Section C (Algorithm implementation using packages)

In this question, you are expected to understand and run Naive Bayes Algorithm. Dataset: Dry Bean Dataset

In [294]:
```
#importing libraries
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
%matplotlib inline
df = pd.read_csv('Dry_Bean_Dataset.csv')
```

In [279]:
```
df.head()
```

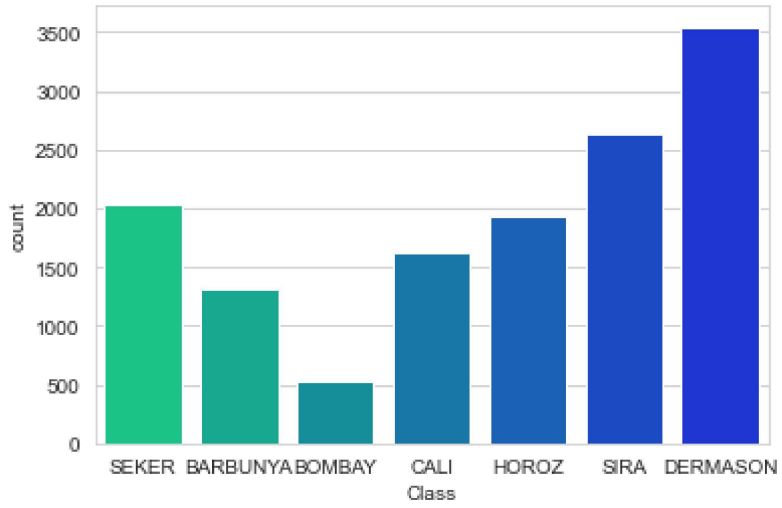
Out[279]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	E
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	28715	
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	29172	
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	29690	
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	30724	
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	30417	

(a) For the given dataset, plot the class distribution and analyze.

In [280]:
```
1 sns.countplot(x='Class',data=df,palette="winter_r")
```

Out[280]: <matplotlib.axes._subplots.AxesSubplot at 0x138c0abcac0>



Analysis:

There are 7 unique class values

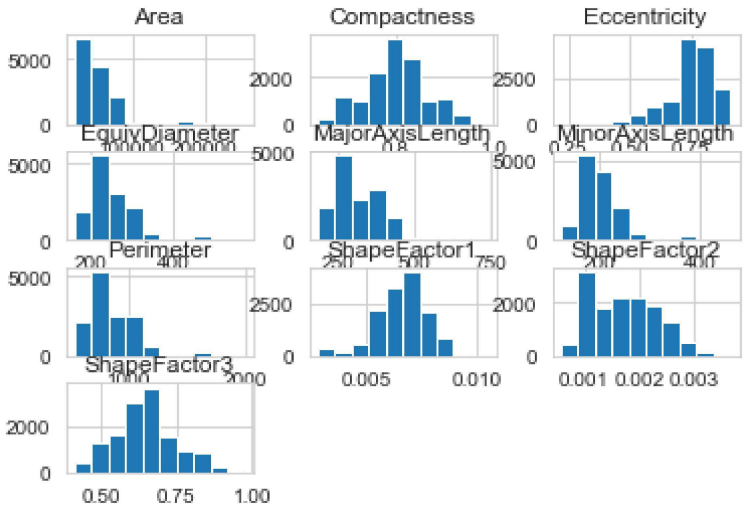
The count value for Bombey is very low but counts are increasing as we are moving till Dermason class

Data is not balanced

In [303]:
```
1 plt.figure (figsize= (10,10 ))
2 df.hist()
```

Out[303]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000138BB513310>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000138BB44AA00>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000138BAF833D0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000138BAF01AF0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000138BAECA2E0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001388B2126A0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001388B2129D0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000138B60EB940>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000138AB2BB430>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000138AE407D90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000138AE2E38E0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000138AE290EB0>]],
      dtype=object)
```

```
<Figure size 720x720 with 0 Axes>
```



(b) Perform EDA (histograms, box plots, scatterplots, etc.) and give at least

five insights on the data. Check the missing values in the dataset.

In [5]:
```
1 df.columns
```

Out[5]:
```
Index(['Area', 'Perimeter', 'MajorAxisLength', 'MinorAxisLength',
       'AspectRation', 'Eccentricity', 'ConvexArea', 'EquivDiameter', 'Extent',
       'Solidity', 'roundness', 'Compactness', 'ShapeFactor1', 'ShapeFactor2',
       'ShapeFactor3', 'ShapeFactor4', 'Class'],
      dtype='object')
```

In [6]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13611 entries, 0 to 13610
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Area             13611 non-null  int64  
 1   Perimeter        13611 non-null  float64
 2   MajorAxisLength  13611 non-null  float64
 3   MinorAxisLength  13611 non-null  float64
 4   AspectRation     13611 non-null  float64
 5   Eccentricity     13611 non-null  float64
 6   ConvexArea       13611 non-null  int64  
 7   EquivDiameter    13611 non-null  float64
 8   Extent           13611 non-null  float64
 9   Solidity         13611 non-null  float64
 10  roundness        13611 non-null  float64
 11  Compactness      13611 non-null  float64
 12  ShapeFactor1     13611 non-null  float64
 13  ShapeFactor2     13611 non-null  float64
 14  ShapeFactor3     13611 non-null  float64
 15  ShapeFactor4     13611 non-null  float64
 16  Class            13611 non-null  object 
dtypes: float64(14), int64(2), object(1)
memory usage: 1.8+ MB
```

In [7]:
```
1 df.describe()
```

Out[7]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity
count	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000
mean	53048.284549	855.283459	320.141867	202.270714	1.583242	0.750895
std	29324.095717	214.289696	85.694186	44.970091	0.246678	0.092002
min	20420.000000	524.736000	183.601165	122.512653	1.024868	0.218951
25%	36328.000000	703.523500	253.303633	175.848170	1.432307	0.715928
50%	44652.000000	794.941000	296.883367	192.431733	1.551124	0.764441
75%	61332.000000	977.213000	376.495012	217.031741	1.707109	0.810466
max	254616.000000	1985.370000	738.860154	460.198497	2.430306	0.911423

In [9]:

```
#checking for null values in data set/ preprocessing
df.isnull().sum()
df.isnull()
```

Out[9]:

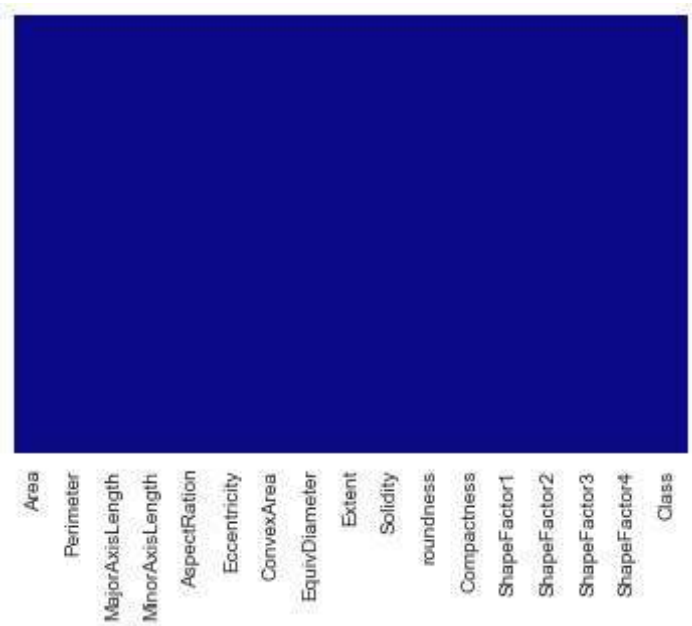
ajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter	Extent	So
False	False	False	False	False	False	False	
False	False	False	False	False	False	False	
False	False	False	False	False	False	False	
False	False	False	False	False	False	False	
False	False	False	False	False	False	False	
...	...	...	...	...	...	...	
False	False	False	False	False	False	False	
False	False	False	False	False	False	False	
False	False	False	False	False	False	False	
False	False	False	False	False	False	False	
False	False	False	False	False	False	False	

In [11]:

```
sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='plasma')
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1388604abe0>
```

