1. Dataset has been downloaded

In [3]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

2. Load the dataset into the tool

In [4]:
```
data=pd.read_csv("abalone.csv")
data.head()
```

Out[4]:

	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

Let's know the shape of the data

In [5]:
```
data.shape
```

Out[5]: (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

In [6]:
```
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()
```

Out[6]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

3. Perform Below Visualizations.

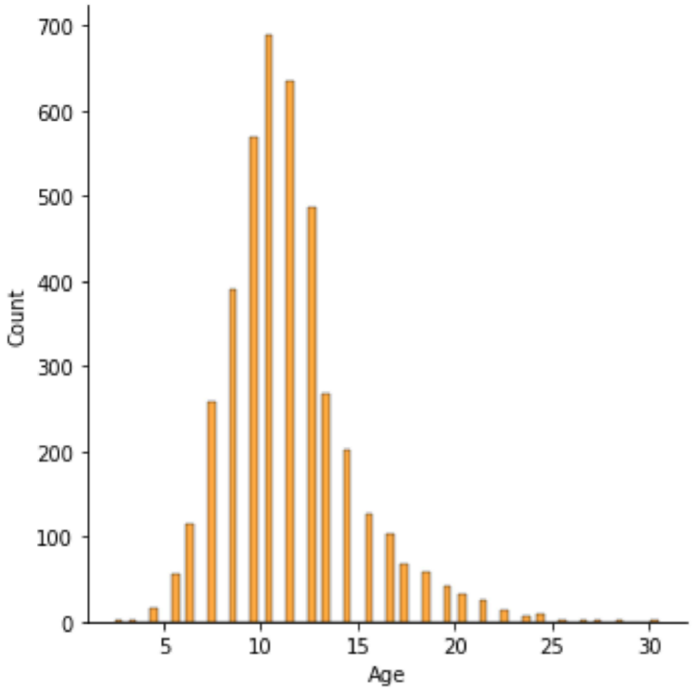
(i) Univariate Analysis

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

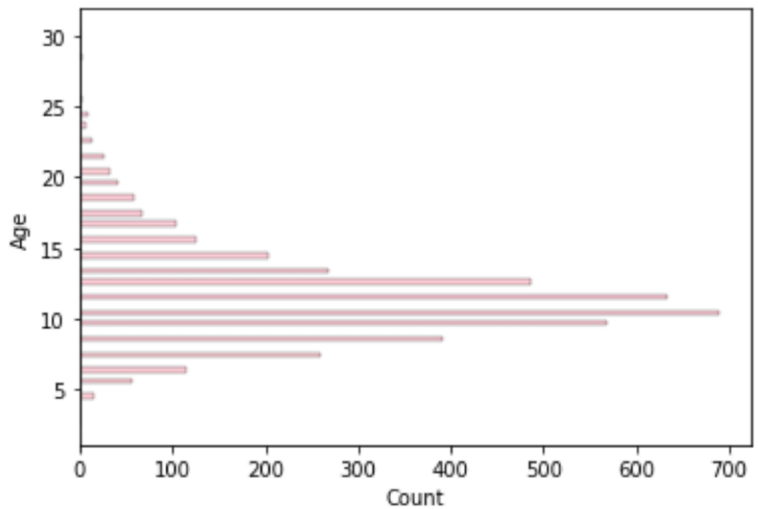
In [7]:
```
sns.displot(data["Age"], color='darkorange')
```

