# Assignment -3

# Abalone Age Prediction

| | |
|---|---|
| Assignment Date | 10october2022 |
| Student Name | VISHWA KUMAR K |
| Student Roll Number | 820419104086 |
| Maximum Marks | 2 Marks |

**1.Importing necessary packages & Downloading the packages**

***Solution:***

```
import pandas as pd
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
import numpy as np
from collections import Counter
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import Ridge, Lasso
from sklearn.model_selection import GridSearchCV
from sklearn.exceptions import NotFittedError
from sklearn.metrics import r2_score,mean_absolute_error
```

**2. Download the dataset**

***Solution:***

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

***Output:***

| | 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. Visualizations**

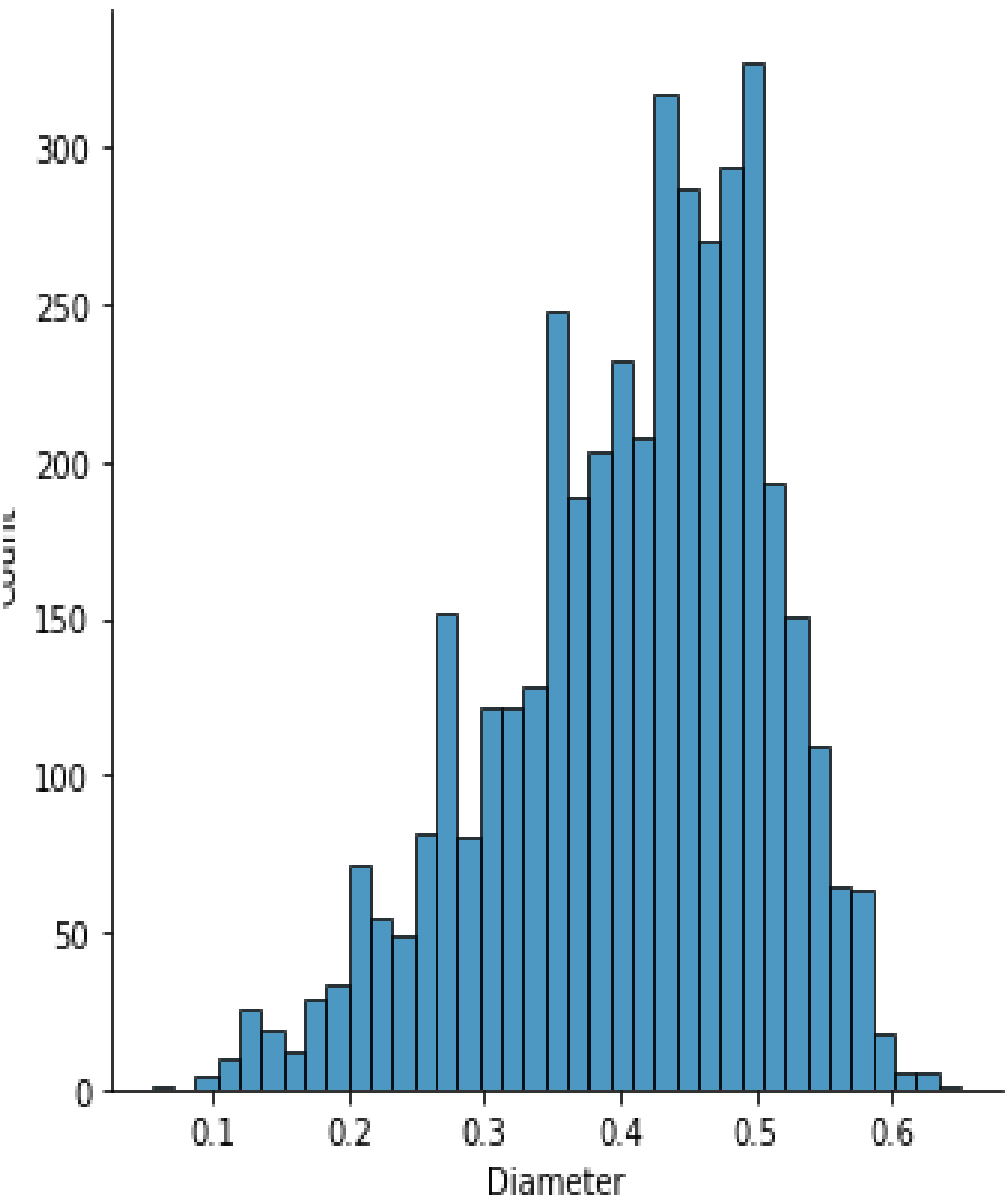
**(i) Univariate Analysis**

***Solution:***

```
sns.displot(df["Diameter"])
```

***Output:***

<seaborn.axisgrid.FacetGrid at 0x1a7c3cc60a0>

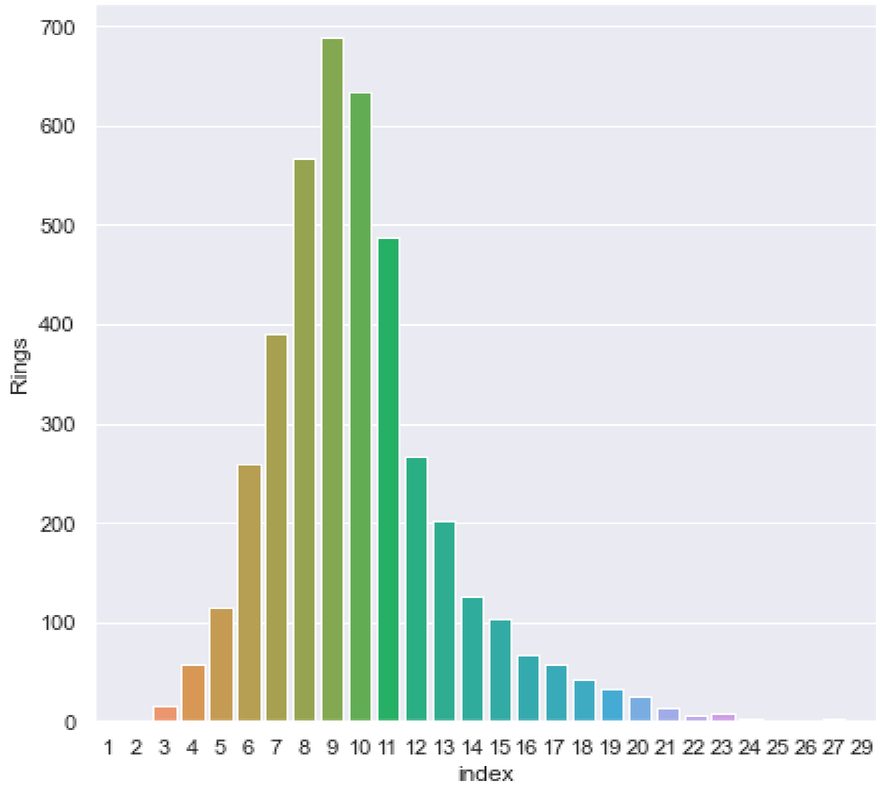



***Solution:***

```
sns.set(rc={'figure.figsize':(7,7)})
depth = df['Rings'].value_counts(normalize=False).reset_index()
sns.barplot(data=depth,x='index',y='Rings')
```

***Output:***

<AxesSubplot:xlabel='index', ylabel='Rings'>

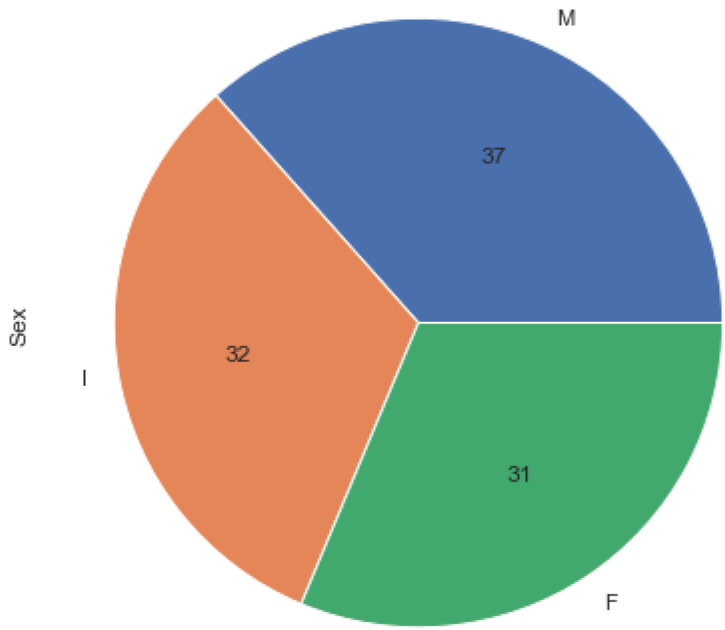



***Solution:***

df['Sex'].value_counts().plot(kind='pie',autopct='%.0f')

***Output:***

<AxesSubplot:ylabel='Sex'>

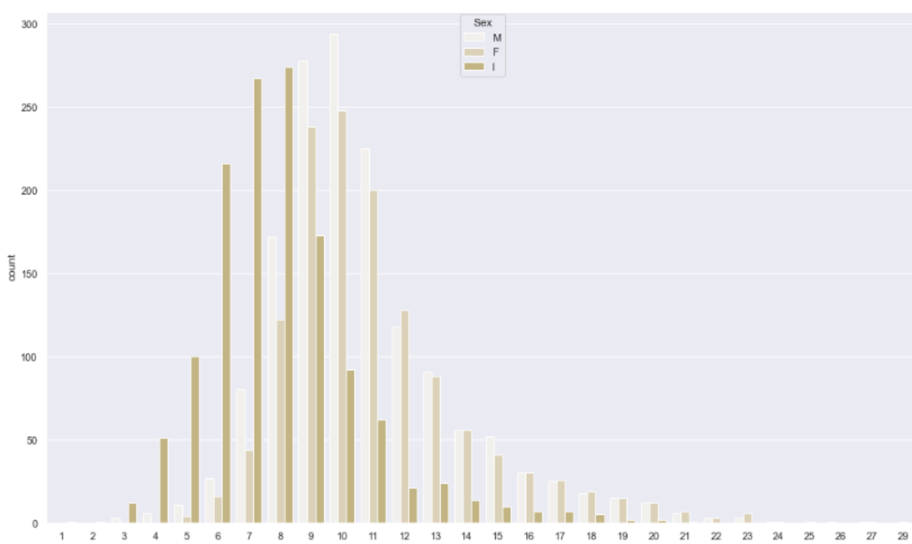



**(ii) BiVariate Analysis**

***Solution:***

```
sns.set(rc={'figure.figsize':(17,10)})
sns.countplot(df['Rings'] ,hue = df['Sex'] ,color ='y')
```

<AxesSubplot:xlabel='Rings', ylabel='count'>

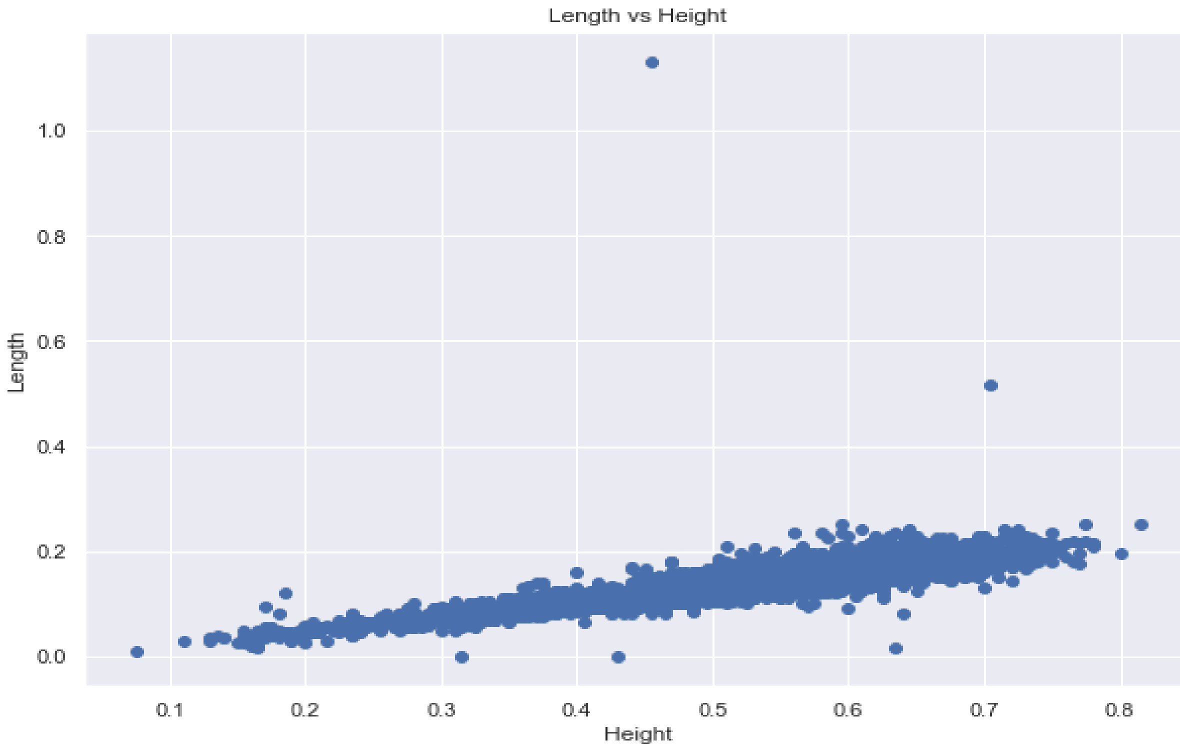


***Solution:***

```
sns.set(rc={'figure.figsize':(10,7)})
plt.scatter(df.Length, df.Height)
plt.title('Length vs Height')
plt.xlabel('Height')
plt.ylabel('Length')
```

***Output:***

Text(0, 0.5, 'Length')




**(iii) MultiVariate Analysis**

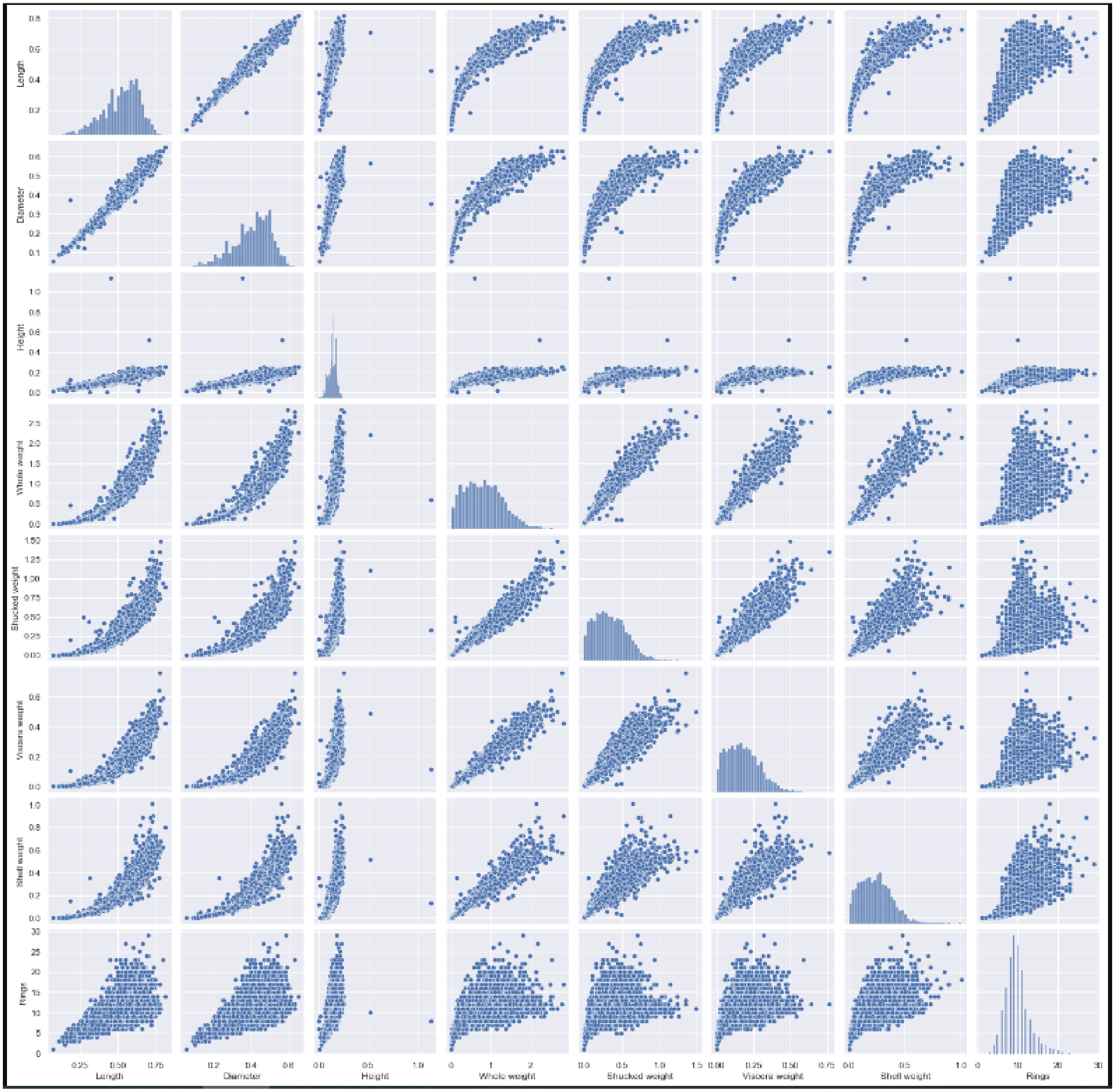
***Solution:***

```
plt.figure(figsize=(12,10))
sns.pairplot(df)
```

***Output:***

<seaborn.axisgrid.PairGrid at 0x1a8005d43a0>

<Figure size 864x720 with 0 Axes>

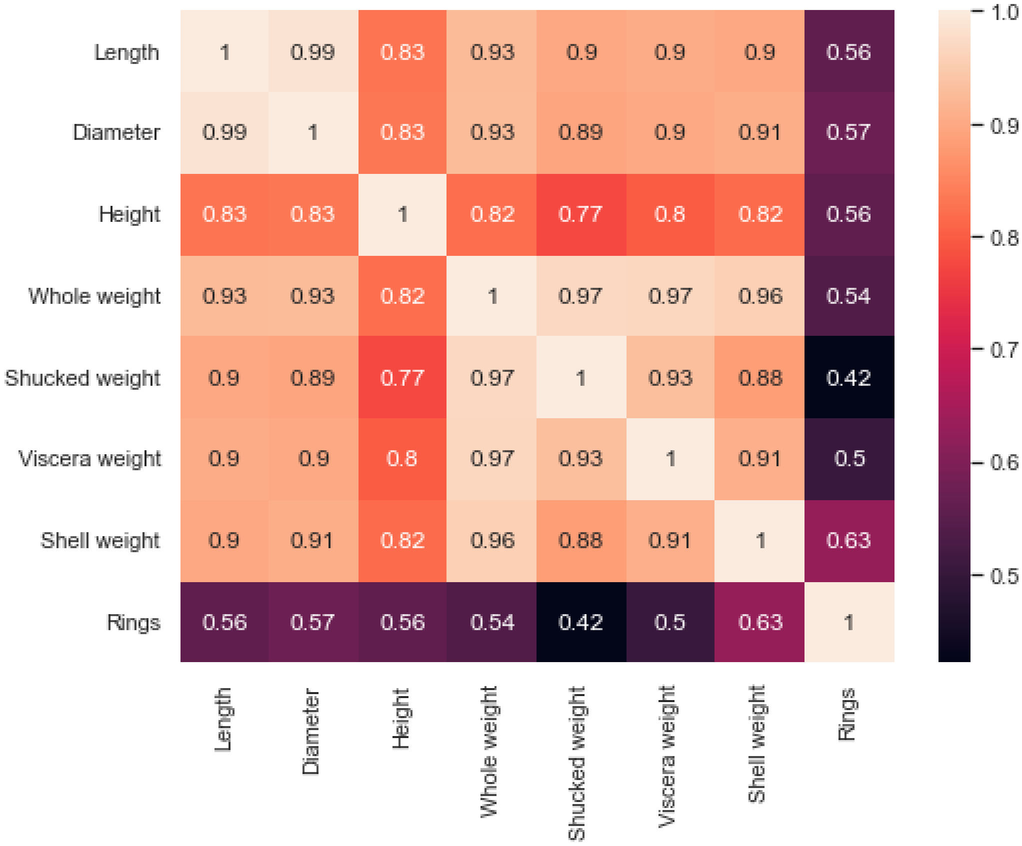



***Solution:***

```
plt.figure(figsize = (8,6))
corr = df.corr()
sns.heatmap(corr, annot = True)
```

***Output:***

<AxesSubplot:>




**4.Descriptive Statistics**

***Solution:***

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Sex             4177 non-null   object
 1   Length          4177 non-null   float64
 2   Diameter        4177 non-null   float64
 3   Height          4177 non-null   float64
 4   Whole weight    4177 non-null   float64
 5   Shucked weight  4177 non-null   float64
 6   Viscera weight  4177 non-null   float64
 7   Shell weight    4177 non-null   float64
 8   Rings           4177 non-null   int64
dtypes: float64(7), int64(1), object(1)
memory usage: 293.8+ KB
```

***Solution:***

df.describe()

***Output:***

| | 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 Missing Values**

***Solution:***

```
df.isna().sum()
```

***Output:***

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

**6. Outlier Detection**

***Solution:***

```
outlier_correction_df = df.drop(columns=['Sex'],axis=1)
outlier_correction_df.head()
```

***Output:***

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

***Solution:***

```
def detection(df,features):
    outlier_indices=[]

    for c in features:
        Q1 = np.percentile(df[c],25)

        Q3 = np.percentile(df[c],75)

        IQR = Q3 - Q1
        outlier_step = IQR * 1.5
        lower_range = Q1 - (outlier_step)
        upper_range = Q3 + (outlier_step)

        outlier_list_col=df[  (df[c] < lower_range) | (df[c] > upper_range)  ].index

        outlier_indices.extend(outlier_list_col)
    return outlier_indices

def multiple_outlier_indices(outlier_indices):

    outlier_indices=Counter(outlier_indices)
    multiple_outliers = list(i for i, v in outlier_indices.items() if v > 2 )

    return multiple_outliers
```

***Solution:***

```
outlier_correction_df.columns
```

***Output:***

```
Index(['Length', 'Diameter', 'Height', 'Whole weight', 'Shucked weight',
       'Viscera weight', 'Shell weight', 'Rings'],
      dtype='object')
```

***Solution:***

```
outliers=detection(df,['Length', 'Diameter', 'Height', 'Whole weight', 'Shucked weight',
       'Viscera weight', 'Shell weight'])
```

***Solution:***

```
Counter(outliers)
```

***Output:***

```
Counter({148: 2,
         149: 2,
         236: 3,
         237: 3,
         238: 3,
         239: 3,
         305: 2,
         306: 3,
         321: 2,
         465: 2,
         523: 2,
         525: 2,
         526: 2,
         611: 2,
         694: 3,
         696: 2,
         718: 3,
         719: 3,
         720: 3,
         1053: 2,
         1054: 2,
         1055: 2,
         1056: 1,
         1210: 1,
         1429: 3,
         1824: 2,
         1986: 2,
         1987: 3,
         2114: 3,
         2115: 2,
         2169: 3,
         2171: 3,
         2343: 2,
         2371: 2,
         2380: 2,
         2381: 3,
         2458: 2,
         2711: 3,
         3141: 2,
         3143: 2,
         3190: 3,
         3318: 2,
         3380: 2,
         3472: 2,
         3600: 2,
```

3837: 3,
3899: 3,
3902: 3,
3994: 2,
43: 1,
44: 1,
520: 1,
892: 1,
898: 1,
1988: 1,
2172: 2,
2545: 1,
2712: 1,
3473: 1,
3521: 1,
3716: 1,
1174: 1,
1257: 1,
1417: 2,
1428: 3,
1763: 4,
2051: 1,
2179: 1,
3996: 1,
165: 3,
358: 2,
891: 3,
1051: 2,
1052: 3,
1193: 3,
1206: 3,
1207: 4,
1209: 3,
1426: 2,
1427: 3,
1761: 3,
1762: 4,
2265: 1,
2334: 2,
2623: 3,
2624: 3,
2811: 3,
2862: 2,
2863: 3,
3007: 2,
3008: 2,

3188: 2,
3427: 3,
3599: 2,
3715: 4,
3800: 1,
3993: 2,
1048: 2,
1197: 1,
1199: 1,
1202: 1,
1418: 1,
1527: 1,
1528: 1,
1749: 1,
1750: 2,
1754: 1,
1756: 1,
1821: 1,
1982: 1,
2544: 1,
2625: 1,
2675: 1,
2710: 2,
2810: 2,
2970: 1,
2972: 1,
3082: 1,
3713: 1,
3961: 1,
3962: 1,
170: 1,
1204: 1,
1422: 1,
1757: 1,
1759: 1,
2709: 1,
3628: 1,
4148: 1,
81: 1,
129: 1,
157: 1,
163: 1,
164: 1,
166: 1,
167: 1,
168: 1,

```
277: 1,
334: 1,
1823: 1,
1985: 1,
2090: 1,
2108: 1,
2157: 1,
2161: 1,
2208: 1,
2274: 1,
2368: 1,
3148: 1,
3149: 1,
3151: 1,
3928: 1,
4145: 1})
```

***Solution:***

```
multiple_outlier_indices = multiple_outlier_indices(outliers)
```

***Solution:***

```
print(Counter(multiple_outlier_indices))
```

```
Counter({236: 1, 237: 1, 238: 1, 239: 1, 306: 1, 694: 1, 718: 1, 719: 1, 720: 1, 1429: 1, 1987: 1, 2
114: 1, 2169: 1, 2171: 1, 2381: 1, 2711: 1, 3190: 1, 3837: 1, 3899: 1, 3902: 1, 1428: 1, 1763: 1, 1
65: 1, 891: 1, 1052: 1, 1193: 1, 1206: 1, 1207: 1, 1209: 1, 1427: 1, 1761: 1, 1762: 1, 2623: 1, 262
4: 1, 2811: 1, 2863: 1, 3427: 1, 3715: 1})
```

***Solution:***

```
df=df.drop(multiple_outlier_indices,axis=0).reset_index(drop = True)
df
```

***Output:***

| | 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 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **4134** | F | 0.565 | 0.450 | 0.165 | 0.8870 | 0.3700 | 0.2390 | 0.2490 | 11 |
| **4135** | M | 0.590 | 0.440 | 0.135 | 0.9660 | 0.4390 | 0.2145 | 0.2605 | 10 |
| **4136** | M | 0.600 | 0.475 | 0.205 | 1.1760 | 0.5255 | 0.2875 | 0.3080 | 9 |
| **4137** | F | 0.625 | 0.485 | 0.150 | 1.0945 | 0.5310 | 0.2610 | 0.2960 | 10 |
| **4138** | M | 0.710 | 0.555 | 0.195 | 1.9485 | 0.9455 | 0.3765 | 0.4950 | 12 |

4139 rows × 9 columns

***Solution:***

```
df.shape
```

***Output:***

(4139, 9)

**7. Categorical Attribute Encoding**

*Solution:*

```
le=LabelEncoder()
df['Sex']=le.fit_transform(df['Sex'])
```

*Solution:*

```
df.head()
```

*Output:*

| | 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 |
| **1** | 2 | 0.350 | 0.265 | 0.090 | 0.2255 | 0.0995 | 0.0485 | 0.070 | 7 |
| **2** | 0 | 0.530 | 0.420 | 0.135 | 0.6770 | 0.2565 | 0.1415 | 0.210 | 9 |
| **3** | 2 | 0.440 | 0.365 | 0.125 | 0.5160 | 0.2155 | 0.1140 | 0.155 | 10 |
| **4** | 1 | 0.330 | 0.255 | 0.080 | 0.2050 | 0.0895 | 0.0395 | 0.055 | 7 |

**8. Seperate dataframe into Predictor and Target**

*Solution:*

```
feature =pd.DataFrame(df.drop(['Rings'], axis = 1))
label = pd.DataFrame(df.Rings)
```

**9. Scaling the Predictor variables**

*Solution:*

```
convert = StandardScaler()
feature = pd.DataFrame(convert.fit_transform(feature))
```

**10. Perform the train test split**

***Solution:***

```
X_train, X_test, y_train, y_test = train_test_split(feature, label, test_size = 0.2, random_state = 0)
```

***Solution:***

```
print('X_train : ')
print(X_train)
print(X_train.shape)

print('')
print('X_test : ')
print(X_test)
print(X_test.shape)

print('')
print('y_train : ')
print(y_train)
print(y_train.shape)

print('')
print('y_test : ')
print(y_test)
print(y_test.shape)
```

```
X_train :
             0         1         2         3         4         5         6  \
64    1.151942 -0.040971 -0.087769 -0.481759 -0.514480 -0.574405 -0.453057
1521 -0.062807 -1.409929 -1.432469 -1.091508 -1.310493 -1.322352 -1.158735
3436  1.151942  1.670227  1.618965  1.469438  2.013909  1.674082  1.916340
3444 -0.062807 -0.768230 -0.760119 -0.725659 -0.868496 -0.720742 -0.798886
3993 -0.062807 -0.725450 -0.863557 -0.725659 -0.689393 -0.462910 -0.565218
...        ...       ...       ...       ...       ...       ...       ...
1033  1.151942  1.413547  1.205212  0.859689  1.832711  2.173488  1.701365
3264  1.151942  1.028527  0.946616  1.225538  0.845026  0.772829  0.916240
1653 -1.277555  0.729068  0.688019  0.493839  0.607270  0.120118  0.402169
2607 -0.062807 -0.725450 -0.708400 -0.969558 -0.876875 -0.690546 -0.995167
2732 -0.062807  0.215709  0.119108  0.371889  0.180984  0.638106  0.004933

             7
64   -0.390700
1521 -1.300351
3436  2.132846
3444 -1.014251
3993 -0.959232
...        ...
```

```
1033  1.223195
3264  1.149837
1653  1.032462
2607 -0.992243
2732 -0.243983

[3311 rows x 8 columns]
(3311, 8)

X_test :
            0         1         2         3         4         5         6  \
958   1.151942 -0.126531  0.015669  0.127990 -0.062009  0.134054  0.014280
2613 -0.062807 -0.425991 -0.346365 -0.603709 -0.639119 -0.579050 -0.569891
45   -0.062807 -1.153250 -1.173873 -1.091508 -1.304208 -1.254990 -1.261549
3145 -1.277555 -0.169311  0.015669 -0.115910 -0.353182 -0.309604 -0.439037
3994 -0.062807 -0.340431 -0.449804 -1.213458 -0.365751 -0.191140 -0.448384
...        ...       ...       ...       ...       ...       ...       ...
620  -1.277555 -0.853790 -0.760119 -1.091508 -1.054931 -1.101684 -1.112002
1544 -0.062807 -0.597110 -0.501523 -0.603709 -0.772137 -0.692869 -0.883007
2954  1.151942  0.087369 -0.036050  0.859689  0.931959  0.884324  1.369556
177  -0.062807 -2.564988 -2.570292 -2.311006 -1.632040 -1.545343 -1.541951
50   -0.062807 -0.040971  0.015669 -0.481759 -0.483058 -0.553499 -0.644665

            7
958  -0.313674
2613 -0.680468
45   -1.197648
3145 -0.317342
3994 -0.427380
...        ...
620  -0.830854
1544 -0.669464
2954  0.724355
177  -1.637802
50   -0.354021

[828 rows x 8 columns]
(828, 8)

y_train :
      Rings
64        8
1521      8
3436     11
3444      7
3993      8
```

```
...     ...
1033      8
3264     17
1653     10
2607      7
2732      9

[3311 rows x 1 columns]
(3311, 1)

y_test :
      Rings
958       8
2613      7
45        7
3145     15
3994      8
...     ...
620      10
1544     10
2954     13
177       4
50        8

[828 rows x 1 columns]
(828, 1)
```

**11.Build Model**

***Solution:***

```
pipelines={
'rf':make_pipeline(RandomForestRegressor(random_state=1234)),
'ridge':make_pipeline(Ridge(random_state=1234)),
'lasso':make_pipeline(Lasso(random_state=1234)),
}
```

***Solution:***

```
hyperparagrid={
'rf':{
'randomforestregressor__min_samples_split':[2,4,6],
'randomforestregressor__min_samples_leaf':[1,2,3]
},

'ridge':{
    'ridge__alpha':[0.001,0.005,0.01,0.05,0.1,0.5,0.99]
```

```
},
'lasso':{
  'lasso__alpha':[0.001,0.005,0.01,0.05,0.1,0.5,0.99]
}
}
```

**12. Traning the Model**

***Solution:***

```
fit_models={}
for algo,pipeline in pipelines.items():
  model=GridSearchCV(pipeline,hyperparagrid[algo],cv=10,n_jobs=-1)
  try:
    print('Start training for {}'.format(algo))
    model.fit(X_train,y_train)
    fit_models[algo]=model
  except NotFittedError as e:
    print(repr(e))
```

```
Start training for rf
Start training for ridge
Start training for lasso
```

**13,14 Testing and Measuring Performance**

***Solution:***

```
best_model_rf=fit_models['rf']
best_model_rf
```

***Output:***

```
GridSearchCV(cv=10,
       estimator=Pipeline(steps=[('randomforestregressor',
                    RandomForestRegressor(random_state=1234))]),
       n_jobs=-1,
       param_grid={'randomforestregressor__min_samples_leaf': [1, 2, 3],
             'randomforestregressor__min_samples_split': [2, 4, 6]})
```

***Solution:***

```
best_model_ridge=fit_models['ridge']
```

```
best_model_ridge
```

***Output:***

```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('ridge', Ridge(random_state=1234))]),
             n_jobs=-1,
             param_grid={'ridge__alpha': [0.001, 0.005, 0.01, 0.05, 0.1, 0.5,
                                          0.99]})
```

***Solution:***

```
best_model_lasso=fit_models['lasso']
best_model_lasso
```

***Output:***

```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('lasso', Lasso(random_state=1234))]),
             n_jobs=-1,
             param_grid={'lasso__alpha': [0.001, 0.005, 0.01, 0.05, 0.1, 0.5,
                                          0.99]})
```

***Solution:***

```
for algo,model in fit_models.items():
    ya=model.predict(X_test)
    print('{} scores-R2:{} MAE:{}'.format(algo,r2_score(y_test,ya),
mean_absolute_error(y_test,ya)))
```

```
rf scores-R2:0.5255029479701915 MAE:1.570513566816263
ridge scores-R2:0.5189099860811324 MAE:1.6528099660919895
lasso scores-R2:0.5190720174119673 MAE:1.6525494856846143
```