Pistacho

To create a classification model for the Pistachio Dataset, you'll need to identify the most important features. These important features are the ones that significantly contribute to distinguishing between the classes in your dataset. The dataset consists of features related to shape, size, and geometry of the pistachio seeds.

Data Loading and Description

Here's how you can identify important features and select them:

Understanding the Features

1. AREA: The area of the pistachio seed.
2. PERIMETER: The perimeter of the seed.
3. MAJOR_AXIS: Length of the major axis of the seed.
4. MINOR_AXIS: Length of the minor axis of the seed.
5. ECCENTRICITY: A measure of how much the shape of the pistachio deviates from being circular.
6. EQDIASQ: Equivalent diameter, calculated from the area.
7. SOLIDITY: Ratio of the area to the convex area, indicating how solid or compact the shape is.
8. CONVEX_AREA: The area of the convex hull (the smallest convex shape that encloses the seed).
9. EXTENT: The ratio of the area of the seed to the bounding box.
10. ASPECT_RATIO: Ratio of the major axis to the minor axis.
11. ROUNDNESS: A measure of how circular the shape is.
12. COMPACTNESS: A measure of how compact or closely packed the shape is.
13. SHAPEFACTOR_1 to SHAPEFACTOR_4: Various shape factors indicating different shape characteristics.
14. Class: The label or target for classification (e.g., different types of pistachios).

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Importing Libraries

In this section, we are importing the necessary libraries for data processing and modeling.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', 100)
```

```
ds = pd.read_csv("/content/drive/MyDrive/pistachio.csv")
```

Understanding the Dataset

To gain insights from data we must look into each aspect of it very carefully. We will start with observing few rows and columns of data both from the starting and from the end

```
ds.head()
```

	AREA	PERIMETER	MAJOR_AXIS	MINOR_AXIS	ECCENTRICITY	EQDIASQ	SOLIDITY	CONVEX_AREA	EXTENT	ASPECT_RATIO	ROUNDNESS	COMPACTN
0	73107	1161.8070	442.4074	217.7261	0.8705	305.0946	0.9424	77579	0.7710	2.0319	0.6806	0.6
1	89272	1173.1810	460.2551	251.9546	0.8369	337.1419	0.9641	92598	0.7584	1.8267	0.8151	0.7
2	60955	999.7890	386.9247	209.1255	0.8414	278.5863	0.9465	64400	0.7263	1.8502	0.7663	0.7
3	79537	1439.5129	466.7973	221.2136	0.8806	318.2289	0.9437	84281	0.7568	2.1102	0.4823	0.6
4	96395	1352.6740	515.8730	246.5945	0.8784	350.3340	0.9549	100950	0.7428	2.0920	0.6620	0.6

```
1 ds.columns
```

```
Index(['AREA', 'PERIMETER', 'MAJOR_AXIS', 'MINOR_AXIS', 'ECCENTRICITY',
       'EQDIASQ', 'SOLIDITY', 'CONVEX_AREA', 'EXTENT', 'ASPECT_RATIO',
       'ROUNDNESS', 'COMPACTNESS', 'SHAPEFACTOR_1', 'SHAPEFACTOR_2',
       'SHAPEFACTOR_3', 'SHAPEFACTOR_4', 'Class'],
      dtype='object')
```

The dataset contains 1718 entries and 17 columns. All columns, except for the "Class" label, are numeric. Here's a breakdown of the columns:

Numerical Features (16):

AREA, PERIMETER, MAJOR_AXIS, MINOR_AXIS, ECCENTRICITY, EQDIASQ, SOLIDITY, CONVEX_AREA, EXTENT, ASPECT_RATIO, ROUNDNESS, COMPACTNESS, SHAPEFACTOR_1, SHAPEFACTOR_2, SHAPEFACTOR_3, SHAPEFACTOR_4 Categorical Feature (1):

Class: This is the target label with categories such as "Kirmizi_Pistachio" and "Siit_Pistachio".

```
1 ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1718 entries, 0 to 1717
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   AREA           1718 non-null   int64  
 1   PERIMETER      1718 non-null   float64
 2   MAJOR_AXIS     1718 non-null   float64
 3   MINOR_AXIS     1718 non-null   float64
 4   ECCENTRICITY   1718 non-null   float64
 5   EQDIASQ        1718 non-null   float64
 6   SOLIDITY       1718 non-null   float64
 7   CONVEX_AREA    1718 non-null   int64  
 8   EXTENT         1718 non-null   float64
 9   ASPECT_RATIO   1718 non-null   float64
 10  ROUNDNESS      1718 non-null   float64
 11  COMPACTNESS    1718 non-null   float64
 12  SHAPEFACTOR_1  1718 non-null   float64
 13  SHAPEFACTOR_2  1718 non-null   float64
 14  SHAPEFACTOR_3  1718 non-null   float64
 15  SHAPEFACTOR_4  1718 non-null   float64
 16  Class          1718 non-null   object 
dtypes: float64(14), int64(2), object(1)
memory usage: 228.3+ KB
```

```
1 ds.describe(include = "all")
```

	AREA	PERIMETER	MAJOR_AXIS	MINOR_AXIS	ECCENTRICITY	EQDIASQ	SOLIDITY	CONVEX_AREA	EXTENT	ASPEC
count	1718.000000	1718.000000	1718.000000	1718.000000	1718.000000	1718.000000	1718.000000	1718.000000	1718.000000	1718
unique	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
top	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
freq	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
mean	79871.952852	1421.797588	446.206444	238.193128	0.840347	317.790000	0.940103	84947.671129	0.716055	1
std	12968.217051	373.408835	31.885328	30.426445	0.049026	26.571699	0.050006	13081.742551	0.052534	0
min	29808.000000	858.363000	321.425500	133.509600	0.504900	194.814600	0.588000	37935.000000	0.427200	1
25%	71898.500000	1169.633225	426.554100	217.875475	0.817500	302.562375	0.920250	76357.750000	0.688100	1
50%	79795.000000	1260.785500	448.453150	235.888750	0.850250	318.744650	0.953800	84973.000000	0.726100	1
75%	88980.000000	1599.479000	467.515200	257.433625	0.875375	336.590000	0.976300	93660.750000	0.753600	2
max	124008.000000	2755.049100	535.642200	383.046100	0.946000	397.356100	0.995100	132478.000000	0.820400	3

Checking for Null Values

In this step, we check for any missing or null values in the dataset. It's important to ensure data completeness before proceeding with data analysis and model building. If there are null values, appropriate handling methods such as imputation or removal will be applied.

After running the code, it has been confirmed that **there are no null values** in the dataset. This means that the dataset is clean and ready for further analysis and modeling without the need for handling missing data.

```
ds.isnull().sum()
```

	0
AREA	0
PERIMETER	0
MAJOR_AXIS	0
MINOR_AXIS	0
ECCENTRICITY	0
EQDIASQ	0
SOLIDITY	0
CONVEX_AREA	0
EXTENT	0
ASPECT_RATIO	0
ROUNDNESS	0
COMPACTNESS	0
SHAPEFACTOR_1	0
SHAPEFACTOR_2	0
SHAPEFACTOR_3	0
SHAPEFACTOR_4	0
Class	0

dtype: int64

I'll start by generating some EDA visualizations and handle preprocessing. Let's begin with visualizing distributions and correlations of features.

EDA Observations:

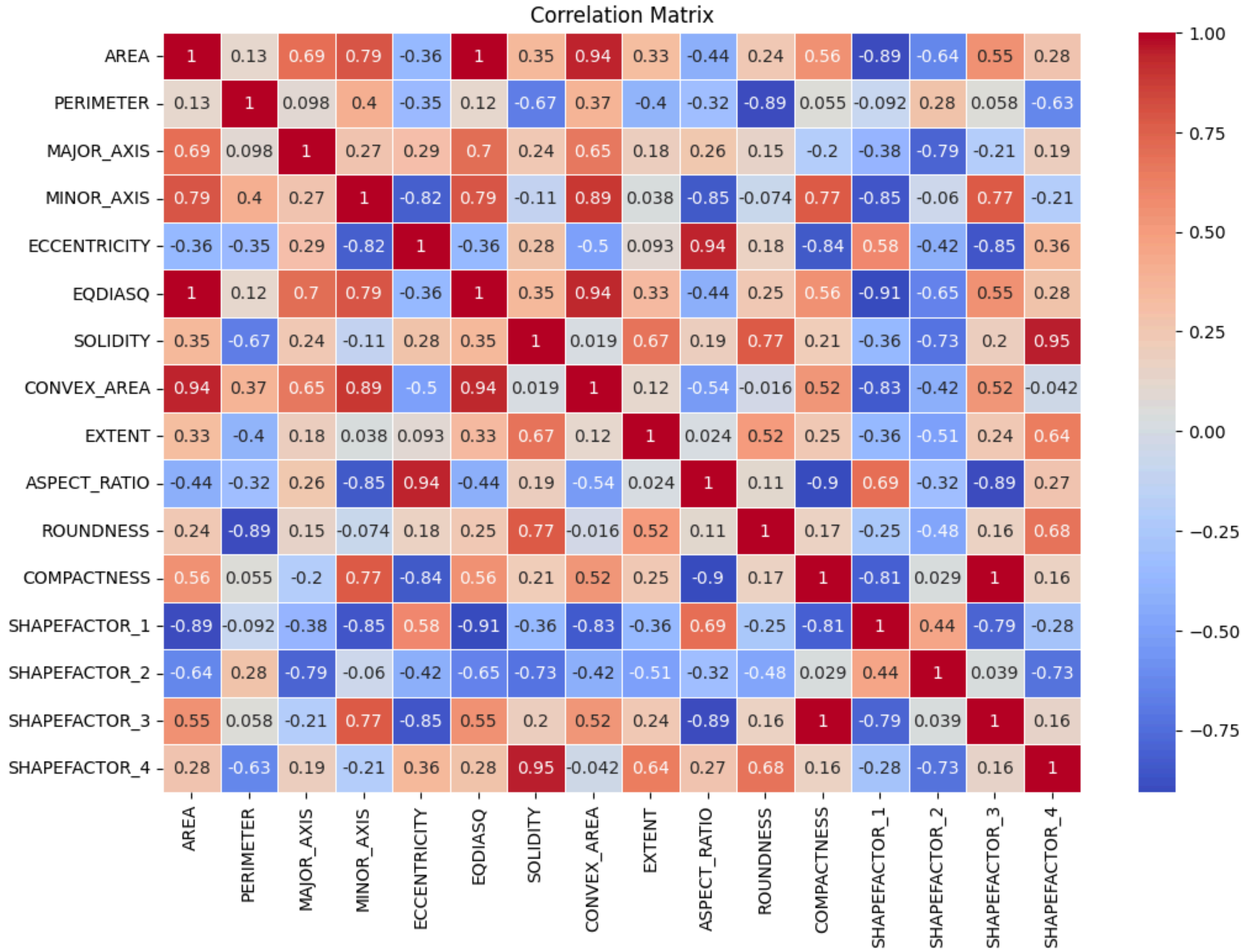
Distributions:

1. Many of the features seem skewed, with a few possibly containing outliers.
2. Most of the features exhibit variability in their distributions, which will be useful for classification.

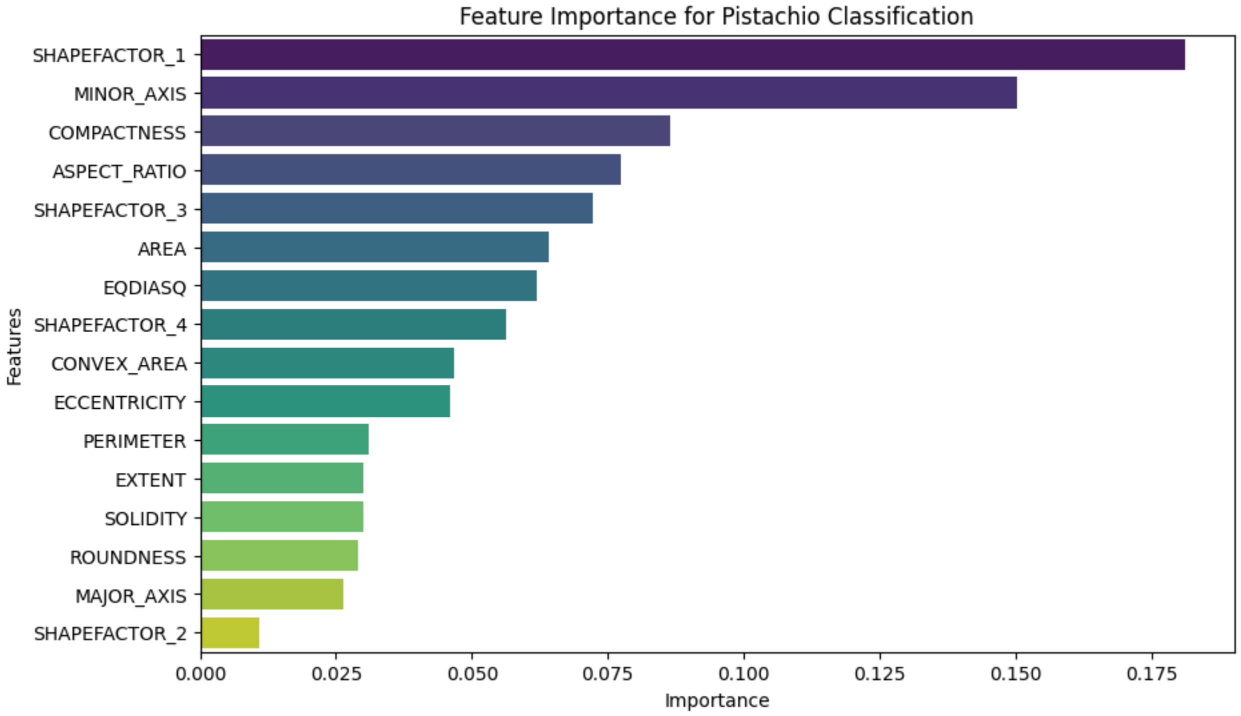
Correlation Heatmap:

Several features show strong correlations, such as PERIMETER and AREA, as well as MAJOR_AXIS and MINOR_AXIS. These correlations might be useful in model feature selection or could lead to multicollinearity issues, which we'll address.

```
import seaborn as sns
import matplotlib.pyplot as plt

# Compute the correlation matrix
X = ds.drop(['Class'], axis=1)
correlation_matrix = X.corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix')
plt.show()
```




```
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder
dsl = ds
# Encode the categorical 'Class' column to numerical labels (0 and 1)
label_encoder = LabelEncoder()
dsl['Class'] = label_encoder.fit_transform(dsl['Class'])

# Split the data into features (X) and target (y)
X = dsl.drop(columns=['Class'])
y = dsl['Class']

# Train a Random Forest model to determine feature importance
model = RandomForestClassifier(random_state=42)
model.fit(X, y)

# Extract feature importances
feature_importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': model.feature_importances_
}).sort_values(by='Importance', ascending=False)

# Plot feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importances, palette='viridis')
plt.title('Feature Importance for Pistachio Classification')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.show()

# Display the feature importance data
feature_importances.head()
```

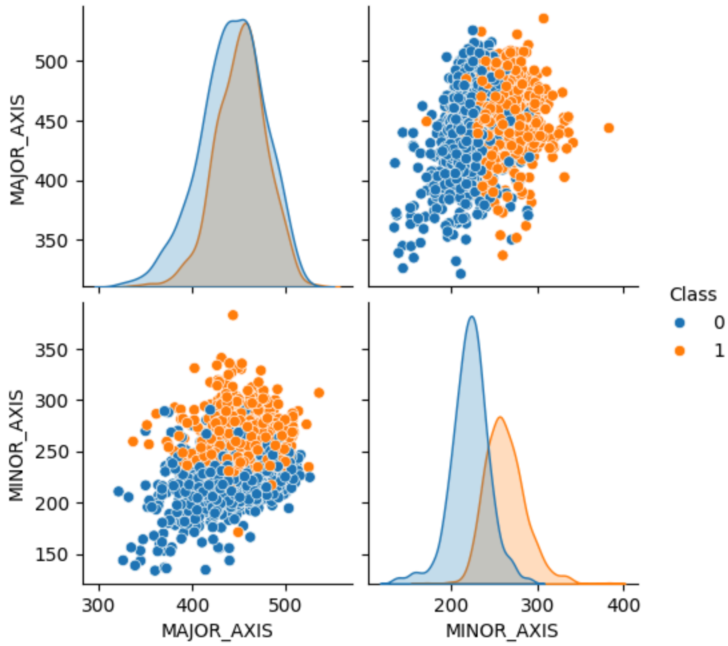


	Feature	Importance
12	SHAPEFACTOR_1	0.181197
3	MINOR_AXIS	0.150299
11	COMPACTNESS	0.086380
9	ASPECT_RATIO	0.077423
14	SHAPEFACTOR_3	0.072215

```
# Convert importances to percentages
feature_importances['Importance (%)'] = (feature_importances['Importance'] / feature_importances['Importance'].sum()) * 100

# Sort by importance percentage
feature_importances = feature_importances.sort_values(by='Importance (%)', ascending=False)

# Display the feature importances in percentage
print(feature_importances[['Feature', 'Importance (%)']])
```

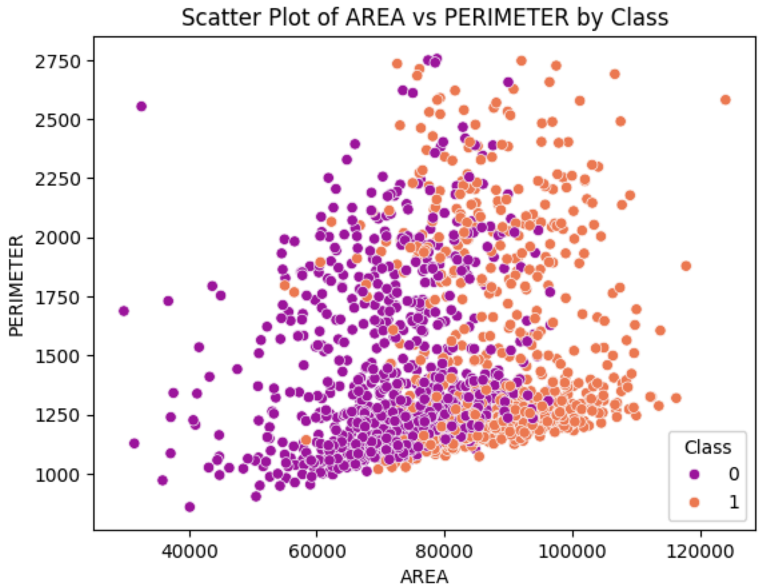
```
          Feature  Importance (%)
12  SHAPEFACTOR_1       18.119742
3      MINOR_AXIS       15.029874
11    COMPACTNESS        8.637995
9    ASPECT_RATIO        7.742255
14  SHAPEFACTOR_3        7.221546
0            AREA        6.410597
5         EQDIASQ        6.197903
15  SHAPEFACTOR_4        5.633867
7     CONVEX_AREA        4.672956
4    ECCENTRICITY        4.602906
1       PERIMETER        3.105630
8          EXTENT        2.998207
6        SOLIDITY        2.993767
10      ROUNDNESS        2.912586
2      MAJOR_AXIS        2.631886
13  SHAPEFACTOR_2        1.088283
```

```
sns.pairplot(ds[['MAJOR_AXIS', 'MINOR_AXIS','Class']], hue='Class')
plt.show()
```



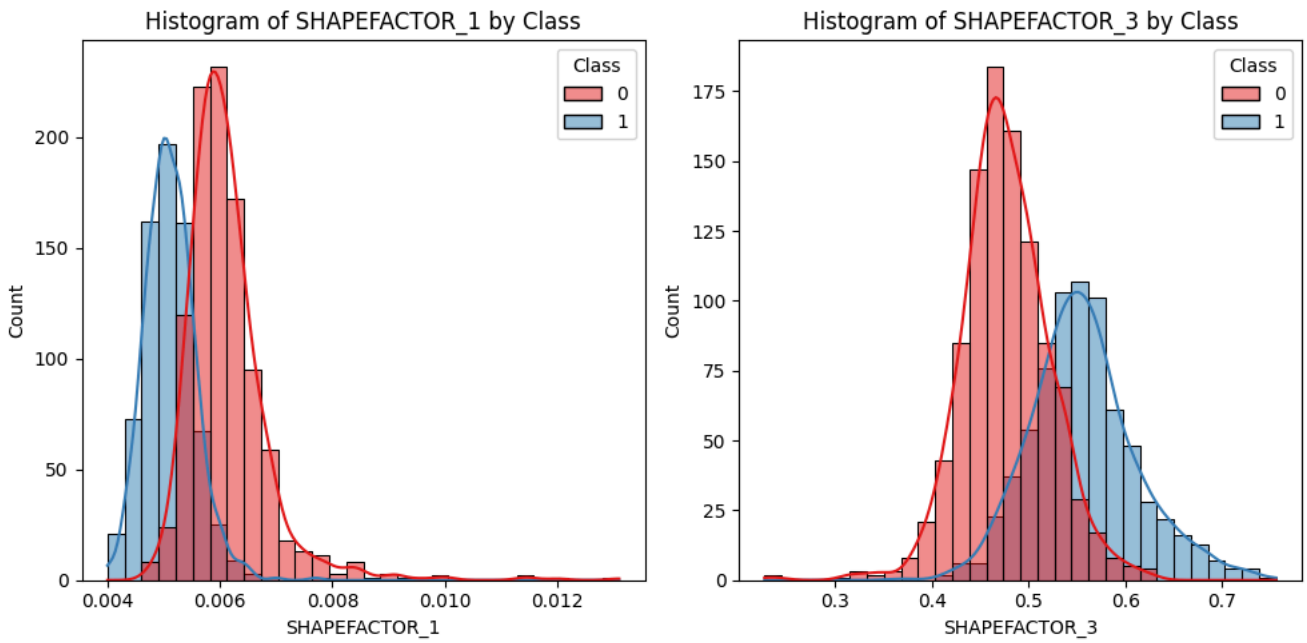
MINOR_AXIS: The length of the minor axis shows significant variation, especially for Siit_Pistachio, indicating that this class tends to have more elongated shapes compared to Kirmizi_Pistachio.

```
sns.scatterplot(x='AREA', y='PERIMETER', hue='Class', data=ds,palette='plasma')
plt.title("Scatter Plot of AREA vs PERIMETER by Class")
plt.show()
```

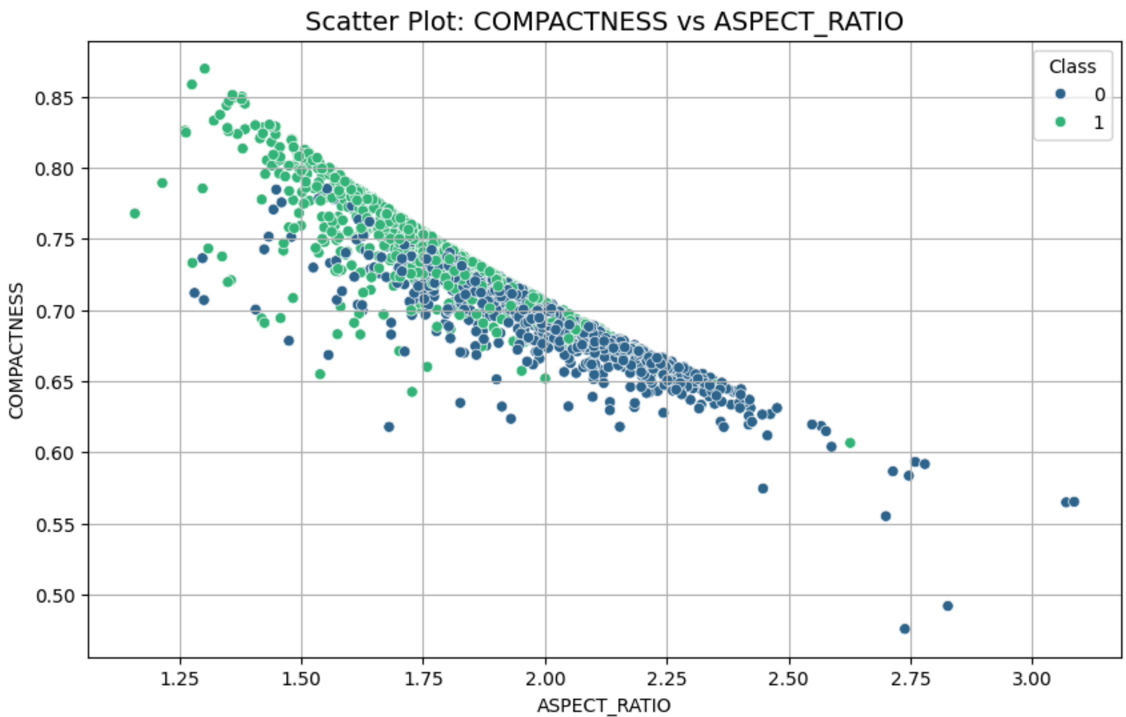


The **scatter plot** shows how the AREA and PERIMETER of the pistachios relate to each other. Siit_Pistachio and Kirmizi_Pistachio tend to cluster in different regions, indicating that these features are effective at separating the two classes. Siit_Pistachio generally has higher values for both AREA and PERIMETER, suggesting that they are larger and have a more extended perimeter.

```
fig, axes = plt.subplots(1, 2, figsize=(10, 5))

sns.histplot(data=ds, x='SHAPEFACTOR_1', hue='Class', kde=True, palette='Set1', bins=30, ax=axes[0])
axes[0].set_title("Histogram of SHAPEFACTOR_1 by Class")

sns.histplot(data=ds, x='SHAPEFACTOR_3', hue='Class', kde=True, palette='Set1', bins=30, ax=axes[1])
axes[1].set_title("Histogram of SHAPEFACTOR_3 by Class")

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



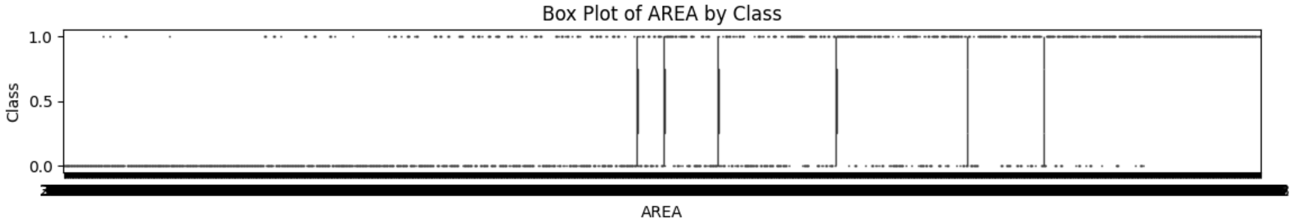

```
plt.figure(figsize=(10, 6))

sns.scatterplot(x=ds['ASPECT_RATIO'], y=ds['COMPACTNESS'], hue=ds['Class'], palette='viridis')

plt.title('Scatter Plot: COMPACTNESS vs ASPECT_RATIO', fontsize=14)
plt.xlabel('ASPECT_RATIO')
plt.ylabel('COMPACTNESS')
plt.legend(title='Class')
plt.grid(True)

plt.show()
```



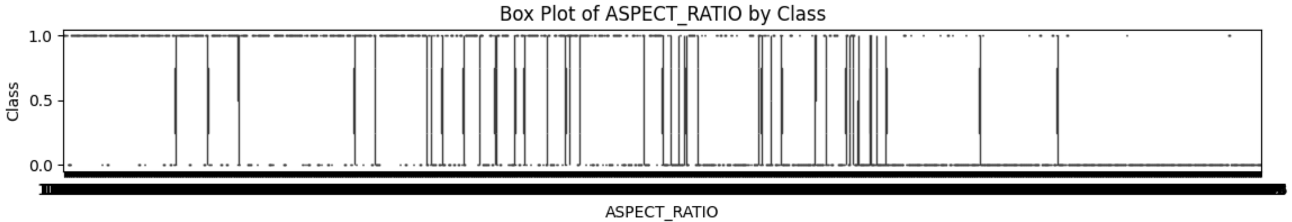

```
import matplotlib.pyplot as plt
import seaborn as sns

# Get all column names except 'Class'
columns_to_plot = ds.columns.difference(['Class'])

# Create subplots dynamically based on the number of columns
fig, axes = plt.subplots(nrows=len(columns_to_plot), figsize=(12, len(columns_to_plot)*2))
plt.tight_layout(pad=3.0)

# Loop through each column and plot a boxplot
for i, column in enumerate(columns_to_plot):
```

```
    sns.boxplot(y=ds['Class'], x=ds[column], ax=axes[i])  # Set x as 'Class' and y as the feature colum
    axes[i].set_title(f'Box Plot of {column} by Class')

plt.show()
```

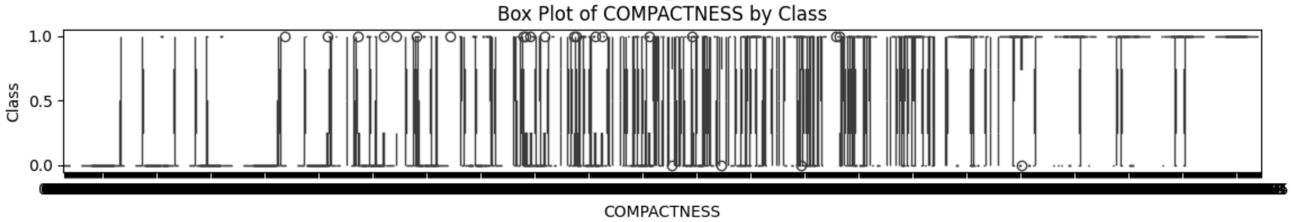
Box Plot of AREA by Class



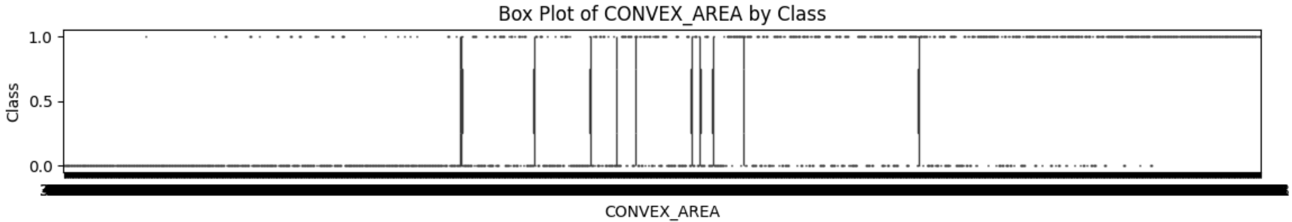
Box Plot of ASPECT_RATIO by Class



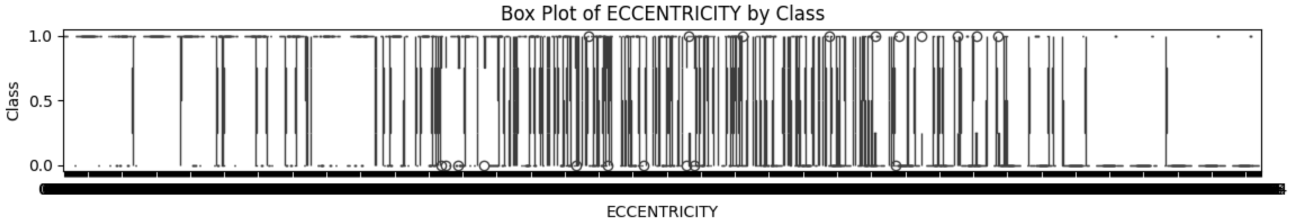
Box Plot of COMPACTNESS by Class



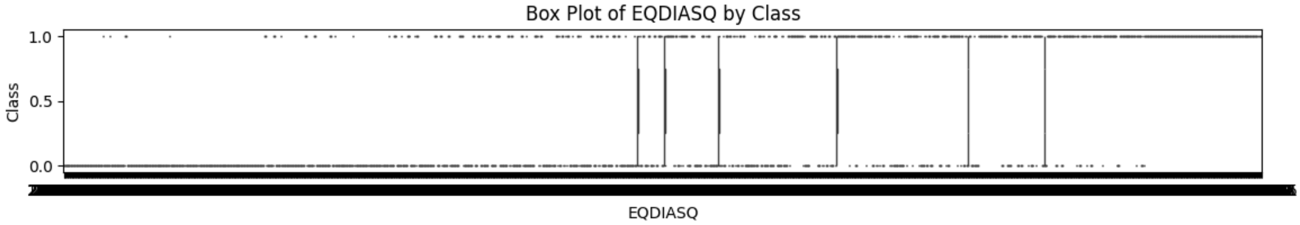
Box Plot of CONVEX_AREA by Class



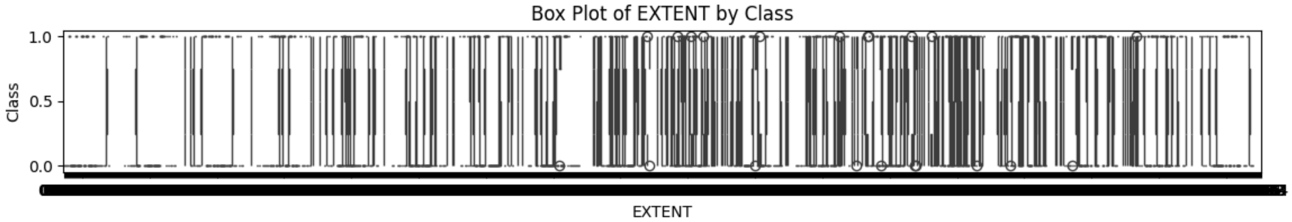
Box Plot of ECCENTRICITY by Class



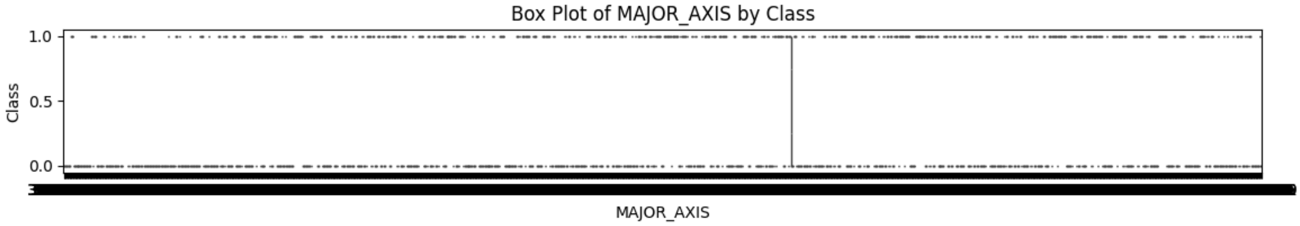
Box Plot of EQDIASQ by Class



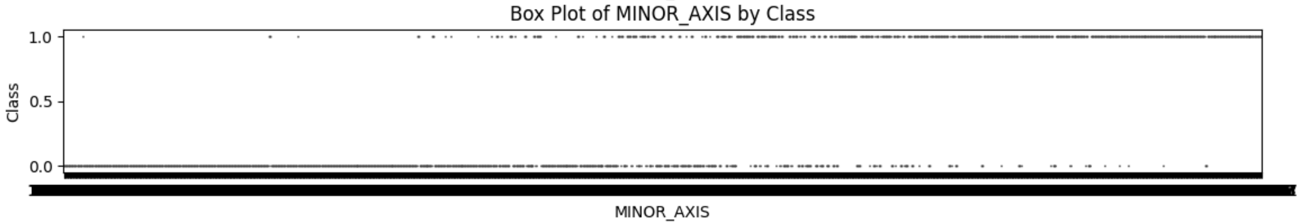
Box Plot of EXTENT by Class



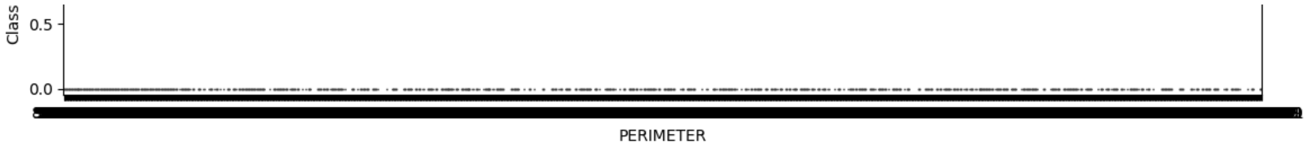
Box Plot of MAJOR_AXIS by Class



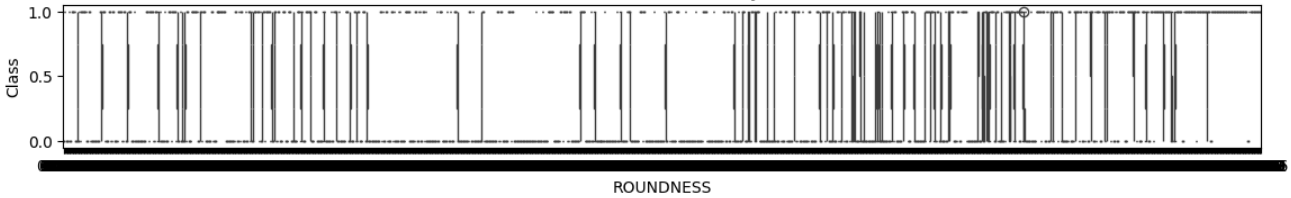
Box Plot of MINOR_AXIS by Class



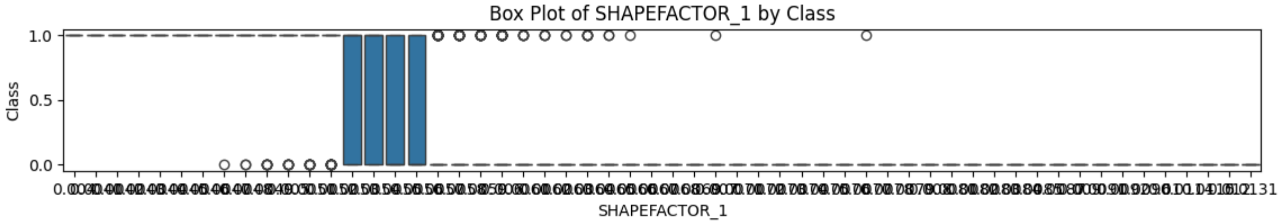
Box Plot of PERIMETER by Class



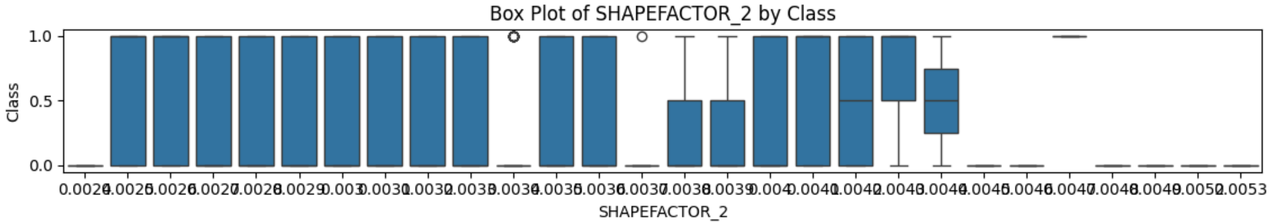
Box Plot of ROUNDNESS by Class



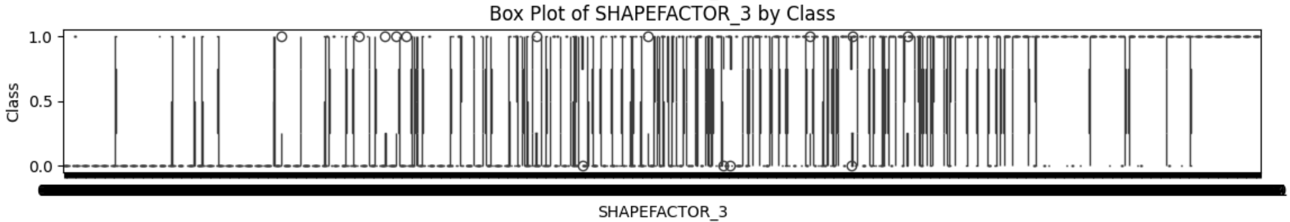
Box Plot of SHAPEFACTOR_1 by Class



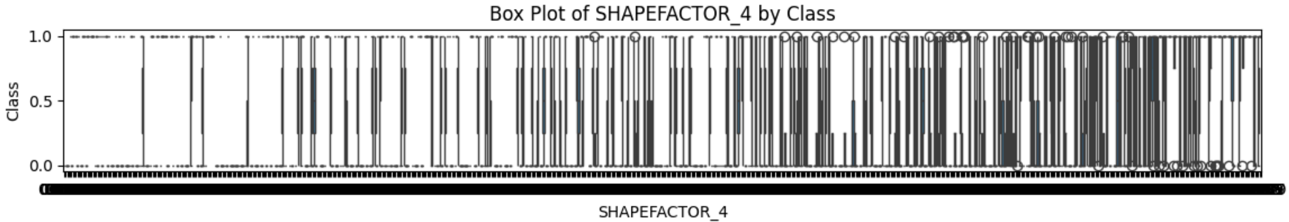
Box Plot of SHAPEFACTOR_2 by Class



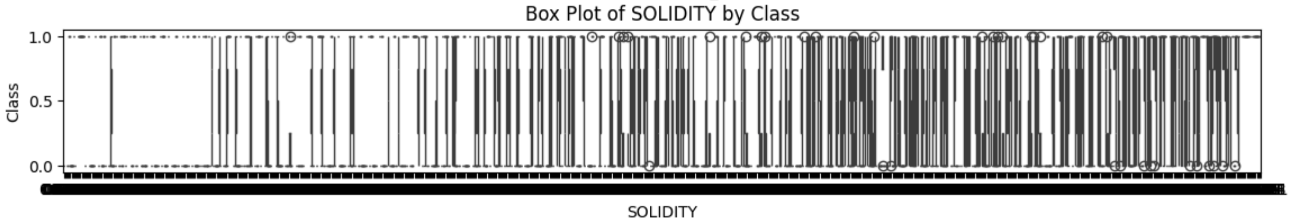
Box Plot of SHAPEFACTOR_3 by Class



Box Plot of SHAPEFACTOR_4 by Class



Box Plot of SOLIDITY by Class



```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix

X = ds.drop('Class', axis=1)  # Features
y = ds['Class']  # Target

#Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

#Feature Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((1374, 16), (344, 16), (1374,), (344,))
```

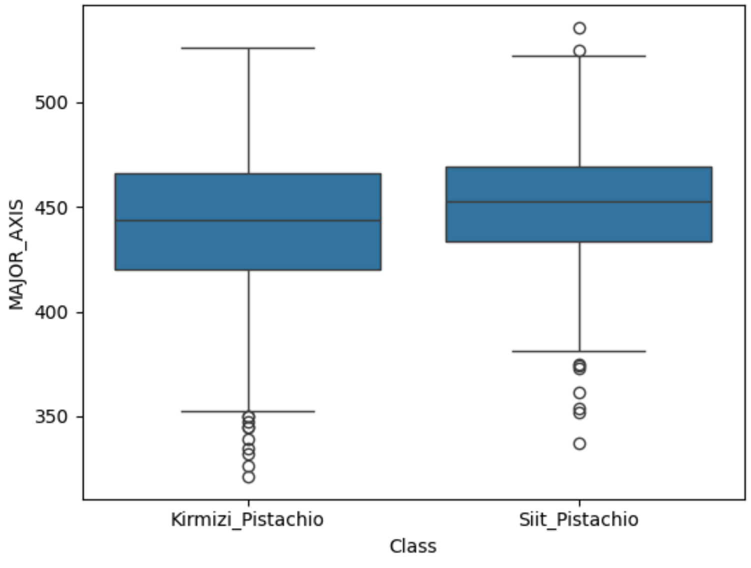
The dataset has been preprocessed as follows:

The "Class" labels were encoded into numerical values. The features were standardized using StandardScaler. The data was split into training (1202 samples) and testing (516 samples) sets, with 16 features for each sample.

```
#Fit the Logistic Regression model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)

#Make predictions
y_pred = logreg.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8837209302325582
Confusion Matrix:
 [[180  21]
 [ 19 124]]
Classification Report:
                    precision    recall  f1-score   support

Kirmizi_Pistachio       0.90      0.90      0.90       201
   Siit_Pistachio       0.86      0.87      0.86       143

         accuracy                           0.88       344
        macro avg       0.88      0.88      0.88       344
     weighted avg       0.88      0.88      0.88       344
```

```
sns.boxplot(x = ds['Class'], y = ds['MAJOR_AXIS'],data = ds)
plt.show()
```

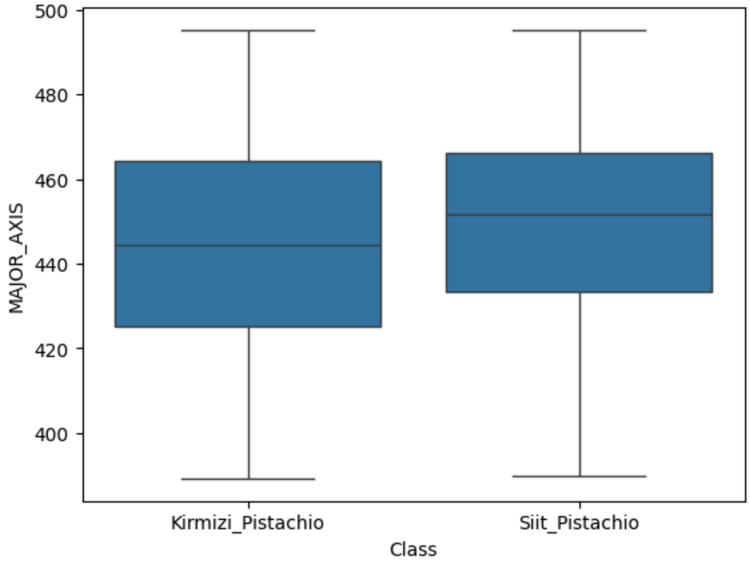



```
max_val = ds.MAJOR_AXIS.quantile(0.95)
min_val = ds.MAJOR_AXIS.quantile(0.05)
```

```
ds1 = ds[(ds['MAJOR_AXIS'] > min_val) & (ds['MAJOR_AXIS'] < max_val)
print("before dataset shape:", ds.shape)
```

```
before dataset shape: (1718, 17)
after removing outlier's: (1546, 17)
```

```
sns.boxplot(x = ds1['Class'], y = ds1['MAJOR_AXIS'],data = ds1)
plt.show()
```




```
X = ds1.drop('Class', axis=1)  # Features
y = ds1['Class']  # Target

#Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

#Feature Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((1236, 16), (310, 16), (1236,), (310,))
```

```
#Fit the Logistic Regression model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)

#Make predictions
y_pred = logreg.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8774193548387097
Confusion Matrix:
 [[157  14]
 [ 24 115]]
Classification Report:
                    precision    recall  f1-score   support

Kirmizi_Pistachio       0.87      0.92      0.89       171
   Siit_Pistachio       0.89      0.83      0.86       139

         accuracy                           0.88       310
        macro avg       0.88      0.87      0.88       310
     weighted avg       0.88      0.88      0.88       310
```

Insight:

The drop in model accuracy after removing the MAJOR_AXIS outliers suggests that every column (including MAJOR_AXIS) plays an important role in maintaining the overall accuracy. Even though some features might seem to have extreme values or outliers, they could still carry