Clustrering analysis and validation of KMeans and DBSCAN clustering algorithm

(1) Analysis of Kmeans Clustering Algorithm

Importing the libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.cluster import KMeans
%matplotlib inline
```

Importing Dataset

```
dataset = pd.read_csv('soildataset.csv')
X = dataset.iloc[:, 1:4].values
```

```
dataset.head()
```

```
   Id  Nitrogen  Phosphorous  Potassium Content of Nitrogen  \
0   1      3.67         2.45      2.990                 Low
1   2      3.99         2.51      2.890              Medium
2   3      4.31         2.57      2.019                High
3   4      3.53         2.63      3.040                 Low
4   5      3.56         2.69      2.880                 Low

  Content of Phosphorous Content of Potassium
0                    Low                High
1                    Low                High
2                    Low                 Low
3                    Low                High
4                    Low                High
```

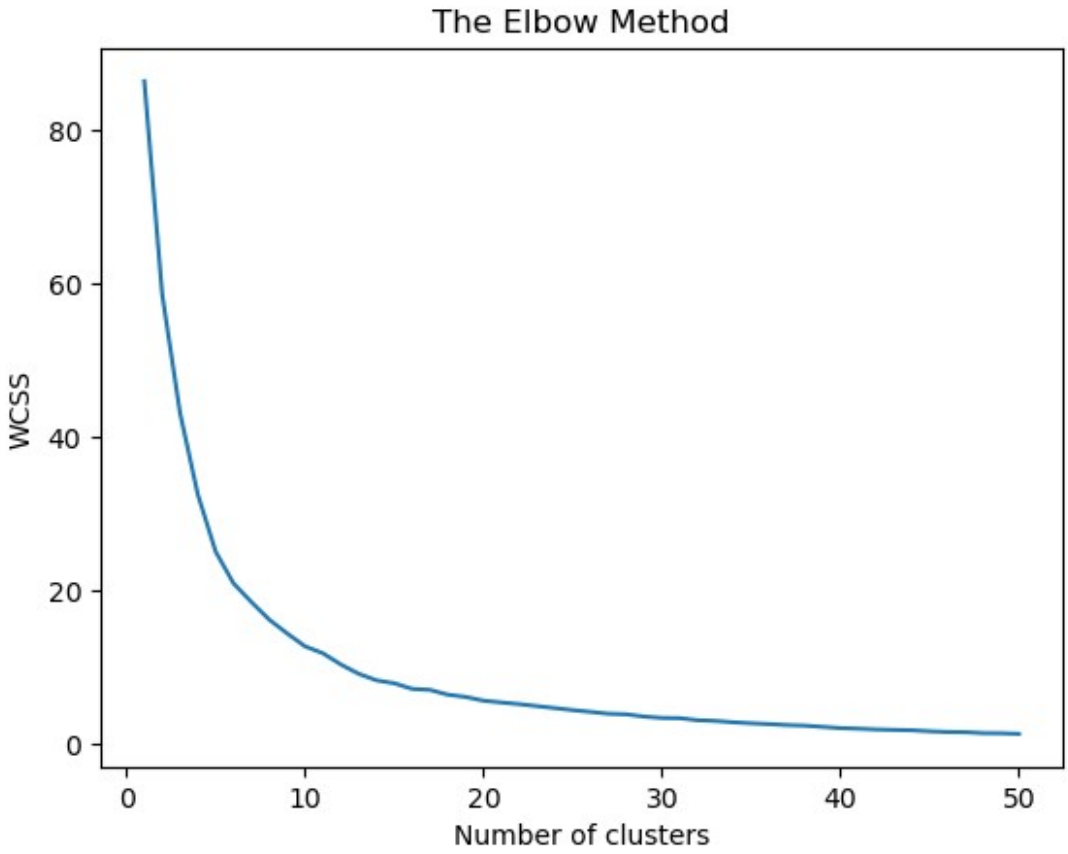
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Id                      150 non-null    int64
 1   Nitrogen                150 non-null    float64
 2   Phosphorous             150 non-null    float64
 3   Potassium               150 non-null    float64
 4   Content of Nitrogen     150 non-null    object
 5   Content of Phosphorous  150 non-null    object
 6   Content of Potassium    150 non-null    object
dtypes: float64(3), int64(1), object(3)
memory usage: 8.3+ KB
```

Using the elbow method to find the optimal number of clusters

```
wcss = []
for i in range(1, 51):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state =
42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 51), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

```
C:\Users\Shubham\anaconda3\lib\site-packages\sklearn\cluster\
_kmeans.py:1036: UserWarning: KMeans is known to have a memory leak on
Windows with MKL, when there are less chunks than available threads.
You can avoid it by setting the environment variable
OMP_NUM_THREADS=1.
  warnings.warn(
```



From the above elbow we can clearly depict that the optimal no of clusters are between 5 to 10 So finding the silhoutte coefficient for the range 5 to 10 will give us the correct value of Optimum Clusters.

Finding Silhouette score to get the accurate no of clusters

```
sil_score = []
n_clusters = []
for i in range(5, 15):
    test_kmeans = KMeans(n_clusters=i, init='k-means++',
random_state=42)
    test_kmeans.fit(X)
    test_labels = test_kmeans.predict(X)
    n_clusters.append(i)
    sil_score.append(metrics.silhouette_score(X,test_labels))
    #print("Silhoutte_score for n_cluster = " + str(i) + " is : " +
str(metrics.silhouette_score(X,test_labels)))
data = {"No of clusters": n_clusters, "Silhouette_Score": sil_score}
accuracy = pd.DataFrame(data)
accuracy
```

	No of clusters	Silhouette_Score
0	5	0.384627
1	6	0.401305
2	7	0.417535
3	8	0.436840
4	9	0.408780
5	10	0.429608
6	11	0.441726
7	12	0.388546
8	13	0.445551
9	14	0.404723

According to elbow method optimum value of K is 8 and according to silhouette score optimum value of K is 13 but as silhouette score of both K=8 and K=13 is haning difference of 0.01 so we can consider K=8 as K=13 will generate much more clusters

Training the Kmeans model on Dataset

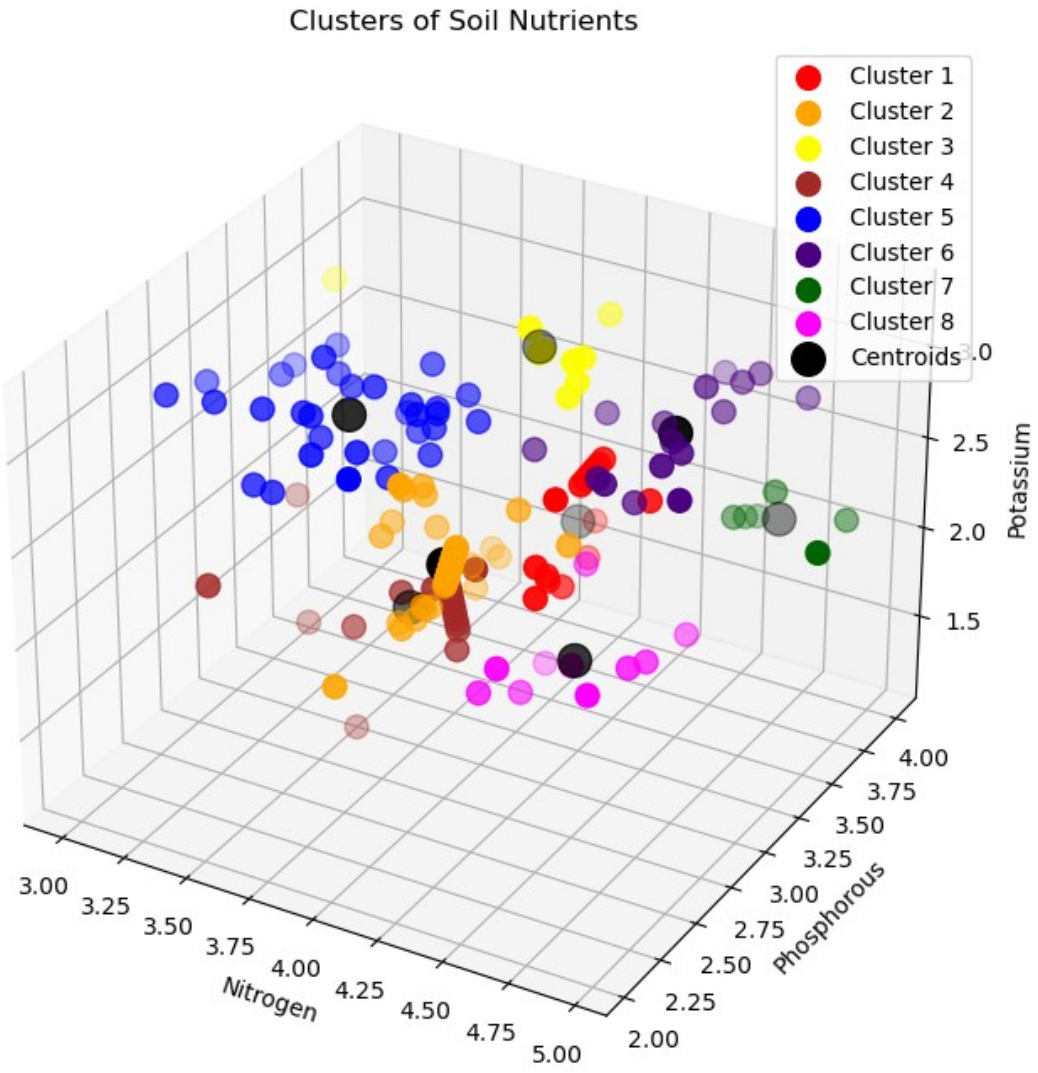
```
kmeans = KMeans(n_clusters=8, init='k-means++', random_state=42)
kmeans.fit(X)
labels = kmeans.predict(X)
```

Visualizing the clusters using 3D scatter plot

```
fig = plt.figure(figsize=(10,8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(X[labels==0, 0], X[labels==0, 1], X[labels==0, 2], s=100,
c='red', label='Cluster 1')
ax.scatter(X[labels==1, 0], X[labels==1, 1], X[labels==1, 2], s=100,
c='orange', label='Cluster 2')
ax.scatter(X[labels==2, 0], X[labels==2, 1], X[labels==2, 2], s=100,
c='yellow', label='Cluster 3')
```

```
ax.scatter(X[labels==3, 0], X[labels==3, 1], X[labels==3, 2], s=100,
c='brown', label='Cluster 4')
ax.scatter(X[labels==4, 0], X[labels==4, 1], X[labels==4, 2], s=100,
c='blue', label='Cluster 5')
ax.scatter(X[labels==5, 0], X[labels==5, 1], X[labels==5, 2], s=100,
c='indigo', label='Cluster 6')
ax.scatter(X[labels==6, 0], X[labels==6, 1], X[labels==6, 2], s=100,
c='darkgreen', label='Cluster 7')
ax.scatter(X[labels==7, 0], X[labels==7, 1], X[labels==7, 2], s=100,
c='#ff00ff', label='Cluster 8')

ax.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,
1], kmeans.cluster_centers_[:, 2], s=200, c='black',
label='Centroids')
ax.set_title('Clusters of Soil Nutrients')
ax.set_xlabel('Nitrogen')
ax.set_ylabel('Phosphorous')
ax.set_zlabel('Potassium')
plt.legend()
plt.show()
```



(2) Analysis of DBSCAN algorithm

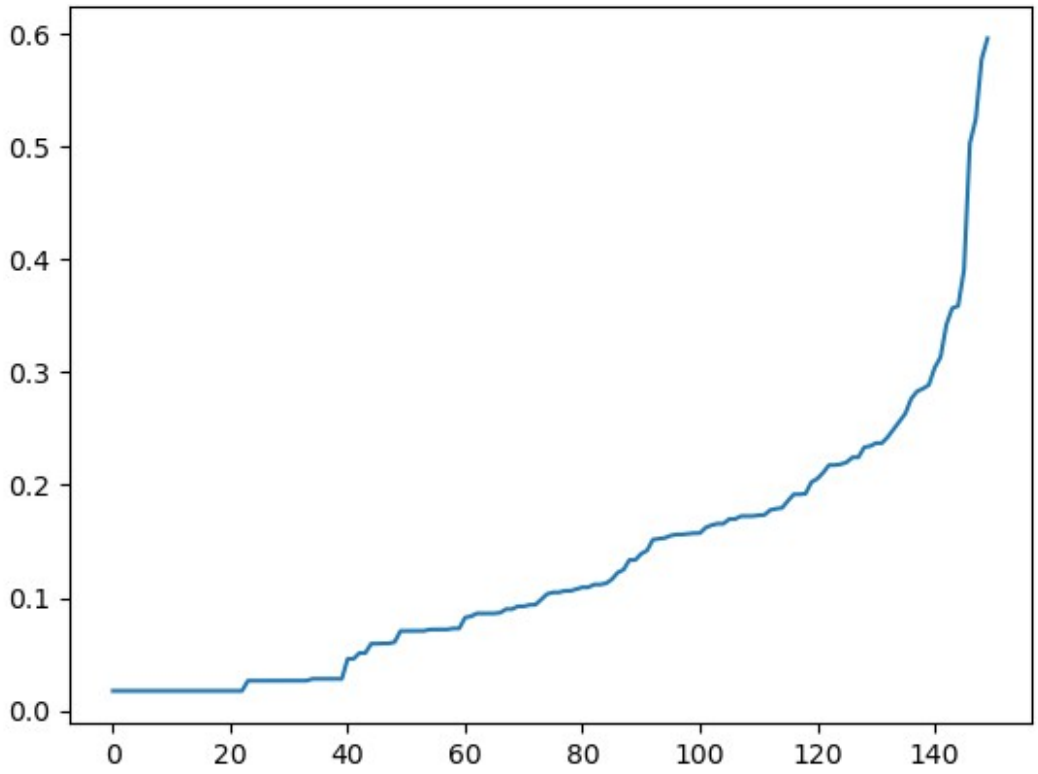
Importing the libraries