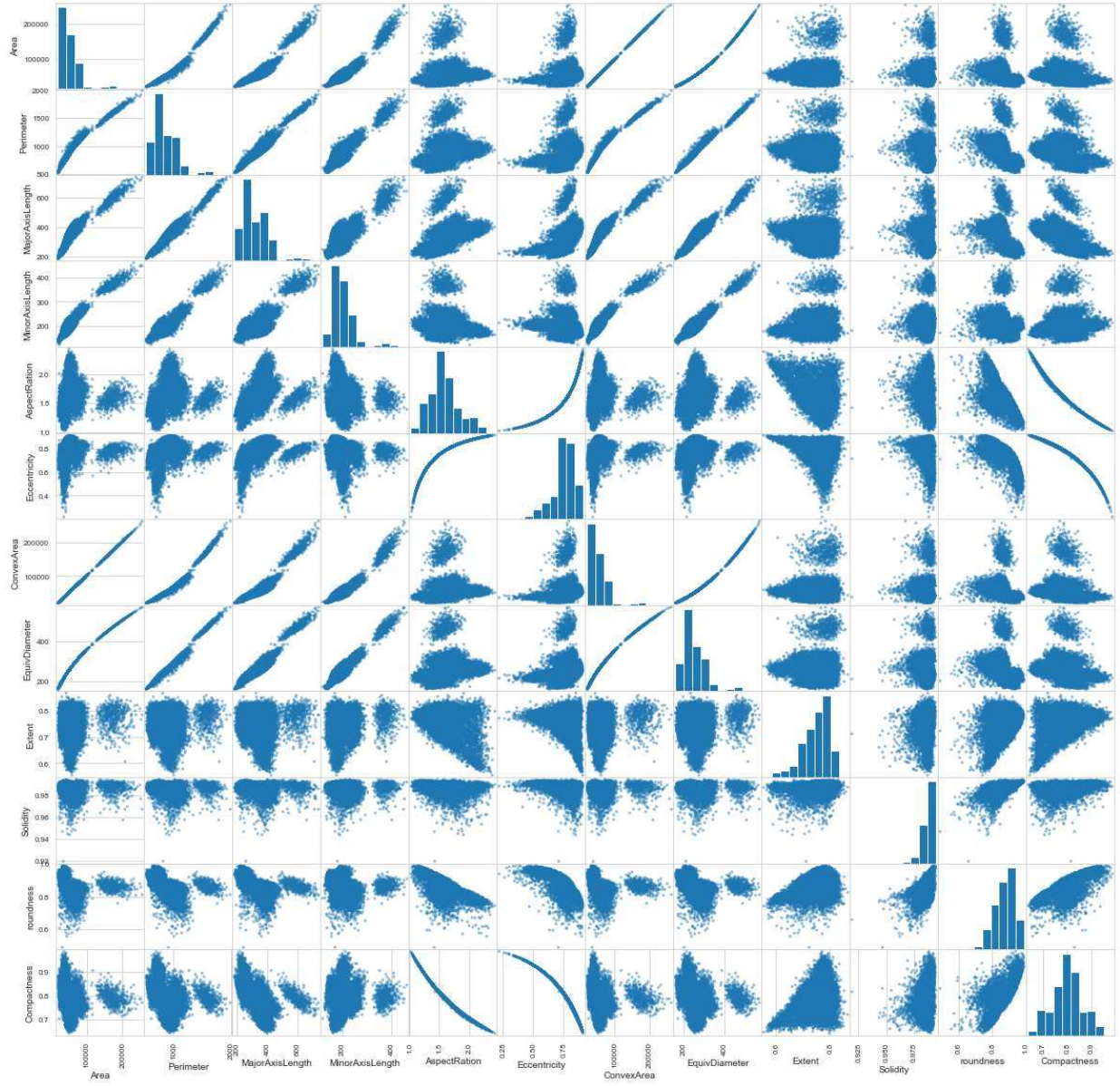


In [14]:
```
df = df.dropna(axis=0)  #data clean
[c for c in df.columns if df[c].isnull().sum()>0]
```

Out[14]:
```
[]
```

There are no missing value present in the given data set

In [44]:
```
# Performing EDA
features = list(df.columns)[0:12]
sm = pd.plotting.scatter_matrix(df[features], figsize=(20,20))
```



Insights:-

```
From the above plots we can say that there are almost linear relationship
between some variables:

1-> Area & Perimeter (Positive)
2-> Area & Convex area (Positive)
```

```
3-> Convex area & EquiDiameter (Positive)
4-> Area & Major Axis length (Positive)
5-> Area & Minor Axis length (Positive)
6-> Area & ShapeFactor1 (Negitive)
7-> Perimeter & ShapeFactor1 (Negitive)
8-> Perimeter & Major Axis length (Positive)
9-> Perimeter & Minor Axis length (Positive)'
10-> Eccentricity & Aspect Ration (Expotential)
11-> Major Axis length & Minor Axis length (Positive)
12-> Some variable are also showing clustering
```

In [21]:
```
#checking correlation
correlationMatrix = df.corr(method='pearson')
```

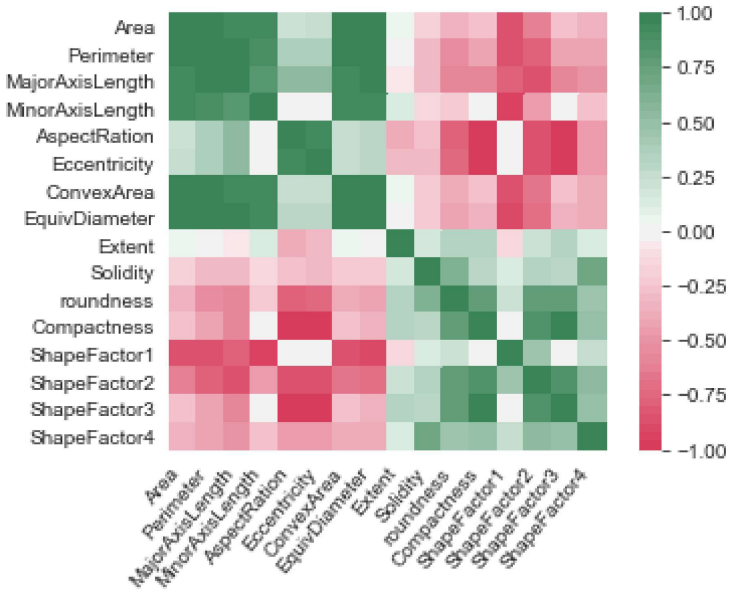
In [22]:
```
correlationMatrix
```

Out[22]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentrici
Area	1.000000	0.966722	0.931834	0.951602	0.241735	0.2674
Perimeter	0.966722	1.000000	0.977338	0.913179	0.385276	0.3910
MajorAxisLength	0.931834	0.977338	1.000000	0.826052	0.550335	0.5419
MinorAxisLength	0.951602	0.913179	0.826052	1.000000	-0.009161	0.0195
AspectRation	0.241735	0.385276	0.550335	-0.009161	1.000000	0.9242
Eccentricity	0.267481	0.391066	0.541972	0.019574	0.924293	1.0000
ConvexArea	0.999939	0.967689	0.932607	0.951339	0.243301	0.2692
EquivDiameter	0.984968	0.991380	0.961733	0.948539	0.303647	0.3186
Extent	0.054345	-0.021160	-0.078062	0.145957	-0.370184	-0.3193
Solidity	-0.196585	-0.303970	-0.284302	-0.155831	-0.267754	-0.2975
roundness	-0.357530	-0.547647	-0.596358	-0.210344	-0.766979	-0.7222
Compactness	-0.268067	-0.406857	-0.568377	-0.015066	-0.987687	-0.9703
ShapeFactor1	-0.847958	-0.864623	-0.773609	-0.947204	0.024593	0.0199
ShapeFactor2	-0.639291	-0.767592	-0.859238	-0.471347	-0.837841	-0.8601
ShapeFactor3	-0.272145	-0.408435	-0.568185	-0.019326	-0.978592	-0.9810
ShapeFactor4	-0.355721	-0.429310	-0.482527	-0.263749	-0.449264	-0.4493

In [281]:
```
# corelation plot
pl = sns.heatmap(correlationMatrix,vmin=-1, vmax=1, center=0,cmap=sns.diverg
pl.set_xticklabels(ax.get_xticklabels(),rotation = 50, horizontalalignment='
```

Out[281]:
```
[Text(0.5, 0, 'Area'),
 Text(1.5, 0, 'Perimeter'),
 Text(2.5, 0, 'MajorAxisLength'),
 Text(3.5, 0, 'MinorAxisLength'),
 Text(4.5, 0, 'AspectRation'),
 Text(5.5, 0, 'Eccentricity'),
 Text(6.5, 0, 'ConvexArea'),
 Text(7.5, 0, 'EquivDiameter'),
 Text(8.5, 0, 'Extent'),
 Text(9.5, 0, 'Solidity'),
 Text(10.5, 0, 'roundness'),
 Text(11.5, 0, 'Compactness'),
 Text(12.5, 0, 'ShapeFactor1'),
 Text(13.5, 0, 'ShapeFactor2'),
 Text(14.5, 0, 'ShapeFactor3'),
 Text(15.5, 0, 'ShapeFactor4')]
```



In [30]:
```
# converting classes into numbers (0-7)
# 0: 'BARBUNYA', 1: 'BOMBAY', 2: 'CALI', 3: 'DERMASON', 4: 'HOROZ', 5: 'SEKE

df['Class'] = pd.factorize(df['Class'])[0] + 1
```

In [37]:
```
# correlation of features with target value
Corelation_with_target=pd.DataFrame(df.corr().unstack().sort_values(ascendin
Corelation_with_target.style.background_gradient(cmap=sns.light_palette("red
```

Out[37]:

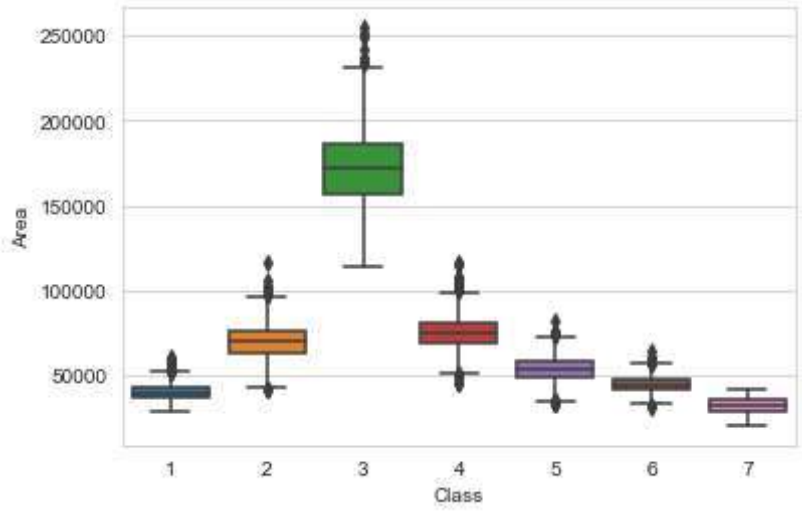
	Correlation to the target
MinorAxisLength	-0.511069
EquivDiameter	-0.385540
Perimeter	-0.369302
ShapeFactor3	-0.352531
ConvexArea	-0.340615
Area	-0.340545
Compactness	-0.331373
MajorAxisLength	-0.257785
Extent	-0.137064
ShapeFactor4	-0.038765
ShapeFactor2	-0.025269
roundness	0.024766
Solidity	0.034980
AspectRation	0.270598
Eccentricity	0.426551
ShapeFactor1	0.622466
Class	1.000000

