CSCI 6516 - Machine Learning for Big Data

(Fall 2023)

Assignment 3

Submitted by:

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In [116]:

```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, classification_r
from sklearn.metrics import silhouette_score
from sklearn.decomposition import PCA
import skfuzzy as fuzz
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import Adam
```

[1] Prepare the dataset by applying data transformation. Which method of transformation did you choose? Explain your rationality behind it.

In [2]:

```
training_data = pd.read_csv('data/sign_mnist_train.csv')
testing_data = pd.read_csv('data/sign_mnist_test.csv')
training_data.head()
```

Out[2]:

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel776	pixel777	pixel778	pixel779
0	3	107	118	127	134	139	143	146	150	153	...	207	207	207	207	206
1	6	155	157	156	156	156	157	156	158	158	...	69	149	128	87	94
2	2	187	188	188	187	187	186	187	188	187	...	202	201	200	199	198
3	2	211	211	212	212	211	210	211	210	210	...	235	234	233	231	230
4	13	164	167	170	172	176	179	180	184	185	...	92	105	105	108	133

5 rows × 785 columns

In [3]:

```
print('\x1b[1;31m'+'Check for NaN values in data :'+'\x1b[0m')
training_data.isna().sum()
```

```
Check for NaN values in data :
```

Out[3]:

```
label       0
pixel1      0
pixel2      0
pixel3      0
pixel4      0
           ..
pixel780    0
pixel781    0
pixel782    0
pixel783    0
pixel784    0
Length: 785, dtype: int64
```

In [4]:

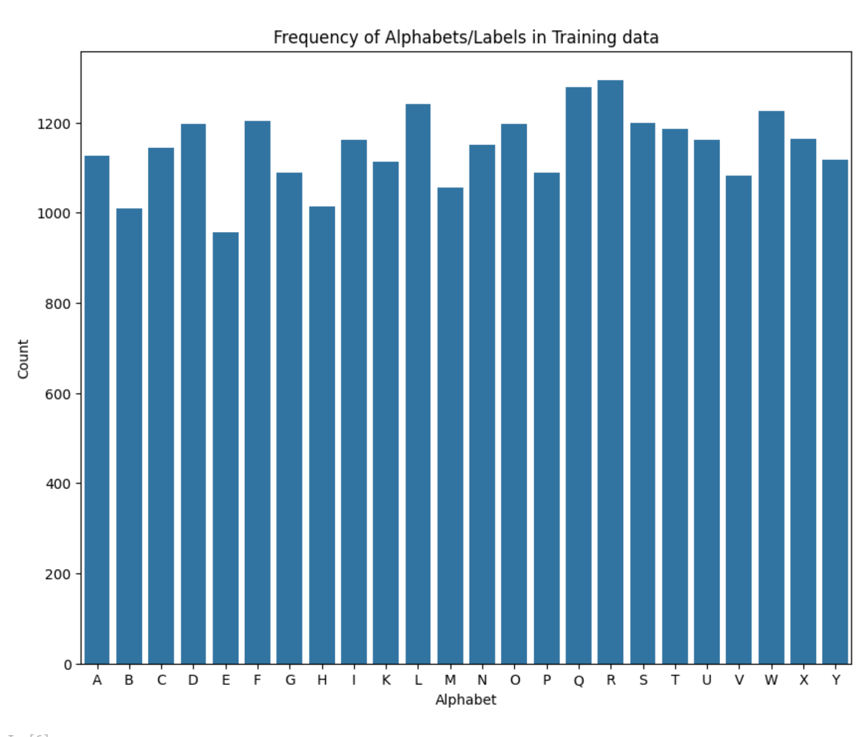
```
print('\x1b[1;31m'+'Total Records :'+'\x1b[0m', len(training_data))
print('\x1b[1;31m'+'Duplicate Records :'+'\x1b[0m', len(training_data[training_data.duplicated()]))
```

```
Total Records : 27455
Duplicate Records : 0
```

In [5]:

```
label_counts = training_data['label'].value_counts().reset_index().sort_values(by='label')
label_counts.reset_index(drop=True, inplace=True)
label_counts['Alphabet'] = label_counts['label'].apply(lambda x: chr(x + ord('A')))
label_counts.columns = ['Labels', 'Count', 'Alphabet']
print(label_counts)

print('\n\n\x1b[1;31m'+'Visual Analysis of data training data :'+'\x1b[0m\n\n')

plt.figure(figsize=(10,8))
sns.barplot(data=label_counts, x="Alphabet", y="Count")
plt.title('Frequency of Alphabets/Labels in Training data')
plt.show()
```

```
    Labels  Count Alphabet
0        0   1126        A
1        1   1010        B
2        2   1144        C
3        3   1196        D
4        4    957        E
5        5   1204        F
6        6   1090        G
7        7   1013        H
8        8   1162        I
9       10   1114        K
10      11   1241        L
11      12   1055        M
12      13   1151        N
13      14   1196        O
14      15   1088        P
15      16   1279        Q
16      17   1294        R
17      18   1199        S
18      19   1186        T
19      20   1161        U
20      21   1082        V
21      22   1225        W
22      23   1164        X
23      24   1118        Y


Visual Analysis of data training data :
```



In [6]:

```
images = training_data.drop('label', axis=1).values / 255.0

# Set up the figure for displaying images
plt.figure(figsize=(12, 12))

# Iterate through labels to display corresponding images
for i, label in enumerate(label_counts['Alphabet']):
    if i >= 9:
        i = i+1
    # Find the index of the first occurrence of the current label
    idx = training_data[training_data['label'] == i].index[0]

    # Extract the image corresponding to the label
    img = images[idx].reshape(28, 28)

    # Create subplots to display images
    plt.subplot(4, 7, i + 1)
    plt.title(label)
    plt.imshow(img, cmap='gray')
    plt.axis('off')

plt.tight_layout()  # Adjust layout for better spacing
plt.show()
```

In [165]:

```
X_train = training_data.drop('label', axis=1).values
y_train = training_data['label'].values

X_test = testing_data.drop('label', axis=1).values
y_test = testing_data['label'].values

# Split the data into training and validation sets (80% training, 20% testing)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2)

pca = PCA(n_components = 2)
X_train, X_test, X_val = pca.fit_transform(X_train), pca.fit_transform(X_test), pca.fit_transform(X_val)
```

I have used PCA to reduce the number of features (or dimensions) while retaining most of the important information. In this case, by setting n_components to 2, PCA is reducing the high-dimensional data to a two-dimensional space. This reduction is beneficial for visualization purposes, especially when dealing with datasets with many features.

