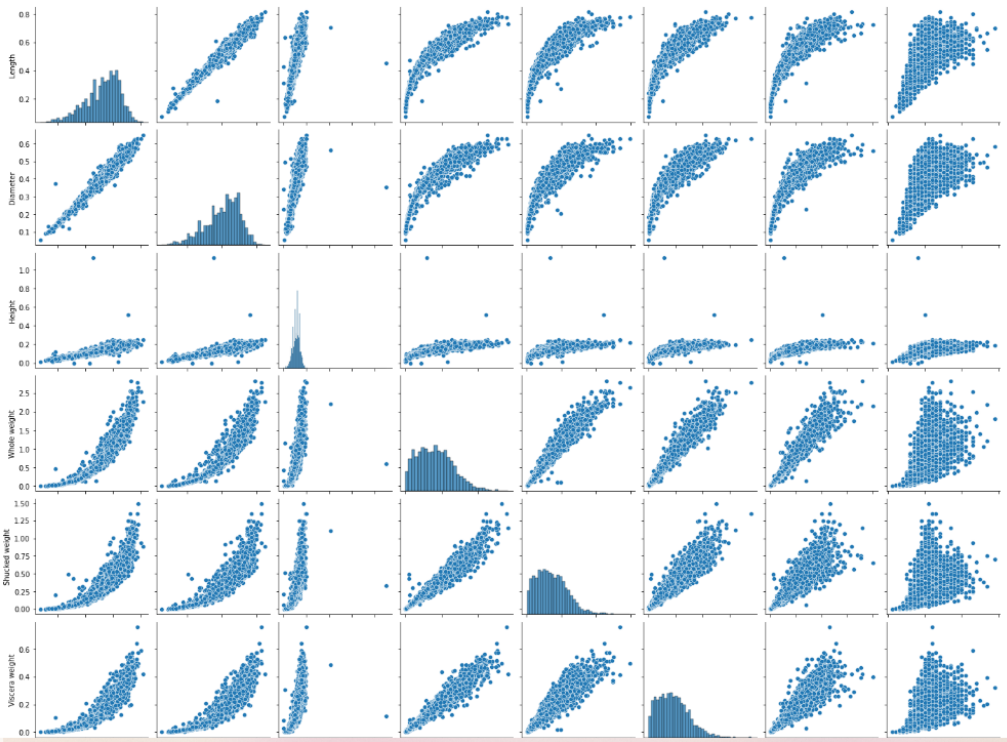


- Multi - Variate Analysis

```
In [10]: ## 3iii.multi-variate analysis

         df=pd.read_csv('abalone.csv')
         df.head()
         sns.pairplot(df)
```

```
Out[10]: <seaborn.axisgrid.PairGrid at 0x25d0a07d970>
```



4. Perform descriptive statistics on the dataset

In [11]:
```
## 4.descriptive statistics
data.describe()
```

Out[11]:

	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

5. Handle the missing values

In [12]:
```
## 5.missing values
data.isnull().any()
```

Out[12]:
```
Sex               False
Length            False
Diameter          False
Height            False
Whole weight      False
Shucked weight    False
Viscera weight    False
Shell weight      False
Rings             False
dtype: bool
```

6. Find the outliers and replace the outliers

In [13]:
```
## 6.find the outlier

df=pd.read_csv('abalone.csv')
df.head()
Q1=df.Length.quantile(0.25)
Q3=df.Length.quantile(0.75)
Q1,Q3
```

Out[13]: (0.45, 0.615)

In [14]:
```
## 6.replace the outlier

df=pd.read_csv('abalone.csv')
df.head()
Q1=df.Length.quantile(0.25)
Q3=df.Length.quantile(0.75)
Q1,Q3
IQR=Q3-Q1
IQR
lower_limit = Q1-1.5*IQR
upper_limit = Q3+1.5*IQR
lower_limit,upper_limit
df_no_outlier = df[(df.Length>lower_limit)&(df.Length<upper_limit)]
df_no_outlier
```

Out[14]:

	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	0.1500	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	7
...	...	...	...	...	...	...	...	...	...
4172	F	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11
4173	M	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	10
4174	M	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	9
4175	F	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	10
4176	M	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	12