Insights:-

By the above correlation we can see that shape factor 1 is highly positively correlated with the the classes

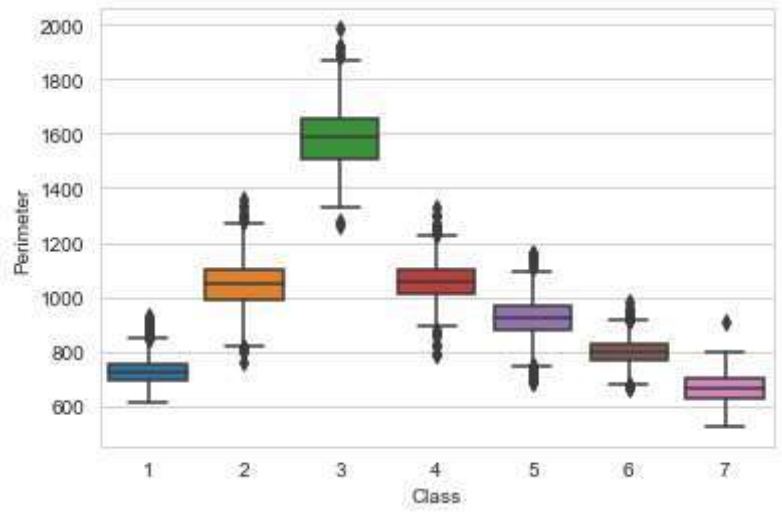
In [40]:
```
#  box plots
sns.boxplot(x="Class", y="Area", data=df)
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x1389ccf0880>



In [45]:
```
sns.boxplot(x="Class", y="Perimeter", data=df)
```

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x1389c45e5b0>



Insights:-

1 -> By the above box plots we can conclude the following:

2 -> Differennce of classes are affecting the area and perimeter Bombay has highest rank in terms of this

In [ ]:
```
# Looking for outliers
sns.pairplot(df,hue="Class")
```

In [ ]:
```
a = df[df['ShapeFactor4'] < 0.96]
b = df[df['ShapeFactor1'] > 0.01]
c = df[df['Solidity'] < 0.95]
d = df[df['roundness'] < 0.61]
df.drop(a, inplace=True)
df.drop(b, inplace=True)
df.drop(c, inplace=True)
df.drop(d, inplace=True)
```

(c) Use TSNE (t-distributed stochastic neighbor embedding) algorithm toreduce data dimensions to 2 and plot the resulting data as a scatter plot. Commenton the separability of the data.

In [231]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.manifold import TSNE
```

In [245]:
```
x = df.iloc[:,1:16].values
x.reshape(1,-1)
y = df.iloc[:,-1]
```

In [247]:
```
lb=LabelEncoder()
y = lb.fit_transform(y.astype('str'))
```

In [248]:
```
sc = StandardScaler()
transformed_x=sc.fit_transform(x)
```

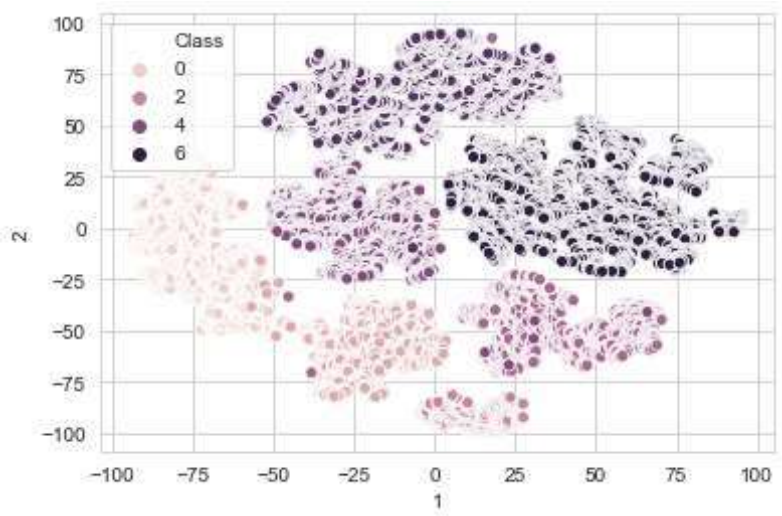
In [249]:
```
mod=TSNE(n_components=2,random_state=0)
```

In [250]:
```
data=mod.fit_transform(transformed_x)
```

In [251]:
```
tsne=np.vstack((data.T,y)).T
tsne=pd.DataFrame(data=tsne,columns=("1","2","Class"))
```

In [252]:
```
1 sns.scatterplot(x="1",y="2",hue='Class',data=tsne)
```

Out[252]: <matplotlib.axes._subplots.AxesSubplot at 0x138bced3f40>



Comments:

1 -> Clustring is quite well using T-sne

2 -> It basically expands dense clusters(group of points) And shrinks sparse clusters

3 -> It does not preserve distances between the clusters

(d) Run the sklearn's implementation of Naive Bayes (Any 2 of your choice -refer here). Report Accuracy, Recall, and Precision. Comment on the results and their differences from the two implementations of Naive Bayes. (80:20 train test split)

In [99]:

```
#Naive Bayes Gaussian
dataset = pd.read_csv('Dry_Bean_Dataset.csv')

# xx=dataset.iloc[:,1:6]
a=ds.iloc[:,:-1]
b=ds.iloc[:,-1]

a_train,a_test,b_train,b_test=train_test_split(a,b,test_size=0.20,random_sta

from sklearn.naive_bayes import GaussianNB
NBModel=GaussianNB()
NBModel.fit(a_train,b_train)

b_predicted=NBModel.predict(a_test)

# b_predicted

from sklearn.metrics import accuracy_score,precision_score, confusion_matrix

accuracy_score(b_test,b_predicted)*100
```

Out[99]: 79.1039294895336

In [106]:

```
#Naive Bayes Gaussian
dataset = pd.read_csv('Dry_Bean_Dataset.csv')

# xx=dataset.iloc[:,1:6]
xx=dataset.iloc[:,1:16]
yy=dataset.iloc[:,16]

xx_train,xx_test,yy_train,yy_test=train_test_split(xx,yy,test_size=0.20,rand

from sklearn.naive_bayes import GaussianNB
NBModel=GaussianNB()
NBModel.fit(xx_train,yy_train)

yy_predicted=NBModel.predict(xx_test)

# yy_predicted

from sklearn.metrics import accuracy_score,precision_score, confusion_matrix
output=pd.DataFrame(['Gussian NB'],columns=['Algorithm'])
output.loc[0,'Precision']=precision_score(yy_test, yy_predicted, average='mi
output.loc[0,'Accuracy']=accuracy_score(yy_test,yy_predicted)*100
output.loc[0,'F1 Score']=f1_score(yy_test, yy_predicted, average='micro')
output.loc[0,'Recall']=recall_score(yy_test, yy_predicted, average='micro')
```

Out[106]:

	Algorithm	Precision	Accuracy	F1 Score	Recall
0	Gussian NB	0.800955	80.095483	0.800955	0.800955

In [59]:
```
import sklearn.metrics as metrics
print(metrics.classification_report(yy_test,yy_predicted))
```

```
              precision    recall  f1-score   support

    BARBUNYA       0.75      0.53      0.62       280
      BOMBAY       0.99      1.00      0.99        98
        CALI       0.71      0.84      0.77       337
    DERMASON       0.89      0.87      0.88       690
       HOROZ       0.82      0.82      0.82       409
       SEKER       0.75      0.74      0.74       392
        SIRA       0.76      0.83      0.80       517

    accuracy                           0.80      2723
   macro avg       0.81      0.80      0.80      2723
weighted avg       0.80      0.80      0.80      2723
```

In [60]:
```
print(metrics.confusion_matrix(yy_test,yy_predicted))
```

```
[[147   1  95   0  26   0  11]
 [  0  98   0   0   0   0   0]
 [ 42   0 284   0  10   0   1]
 [  0   0   0 599   0  60  31]
 [  5   0  23   4 335   0  42]
 [  2   0   0  50   4 289  47]
 [  0   0   0  19  33  36 429]]
```

In [61]:
```
# Naive bayes Multinomial
dataset1 = pd.read_csv('Dry_Bean_Dataset.csv')

# xxx=dataset.iloc[:,1:6]
xxx=dataset1.iloc[:,1:16]
yyy=dataset1.iloc[:,16]

xxx_train,xxx_test,yyy_train,yyy_test=train_test_split(xxx,yyy,test_size=0.2

from sklearn.naive_bayes import MultinomialNB
NBModelMulti=MultinomialNB()
NBModelMulti.fit(xxx_train,yyy_train)
# MultinomialNB

yyy_predicted=NBModelMulti.predict(xxx_test)

# yyy_predicted

from sklearn.metrics import accuracy_score,precision_score, confusion_matrix

accuracy_score(yyy_test,yyy_predicted)*100
```

Out[61]: 79.17737789203085

In [110]:
```
output.loc[1,'Algorithm']='Multinomial NB'
output.loc[1,'Precision']=precision_score(yyy_test, yyy_predicted, average='
output.loc[1,'Accuracy']=accuracy_score(yyy_test,yyy_predicted)*100
output.loc[1,'F1 Score']=f1_score(yyy_test, yyy_predicted, average='micro')
output.loc[1,'Recall']=recall_score(yyy_test, yyy_predicted, average='micro'
output[1:2]
```

Out[110]:

	Algorithm	Precision	Accuracy	F1 Score	Recall
1	Multinomial NB	0.791774	79.177378	0.791774	0.791774

In [63]:
```
print(metrics.classification_report(yy_test,yy_predicted))
```

```
              precision    recall  f1-score   support

    BARBUNYA       0.75      0.53      0.62       280
      BOMBAY       0.99      1.00      0.99        98
        CALI       0.71      0.84      0.77       337
    DERMASON       0.89      0.87      0.88       690
       HOROZ       0.82      0.82      0.82       409
       SEKER       0.75      0.74      0.74       392
        SIRA       0.76      0.83      0.80       517

    accuracy                           0.80      2723
   macro avg       0.81      0.80      0.80      2723
weighted avg       0.80      0.80      0.80      2723
```

In [64]:
```
print(metrics.confusion_matrix(yy_test,yy_predicted))
```

```
[[147   1  95   0  26   0  11]
 [  0  98   0   0   0   0   0]
 [ 42   0 284   0  10   0   1]
 [  0   0   0 599   0  60  31]
 [  5   0  23   4 335   0  42]
 [  2   0   0  50   4 289  47]
 [  0   0   0  19  33  36 429]]
```

In [112]:
```
# Comparision
output
```

Out[112]:

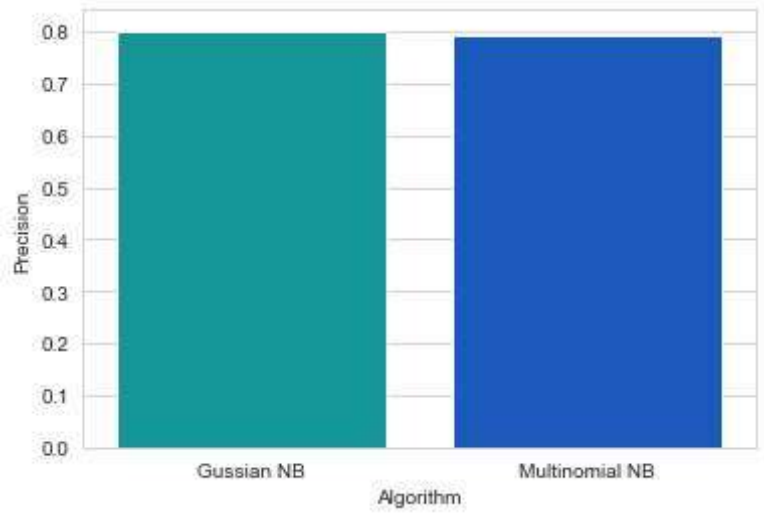
	Algorithm	Precision	Accuracy	F1 Score	Recall
0	Gussian NB	0.800955	80.095483	0.800955	0.800955
1	Multinomial NB	0.791774	79.177378	0.791774	0.791774

We can conclude that Gaussian Naive Bayes gives better accuracy than Multinomial Naive Bayes

Gaussian Naive Bayes works well with continuous values ,probabilities modeled using Gaussian distribution where as Multinomial Naive Bayes works well when their is given the number of frequencies or occurances

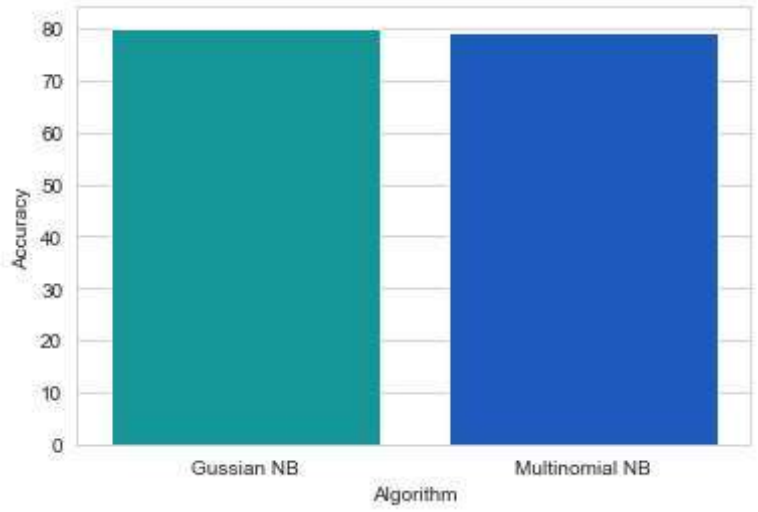
In [258]:
```
1 sns.barplot(x='Algorithm',y='Precision',data=output,palette="winter_r")
```

Out[258]: <matplotlib.axes._subplots.AxesSubplot at 0x138befa27c0>



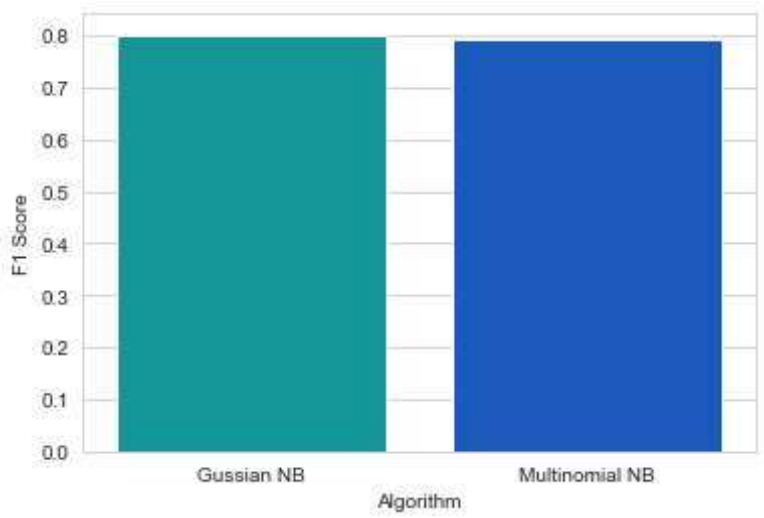
In [255]:
```
1 sns.barplot(x='Algorithm',y='Accuracy',data=output,palette="winter_r")
```

Out[255]: <matplotlib.axes._subplots.AxesSubplot at 0x138bd40f7f0>



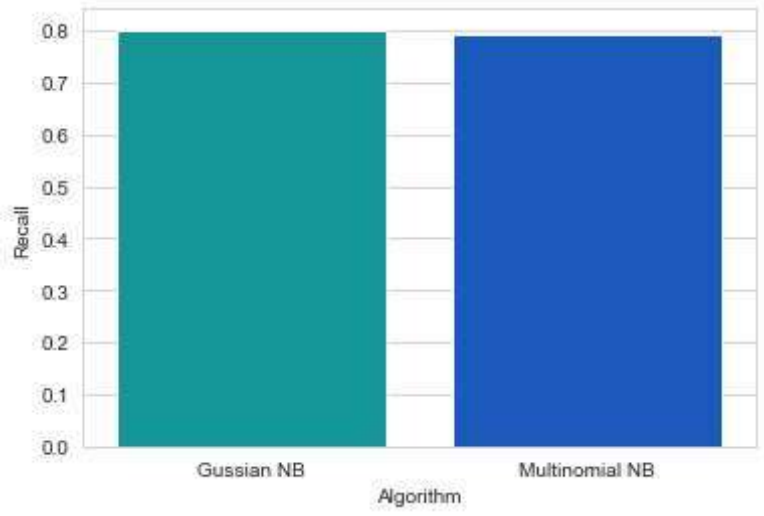
In [256]:
```
1 sns.barplot(x='Algorithm',y='F1 Score',data=output,palette="winter_r")
```

Out[256]: <matplotlib.axes._subplots.AxesSubplot at 0x138bd3c4a90>



In [257]:
```
1 sns.barplot(x='Algorithm',y='Recall',data=output,palette="winter_r")
```

Out[257]: <matplotlib.axes._subplots.AxesSubplot at 0x138bef0b3a0>



(e) Use Principal Component Analysis (PCA) to reduce the number of fea-tures and use the

reduced data set for model training. Use values 4,6,8,10 and 12 for the number of components. Compare results (Accuracy, Precision, Recall, and F-1 score). (80:20 train test split)

In [135]:
```
# for n=4
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
dataset3 = pd.read_csv('Dry_Bean_Dataset.csv')

xa=dataset3.iloc[:,1:16]
ya=dataset3.iloc[:,16]

dataset3['Class'] = pd.factorize(dataset3['Class'])[0] + 1
# dataset3['Class']

scaler=StandardScaler()
scaler.fit(dataset3)
scaled_data=scaler.transform(dataset3)
# scaled_data
```

In [136]:
```
from sklearn.decomposition import PCA
pca=PCA(n_components=4)
pca.fit(scaled_data)
```

Out[136]:
```
PCA(n_components=4)
```

In [137]:
```
x_pca=pca.transform(scaled_data)
```

In [138]:
```
scaled_data.shape
```

Out[138]:
```
(13611, 17)
```

In [124]:
```
x_pca.shape
```

Out[124]:
```
(13611, 4)
```

In [125]:
```
x_pca
```

Out[125]:
```
array([[-4.85009331,  2.4335456 ,  0.99737597, -0.74460882],
       [-5.28453549,  3.54428992,  2.37538837, -0.6623527 ],
       [-4.62724508,  2.42490511,  0.75961978, -0.57801947],
       ...,
       [-1.47557195, -0.17211656, -0.58522406,  0.01509711],
       [-1.17761957, -0.50759167, -0.02808485, -0.23375543],
       [-0.83843459, -0.95679712, -1.16775889,  0.8613876 ]])
```

In [157]:
```
# Gaussian Naive Bayes on PCA
xxp=x_pca
yyp=dataset3.iloc[:,16]
xxp_train,xxp_test,yyp_train,yyp_test=train_test_split(xxp,yyp,test_size=0.2

from sklearn.naive_bayes import GaussianNB
NBModel=GaussianNB()
NBModel.fit(xxp_train,yyp_train)

yyp_predicted=NBModel.predict(xxp_test)
# yyp_predicted

from sklearn.metrics import accuracy_score,precision_score, confusion_matrix
outputPCA=pd.DataFrame(['n=4'],columns=['PCA'])
outputPCA.loc[0,'Precision']=precision_score(yyp_test, yyp_predicted, averag
outputPCA.loc[0,'Accuracy']=accuracy_score(yyp_test,yyp_predicted)*100
outputPCA.loc[0,'F1 Score']=f1_score(yyp_test, yyp_predicted, average='micro
outputPCA.loc[0,'Recall']=recall_score(yyp_test, yyp_predicted, average='mic
```

In [158]:
```
outputPCA
```

Out[158]:

	PCA	Precision	Accuracy	F1 Score	Recall
0	n=4	0.903783	90.378259	0.903783	0.903783

In [159]:
```
#For n=6
pca6=PCA(n_components=6)
pca6.fit(scaled_data)
```

Out[159]:
```
PCA(n_components=6)
```

In [160]:
```
x_pca6=pca6.transform(scaled_data)
x_pca6.shape
```

Out[160]:
```
(13611, 6)
```

In [161]:
```
x_pca6
```

Out[161]:
```
array([[-4.85009331,  2.4335456 ,  0.99737597, -0.74460882, -0.50967491,
        -0.43507233],
       [-5.28453549,  3.54428992,  2.37538837, -0.6623527 , -0.84884451,
         0.60872936],
       [-4.62724508,  2.42490511,  0.75961978, -0.57801947, -0.76152539,
        -0.36434234],
       ...,
       [-1.47557195, -0.17211656, -0.58522406,  0.01509711,  1.03542682,
         0.11394941],
       [-1.17761957, -0.50759167, -0.02808485, -0.23375543,  1.2843959 ,
         0.08367859],
       [-0.83843459, -0.95679712, -1.16775889,  0.8613876 , -0.11195367,
         0.43442545]])
```

In [162]:

```
# Gaussian Naive Bayes on PCA n=6
xxp6=x_pca6
yyp6=dataset3.iloc[:,16]
xxp6_train,xxp6_test,yyp6_train,yyp6_test=train_test_split(xxp6,yyp6,test_si

from sklearn.naive_bayes import GaussianNB
NBModel=GaussianNB()
NBModel.fit(xxp6_train,yyp6_train)

yyp6_predicted=NBModel.predict(xxp6_test)
# yyp_predicted

from sklearn.metrics import accuracy_score,precision_score, confusion_matrix
outputPCA.loc[1,'PCA']='n=6'
outputPCA.loc[1,'Precision']=precision_score(yyp6_test, yyp6_predicted, aver
outputPCA.loc[1,'Accuracy']=accuracy_score(yyp6_test,yyp6_predicted)*100
outputPCA.loc[1,'F1 Score']=f1_score(yyp6_test, yyp6_predicted, average='mic
outputPCA.loc[1,'Recall']=recall_score(yyp6_test, yyp6_predicted, average='m
```

In [163]:

```
outputPCA
```

Out[163]:

	PCA	Precision	Accuracy	F1 Score	Recall
0	n=4	0.903783	90.378259	0.903783	0.903783
1	n=6	0.924348	92.434815	0.924348	0.924348

In [164]:

```
#For n=8
pca8=PCA(n_components=8)
pca8.fit(scaled_data)
x_pca8=pca8.transform(scaled_data)
x_pca8.shape
```

Out[164]: (13611, 8)

In [169]:
```
# Gaussian Naive Bayes on PCA n=8
xxp8=x_pca8
yyp8=dataset3.iloc[:,16]
xxp8_train,xxp8_test,yyp8_train,yyp8_test=train_test_split(xxp8,yyp8,test_si

from sklearn.naive_bayes import GaussianNB
NBModel=GaussianNB()
NBModel.fit(xxp8_train,yyp8_train)

yyp8_predicted=NBModel.predict(xxp8_test)
# yyp_predicted

from sklearn.metrics import accuracy_score,precision_score, confusion_matrix
outputPCA.loc[2,'PCA']='n=8'
outputPCA.loc[2,'Precision']=precision_score(yyp8_test, yyp8_predicted, aver
outputPCA.loc[2,'Accuracy']=accuracy_score(yyp8_test,yyp8_predicted)*100
outputPCA.loc[2,'F1 Score']=f1_score(yyp8_test, yyp8_predicted, average='mic
outputPCA.loc[2,'Recall']=recall_score(yyp8_test, yyp8_predicted, average='m
```

In [170]:
```
outputPCA
```

Out[170]:

	PCA	Precision	Accuracy	F1 Score	Recall
0	n=4	0.903783	90.378259	0.903783	0.903783
1	n=6	0.924348	92.434815	0.924348	0.924348
2	n=8	0.928021	92.802057	0.928021	0.928021

In [171]:
```
#For n=10
pca10=PCA(n_components=10)
pca10.fit(scaled_data)
x_pca10=pca10.transform(scaled_data)
x_pca10.shape
```

Out[171]: (13611, 10)

In [173]:

```
# Gaussian Naive Bayes on PCA n=10
xxp10=x_pca10
yyp10=dataset3.iloc[:,16]
xxp10_train,xxp10_test,yyp10_train,yyp10_test=train_test_split(xxp10,yyp10,t

from sklearn.naive_bayes import GaussianNB
NBModel=GaussianNB()
NBModel.fit(xxp10_train,yyp10_train)

yyp10_predicted=NBModel.predict(xxp10_test)
# yyp_predicted

from sklearn.metrics import accuracy_score,precision_score, confusion_matrix
outputPCA.loc[3,'PCA']='n=10'
outputPCA.loc[3,'Precision']=precision_score(yyp10_test, yyp10_predicted, av
outputPCA.loc[3,'Accuracy']=accuracy_score(yyp10_test,yyp10_predicted)*100
outputPCA.loc[3,'F1 Score']=f1_score(yyp10_test, yyp10_predicted, average='m
outputPCA.loc[3,'Recall']=recall_score(yyp10_test, yyp10_predicted, average=
outputPCA
```

Out[173]:

	PCA	Precision	Accuracy	F1 Score	Recall
0	n=4	0.903783	90.378259	0.903783	0.903783
1	n=6	0.924348	92.434815	0.924348	0.924348
2	n=8	0.928021	92.802057	0.928021	0.928021
3	n=10	0.919574	91.957400	0.919574	0.919574

In [174]:

```
#For n=12
pca12=PCA(n_components=12)
pca12.fit(scaled_data)
x_pca12=pca12.transform(scaled_data)
x_pca12.shape
```

Out[174]: (13611, 12)

In [176]:

```
# Gaussian Naive Bayes on PCA n=12
xxp12=x_pca12
yyp12=dataset3.iloc[:,16]
xxp12_train,xxp12_test,yyp12_train,yyp12_test=train_test_split(xxp12,yyp12,t

from sklearn.naive_bayes import GaussianNB
NBModel=GaussianNB()
NBModel.fit(xxp12_train,yyp12_train)

yyp12_predicted=NBModel.predict(xxp12_test)
# yyp_predicted

from sklearn.metrics import accuracy_score,precision_score, confusion_matrix
outputPCA.loc[4,'PCA']='n=12'
outputPCA.loc[4,'Precision']=precision_score(yyp12_test, yyp12_predicted, av
outputPCA.loc[4,'Accuracy']=accuracy_score(yyp12_test,yyp12_predicted)*100
outputPCA.loc[4,'F1 Score']=f1_score(yyp12_test, yyp12_predicted, average='m
outputPCA.loc[4,'Recall']=recall_score(yyp12_test, yyp12_predicted, average=
outputPCA
```

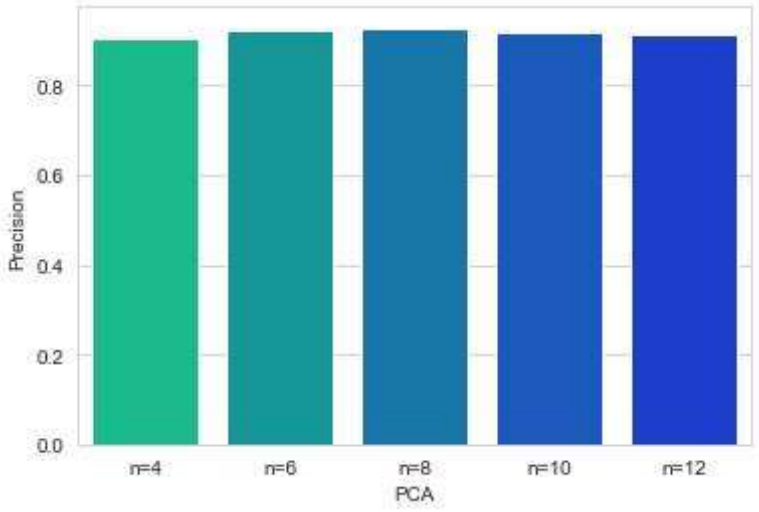
Out[176]:

	PCA	Precision	Accuracy	F1 Score	Recall
0	n=4	0.903783	90.378259	0.903783	0.903783
1	n=6	0.924348	92.434815	0.924348	0.924348
2	n=8	0.928021	92.802057	0.928021	0.928021
3	n=10	0.919574	91.957400	0.919574	0.919574
4	n=12	0.912596	91.259640	0.912596	0.912596

In [261]:

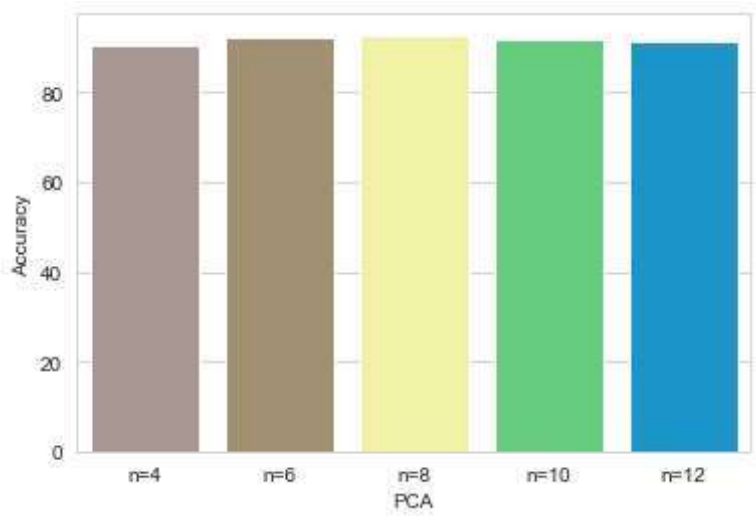
```
# Comparision between all the outputs of PCA on different n values
sns.barplot(x='PCA',y='Precision',data=outputPCA,palette="winter_r")
```

Out[261]: <matplotlib.axes._subplots.AxesSubplot at 0x138c06966a0>



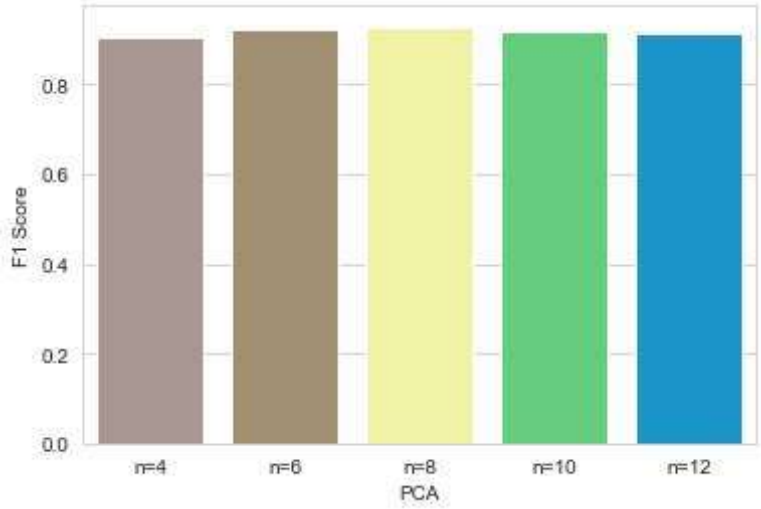
In [264]:
```
1 sns.barplot(x='PCA',y='Accuracy',data=outputPCA,palette="terrain_r")
```

Out[264]: <matplotlib.axes._subplots.AxesSubplot at 0x138c0757e50>



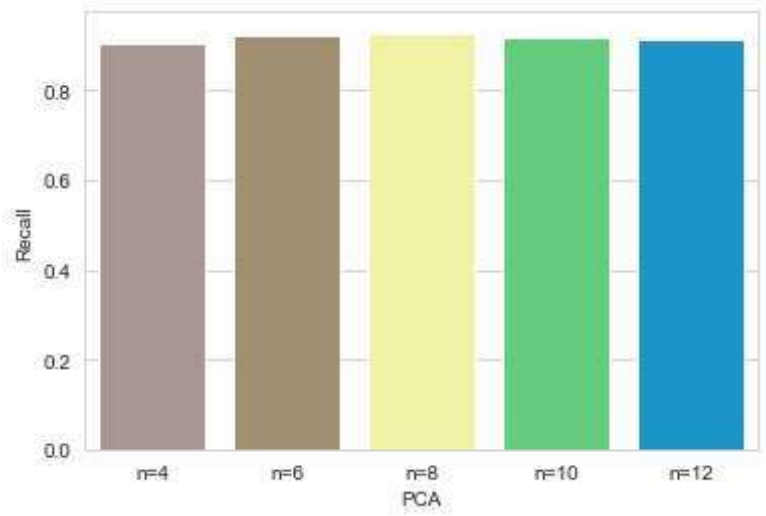
In [265]:
```
1 sns.barplot(x='PCA',y='F1 Score',data=outputPCA,palette="terrain_r")
```

Out[265]: <matplotlib.axes._subplots.AxesSubplot at 0x138c07d4610>



In [266]:
```
1 sns.barplot(x='PCA',y='Recall',data=outputPCA,palette="terrain_r")
```

Out[266]: <matplotlib.axes._subplots.AxesSubplot at 0x138c0830c40>



(f) Use Scikit-learn to plot the ROC-AUC curves and comment on the out-put.

In [184]:
```
1 rf = pd.read_csv('Dry_Bean_Dataset.csv')
2 rx=rf.iloc[:,1:16]
3 ry=rf.iloc[:,16]
4 classes = rf['Class'] = pd.factorize(rf['Class'])[0] + 1
5 # rf['Class']
6 classes
```

Out[184]: array([1, 1, 1, ..., 7, 7, 7], dtype=int64)

In [185]:
```
1 from sklearn.model_selection import train_test_split
2 xr_train, xr_test, yr_train, yr_test = train_test_split(rx,ry,test_size=0.2)
```

In [186]:
```
from sklearn.naive_bayes import GaussianNB
NBModel=GaussianNB()
NBModel.fit(xr_train,yr_train)
```

Out[186]:
```
GaussianNB()
```

In [194]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
yr_pred = NBModel.predict(xr_test)
yr_pred
```

Out[194]:
```
array(['SIRA', 'SIRA', 'BARBUNYA', ..., 'CALI', 'CALI', 'DERMASON'],
      dtype='<U8')
```

In [195]:
```
yr_pred_proba = NBModel.predict_proba(xr_test)
```

In [196]:
```
yr_pred_proba
```

Out[196]:
```
array([[4.62651809e-09, 3.26783144e-51, 1.33320868e-15, ...,
        2.62400460e-04, 1.48579061e-03, 9.98251765e-01],
       [1.29264038e-08, 6.39082486e-51, 7.97618636e-15, ...,
        1.88670519e-03, 1.03196764e-04, 9.98010078e-01],
       [5.71491927e-01, 4.76824295e-28, 4.28507798e-01, ...,
        2.75005405e-07, 5.01650114e-35, 2.02863979e-27],
       ...,
       [2.35464376e-01, 1.48999789e-30, 7.34750750e-01, ...,
        2.97848742e-02, 2.02842564e-41, 3.09105278e-25],
       [8.67621163e-02, 2.43353232e-23, 9.13237884e-01, ...,
        7.77337973e-12, 1.24024007e-55, 1.85615832e-45],
       [3.40084309e-16, 5.88663667e-61, 2.38297081e-28, ...,
        2.81979404e-11, 4.70590781e-01, 1.21902082e-05]])
```

In [198]:
```
# probablity prediction
r_probs = [0 for _ in range (len(yr_test))]
nb_probs = NBModel.predict_proba(xr_test)
# ROC AUC Score using naive bayes
nb_auc = roc_auc_score(yr_test, nb_probs, multi_class='ovr' )
```

In [199]:
```
nb_auc
```

Out[199]:
```
0.969320834251782
```

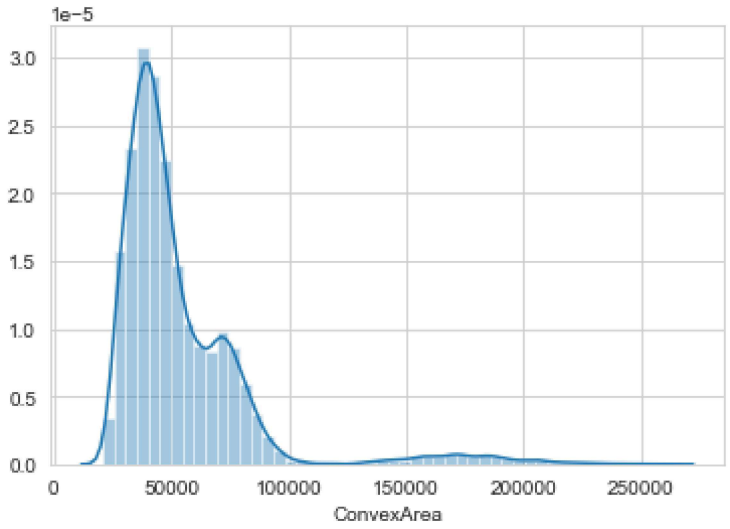
In [ ]:

```
from sklearn.preprocessing import label_binarize
y_bin=label_binarize(yr_test,classes=np.unique(yr_test))
fpr = {}
tpr = {}
thresh ={}
roc_auc = dict()
nclass = classes.shape[0]

for i in range(nclass):
    fpr[i], tpr[i], thresh[i] = roc_curve(y_bin[:,i], yr_pred_proba[:,i])
    roc_auc[i] = auc(fpr[i], tpr[i])

    # plotting
plt.plot(fpr[i], tpr[i], linestyle='dotted')

plt.plot([0,1],[0,1],'b**')
plt.xlim([0,1])
plt.ylim([0,1.05])
plt.title('Multiclass ROC curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive rate')
plt.legend(loc='lower right')
plt.show()
```

(g) Train your model using Sklearn's implementation of Logistic Regression, choose appropriate parameters, and comment on your choice. Compare the results with the ones obtained from Naive Bayes models. (80:20 train test split)

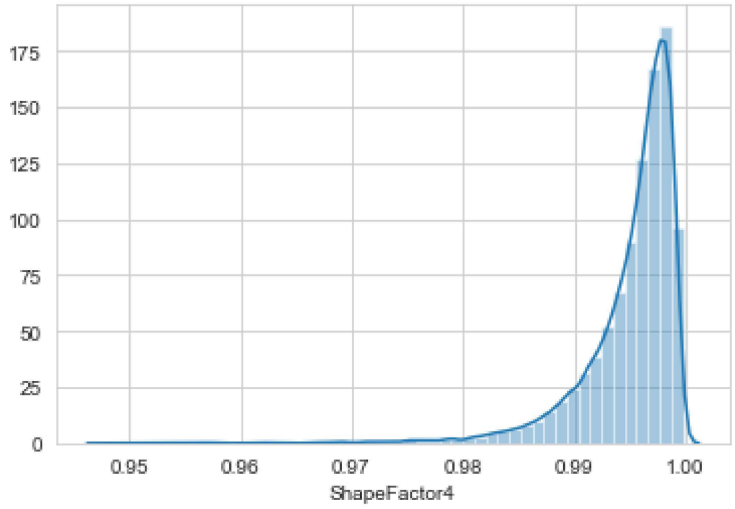
In [295]:
```
# Quality check to check if the data is symetric skewed etc or not
sns.distplot(df.ConvexArea)
```

Out[295]: <matplotlib.axes._subplots.AxesSubplot at 0x138c101ff70>



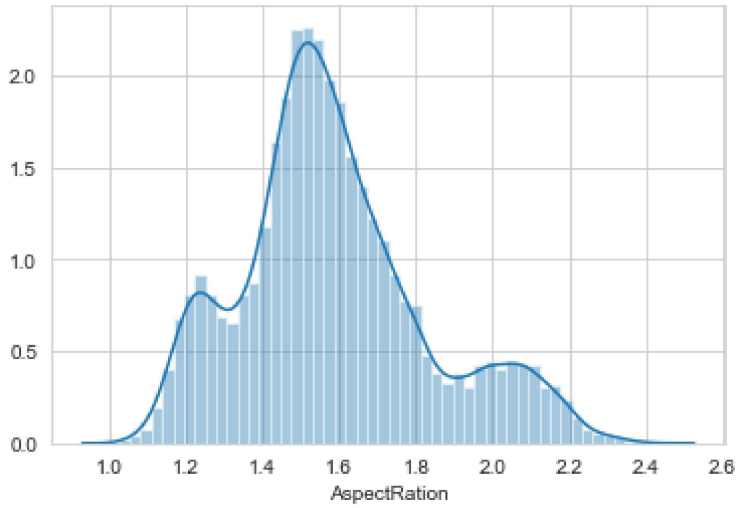
In [296]:
```
sns.distplot(df.ShapeFactor4)
```

Out[296]: <matplotlib.axes._subplots.AxesSubplot at 0x138c239e310>



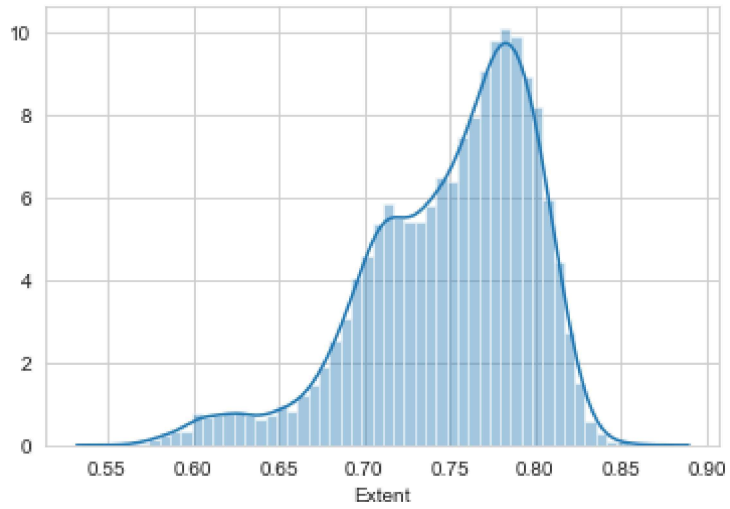
In [297]:
```
1 sns.distplot(df.AspectRation)
```

Out[297]: <matplotlib.axes._subplots.AxesSubplot at 0x138c2460430>



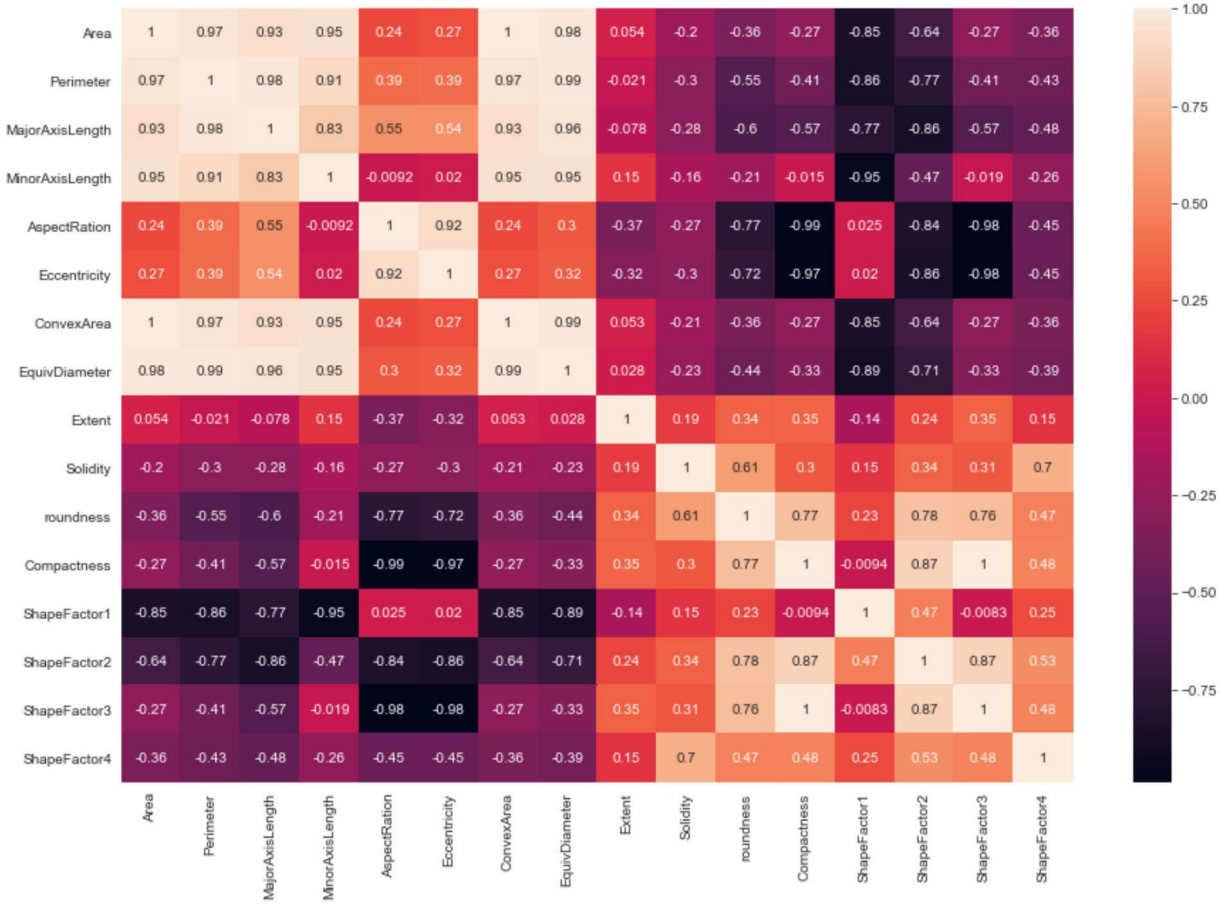
In [298]:
```
1 sns.distplot(df.Extent)
```

Out[298]: <matplotlib.axes._subplots.AxesSubplot at 0x138c2563df0>



In [299]:
```
ds = df
plt.figure(figsize=(15,10))
sns.heatmap(ds.corr(),annot=True)
```

Out[299]: <matplotlib.axes._subplots.AxesSubplot at 0x138c09ab9a0>



In [300]:
```
#droping attributes
ds.drop(['ConvexArea','Solidity', 'roundness'], axis=1, inplace=True)
ds.drop(['ShapeFactor4','Extent', 'AspectRation'], axis=1, inplace=True)
```

Comments:

By plotting we can see that many features are not balanced so we can remove them

We can see that many the features have high correlation with the class

'Area','ConvexArea', 'EquivDiameter' have very high multi colinearity

In [216]:
```
1 ds
```

Out[216]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	Eccentricity	EquivDiameter	Compactr
0	28395	610.291	208.178117	173.888747	0.549812	190.141097	0.913
1	28734	638.018	200.524796	182.734419	0.411785	191.272751	0.953
2	29380	624.110	212.826130	175.931143	0.562727	193.410904	0.908
3	30008	645.884	210.557999	182.516516	0.498616	195.467062	0.928
4	30140	620.134	201.847882	190.279279	0.333680	195.896503	0.970
...	...	...	...	...	...	...	
13606	42097	759.696	288.721612	185.944705	0.765002	231.515799	0.801
13607	42101	757.499	281.576392	190.713136	0.735702	231.526798	0.822
13608	42139	759.321	281.539928	191.187979	0.734065	231.631261	0.822
13609	42147	763.779	283.382636	190.275731	0.741055	231.653248	0.817
13610	42159	772.237	295.142741	182.204716	0.786693	231.686223	0.784

13611 rows × 11 columns

In [217]:
```
1 # Application of Logistic Regression on choosed paramenter
2 # as explained above
```

In [219]:
```
1 xl=dataset1.iloc[:,1:16]
2 yl=dataset1.iloc[:,16]
3 xl_train,xl_test,yl_train,yl_test=train_test_split(xl,yl,test_size=0.20,rand
```

In [224]:
```
1 from sklearn.linear_model import LogisticRegression
2 r=LogisticRegression(random_state=0)
3 r.fit(xl_train,yl_train)
4 yl_predicted=r.predict(xl_test)
```

```
C:\Users\user\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:76
2: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  n_iter_i = _check_optimize_result(
```

In [225]:
```
1 r.score(xl_test,yl_test)
```

Out[225]: 0.8659566654425266

In [226]:
```
1 outputlr=pd.DataFrame([ 'Logistic Regression' '],columns=['Algo'])
2 outputlr.loc[0,'Precision ']=precision_score(yl_test, yl_predicted, average='
3 outputlr.loc[0,'Accuracy']=accuracy_score(yl_test,yl_predicted)*100
4 outputlr.loc[0,'F1 Score']=f1_score(yl_test, yl_predicted, average='micro')
5 outputlr.loc[0,'Recall']=recall_score(yl_test, yl_predicted, average='micro'
```

In [227]:
```
1 outputlr
```

Out[227]:

	Algo	Precision	Accuracy	F1 Score	Recall
0	Linear Regression	0.865957	86.595667	0.865957	0.865957

In [268]:
```
1  outputcmp=pd.DataFrame([' Logistic Regression '],columns=['Algorithm'])
2  outputcmp.loc[0,'Precision']=precision_score(yl_test, yl_predicted, average=
3  outputcmp.loc[0,'Accuracy']=accuracy_score(yl_test,yl_predicted)*100
4  outputcmp.loc[0,'F1 Score']=f1_score(yl_test, yl_predicted, average='micro')
5  outputcmp.loc[0,'Recall']=recall_score(yl_test, yl_predicted, average='micro
6  outputcmp.loc[1,'Algorithm']='Gaussian NB'
7  outputcmp.loc[1,'Precision']=precision_score(yy_test, yy_predicted, average=
8  outputcmp.loc[1,'Accuracy']=accuracy_score(yy_test,yy_predicted)*100
9  outputcmp.loc[1,'F1 Score']=f1_score(yy_test, yy_predicted, average='micro')
10 outputcmp.loc[1,'Recall']=recall_score(yy_test, yy_predicted, average='micro
```

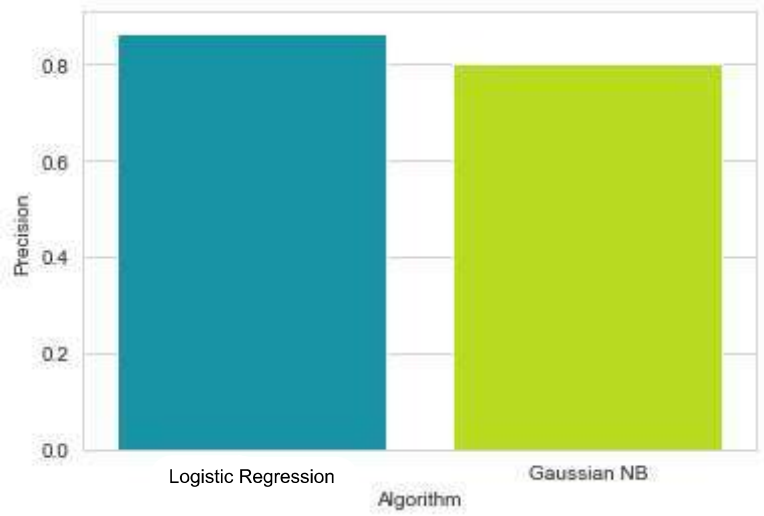
In [269]:
```
1 outputcmp
```

Out[269]:

	Algorithm	Precision	Accuracy	F1 Score	Recall
0	Logistic Regression	0.865957	86.595667	0.865957	0.865957
1	Gaussian NB	0.800955	80.095483	0.800955	0.800955

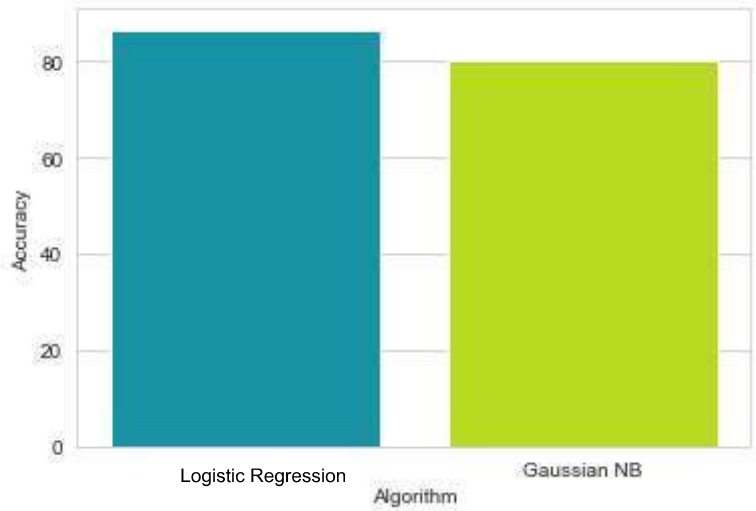
In [273]:
```
1 sns.barplot(x='Algorithm',y='Precision',data=outputcmp,palette="nipy_spectra
```

Out[273]: <matplotlib.axes._subplots.AxesSubplot at 0x138c096b0a0>



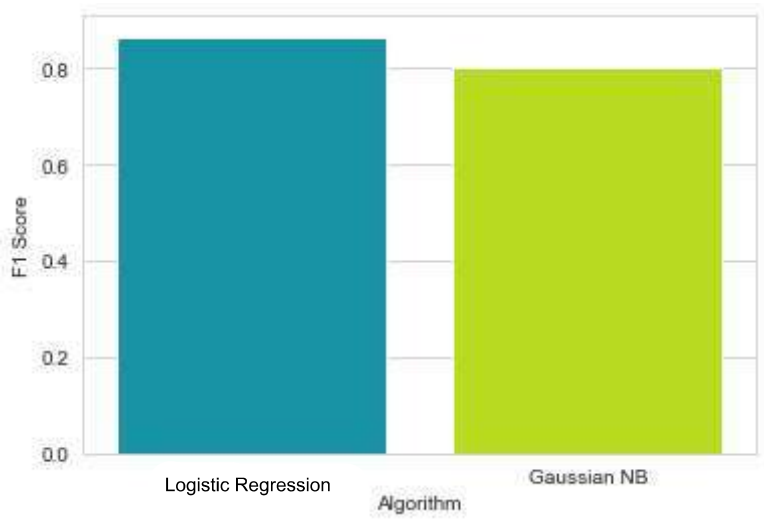
In [274]:
```
1 sns.barplot(x='Algorithm',y='Accuracy',data=outputcmp,palette="nipy_spectral
```

Out[274]: <matplotlib.axes._subplots.AxesSubplot at 0x138c09b1f10>



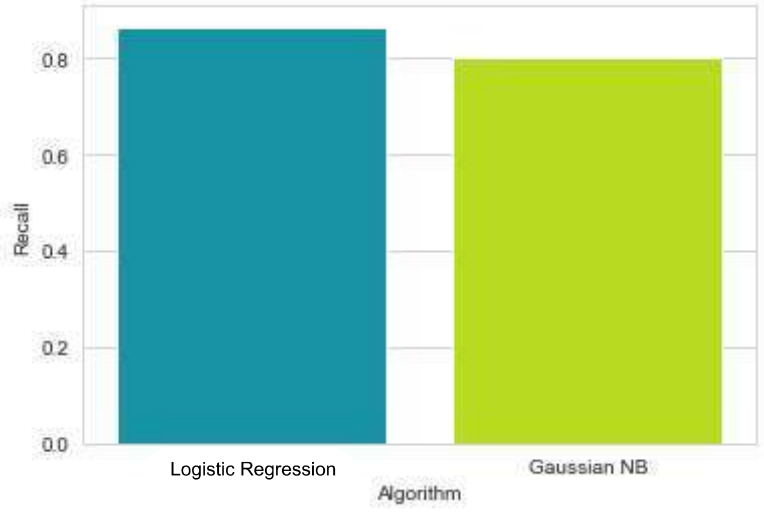
In [275]:
```
1 sns.barplot(x='Algorithm',y='F1 Score',data=outputcmp,palette="nipy_spectral
```

Out[275]: <matplotlib.axes._subplots.AxesSubplot at 0x138c09f8fa0>



In [276]:
```
1 sns.barplot(x='Algorithm',y='Recall',data=outputcmp,palette="nipy_spectral")
```

Out[276]: <matplotlib.axes._subplots.AxesSubplot at 0x138c0a3f790>



Comments:

Here, Logistic regression gives better accuracy than Gaussian Naive Bayes

In [ ]:
```
1
```