[2] Apply the k-means algorithm to Sign Language MNIST dataset.

a. Change the number of clusters from 10 to 200 with the step size of 10. Show the performance of the algorithm based on accuracy and the objective function value for each cluster number

In [26]:

```
# Initialize lists to store accuracy, inertia and silhouette Avg
accuracy_list_kmeans = []
inertia_list_kmeans = []
silhouette_avg_kmeans = []

# Range of clusters from 10 to 200 with step size 10
for i in range(10, 201, 10):
    kmeans = KMeans(n_clusters=i, random_state=42, n_init='auto')
    kmeans.fit(X_train)

    y_pred = kmeans.predict(X_val)

    # Calculate accuracy and inertia
    accuracy = accuracy_score(y_val, y_pred)
    inertia = kmeans.inertia_

    # Append accuracy and inertia to the lists
    accuracy_list_kmeans.append(accuracy)
    inertia_list_kmeans.append(inertia)
    silhouette_avg_kmeans.append(silhouette_score(X_val, y_pred))
```

In [27]:

```
j = 0
for i in range(10, 201, 10):
    print('\n\x1b[1;31m'+'Clusters :'+'\x1b[0m', i)
    print('\x1b[1;31m'+'Accuracy :'+'\x1b[0m', accuracy_list_kmeans[j]*100, '%')
    print('\x1b[1;31m'+'Objective Function :'+'\x1b[0m', inertia_list_kmeans[j])
    print('\x1b[1;31m'+'Silhouette Average :'+'\x1b[0m', silhouette_avg_kmeans[j])
    j+=1
```

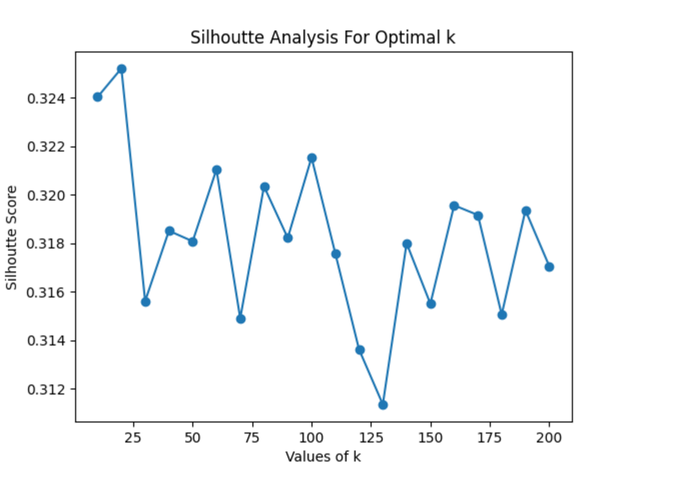
```
Clusters : 10
Accuracy : 6.064469131305773 %
Objective Function : 30287.278941159886
Silhoutte Average : 0.32403036364251947

Clusters : 20
Accuracy : 5.026406847568749 %
Objective Function : 15852.660861665832
Silhoutte Average : 0.3252065306064282

Clusters : 30
Accuracy : 3.64232380258605 %
Objective Function : 10766.456262085001
Silhoutte Average : 0.31561292562607624

Clusters : 40
Accuracy : 2.622473137861956 %
Objective Function : 8217.989680130326
Silhoutte Average : 0.31851338291115644

Clusters : 50
Accuracy : 2.1671826625387 %
Objective Function : 6528.9708099390555
Silhoutte Average : 0.31807936517529123

Clusters : 60
Accuracy : 1.2930249499180477 %
Objective Function : 5514.246403473899
Silhoutte Average : 0.32104072578113174

Clusters : 70
Accuracy : 1.238390092879257 %
Objective Function : 4776.539343340957
Silhoutte Average : 0.31490434049626365

Clusters : 80
Accuracy : 1.2019668548533966 %
Objective Function : 4134.935486018572
Silhoutte Average : 0.3203439862576019

Clusters : 90
Accuracy : 1.0926971407758148 %
Objective Function : 3724.395014585004
Silhoutte Average : 0.3182170535113167

Clusters : 100
Accuracy : 1.0380622837370241 %
Objective Function : 3295.2780113445415
Silhoutte Average : 0.32153563882277497

Clusters : 110
Accuracy : 0.9652158076853032 %
Objective Function : 2986.264214924753
Silhoutte Average : 0.3175819859016003

Clusters : 120
Accuracy : 0.9287925696594427 %
Objective Function : 2750.2427264159087
Silhoutte Average : 0.3136202959214134

Clusters : 130
Accuracy : 1.0016390457111637 %
Objective Function : 2564.0212323312358
Silhoutte Average : 0.31135576793382463

Clusters : 140
Accuracy : 0.874157712620652 %
Objective Function : 2356.2113417410624
Silhoutte Average : 0.3179985732706858

Clusters : 150
Accuracy : 0.47350209433618645 %
Objective Function : 2187.189003559469
Silhoutte Average : 0.3155046440913891

Clusters : 160
Accuracy : 0.5463485703879074 %
Objective Function : 2048.4871403782754
Silhoutte Average : 0.31956330240023356

Clusters : 170
Accuracy : 0.509925332362047 %
Objective Function : 1926.7904113543414
Silhoutte Average : 0.3191625593266038

Clusters : 180
Accuracy : 0.49171371334911673 %
Objective Function : 1816.9048499887808
Silhoutte Average : 0.31505814543116906

Clusters : 190
Accuracy : 0.3824439992715352 %
Objective Function : 1709.8198288586757
Silhoutte Average : 0.3193565583317822

Clusters : 200
Accuracy : 0.291385904206884 %
Objective Function : 1627.5496091272528
Silhoutte Average : 0.31706015481453703
```

b. What is the optimal number of clusters? Justify your answer.