```
from sklearn.neighbors import NearestNeighbors
from matplotlib import pyplot as plt
from sklearn.cluster import DBSCAN
```

Using K-Distance Graph to find the optimal value of epsilon and minpoints

```
neighbors = NearestNeighbors(n_neighbors=3)
neighbors_fit = neighbors.fit(X)
distances, indices = neighbors_fit.kneighbors(X)
distances = np.sort(distances, axis=0)
distances = distances[:,1]
plt.plot(distances)
```

```
[<matplotlib.lines.Line2D at 0x26e3c989370>]
```



According to above graph we are getting elbow nearly at 0.25 so we can consider eps=0.25

Finding Silhouette score to get the accurate no of clusters

```
sil_score = []
n_cluster = []
epsilon = []
minpts = []
for i in range(3,7):
    for j in np.arange(0.15,0.35,0.05):
        dbscan = DBSCAN(eps=j,min_samples=i)
        epsilon.append(j)
        minpts.append(i)
        model = dbscan.fit(X)
        labels = model.labels_
        sample_cores = np.zeros_like(labels,dtype=bool)
        sample_cores[dbscan.core_sample_indices_] = True
        n_clusters = len(set(labels))- (1 if -1 in labels else 0)
        sil_score.append(metrics.silhouette_score(X,labels))
        n_cluster.append(n_clusters)
data = {"Epsilon":epsilon,"Minpts":minpts,"No of clusters": n_cluster,
"Silhouette_Score": sil_score}
accuracy = pd.DataFrame(data)
accuracy
```

