```
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

print("All libraries are ready to use!")
```

```
All libraries are ready to use!
```

```
#from sklearn.datasets import load_iris
import pandas as pd

# Load the CSV file
iris = pd.read_csv('/content/iris_data.csv')

# Separate features (X) and target (y)
X = iris[['sepal length', 'sepal width', 'petal length', 'petal width']]  # Features
y = iris['label']  # Target (species)

# Display the features and target
print("Features (X):")
print(X)

print("\nTarget (y):")
print(y)
```

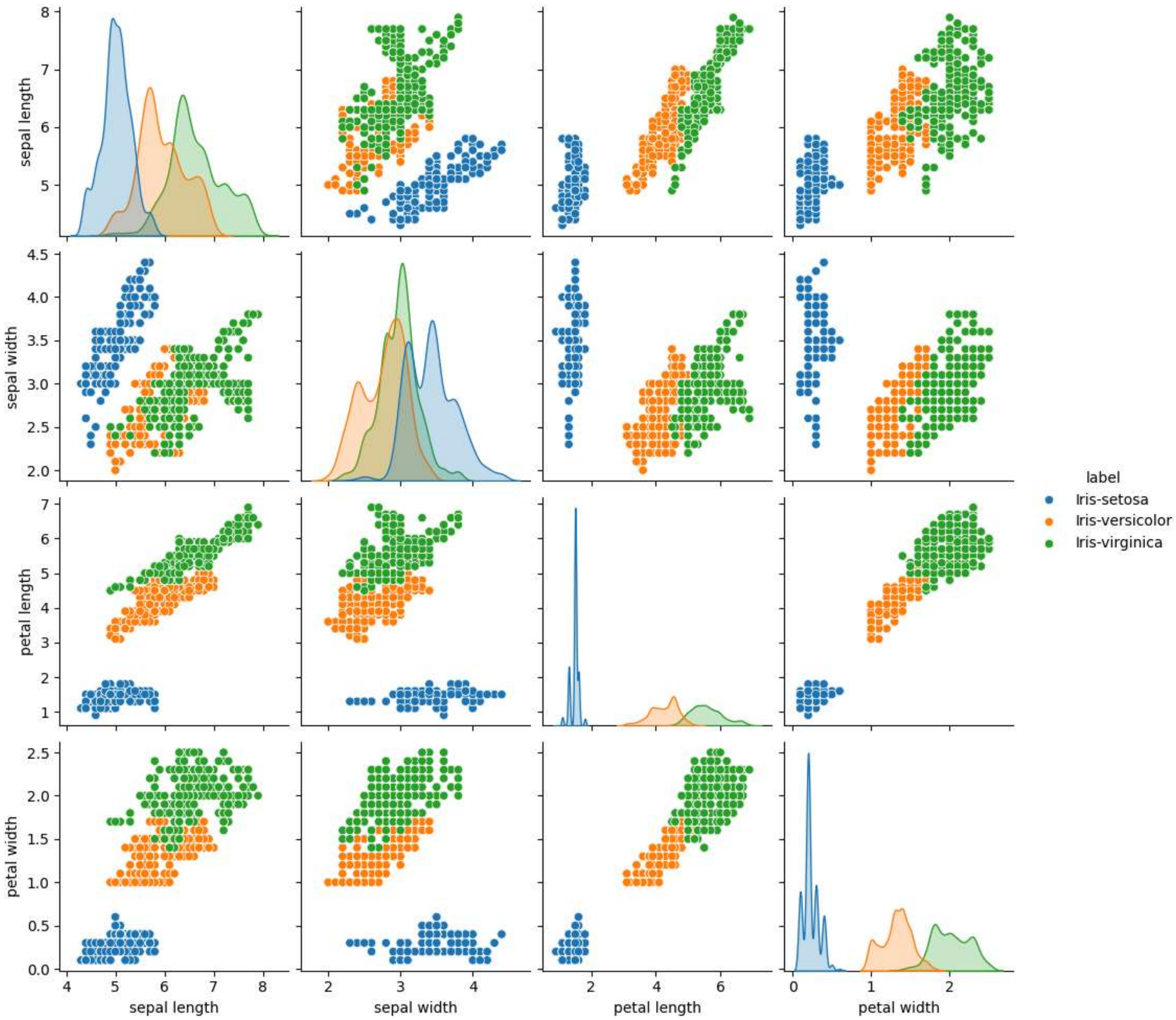
```
Features (X):
      sepal length  sepal width  petal length  petal width
0              5.2          3.8           1.5          0.3
1              5.3          4.1           1.5          0.1
2              4.8          3.1           1.5          0.2
3              5.2          3.7           1.5          0.2
4              4.9          3.0           1.5          0.3
...            ...          ...           ...          ...
2995           7.2          3.6           6.0          2.5
2996           7.3          3.0           6.2          2.1
2997           6.9          3.2           5.7          2.3
2998           7.5          2.8           6.0          2.0
2999           6.7          3.0           5.3          2.3

[3000 rows x 4 columns]

Target (y):
0          Iris-setosa
1          Iris-setosa
2          Iris-setosa
3          Iris-setosa
4          Iris-setosa
             ...
2995    Iris-virginica
2996    Iris-virginica
2997    Iris-virginica
2998    Iris-virginica
2999    Iris-virginica
Name: label, Length: 3000, dtype: object
```

```
#View the first few rows:
print(X.head())
#Check dataset dimensions:
print(X.shape)
#Get summary statistics:
print(X.describe())
#Check for missing values:
print(X.isnull().sum())
#Analyze target distribution:
print(y.value_counts())
```

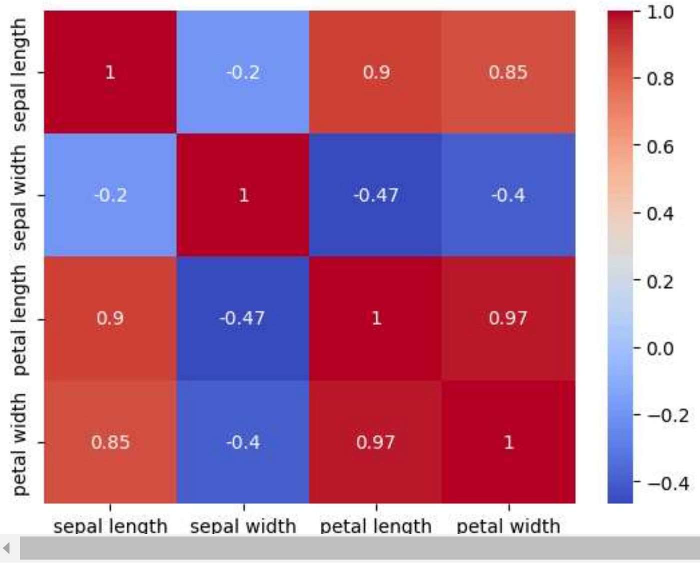
```
   sepal length  sepal width  petal length  petal width
0           5.2          3.8           1.5          0.3
1           5.3          4.1           1.5          0.1
2           4.8          3.1           1.5          0.2
3           5.2          3.7           1.5          0.2
4           4.9          3.0           1.5          0.3
(3000, 4)
       sepal length  sepal width  petal length  petal width
count   3000.000000  3000.000000   3000.000000  3000.000000
mean       5.865267     3.051833      3.767367     1.191000
std        0.805073     0.412472      1.751183     0.758022
min        4.300000     2.000000      0.900000     0.100000
25%        5.100000     2.800000      1.500000     0.300000
50%        5.800000     3.000000      4.300000     1.300000
```

```
75%        6.400000     3.300000      5.200000     1.800000
max        7.900000     4.400000      6.900000     2.500000
sepal length    0
sepal width     0
petal length    0
petal width     0
dtype: int64
label
Iris-setosa        1000
Iris-versicolor    1000
Iris-virginica     1000
Name: count, dtype: int64
```

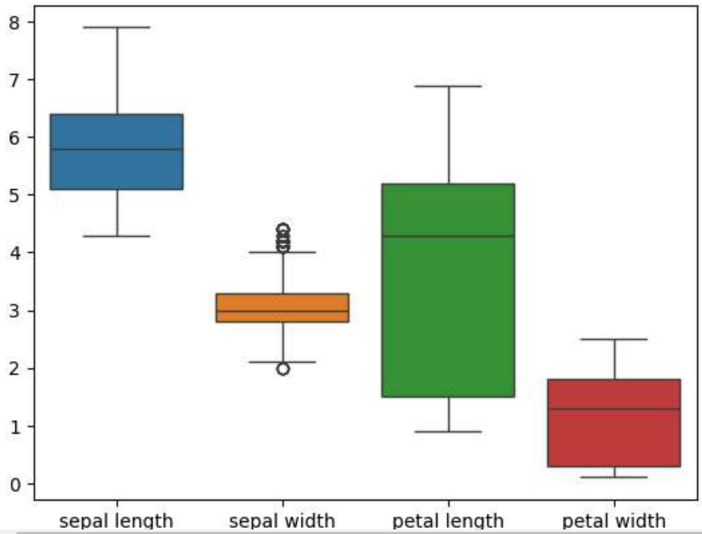
```
# prompt: Pair plots to see feature relationships

# Create a pair plot
#sns.pairplot(pd.concat([X, y], axis=1), hue=0)
#plt.show()
import seaborn as sns
import matplotlib.pyplot as plt

# Combine features (X) and target (y) into a single DataFrame
df = pd.concat([X, y], axis=1)

# Create a pair plot with 'label' as the hue
sns.pairplot(df, hue='label')  # Use the column name 'label' for hue
plt.show()
```



```
#Correlation heatmap
sns.heatmap(X.corr(), annot=True, cmap='coolwarm')
plt.show()
```




```
#Box plots for feature distributions
sns.boxplot(data=X)
plt.show()
```




```
#Split Data into Features and Target

#Separate the dataset into features (X) and target (y).
from sklearn.model_selection import train_test_split

# Split data 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, stratify=y)


#Train and Evaluate Models

#Train multiple classifiers (Logistic Regression, Decision Tree, SVM) and evaluate their performance.
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# Train model
model = LogisticRegression(max_iter=10000)
model.fit(X_train, y_train)

# Evaluate model
y_pred = model.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: 0.995
Confusion Matrix:
```

```
[[200   0   0]
 [  0 197   3]
 [  0   0 200]]
Classification Report:
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00       200
Iris-versicolor       1.00      0.98      0.99       200
 Iris-virginica       0.99      1.00      0.99       200

       accuracy                           0.99       600
      macro avg       1.00      0.99      0.99       600
   weighted avg       1.00      0.99      0.99       600
```

```
#Compare Classifier Performance

#Compare models using metrics like accuracy, precision, recall, and F1-score.

from sklearn.metrics import precision_score, recall_score, f1_score

# Example for Logistic Regression
print("Precision:", precision_score(y_test, y_pred, average='weighted'))
print("Recall:", recall_score(y_test, y_pred, average='weighted'))
print("F1-Score:", f1_score(y_test, y_pred, average='weighted'))
```

```
Precision: 0.9950738916256158
Recall: 0.995
F1-Score: 0.9949997187341789
```

```
#Feature Scaling and Impact Analysis

#Use StandardScaler to scale features and analyze the impact on model performance.
from sklearn.preprocessing import StandardScaler

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

# Train and evaluate model with scaled data
model = LogisticRegression(solver='liblinear',max_iter=10000)#can use default one too
model.fit(X_train_scaled, y_train)
y_pred_scaled = model.predict(X_test_scaled)
print("Accuracy with Scaling:", accuracy_score(y_test, y_pred_scaled))
```

```
Accuracy with Scaling: 0.9833333333333333
```

```
 #Hyperparameter Tuning

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler

# Scale the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Define parameter grid
param_grid = {'C': [0.1, 1, 10], 'solver': ['liblinear', 'lbfgs']}

# Perform grid search with scaled data
grid_search = GridSearchCV(LogisticRegression(max_iter=1000), param_grid, cv=5)
grid_search.fit(X_train_scaled, y_train)

# Best parameters
print("Best Parameters:", grid_search.best_params_)
```

```
Best Parameters: {'C': 10, 'solver': 'lbfgs'}
```

```
#Save the Best Model

#Save the best-performing model using joblib.
import joblib
# Save model
joblib.dump(grid_search.best_estimator_, 'best_model.pkl')
# Load model
loaded_model = joblib.load('best_model.pkl')
```

```
#for best model

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Predict on the test set
y_pred = grid_search.best_estimator_.predict(X_test_scaled)

# Evaluate performance
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: 0.995
Confusion Matrix:
 [[200   0   0]
 [  0 197   3]
 [  0   0 200]]
Classification Report:
                  precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00       200
Iris-versicolor       1.00      0.98      0.99       200
 Iris-virginica       0.99      1.00      0.99       200

       accuracy                           0.99       600
      macro avg       1.00      0.99      0.99       600
   weighted avg       1.00      0.99      0.99       600
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Train Logistic Regression
log_reg = LogisticRegression(max_iter=10000)
log_reg.fit(X_train_scaled, y_train)

# Predict and evaluate
y_pred_log_reg = log_reg.predict(X_test_scaled)
accuracy_log_reg = accuracy_score(y_test, y_pred_log_reg)
print("Logistic Regression Accuracy:", accuracy_log_reg)

from sklearn.tree import DecisionTreeClassifier

# Train Decision Tree
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)

# Predict and evaluate
y_pred_dt = dt.predict(X_test)
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print("Decision Tree Accuracy:", accuracy_dt)

from sklearn.svm import SVC

# Train SVM
svm = SVC()
svm.fit(X_train_scaled, y_train)

# Predict and evaluate
y_pred_svm = svm.predict(X_test_scaled)
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print("SVM Accuracy:", accuracy_svm)
```

```
Logistic Regression Accuracy: 0.995
Decision Tree Accuracy: 1.0
SVM Accuracy: 0.99
```

```
#stroing the accuracy scores
accuracy_scores = [accuracy_log_reg, accuracy_dt, accuracy_svm]
print("Accuracy Scores:", accuracy_scores)
```

```
Accuracy Scores: [0.995, 1.0, 0.99]
```

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

# Classifier names
classifiers = ['Logistic Regression', 'Decision Tree', 'SVM']

# Plot
sns.barplot(x=classifiers, y=accuracy_scores)
plt.title("Classifier Accuracy Comparison")
plt.ylabel("Accuracy")
```

```
plt.ylabel('Accuracy')
plt.ylim(0, 2)  # Set y-axis limit between 0 and 1
plt.show()
```