Out[7]: <seaborn.axisgrid.FacetGrid at 0x7f5d2388cc90>



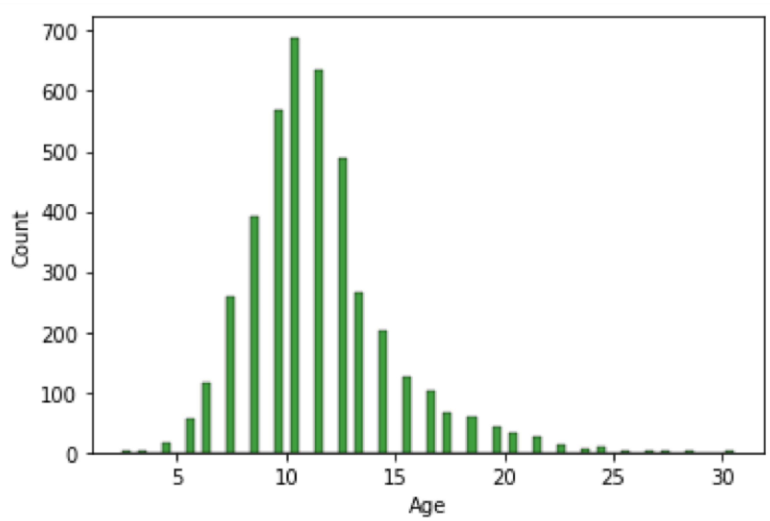
In [8]:
```
sns.histplot(y=data.Age,color='pink')
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d20e8f950>



In [9]:
```
sns.histplot(x=data.Age,color='green')
```

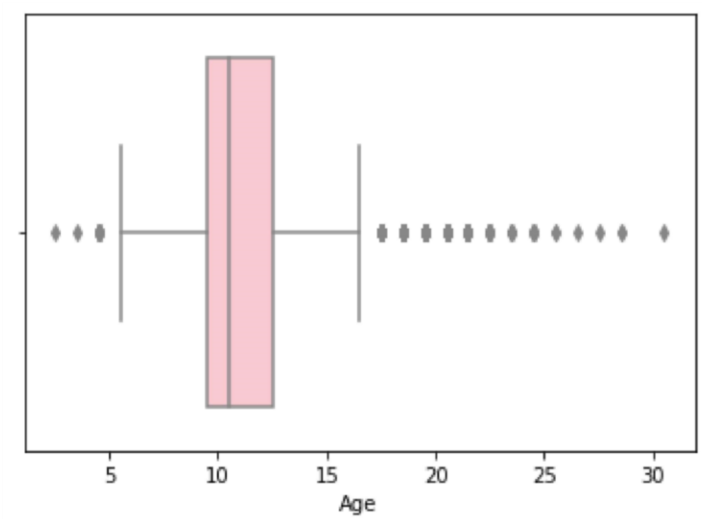
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d2382ef90>



Boxplot

In [10]:
```
sns.boxplot(x=data.Age,color='pink')
```

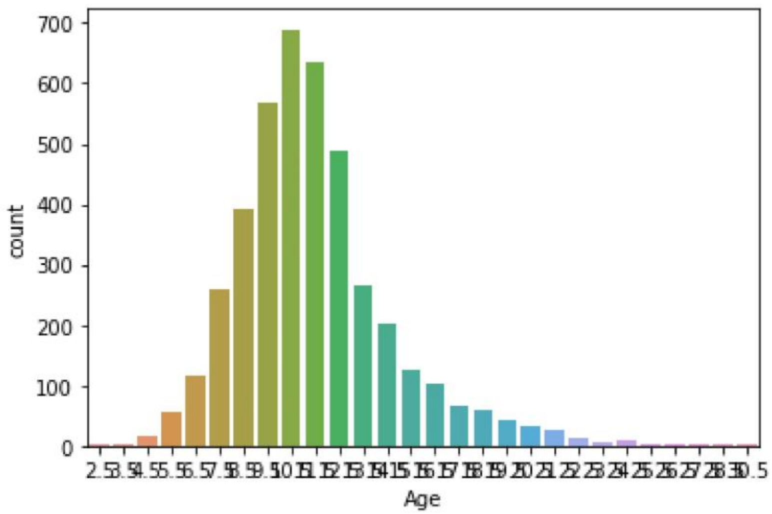
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d23938510>



Countplot

In [11]:
```
sns.countplot(x=data.Age)
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d2095ab10>



