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

from sklearn.preprocessing import LabelEncoder #7
from sklearn.preprocessing import scale #9
from sklearn.model_selection import train_test_split #10
from sklearn.ensemble import RandomForestClassifier #11
from sklearn.metrics import
accuracy_score,confusion_matrix,classification_report #12
```

1.Load the dataset into the tool

In [3]:

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

In [4]:

```
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

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.

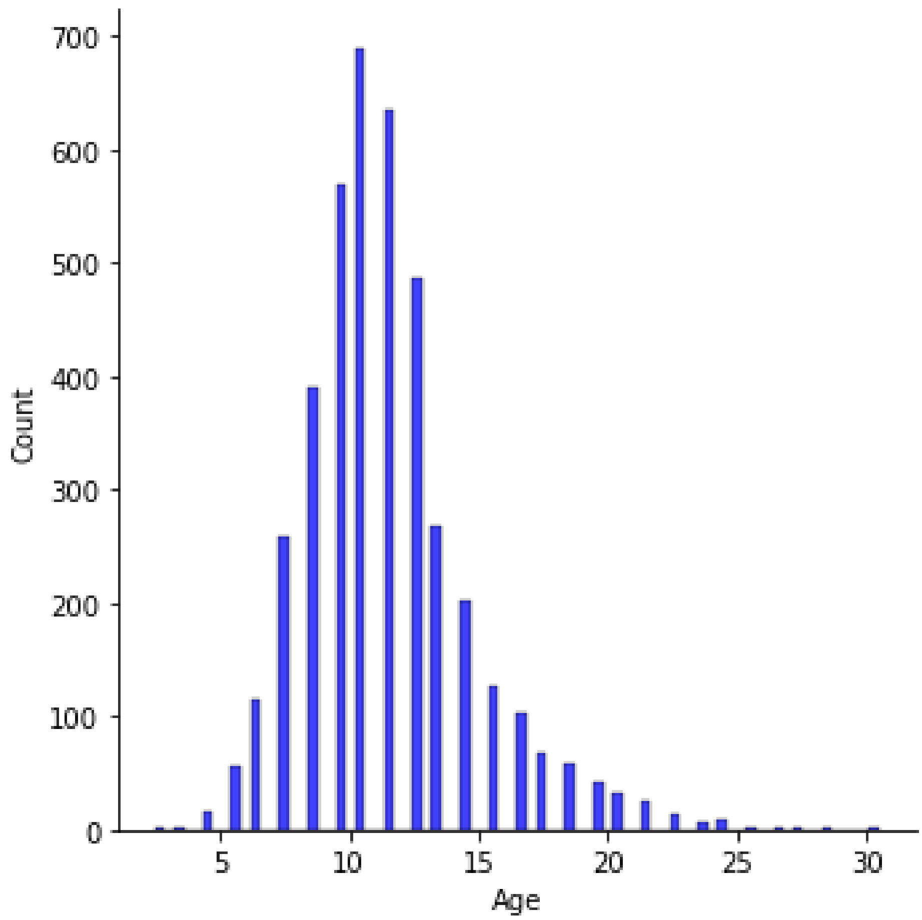
(i) Univariate Analysis

Histogram

In [7]:

```
sns.displot(data["Age"], color='blue')
```

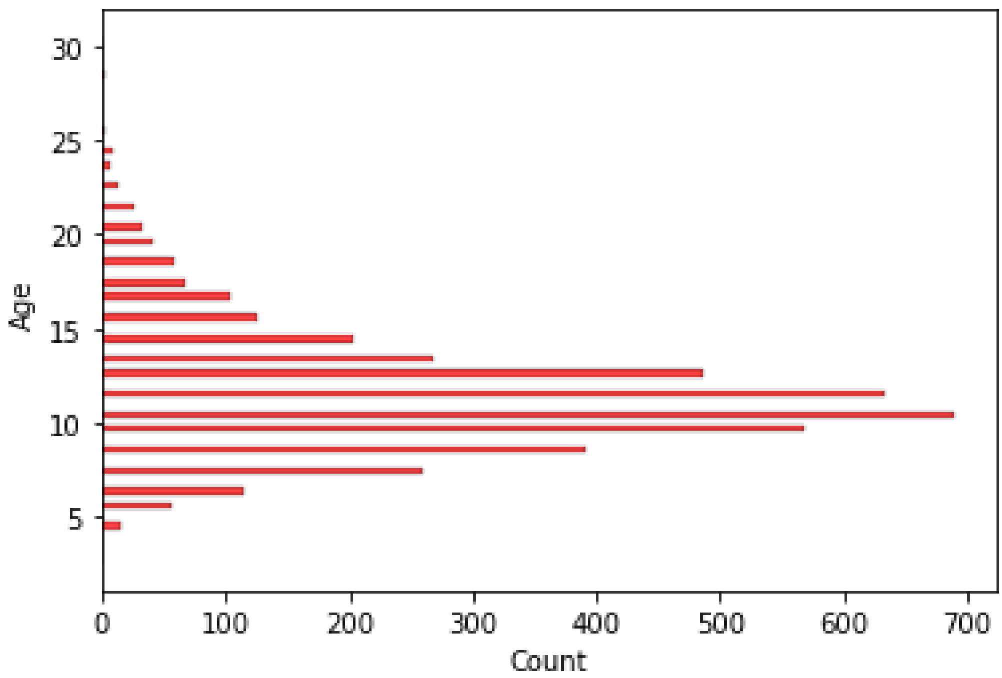
Out[7]:



In [8]:

```
sns.histplot(y=data.Age,color='red')
```

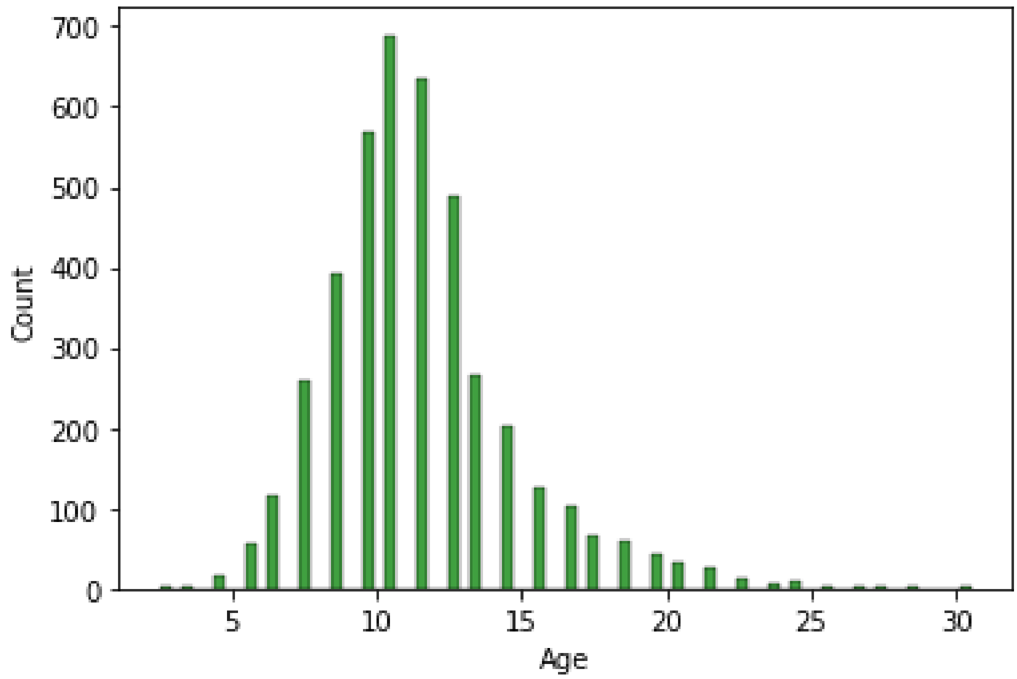
Out[8]:



In [9]:

```
sns.histplot(x=data.Age,color='green')
```

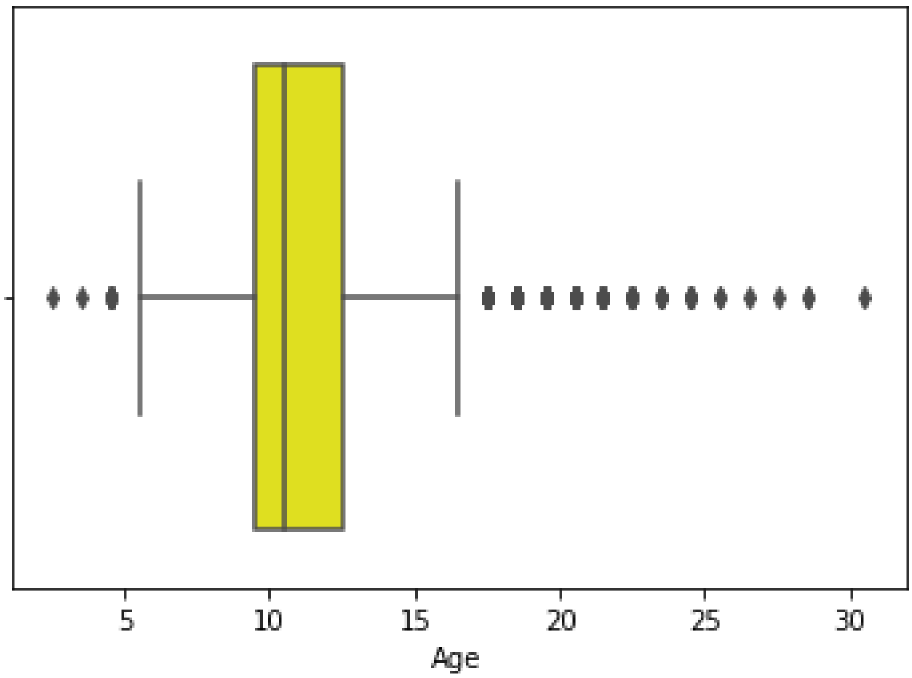
Out[9]:



In [10]:

```
sns.boxplot(x=data.Age,color='yellow')
```

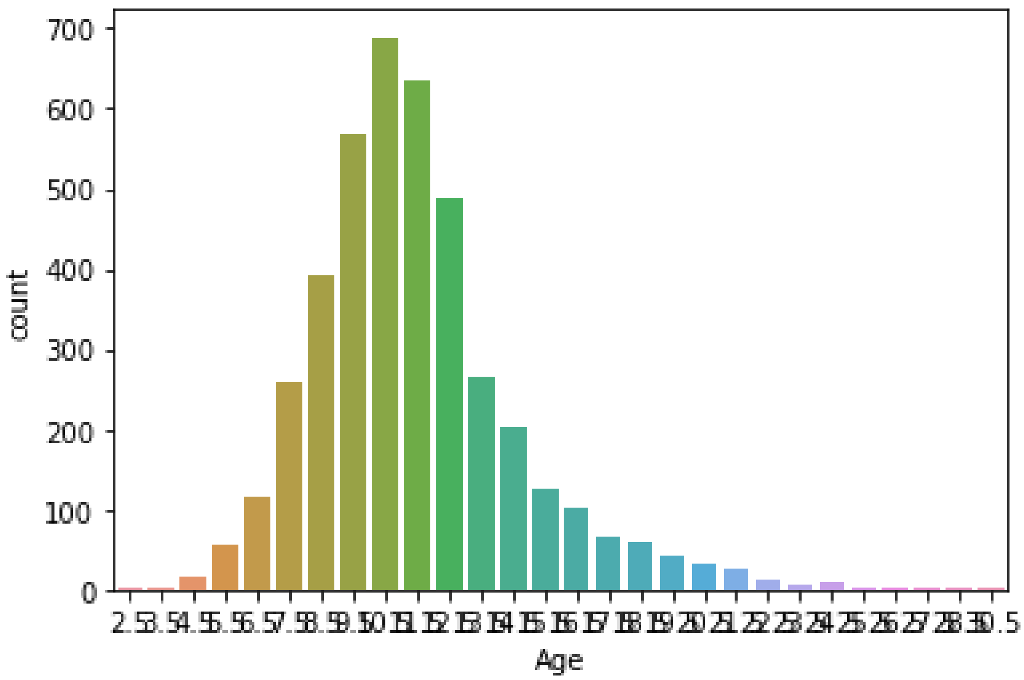
Out[10]:



In [11]:

```
sns.countplot(x=data.Age)
```

Out[11]:



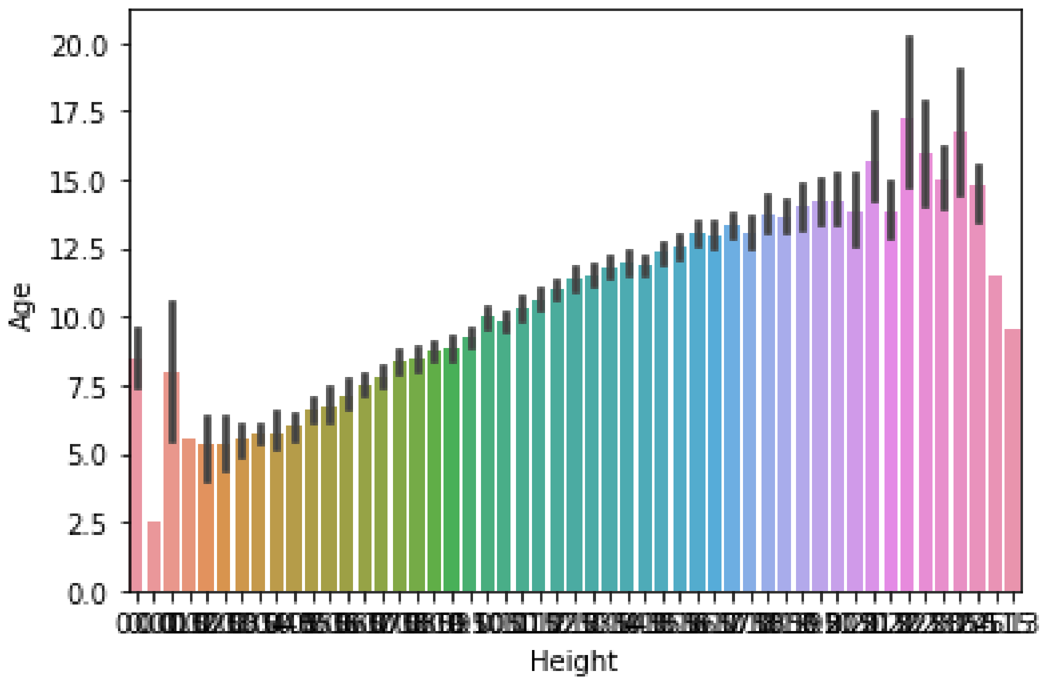
(ii) Bi-Variate Analysis

Barplot

In [12]:

```
sns.barplot(x=data.Height,y=data.Age)
```

Out[12]:

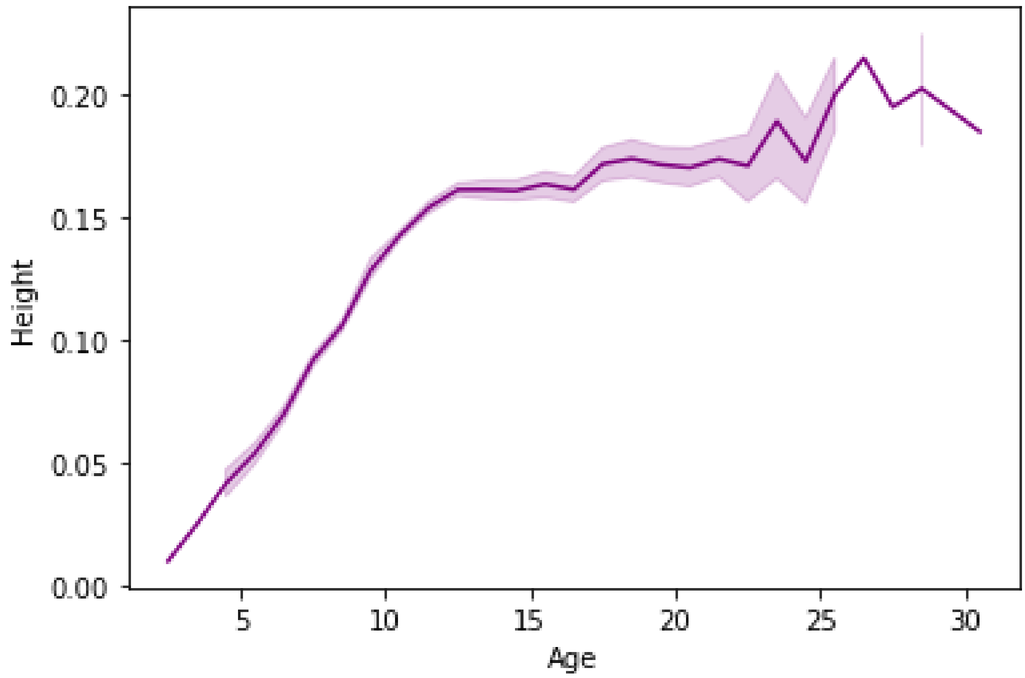


Linearplot

In [13]:

```
sns.lineplot(x=data.Age,y=data.Height, color='purple')
```

Out[13]:

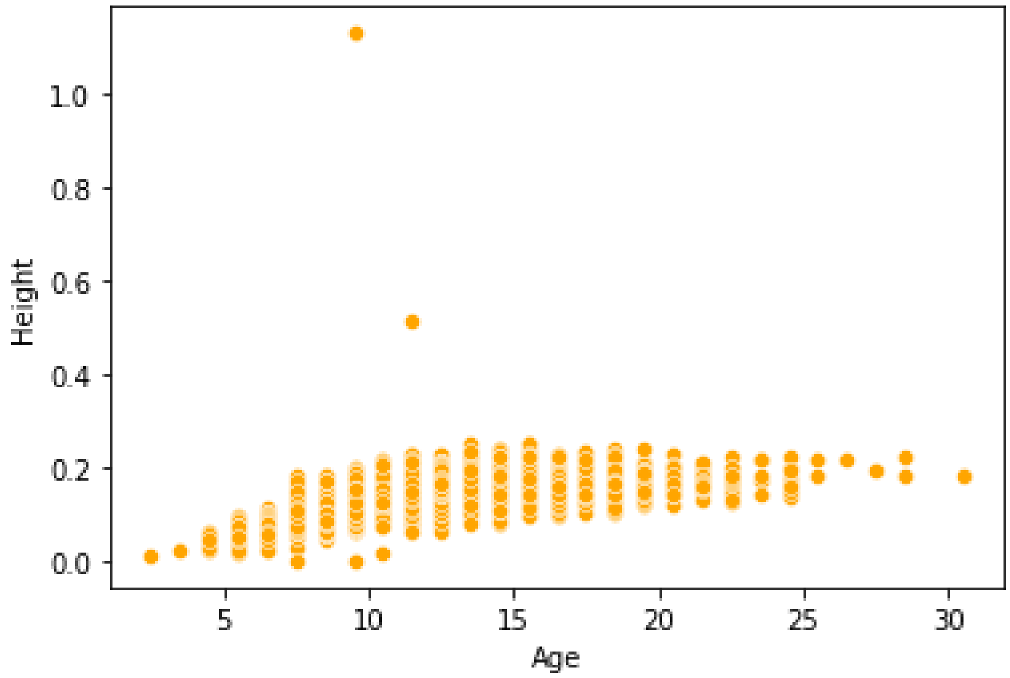


Scatterplot

In [14]:

```
sns.scatterplot(x=data.Age,y=data.Height,color='orange')
```

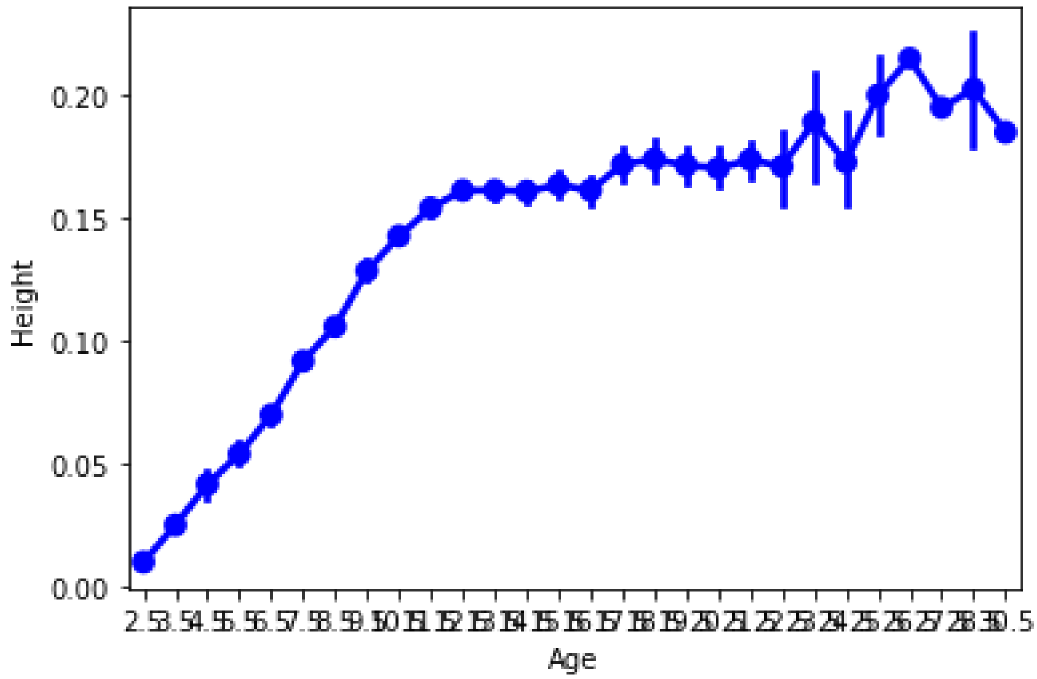
Out[14]:



In [15]:

```
sns.pointplot(x=data.Age, y=data.Height, color="blue")
```

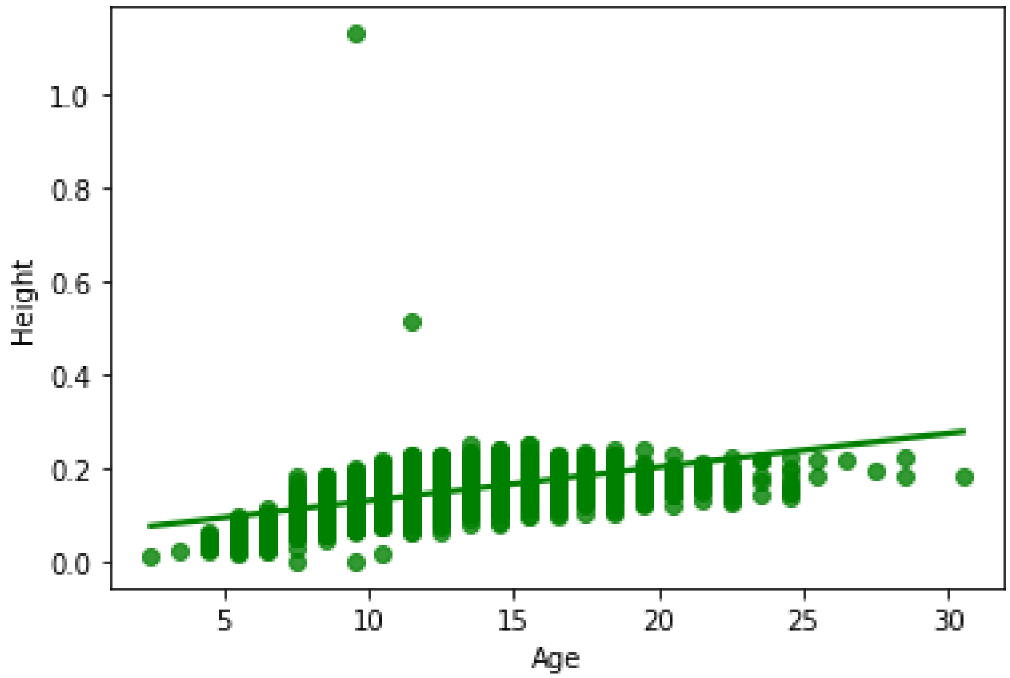
Out[15]:



