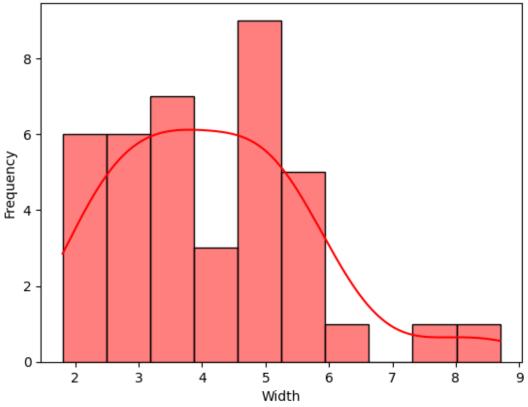
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn.preprocessing import StandardScaler
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.linear model import LinearRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
# Load dataset
file path = "/content/dataset.xlsx"
df = pd.read excel(file path, sheet name="Sheet1")
print(df)
    Sno width
                Length
0
           3.7
                   19.4
      1
1
      2
           2.9
                   15.3
2
      3
           3.9
                  22.6
3
      4
           2.2
                  18.3
4
      5
           3.0
                  19.3
5
      6
           2.3
                  11.5
6
      7
           2.4
                  11.7
7
      8
           3.4
                  22.7
8
      9
           2.3
                  13.4
9
     10
           1.8
                  10.7
10
           3.1
     11
                  19.7
11
     12
           2.5
                  16.5
12
           2.2
     13
                  13.2
13
     14
           3.6
                  19.7
14
     15
           3.6
                  20.5
15
           5.0
                  14.5
     16
16
     17
           4.6
                  12.5
17
     18
           5.1
                  13.2
18
     19
           3.8
                  11.0
19
     20
           5.4
                  12.2
20
     21
           3.4
                  8.7
21
     22
           4.6
                  10.2
22
     23
           3.0
                   6.7
23
     24
           4.8
                  12.2
24
     25
           5.6
                  14.3
25
     26
           4.8
                  11.0
26
     27
           2.7
                  11.7
27
     28
           4.6
                  18.0
28
     29
           4.5
                  16.2
29
     30
           5.2
                  18.7
30
     31
           3.8
                   15.2
```

```
31
     32
            4.8
                    9.0
32
     33
            5.6
                   10.0
            6.4
33
     34
                   11.0
            5.8
34
     35
                   10.8
35
     36
            4.0
                   8.5
36
            7.8
                   16.3
     37
37
     38
            5.8
                    9.7
38
     39
            8.7
                   13.5
```

Histogram between L&W

```
# Histogram with KDE of Width
sns.histplot(df['width'], bins=10, kde=True, color='red',
edgecolor='black', alpha=0.5)
# Labels and title
plt.xlabel('Width')
plt.ylabel('Frequency')
plt.title('Histogram of Width with KDE of Width')
plt.show()
```

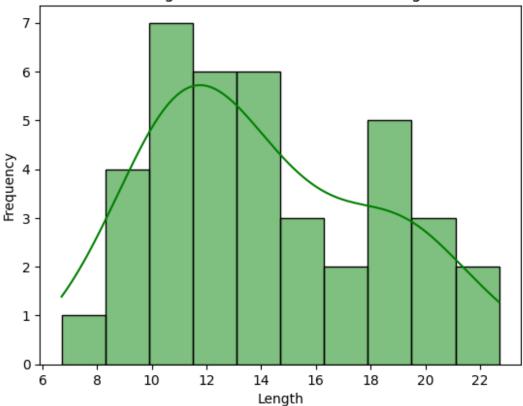
Histogram of Width with KDE of Width



```
# Histogram with KDE of Length
sns.histplot(df['Length'], bins=10, kde=True, color='green',
```

```
edgecolor='black', alpha=0.5)
# Labels and title
plt.xlabel('Length')
plt.ylabel('Frequency')
plt.title('Histogram of Width with KDE of Length')
plt.show()
```

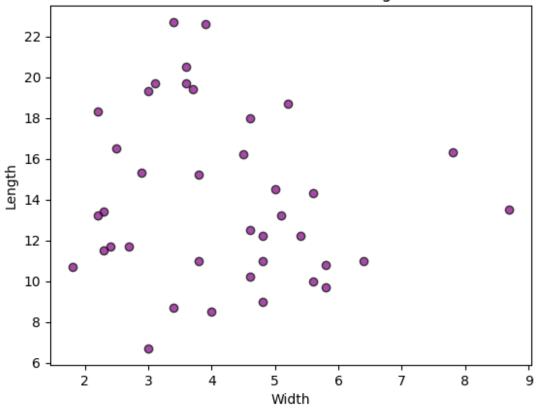
Histogram of Width with KDE of Length



Scatter plot

```
# Scatter Plot of Width vs Length
plt.figure()
plt.scatter(df['width'], df['Length'], color='purple', alpha=0.7,
edgecolors='k')
plt.xlabel('Width')
plt.ylabel('Length')
plt.title('Scatter Plot: Width vs Length')
plt.show()
```

Scatter Plot: Width vs Length

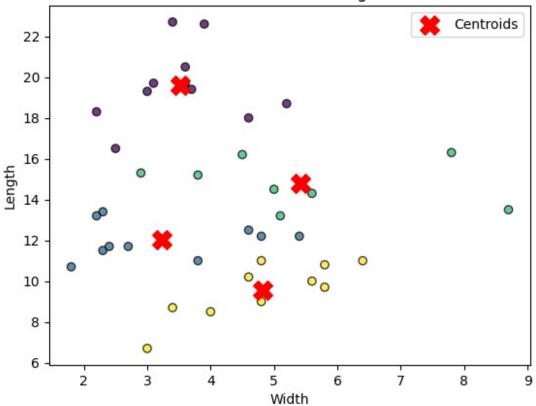


Clustering

```
# Clustering (K-Means)
X_cluster = df[['width', 'Length']]
kmeans = KMeans(n_clusters=4, random_state=42, n_init=10)
df['Cluster'] = kmeans.fit_predict(X_cluster)

plt.scatter(df['width'], df['Length'], c=df['Cluster'],
cmap='viridis', edgecolors='k', alpha=0.75)
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,
1], c='red', marker='X', s=200, label='Centroids')
plt.xlabel('Width')
plt.ylabel('Length')
plt.title('K-Means Clustering')
plt.legend()
plt.show()
```

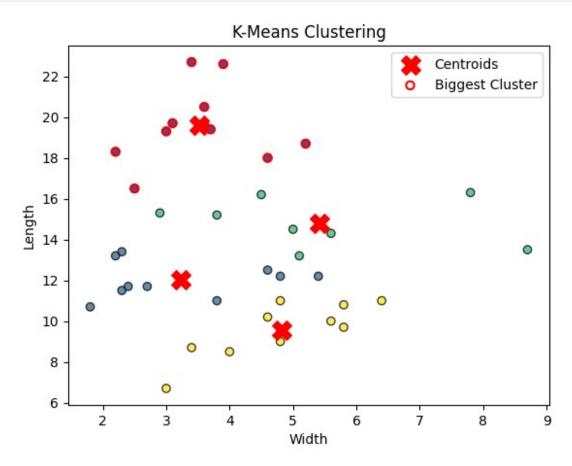




```
# Find the largest cluster
cluster sizes = df['Cluster'].value counts()
biggest cluster = cluster sizes.idxmax()
biggest cluster size = cluster sizes.max()
print(f"Biggest Cluster: {biggest cluster} with {biggest cluster size}
points")
# Plotting
plt.scatter(df['width'], df['Length'], c=df['Cluster'],
cmap='viridis', edgecolors='k', alpha=0.75)
plt.scatter(kmeans.cluster centers [:, 0], kmeans.cluster centers [:,
1], c='red', marker='X', s=200, label='Centroids')
# Highlight the biggest cluster
biggest cluster points = df[df['Cluster'] == biggest cluster]
plt.scatter(biggest cluster points['width'],
biggest cluster points['Length'],
            edgecolors='red', facecolors='none', linewidths=1.5,
label='Biggest Cluster')
plt.xlabel('Width')
plt.ylabel('Length')
```

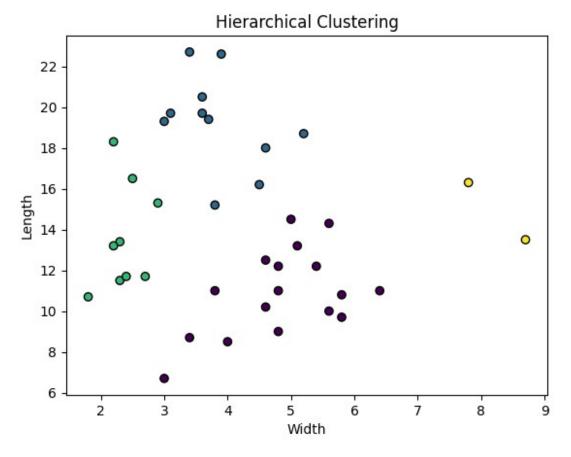
```
plt.title('K-Means Clustering')
plt.legend()
plt.show()

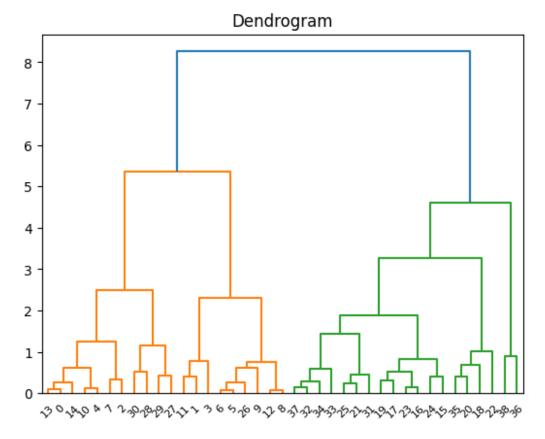
Biggest Cluster: 0 with 11 points
```



```
# Hierarchical Clustering
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_cluster)
# Perform hierarchical clustering
hierarchical_clustering = AgglomerativeClustering(n_clusters=4,
linkage='ward')
df['Hierarchical_Cluster'] =
hierarchical_clustering.fit_predict(X_scaled)

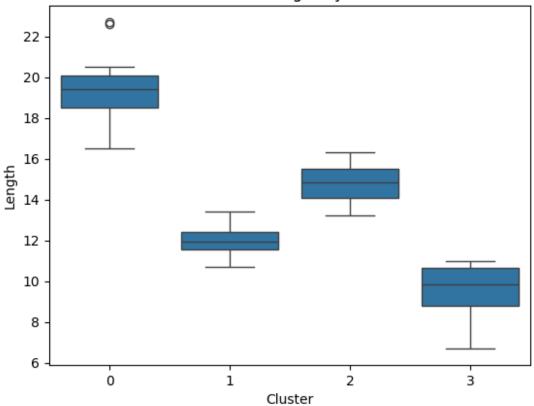
# Plot the results
plt.scatter(df['width'], df['Length'], c=df['Hierarchical_Cluster'],
cmap='viridis', edgecolors='k', alpha=1)
plt.xlabel('Width')
plt.ylabel('Length')
plt.title('Hierarchical Clustering')
plt.show()
```



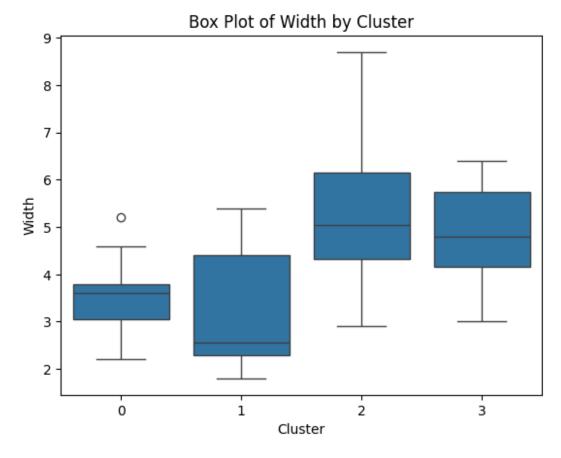


```
#Box plot of length by Cluster
sns.boxplot(x='Cluster', y='Length', data=df)
plt.title('Box Plot of Length by Cluster')
plt.xlabel('Cluster')
plt.ylabel('Length')
plt.show()
```

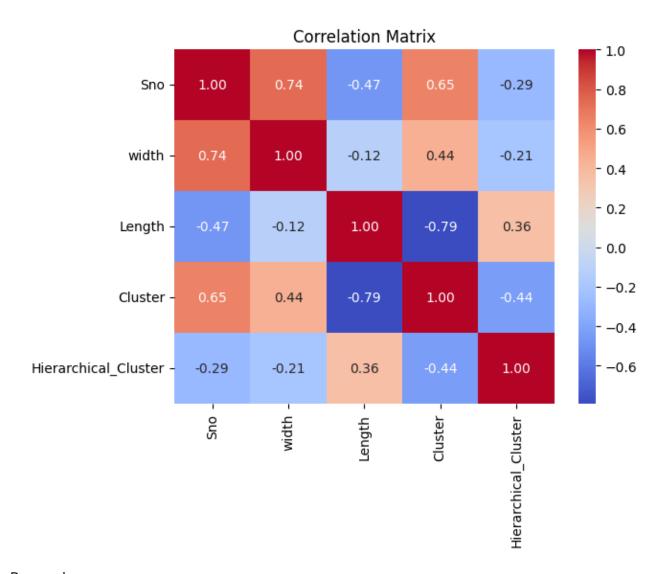
Box Plot of Length by Cluster



```
#Box plot of Width by Cluster
sns.boxplot(x='Cluster', y='width', data=df)
plt.title('Box Plot of Width by Cluster')
plt.xlabel('Cluster')
plt.ylabel('Width')
plt.show()
```



```
# Correlation Matrix
correlation_matrix = df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



Regression

```
#Linear Regression for biggest cluster
# Extract data for the biggest cluster
biggest_cluster_points = df[df['Cluster'] == biggest_cluster]

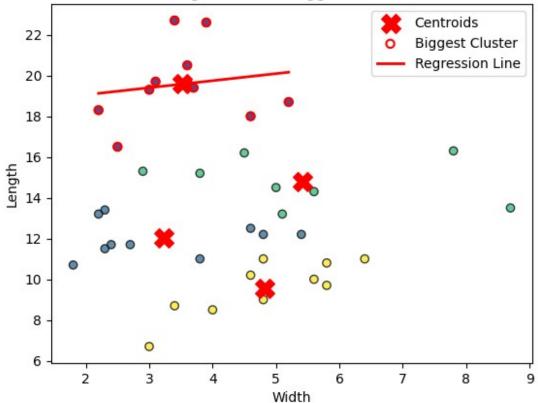
# Fit a linear regression model
X = biggest_cluster_points[['width']].values # Independent variable
y = biggest_cluster_points['Length'].values # Dependent variable
regressor = LinearRegression()
regressor.fit(X, y)

# Predict values for regression line
x_range = np.linspace(X.min(), X.max(), 100).reshape(-1, 1)
y_pred = regressor.predict(x_range)

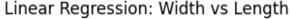
# Plot clusters
```

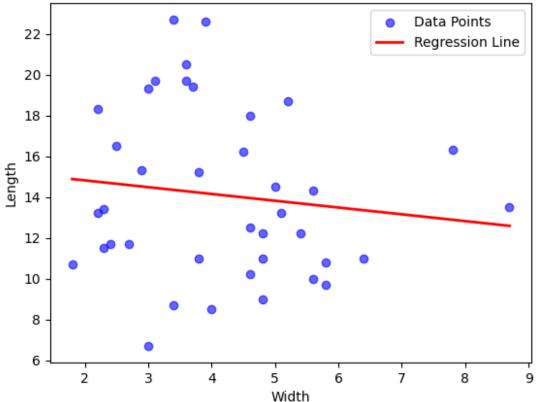
```
plt.scatter(df['width'], df['Length'], c=df['Cluster'],
cmap='viridis', edgecolors='k', alpha=0.75)
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,
1], c='red', marker='X', s=200, label='Centroids')
# Highlight the biggest cluster
plt.scatter(biggest_cluster_points['width'],
biggest cluster points['Length'],
            edgecolors='red', facecolors='none', linewidths=1.5,
label='Biggest Cluster')
# Plot regression line
plt.plot(x_range, y_pred, color='red', linewidth=2, label='Regression
Line')
# Labels and title
plt.xlabel('Width')
plt.ylabel('Length')
plt.title('Regression for Biggest Cluster')
plt.legend()
plt.show()
```

Regression for Biggest Cluster

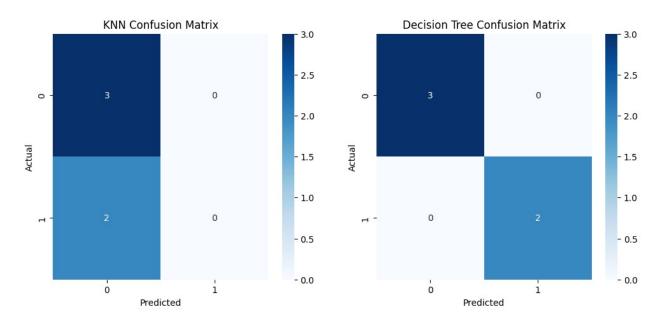


```
# Regression (Linear Regression on whole data)
X reg = df[['width']]
y_reg = df['Length']
reg model = LinearRegression()
reg model.fit(X reg, y reg)
X_{\text{range}} = \text{np.linspace}(\overline{X}_{\text{reg.min}}(), X_{\text{reg.max}}(), 100).\text{reshape}(-1, 1)
y pred = reg model.predict(X range)
plt.scatter(df['width'], df['Length'], color='blue', label='Data
Points', alpha=0.6)
plt.plot(X range, y pred, color='red', linewidth=2, label='Regression
Line')
plt.xlabel('Width')
plt.ylabel('Length')
plt.title('Linear Regression: Width vs Length')
plt.legend()
plt.show()
/usr/local/lib/python3.11/dist-packages/sklearn/utils/
validation.py:2739: UserWarning: X does not have valid feature names,
but LinearRegression was fitted with feature names
  warnings.warn(
```





```
# Given points and labels
X = np.array([[3, 19], [8, 16], [5, 13], [6, 9], [2, 11]])
y = np.array([0, 1, 0, 1, 0]) # Example labels (can be changed based
on problem context)
# Test point to classify
test point = np.array([[10, 10]])
# Method 1: K-Nearest Neighbors (KNN) with different k value
knn = KNeighborsClassifier(n neighbors=5)
knn.fit(X, y)
knn pred = knn.predict(X)
print(f"KNN Prediction for {test point[0]}: {knn.predict(test point)
[0]
KNN Prediction for [10 10]: 0
# Method 2: Decision Tree Classifier
dt = DecisionTreeClassifier()
dt.fit(X, y)
dt pred = dt.predict(X)
print(f"Decision Tree Prediction for {test point[0]}:
{dt.predict(test point)[0]}")
Decision Tree Prediction for [10 10]: 1
# Compute confusion matrices
knn cm = confusion matrix(y, knn pred)
dt cm = confusion matrix(y, dt pred)
# Plot confusion matrices
fig, axes = plt.subplots(\frac{1}{2}, figsize=(\frac{12}{5}))
sns.heatmap(knn_cm, annot=True, fmt='d', cmap='Blues', ax=axes[0])
axes[0].set title("KNN Confusion Matrix")
axes[0].set xlabel("Predicted")
axes[0].set ylabel("Actual")
sns.heatmap(dt cm, annot=True, fmt='d', cmap='Blues', ax=axes[1])
axes[1].set title("Decision Tree Confusion Matrix")
axes[1].set xlabel("Predicted")
axes[1].set ylabel("Actual")
plt.show()
```



```
# Visualization
plt.scatter(X[:, 0], X[:, 1], c=y, cmap='coolwarm', label='Training
Data')
plt.scatter(test_point[:, 0], test_point[:, 1], color='green',
marker='x', s=100, label='Test Point')
plt.xlabel("X1")
plt.ylabel("X2")
plt.legend()
plt.title("Classification using KNN and Decision Tree")
plt.show()
```