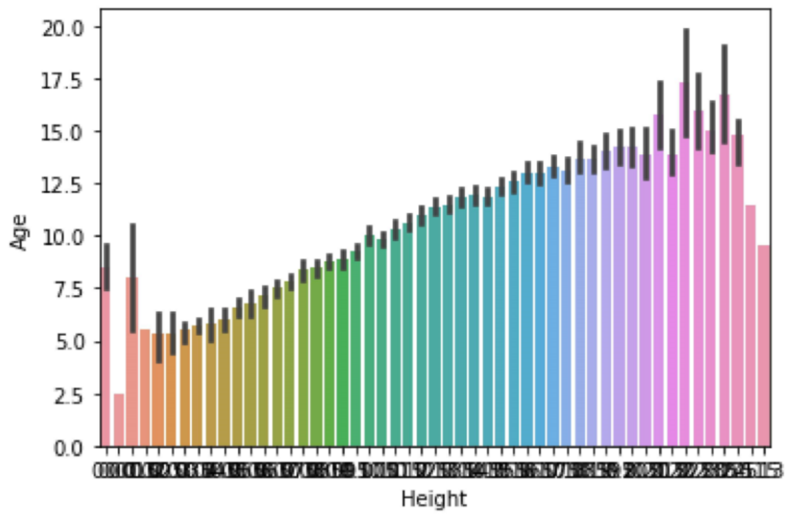
(ii) Bi-Variate Analysis

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).

Barplot

In [12]:
```
sns.barplot(x=data.Height,y=data.Age)
```

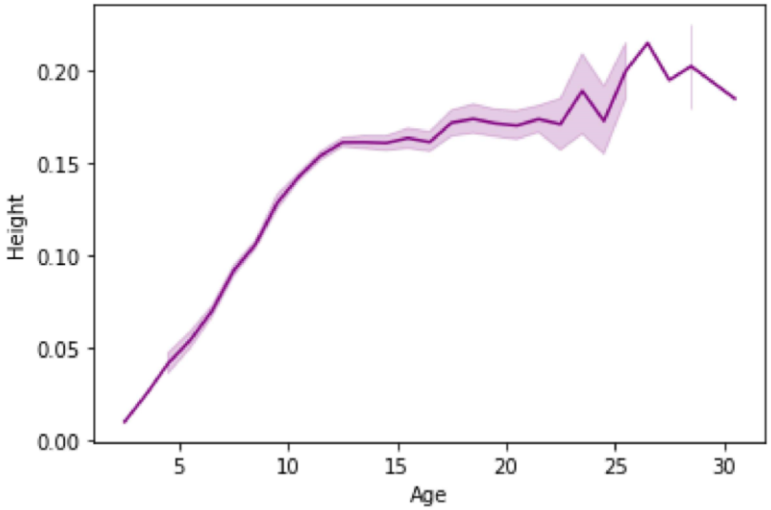
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d20633a50>



Linearplot

In [13]:
```
sns.lineplot(x=data.Age,y=data.Height, color='purple')
```

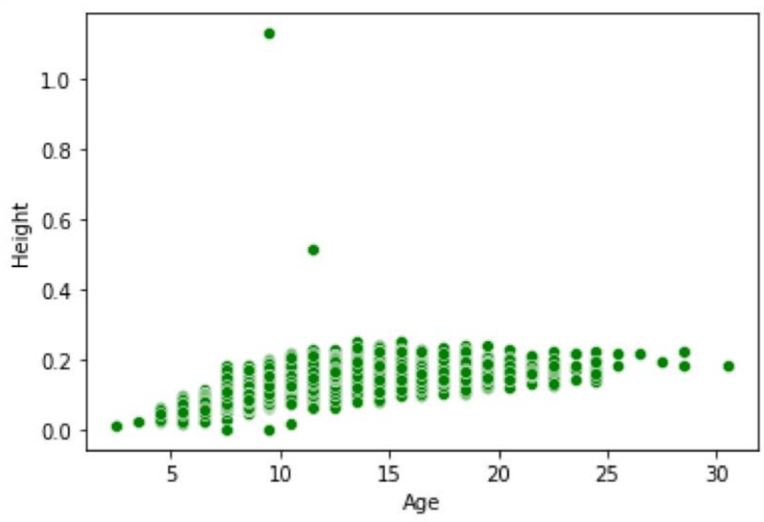
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d207844d0>