In [28]:

```
print('\n\n\x1b[1;31m'+'Silhoutte Analysis For Optimal k :'+'\x1b[0m\n\n')
plt.plot(range(10, 201, 10), silhouette_avg_kmeans, marker='o')
plt.xlabel('Values of k')
plt.ylabel('Silhoutte Score')
plt.title('Silhoutte Analysis For Optimal k')
plt.show()
```

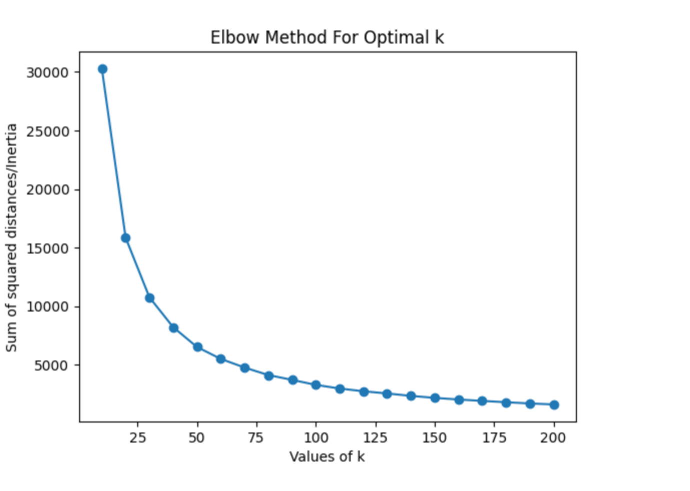
```
Silhoutte Analysis For Optimal k :
```



In [29]:

```
print('\n\n\x1b[1;31m'+'Elbow Method For Optimal k :'+'\x1b[0m\n\n')
plt.plot(range(10, 201, 10), inertia_list_kmeans, marker='o')
plt.xlabel('Values of k')
plt.ylabel('Sum of squared distances/Inertia')
plt.title('Elbow Method For Optimal k')
plt.show()
```

```
Elbow Method For Optimal k :
```



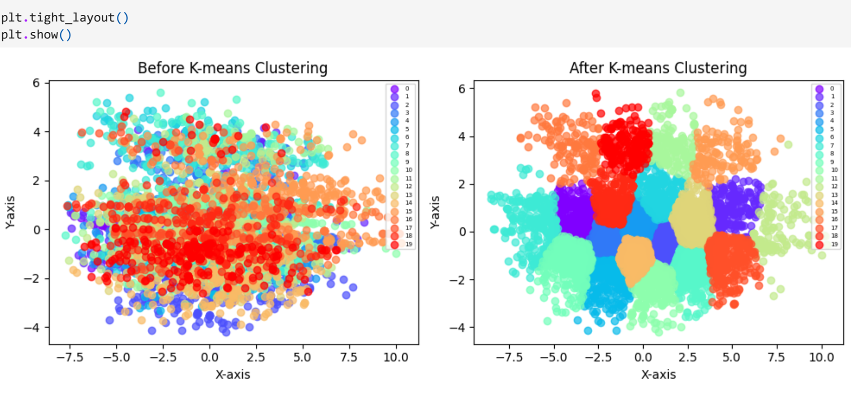
In [92]:

```
num_clusters = 20
kmeans = KMeans(n_clusters=20, random_state=42, n_init='auto')
kmeans.fit(X_train)

y_pred_kmeans = kmeans.predict(X_test)

# Calculate accuracy and inertia
accuracy = accuracy_score(y_test, y_pred_kmeans)
inertia = kmeans.inertia_

# Append accuracy and inertia to the lists
print('\n\x1b[1;31m'+'Clusters :'+'\x1b[0m', num_clusters)
print('\x1b[1;31m'+'Accuracy :'+'\x1b[0m', accuracy*100, '%')
print('\x1b[1;31m'+'Inertia :'+'\x1b[0m', inertia)
print('\x1b[1;31m'+'Silhoutte Average :'+'\x1b[0m', silhouette_score(X_test, y_pred_kmeans))
```

```
Clusters : 20
Accuracy : 3.8761851645287226 %
Inertia : 15860.71562139212
Silhoutte Average : 0.31943650284499914
```

In [93]:

```
plt.figure(figsize=(10,4))

# Plot before clustering
plt.subplot(1, 2, 1)
colors = plt.cm.rainbow(np.linspace(0, 1, 20))
for i,c in enumerate(colors):
  plt.scatter(X_test[y_test==i, 0], X_test[y_test==i, 1], marker='o',color = c, label=i, alpha =0.7)
plt.legend(fontsize=5, title_fontsize=5)
plt.title('Before K-means Clustering')
plt.xlabel('X-axis')
plt.ylabel('Y-axis')

# Plot after clustering
plt.subplot(1, 2, 2)
colors = plt.cm.rainbow(np.linspace(0, 1, 20))
for i,c in enumerate(colors):
  plt.scatter(X_test[y_pred_kmeans==i, 0], X_test[y_pred_kmeans==i, 1], marker='o',color = c, label=i, alpha =0.7)
plt.legend(fontsize=5, title_fontsize=5)
plt.title('After K-means Clustering')
plt.xlabel('X-axis')
plt.ylabel('Y-axis')

plt.tight_layout()
plt.show()
```



The most suitable cluster count appears to be 20, as observed from the point where the Silhouette score reaches its peak, followed by a slight decline before gradually rising again. Moreover, the elbow method suggests an optimal k value around 20, marking a notable inflection point in the plot. This optimal number is reinforced by utilizing both the Silhouette Method and the Elbow Method in conjunction, strengthening the confidence in determining the ideal number of clusters

[3] Apply the fuzzy k-means algorithm to Sign Language MNIST dataset.

a. Change the number of clusters from 10 to 200 with the step size of 10. Show the performance of the algorithm based on accuracy and the objective function value for each cluster number.