In [16]:

```
sns.regplot(x=data.Age,y=data.Height,color='green')
```

Out[16]:



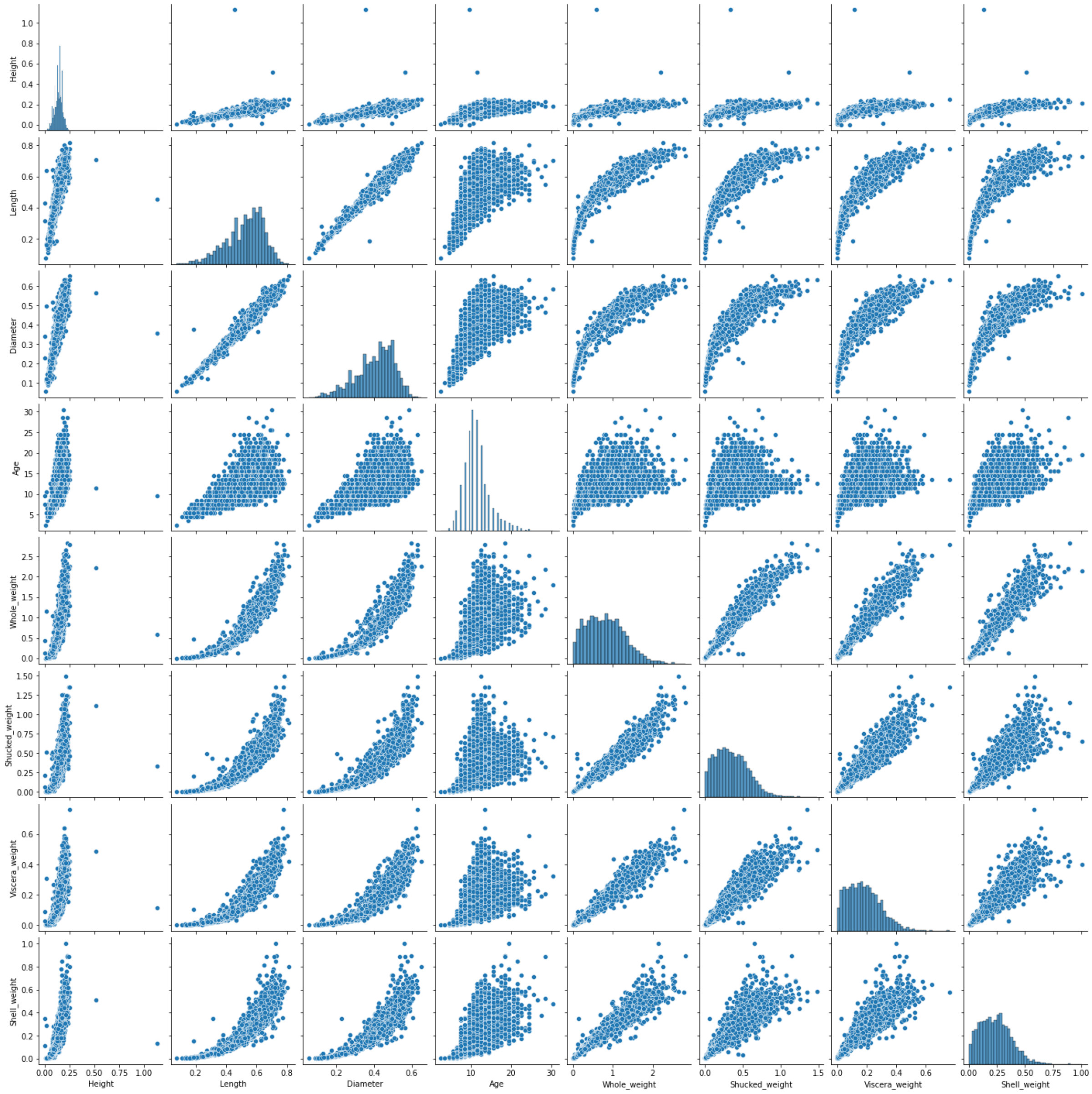
(iii) Multi-Variate Analysis

Pairplot

In [17]:

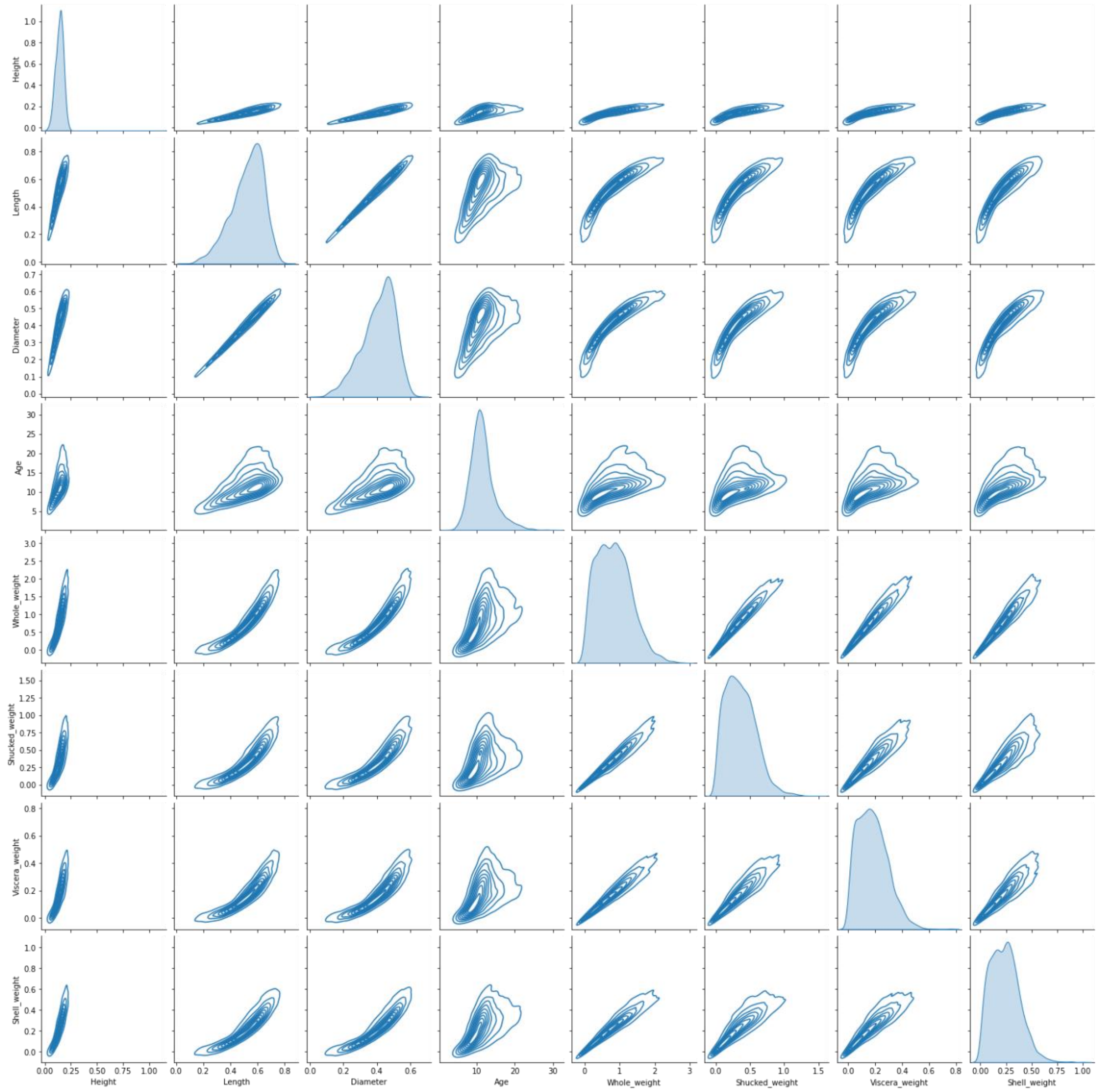
```
sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","
Shucked_weight","Viscera_weight","Shell_weight"]])
```

Out[17]:



In [19]:

```
A =
sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","Shucked_weight","Viscera_weight","Shell_weight"]],kind="kde")
```



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

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
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
```

In [22]:

```
### 6. Find the outliers and replace them outliers
```

In [23]:

```
outliers=data.quantile(q=(0.25,0.75))
```

In [24]:

```
outliers
```

Out[24]:

	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 [25]:

```
a = data.Age.quantile(0.25)
b = data.Age.quantile(0.75)
```

In [26]:

```
c = b - a
```

In [27]:

```
lower_limit = a - 1.5 * c
data.median(numeric_only=True)
```

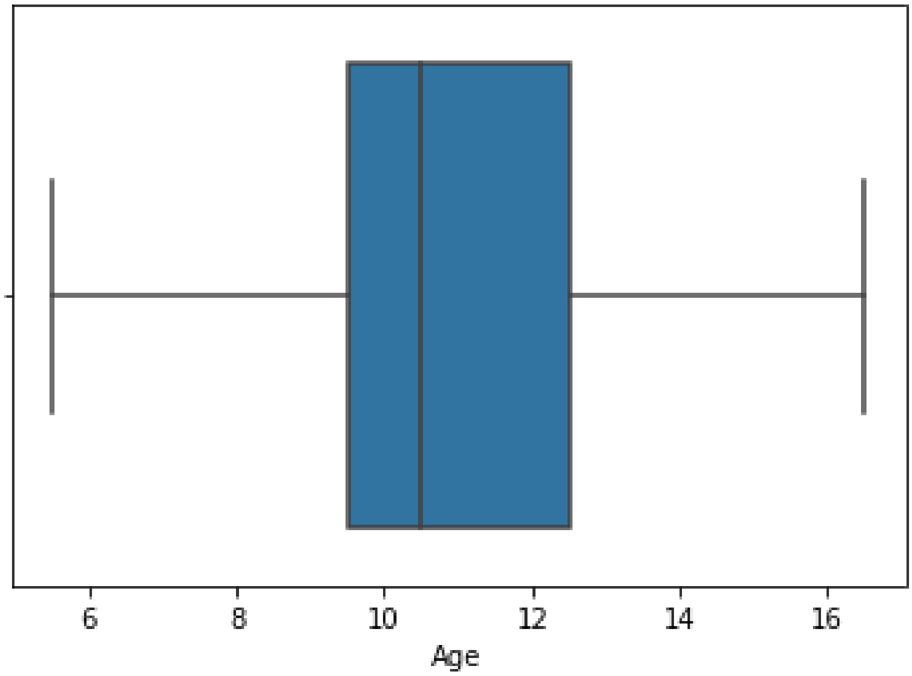
Out[27]:

```
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 [28]:

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

Out[28]:



7. Check for Categorical columns and perform encoding

In [30]:

```
data.head()
```

Out[30]:

	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 [32]:

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

Out[32]:

	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 [33]:

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

Out[33]:

```
0    2
1    2
2    0
3    2
4    1
Name: Sex, dtype: int32
```

In [34]:

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

Out[34]:

	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 [37]:

```
X_Scaled = pd.DataFrame(scale(x), columns=x.columns)
X_Scaled.head()
```

Out[37]:

	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 [39]:

```
X_Train, X_Test, Y_Train, Y_Test = train_test_split(X_Scaled, y, test_size=0.2, random_state=0)
```

In [40]:

```
X_Train.shape,X_Test.shape
```

Out[40]:

```
((3341, 8), (836, 8))
```

In [41]:

```
Y_Train.shape,Y_Test.shape
```

Out[41]:

```
((3341,), (836,))
```

In [42]:

```
X_Train.head()
```

Out[42]:

	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 [43]:

```
X_Test.head()
```

Out[43]:

	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 [44]:

```
Y_Train.head()
```

Out[44]:

```
3141    1
3521    1
```

```
883     2
3627    2
2106    2
Name: Sex, dtype: int32
```

In [45]:

```
Y_Test.head()
```

Out[45]:

```
668     2
1580    1
3784    2
463     1
2615    2
Name: Sex, dtype: int32
```

11. Build the Model

In [47]:

```
model = RandomForestClassifier(n_estimators=10,criterion='entropy')
```

In [48]:

```
model.fit(X_Train,Y_Train)
```

Out[48]:

```
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

In [49]:

```
y_predict = model.predict(X_Test)
```

In [50]:

```
y_predict_train = model.predict(X_Train)
```

12. Train the Model

In [51]:

```
print('Training accuracy: ',accuracy_score(Y_Train,y_predict_train))
```

```
Training accuracy:  0.9796468123316372
```

13.Test the Model

In [52]:

```
print('Testing accuracy: ',accuracy_score(Y_Test,y_predict))
```

```
Testing accuracy:  0.5311004784688995
```

14. Measure the performance using Metrics

In [53]:

```
pd.crosstab(Y_Test,y_predict)
```

Out[53]:

col_0	0	1	2
Sex			
0	121	31	97
1	42	217	32
2	133	57	106

In [56]:

```
print(classification_report(Y_Test,y_predict))
```

```
              precision    recall  f1-score   support

           0       0.41      0.49      0.44       249
           1       0.71      0.75      0.73       291
           2       0.45      0.36      0.40       296

    accuracy                           0.53       836
   macro avg       0.52      0.53      0.52       836
weighted avg       0.53      0.53      0.53       836
```