Scatterplot

In [14]:
```
sns.scatterplot(x=data.Age,y=data.Height,color='green')
```

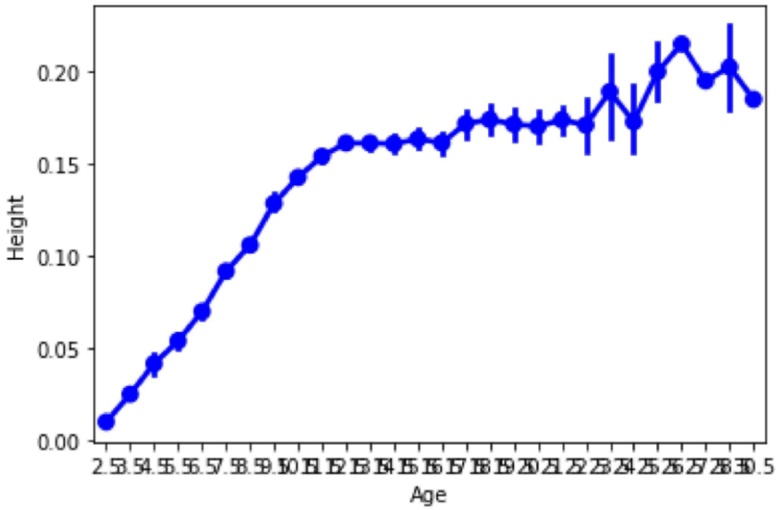
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d20541650>



Pointplot

In [15]:
```
sns.pointplot(x=data.Age, y=data.Height, color="blue")
```

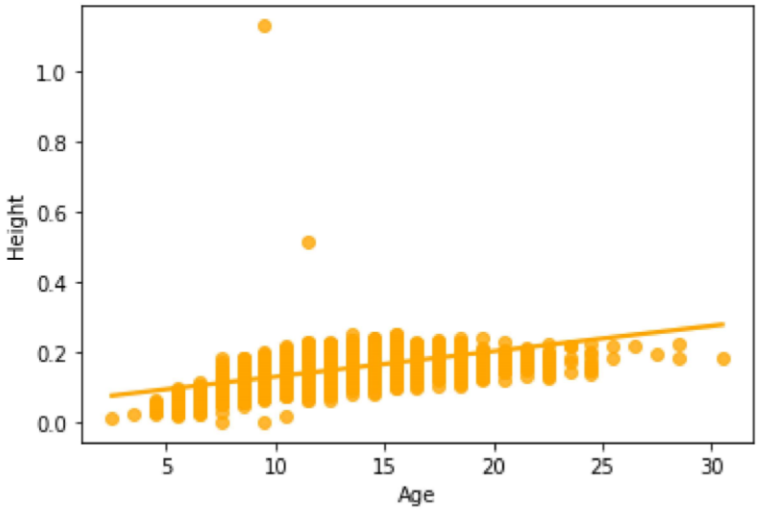
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d202b7f10>



