In [78]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
import sklearn.tree as tree
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_repo

import warnings
warnings.filterwarnings('ignore')
```

Problem statement/Business problem

In [2]:
```
Multiclass classification of dry beans
```

Data gathering

In [3]:
```
df=pd.read_excel('Dry_Bean_Dataset.xlsx')
df
```

Out[3]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexAre
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	2871
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	2917
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	2969
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	3072
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	3041
...	...	...	...	...	...	...	
13606	42097	759.696	288.721612	185.944705	1.552728	0.765002	4250
13607	42101	757.499	281.576392	190.713136	1.476439	0.735702	4249
13608	42139	759.321	281.539928	191.187979	1.472582	0.734065	4256
13609	42147	763.779	283.382636	190.275731	1.489326	0.741055	4266
13610	42159	772.237	295.142741	182.204716	1.619841	0.786693	4260

13611 rows × 17 columns

```
[13611 rows x 17 columns]>
```

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

Out[5]:
```
(13611, 17)
```

In [6]:
```
df.describe()
```

Out[6]:

	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	738.860153	460.198497	2.430306	0.911423

In [7]:
```
df['Area'].median()
```

Out[7]:
```
44652.0
```

In [8]:
```
df['Area'].mode()
```

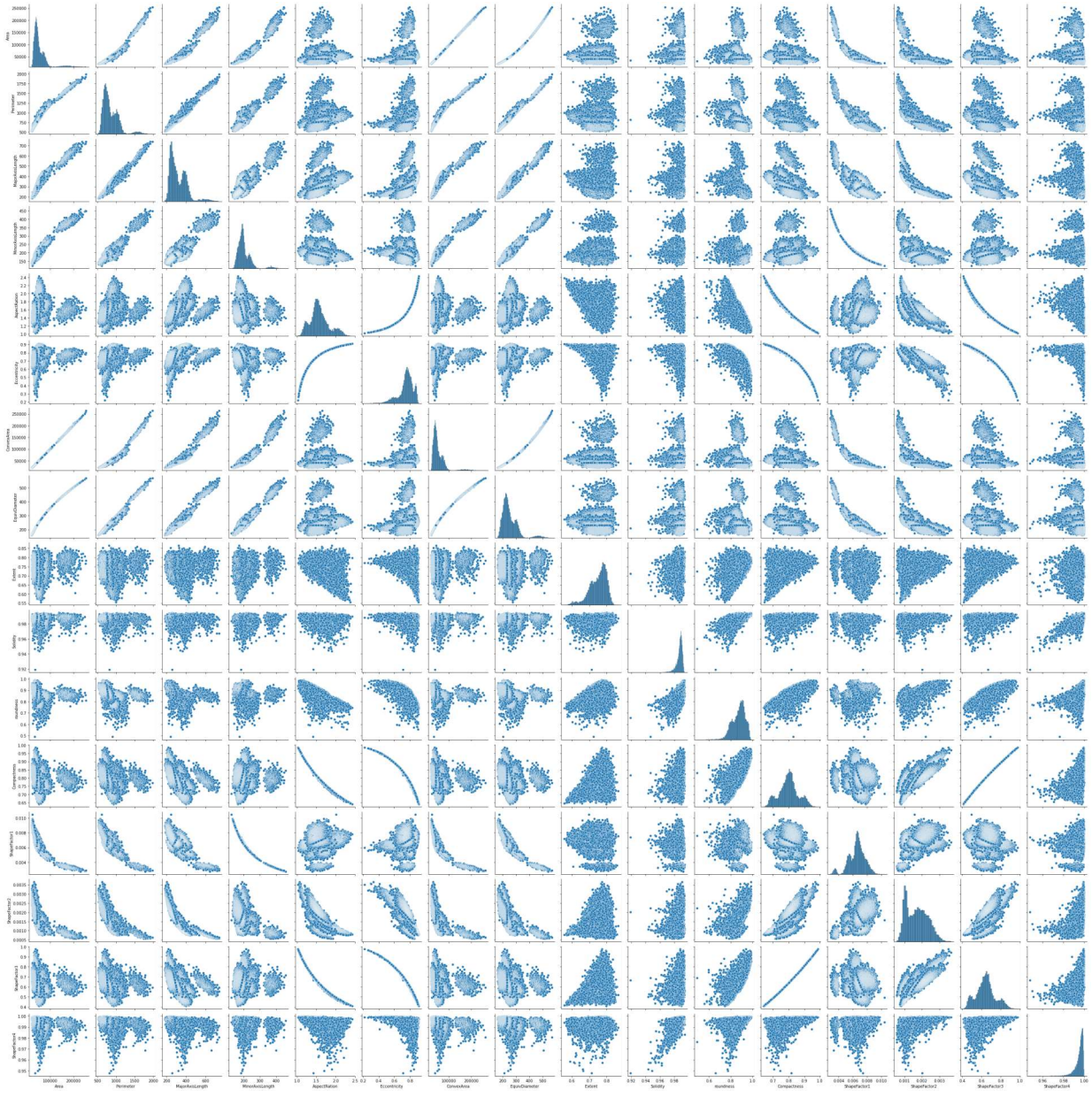
Out[8]:
```
0     28122
1     29709
2     30529
3     33518
4     34594
5     34774
6     35354
7     35442
8     36109
9     38273
10    38426
11    38542
12    38945
13    40504
14    44710
15    47134
16    52266
dtype: int64
```

In [ ]:
```

```

In [11]:
```
sns.pairplot(df)
```

Out[11]:
```
<seaborn.axisgrid.PairGrid at 0x2772f354d60>
```



In [15]:
```
df[['Area']].value_counts()
```

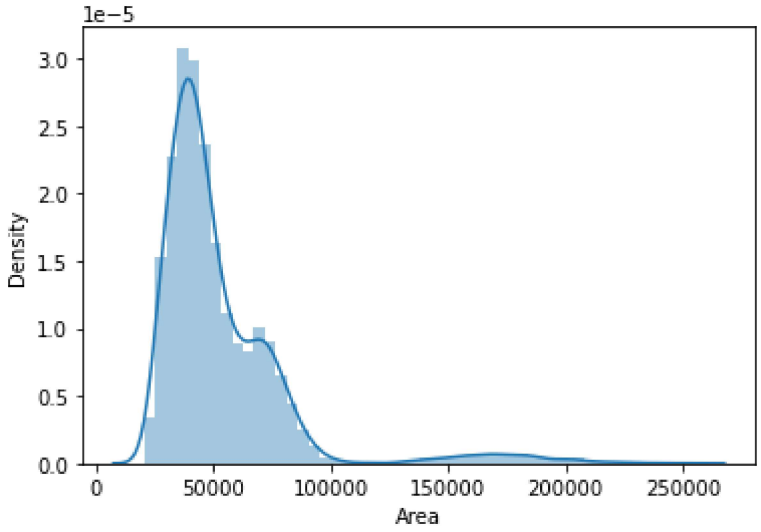
Out[15]:
```
Area
34774     4
44710     4
29709     4
35442     4
38945     4
         ..
40127     1
40130     1
40138     1
40142     1
254616    1
Length: 12011, dtype: int64
```

In [16]:
```
df[['Area']].nunique()
```

Out[16]:
```
Area    12011
dtype: int64
```

In [17]:
```
sns.distplot(df['Area'])
```

Out[17]:
```
<AxesSubplot:xlabel='Area', ylabel='Density'>
```



In [19]:
```
len(dir(sns))
```

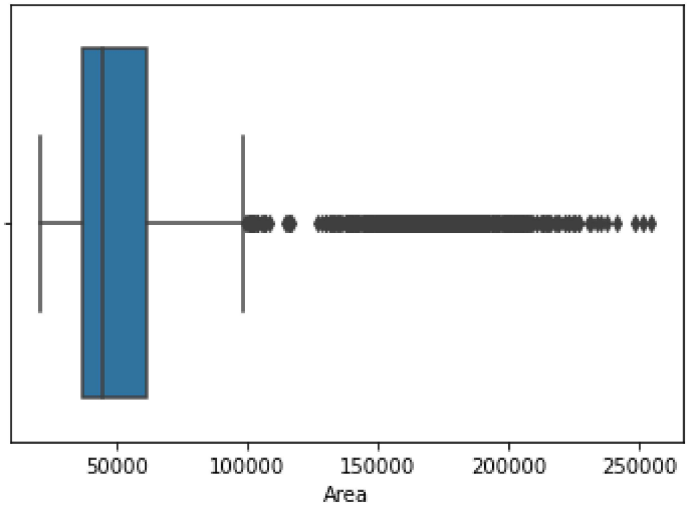
Out[19]: 98

In [20]:
```
len(dir(plt))
```

Out[20]: 256

In [21]:
```
sns.boxplot(df['Area']) # The area feature contains outliers
```

Out[21]: <AxesSubplot:xlabel='Area'>

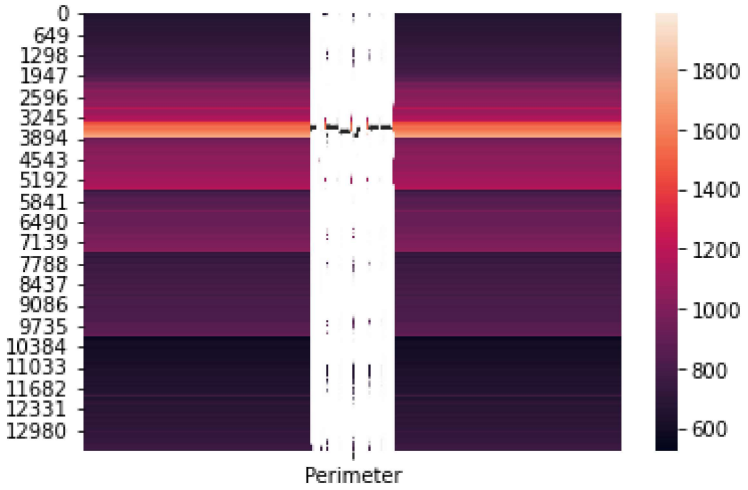


In [22]:
```
# Handling outliers using iqr
q1=df['Area'].quantile(0.25)
q3=df['Area'].quantile(0.75)
iqr=q3-q1
upper_limit=q3+1.5*iqr
```

In [23]:
```
df['Area']=np.where(df['Area']>upper_limit, upper_limit, df['Area'])
```

In [26]:
```
sns.heatmap(df[['Perimeter']], annot=True)
plt.figure(figsize=(10, 50))
```

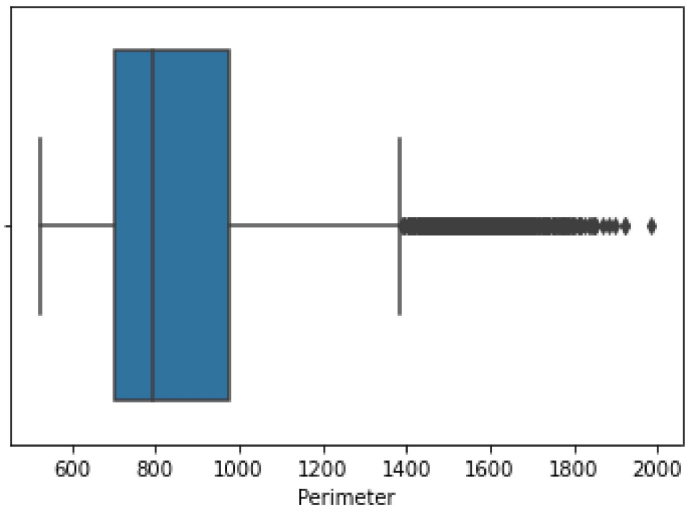
Out[26]: <Figure size 720x3600 with 0 Axes>



<Figure size 720x3600 with 0 Axes>

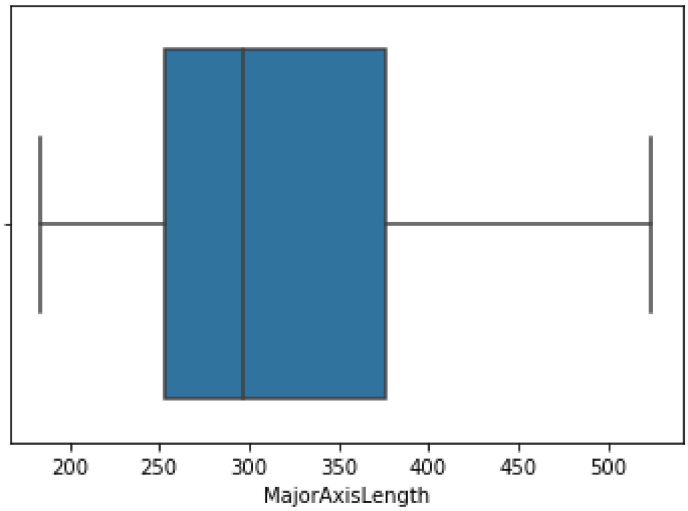
In [27]:
```
sns.boxplot(df['Perimeter']) # The feature perimeter contains outliers
```

Out[27]: <AxesSubplot:xlabel='Perimeter'>



In [30]:
```
# Handling outliers using iqr
q1=df['MajorAxisLength'].quantile(0.25)
q3=df['MajorAxisLength'].quantile(0.75)
iqr=q3-q1
upper_limit=q3+1.2*iqr
df['MajorAxisLength']=np.where(df['MajorAxisLength']>upper_limit, upper_limit, df
sns.boxplot(df['MajorAxisLength'])
```

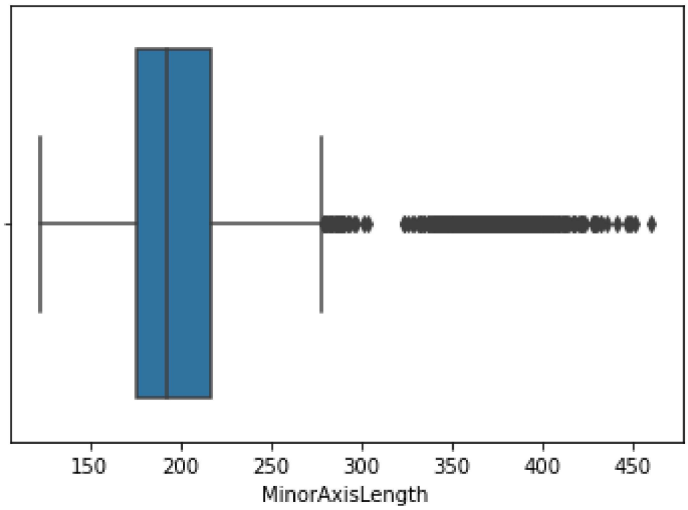
Out[30]: <AxesSubplot:xlabel='MajorAxisLength'>



4. MinorAxisLength

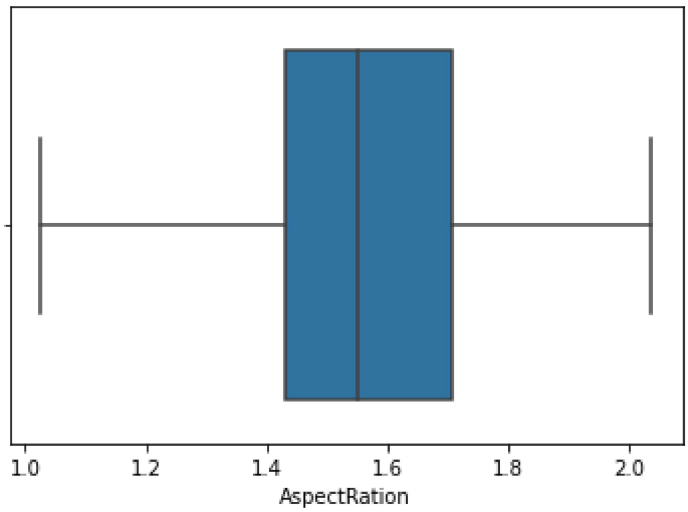
In [31]:
```
sns.boxplot(df['MinorAxisLength'])
```

Out[31]: <AxesSubplot:xlabel='MinorAxisLength'>



In [34]:
```
# Handling outliers using iqr
q1=df['AspectRation'].quantile(0.25)
q3=df['AspectRation'].quantile(0.75)
iqr=q3-q1
upper_limit=q3+1.2*iqr
df['AspectRation']=np.where(df['AspectRation']>upper_limit, upper_limit, df['Aspe
sns.boxplot(df['AspectRation'])
```

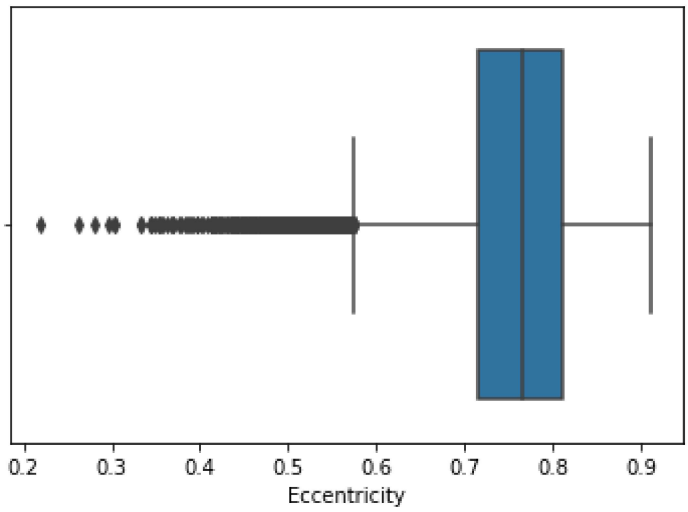
Out[34]: <AxesSubplot:xlabel='AspectRation'>



6. Eccentricity

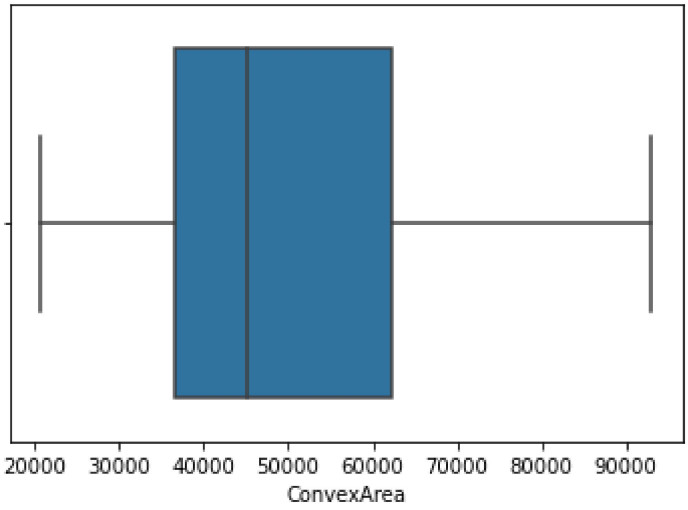
In [35]:
```
sns.boxplot(df['Eccentricity'])
```

Out[35]: <AxesSubplot:xlabel='Eccentricity'>



In [38]:
```
# Handling outliers using iqr
q1=df['ConvexArea'].quantile(0.25)
q3=df['ConvexArea'].quantile(0.75)
iqr=q3-q1
upper_limit=q3+1.2*iqr
df['ConvexArea']=np.where(df['ConvexArea']>upper_limit, upper_limit, df['ConvexAr
sns.boxplot(df['ConvexArea'])
```

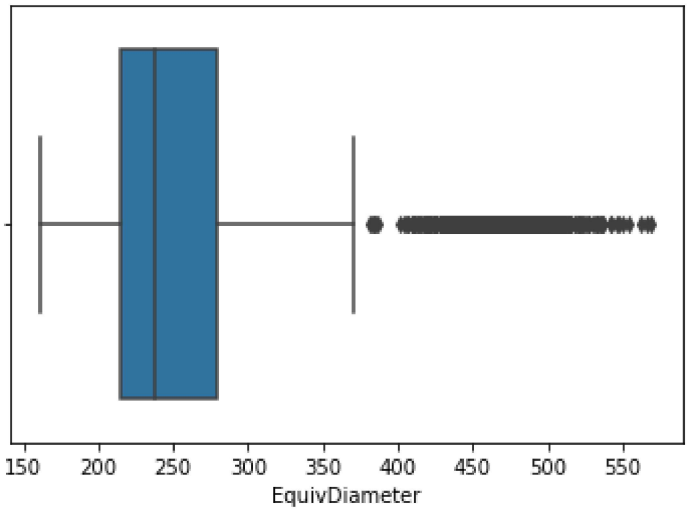
Out[38]: <AxesSubplot:xlabel='ConvexArea'>



8. EquivDiameter

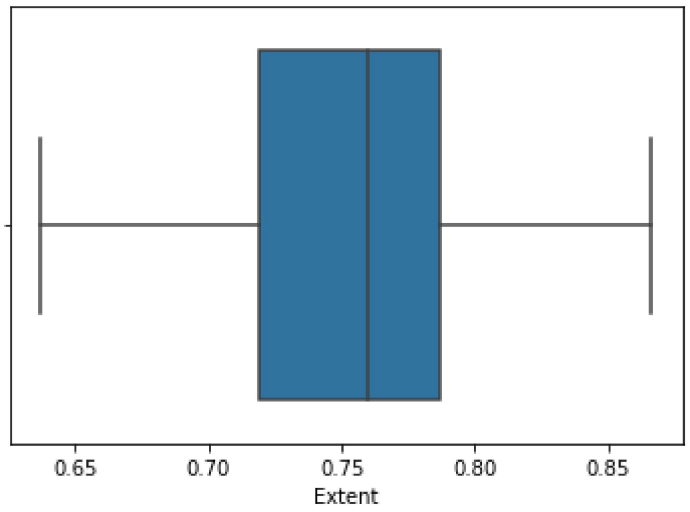
In [39]:
```
sns.boxplot(df['EquivDiameter'])
```

Out[39]: <AxesSubplot:xlabel='EquivDiameter'>



In [42]:
```
# Handling outliers using iqr
q1=df['Extent'].quantile(0.25)
q3=df['Extent'].quantile(0.75)
iqr=q3-q1
lower_limit=q1-1.2*iqr
df['Extent']=np.where(df['Extent']<lower_limit, lower_limit, df['Extent'])
sns.boxplot(df['Extent'])
```

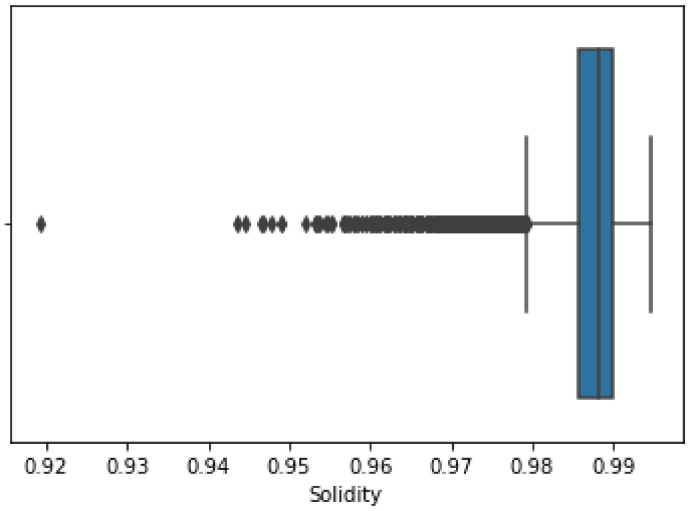
Out[42]: <AxesSubplot:xlabel='Extent'>



10. Solidity

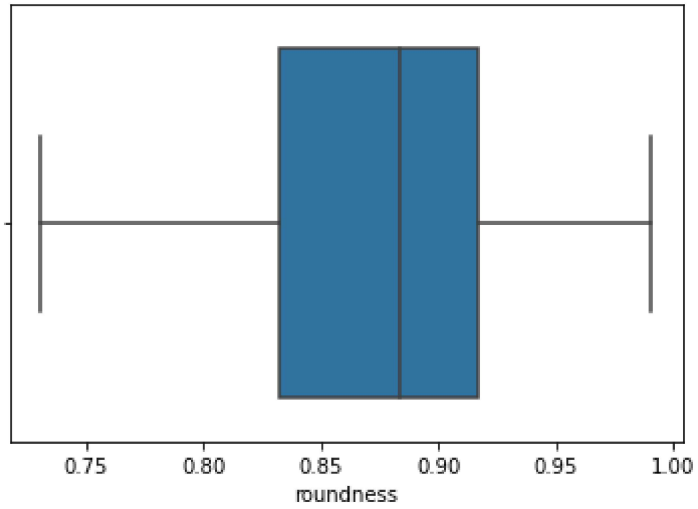
In [43]:
```
sns.boxplot(df['Solidity'])
```

Out[43]: <AxesSubplot:xlabel='Solidity'>



In [46]:
```
# Handling outliers using iqr
q1=df['roundness'].quantile(0.25)
q3=df['roundness'].quantile(0.75)
iqr=q3-q1
lower_limit=q1-1.2*iqr
df['roundness']=np.where(df['roundness']<lower_limit, lower_limit, df['roundness'
sns.boxplot(df['roundness'])
```

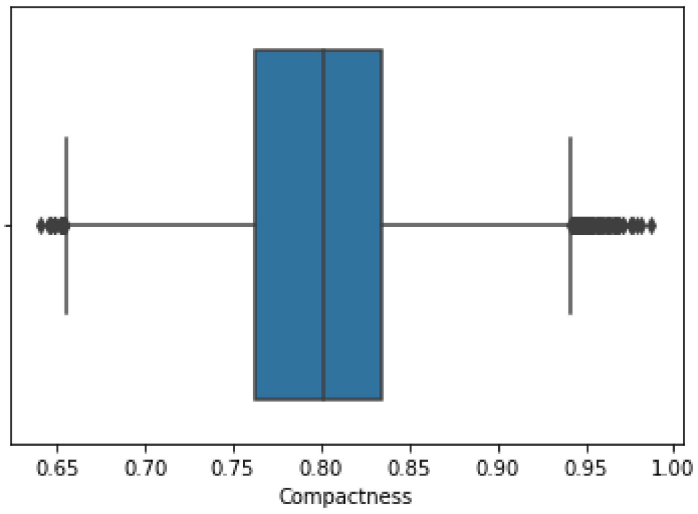
Out[46]: <AxesSubplot:xlabel='roundness'>



12. Compactness

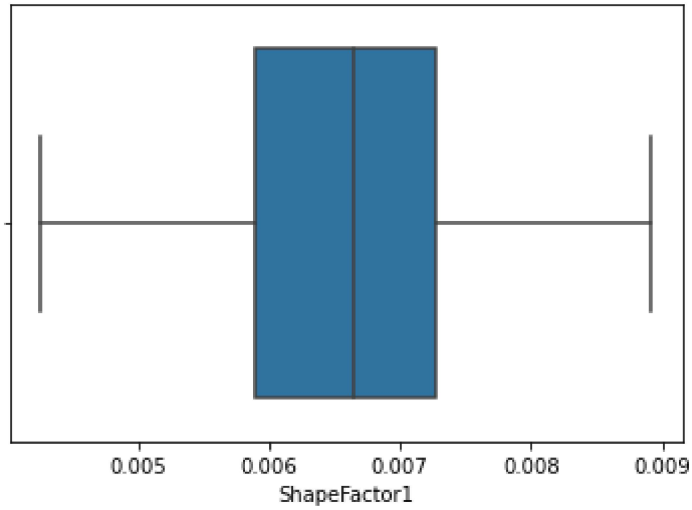
In [47]:
```
sns.boxplot(df['Compactness'])
```

Out[47]: <AxesSubplot:xlabel='Compactness'>



In [50]:
```
# Handling outliers using iqr
q1=df['ShapeFactor1'].quantile(0.25)
q3=df['ShapeFactor1'].quantile(0.75)
iqr=q3-q1
upper_limit=q3+1.2*iqr
lower_limit=q1-1.2*iqr
df['ShapeFactor1']=np.where(df['ShapeFactor1']>upper_limit, upper_limit, df['Shap
df['ShapeFactor1']=np.where(df['ShapeFactor1']<lower_limit, lower_limit, df['Shap
sns.boxplot(df['ShapeFactor1'])
```

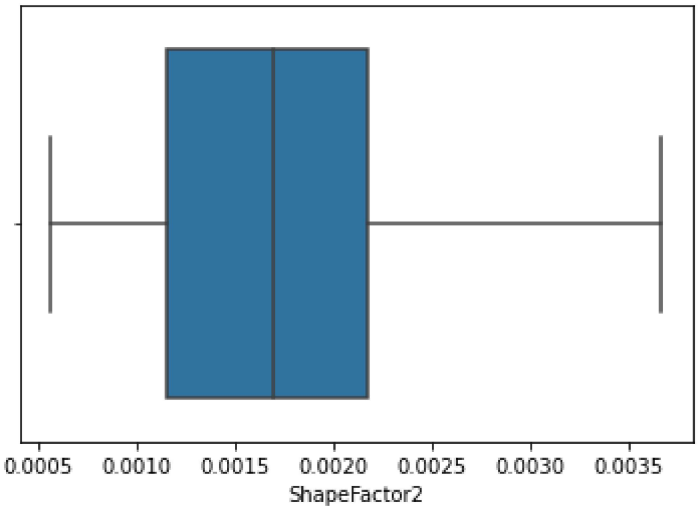
Out[50]: <AxesSubplot:xlabel='ShapeFactor1'>



14. ShapeFactor2

In [51]:
```
sns.boxplot(df['ShapeFactor2'])
```

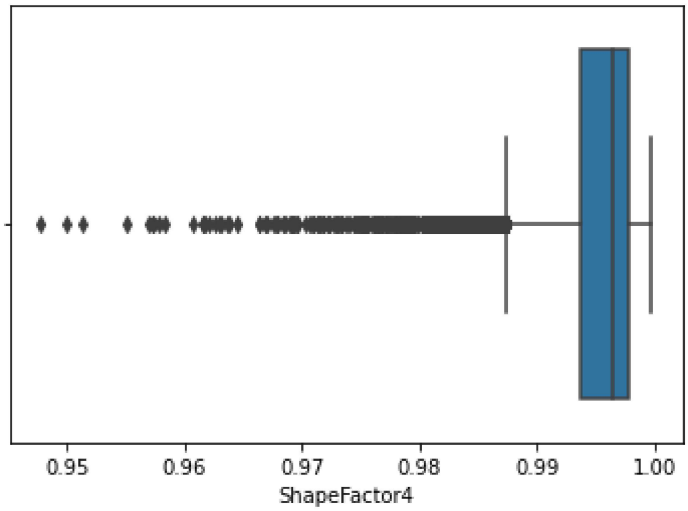
Out[51]: <AxesSubplot:xlabel='ShapeFactor2'>



15. ShapeFactor3

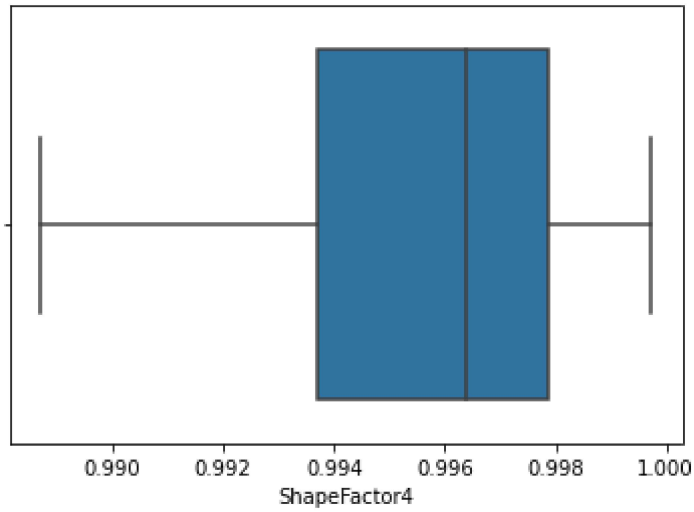
In [54]:
```
sns.boxplot(df['ShapeFactor4'])
```

Out[54]: <AxesSubplot:xlabel='ShapeFactor4'>



In [55]:
```
# Handling outliers using iqr
q1=df['ShapeFactor4'].quantile(0.25)
q3=df['ShapeFactor4'].quantile(0.75)
iqr=q3-q1
lower_limit=q1-1.2*iqr
df['ShapeFactor4']=np.where(df['ShapeFactor4']<lower_limit, lower_limit, df['Shap
sns.boxplot(df['ShapeFactor4'])
```

Out[55]: <AxesSubplot:xlabel='ShapeFactor4'>



17. Class

In [61]:
```
y.head()
```

Out[61]:
```
0    5
1    5
2    5
3    5
4    5
Name: Class, dtype: int32
```

Model training

In [62]:
```
x_train, x_test, y_train, y_test= train_test_split(x, y, random_state=5, test_si
```

In [63]:
```
x_train.shape
```

Out[63]:
```
(10888, 16)
```

In [64]:
```
x_test.shape
```

Out[64]:
```
(2723, 16)
```

Model building

1. Logistic Model

In [65]:
```
lgt_model=LogisticRegression()
```

In [66]:
```
lgt_model.fit(x_train, y_train)
```

Out[66]:
```
LogisticRegression()
```

In [68]:
```
# Training Accuracy
y_pred_train=lgt_model.predict(x_train)
accu_score=accuracy_score(y_train, y_pred_train)
print('Accuracy score: ', accu_score)
print('*'*30)
cnf_matrix=confusion_matrix(y_train, y_pred_train)
print('Confusion matrix:\n', cnf_matrix)
print('*'*30)
clf_report=classification_report(y_train, y_pred_train)
print('Classification report: \n', clf_report)
print('*'*30)
```

```
Accuracy score:  0.7521124173401911
******************************
Confusion matrix:
 [[ 555    5  316    0  143    0   38]
 [   0  418    0    0    0    0    0]
 [ 317   20  916    0   47    0    4]
 [   0    0    0 2465    0  221  151]
 [ 126    0    7   98 1139    1  171]
 [  49    0    0  316    2 1078  176]
 [  35    0    0  182  127  147 1618]]
******************************
Classification report:
               precision    recall  f1-score   support

           0       0.51      0.53      0.52      1057
           1       0.94      1.00      0.97       418
           2       0.74      0.70      0.72      1304
           3       0.81      0.87      0.84      2837
           4       0.78      0.74      0.76      1542
           5       0.74      0.67      0.70      1621
           6       0.75      0.77      0.76      2109

    accuracy                           0.75     10888
   macro avg       0.75      0.75      0.75     10888
weighted avg       0.75      0.75      0.75     10888

******************************
```

2. KNN

In [69]:
```
knn_clf=KNeighborsClassifier()
knn_clf
```

Out[69]:
```
KNeighborsClassifier()
```

In [70]:
```
knn_clf.fit(x_train, y_train)
```

Out[70]:
```
KNeighborsClassifier()
```

In [72]:
```
# Testing Accuracy
y_pred=knn_clf.predict(x_test)
accu_score=accuracy_score(y_test, y_pred)
print('Accuracy score: ', accu_score)
print('*'*30)
cnf_matrix=confusion_matrix(y_test, y_pred)
print('Confusion matrix:\n', cnf_matrix)
print('*'*30)
clf_report=classification_report(y_test, y_pred)
print('Classification report: \n', clf_report)
print('*'*30)
```

```
Accuracy score:  0.7275064267352185
******************************
Confusion matrix:
 [[138   0  86   0  35   0   6]
 [  0 104   0   0   0   0   0]
 [ 98   1 203   0  21   1   2]
 [  0   0   0 638   0  34  37]
 [ 29   0  27   9 273   0  48]
 [  0   0   1  71   2 249  83]
 [  0   0   0  57  72  22 376]]
******************************
Classification report:
               precision    recall  f1-score   support

           0       0.52      0.52      0.52       265
           1       0.99      1.00      1.00       104
           2       0.64      0.62      0.63       326
           3       0.82      0.90      0.86       709
           4       0.68      0.71      0.69       386
           5       0.81      0.61      0.70       406
           6       0.68      0.71      0.70       527

    accuracy                           0.73      2723
   macro avg       0.74      0.73      0.73      2723
weighted avg       0.73      0.73      0.73      2723

******************************
```

3. Decision Tree

In [80]:
```
dt_clf=DecisionTreeClassifier(criterion='entropy', max_depth=8)
```

In [81]:
```
dt_clf.fit(x_train, y_train)
```

Out[81]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=8)
```

In [83]:
```
# Testing Accuracy
y_pred=dt_clf.predict(x_test)
accu_score=accuracy_score(y_test, y_pred)
print('Accuracy score: ', accu_score)
print('*'*30)
cnf_matrix=confusion_matrix(y_test, y_pred)
print('Confusion matrix:\n', cnf_matrix)
print('*'*30)
clf_report=classification_report(y_test, y_pred)
print('Classification report: \n', clf_report)
print('*'*30)
```

```
Accuracy score:  0.9177377892030848
******************************
Confusion matrix:
 [[241   0   8   0   6   4   6]
 [  0 104   0   0   0   0   0]
 [ 13   0 305   0   6   2   0]
 [  0   0   0 659   1   7  42]
 [  2   0   9   2 369   0   4]
 [  1   0   1  25   0 373   6]
 [  4   0   3  51  10  11 448]]
******************************
Classification report:
               precision    recall  f1-score   support

           0       0.92      0.91      0.92       265
           1       1.00      1.00      1.00       104
           2       0.94      0.94      0.94       326
           3       0.89      0.93      0.91       709
           4       0.94      0.96      0.95       386
           5       0.94      0.92      0.93       406
           6       0.89      0.85      0.87       527

    accuracy                           0.92      2723
   macro avg       0.93      0.93      0.93      2723
weighted avg       0.92      0.92      0.92      2723

******************************
```

In [86]:
```
# Training Accuracy
y_pred_train=rf_clf.predict(x_train)
accu_score=accuracy_score(y_train, y_pred_train)
print('Accuracy score: ', accu_score)
print('*'*30)
cnf_matrix=confusion_matrix(y_train, y_pred_train)
print('Confusion matrix:\n', cnf_matrix)
print('*'*30)
clf_report=classification_report(y_train, y_pred_train)
print('Classification report: \n', clf_report)
print('*'*30)
```

```
Accuracy score:  0.9997244673034533
******************************
Confusion matrix:
 [[1057    0    0    0    0    0    0]
 [   0  418    0    0    0    0    0]
 [   0    0 1304    0    0    0    0]
 [   0    0    0 2837    0    0    0]
 [   0    0    0    0 1542    0    0]
 [   0    0    0    2    0 1619    0]
 [   0    0    0    0    1    0 2108]]
******************************
Classification report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      1057
           1       1.00      1.00      1.00       418
           2       1.00      1.00      1.00      1304
           3       1.00      1.00      1.00      2837
           4       1.00      1.00      1.00      1542
           5       1.00      1.00      1.00      1621
           6       1.00      1.00      1.00      2109

    accuracy                           1.00     10888
   macro avg       1.00      1.00      1.00     10888
weighted avg       1.00      1.00      1.00     10888

******************************
```

In [88]:
```
rf_model = RandomForestClassifier(random_state=10)

hyp = {
    'n_estimators': np.arange(10,150),
    'criterion':['gini','entropy'],
    'max_depth':np.arange(5,15),
    'min_samples_split':np.arange(5,20) ,
    'min_samples_leaf': np.arange(4,15) ,
    'max_features':['auto','log2'],
    'random_state' : np.arange(1,10)
}

rscv_rf_clf = RandomizedSearchCV(rf_model, hyp, cv=5)
rscv_rf_clf.fit(x_train, y_train)
rscv_rf_clf.best_params_
```

Out[88]:
```
{'random_state': 2,
 'n_estimators': 92,
 'min_samples_split': 15,
 'min_samples_leaf': 6,
 'max_features': 'log2',
 'max_depth': 11,
 'criterion': 'entropy'}
```

In [90]:
```
# Testing Accuracy
y_pred=rscv_rf_clf.predict(x_test)
accu_score=accuracy_score(y_test, y_pred)
print('Accuracy score: ', accu_score)
print('*'*30)
cnf_matrix=confusion_matrix(y_test, y_pred)
print('Confusion matrix:\n', cnf_matrix)
print('*'*30)
clf_report=classification_report(y_test, y_pred)
print('Classification report: \n', clf_report)
print('*'*30)
```

```
Accuracy score:  0.9357326478149101
******************************
Confusion matrix:
 [[244   0  11   0   2   2   6]
 [  0 104   0   0   0   0   0]
 [ 10   0 306   0   7   1   2]
 [  0   0   0 669   0   7  33]
 [  0   0   5   2 372   0   7]
 [  1   0   0  11   0 385   9]
 [  2   0   3  41   6   7 468]]
******************************
Classification report:
               precision    recall  f1-score   support

           0       0.95      0.92      0.93       265
           1       1.00      1.00      1.00       104
           2       0.94      0.94      0.94       326
           3       0.93      0.94      0.93       709
           4       0.96      0.96      0.96       386
           5       0.96      0.95      0.95       406
           6       0.89      0.89      0.89       527

    accuracy                           0.94      2723
   macro avg       0.95      0.94      0.94      2723
weighted avg       0.94      0.94      0.94      2723

******************************
```

Creating pickle file

In [91]:
```
import pickle
```

In [92]:
```
with open('rf_clf.pkl', 'wb') as f:
    pickle.dump(rscv_rf_clf, f)
```