```
    Epsilon  Minpts  No of clusters  Silhouette_Score
0      0.15       3              11          0.052748
```

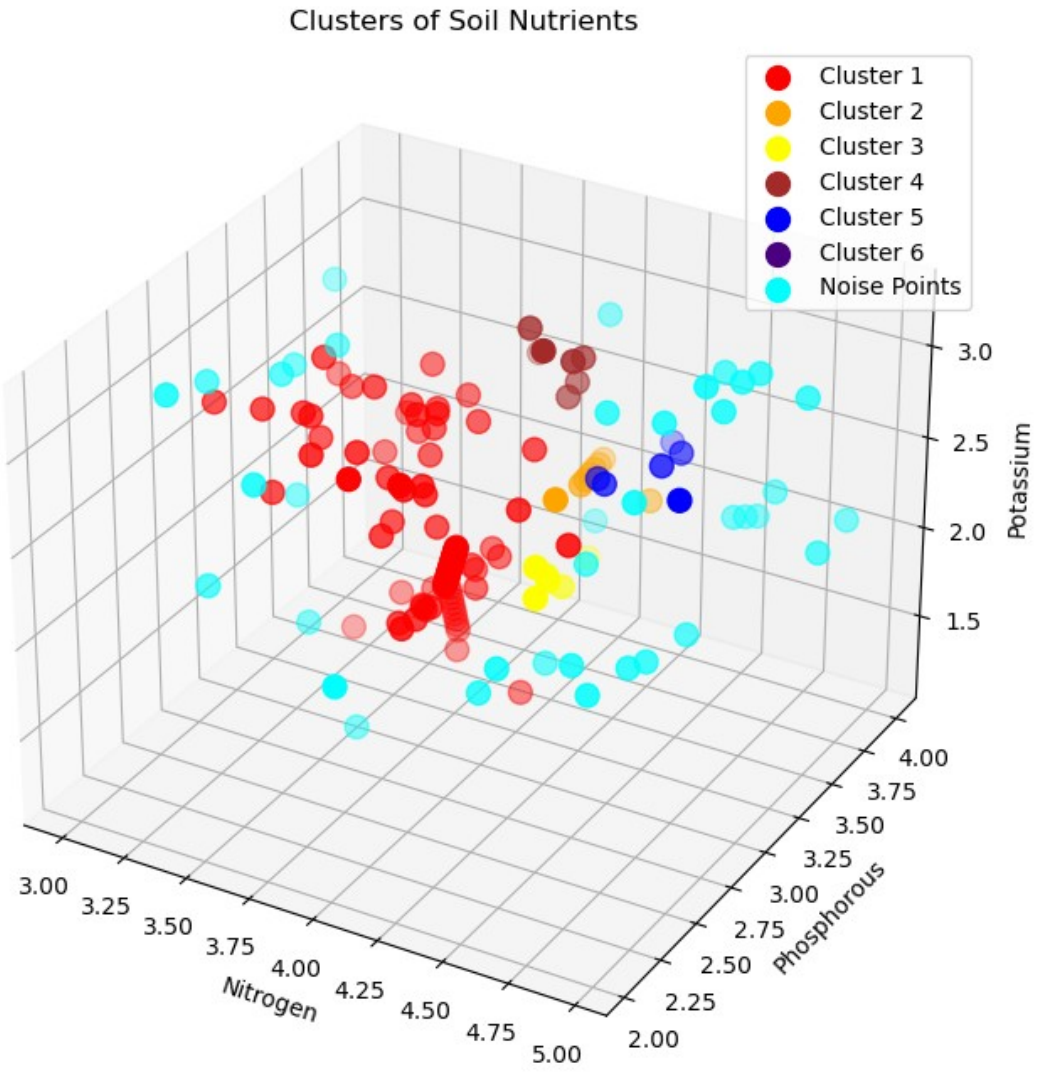
1	0.20	3	13	0.192641
2	0.25	3	8	0.163395
3	0.30	3	6	0.259036
4	0.15	4	7	0.015147
5	0.20	4	10	0.151316
6	0.25	4	6	0.221395
7	0.30	4	7	0.214950
8	0.15	5	6	-0.001323
9	0.20	5	7	0.093662
10	0.25	5	6	0.159940
11	0.30	5	6	0.258532
12	0.15	6	3	0.005443
13	0.20	6	5	0.044160
14	0.25	6	6	0.067092
15	0.30	6	5	0.147643

Using the K-distance graph and Silhouette score optimum value of eps = 0.30, K = 6 with minpts = 3 for the best silhouette score = 0.259

Visualizing the clusters using 3D scatter plot

```
fig = plt.figure(figsize=(10,8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(X[labels==0, 0], X[labels==0, 1], X[labels==0, 2], s=100,
c='red', label='Cluster 1')
ax.scatter(X[labels==1, 0], X[labels==1, 1], X[labels==1, 2], s=100,
c='orange', label='Cluster 2')
ax.scatter(X[labels==2, 0], X[labels==2, 1], X[labels==2, 2], s=100,
c='yellow', label='Cluster 3')
ax.scatter(X[labels==3, 0], X[labels==3, 1], X[labels==3, 2], s=100,
c='brown', label='Cluster 4')
ax.scatter(X[labels==4, 0], X[labels==4, 1], X[labels==4, 2], s=100,
c='blue', label='Cluster 5')
ax.scatter(X[labels==5, 0], X[labels==5, 1], X[labels==5, 2], s=100,
c='indigo', label='Cluster 6')
ax.scatter(X[labels==-1, 0], X[labels==-1, 1], X[labels==-1, 2],
s=100, c='cyan', label='Noise Points')

#ax.scatter(DBSCAN.cluster_centers_[:, 0], DBSCAN.cluster_centers_[:,
1], DBSCAN.cluster_centers_[:, 2], s=200, c='cyan', label='Centroids')
ax.set_title('Clusters of Soil Nutrients')
ax.set_xlabel('Nitrogen')
ax.set_ylabel('Phosphorous')
ax.set_zlabel('Potassium')
plt.legend()
plt.show()
```


Clusters of Soil Nutrients
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Cluster 6
Noise Points
Nitrogen
Phosphorous
Potassium
3.00
3.25
3.50
3.75
4.00
4.25
4.50
4.75
5.00
2.00
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00
1.5
2.0
2.5
3.0