Regplot

In [16]:
```
sns.regplot(x=data.Age,y=data.Height,color='orange')
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d202bf410>



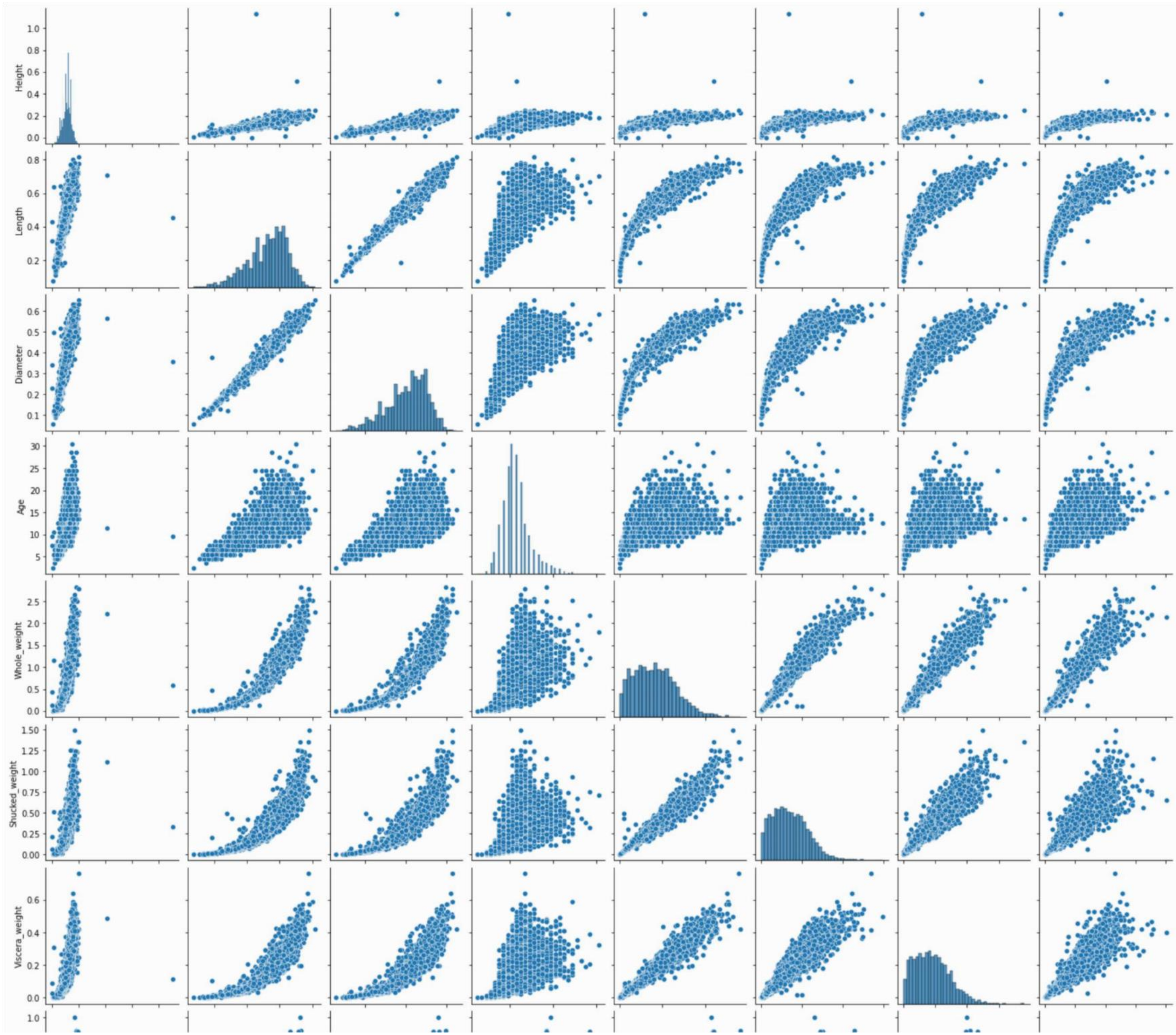
In [17]:
```
sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","Shucked_weight","Viscera_weight",
"Shell_weight"]])
```

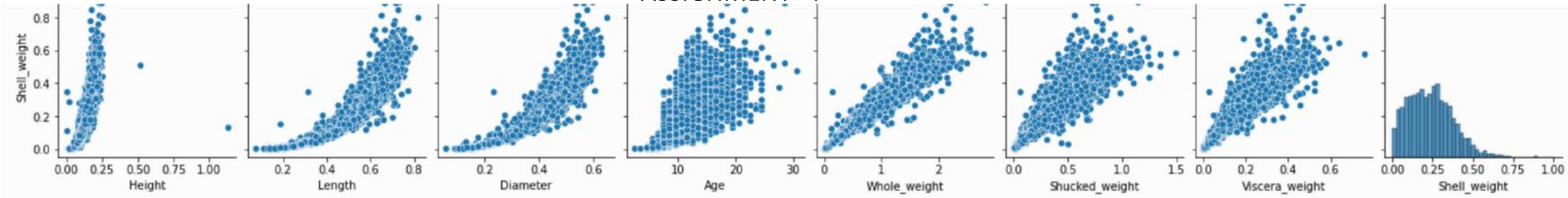
Out[17]: <seaborn.axisgrid.PairGrid at 0x7f5d201a0450>

(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


Height
Length
Diameter
Age
Whole_weight
Shucked_weight
Viscera_weight



4. Perform descriptive statistics on the dataset

In [20]:
```
data.describe(include='all')
```

Out[20]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
count	4177	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
unique	3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	M	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	1528	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	11.433684
std	NaN	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
min	NaN	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	2.500000
25%	NaN	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	9.500000
50%	NaN	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	10.500000
75%	NaN	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	12.500000
max	NaN	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	30.500000

5. Check for Missing values and deal with them

In [21]:
```
data.isnull().sum()
```

Out[21]:
```
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