In [87]:

```
# Lists to store accuracy, objective function and silhouette avg values for each cluster count
accuracy_list_fcm = []
objective_function_list_fcm = []
silhouette_avg_fcm = []

for num_clusters in np.arange(10, 201, 10):
    # Fuzzy K-means clustering
    cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
        X_train.T, num_clusters, m=2, error=0.005, maxiter=200, init=None
    )

    # Predicting cluster labels for the test set
    u_test, u0_test, d_test, jm_test, p_test, fpc_test = fuzz.cluster.cmeans_predict(X_val.T, cntr, 2, error=0.005, max
    y_pred = np.argmax(u_test, axis=0)

    # Calculating accuracy
    accuracy = accuracy_score(y_val, y_pred)
    accuracy_list_fcm.append(accuracy)

    objective_function_list_fcm.append(jm[-1])
    silhouette_avg_fcm.append(silhouette_score(X_val, y_pred))
```

In [88]:

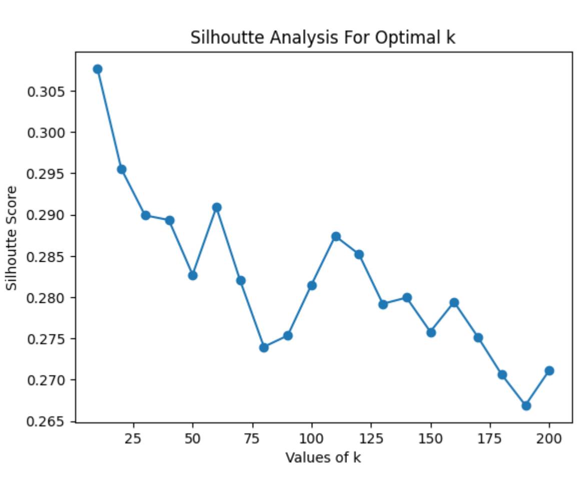
```
j = 0
for i in range(10, 201, 10):
    print('\n\x1b[1;31m'+'Clusters :'+'\x1b[0m', i)
    print('\x1b[1;31m'+'Accuracy :'+'\x1b[0m', accuracy_list_fcm[j]*100, '%')
    print('\x1b[1;31m'+'Objective Function :'+'\x1b[0m', objective_function_list_fcm[j])
    print('\x1b[1;31m'+'Silhoutte Average :'+'\x1b[0m', silhouette_avg_fcm[j])
    j+=1
```

```
Clusters : 10
Accuracy : 3.077763613185212 %
Objective Function : 13041.229441263124
Silhoutte Average : 0.30768772480701195

Clusters : 20
Accuracy : 3.9701329448187948 %
Objective Function : 5712.478111992527
Silhoutte Average : 0.2955477331794089

Clusters : 30
Accuracy : 3.7515935166636316 %
Objective Function : 3564.561226643499
Silhoutte Average : 0.2899062576071015

Clusters : 40
Accuracy : 2.2400291385904207 %
Objective Function : 2552.7054699784608
Silhoutte Average : 0.2893426121290873

Clusters : 50
Accuracy : 1.8940083773447458 %
Objective Function : 1976.1379318421018
Silhoutte Average : 0.28271591115883543

Clusters : 60
Accuracy : 1.7118921872154433 %
Objective Function : 1600.6408735346645
Silhoutte Average : 0.2908806590863176

Clusters : 70
Accuracy : 1.2019668548533966 %
Objective Function : 1353.4561958567706
Silhoutte Average : 0.28201461449108994

Clusters : 80
Accuracy : 2.22181751957749 %
Objective Function : 1153.2358437812863
Silhoutte Average : 0.27397938273006356

Clusters : 90
Accuracy : 1.165543616827536 %
Objective Function : 1015.8964456885896
Silhoutte Average : 0.2753446454598815

Clusters : 100
Accuracy : 0.9470041886723729 %
Objective Function : 898.2160613830052
Silhoutte Average : 0.28149367637521844

Clusters : 110
Accuracy : 0.801311236568931 %
Objective Function : 806.9501223840429
Silhoutte Average : 0.28740492545870455

Clusters : 120
Accuracy : 0.655618284465489 %
Objective Function : 733.2342826732539
Silhoutte Average : 0.2851966661759188

Clusters : 130
Accuracy : 0.72846476051721 %
Objective Function : 673.7986265843433
Silhoutte Average : 0.2791883653579495

Clusters : 140
Accuracy : 0.874157712620652 %
Objective Function : 621.5109719540933
Silhoutte Average : 0.27994307916172684

Clusters : 150
Accuracy : 0.6191950464396285 %
Objective Function : 575.8386137813051
Silhoutte Average : 0.27580790286649987

Clusters : 160
Accuracy : 0.6738299034784192 %
Objective Function : 534.462638480415
Silhoutte Average : 0.27940947425595647

Clusters : 170
Accuracy : 0.801311236568931 %
Objective Function : 504.76881663519043
Silhoutte Average : 0.2751711882656107

Clusters : 180
Accuracy : 0.47350209433618645 %
Objective Function : 479.3581153280265
Silhoutte Average : 0.2706314505106149

Clusters : 190
Accuracy : 0.49171371334911673 %
Objective Function : 453.61285052861854
Silhoutte Average : 0.2669010921574156

Clusters : 200
Accuracy : 0.3824439992715352 %
Objective Function : 430.7244621158965
Silhoutte Average : 0.27112290554146423
```

