iris-class-classification

July 12, 2023

Iris flower classification

[229]:
```
# import libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[230]:
```
iris_df = pd.read_csv("./Iris_data.csv")
```

[231]:
```
# View the first few rows of the dataset
iris_df.head()
```

[231]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

[232]:
```
iris_df.drop("Id", axis=1, inplace=True)
```

[233]:
```
iris_df.info()
```

```
<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
```

From above we can see that there's no null values

[234]:
```python
# Summary statistics
iris_df.describe()
```

[234]:

	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

[240]:
```python
# Summary statistics include object datatype
iris_df.describe(include="object")
```

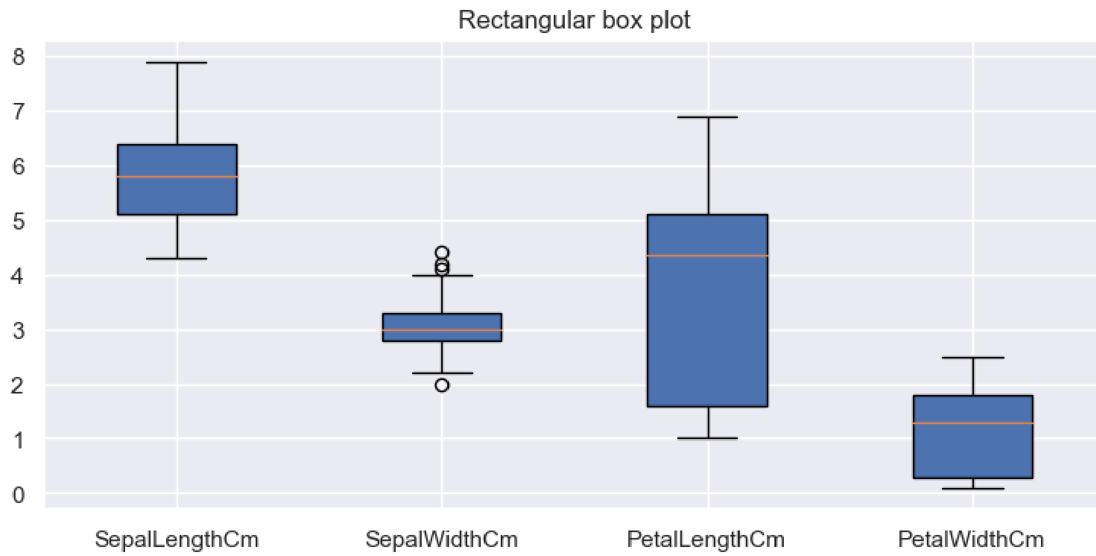
[240]:

	Species
count	150
unique	3
top	Iris-setosa
freq	50

[236]:
```python
# Class distribution
class_counts = iris_df['Species'].value_counts()
print(class_counts)
```

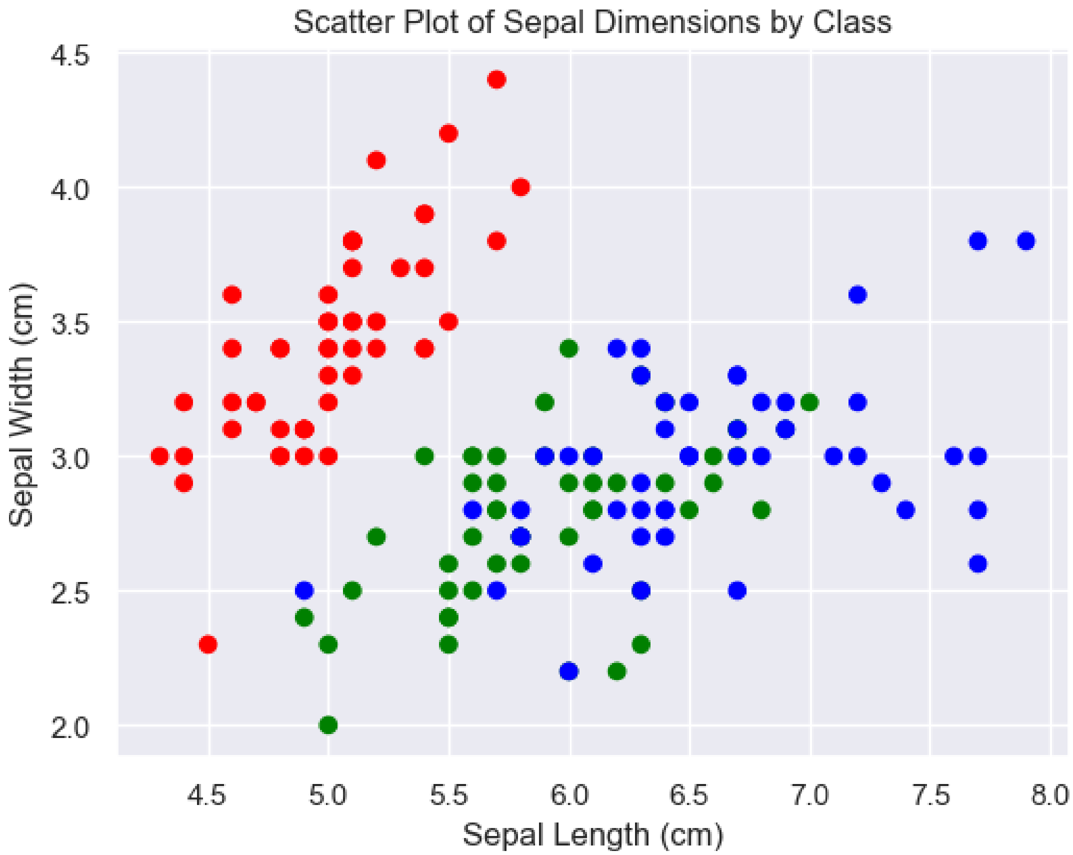
```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: Species, dtype: int64
```

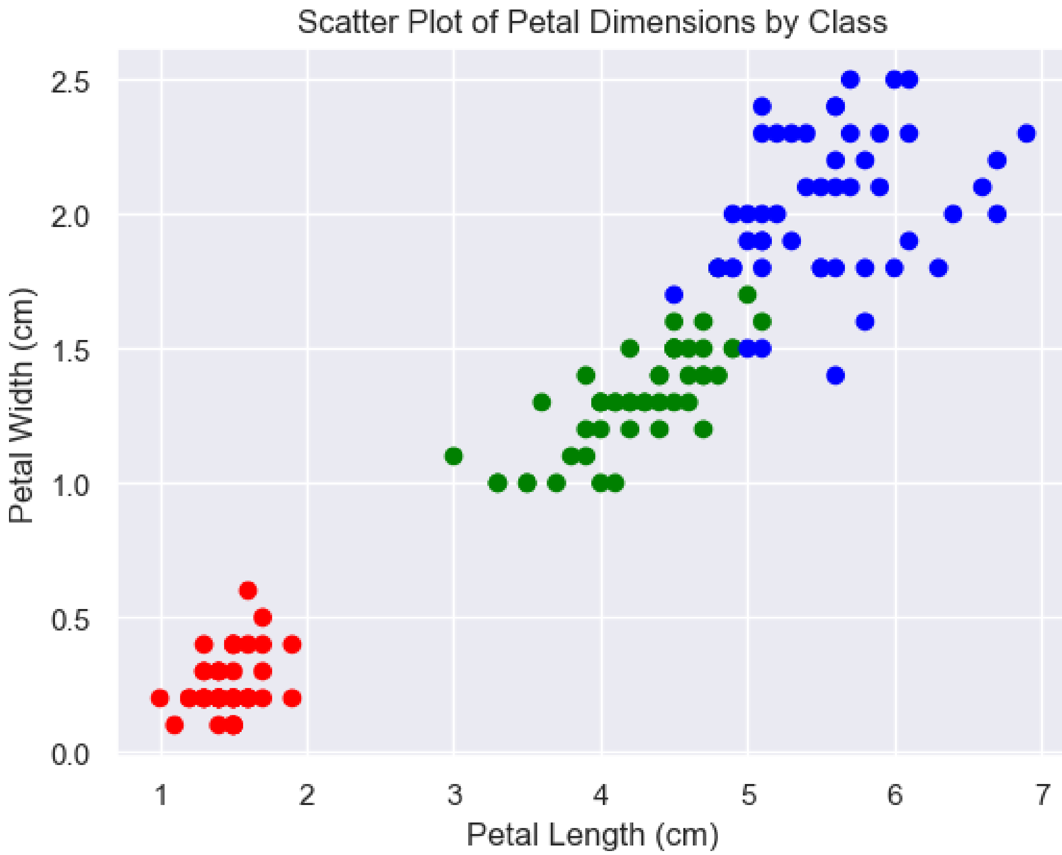
[237]:
```python
fig, ax = plt.subplots(nrows=1, figsize=(9, 4))
labels =['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']
ax.boxplot(iris_df.drop("Species",axis=1),
                        labels=labels,
                        patch_artist=True)  # will be used to label x-ticks
ax.set_title('Rectangular box plot')
sns.set_theme()
%matplotlib inline
```



[239]:
```
# Scatter plot by class
colors = {'Iris-setosa': 'red', 'Iris-versicolor': 'green', 'Iris-virginica':␣
↪'blue'}
plt.scatter(iris_df['SepalLengthCm'], iris_df['SepalWidthCm'],␣
↪c=iris_df['Species'].map(colors))
plt.xlabel('Sepal Length (cm)')
plt.ylabel('Sepal Width (cm)')
plt.title('Scatter Plot of Sepal Dimensions by Class')
plt.show()