In [22]:
```
outliers=data.quantile(q=(0.25,0.75))
outliers
```

Out[22]:

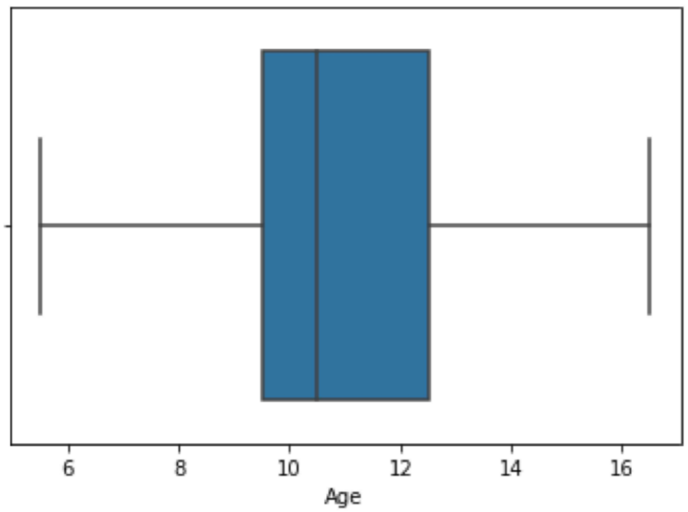
	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0.25	0.450	0.35	0.115	0.4415	0.186	0.0935	0.130	9.5
0.75	0.615	0.48	0.165	1.1530	0.502	0.2530	0.329	12.5

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

Out[23]:
```
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
```

In [24]:
```
data['Age'] = np.where(data['Age'] < lower_limit, 7, data['Age'])
sns.boxplot(x=data.Age,showfliers = False)
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d1b0a0050>



7. Check for Categorical columns and perform encoding

In [27]:
```
data.head()
```

Out[27]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

In [28]:
```
from sklearn.preprocessing import LabelEncoder

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

data.head()
```

Out[28]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	1	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

8. Split the data into dependent and independent variables

In [29]:
```
y = data["Sex"]
y.head()
```

Out[29]:
```
0    2
1    2
2    0
3    2
4    1
Name: Sex, dtype: int64
```

In [30]:
```
x=data.drop(columns=["Sex"],axis=1)
x.head()
```

Out[30]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

9. Scale the independent variables

In [31]:
```
from sklearn.preprocessing import scale
X_Scaled = pd.DataFrame(scale(x), columns=x.columns)
X_Scaled.head()
```

Out[31]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	-0.574558	-0.432149	-1.064424	-0.641898	-0.607685	-0.726212	-0.638217	1.577830
1	-1.448986	-1.439929	-1.183978	-1.230277	-1.170910	-1.205221	-1.212987	-0.919022
2	0.050033	0.122130	-0.107991	-0.309469	-0.463500	-0.356690	-0.207139	-0.294809
3	-0.699476	-0.432149	-0.347099	-0.637819	-0.648238	-0.607600	-0.602294	0.017298
4	-1.615544	-1.540707	-1.423087	-1.272086	-1.215968	-1.287337	-1.320757	-0.919022

10. Split the data into training and testing

In [32]:
```
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)
```

In [33]:
```
X_Train.shape,X_Test.shape
```

Out[33]: ((3341, 8), (836, 8))

In [34]:
```
Y_Train.shape,Y_Test.shape
```

Out[34]: ((3341,), (836,))

In [35]:
```
X_Train.head()
```

Out[35]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
3141	-2.864726	-2.750043	-1.423087	-1.622870	-1.553902	-1.583867	-1.644065	-1.543234
3521	-2.573250	-2.598876	-2.020857	-1.606554	-1.551650	-1.565619	-1.626104	-1.387181
883	1.132658	1.230689	0.728888	1.145672	1.041436	0.286552	1.538726	1.577830
3627	1.590691	1.180300	1.446213	2.164373	2.661269	2.330326	1.377072	0.017298
2106	0.591345	0.474853	0.370226	0.432887	0.255175	0.272866	0.906479	1.265723

In [38]:
```
X_Test.head()
```

Out[38]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
668	0.216591	0.172519	0.370226	0.181016	-0.368878	0.569396	0.690940	0.953617
1580	-0.199803	-0.079426	-0.466653	-0.433875	-0.443224	-0.343004	-0.325685	-0.606915
3784	0.799543	0.726798	0.370226	0.870348	0.755318	1.764639	0.565209	0.329404
463	-2.531611	-2.447709	-2.020857	-1.579022	-1.522362	-1.538247	-1.572219	-1.543234
2615	1.007740	0.928354	0.848442	1.390405	1.415417	1.778325	0.996287	0.641511

In [36]:
```
Y_Train.head()
```

Out[36]:
```
3141    1
3521    1
883     2
3627    2
2106    2
Name: Sex, dtype: int64
```

In [37]:
```
Y_Test.head()
```

Out[37]:
```
668     2
1580    1
3784    2
463     1
2615    2
Name: Sex, dtype: int64
```

11. Build the Model

In [39]:
```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=10,criterion='entropy')
```

In [40]:
```
model.fit(X_Train,Y_Train)
```

Out[40]:
```
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

In [41]:
```
y_predict = model.predict(X_Test)
```

In [42]:
```
y_predict_train = model.predict(X_Train)
```

12. Train the Model

In [43]:
```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [44]:
```
print('Training accuracy: ',accuracy_score(Y_Train,y_predict_train))
```

```
Training accuracy:  0.98263992816522
```

13.Test the Model

In [45]:
```
print('Testing accuracy: ',accuracy_score(Y_Test,y_predict))
```

```
Testing accuracy:  0.5478468899521531
```

14. Measure the performance using Metrics

In [46]:
```
pd.crosstab(Y_Test,y_predict)
```

Out[46]:

col_0	0	1	2
Sex			
0	132	24	93
1	45	211	35
2	125	56	115

In [47]:
```
print(classification_report(Y_Test,y_predict))
```

```
              precision    recall  f1-score   support

           0       0.44      0.53      0.48       249
           1       0.73      0.73      0.73       291
           2       0.47      0.39      0.43       296

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