4128 rows × 9 columns

7.Check for categorical columns and perform encoding

In [16]:
```
## 7.categorical columns encoding
from sklearn.preprocessing import LabelEncoder

data=pd.read_csv('abalone.csv')
le=LabelEncoder()
data.Gender=le.fit_transform(df.Length)
data.Geographyr=le.fit_transform(df.Diameter)
data.head()
```

Out[16]:

	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

8. Split the data into dependent and independent variables

In [17]:
```
## 8.independent variable-x
x = data.drop("Rings",axis = 1)
y = data["Rings"]
x
```

Out[17]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550
...	...	...	...	...	...	...	...	...
4172	F	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490
4173	M	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605
4174	M	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080
4175	F	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960
4176	M	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950

4177 rows × 8 columns

In [18]:
```
## 8.dependent variable-y
y
```

Out[18]:
```
0       15
1        7
2        9
3       10
4        7
        ..
4172    11
4173    10
4174     9
4175    10
4176    12
Name: Rings, Length: 4177, dtype: int64
```

9. Scale the independent variables

```
In [22]: ## 9.scaling

         from sklearn.preprocessing import StandardScaler
         from sklearn.model_selection import train_test_split

         X_train = pd.DataFrame(x)
         X_train.head()
```

Out[22]:

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

10. Split the data into training and testing

```
In [47]: X_train
```

Out[47]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight
1794	1	0.575	0.450	0.130	0.8145	0.4030	0.1715	0.2130
1466	2	0.515	0.425	0.145	0.9365	0.4970	0.1810	0.2185
2275	2	0.655	0.525	0.185	1.2590	0.4870	0.2215	0.4450
3929	0	0.650	0.515	0.215	1.4980	0.5640	0.3230	0.4250
1955	0	0.645	0.510	0.180	1.6195	0.7815	0.3220	0.4675
...	...	...	...	...	...	...	...	...
2103	2	0.375	0.290	0.100	0.2760	0.1175	0.0565	0.0850
3603	1	0.420	0.325	0.110	0.3250	0.1245	0.0755	0.1025
3340	1	0.540	0.435	0.145	0.9700	0.4285	0.2200	0.2640
3064	2	0.635	0.500	0.180	1.1540	0.4405	0.2315	0.3870
3398	2	0.365	0.285	0.085	0.2205	0.0855	0.0515	0.0700

3341 rows × 8 columns

```
In [48]: y_train
```

Out[48]:

```
1794    10
1466     8
2275    20
3929    16
1955    12
        ..
2103     9
3603     7
3340    17
3064     9
3398     9
```

11.Build the model

12.Train the model

13.Test the model

Build the model

In [61]:
```
logreg = LogisticRegression()
```

Train and Test the model

In [53]:
```
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.3f}'. format(logreg.score (X_test, y_test)))
```

```
Accuracy of logistic regression classifier on test set: 0.261
```

Measure the performance using metrics

In [59]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print('Confusion matrix\n\n', cm)
```

```
Confusion matrix

 [[ 0  5  4  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  2 15  5  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  2  9 30  5  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  7 32 27  7  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  2 22 43 36 12  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  2 11 25 70 30  5  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  9 12 37 47 14  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  5  9 29 32 15  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  3 10 13 20 15  0  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  2  5  9 20 13  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  5  6 12  9  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
```

14.Measure the performance

In [55]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           4       0.00      0.00      0.00         9
           5       0.22      0.09      0.12        23
           6       0.23      0.20      0.21        46
           7       0.27      0.43      0.33        74
           8       0.30      0.37      0.33       115
           9       0.32      0.49      0.39       143
          10       0.23      0.39      0.29       119
          11       0.16      0.17      0.16        90
          12       0.00      0.00      0.00        62
          13       0.00      0.00      0.00        49
          14       0.00      0.00      0.00        32
          15       0.00      0.00      0.00        14
          16       0.00      0.00      0.00        14
          17       0.00      0.00      0.00        12
          18       0.00      0.00      0.00         9
          19       0.00      0.00      0.00         9
          20       0.00      0.00      0.00         5
          21       0.00      0.00      0.00         4
          22       0.00      0.00      0.00         1
          23       0.00      0.00      0.00         4
          26       0.00      0.00      0.00         1
          27       0.00      0.00      0.00         1

    accuracy                           0.26       836
   macro avg       0.08      0.10      0.08       836
weighted avg       0.19      0.26      0.21       836
```