Sepal Length	Sepal Width	Petal Length	Petal Width	Class
5.1	3.5	1.4	0.2	Iris-setosa
4.9	3	1.4	0.2	Iris-setosa
4.7	3.2	1.3	0.2	Iris-setosa
4.6	3.1	1.5	0.2	Iris-setosa
5	3.6	1.4	0.2	Iris-setosa
5.4	3.9	1.7	0.4	Iris-setosa
4.6	3.4	1.4	0.3	Iris-setosa
5	3.4	1.5	0.2	Iris-setosa
4.4	2.9	1.4	0.2	Iris-setosa
4.9	3.1	1.5	0.1	Iris-setosa
5.4	3.7	1.5	0.2	Iris-setosa
4.8	3.4	1.6	0.2	Iris-setosa
4.8	3	1.4	0.1	Iris-setosa
4.3	3	1.1	0.1	Iris-setosa
5.8	4	1.2	0.2	Iris-setosa
5.7	4.4	1.5	0.4	Iris-setosa
5.4	3.9	1.3	0.4	Iris-setosa
5.1	3.5	1.4	0.3	Iris-setosa
5.7	3.8	1.7	0.3	Iris-setosa
5.1	3.8	1.5	0.3	Iris-setosa
5.4	3.4	1.7	0.2	Iris-setosa
5.1	3.7	1.5	0.4	Iris-setosa
4.6	3.6	1	0.2	Iris-setosa
5.1	3.3	1.7	0.5	Iris-setosa
4.8	3.4	1.9	0.2	Iris-setosa
5	3	1.6	0.2	Iris-setosa
5	3.4	1.6	0.4	Iris-setosa
5.2	3.5	1.5	0.2	Iris-setosa
5.2	3.4	1.4	0.2	Iris-setosa
4.7	3.2	1.6	0.2	Iris-setosa
4.8	3.1	1.6	0.2	Iris-setosa
5.4	3.4	1.5	0.4	Iris-setosa
5.2	4.1	1.5	0.1	Iris-setosa
5.5	4.2	1.4	0.2	Iris-setosa
4.9	3.1	1.5	0.1	Iris-setosa
5	3.2	1.2	0.2	Iris-setosa
5.5	3.5	1.3	0.2	Iris-setosa
4.9	3.1	1.5	0.1	Iris-setosa
4.4	3	1.3	0.2	Iris-setosa
5.1	3.4	1.5	0.2	Iris-setosa
5	3.5	1.3	0.3	Iris-setosa
4.5	2.3	1.3	0.3	Iris-setosa
4.4	3.2	1.3	0.2	Iris-setosa
5	3.5	1.6	0.6	Iris-setosa
5.1	3.8	1.9	0.4	Iris-setosa
4.8	3	1.4	0.3	Iris-setosa
5.1	3.8	1.6	0.2	Iris-setosa

4.6	3.2	1.4	0.2	Iris-setosa
5.3	3.7	1.5	0.2	Iris-setosa
5	3.3	1.4	0.2	Iris-setosa
7	3.2	4.7	1.4	Iris-versicolor
6.4	3.2	4.5	1.5	Iris-versicolor
6.9	3.1	4.9	1.5	Iris-versicolor
5.5	2.3	4	1.3	Iris-versicolor
6.5	2.8	4.6	1.5	Iris-versicolor
5.7	2.8	4.5	1.3	Iris-versicolor
6.3	3.3	4.7	1.6	Iris-versicolor
4.9	2.4	3.3	1	Iris-versicolor
6.6	2.9	4.6	1.3	Iris-versicolor
5.2	2.7	3.9	1.4	Iris-versicolor
5	2	3.5	1	Iris-versicolor
5.9	3	4.2	1.5	Iris-versicolor
6	2.2	4	1	Iris-versicolor
6.1	2.9	4.7	1.4	Iris-versicolor
5.6	2.9	3.6	1.3	Iris-versicolor
6.7	3.1	4.4	1.4	Iris-versicolor
5.6	3	4.5	1.5	Iris-versicolor
5.8	2.7	4.1	1	Iris-versicolor
6.2	2.2	4.5	1.5	Iris-versicolor
5.6	2.5	3.9	1.1	Iris-versicolor
5.9	3.2	4.8	1.8	Iris-versicolor
6.1	2.8	4	1.3	Iris-versicolor
6.3	2.5	4.9	1.5	Iris-versicolor
6.1	2.8	4.7	1.2	Iris-versicolor
6.4	2.9	4.3	1.3	Iris-versicolor
6.6	3	4.4	1.4	Iris-versicolor
6.8	2.8	4.8	1.4	Iris-versicolor
6.7	3	5	1.7	Iris-versicolor
6	2.9	4.5	1.5	Iris-versicolor
5.7	2.6	3.5	1	Iris-versicolor
5.5	2.4	3.8	1.1	Iris-versicolor
5.5	2.4	3.7	1	Iris-versicolor
5.8	2.7	3.9	1.2	Iris-versicolor
6	2.7	5.1	1.6	Iris-versicolor
5.4	3	4.5	1.5	Iris-versicolor
6	3.4	4.5	1.6	Iris-versicolor
6.7	3.1	4.7	1.5	Iris-versicolor
6.3	2.3	4.4	1.3	Iris-versicolor
5.6	3	4.1	1.3	Iris-versicolor
5.5	2.5	4	1.3	Iris-versicolor
5.5	2.6	4.4	1.2	Iris-versicolor
6.1	3	4.6	1.4	Iris-versicolor
5.8	2.6	4	1.2	Iris-versicolor
5	2.3	3.3	1	Iris-versicolor
5.6	2.7	4.2	1.3	Iris-versicolor

5.7	3	4.2	1.2	Iris-versicolor
5.7	2.9	4.2	1.3	Iris-versicolor
6.2	2.9	4.3	1.3	Iris-versicolor
5.1	2.5	3	1.1	Iris-versicolor
5.7	2.8	4.1	1.3	Iris-versicolor
6.3	3.3	6	2.5	Iris-virginica
5.8	2.7	5.1	1.9	Iris-virginica
7.1	3	5.9	2.1	Iris-virginica
6.3	2.9	5.6	1.8	Iris-virginica
6.5	3	5.8	2.2	Iris-virginica
7.6	3	6.6	2.1	Iris-virginica
4.9	2.5	4.5	1.7	Iris-virginica
7.3	2.9	6.3	1.8	Iris-virginica
6.7	2.5	5.8	1.8	Iris-virginica
7.2	3.6	6.1	2.5	Iris-virginica
6.5	3.2	5.1	2	Iris-virginica
6.4	2.7	5.3	1.9	Iris-virginica
6.8	3	5.5	2.1	Iris-virginica
5.7	2.5	5	2	Iris-virginica
5.8	2.8	5.1	2.4	Iris-virginica
6.4	3.2	5.3	2.3	Iris-virginica
6.5	3	5.5	1.8	Iris-virginica
7.7	3.8	6.7	2.2	Iris-virginica
7.7	2.6	6.9	2.3	Iris-virginica
6	2.2	5	1.5	Iris-virginica
6.9	3.2	5.7	2.3	Iris-virginica
5.6	2.8	4.9	2	Iris-virginica
7.7	2.8	6.7	2	Iris-virginica
6.3	2.7	4.9	1.8	Iris-virginica
6.7	3.3	5.7	2.1	Iris-virginica
7.2	3.2	6	1.8	Iris-virginica
6.2	2.8	4.8	1.8	Iris-virginica
6.1	3	4.9	1.8	Iris-virginica
6.4	2.8	5.6	2.1	Iris-virginica
7.2	3	5.8	1.6	Iris-virginica
7.4	2.8	6.1	1.9	Iris-virginica
7.9	3.8	6.4	2	Iris-virginica
6.4	2.8	5.6	2.2	Iris-virginica
6.3	2.8	5.1	1.5	Iris-virginica
6.1	2.6	5.6	1.4	Iris-virginica
7.7	3	6.1	2.3	Iris-virginica
6.3	3.4	5.6	2.4	Iris-virginica
6.4	3.1	5.5	1.8	Iris-virginica
6	3	4.8	1.8	Iris-virginica
6.9	3.1	5.4	2.1	Iris-virginica
6.7	3.1	5.6	2.4	Iris-virginica
6.9	3.1	5.1	2.3	Iris-virginica
5.8	2.7	5.1	1.9	Iris-virginica

6.8	3.2	5.9	2.3	Iris-virginica
6.7	3.3	5.7	2.5	Iris-virginica
6.7	3	5.2	2.3	Iris-virginica
6.3	2.5	5	1.9	Iris-virginica
6.5	3	5.2	2	Iris-virginica
6.2	3.4	5.4	2.3	Iris-virginica
5.9	3	5.1	1.8	Iris-virginica

ANALYSIS CODE

```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = iris.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

log_reg = LogisticRegression()
dt_classifier = DecisionTreeClassifier()
rf_classifier = RandomForestClassifier()
svm_classifier = SVC()
knn_classifier = KNeighborsClassifier()

classifiers = {
   'Logistic Regression': log_reg,
   'Decision Tree': dt_classifier,
   'Random Forest': rf_classifier,
   'SVM': svm_classifier,
   'KNN': knn_classifier
}

for name, classifier in classifiers.items():
   classifier.fit(X_train_scaled, y_train)
   y_pred = classifier.predict(X_test_scaled)

   accuracy = accuracy_score(y_test, y_pred)
   precision = precision_score(y_test, y_pred, average='weighted')
   recall = recall_score(y_test, y_pred, average='weighted')
   f1 = f1_score(y_test, y_pred, average='weighted')
```

```
    print(f'{name}:')
    print(f'  Accuracy: {accuracy:.2f}')
    print(f'  Precision: {precision:.2f}')
    print(f'  Recall: {recall:.2f}')
    print(f'  F1-score: {f1:.2f}')
    print('---')
```

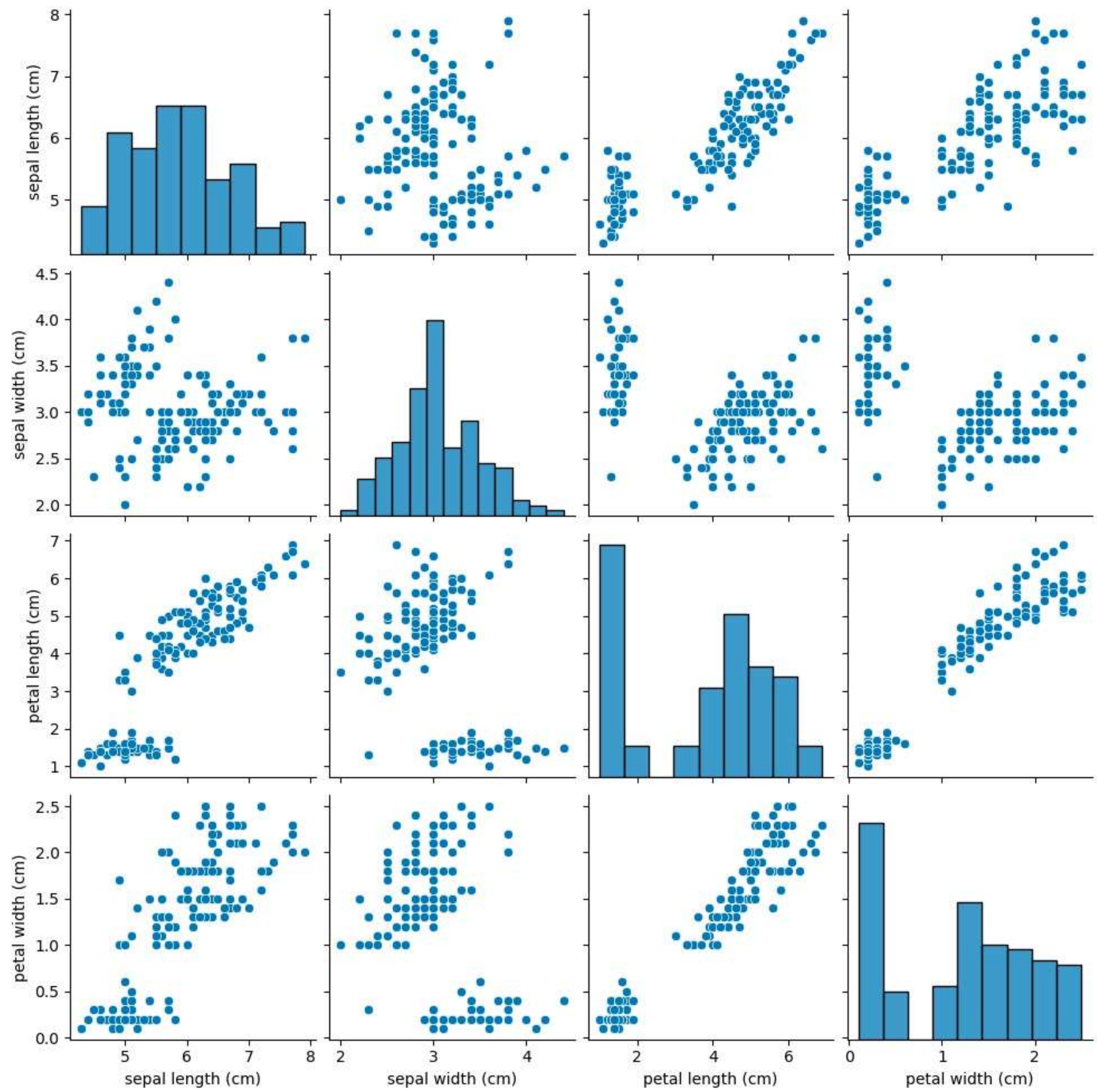
OUTPUT

```
Logistic Regression:
  Accuracy: 1.00
  Precision: 1.00
  Recall: 1.00
  F1-score: 1.00
---
Decision Tree:
  Accuracy: 1.00
  Precision: 1.00
  Recall: 1.00
  F1-score: 1.00
---
Random Forest:
  Accuracy: 1.00
  Precision: 1.00
  Recall: 1.00
  F1-score: 1.00
---
SVM:
  Accuracy: 1.00
  Precision: 1.00
  Recall: 1.00
  F1-score: 1.00
---
KNN:
  Accuracy: 1.00
  Precision: 1.00
  Recall: 1.00
  F1-score: 1.00
---
```

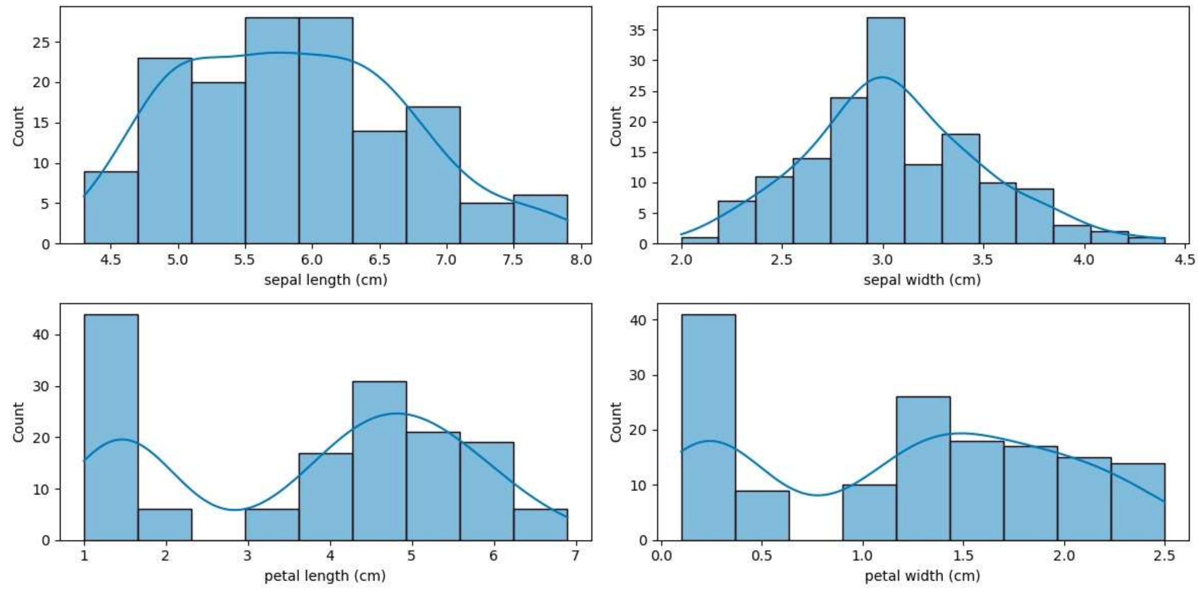
VISUALIZATIONS

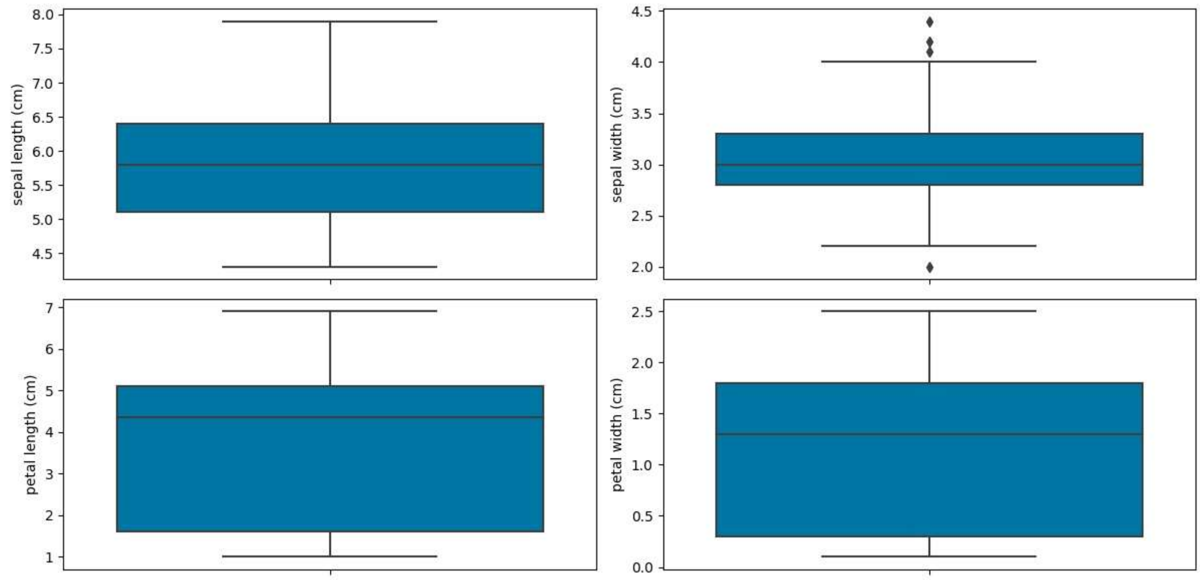
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.pairplot(pd.DataFrame(iris.data, columns=iris.feature_names))
plt.show()

plt.figure(figsize=(12, 6))
for i, feature in enumerate(iris.feature_names):
    plt.subplot(2, 2, i + 1)
    sns.histplot(data=X, x=feature, kde=True)
plt.tight_layout()
plt.show()

plt.figure(figsize=(12, 6))
for i, feature in enumerate(iris.feature_names):
    plt.subplot(2, 2, i + 1)
    sns.boxplot(data=X, y=feature)
plt.tight_layout()
plt.show()

plt.figure(figsize=(12, 6))
for i, feature in enumerate(iris.feature_names):
    plt.subplot(2, 2, i + 1)
    sns.violinplot(data=X, y=feature)
plt.tight_layout()
plt.show()

plt.figure(figsize=(8, 6))
sns.heatmap(X.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```

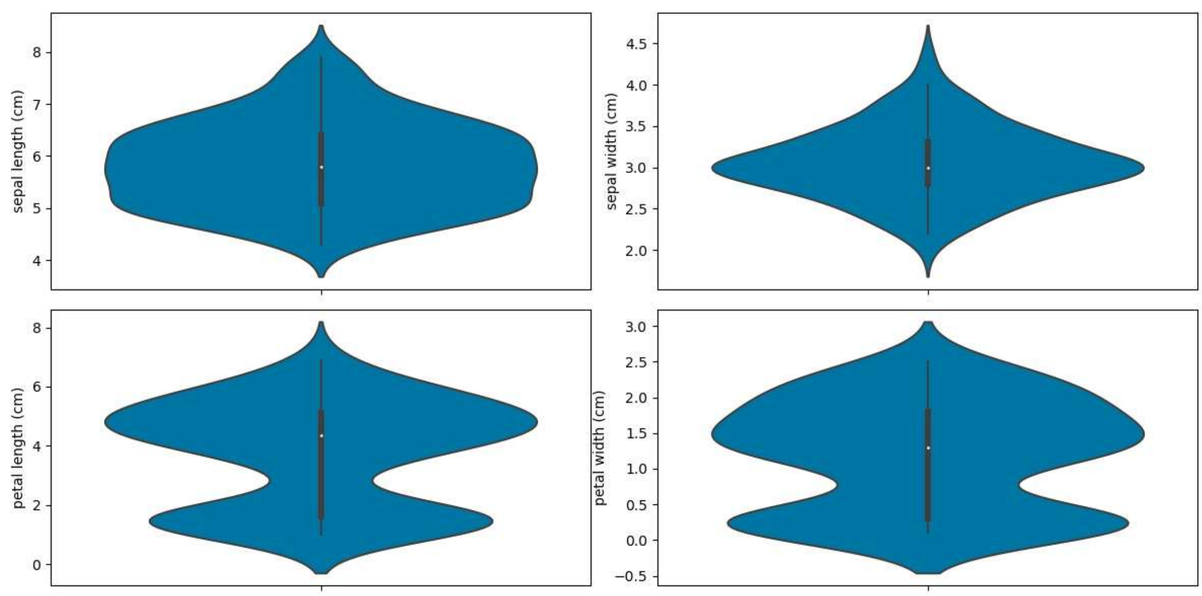
OUTPUT

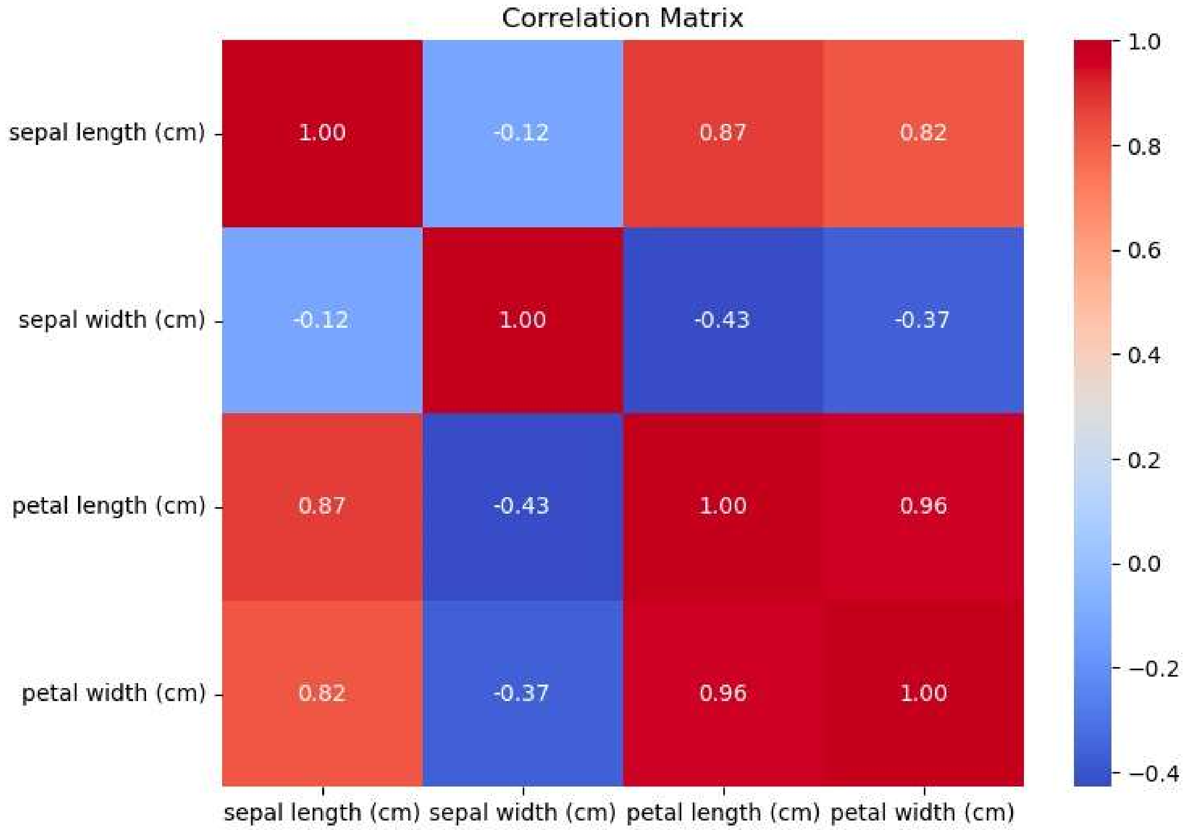


sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)


Count
sepal length (cm)
Count
sepal width (cm)
Count
petal length (cm)
Count
petal width (cm)


sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)


sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)


Correlation Matrix
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
1.00
-0.12
0.87
0.82
-0.12
1.00
-0.43
-0.37
0.87
-0.43
1.00
0.96
0.82
-0.37
0.96
1.00
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

INTERPRETATIONS

Pairplot:
The pairplot shows scatterplots for each pair of features in the dataset. It helps visualize the relationships between different features. For example, we can observe that some features have linear relationships, while others may have non-linear relationships or no apparent relationship.

Histograms:
Histograms display the distribution of each feature. They provide insights into the range and frequency of values for each feature. For instance, we can see the distribution of sepal length, sepal width, petal length, and petal width.

Boxplots:
Boxplots summarize the distribution of each feature by displaying key statistics such as median, quartiles, and outliers .They help identify the central tendency and variability of each feature. For instance, we can observe the spread of values for each feature and identify any outliers.

Violin plots:
Violin plots combine the features of boxplots and kernel density plots. They provide insights into the distribution of each feature, similar to boxplots, but also show the probability density of the data at different values. For example, we can see the density of values for each feature and compare their distributions.

Correlation matrix:
The correlation matrix heatmap shows the correlation coefficients between each pair of features. It helps identify relationships and dependencies between features .For instance, we can observe the strength and direction of correlations between sepal length, sepal width, petal length, and petal width. Positive values indicate a positive correlation, while negative values indicate a negative correlation.