Machine Learning Lab A3

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ASSIGNMENT - 4

Github Link:

https://github.com/cryptasim/MACHINE-LEARNING-LAB

In [1]:
```
!pip install numpy==1.26.4
!pip install scikit-learn-extra
```

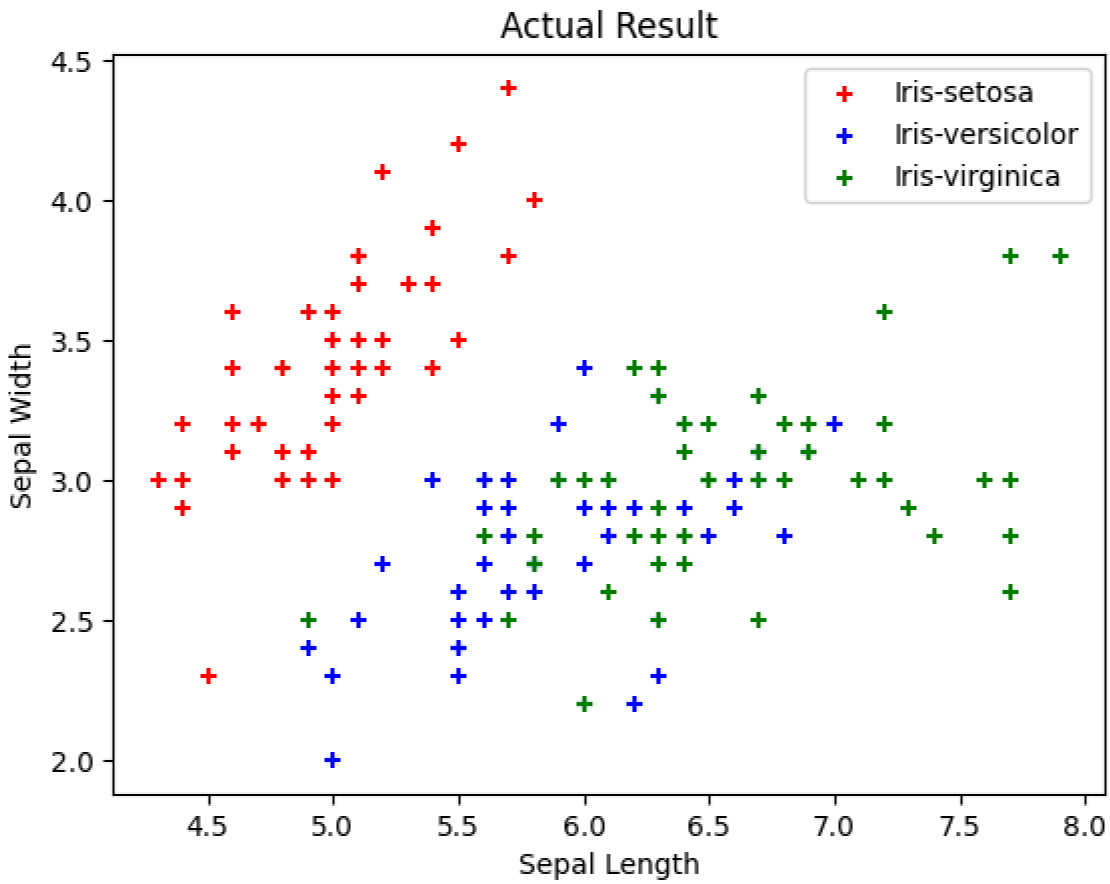
```
Requirement already satisfied: numpy==1.26.4 in /usr/local/lib/python3.12/dist-
packages (1.26.4)
Requirement already satisfied: scikit-learn-extra in /usr/local/lib/python3.12/
dist-packages (0.3.0)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.12/dist-
packages (from scikit-learn-extra) (1.26.4)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.12/dist-
packages (from scikit-learn-extra) (1.16.2)
Requirement already satisfied: scikit-learn>=0.23.0 in /usr/local/lib/python3.1
2/dist-packages (from scikit-learn-extra) (1.6.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.12/dist-
packages (from scikit-learn>=0.23.0->scikit-learn-extra) (1.5.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.1
2/dist-packages (from scikit-learn>=0.23.0->scikit-learn-extra) (3.6.0)
```

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import silhouette_score, calinski_harabasz_score,davies_b
```

Clustering in Iris Dataset

In [3]:
```
from sklearn.datasets import load_iris
import pandas as pd
import matplotlib.pyplot as plt

# Load iris dataset
iris = load_iris()
df_iris = pd.DataFrame(iris.data, columns=iris.feature_names)
df_iris['species'] = [iris.target_names[i] for i in iris.target]

# Rename columns to match your plotting code
df_iris.columns = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width

# Prepare data
X = df_iris.drop('species', axis=1)
y = df_iris.species

# Actual Clustering Result
newDf0 = df_iris[df_iris.species == "setosa"]
newDf1 = df_iris[df_iris.species == "versicolor"]
newDf2 = df_iris[df_iris.species == "virginica"]

# Plot
plt.title("Actual Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(newDf0.sepal_length, newDf0.sepal_width, color="red", marker="+",
plt.scatter(newDf1.sepal_length, newDf1.sepal_width, color="blue", marker="+",
```

```
plt.scatter(newDf2.sepal_length, newDf2.sepal_width, color="green", marker="+"
plt.legend()

# 👇 This line displays the plot
plt.show()
```



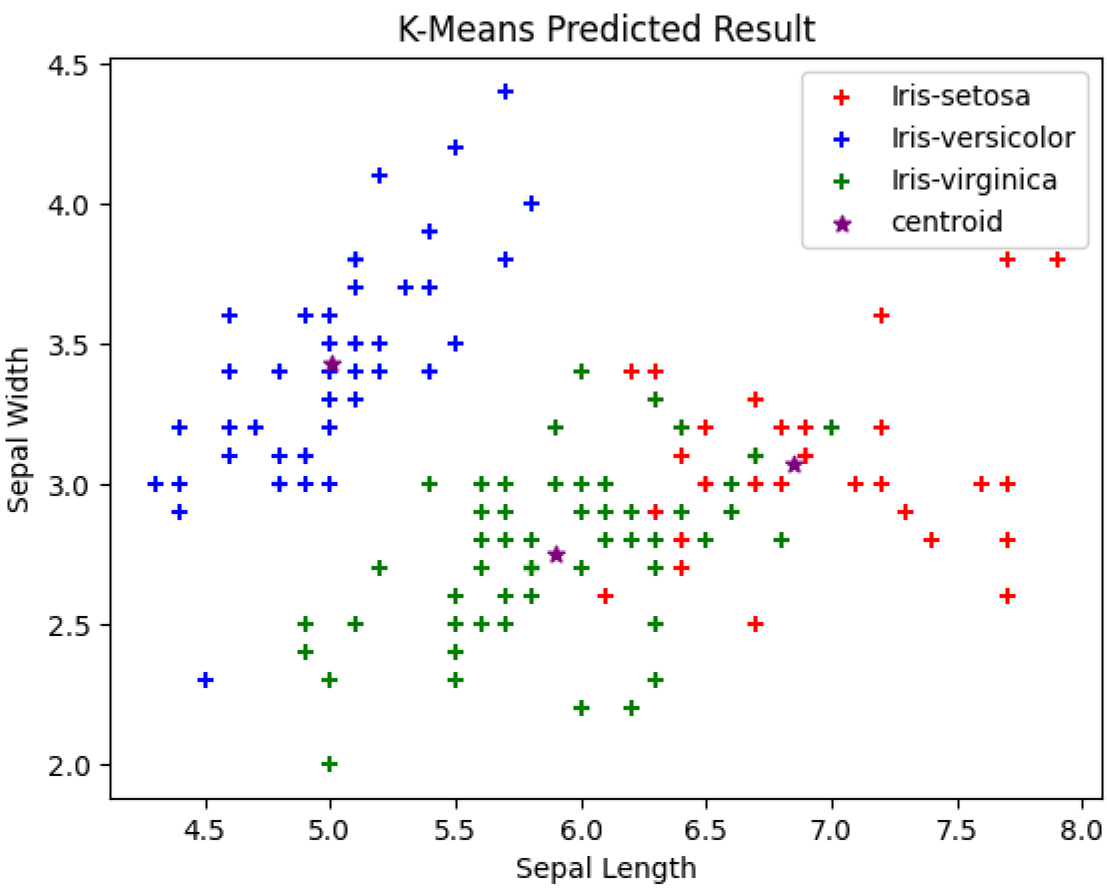
Partition Based: K-means Clustering in Iris Dataset

In [4]:

```
from sklearn.cluster import KMeans
km = KMeans(n_clusters=3, n_init=10)
y_predicted = km.fit_predict(X)
newDf = df_iris
newDf["cluster"] = y_predicted
newDf0 = newDf[newDf.cluster==0]
newDf1 = newDf[newDf.cluster==1]
newDf2 = newDf[newDf.cluster==2]
plt.title("K-Means Predicted Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(newDf0.sepal_length, newDf0.sepal_width, color="red",
marker="+", label="Iris-setosa")
plt.scatter(newDf1.sepal_length, newDf1.sepal_width, color="blue",
```

```
marker="+", label="Iris-versicolor")
plt.scatter(newDf2.sepal_length, newDf2.sepal_width, color="green",
marker="+", label="Iris-virginica")
plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:,1], color="purple"
plt.legend()
```

Out[4]: <matplotlib.legend.Legend at 0x7f0d488d8a70>



In [5]:

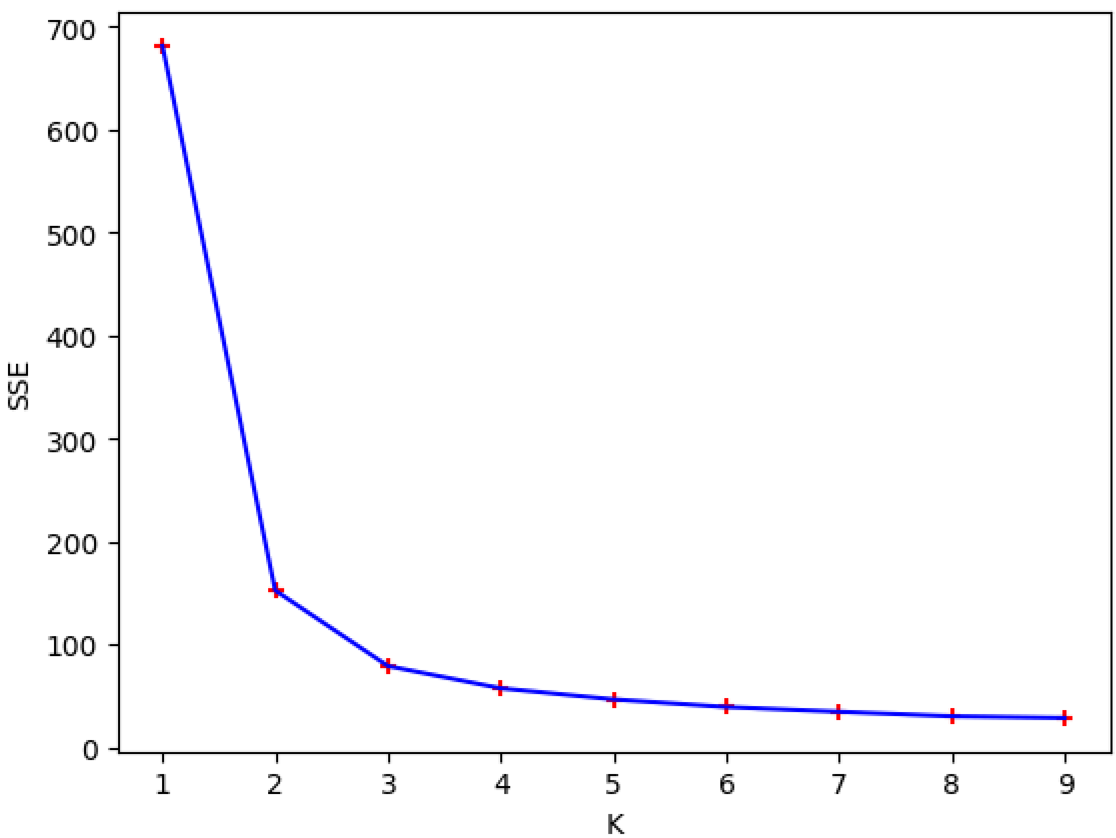
```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels
y_true = df_iris['species']

# Predicted cluster labels
y_pred = newDf['cluster']

# Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)
```

```
# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.8797
Adjusted Rand Index: 0.7302
Mutual Information: 0.8256
Adjusted Mutual Information: 0.7551
Normalized Mutual Information: 0.7582
```

In [6]:
```
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
```

Out[6]:
```
[<matplotlib.lines.Line2D at 0x7f0d47cef7d0>]
```



In [7]:
```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
```

```
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion_scores}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.31200096891430773
Calinski Harabasz Score:  404.68828649587556
Davies Bouldin Score:  0.9969403146109168

Cohesion Score: sepal_length    0.053116
sepal_width     0.052725
petal_length    0.054776
petal_width     0.028959
dtype: float64
Separation Score: 0.07235617715617715
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86: FutureWar
ning: The behavior of DataFrame.sum with axis=None is deprecated, in a future v
ersion this will reduce over both axes and return a scalar. To retain the old b
ehavior, pass axis=0 (or do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

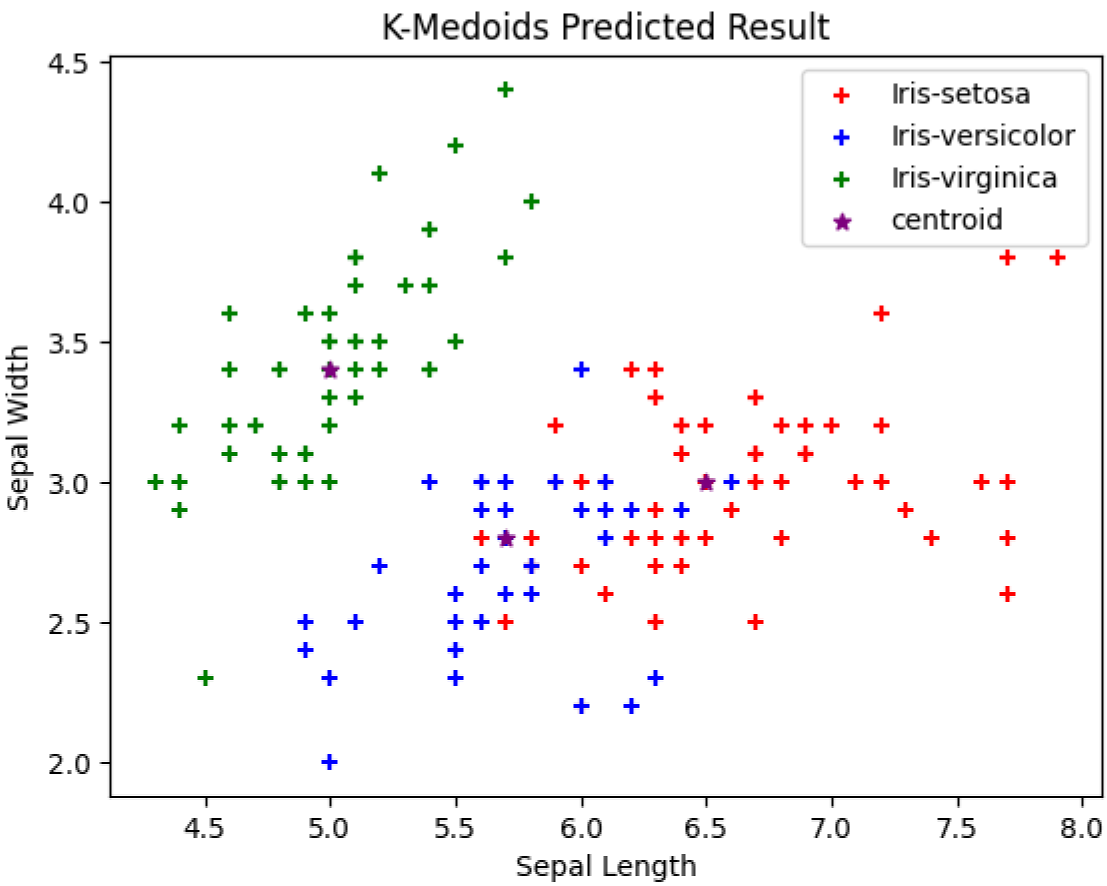
Partition Based: K-medoids Clustering in Iris Dataset

In [8]:

```
# Clustering using K-medoids algorithm
from sklearn_extra.cluster import KMedoids
km = KMedoids(n_clusters=3)
y_predicted = km.fit_predict(X)
newDf = df_iris
newDf["cluster"] = y_predicted
newDf0 = newDf[newDf.cluster==0]
newDf1 = newDf[newDf.cluster==1]
newDf2 = newDf[newDf.cluster==2]
plt.title("K-Medoids Predicted Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(newDf0.sepal_length, newDf0.sepal_width, color="red",
```

```
marker="+", label="Iris-setosa")
plt.scatter(newDf1.sepal_length, newDf1.sepal_width, color="blue",
marker="+", label="Iris-versicolor")
plt.scatter(newDf2.sepal_length, newDf2.sepal_width, color="green",
marker="+", label="Iris-virginica")
plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:,1],
color="purple", marker="*", label="centroid")
plt.legend()
```

Out[8]: <matplotlib.legend.Legend at 0x7f0d47d83560>



In [9]:
```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels
y_true = df_iris['species']

# Predicted cluster labels
y_pred = newDf['cluster']

# Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
```

```
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

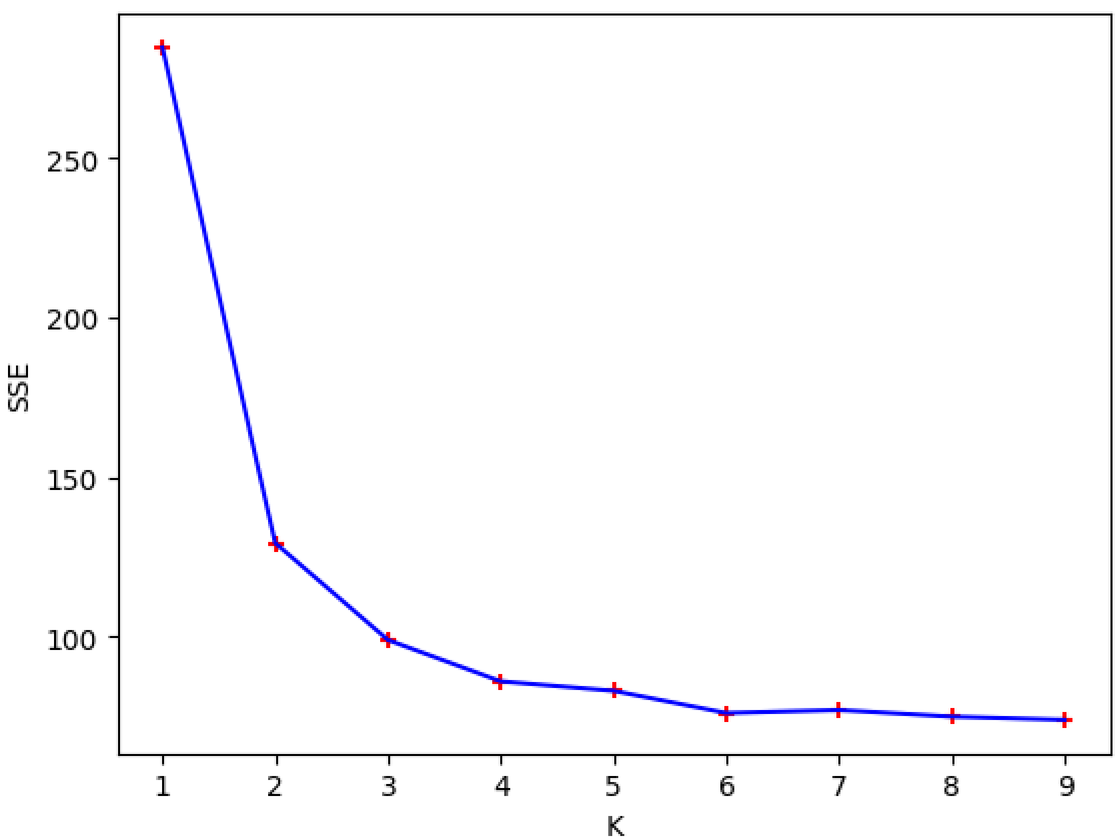
```
Rand Index: 0.8923
Adjusted Rand Index: 0.7583
Mutual Information: 0.8555
Adjusted Mutual Information: 0.7830
Normalized Mutual Information: 0.7857
```

In [10]:

```
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMedoids(n_clusters=k)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
```

Out[10]:

```
[<matplotlib.lines.Line2D at 0x7f0d459da2a0>]
```



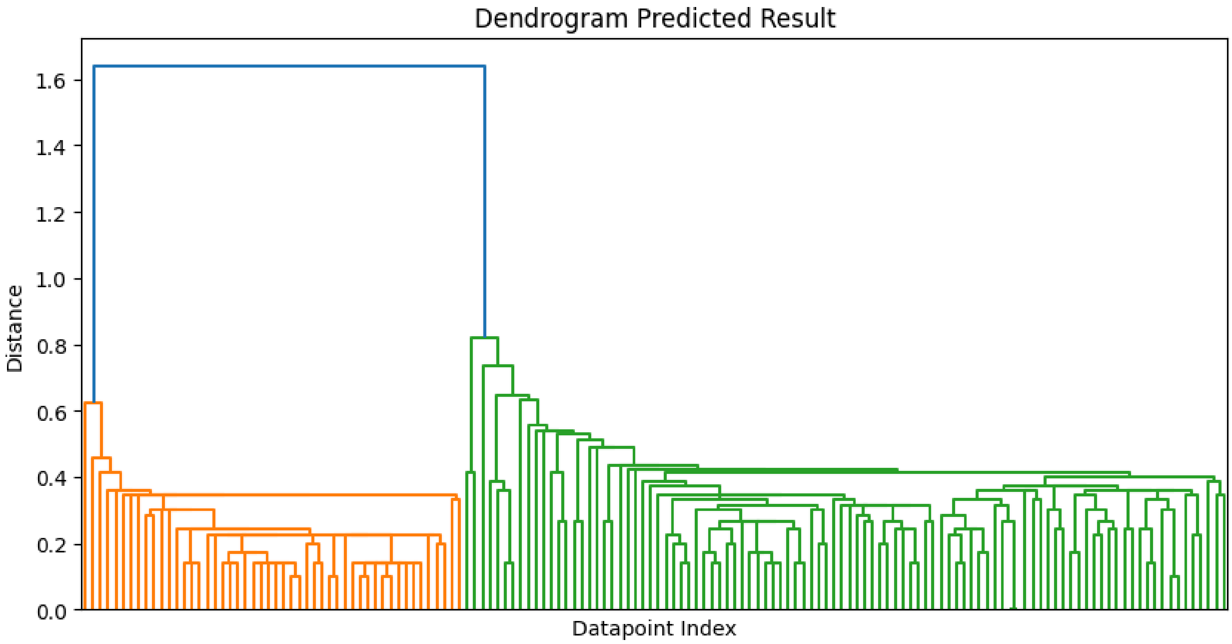
In [11]:
```python
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.37568265737828305
Calinski Harabasz Score:  237.92818231224678
Davies Bouldin Score:  1.1192653552269658

Cohesion Score: 0.08663333333333338
Separation Score: 0.06466666666666666
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86: FutureWar
ning: The behavior of DataFrame.sum with axis=None is deprecated, in a future v
ersion this will reduce over both axes and return a scalar. To retain the old b
ehavior, pass axis=0 (or do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

Hierarchical: Dendrogram Clustering in Iris Dataset

In [12]:
```python
# Clustering using Dendrogram Clustering algorithm
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
Z = linkage(X, method='single')
# Create and plot the dendrogram
plt.figure(figsize=(10, 5))
dn = dendrogram(Z, no_labels=True)
plt.title('Dendrogram Predicted Result')
plt.xlabel('Datapoint Index')
plt.ylabel('Distance')
plt.show()
```



In [13]:
```
from scipy.cluster.hierarchy import fcluster
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels (numeric)
y_true = df_iris['species']

# Cut the dendrogram to form 3 clusters
y_pred = fcluster(Z, t=3, criterion='maxclust')

# Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7766
Adjusted Rand Index: 0.5638
Mutual Information: 0.6459
Adjusted Mutual Information: 0.7126
Normalized Mutual Information: 0.7175
```

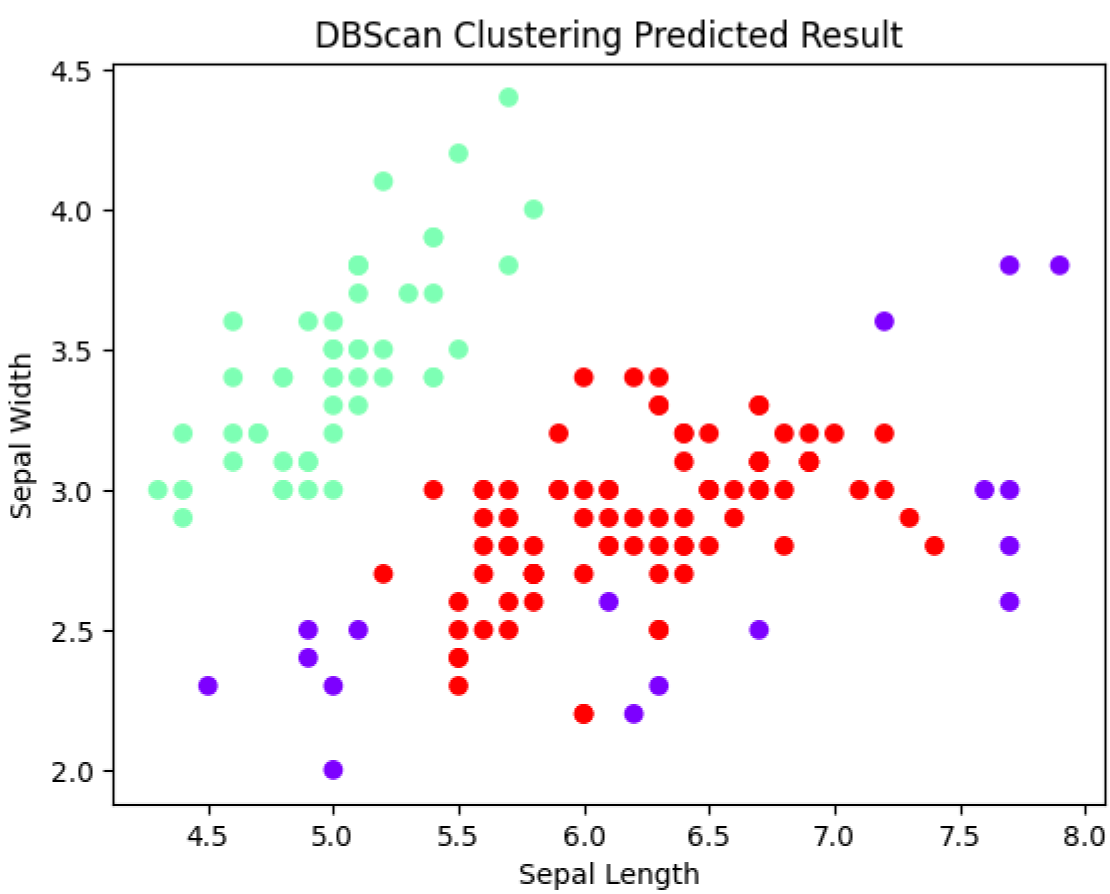
In [14]:
```
labels = fcluster(Z, 3, criterion='maxclust')
```

```
silhouette_result = silhouette_score(X, labels)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, labels)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, labels)
print("Davies Bouldin Score: ", davies_result)
```

```
Silhouette Score:  0.5121107753649307
Calinski Harabasz Score:  277.99467626461944
Davies Bouldin Score:  0.4471537628542408
```

Density Based: DBSCAN Clustering in Iris Dataset

In [15]:
```
# Clustering using DBSCAN Clustering algorithm
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps=0.5, algorithm='auto', metric='euclidean')
y = dbscan.fit_predict(X)
plt.scatter(df_iris.sepal_length, df_iris.sepal_width,
c=dbscan.labels_, cmap='rainbow')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('DBScan Clustering Predicted Result')
plt.show()
```



In [16]:
```python
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels
y_true = df_iris['species']

# Predicted cluster labels from DBSCAN
y_pred = dbscan.labels_

# If you want to ignore noise points (-1), you can filter them:
# mask = y_pred != -1
# y_true_filtered = y_true[mask]
# y_pred_filtered = y_pred[mask]

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7719
Adjusted Rand Index: 0.5206
Mutual Information: 0.6152
Adjusted Mutual Information: 0.5990
Normalized Mutual Information: 0.6044
```

In [17]:
```python
y_pred
```

Out[17]:
```
array([ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  1,
        1,  1,  1,  1,  1,  1, -1,  1,  1, -1,  1,  1,  1,  1,  1,  1,  1,
       -1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1, -1,  1,  1,  1,  1,  1, -1,  1,  1,  1,  1, -1,  1,  1,  1,
        1,  1,  1, -1, -1,  1, -1, -1,  1,  1,  1,  1,  1,  1,  1, -1, -1,
        1,  1,  1, -1,  1,  1,  1,  1,  1,  1,  1,  1, -1,  1,  1, -1, -1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1])
```

In [18]:
```python
# Evaluating Metrics
silhouette_result = silhouette_score(X, dbscan.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, dbscan.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, dbscan.labels_)
```

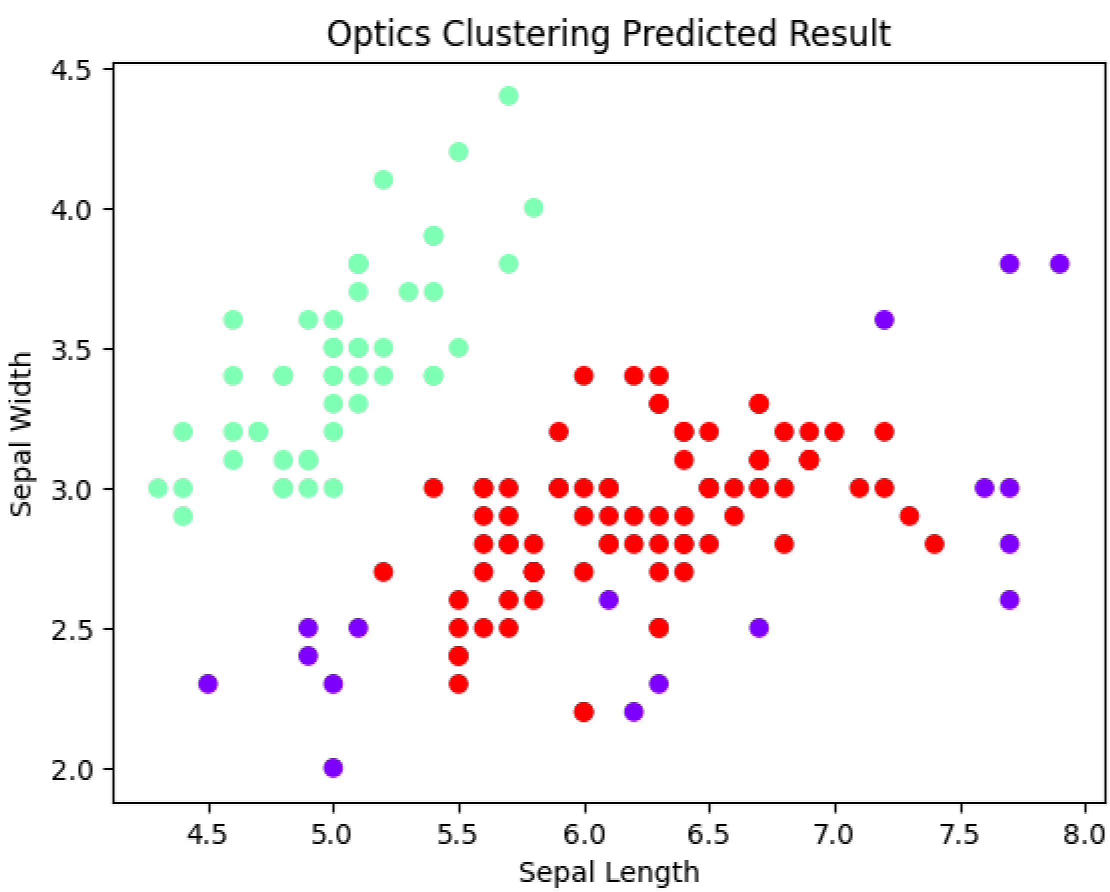
```
print("Davies Bouldin Score: ", davies_result)
```

```
Silhouette Score:  0.48603419703456857
Calinski Harabasz Score:  220.29751498443005
Davies Bouldin Score:  7.222448016359581
```

Density Based: Optics Clustering in Iris Dataset

In [19]:

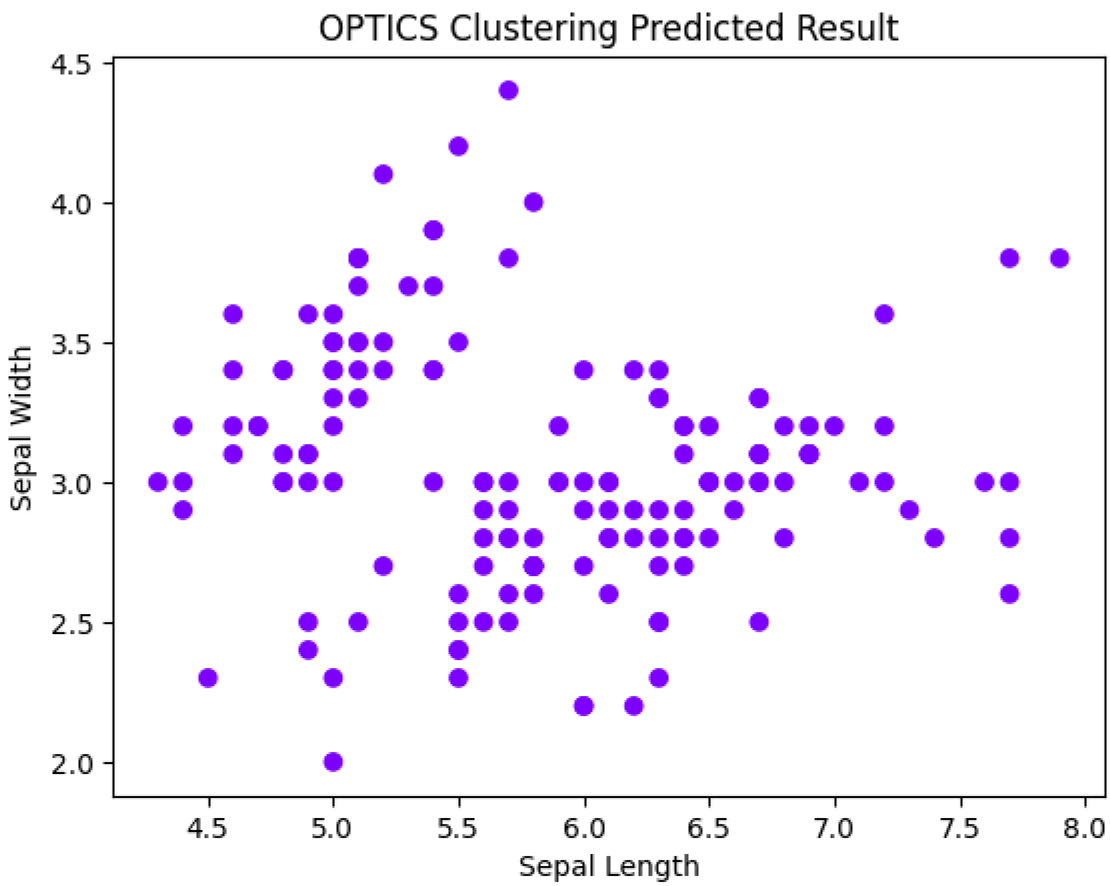
```
# Clustering using Optics Clustering algorithm
from sklearn.cluster import OPTICS
optics_cluster = OPTICS(min_samples=5, xi=0.05,
cluster_method='dbscan')
optics_cluster.fit(X)
plt.scatter(df_iris.sepal_length, df_iris.sepal_width,
c=dbscan.labels_, cmap='rainbow')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('Optics Clustering Predicted Result')
plt.show()
```



In [20]:

```
from sklearn.cluster import OPTICS
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor
```

```
import matplotlib.pyplot as plt

# Run OPTICS
optics_cluster = OPTICS(min_samples=5, xi=0.05, cluster_method='dbscan')
y_pred = optics_cluster.fit_predict(X)  # predicted cluster labels

# Plot clusters
plt.scatter(df_iris.sepal_length, df_iris.sepal_width, c=y_pred, cmap='rainbow
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('OPTICS Clustering Predicted Result')
plt.show()

# True labels
y_true = df_iris['species']

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

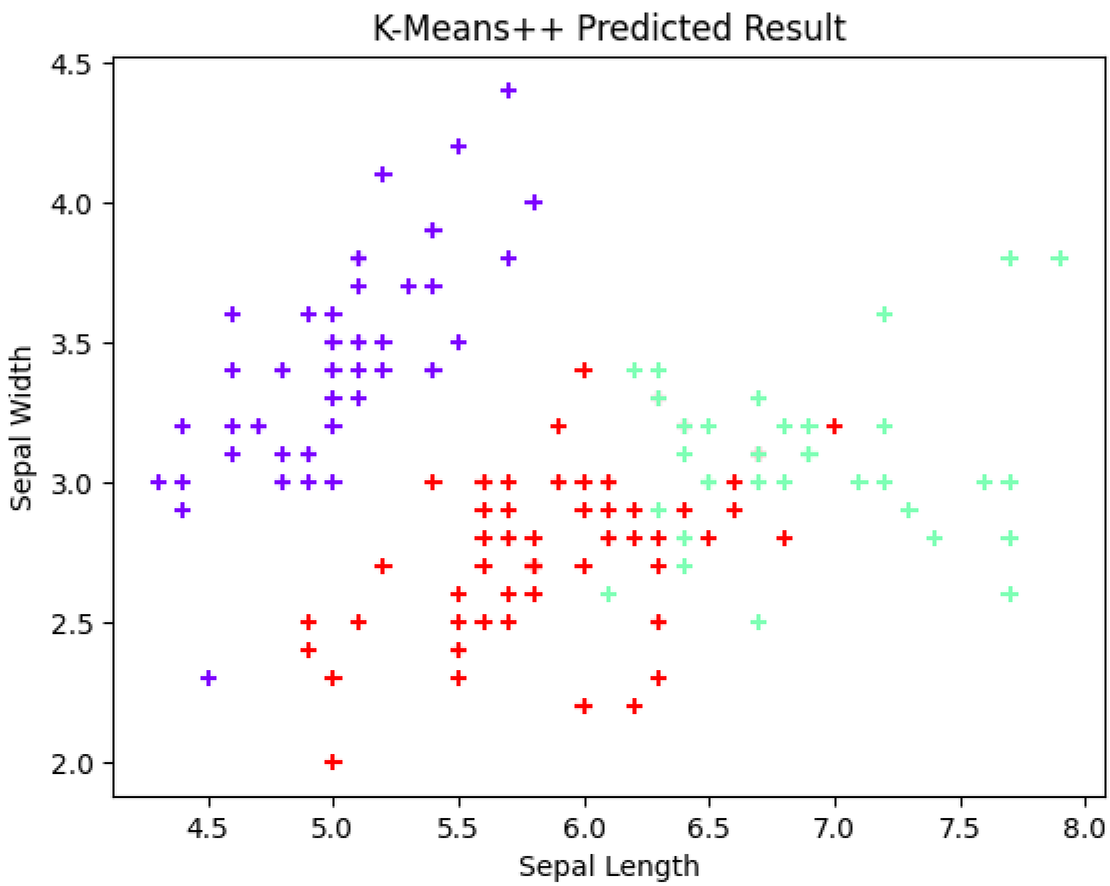



```
Rand Index: 0.3289
Adjusted Rand Index: 0.0000
Mutual Information: 0.0000
Adjusted Mutual Information: 0.0000
Normalized Mutual Information: 0.0000
```

K-means++ Clustering in Iris Dataset

In [21]:

```
# Clustering using K-means++ algorithm
from sklearn.cluster import KMeans
km = KMeans(init='k-means++', n_clusters=3, n_init=10, max_iter=300,
random_state=42)
km = KMeans(n_clusters=3, n_init=10)
y_predicted = km.fit_predict(X)
plt.title("K-Means++ Predicted Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(df_iris.sepal_length, df_iris.sepal_width, c=km.labels_,
cmap='rainbow', marker="+")
plt.show()
```



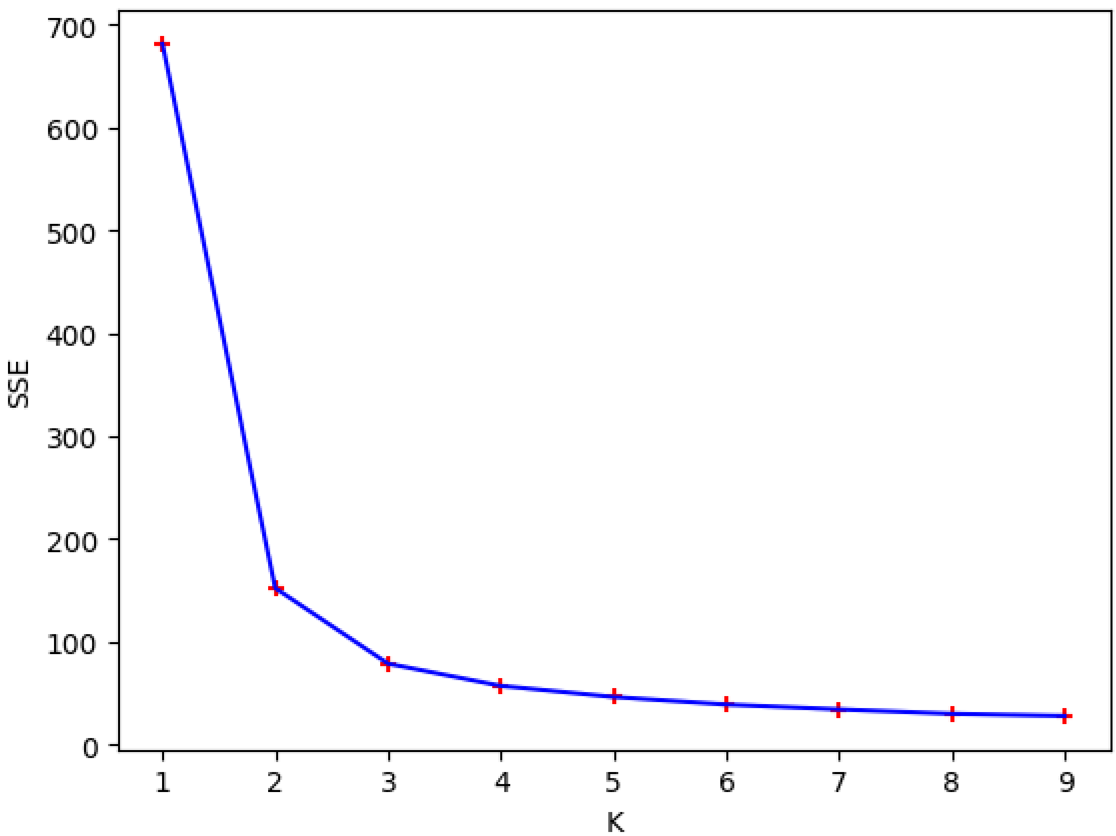
In [22]:

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels
y_true = df_iris['species']

# Predicted cluster labels from K-Means++
y_pred = km.labels_  # or y_predicted

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.8797
Adjusted Rand Index: 0.7302
Mutual Information: 0.8256
Adjusted Mutual Information: 0.7551
Normalized Mutual Information: 0.7582
```

In [23]:
```python
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

Out[23]:
```
[<matplotlib.lines.Line2D at 0x7f0d4580af60>]
```



In [24]:
```python
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
```

```python
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

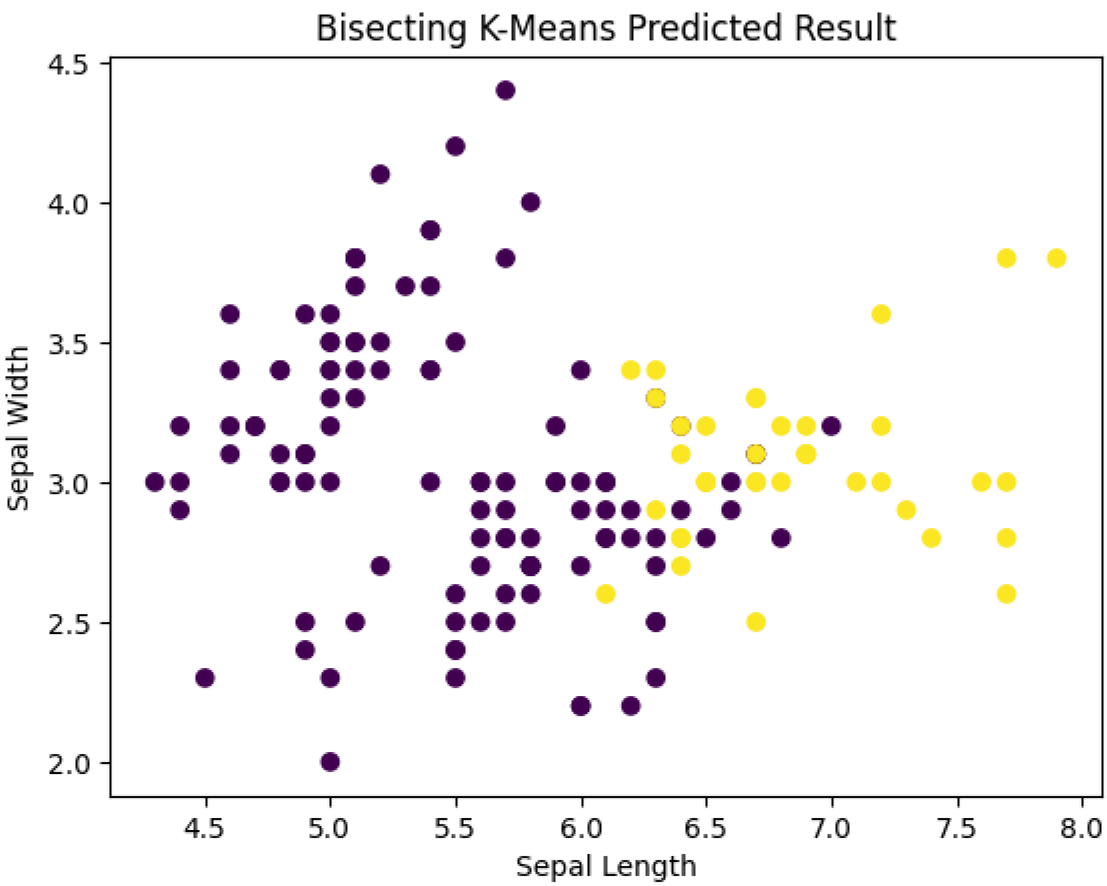
```
Silhouette Score:  0.3416185449488845
Calinski Harabasz Score:  411.50528902921917
Davies Bouldin Score:  0.933140542284917

Cohesion Score: 0.046641455722639925
Separation Score: 0.06232722222222222
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86: FutureWar
ning: The behavior of DataFrame.sum with axis=None is deprecated, in a future v
ersion this will reduce over both axes and return a scalar. To retain the old b
ehavior, pass axis=0 (or do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

Bisecting K-means Clustering in Iris Dataset

In [25]:

```python
# Clustering using Bisecting K-means algorithm
from sklearn.cluster import KMeans
km = KMeans(n_clusters=1, n_init=10, random_state=0).fit(X)
K=3
for i in range(K-1):
 largest_cluster = np.argmax(np.bincount(km.labels_))
 largest_cluster_mask = (km.labels_ == largest_cluster)
 X_split = X[largest_cluster_mask]
 km.labels_[largest_cluster_mask] = KMeans(n_clusters=2, n_init=10,
random_state=0).fit(X_split).labels_
plt.title("Bisecting K-Means Predicted Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(df_iris.sepal_length, df_iris.sepal_width, c=km.labels_,
cmap='viridis')
plt.show()
```



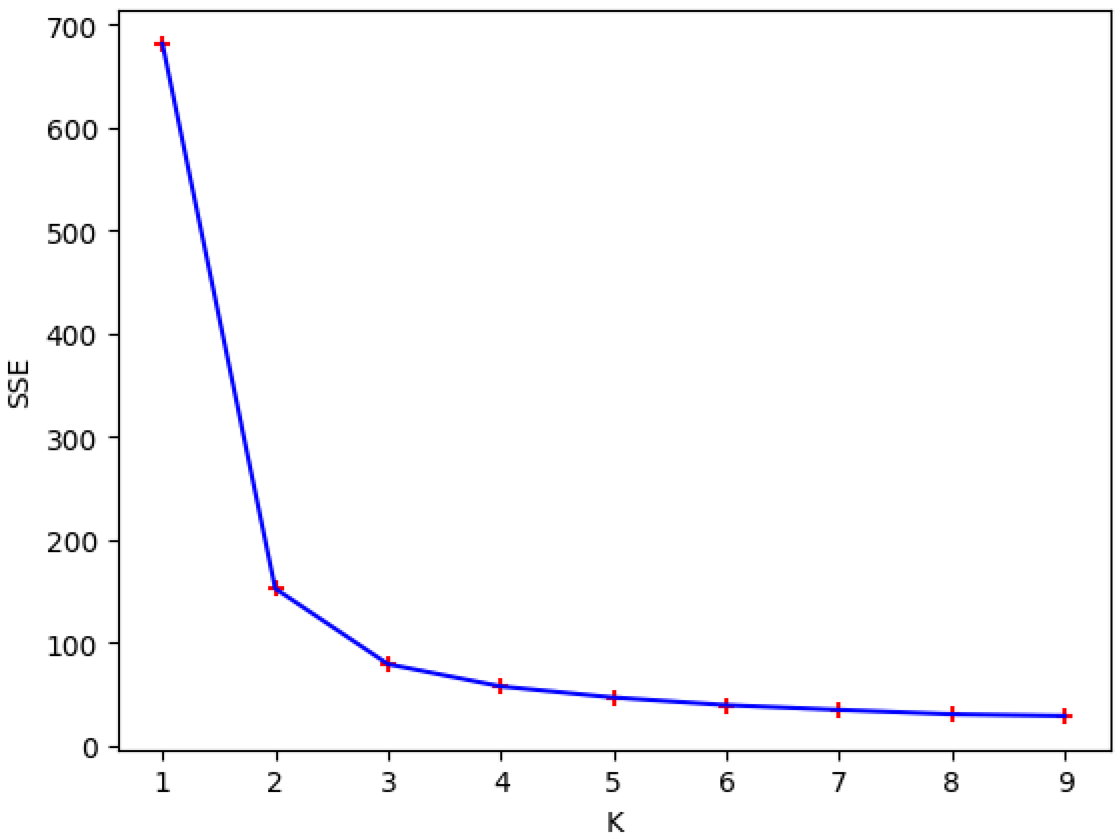
In [26]:

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels
y_true = df_iris['species']

# Predicted cluster labels from Bisecting K-Means
y_pred = km.labels_

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.6023
Adjusted Rand Index: 0.2646
Mutual Information: 0.3123
Adjusted Mutual Information: 0.3701
Normalized Mutual Information: 0.3753
```

In [27]:
```python
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

Out[27]:
```
[<matplotlib.lines.Line2D at 0x7f0d45641700>]
```



In [28]:
```python
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
```

```
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.3383490904961073
Calinski Harabasz Score:  403.26070549187233
Davies Bouldin Score:  0.9782372259014865

Cohesion Score: 0.04755509895877542
Separation Score: 0.08940774410774412
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a future version this will reduce over both axes and return a scalar. To retain the old behavior, pass axis=0 (or do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

WINE DATASET

In [29]:

```
pip install ucimlrepo
```

```
Collecting ucimlrepo
  Downloading ucimlrepo-0.0.7-py3-none-any.whl.metadata (5.5 kB)
Requirement already satisfied: pandas>=1.0.0 in /usr/local/lib/python3.12/dist-packages (from ucimlrepo) (2.2.2)
Requirement already satisfied: certifi>=2020.12.5 in /usr/local/lib/python3.12/dist-packages (from ucimlrepo) (2025.10.5)
Requirement already satisfied: numpy>=1.26.0 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0->ucimlrepo) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0->ucimlrepo) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0->ucimlrepo) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0->ucimlrepo) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.8.2->pandas>=1.0.0->ucimlrepo) (1.17.0)
Downloading ucimlrepo-0.0.7-py3-none-any.whl (8.0 kB)
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.7
```

In [30]:

```
from ucimlrepo import fetch_ucirepo
```

```python
# fetch dataset
wine = fetch_ucirepo(id=109)

# data (as pandas dataframes)
X = wine.data.features
y = wine.data.targets

# metadata
print(wine.metadata)

# variable information
print(wine.variables)
df = X.copy()
df['class'] = y  # add target column
print(df.head())
```

{'uci_id': 109, 'name': 'Wine', 'repository_url': 'https://archive.ics.uci.edu/
dataset/109/wine', 'data_url': 'https://archive.ics.uci.edu/static/public/109/d
ata.csv', 'abstract': 'Using chemical analysis to determine the origin of wine
s', 'area': 'Physics and Chemistry', 'tasks': ['Classification'], 'characterist
ics': ['Tabular'], 'num_instances': 178, 'num_features': 13, 'feature_types':
['Integer', 'Real'], 'demographics': [], 'target_col': ['class'], 'index_col':
None, 'has_missing_values': 'no', 'missing_values_symbol': None, 'year_of_datas
et_creation': 1992, 'last_updated': 'Mon Aug 28 2023', 'dataset_doi': '10.2443
2/C5PC7J', 'creators': ['Stefan Aeberhard', 'M. Forina'], 'intro_paper': {'ID':
246, 'type': 'NATIVE', 'title': 'Comparative analysis of statistical pattern re
cognition methods in high dimensional settings', 'authors': 'S. Aeberhard, D. C
oomans, O. Vel', 'venue': 'Pattern Recognition', 'year': 1994, 'journal': None,
'DOI': '10.1016/0031-3203(94)90145-7', 'URL': 'https://www.semanticscholar.org/
paper/83dc3e4030d7b9fbdbb4bde03ce12ab70ca10528', 'sha': None, 'corpus': None,
'arxiv': None, 'mag': None, 'acl': None, 'pmid': None, 'pmcid': None}, 'additio
nal_info': {'summary': 'These data are the results of a chemical analysis of wi
nes grown in the same region in Italy but derived from three different cultivar
s. The analysis determined the quantities of 13 constituents found in each of t
he three types of wines. \r\n\r\nI think that the initial data set had around 3
0 variables, but for some reason I only have the 13 dimensional version. I had
a list of what the 30 or so variables were, but a.) I lost it, and b.), I woul
d not know which 13 variables are included in the set.\r\n\r\nThe attributes ar
e (dontated by Riccardo Leardi, riclea@anchem.unige.it)\r\n1) Alcohol\r\n2) Ma
lic acid\r\n3) Ash\r\n4) Alcalinity of ash \r\n5) Magnesium\r\n6) Total phenol
s\r\n7) Flavanoids\r\n8) Nonflavanoid phenols\r\n9) Proanthocyanins\r\n10)Color
intensity\r\n11)Hue\r\n12)OD280/OD315 of diluted wines\r\n13)Proline \r\n\r\nIn
a classification context, this is a well posed problem with "well behaved" clas
s structures. A good data set for first testing of a new classifier, but not ve
ry challenging.   ', 'purpose': 'test', 'funded_by': None, 'instances_r
epresent': None, 'recommended_data_splits': None, 'sensitive_data': None, 'prep
rocessing_description': None, 'variable_info': 'All attributes are continuous\
r\n\t\r\nNo statistics available, but suggest to standardise variables for cert
ain uses (e.g. for us with classifiers which are NOT scale invariant)\r\n\r\nNO
TE: 1st attribute is class identifier (1-3)', 'citation': None}}
```
                            name     role         type demographic  \
0                          class   Target  Categorical        None
1                        Alcohol  Feature   Continuous        None
2                      Malicacid  Feature   Continuous        None
3                            Ash  Feature   Continuous        None
4              Alcalinity_of_ash  Feature   Continuous        None
5                      Magnesium  Feature      Integer        None
6                  Total_phenols  Feature   Continuous        None
7                     Flavanoids  Feature   Continuous        None
8           Nonflavanoid_phenols  Feature   Continuous        None
9                Proanthocyanins  Feature   Continuous        None
10               Color_intensity  Feature   Continuous        None
11                           Hue  Feature   Continuous        None
12  0D280_0D315_of_diluted_wines  Feature   Continuous        None
13                       Proline  Feature      Integer        None

   description units missing_values
0         None  None             no
1         None  None             no
2         None  None             no
```

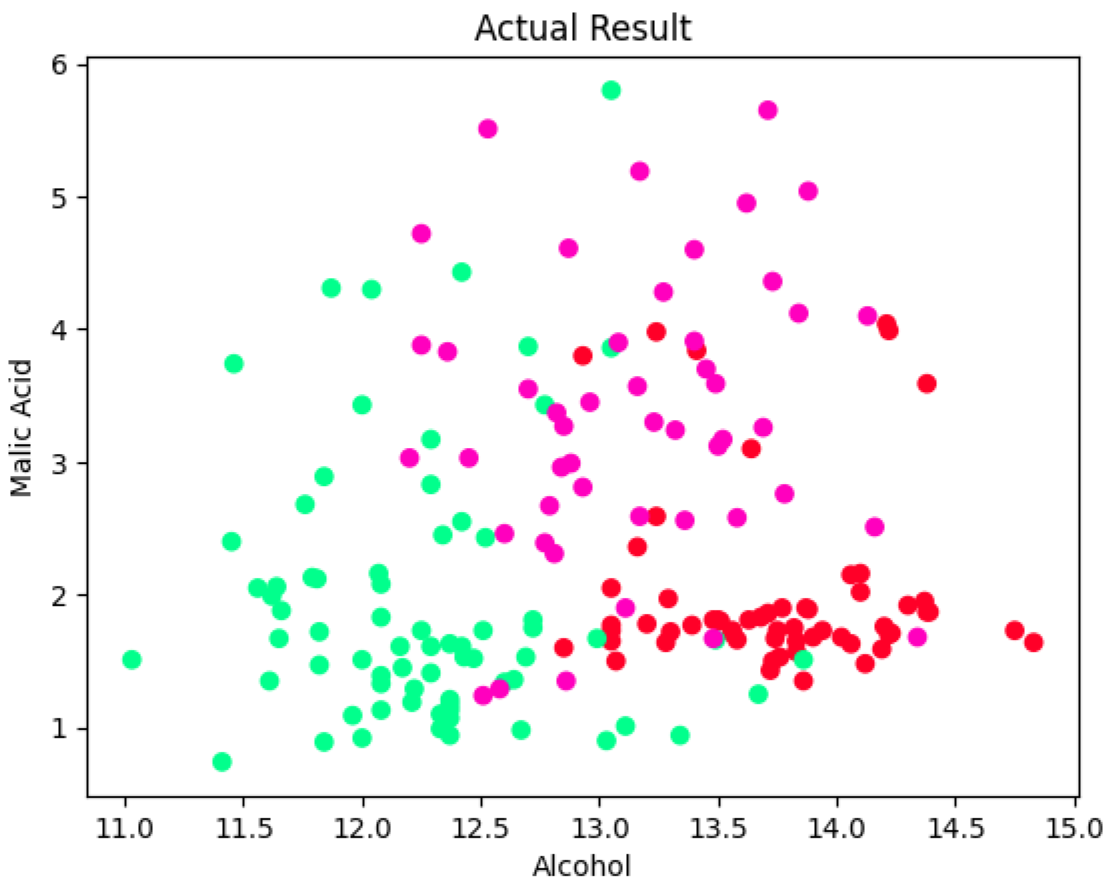
```
3         None  None             no
4         None  None             no
5         None  None             no
6         None  None             no
7         None  None             no
8         None  None             no
9         None  None             no
10        None  None             no
11        None  None             no
12        None  None             no
13        None  None             no
   Alcohol  Malicacid   Ash  Alcalinity_of_ash  Magnesium  Total_phenols  \
0    14.23       1.71  2.43               15.6        127           2.80
1    13.20       1.78  2.14               11.2        100           2.65
2    13.16       2.36  2.67               18.6        101           2.80
3    14.37       1.95  2.50               16.8        113           3.85
4    13.24       2.59  2.87               21.0        118           2.80

   Flavanoids  Nonflavanoid_phenols  Proanthocyanins  Color_intensity   Hue  \
0        3.06                  0.28             2.29             5.64  1.04
1        2.76                  0.26             1.28             4.38  1.05
2        3.24                  0.30             2.81             5.68  1.03
3        3.49                  0.24             2.18             7.80  0.86
4        2.69                  0.39             1.82             4.32  1.04

   0D280_0D315_of_diluted_wines  Proline  class
0                          3.92     1065      1
1                          3.40     1050      1
2                          3.17     1185      1
3                          3.45     1480      1
4                          2.93      735      1
```

In [31]:

```
plt.title("Actual Result")
plt.xlabel('Alcohol')
plt.ylabel('Malic Acid')
plt.scatter(df.Alcohol, df.Malicacid, c=df["class"],
cmap='gist_rainbow')
```

Out[31]:

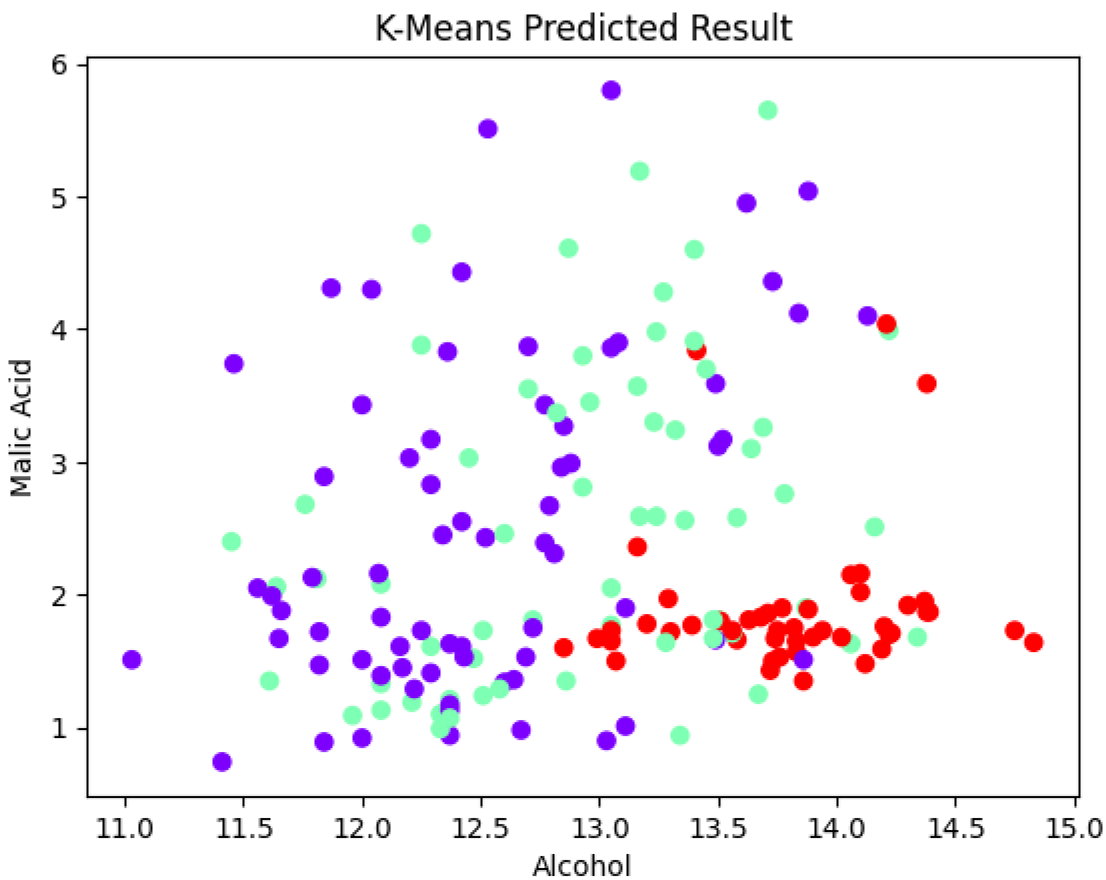
```
<matplotlib.collections.PathCollection at 0x7f0d455177d0>
```



Partition Based: K-means Clustering in Wine Dataset

In [32]:

```
# Clustering using K-means algorithm
from sklearn.cluster import KMeans
km = KMeans(init="random", n_clusters=3, n_init=10, max_iter=300,
random_state=42)
y_predicted = km.fit_predict(X)
plt.title("K-Means Predicted Result")
plt.xlabel("Alcohol")
plt.ylabel("Malic Acid")
plt.scatter(df.Alcohol, df.Malicacid, c=km.labels_, cmap='rainbow')
plt.show()
```



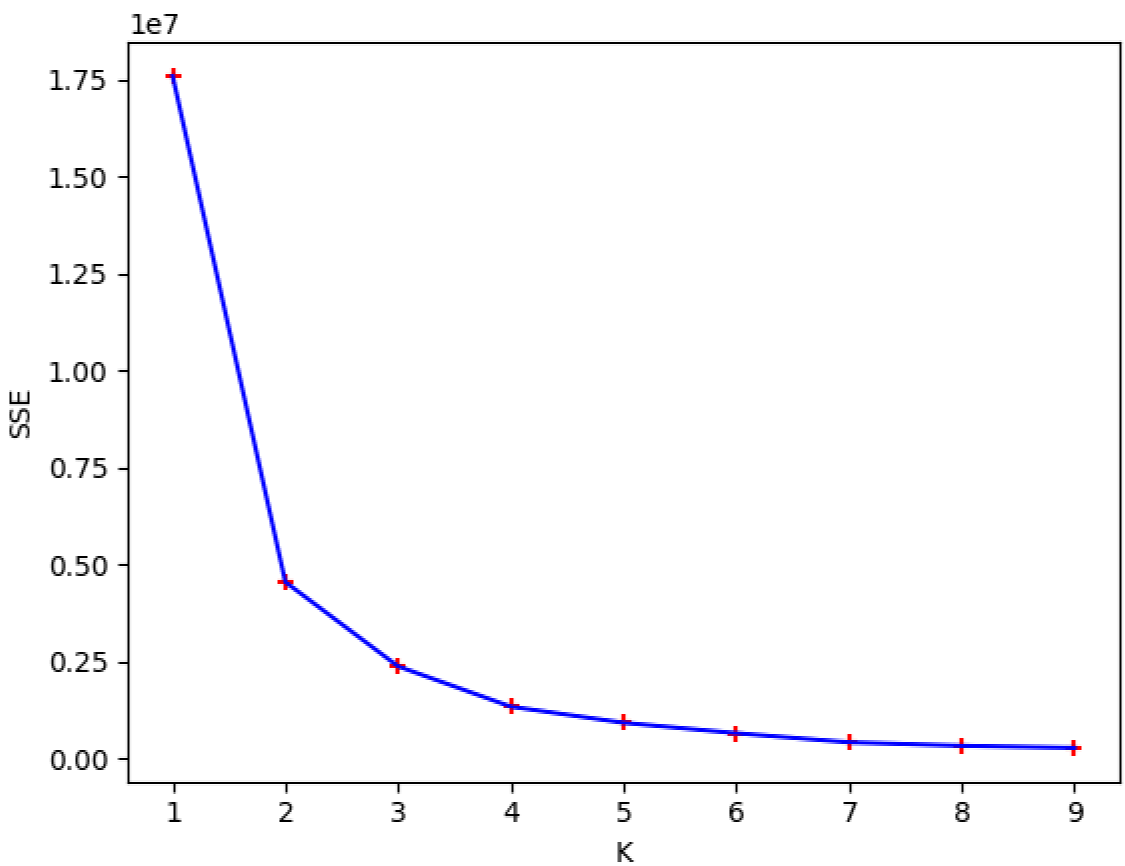
In [33]:

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels (numeric for Wine dataset)
y_true = df['class']

# Predicted cluster labels from K-Means
y_pred = km.labels_  # or y_predicted

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7187
Adjusted Rand Index: 0.3711
Mutual Information: 0.4657
Adjusted Mutual Information: 0.4227
Normalized Mutual Information: 0.4288
```

In [34]:
```python
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

Out[34]: `[<matplotlib.lines.Line2D at 0x7f0d456d77d0>]`



In [35]:
```python
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
```

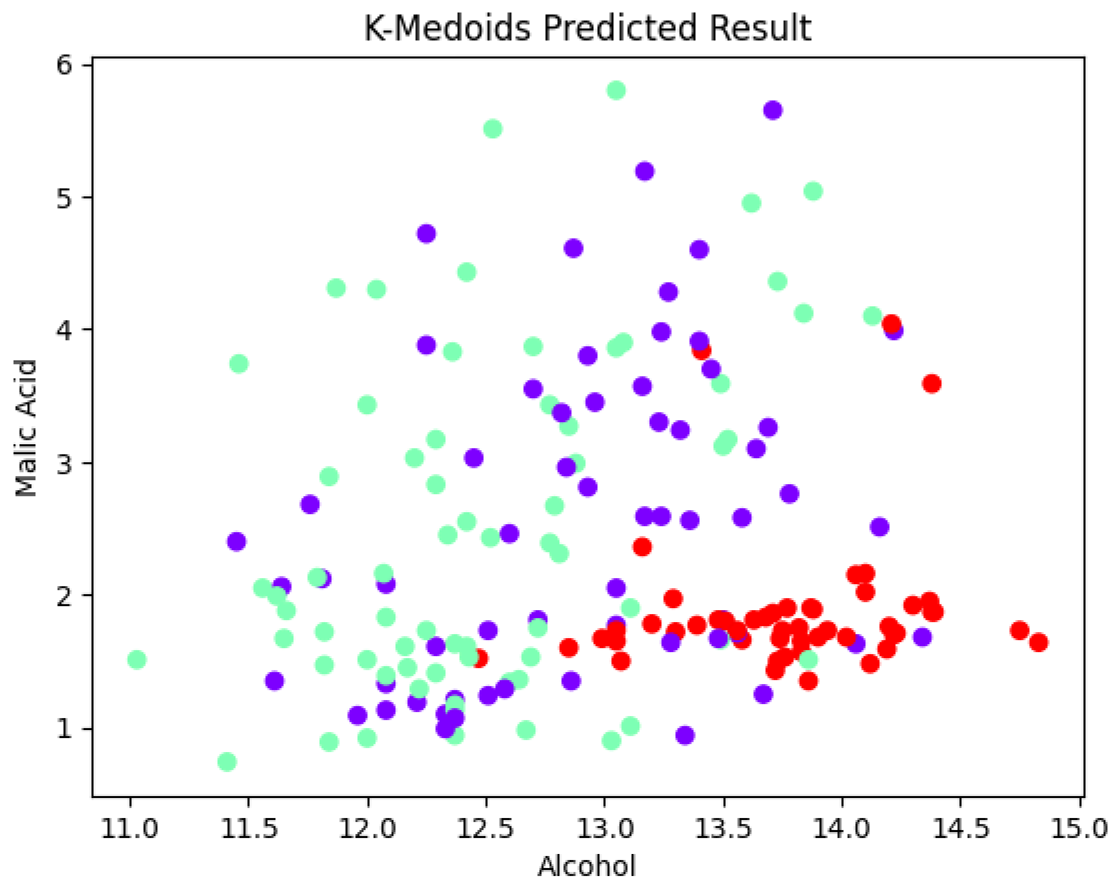
```
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.527941546551372
Calinski Harabasz Score:  1354.5160325267275
Davies Bouldin Score:  0.5307163453404704

Cohesion Score: 116.74835625456451
Separation Score: 578.7648547517636
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86: FutureWar
ning: The behavior of DataFrame.sum with axis=None is deprecated, in a future v
ersion this will reduce over both axes and return a scalar. To retain the old b
ehavior, pass axis=0 (or do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

Partition Based: K-medoids Clustering in Wine Dataset

In [36]:
```
# Clustering using K-medoids algorithm
from sklearn_extra.cluster import KMedoids
km = KMedoids(n_clusters=3)
y_predicted = km.fit_predict(X)
plt.title("K-Medoids Predicted Result")
plt.xlabel("Alcohol")
plt.ylabel("Malic Acid")
plt.scatter(df.Alcohol, df.Malicacid, c=km.labels_, cmap='rainbow')
plt.show()
```



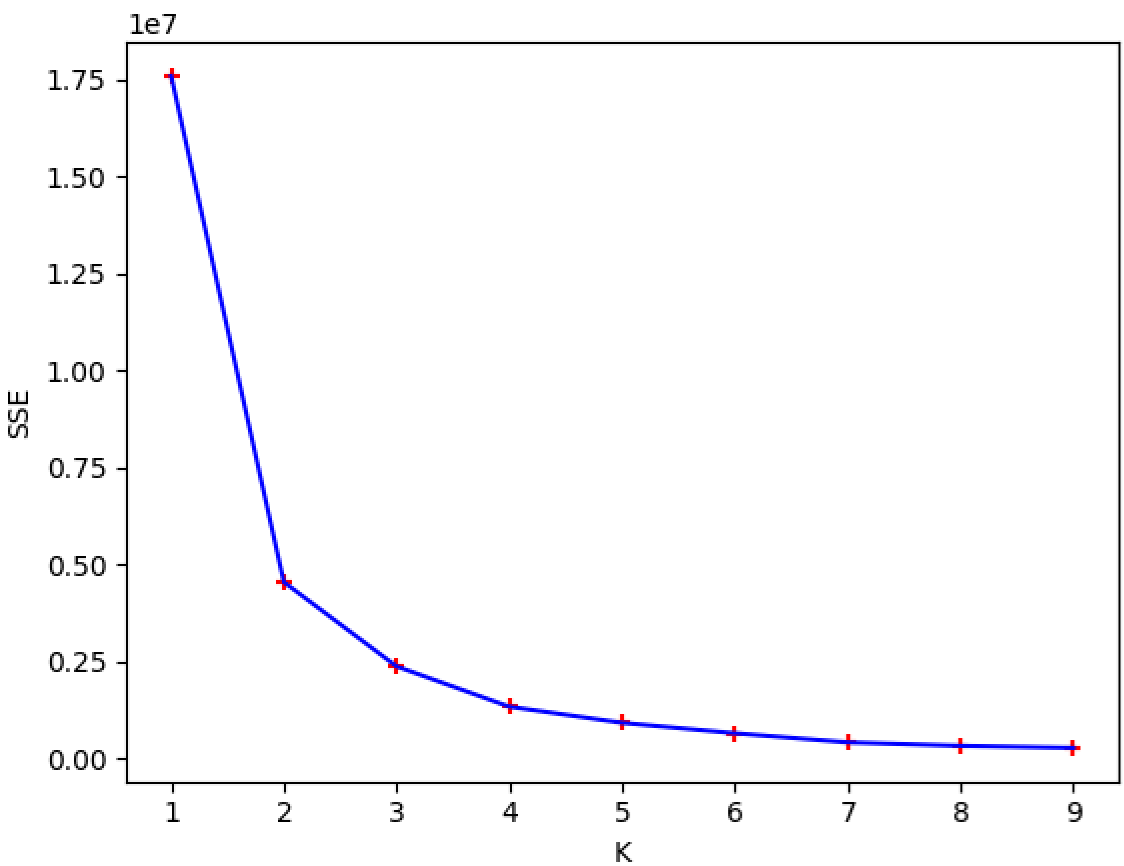
In [37]:

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels (numeric)
y_true = df['class']

# Predicted cluster labels from K-Medoids
y_pred = km.labels_  # or y_predicted

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7295
Adjusted Rand Index: 0.3941
Mutual Information: 0.4737
Adjusted Mutual Information: 0.4292
Normalized Mutual Information: 0.4352
```

In [38]:
```
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

Out[38]:
```
[<matplotlib.lines.Line2D at 0x7f0d45599700>]
```



In [39]:
```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
```

```python
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

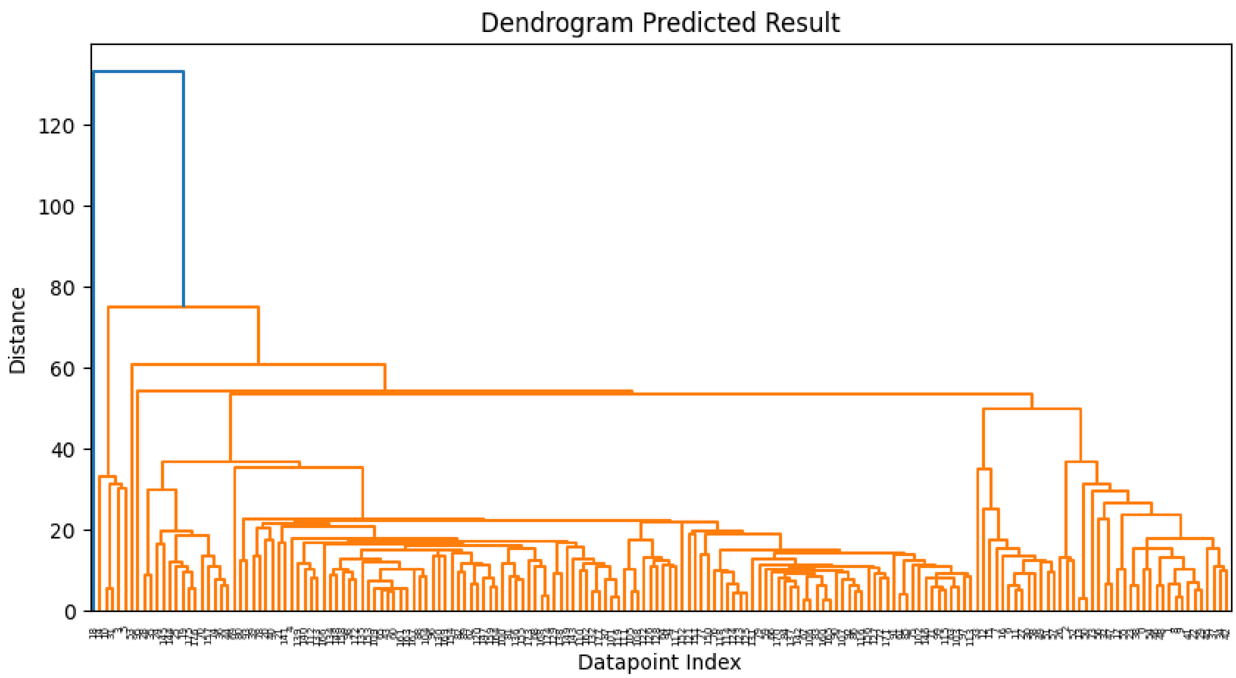
```
Silhouette Score:  0.525162492111064
Calinski Harabasz Score:  1348.7425198414976
Davies Bouldin Score:  0.5341503098266895

Cohesion Score: 117.24040976050752
Separation Score: 528.602659988967
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86: FutureWar
ning: The behavior of DataFrame.sum with axis=None is deprecated, in a future v
ersion this will reduce over both axes and return a scalar. To retain the old b
ehavior, pass axis=0 (or do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

Hierarchical: Dendrogram Clustering in Wine Dataset

In [40]:

```python
# Clustering using Dendrogram Clustering algorithm
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
Z = linkage(X, method='single')
# Create and plot the dendrogram
plt.figure(figsize=(10, 5))
dn = dendrogram(Z)
plt.title('Dendrogram Predicted Result')
plt.xlabel('Datapoint Index')
plt.ylabel('Distance')
plt.show()
```



In [41]:
```
from scipy.cluster.hierarchy import fcluster
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# Cut dendrogram to form 3 clusters
y_pred = fcluster(Z, t=3, criterion='maxclust')

# True labels (numeric)
y_true = df['class']

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.3628
Adjusted Rand Index: 0.0054
Mutual Information: 0.0384
Adjusted Mutual Information: 0.0416
Normalized Mutual Information: 0.0615
```

In [42]:
```
# Evaluating Metrics
```

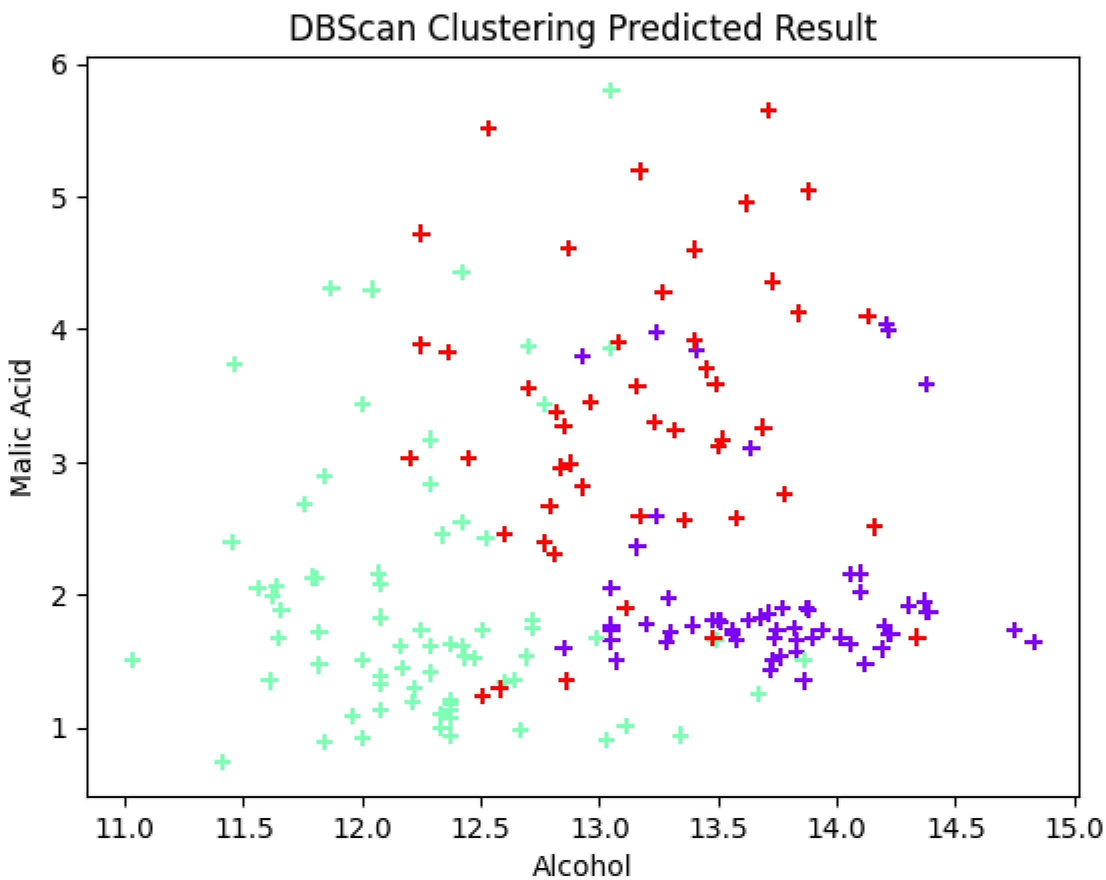
```
labels = fcluster(Z, 3, criterion='maxclust')
from sklearn.metrics import silhouette_score
silhouette_result = silhouette_score(X, labels)
print("Silhouette Score: ", silhouette_result)
from sklearn.metrics import calinski_harabasz_score
calinski_result = calinski_harabasz_score(X, labels)
print("Calinski Harabasz Score: ", calinski_result)
from sklearn.metrics import davies_bouldin_score
davies_result = davies_bouldin_score(X, labels)
print("Davies Bouldin Score: ", davies_result)
```

```
Silhouette Score:  0.4879820335189063
Calinski Harabasz Score:  24.42036238154286
Davies Bouldin Score:  0.30814096183494405
```

Density Based: DBSCAN Clustering in Wine Dataset

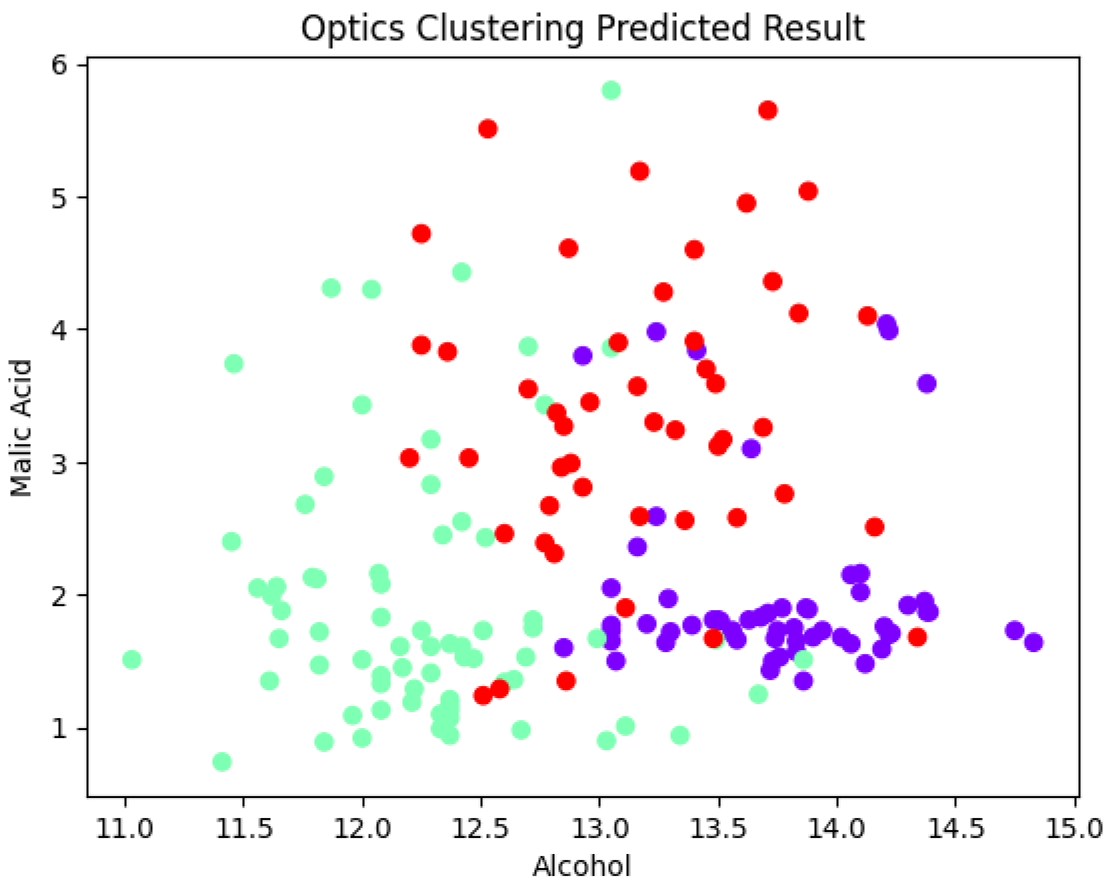
In [43]:

```
# Clustering using DBSCAN Clustering algorithm
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps=0.5, algorithm='auto', metric='euclidean')
y = dbscan.fit_predict(X)
plt.title('DBScan Clustering Predicted Result')
plt.xlabel('Alcohol')
plt.ylabel('Malic Acid')
plt.scatter(df.Alcohol, df.Malicacid, c=df["class"], cmap='rainbow',
marker="+")
plt.show()
```



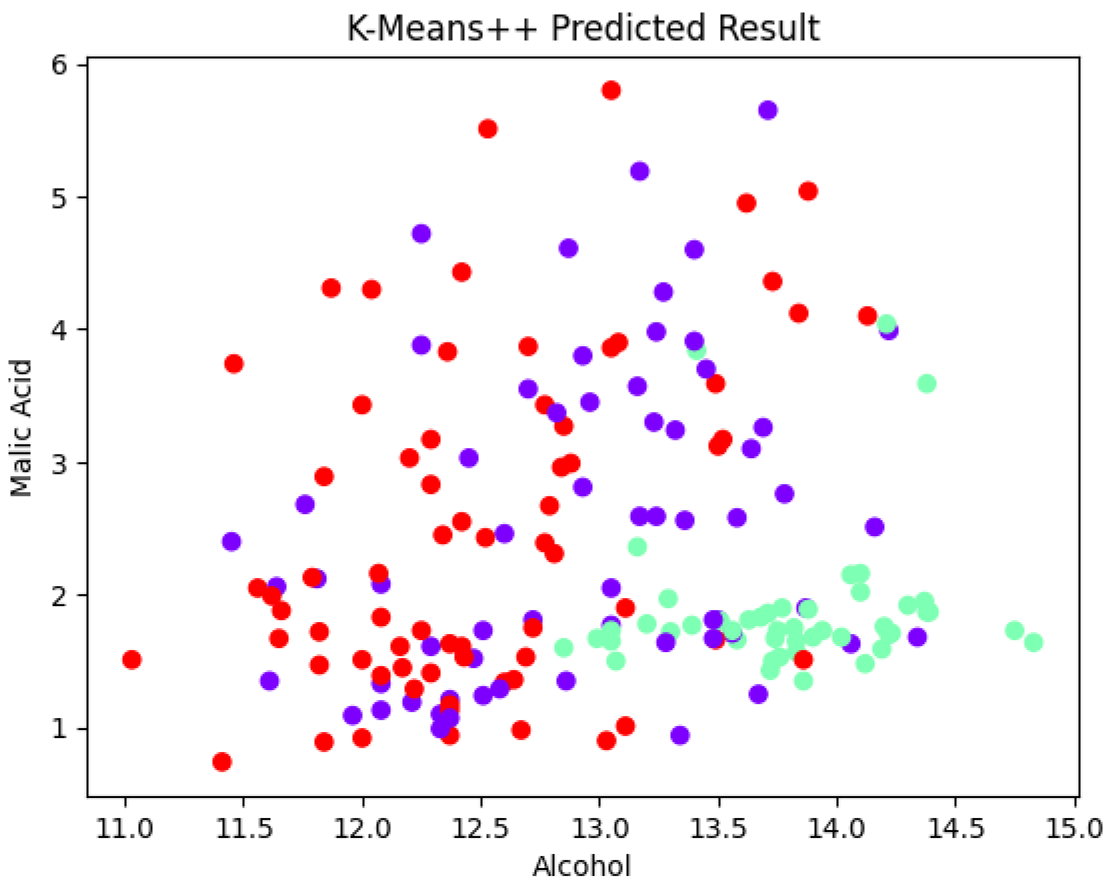
Density Based: Optics Clustering in Wine Dataset

In [44]:
```
# Clustering using Optics Clustering algorithm
from sklearn.cluster import OPTICS
optics_cluster = OPTICS(min_samples=5, xi=0.05,
cluster_method='dbscan')
optics_cluster.fit(X)
plt.scatter(df.Alcohol, df.Malicacid, c=df["class"], cmap='rainbow')
plt.xlabel('Alcohol')
plt.ylabel('Malic Acid')
plt.title('Optics Clustering Predicted Result')
plt.show()
```



K-means++ Clustering in Wine Dataset

In [45]:
```
# Clustering using K-means++ algorithm
from sklearn.cluster import KMeans
km = KMeans(init='k-means++', n_clusters=3, n_init=10, max_iter=300,
random_state=42)
km = KMeans(n_clusters=3, n_init=10)
y_predicted = km.fit_predict(X)
plt.title("K-Means++ Predicted Result")
plt.xlabel("Alcohol")
plt.ylabel("Malic Acid")
plt.scatter(df.Alcohol, df.Malicacid, c=km.labels_, cmap='rainbow')
plt.show()
```

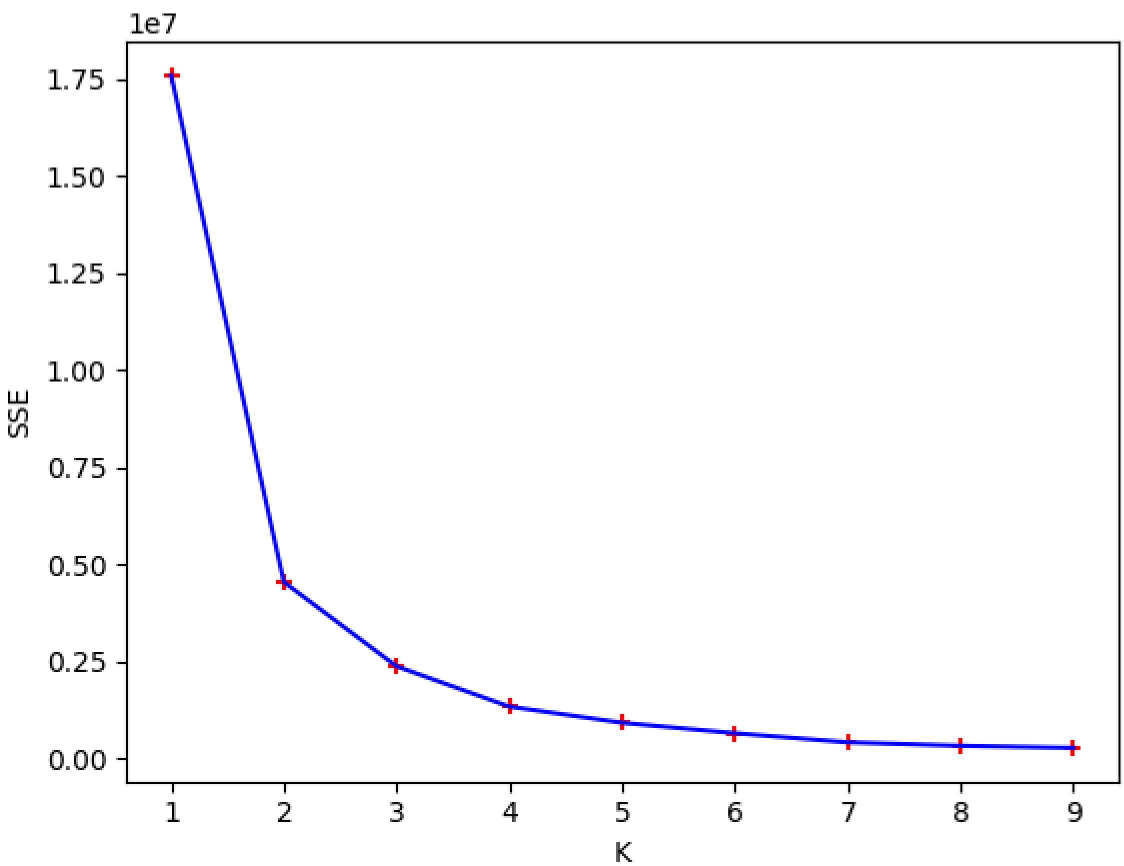


In [46]:
```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels
y_true = df['class']

# Predicted cluster labels from K-Means++
y_pred = km.labels_  # or y_predicted

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7187
Adjusted Rand Index: 0.3711
Mutual Information: 0.4657
Adjusted Mutual Information: 0.4227
Normalized Mutual Information: 0.4288
```

In [47]:
```
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

Out[47]: `[<matplotlib.lines.Line2D at 0x7f0d449c5460>]`



In [48]:
```
# Evaluating Metrics
from sklearn.metrics import silhouette_score
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
from sklearn.metrics import calinski_harabasz_score
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
```

```
from sklearn.metrics import davies_bouldin_score
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

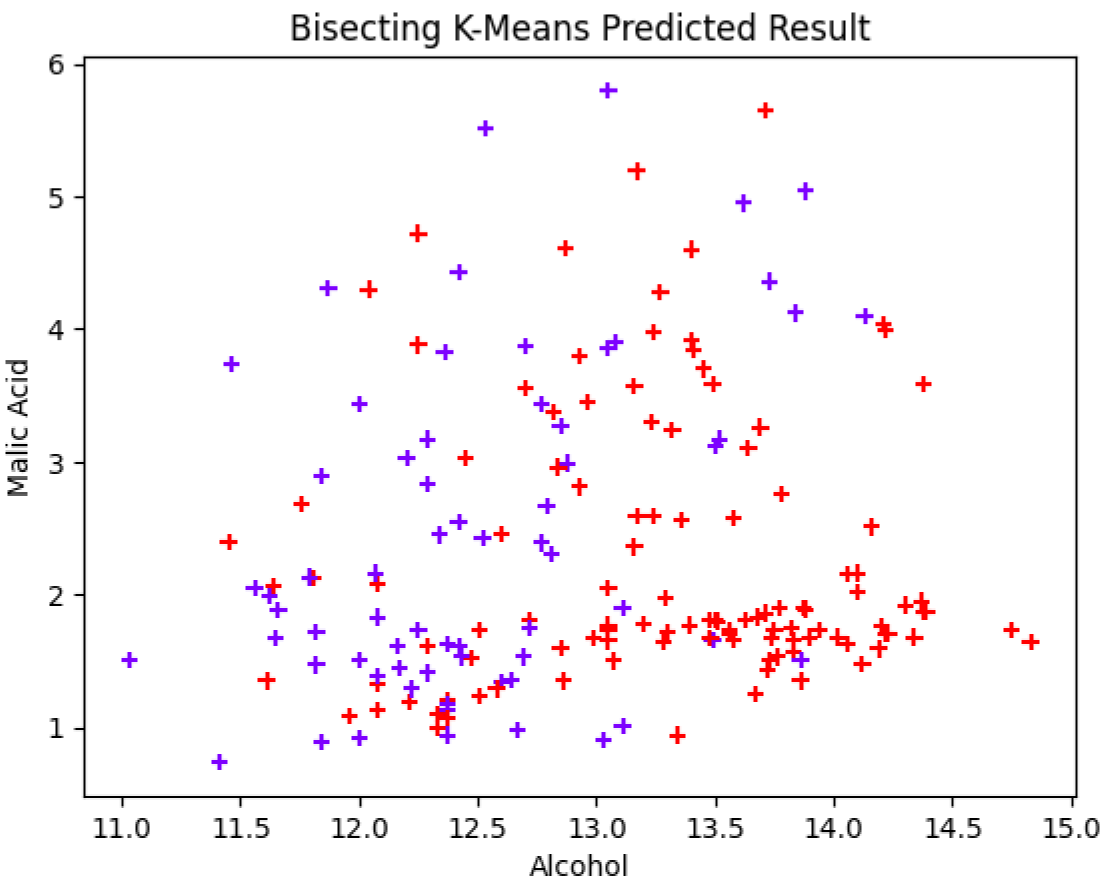
```
Silhouette Score:  0.527941546551372
Calinski Harabasz Score:  1354.5160325267275
Davies Bouldin Score:  0.5307163453404704

Cohesion Score: 116.74835625456451
Separation Score: 450.6268925871702
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86: FutureWar
ning: The behavior of DataFrame.sum with axis=None is deprecated, in a future v
ersion this will reduce over both axes and return a scalar. To retain the old b
ehavior, pass axis=0 (or do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

Bisecting K-means Clustering in Wine Dataset

In [49]:

```
# Clustering using Bisecting K-means algorithm
from sklearn.cluster import KMeans
km = KMeans(n_clusters=1, n_init=10, random_state=0).fit(X)
K=3
for i in range(K-1):
 largest_cluster = np.argmax(np.bincount(km.labels_))
 largest_cluster_mask = (km.labels_ == largest_cluster)
 X_split = X[largest_cluster_mask]
 km.labels_[largest_cluster_mask] = KMeans(n_clusters=2, n_init=10,
random_state=0).fit(X_split).labels_
plt.title("Bisecting K-Means Predicted Result")
plt.xlabel("Alcohol")
plt.ylabel("Malic Acid")
plt.scatter(df.Alcohol, df.Malicacid, c=km.labels_, cmap='rainbow',
marker="+")
plt.show()
```



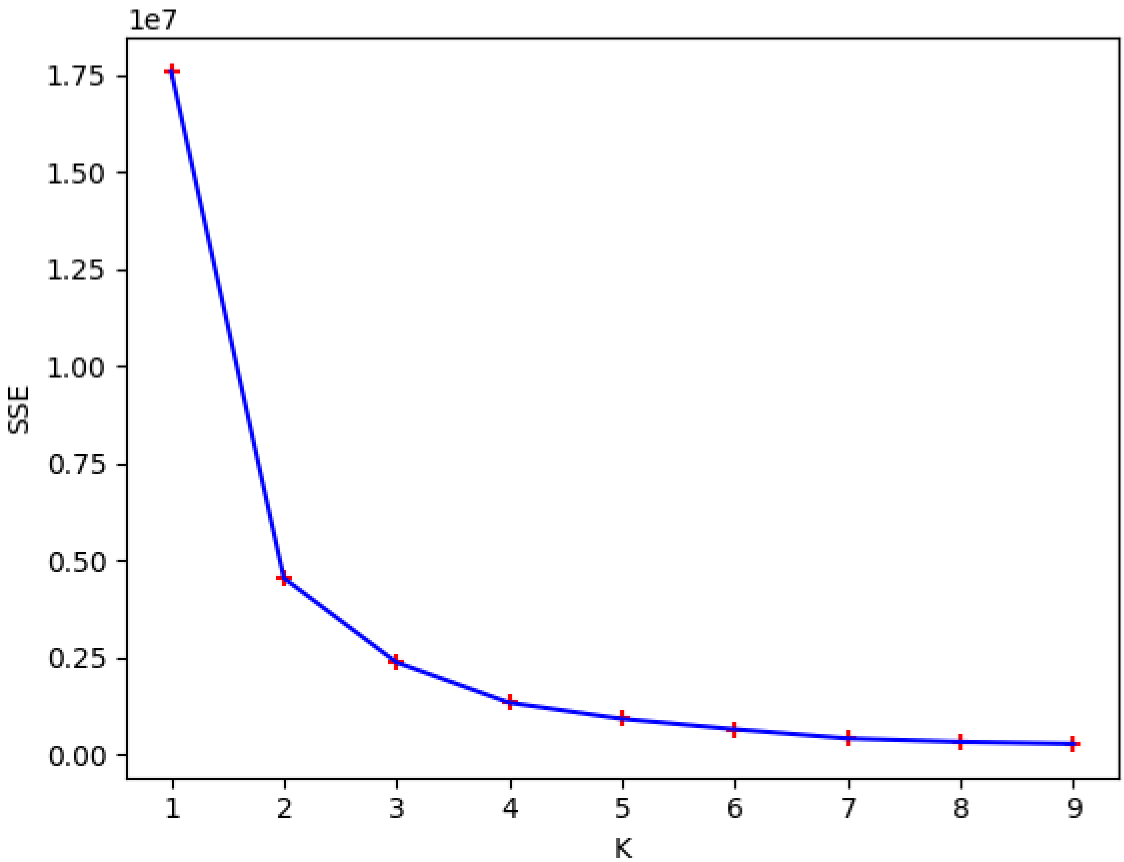
In [50]:

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score, adjusted_mutual_info_score, nor

# True labels
y_true = df['class']

# Predicted cluster labels from Bisecting K-Means
y_pred = km.labels_

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.6034
Adjusted Rand Index: 0.2224
Mutual Information: 0.2372
Adjusted Mutual Information: 0.2670
Normalized Mutual Information: 0.2718
```

In [51]:
```
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

Out[51]: `[<matplotlib.lines.Line2D at 0x7f0d447df7d0>]`



In [52]:
```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
```

```python
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.5382358200331198
Calinski Harabasz Score:  1340.298246818952
Davies Bouldin Score:  0.5274536247334654

Cohesion Score: 117.96759730604572
Separation Score: 603.9396433701444
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86: FutureWar
ning: The behavior of DataFrame.sum with axis=None is deprecated, in a future v
ersion this will reduce over both axes and return a scalar. To retain the old b
ehavior, pass axis=0 (or do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```