1. Loading and Preprocessing

In [1]:
```
# Import necessary libraries
import pandas as pd
from sklearn.datasets import load_iris

# Load the Iris dataset
iris = load_iris()
iris_data = pd.DataFrame(data=iris.data, columns=iris.feature_names)

# Drop the species column
# (Species is not included in the DataFrame since we're using only the feat
iris_data.head()
```

Out[1]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

Clustering Algorithm Implementation

A) KMeans Clustering

Description of KMeans Clustering

KMeans clustering is a partitioning method that divides the dataset into K distinct, non-overlapping subsets (clusters). The algorithm works by:

- Randomly initializing K centroids.
- Assigning each data point to the nearest centroid based on the Euclidean distance.
- Recalculating the centroids as the mean of the assigned points.
- Iterating the assignment and update steps until convergence (i.e., no changes in cluster assignments).

Suitability for the Iris Dataset

KMeans is suitable for the Iris dataset because:

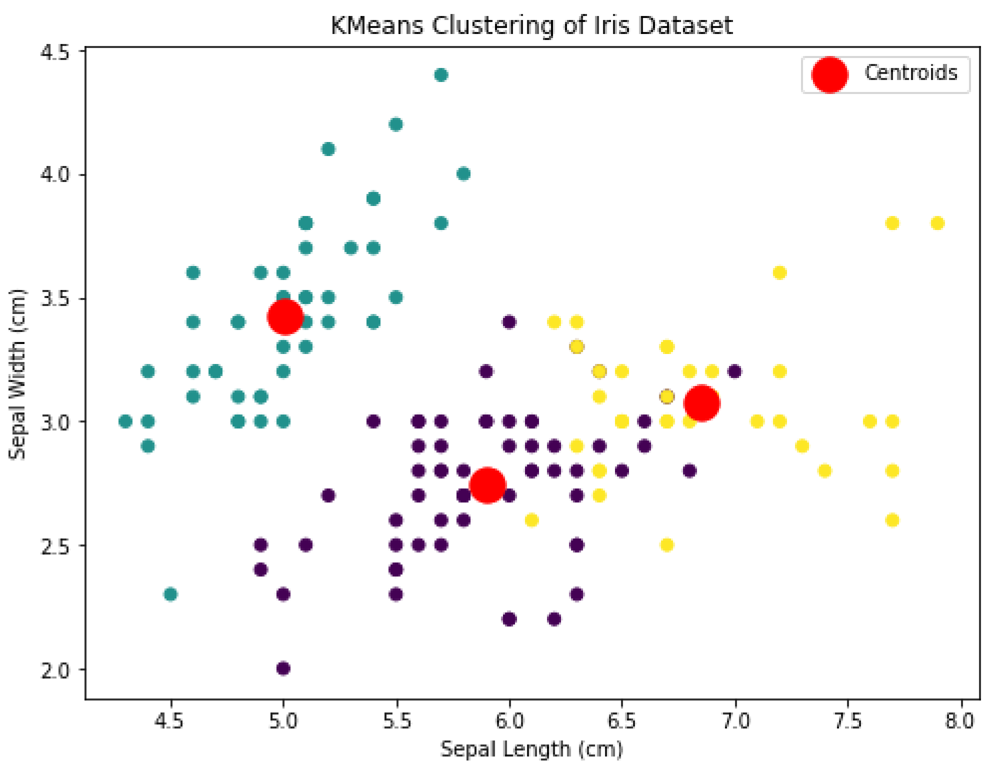
- It has well-defined clusters (setosa, versicolor, and virginica) based on the features (sepal and petal lengths and widths).
- The dataset is relatively small and continuous, making it feasible for KMeans to efficiently find clusters.

In [2]:
```
# Import KMeans
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Apply KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(iris_data)

# Add the cluster labels to the DataFrame
iris_data['Cluster'] = kmeans.labels_

# Visualization
plt.figure(figsize=(8, 6))
plt.scatter(iris_data['sepal length (cm)'], iris_data['sepal width (cm)'],
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s
plt.title('KMeans Clustering of Iris Dataset')
plt.xlabel('Sepal Length (cm)')
plt.ylabel('Sepal Width (cm)')
plt.legend()
plt.show()
```



B) Hierarchical Clustering

Description of Hierarchical Clustering:

Hierarchical clustering is a method that builds a hierarchy of clusters either through:

- Agglomerative Approach: Starting with individual points, merging them into clusters.
- Divisive Approach: Starting with one cluster and splitting it into smaller clusters.

Agglomerative clustering is more commonly used. It creates a dendrogram to illustrate the arrangement of clusters.

Suitability for the Iris Dataset:

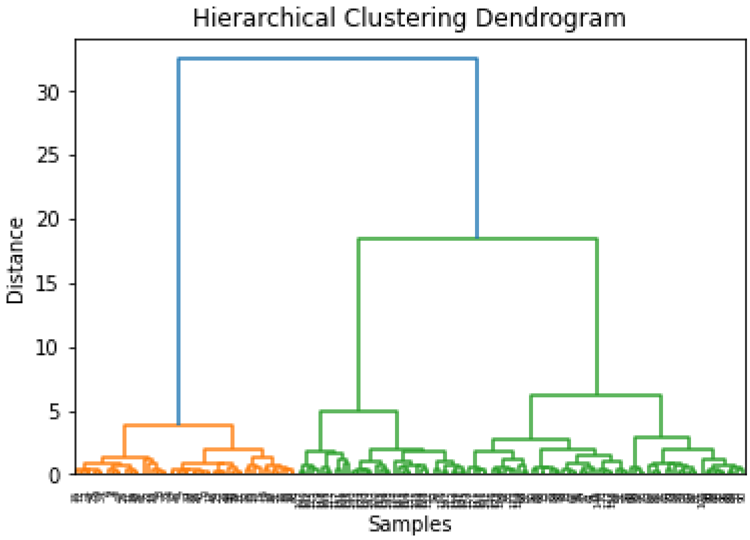
Hierarchical clustering is suitable for the Iris dataset because:

- It allows for visual representation of the relationships between clusters through dendrograms.
- It does not require the number of clusters to be specified beforehand.

In [3]:
```
# Import necessary libraries for Hierarchical Clustering
import scipy.cluster.hierarchy as sch

# Apply Hierarchical clustering
dendrogram = sch.dendrogram(sch.linkage(iris_data, method='ward'))

plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Samples')
plt.ylabel('Distance')
plt.show()
```



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