plt.scatter(iris_df['PetalLengthCm'], iris_df['PetalWidthCm'],␣
↪c=iris_df['Species'].map(colors))
plt.xlabel('Petal Length (cm)')
plt.ylabel('Petal Width (cm)')
plt.title('Scatter Plot of Petal Dimensions by Class')
plt.show()
```


Scatter Plot of Sepal Dimensions by Class
Sepal Width (cm)
4.5
4.0
3.5
3.0
2.5
2.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
Sepal Length (cm)



[ ]:
```
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
```

[ ]:
```
X = iris_df.drop("Species",axis=1)
y = iris_df["Species"]
print(X.shape)
print(y.shape)
```

```
(150, 4)
(150,)
```

[ ]:
```
def test_multiple_models(X, y, cv):
    # Split the 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)
```

```python
    # Define the models to test
    models = [
        ("Logistic Regression", LogisticRegression()),
        ("Decision Tree", DecisionTreeClassifier()),
        ("Random Forest", RandomForestClassifier()),
        ("Support Vector Machine", SVC())
    ]

    # Iterate over each model
    for name, model in models:
        # Perform cross-validation
        scores = cross_val_score(model, X_train, y_train, cv=cv)

        # Train the model
        model.fit(X_train, y_train)

        # Make predictions on the test set
        y_pred = model.predict(X_test)

        # Evaluate the model
        accuracy = accuracy_score(y_test, y_pred)
        print(f"Model: {name}")
        print("Cross-Validation Accuracy:", scores.mean())
        print("Accuracy:", accuracy)

        report = classification_report(y_test, y_pred)
        print("Classification Report:\n", report)
        print("-----------------------------------------");
```

[ ]:
```python
test_multiple_models(X,y,5)
```

```
c:\Users\Jarvis\.conda\envs\myenv\lib\site-
packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
c:\Users\Jarvis\.conda\envs\myenv\lib\site-
packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
Model: Logistic Regression
Cross-Validation Accuracy: 0.9666666666666666
Accuracy: 1.0
Classification Report:
                  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

-----------------------------------------
Model: Decision Tree
Cross-Validation Accuracy: 0.9416666666666668
Accuracy: 1.0
Classification Report:
                  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

-----------------------------------------
Model: Random Forest
Cross-Validation Accuracy: 0.9416666666666667
Accuracy: 1.0
Classification Report:
                  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

----------------------------------------
Model: Support Vector Machine
Cross-Validation Accuracy: 0.95
Accuracy: 1.0
Classification Report:
                 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

----------------------------------------
```

[ ]: