

DONE BY PIYUSH WORLIKAR


The IRIS dataset contains three classes of flowers, Versicolor, Setosa, Virginica, and each class contains 4 features, 'Sepal length', 'Sepal width', 'Petal length', 'Petal width'. The aim of the iris flower classification is to predict flowers based on their specific features.

IMPORT THE NECESSARY LIBRARIES:

```
1 import numpy as np          #NUMPY IS USED FOR NUMERICAL OPERATIONS
2 import pandas as pd # PANDAS FOR IMPORTING THE DATASET
3 from sklearn.model_selection import train_test_split    #TO SPLIT DATA INTO TRAINING AND TESTING DATA
4 from sklearn.tree import DecisionTreeClassifier    #FOR DECISION TREE CLASSIFIER
5 from sklearn.metrics import accuracy_score    #TO CHECK ACCURACY
6 import matplotlib.pyplot as plt    # FOR DATA VISUALIZATION PURPOSE
7 from sklearn import tree    # TO VISUALIZE THE TREE
8 import seaborn as sns    # FOR DATA VISUALIZATION
9
10 from sklearn.preprocessing import StandardScaler
11 from sklearn.neighbors import KNeighborsClassifier
12 from sklearn.metrics import classification_report, confusion_matrix
```

LOAD THE IRIS DATASET:

```
1 data = pd.read_csv("/content/Iris.csv")    # using the Pandas library's read_csv function. The dataset is s
2 data
```




	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows x 5 columns

EXPLORE THE DATASET: The code loads the Iris dataset and assigns the features (all columns except 'species') and target ('species') to separate variables.

```
1 data.head()    # Display the first few rows of the dataset
2
```



	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

```
1 data.shape      # Check the shape of the dataset
2
```

```
(150, 5)
```

```
1 data.columns      # Check the column names
2
```

```
Index(['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
      'Species'],
      dtype='object')
```

```
1 data.describe()      #will display the stats of each column
```

```

SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm
count      150.000000      150.000000      150.000000      150.000000
mean         5.843333         3.054000         3.758667         1.198667
std          0.828066         0.433594         1.764420         0.763161
min          4.300000         2.000000         1.000000         0.100000
25%          5.100000         2.800000         1.600000         0.300000
50%          5.800000         3.000000         4.350000         1.300000
75%          6.400000         3.300000         5.100000         1.800000
max          7.900000         4.400000         6.900000         2.500000

```

```
1 data.info()      # provides a summary of the dataset, including the number of non-null values, data types of
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ---
 0   SepalLengthCm   150 non-null   float64
 1   SepalWidthCm    150 non-null   float64
 2   PetalLengthCm   150 non-null   float64
 3   PetalWidthCm    150 non-null   float64
 4   Species         150 non-null   object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB

```

```
1 data.nunique()      #to check unique values
```

```

      0
SepalLengthCm  35
SepalWidthCm   23
PetalLengthCm  43
PetalWidthCm   22
Species        3

```

```
1 Start coding or generate with AI.
```

```
1 Start coding or generate with AI.
```

```
1 data['Species'].unique()      # Check the unique values in the target variable (species)
2
```

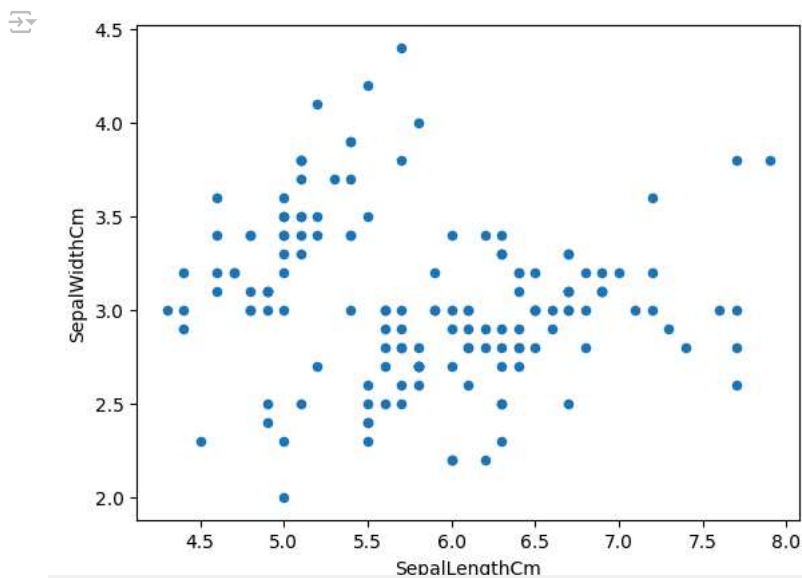
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

```
1 data['Species'].value_counts()
2                                     # Check the distribution of the target variable
```

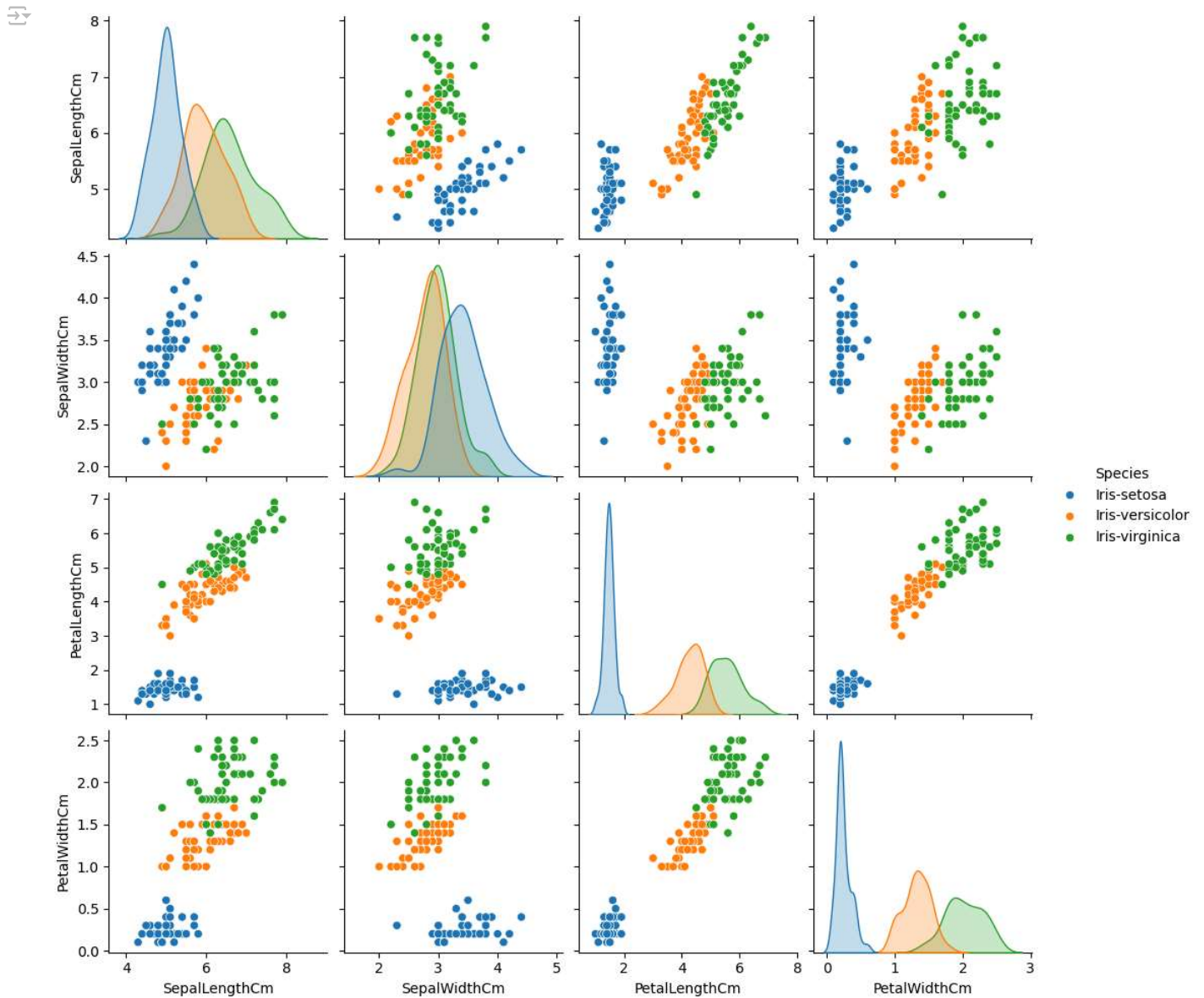
```
Species
Iris-setosa    50
Iris-versicolor 50
Iris-virginica  50
```

DATA VISUALIZATION: This section creates a scatter plot of 'sepal_length' on the x-axis and 'sepal_width' on the y-axis. It visualizes the relationship between these two features in the Iris dataset.

```
1 data.plot(kind='scatter', x='SepalLengthCm', y='SepalWidthCm')
2 plt.show()
3
```



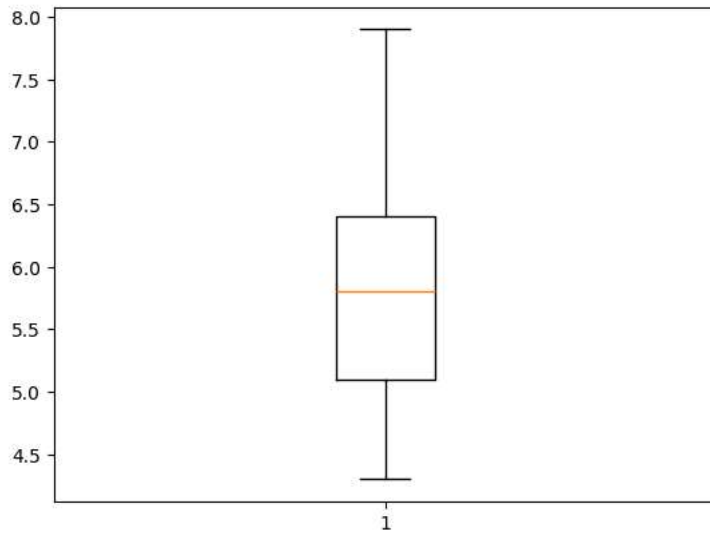
```
1 sns.pairplot(data, hue='Species')
2 plt.show()
```



1 #Boxplots help identify the distribution, central tendency, and outliers in the data.

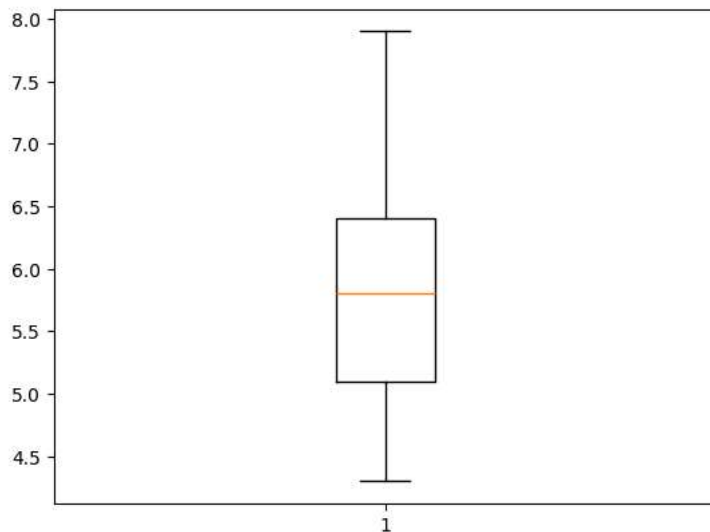
```
1 # boxplot - to check for outliers
2 plt.boxplot(data['SepalLengthCm'])
3
```

```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f229034d0f0>,\n             <matplotlib.lines.Line2D at 0x7f229034d8d0>],\n 'caps': [<matplotlib.lines.Line2D at 0x7f229034f010>,\n          <matplotlib.lines.Line2D at 0x7f229034f460>],\n 'boxes': [<matplotlib.lines.Line2D at 0x7f229034e380>],\n 'medians': [<matplotlib.lines.Line2D at 0x7f229034fa30>],\n 'fliers': [<matplotlib.lines.Line2D at 0x7f229034f880>],\n 'means': []}
```



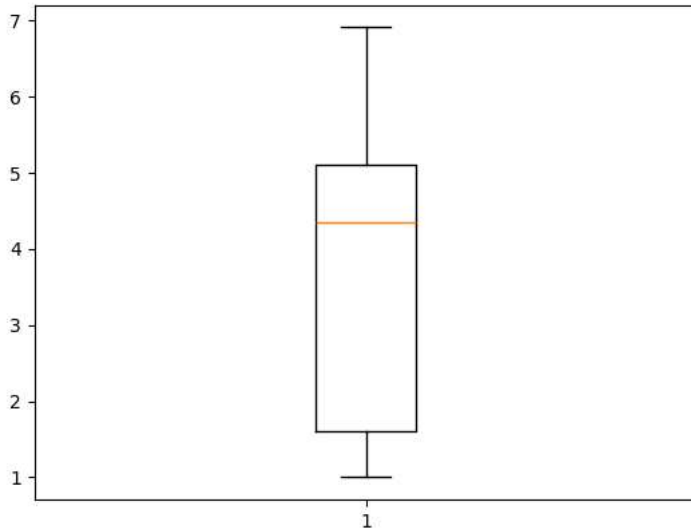
```
1 # boxplot
2 plt.boxplot(data['SepalLengthCm'])
3
```

```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f2290310e20>,\n             <matplotlib.lines.Line2D at 0x7f22903107f0>],\n 'caps': [<matplotlib.lines.Line2D at 0x7f2290310730>,\n          <matplotlib.lines.Line2D at 0x7f22903109d0>],\n 'boxes': [<matplotlib.lines.Line2D at 0x7f2290313f70>],\n 'medians': [<matplotlib.lines.Line2D at 0x7f2290310f40>],\n 'fliers': [<matplotlib.lines.Line2D at 0x7f2290311720>],\n 'means': []}
```



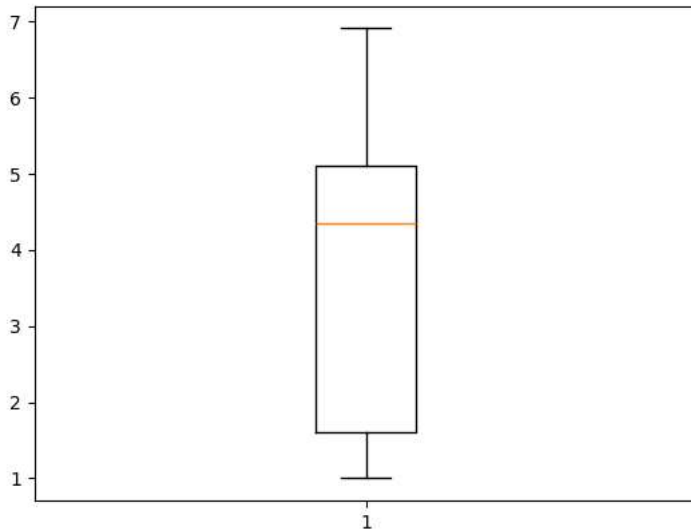
```
1 # boxplot
2 plt.boxplot(data['PetalLengthCm'])
3
```

```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f229692fa90>,\n             <matplotlib.lines.Line2D at 0x7f229692c040>],\n 'caps': [<matplotlib.lines.Line2D at 0x7f229692e320>,\n          <matplotlib.lines.Line2D at 0x7f229692c220>],\n 'boxes': [<matplotlib.lines.Line2D at 0x7f229692ee60>],\n 'medians': [<matplotlib.lines.Line2D at 0x7f229692dc00>],\n 'fliers': [<matplotlib.lines.Line2D at 0x7f229692fdf0>],\n 'means': []}
```



```
1 # boxplot
2 plt.boxplot(data['PetalLengthCm'])
3
```

```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f22977b4940>,\n             <matplotlib.lines.Line2D at 0x7f22977b56f0>],\n 'caps': [<matplotlib.lines.Line2D at 0x7f22977b44f0>,\n          <matplotlib.lines.Line2D at 0x7f22977b6dd0>],\n 'boxes': [<matplotlib.lines.Line2D at 0x7f22977b52a0>],\n 'medians': [<matplotlib.lines.Line2D at 0x7f2294405930>],\n 'fliers': [<matplotlib.lines.Line2D at 0x7f2294405390>],\n 'means': []}
```



DATA PREPARATION: This section prepares the dataset by separating the features (X) and the target variable (y) and then splitting the data into training and testing sets using the `train_test_split` function.

```
1 X = data.drop("Species", axis=1)
2 y =data["Species"]
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

TRAIN THE DECISION TREE CLASSIFIER: A decision tree classifier is instantiated and trained using the training data (x_{train} and y_{train}) using the fit method.

```
1 clf = DecisionTreeClassifier()
2 clf.fit(X_train, y_train)
```

DecisionTreeClassifier

MAKE PREDICTIONS ON THE TEST SET

```
1 y_pred = clf.predict(X_test)
```

CALCULATE THE ACCURACY OF THE MODEL:

```
1 accuracy = accuracy_score(y_test, y_pred)
2 print("Accuracy:", accuracy)
```

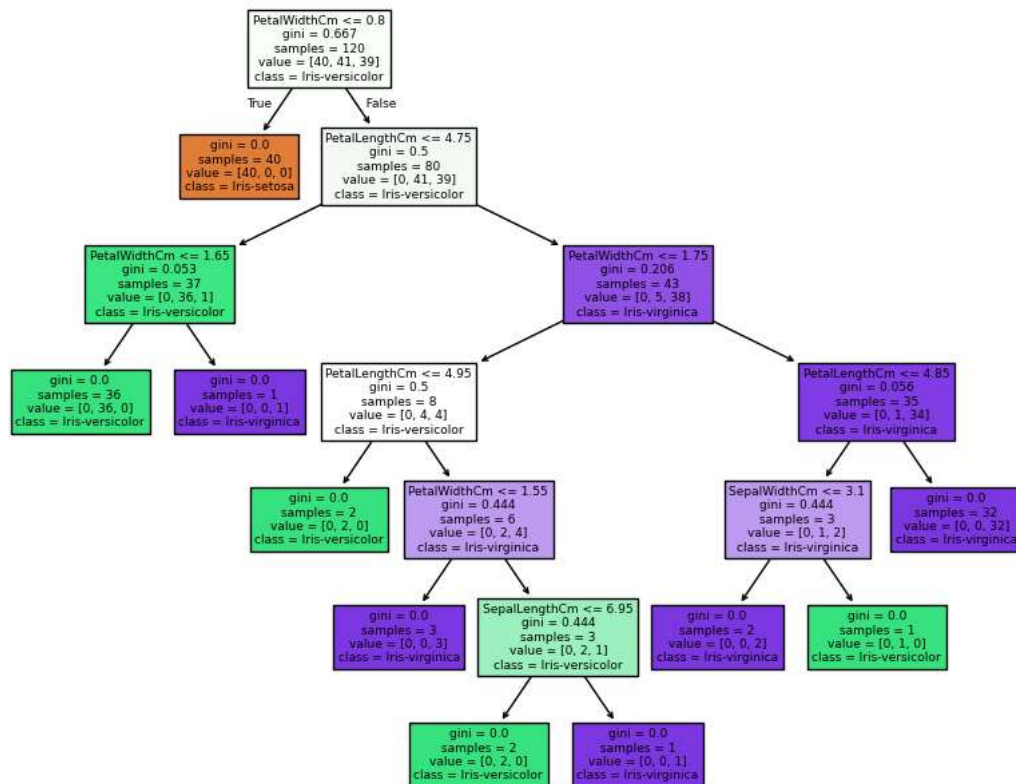
Accuracy: 1.0

VISUALIZE THE DECISION TREE :

```
1 fig = plt.figure(figsize=(10, 8))
2 _ = tree.plot_tree(clf, feature_names=X.columns, class_names=clf.classes_, filled=True)
3 plt.title("Decision Tree Classifier")
4 plt.show()
```



Decision Tree Classifier



USING LOGISTIC REGRESSION:

A logistic regression model is instantiated and trained using the training data (X_{train} and y_{train}) using the fit method.

Prepare the data:

```
1 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
2
```

TRAIN THE LOGISTIC REGRESSION MODEL

```
1 from sklearn.linear_model import LogisticRegression
2 model = LogisticRegression()
3 model.fit(X_train, y_train)
4
```

LogisticRegression ⓘ ?

LogisticRegression()

MAKE PREDICTIONS:

```
1 predictions = model.predict(X_test)
```

EVALUATE THE MODEL:

```
1 accuracy = accuracy_score(y_test, predictions)
2 print("Accuracy:", accuracy)
```

Accuracy: 1.0

USING KNEIGHBORS CLASSIFIER:

```
1 # Standardize the features
2 scaler = StandardScaler()
3 X_train = scaler.fit_transform(X_train)
4 X_test = scaler.transform(X_test)
```

TRAIN THE MODEL:

```
1 knn = KNeighborsClassifier(n_neighbors=3)
2 knn.fit(X_train, y_train)
```

KNeighborsClassifier ⓘ ?

KNeighborsClassifier(n_neighbors=3)

MAKE PREDICTIONS:

```
1 y_pred = knn.predict(X_test)
```

EVALUATE THE MODEL:

```
1 print(confusion_matrix(y_test, y_pred))
2 print(classification_report(y_test, y_pred))
```

[[10 0 0]
[0 9 0]
[0 0 11]]

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-virginica	1.00	1.00	1.00	11
accuracy		1.00		30

macro avg	1.00	1.00	1.00	30
weighted avg	1.00	1.00	1.00	30

PLOT CONFUSION MATRIX:

```
1 sns.heatmap(confusion_matrix(y_test,y_pred), annot=True, fmt='d', cmap='Blues')
2 plt.xlabel("Predicted")
```