Import Libraries

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
```

Import Dataset

```
data = pd.read_csv('abalone.csv')
data
```

	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

4177 rows × 9 columns

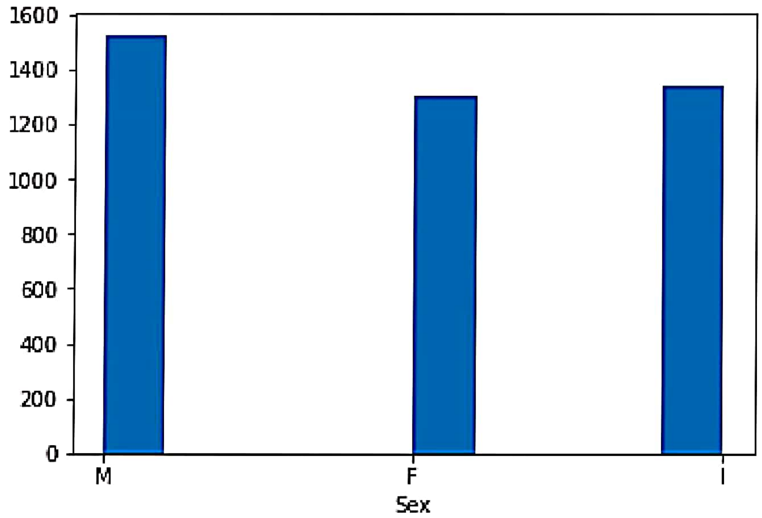
```
data.info()
```

```
<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
```

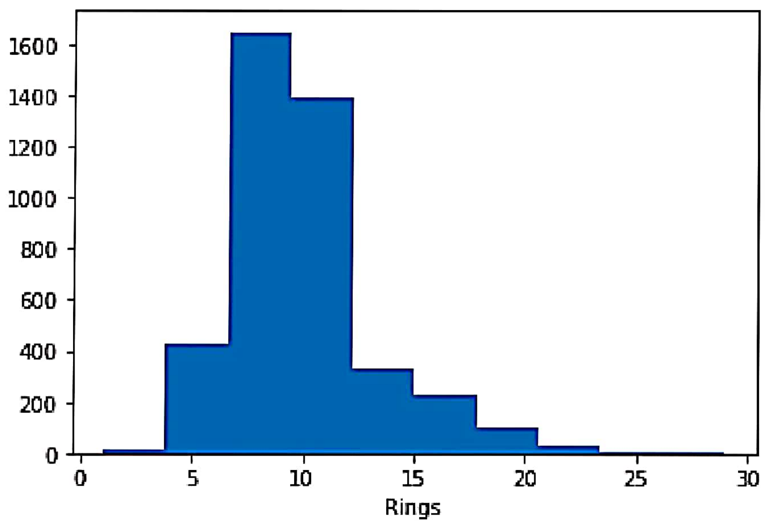
```
 2   Diameter        4177 non-null   float64
 3   Height          4177 non-null   float64
 4   Whole weight    4177 non-null   float64
 5   Shucked weight  4177 non-null   float64
 6   Viscera weight  4177 non-null   float64
 7   Shell weight    4177 non-null   float64
 8   Rings           4177 non-null   int64
dtypes: float64(7), int64(1), object(1)
memory usage: 293.8+ KB
```

Univariate Analysis

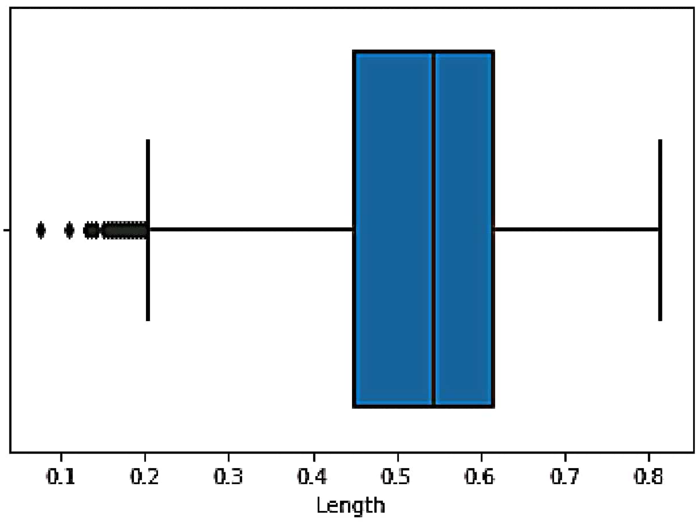
```
plt.hist(data['Sex']);
plt.xlabel('Sex');
```



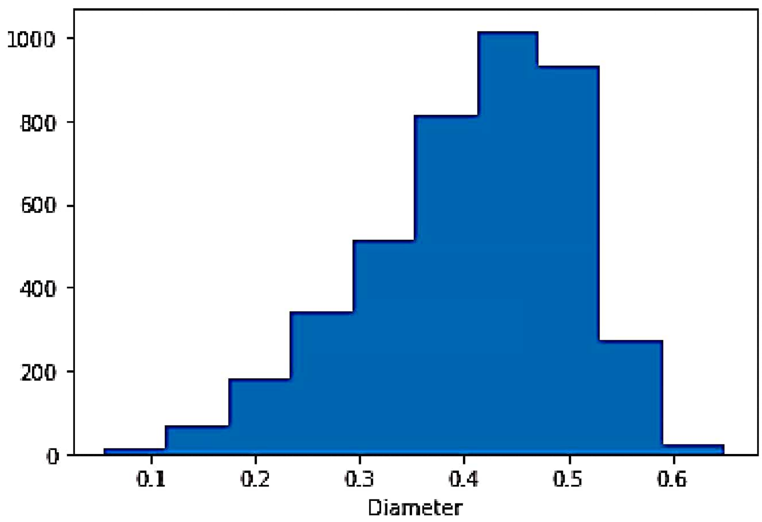

```
plt.hist(data['Rings']);
plt.xlabel('Rings');
```



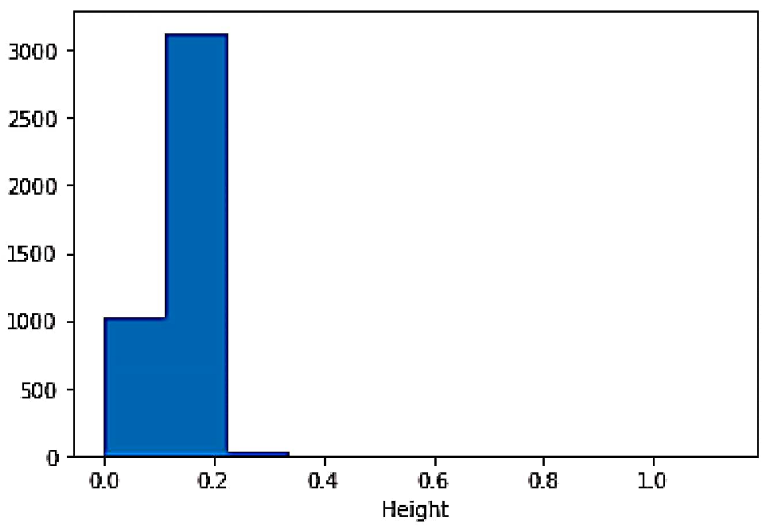

```
sns.boxplot(x=data['Length'])
plt.xlabel('Length');
```



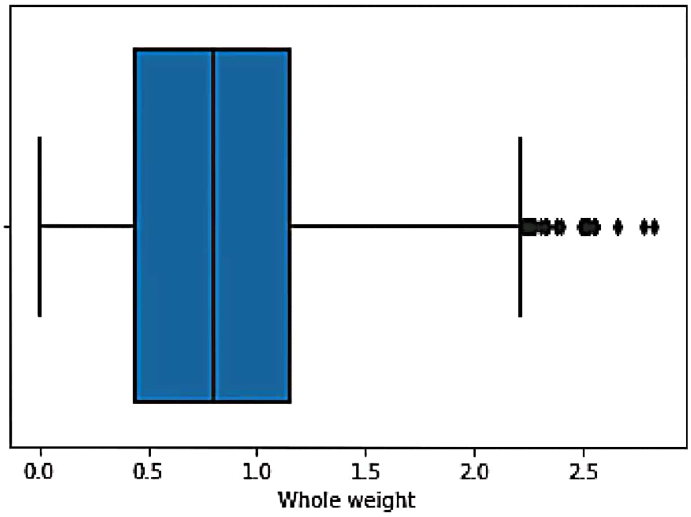

```
plt.hist(data['Diameter']);
plt.xlabel('Diameter');
```



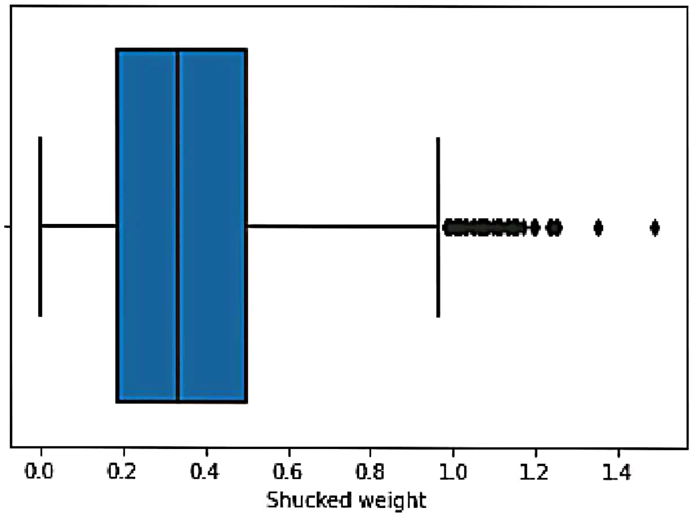

```
plt.hist(data['Height']);
plt.xlabel('Height');
```



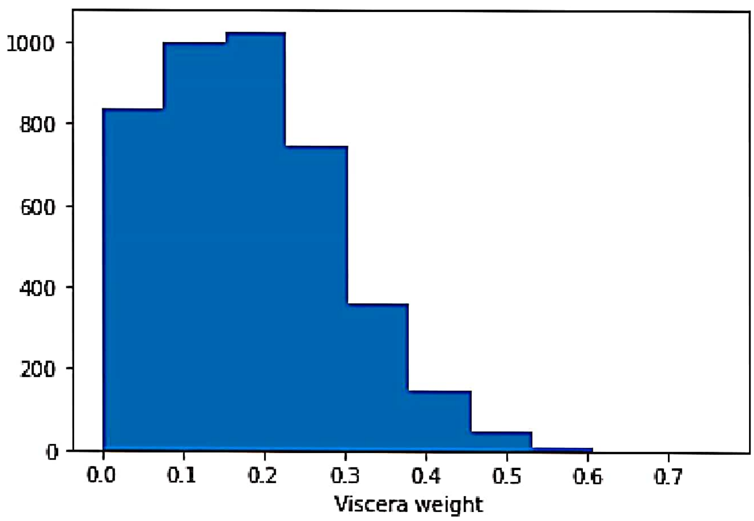

```
sns.boxplot(x=data['Whole weight'])
plt.xlabel('Whole weight');
```



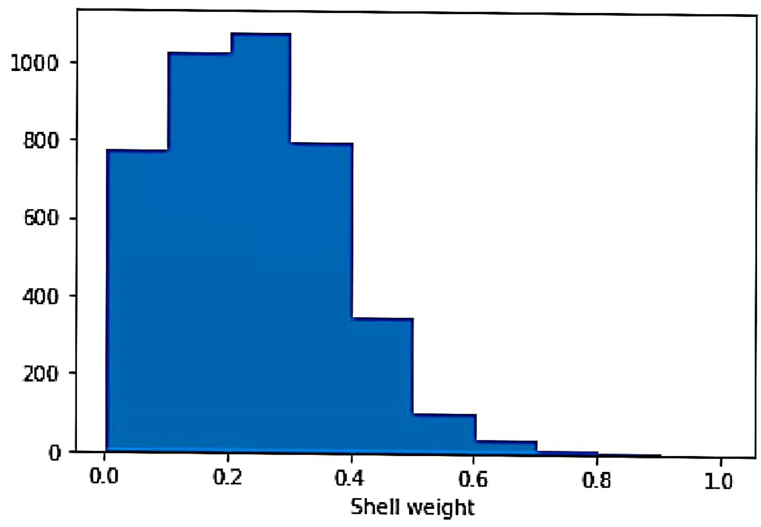

```
sns.boxplot(x=data['Shucked weight'])
plt.xlabel('Shucked weight');
```




```
plt.hist(data['Viscera weight']);
plt.xlabel('Viscera weight');
```

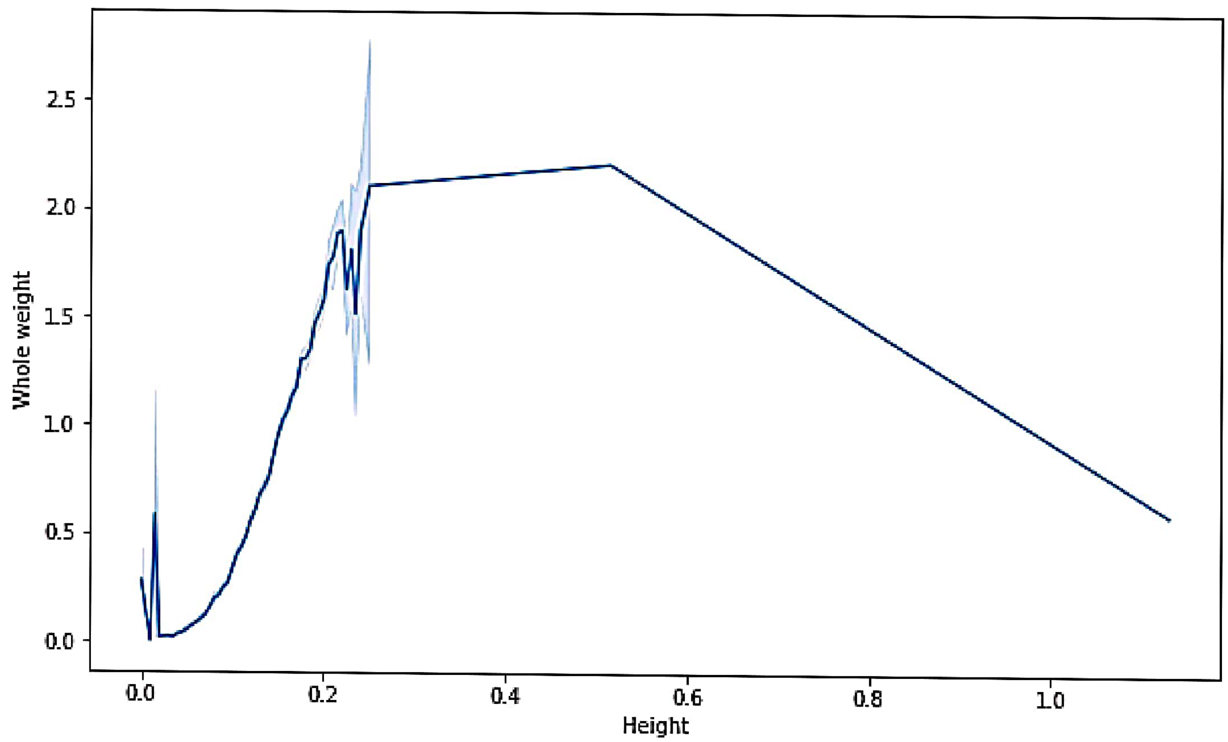



```
plt.hist(data['Shell weight']);
plt.xlabel('Shell weight');
```

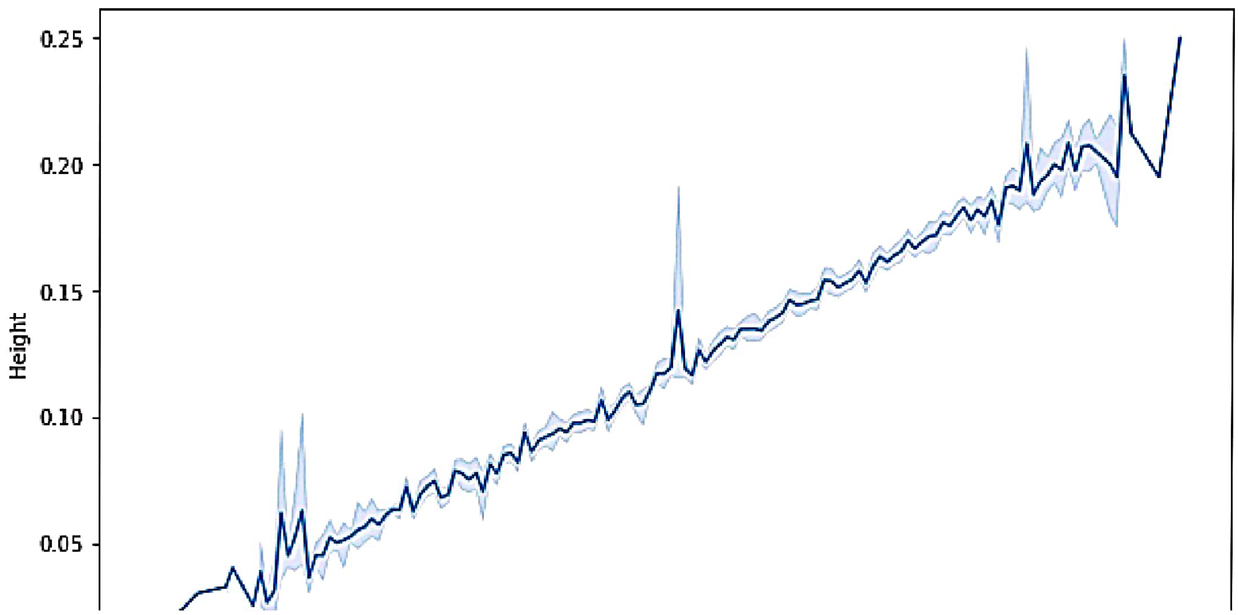


Bivariate Analysis

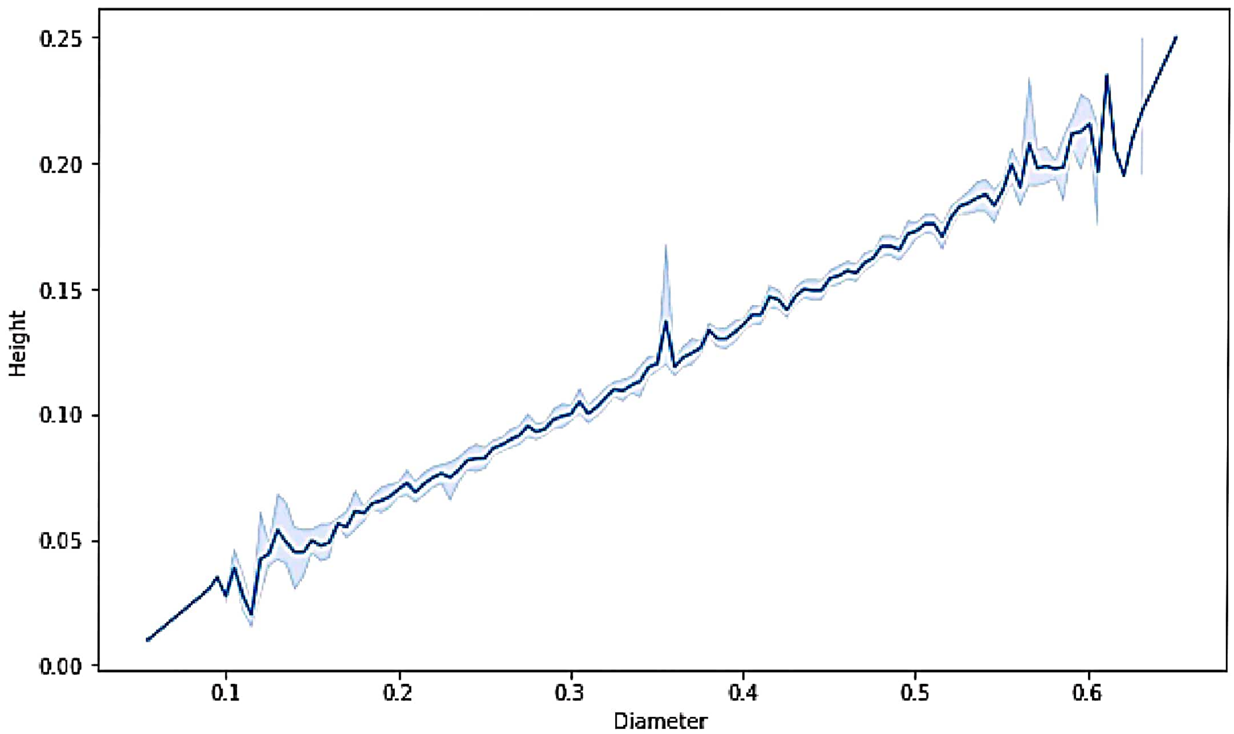
```
plt.figure(figsize=(10, 6))
sns.lineplot(x=data["Height"], y=data["Whole weight"]);
plt.xlabel('Height');
plt.ylabel('Whole weight');
```



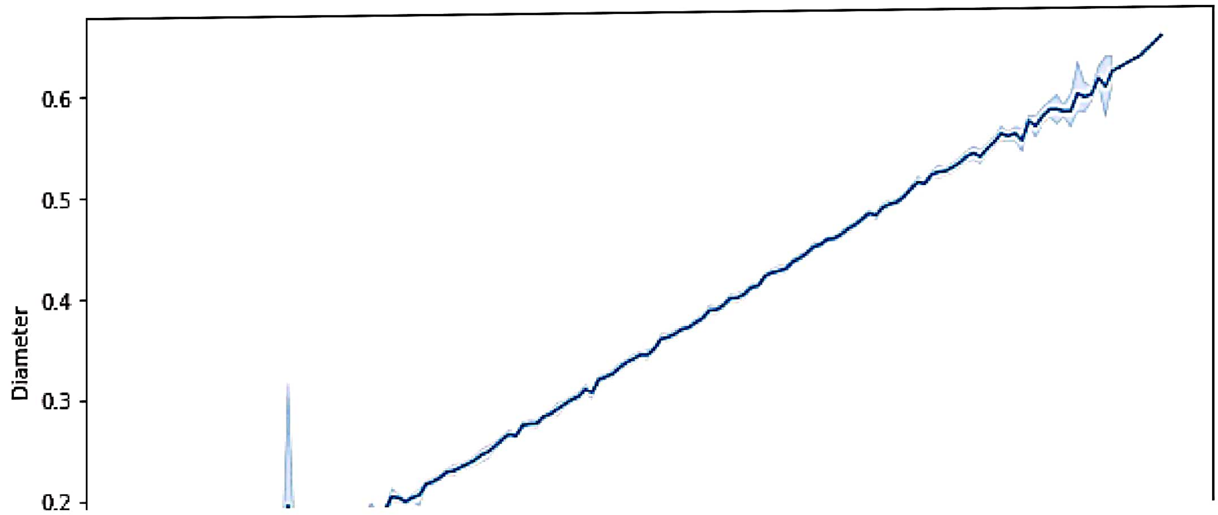

```
plt.figure(figsize=(10, 6))
sns.lineplot(x=data["Length"], y=data["Height"]);
plt.xlabel('Length');
plt.ylabel('Height');
```



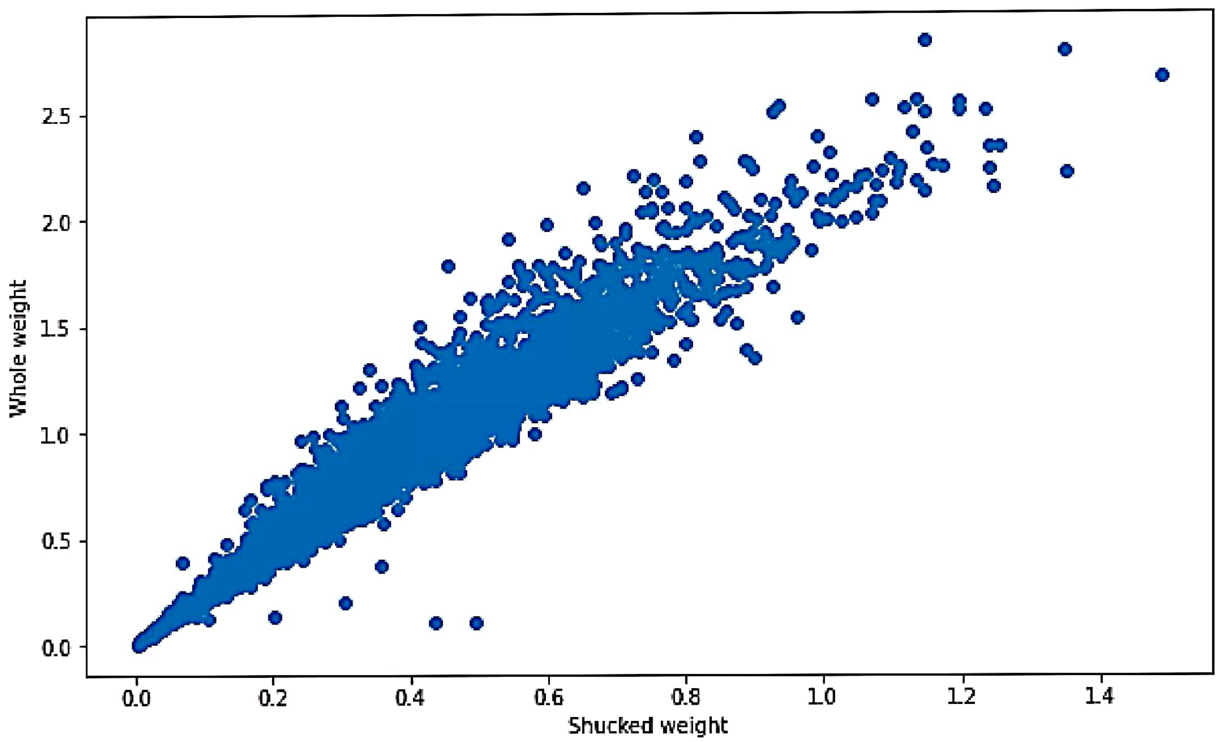

```
plt.figure(figsize=(10, 6))
sns.lineplot(x=data["Diameter"], y=data["Height"]);
plt.xlabel('Diameter');
plt.ylabel('Height');
```



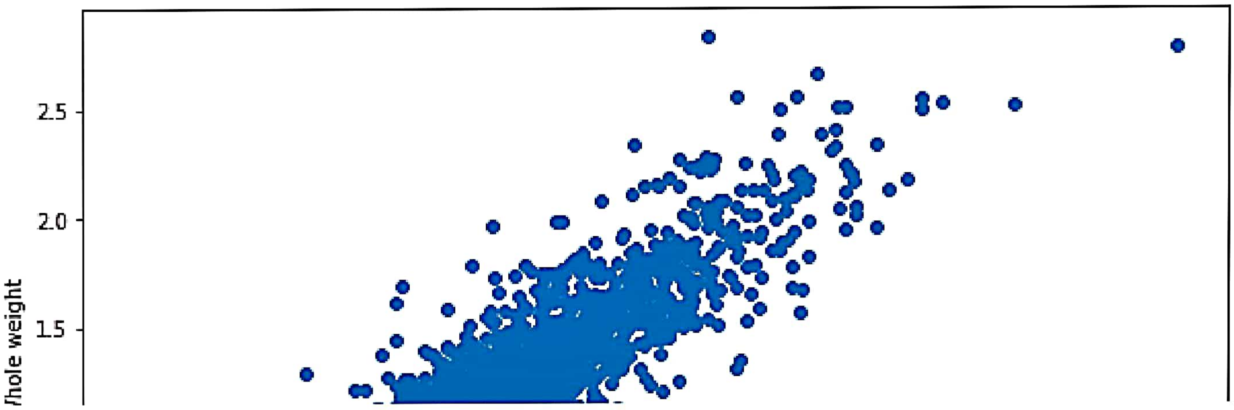

```
plt.figure(figsize=(10, 6))
sns.lineplot(x=data["Length"], y=data["Diameter"]);
plt.xlabel('Length');
plt.ylabel('Diameter');
```




```
plt.figure(figsize=(10, 6))
plt.scatter(x=data["Shucked weight"], y=data["Whole weight"]);
plt.xlabel('Shucked weight');
plt.ylabel('Whole weight');
```

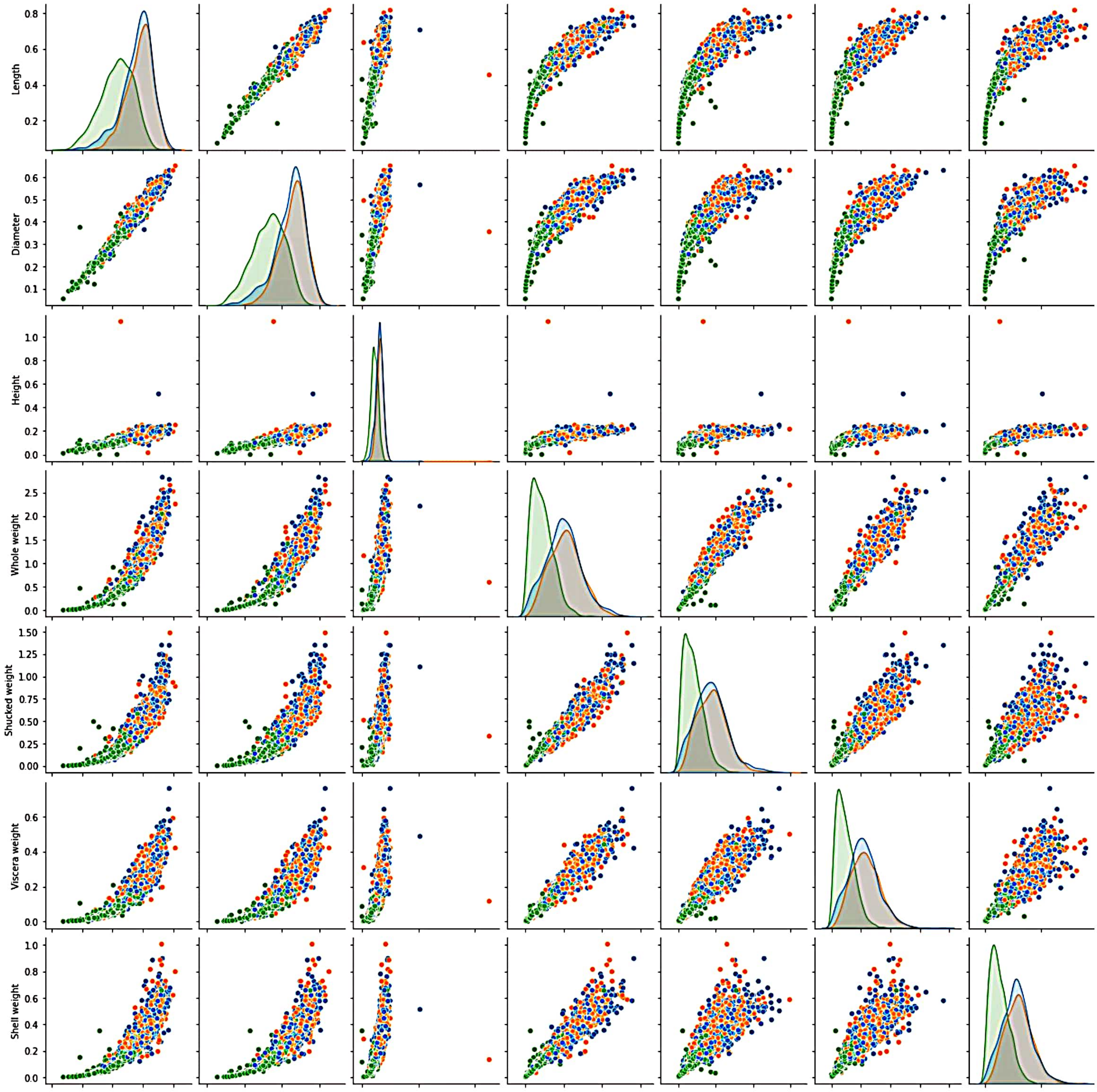



```
plt.figure(figsize=(10, 6))
plt.scatter(x=data["Viscera weight"], y=data["Whole weight"]);
plt.xlabel('Viscera weight');
plt.ylabel('Whole weight');
```

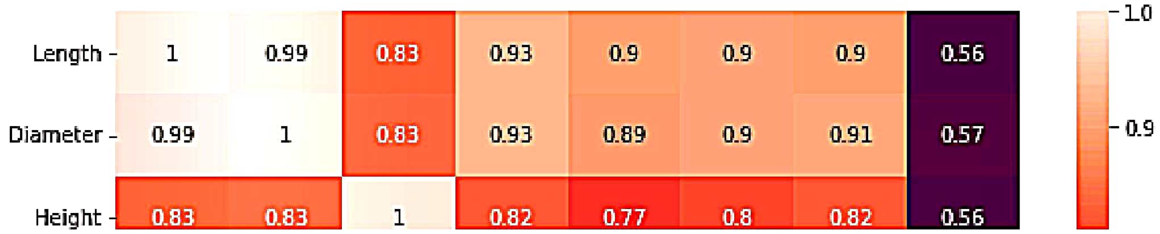


Multi-variate Analysis

```
sns.pairplot(data, hue='Sex');
```




```
plt.figure(figsize=(10, 6));
sns.heatmap(data.corr(), annot=True);
```



Descriptive Statistics


```
data.describe()
```

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	41
mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	

Handling Missing Values

```
data.isna().sum()
```

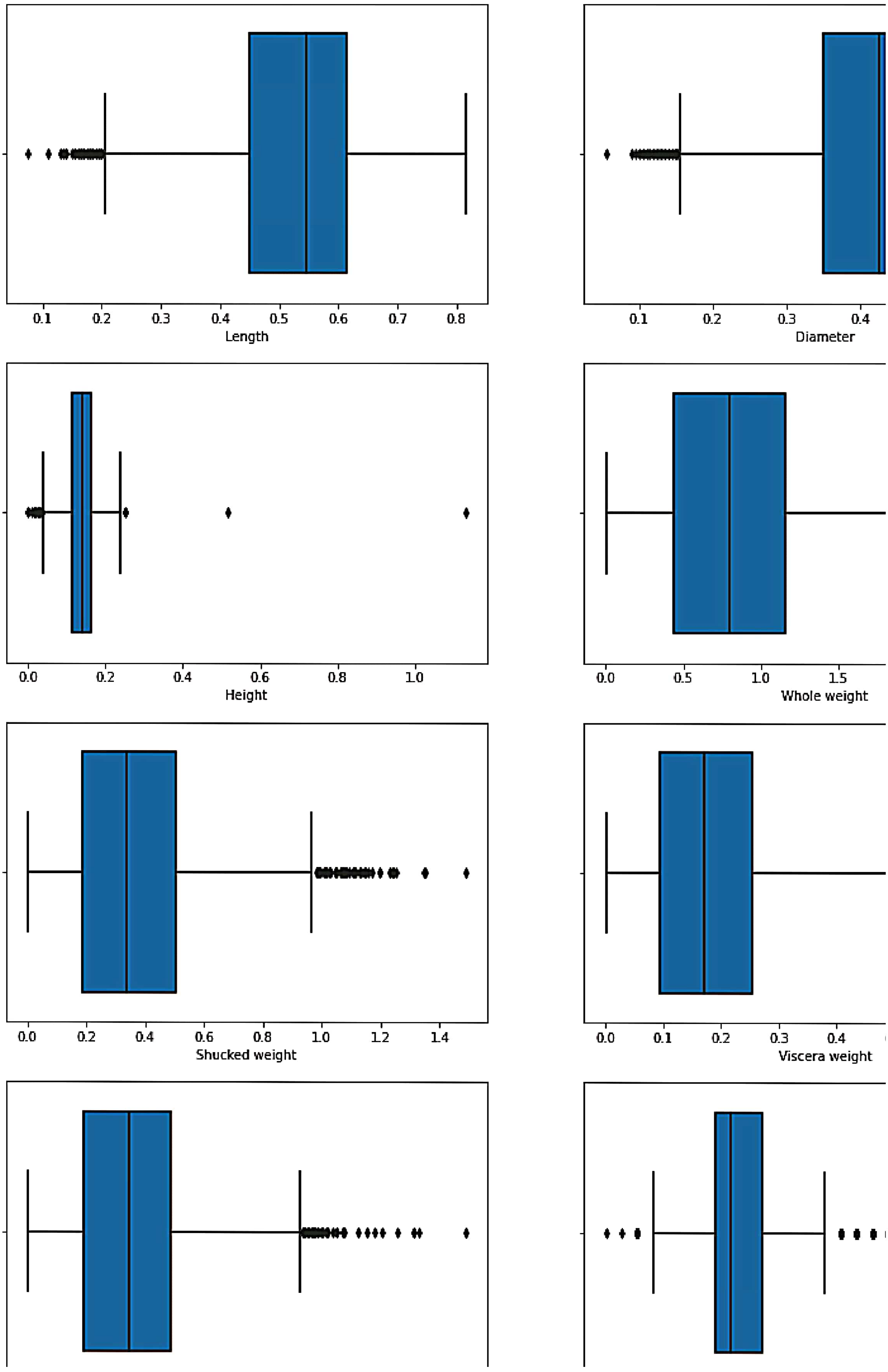
```
Sex               0
Length            0
Diameter          0
Height            0
Whole weight      0
Shucked weight    0
Viscera weight    0
Shell weight      0
Rings             0
dtype: int64
```

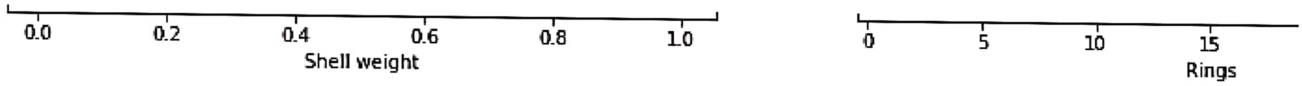
Outlier Handling

```
numeric_cols = ['Length', 'Diameter', 'Height', 'Whole weight', 'Shucked weight', 'Viscera

def boxplots(cols):
```

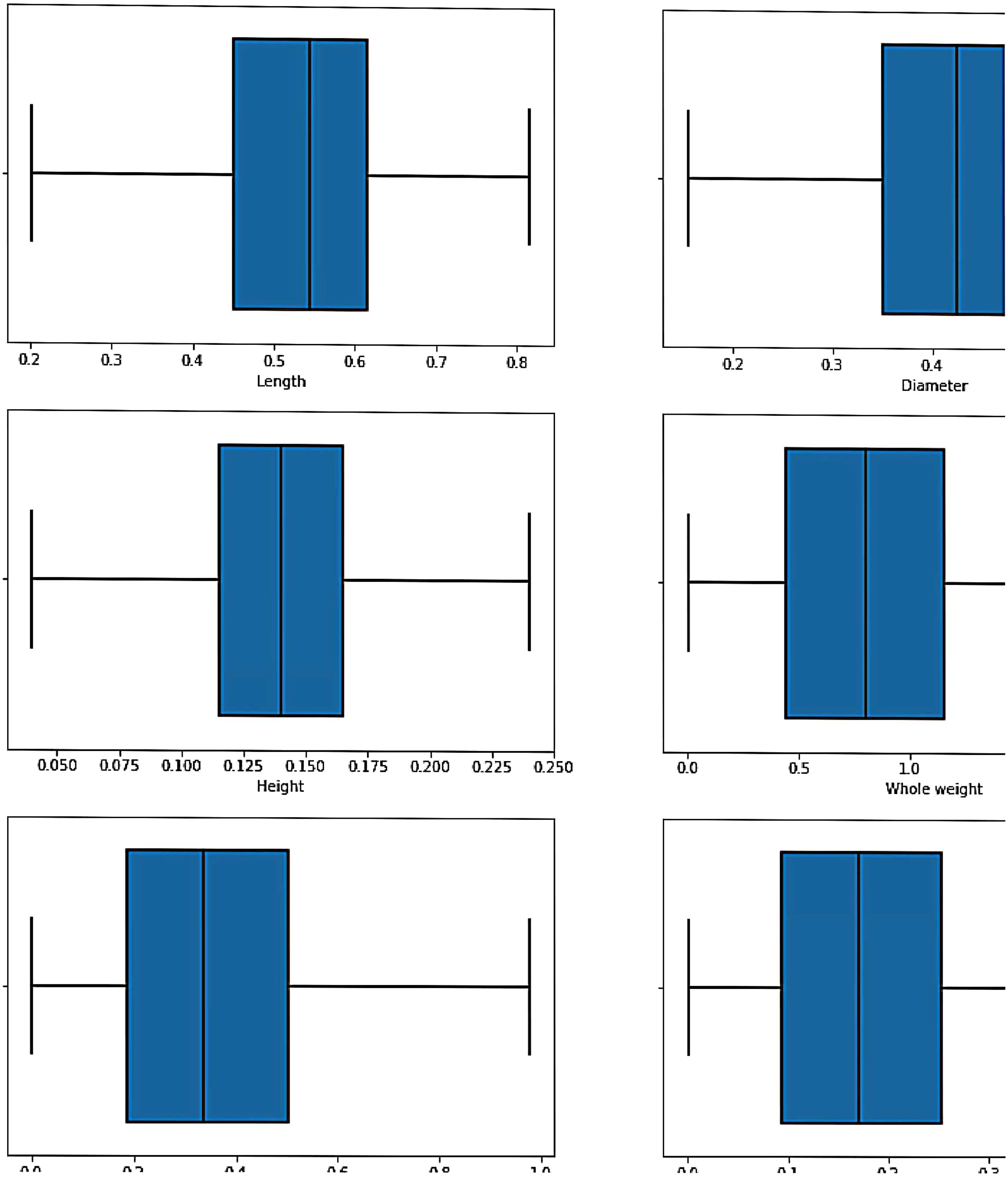
```
    fig, axes = plt.subplots(4, 2, figsize=(15, 20))

    t=0
    for i in range(4):
        for j in range(2):
            sns.boxplot(ax=axes[i][j], data=data, x=cols[t])
            t+=1

    plt.show()


def Flooring_outlier(col):
    Q1 = data[col].quantile(0.25)
    Q3 = data[col].quantile(0.75)
    IQR = Q3 - Q1
    whisker_width = 1.5
    lower_whisker = Q1 -(whisker_width*IQR)
    upper_whisker = Q3 + (whisker_width*IQR)
    data[col]=np.where(data[col]>upper_whisker,upper_whisker,np.where(data[col]<lower_whis


print('Before Outliers Handling')
print('='*100)
boxplots(numeric_cols)
for col in numeric_cols:
    Flooring_outlier(col)
print('\n\n\nAfter Outliers Handling')
print('='*100)
boxplots(numeric_cols)
```

Before Outliers Handling






```
After Outliers Handling
===============================================================================
```



Encode Categorical Columns

```
data = pd.get_dummies(data, columns = ['Sex'])
data
```

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings	Se
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500	15.0	
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700	7.0	
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100	9.0	
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550	10.0	
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	7.0	
...	...	...	...	...	...	...	...	...	
4172	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11.0	
4173	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	10.0	
4174	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	9.0	
4175	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	10.0	
4176	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	12.0	

4177 rows × 11 columns

Split Data into Dependent & Independent Columns

```
Y = data[['Rings']]
X = data.drop(['Rings'], axis=1)
```

Scale the independent Variables

```
scaler = StandardScaler()
X = scaler.fit_transform(X)
X
```

```
array([[-0.58311728, -0.44088378, -1.15809314, ..., -0.67483383,
        -0.68801788,  1.31667716],
       [-1.46569411, -1.45976205, -1.28875125, ..., -0.67483383,
        -0.68801788,  1.31667716],
       [ 0.04729474,  0.11949927, -0.1128283 , ...,  1.48184628,
        -0.68801788, -0.75948762],
       ...,
       [ 0.63567929,  0.67988232,  1.71638519, ..., -0.67483383,
        -0.68801788,  1.31667716],
       [ 0.84581663,  0.78177015,  0.27914602, ...,  1.48184628,
        -0.68801788, -0.75948762],
       [ 1.56028358,  1.49498494,  1.45506898, ..., -0.67483383,
        -0.68801788,  1.31667716]])
```

Train Test Split

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
X_train.shape, X_test.shape, Y_train.shape, Y_test.shape
```

```
((3341, 10), (836, 10), (3341, 1), (836, 1))
```

Model Training & Testing

```
model = LinearRegression()
model.fit(X_train, Y_train)
model.score(X_train, Y_train), model.score(X_test, Y_test)
```

```
(0.5743537797259437, 0.574066914479568)
```

```
model = DecisionTreeRegressor(max_depth=15, max_leaf_nodes=40)
model.fit(X_train, Y_train)
model.score(X_train, Y_train), model.score(X_test, Y_test)
```

```
(0.6299341126842184, 0.5533377990647702)
```