In [89]:

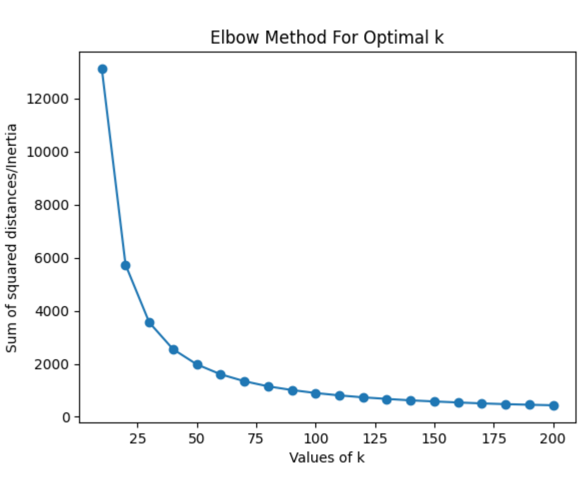
```
print('\n\n\x1b[1;31m'+'Silhoutte Analysis For Optimal k :'+'\x1b[0m\n\n')
plt.plot(range(10, 201, 10), silhouette_avg_fcm, marker='o')
plt.xlabel('Values of k')
plt.ylabel('Silhoutte Score')
plt.title('Silhoutte Analysis For Optimal k')
plt.show()
```

Silhoutte Analysis For Optimal k :



In [63]:
```
print('\n\n\x1b[1;31m'+'Elbow Method For Optimal k :'+'\x1b[0m\n\n')
plt.plot(range(10, 201, 10), objective_function_list_fcm, marker='o')
plt.xlabel('Values of k')
plt.ylabel('Sum of squared distances/Inertia')
plt.title('Elbow Method For Optimal k')
plt.show()
```

Elbow Method For Optimal k :



b. Show the performance of the algorithm based on accuracy and the objective function value by changing the fuzzifier value from 1 to 5 with the step size of 1.

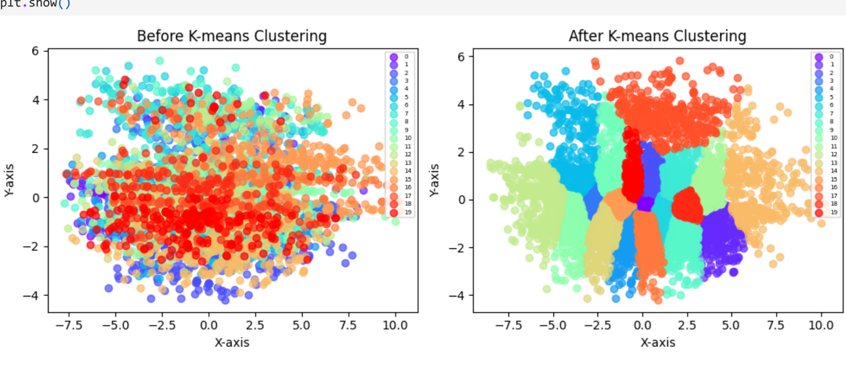
In [64]:
```
# Initialize lists to store performance metrics
accuracy_list = []
objective_function_list = []
silhouette_avg = []

num_clusters=20

# Varying the fuzzifier value from 1.1 to 5
# The value cannot be 1 as it throws DivideByZero error for starting from 1.1 in this case
for m_value in [1.1, 2, 3, 4, 5]:
    # Fuzzy K-means clustering with varying fuzzifier value
    cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
        X_train.T, num_clusters, m=m_value, error=0.005, maxiter=1000, init=None
    )

    # Predicting cluster labels for the validation set
    u_test, u0_test, d_test, jm_test, p_test, fpc_test = fuzz.cluster.cmeans_predict(
        X_val.T, cntr, m=m_value, error=0.005, maxiter=1000
    )

    y_pred = np.argmax(u_test, axis=0)

    # Calculating accuracy
    accuracy = accuracy_score(y_val, y_pred)
    accuracy_list.append(accuracy)

    # Objective function value
    objective_function_list.append(jm[-1])

    # Silhouette score
    silhouette_avg.append(silhouette_score(X_val, y_pred))

j = 0
for i in [1.1, 2, 3, 4, 5]:
    print('\n\x1b[1;31m'+'Fuzzier Value :'+'\x1b[0m', i)
    print('\x1b[1;31m'+'Accuracy :'+'\x1b[0m', accuracy_list[j]*100, '%')
    print('\x1b[1;31m'+'Objective Function :'+'\x1b[0m', objective_function_list[j])
    print('\x1b[1;31m'+'Silhoutte Average :'+'\x1b[0m', silhouette_avg[j])
    j+=1
```

```
Fuzzier Value : 1.1
Accuracy : 2.695319613913677 %
Objective Function : 15881.284565640146
Silhoutte Average : 0.31898606997622175

Fuzzier Value : 2
Accuracy : 4.261518849025679 %
Objective Function : 5729.175169482153
Silhoutte Average : 0.29521344240425795

Fuzzier Value : 3
Accuracy : 4.552904753232562 %
Objective Function : 452.62804182381535
Silhoutte Average : 0.1964151461431643

Fuzzier Value : 4
Accuracy : 2.9502822800947004 %
Objective Function : 25.342097591595962
Silhoutte Average : 0.11772764484877916

Fuzzier Value : 5
Accuracy : 3.7151702786377707 %
Objective Function : 1.3262874835196343
Silhoutte Average : 0.05070670601849837
```

In [90]:
```
num_clusters=20
m_value=3

# Fuzzy K-means clustering with varying fuzzifier value
cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
    X_train.T, num_clusters, m_value, error=0.005, maxiter=1000, init=None
)

# Predicting cluster labels for the validation set
u_test, u0_test, d_test, jm_test, p_test, fpc_test = fuzz.cluster.cmeans_predict(
    X_test.T, cntr, m_value, error=0.005, maxiter=1000
)

y_pred_fcm = np.argmax(u_test, axis=0)

# Calculating accuracy
accuracy = accuracy_score(y_test, y_pred_fcm)
print('\x1b[1;31m'+'Accuracy :'+'\x1b[0m', accuracy*100, '%')
print('\x1b[1;31m'+'Objective Function :'+'\x1b[0m', jm[-1])
print('\x1b[1;31m'+'Silhoutte Average :'+'\x1b[0m', silhouette_score(X_test, y_pred_fcm))
```

```
Accuracy : 2.3703290574456215 %
Objective Function : 448.3808368240723
Silhoutte Average : 0.2087975980546246
```

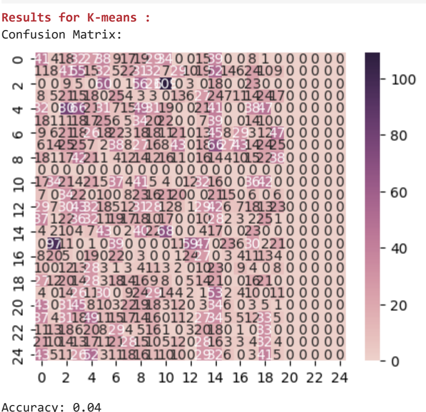
In [91]:
```
plt.figure(figsize=(10,4))

# Plot before clustering
plt.subplot(1, 2, 1)
colors = plt.cm.rainbow(np.linspace(0, 1, 20))
for i,c in enumerate(colors):
  plt.scatter(X_test[y_test==i, 0], X_test[y_test==i, 1], marker='o',color = c, label=i, alpha =0.7)
plt.legend(fontsize=5, title_fontsize=5)
plt.title('Before K-means Clustering')
plt.xlabel('X-axis')
plt.ylabel('Y-axis')

# Plot after clustering
plt.subplot(1, 2, 2)
colors = plt.cm.rainbow(np.linspace(0, 1, 20))
for i,c in enumerate(colors):
  plt.scatter(X_test[y_pred_fcm==i, 0], X_test[y_pred_fcm==i, 1], marker='o',color = c, label=i, alpha =0.7)
plt.legend(fontsize=5, title_fontsize=5)
plt.title('After K-means Clustering')
plt.xlabel('X-axis')
plt.ylabel('Y-axis')

plt.tight_layout()
plt.show()
```



c. Compare k-means and FCM based on the results that you achieved.

In [105]:
```
print('\x1b[1;31m'+'Results for K-means :'+'\x1b[0m')

# Calculate and display the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_kmeans)
print("Confusion Matrix:")

plt.figure(figsize=(5,4))
sns.heatmap(
    conf_matrix, annot = True,
    fmt='d', cmap=sns.cubehelix_palette(as_cmap=True)
)
plt.show()


# Calculate and display accuracy
accuracy = accuracy_score(y_test, y_pred_kmeans)
print(f"Accuracy: {accuracy:.2f}")

# Calculate and display precision, recall, and F1 score
precision = precision_score(y_test, y_pred_kmeans, average='micro')
recall = recall_score(y_test, y_pred_kmeans, average='micro')
f1 = f1_score(y_test, y_pred_kmeans, average='micro')
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")

# Display the classification report
print("Classification Report:")
print(classification_report(y_test, y_pred_kmeans, zero_division=0))
```

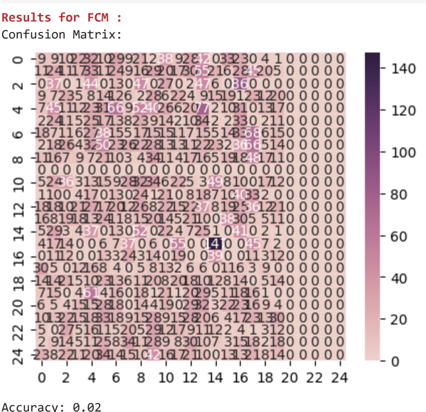
Results for K-means :
Confusion Matrix:



```
Accuracy: 0.04
Precision: 0.04
Recall: 0.04
F1 Score: 0.04
Classification Report:
              precision    recall  f1-score   support

           0       0.09      0.12      0.11       331
           1       0.03      0.02      0.02       432
           2       0.02      0.03      0.02       310
           3       0.03      0.06      0.04       245
           4       0.04      0.04      0.04       498
           5       0.07      0.10      0.08       247
           6       0.07      0.06      0.06       348
           7       0.03      0.02      0.02       436
           8       0.03      0.05      0.03       288
           9       0.00      0.00      0.00         0
          10       0.01      0.01      0.01       331
          11       0.10      0.10      0.10       209
          12       0.01      0.00      0.00       394
          13       0.02      0.03      0.03       291
          14       0.02      0.07      0.04       246
          15       0.18      0.07      0.10       347
          16       0.03      0.02      0.03       164
          17       0.01      0.03      0.02       144
          18       0.05      0.09      0.06       246
          19       0.05      0.04      0.05       248
          20       0.00      0.00      0.00       266
          21       0.00      0.00      0.00       346
          22       0.00      0.00      0.00       206
          23       0.00      0.00      0.00       267
          24       0.00      0.00      0.00       332

    accuracy                           0.04      7172
   macro avg       0.04      0.04      0.03      7172
weighted avg       0.04      0.04      0.04      7172
```

In [166]:
```
print('\x1b[1;31m'+'Results for FCM :'+'\x1b[0m')

# Calculate and display the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_fcm)
print("Confusion Matrix:")

plt.figure(figsize=(5,4))
sns.heatmap(
    conf_matrix, annot = True,
    fmt='d', cmap=sns.cubehelix_palette(as_cmap=True)
)
plt.show()


# Calculate and display accuracy
accuracy = accuracy_score(y_test, y_pred_fcm)
print(f"Accuracy: {accuracy:.2f}")

# Calculate and display precision, recall, and F1 score
precision = precision_score(y_test, y_pred_fcm, average='weighted', zero_division=0)
recall = recall_score(y_test, y_pred_fcm, average='weighted', zero_division=0)
f1 = f1_score(y_test, y_pred_fcm, average='weighted', zero_division=0)
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")

# Display the classification report
print("Classification Report:")
print(classification_report(y_test, y_pred_fcm, zero_division=0))
```

Results for FCM :
Confusion Matrix:



```
Accuracy: 0.02
Precision: 0.03
Recall: 0.02
F1 Score: 0.02
Classification Report:
              precision    recall  f1-score   support

           0       0.04      0.03      0.03       331
           1       0.06      0.06      0.06       432
           2       0.00      0.00      0.00       310
           3       0.02      0.02      0.02       245
           4       0.05      0.05      0.05       498
           5       0.04      0.07      0.05       247
           6       0.04      0.04      0.04       348
           7       0.10      0.06      0.07       436
           8       0.01      0.01      0.01       288
           9       0.00      0.00      0.00         0
          10       0.02      0.02      0.02       331
          11       0.00      0.00      0.00       209
          12       0.06      0.06      0.06       394
          13       0.02      0.03      0.02       291
          14       0.00      0.00      0.00       246
          15       0.00      0.00      0.00       347
          16       0.00      0.00      0.00       164
          17       0.01      0.02      0.01       144
          18       0.03      0.02      0.02       246
          19       0.00      0.00      0.00       248
          20       0.00      0.00      0.00       266
          21       0.00      0.00      0.00       346
          22       0.00      0.00      0.00       206
          23       0.00      0.00      0.00       267
          24       0.00      0.00      0.00       332

    accuracy                           0.02      7172
   macro avg       0.02      0.02      0.02      7172
weighted avg       0.03      0.02      0.02      7172
```

Comparison:

- **Accuracy:** K-means outperforms FCM in terms of accuracy, indicating that K-means achieved a higher ratio of correctly classified samples.
- **Precision, Recall, and F1 Score:** Both K-means and FCM exhibit similar performance across these metrics, with very low scores. Precision indicates the proportion of correctly identified instances among the instances predicted as positive; Recall measures the proportion of actual positive instances that were correctly identified; F1 Score is the harmonic mean of Precision and Recall. The low scores suggest poor performance in capturing true positives and minimizing false positives/negatives for both algorithms.

Analysis:

- **Interpretation of Results:** The low values of Precision, Recall, and F1 Score indicate that both algorithms might struggle in correctly classifying the data points into distinct clusters or classes. The clusters formed by both algorithms might not align well with the ground truth labels.
- **Limitations:** The low performance could be due to various factors such as noisy data, inappropriate choice of clustering algorithms for the given data distribution, or inadequate preprocessing of data before clustering.

Conclusion:

- **Both K-means and FCM** seem to have limitations in effectively capturing the underlying structure in the data, as reflected by the low performance across multiple metrics.

[4] Implement a feedforward neural network and train the network. This network will be trained and tested using the train and test sets of the dataset. Specifically, given an input image (28 x 28 = 784 pixels) from the Sign-MNIST dataset, the network will be trained to classify the image into 1 of 24 classes.

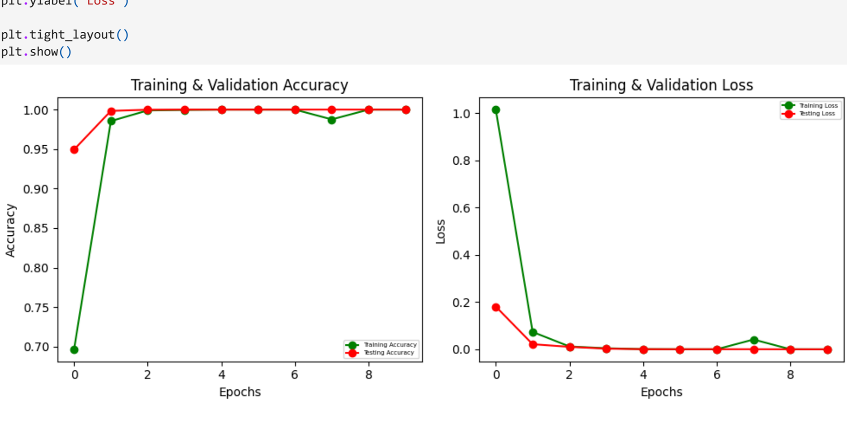
In [138]:
```
def fix_label_gap(l):
    if(l>=9):
        return (l-1)
    else:
        return l

X_train = training_data.drop('label', axis=1).values
y_train = training_data['label'].apply(fix_label_gap).values
y_train = to_categorical(y_train, num_classes=24)

X_test = testing_data.drop('label', axis=1).values
y_test = testing_data['label'].apply(fix_label_gap).values
y_test = to_categorical(y_test, num_classes=24)

# Reshape the data (assuming grayscale images)
X_train = X_train.reshape(-1 , 28, 28, 1)
X_test = X_test.reshape(-1, 28, 28, 1)
```

a. Develop a simple Convolutional Neural Network with maximum 10 hidden layers composed of convolutional, pooling and fully connected layers. Design and build your model. Specify kernel sizes, number of filters, activation functions, learning rate, optimization, and loss functions of your model.

In [154]:
```
# Define model architecture
model = Sequential()

# Convolutional layers
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))

# Flatten layer to transition from convolutional to fully connected layers
model.add(Flatten())

# Fully connected layers
model.add(Dense(128, activation='relu'))
model.add(Dense(24, activation='softmax'))  # Output layer with 24 classes

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])



# Train the model
history = model.fit(X_train, y_train, epochs=10, validation_split=0.2)
y_pred = model.predict(X_test)
accuracy = accuracy_score(np.argmax(y_test, axis = 1), np.argmax(y_pred, axis = 1))
print('\x1b[1;31m'+'Accuracy :'+'\x1b[0m', accuracy)

train_acc = history.history['accuracy']
train_loss = history.history['loss']
val_acc = history.history['val_accuracy']
val_loss = history.history['val_loss']
```

```
Epoch 1/10
687/687 [==============================] - 3s 4ms/step - loss: 1.0154 - accuracy: 0.6965 - val_loss: 0.1812 - val_accur
acy: 0.9494
Epoch 2/10
687/687 [==============================] - 3s 4ms/step - loss: 0.0738 - accuracy: 0.9855 - val_loss: 0.0218 - val_accur
acy: 0.9984
Epoch 3/10
687/687 [==============================] - 3s 4ms/step - loss: 0.0123 - accuracy: 0.9990 - val_loss: 0.0107 - val_accur
acy: 0.9998
Epoch 4/10
687/687 [==============================] - 3s 4ms/step - loss: 0.0047 - accuracy: 0.9995 - val_loss: 0.0030 - val_accur
acy: 1.0000
Epoch 5/10
687/687 [==============================] - 3s 4ms/step - loss: 0.0011 - accuracy: 1.0000 - val_loss: 7.7934e-04 - val_a
ccuracy: 1.0000
Epoch 6/10
687/687 [==============================] - 3s 4ms/step - loss: 5.5250e-04 - accuracy: 1.0000 - val_loss: 4.8180e-04 - v
al_accuracy: 1.0000
Epoch 7/10
687/687 [==============================] - 3s 4ms/step - loss: 3.5634e-04 - accuracy: 1.0000 - val_loss: 6.0043e-04 - v
al_accuracy: 1.0000
Epoch 8/10
687/687 [==============================] - 3s 4ms/step - loss: 0.0418 - accuracy: 0.9876 - val_loss: 7.2788e-04 - val_a
ccuracy: 1.0000
Epoch 9/10
687/687 [==============================] - 3s 4ms/step - loss: 4.7095e-04 - accuracy: 1.0000 - val_loss: 3.6540e-04 - v
al_accuracy: 1.0000
Epoch 10/10
687/687 [==============================] - 3s 4ms/step - loss: 2.4320e-04 - accuracy: 1.0000 - val_loss: 2.2370e-04 - v
al_accuracy: 1.0000
225/225 [==============================] - 0s 1ms/step
Accuracy : 0.8378416062465143
```

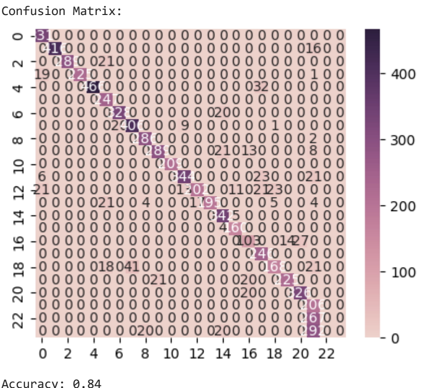
In [156]:
```
plt.figure(figsize=(10,4))
epochs = [i for i in range(10)]

plt.subplot(1, 2, 1)
plt.plot(epochs, train_acc, 'go-' , label = 'Training Accuracy')
plt.plot(epochs, val_acc, 'ro-' , label = 'Testing Accuracy')
plt.legend(fontsize=5, title_fontsize=5)
plt.title('Training & Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs, train_loss, 'g-o' , label = 'Training Loss')
plt.plot(epochs, val_loss, 'r-o' , label = 'Testing Loss')
plt.legend(fontsize=5, title_fontsize=5)
plt.title('Training & Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')

plt.tight_layout()
plt.show()
```



b. Plot the confusion matrix and evaluate the performance of your classification model.

In [163]:
```
print('\x1b[1;31m'+'Results for Neural Network :'+'\x1b[0m')

# Calculate and display the confusion matrix
conf_matrix = confusion_matrix(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1))
print("Confusion Matrix:")

plt.figure(figsize=(5,4))
sns.heatmap(
    conf_matrix, annot = True,
    fmt='d', cmap=sns.cubehelix_palette(as_cmap=True)
)
plt.show()


# Calculate and display accuracy
accuracy = accuracy_score(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1))
print(f"Accuracy: {accuracy:.2f}")

# Calculate and display precision, recall, and F1 score
precision = precision_score(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1), average='weighted', zero_division=0)
recall = recall_score(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1), average='weighted')
f1 = f1_score(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1), average='weighted')
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")

# Display the classification report
print("Classification Report:")
print(classification_report(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1), zero_division=0))
```

Results for Neural Network :
Confusion Matrix:



```
Accuracy: 0.84
Precision: 0.83
Recall: 0.84
F1 Score: 0.82
Classification Report:
              precision    recall  f1-score   support

           0       0.88      1.00      0.94       331
           1       1.00      0.96      0.98       432
           2       1.00      0.93      0.96       310
           3       1.00      0.92      0.96       245
           4       1.00      0.94      0.97       498
           5       0.80      1.00      0.89       247
           6       0.94      0.94      0.94       348
           7       0.91      0.93      0.92       436
           8       0.92      0.99      0.96       288
           9       0.93      0.87      0.90       331
          10       1.00      1.00      1.00       209
          11       0.94      0.87      0.91       394
          12       0.92      0.69      0.79       291
          13       1.00      0.79      0.88       246
          14       0.84      0.99      0.91       347
          15       0.91      0.98      0.94       164
          16       0.66      0.72      0.69       144
          17       0.76      1.00      0.87       246
          18       0.85      0.68      0.76       248
          19       0.94      0.85      0.89       266
          20       0.92      0.94      0.93       346
          21       0.25      1.00      0.39       206
          22       0.00      0.00      0.00       267
          23       0.00      0.00      0.00       332

    accuracy                           0.84      7172
   macro avg       0.81      0.83      0.81      7172
weighted avg       0.83      0.84      0.82      7172
```

References :

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In [ ]: