QUESTION 2

In [1]:

```
## Importing packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
```

A. Load the /public/bmort/python/beans.csv data set into a data frame. Are there any missing values? Perform any necessary data imputation on the data set.

In [2]:

```
## Loading the dataset
beans = pd.read_csv('/public/bmort/python/beans.csv')
beans.head()
```

Out[2]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRatio	Eccentricity	C
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	28
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	29
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	29
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	30
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	30

In [3]:

```
beans.Class.unique()
```

Out[3]:

```
array(['SEKER', 'BARBUNYA', 'BOMBAY', 'CALI', 'HOROZ', 'SIRA', 'DERMASO
N'],
      dtype=object)
```

In [4]:

```
## Finding missing values
beans.isna().sum()
```

Out[4]:

```
Area               0
Perimeter          0
MajorAxisLength    0
MinorAxisLength    0
AspectRatio        0
Eccentricity       0
ConvexArea         0
EquivDiameter      0
Extent             0
Solidity           0
roundness          0
Compactness        0
ShapeFactor1       0
ShapeFactor2       0
ShapeFactor3       1
ShapeFactor4       0
Class              0
dtype: int64
```

There is **one** missing value in the data and it can be seen in the **ShapeFactor3** column.

In [5]:

```
## Dropping the missing value
beans= beans.dropna()
beans.head()
```

Out[5]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRatio	Eccentricity	Co
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	28
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	29
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	29
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	30
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	30

B. Produce a table of summary statistics on the data set. How do the ranges of the values in the columns compare? Does each column of data have similar magnitudes and ranges? Are there any outliers?

In [6]:

```
beans.describe()
```

Out[6]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRati
count	13532.000000	13532.000000	13532.000000	13532.000000	13532.00000
mean	53057.907848	855.070038	319.924170	202.379107	1.581111
std	29402.259447	214.789530	85.836957	45.066500	0.245337
min	20420.000000	524.736000	183.601165	122.512653	1.024868
25%	36268.500000	703.149500	253.056814	175.882616	1.430628
50%	44580.500000	793.896500	296.427483	192.497582	1.549894
75%	61423.750000	977.274000	376.361129	217.263679	1.704026
max	254616.000000	1985.370000	738.860154	460.198497	2.430306

All the variables in the beans data have their various ranges. From the output above, we can observe that variables like Eccentricity, Extent, Solidity, roundness, Compactness, ShapeFactor1, ShapeFactor2, ShapeFactor3 and ShapeFactor4 ranges from 0 to 1.

In detecting outliers, we compare the (min value and 25%) for lower outliers and (max and 75%) for upper outliers. It can be observed that there are upper outliers in Area, Perimeter and MajorAxisLength.

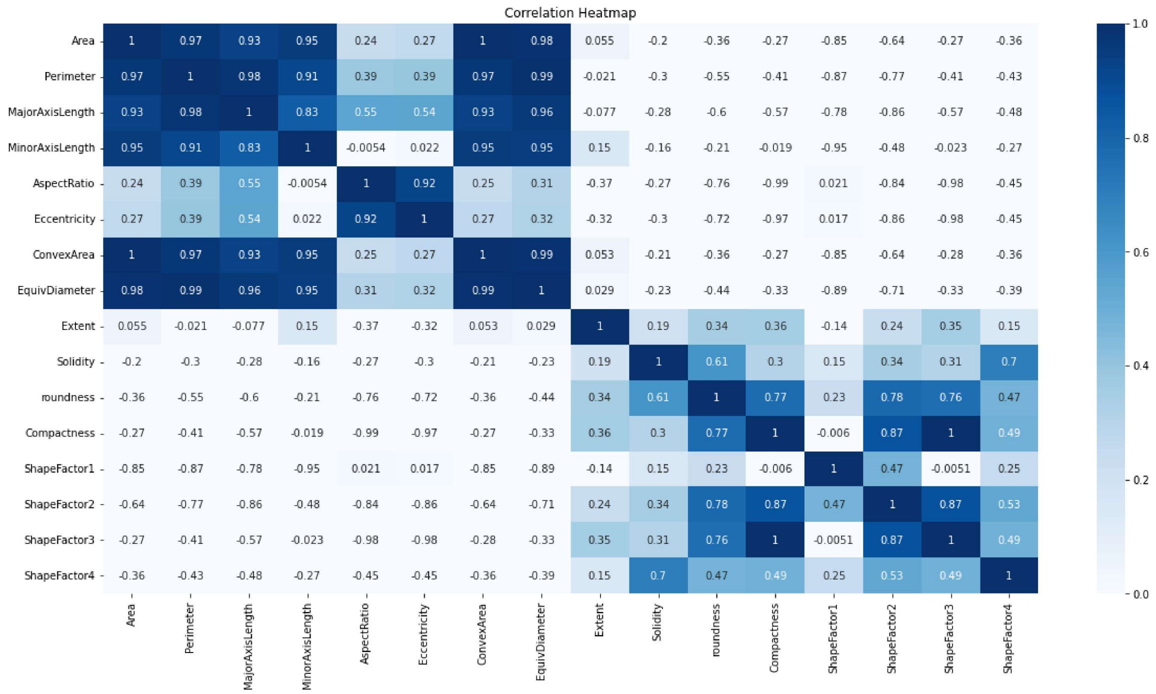
C. Using the Seaborn library's heatmap() function, generate a plot showing the correlations between the numerical data in the data set. Show the commands used to generate the plot and include the plot in your output.

In [7]:

```
## Showing the correlation between the varibales in the data
b_corr = beans.corr()
plt.figure(figsize=(20, 10))
sns.heatmap(data = b_corr, cmap= 'Blues', vmin=0, vmax=1, annot=True)
plt.title('Correlation Heatmap')
```

Out[7]:

```
Text(0.5, 1.0, 'Correlation Heatmap')
```



D. Based on the correlation plot, decide which features to include for machine learning. Decide if any of these features need to be standardized or scaled appropriately.

In [8]:

```
## A function to decide which features to select based on a threshold
def correl(dataset, threshold):
    col_corr = set()
    corr_matrix = dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i, j]) > threshold:
                colname = corr_matrix.columns[i]
                col_corr.add(colname)
    return col_corr
```

In [9]:

```
aa = correl(beans, 0.85)
aa
```

Out[9]:

```
{'Compactness',
 'ConvexArea',
 'Eccentricity',
 'EquivDiameter',
 'MajorAxisLength',
 'MinorAxisLength',
 'Perimeter',
 'ShapeFactor1',
 'ShapeFactor2',
 'ShapeFactor3'}
```

In [10]:

```
bb = beans.drop(aa,axis=1 )
bb.head()
```

Out[10]:

	Area	AspectRatio	Extent	Solidity	roundness	ShapeFactor4	Class
0	28395	1.197191	0.763923	0.988856	0.958027	0.998724	SEKER
1	28734	1.097356	0.783968	0.984986	0.887034	0.998430	SEKER
2	29380	1.209713	0.778113	0.989559	0.947849	0.999066	SEKER
3	30008	1.153638	0.782681	0.976696	0.903936	0.994199	SEKER
4	30140	1.060798	0.773098	0.990893	0.984877	0.999166	SEKER

In [11]:

```
## Using the MinMaxScaler model to tranform the the selected columns
# create a scaler object
features_names = bb[['Area', 'AspectRatio', 'Extent', 'Solidity','roundness','ShapeFact
or4']]
scaler = MinMaxScaler()

# fit and transform the data
scaled_bb = pd.DataFrame(scaler.fit_transform(features_names),
                        columns=features_names.columns)

scaled_bb.head()
```

Out[11]:

	Area	AspectRatio	Extent	Solidity	roundness	ShapeFactor4
0	0.034053	0.122612	0.671024	0.922824	0.934823	0.980620
1	0.035500	0.051577	0.735504	0.871514	0.793138	0.974979
2	0.038259	0.131521	0.716671	0.932141	0.914511	0.987196
3	0.040940	0.091623	0.731365	0.761614	0.826871	0.893675
4	0.041504	0.025565	0.700538	0.949832	0.988408	0.989116

In [12]:

```
## Replacing the transformed columns into the main data
bb[['Area', 'AspectRatio', 'Extent', 'Solidity','roundness','ShapeFactor4']] = scaled_b
b[['Area', 'AspectRatio', 'Extent',
                                                                                  'Solidi
ty','roundness','ShapeFactor4']]
bb.head()
```

Out[12]:

	Area	AspectRatio	Extent	Solidity	roundness	ShapeFactor4	Class
0	0.034053	0.122612	0.671024	0.922824	0.934823	0.980620	SEKER
1	0.035500	0.051577	0.735504	0.871514	0.793138	0.974979	SEKER
2	0.038259	0.131521	0.716671	0.932141	0.914511	0.987196	SEKER
3	0.040940	0.091623	0.731365	0.761614	0.826871	0.893675	SEKER
4	0.041504	0.025565	0.700538	0.949832	0.988408	0.989116	SEKER

In [13]:

```
# label_encoder object knows how to understand word labels.
label_encoder = LabelEncoder()

# Encode labels in column 'Embarked'.
bb['Class']= label_encoder.fit_transform(bb['Class'])

bb['Class'].unique()
```

Out[13]:

```
array([5, 0, 1, 2, 4, 6, 3])
```

In [14]:

```
bb.isnull().sum()
```

Out[14]:

```
Area            1
AspectRatio     1
Extent          1
Solidity        1
roundness       1
ShapeFactor4    1
Class           0
dtype: int64
```

In [15]:

```
bb =bb.dropna()
```

E. Partition the beans data set so that a random sample of 80% of the data will be used for training and 20% will be used for testing your machine learning model.

In [16]:

```
X = bb[['Area', 'AspectRatio', 'Extent', 'Solidity','roundness','ShapeFactor4']].to_num
py()
```

In [17]:

```
y = bb['Class'].to_numpy()
```

In [18]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2)
X_train
```

Out[18]:

```
array([[0.17563067, 0.88438895, 0.58689371, 0.94849764, 0.58003046,
        0.96728057],
       [0.09041572, 0.24418844, 0.50950527, 0.94147436, 0.88770772,
        0.93515237],
       [0.11555278, 0.45633625, 0.47378294, 0.91030518, 0.77003583,
        0.85879414],
       ...,
       [0.01752378, 0.29159808, 0.76915076, 0.90243883, 0.8195333 ,
        0.9434162 ],
       [0.10664999, 0.40520241, 0.55050803, 0.89393413, 0.74447526,
        0.92885895],
       [0.06117952, 0.05628083, 0.69207079, 0.95783437, 0.96841035,
        0.98991808]])
```

F. Generate a Random Forest machine learning model for classifying the 7 types of beans based on the chosen features from the data set. Use 50 trees to build the model.

In [19]:

```
#Create a Random Forest Classifier
classif =RandomForestClassifier(n_estimators=50)

# #Train the model using the training sets
classif.fit(X_train,y_train)
```

Out[19]:

```
RandomForestClassifier(n_estimators=50)
```

G. Use the test data set (i.e. the 20% of the data that was kept aside earlier) to generate a final validation for your model. Generate a multi-class confusion matrix for the test data to demonstrate the accuracy of the model. Comment on the accuracy of the model.

In [20]:

```
# #y_pred=clf.predict(X_test)
y_pred=classif.predict(X_test)


## Generating a confusion matrix
conf_mat = confusion_matrix(y_test, y_pred)
conf_mat
# sns.he
```

Out[20]:

```
array([[223,   0,   9,   0,   0,   1,   4],
       [  0, 103,   2,   0,   0,   0,   0],
       [  7,   0, 335,   0,   7,   1,   3],
       [  0,   0,   0, 671,   1,  12,  35],
       [  0,   0,   7,   5, 334,   0,   6],
       [  1,   0,   0,   4,   0, 376,  11],
       [  2,   0,   1,  56,  11,   4, 475]])
```

From the confusion matrix, it can be said that the model rightly predicted 261 of the trees to belong to Bombay and made wrong predictions of the other trees. This can be said for the other trees in their respective rows.

In [21]:

```
acc = accuracy_score(y_test, y_pred)
print(f'The accuracy score of the model is {round(acc, 4)*100}%')
```

```
The accuracy score of the model is 92.97999999999999%
```

H. Based on your model, classify the beans provided in the unlabeled /public/bmort/python/beans-unknown.csv data set. Indicate which classification of the 7 available types has been assigned to each of the 5 unlabeled beans.

In [22]:

```
## Loading the new data
new_bb = pd.read_csv('/public/bmort/python/beans-unknown.csv')
new_bb
```

Out[22]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRatio	Eccentricity	C
0	37500	728.191	275.840463	173.818266	1.586948	0.776481	37
1	37500	715.578	272.171813	175.668301	1.549351	0.763818	37
2	37511	718.350	267.039757	179.141937	1.490660	0.741599	37
3	37513	720.028	269.589608	177.510928	1.518721	0.752626	37
4	37514	725.847	269.881174	177.418223	1.521158	0.753547	37

In [23]:

```
## Using the MinMaxScaler model to tranform the the selected columns
# create a scaler object
features_names1 = new_bb[['Area', 'AspectRatio', 'Extent', 'Solidity','roundness','Shap
eFactor4']]
scaler = MinMaxScaler()

# fit and transform the data
scaled_bb1 = pd.DataFrame(scaler.fit_transform(features_names1),
                          columns=features_names1.columns)

scaled_bb1.head()
```

Out[23]:

	Area	AspectRatio	Extent	Solidity	roundness	ShapeFactor4
0	0.000000	1.000000	0.000000	0.138994	0.000000	0.000000
1	0.000000	0.609536	0.921252	1.000000	1.000000	1.000000
2	0.785714	0.000000	0.155260	0.648375	0.784179	0.910090
3	0.928571	0.291430	0.858025	0.000000	0.651155	0.801589
4	1.000000	0.316739	1.000000	0.361813	0.192469	0.611644

In [24]:

```
new_bb[['Area', 'AspectRatio', 'Extent', 'Solidity','roundness','ShapeFactor4']] = scal
ed_bb1[['Area', 'AspectRatio', 'Extent',
                                                                                 'Solidi
ty','roundness','ShapeFactor4']]
new_bb
```

Out[24]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRatio	Eccentricity
0	0.000000	728.191	275.840463	173.818266	1.000000	0.776481
1	0.000000	715.578	272.171813	175.668301	0.609536	0.763818
2	0.785714	718.350	267.039757	179.141937	0.000000	0.741599
3	0.928571	720.028	269.589608	177.510928	0.291430	0.752626
4	1.000000	725.847	269.881174	177.418223	0.316739	0.753547

In [25]:

```
X_new = new_bb[['Area', 'AspectRatio', 'Extent', 'Solidity','roundness','ShapeFactor
4']]
X_new
```

Out[25]:

	Area	AspectRatio	Extent	Solidity	roundness	ShapeFactor4
0	0.000000	1.000000	0.000000	0.138994	0.000000	0.000000
1	0.000000	0.609536	0.921252	1.000000	1.000000	1.000000
2	0.785714	0.000000	0.155260	0.648375	0.784179	0.910090
3	0.928571	0.291430	0.858025	0.000000	0.651155	0.801589
4	1.000000	0.316739	1.000000	0.361813	0.192469	0.611644

In [26]:

```
##Classifying the new the data
new_cl =classif.predict(X_new)
new_cl
```

Out[26]:

```
array([4, 3, 0, 1, 1])
```

In [27]:

```
print(f'The model classifies the new data into 4 = HOROZ, 3 = DEMARSON, 1 = BOMBAY, 1 =
BOMBAY, 1 = BOMBAY')
```

```
The model classifies the new data into 4 = HOROZ, 3 = DEMARSON, 1 = BOMBA
Y, 1 = BOMBAY, 1 = BOMBAY
```