Hanin Firginita Gilty

# Visualizing the Iris Dataset

### 1. Import Libraries

```
# Importing multiple library to read,analysed and visualized the dataset

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.tree import plot_tree
```

```
# Loading dataset
iris = sns.load_dataset('iris')
iris.head()
```

| | sepal_length | sepal_width | petal_length | petal_width | species |
|---|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | setosa |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | setosa |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 | setosa |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 | setosa |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | setosa |

### 2. Exploratory Data Analysis

```
# DataFrame Information
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
```

```
 4   species       150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

```
# Desciribing Data
iris.describe()
```

| | sepal_length | sepal_width | petal_length | petal_width |
|---|---|---|---|---|
| **count** | 150.000000 | 150.000000 | 150.000000 | 150.000000 |
| **mean** | 5.843333 | 3.057333 | 3.758000 | 1.199333 |
| **std** | 0.828066 | 0.435866 | 1.765298 | 0.762238 |
| **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 |

```
# DataFrame Shape
iris.shape
```

```
(150, 5)
```

```
# Checking Missing Value
print("Checking Missing Value: ")
iris.isnull().sum()
```

```
Checking Missing Value:
```

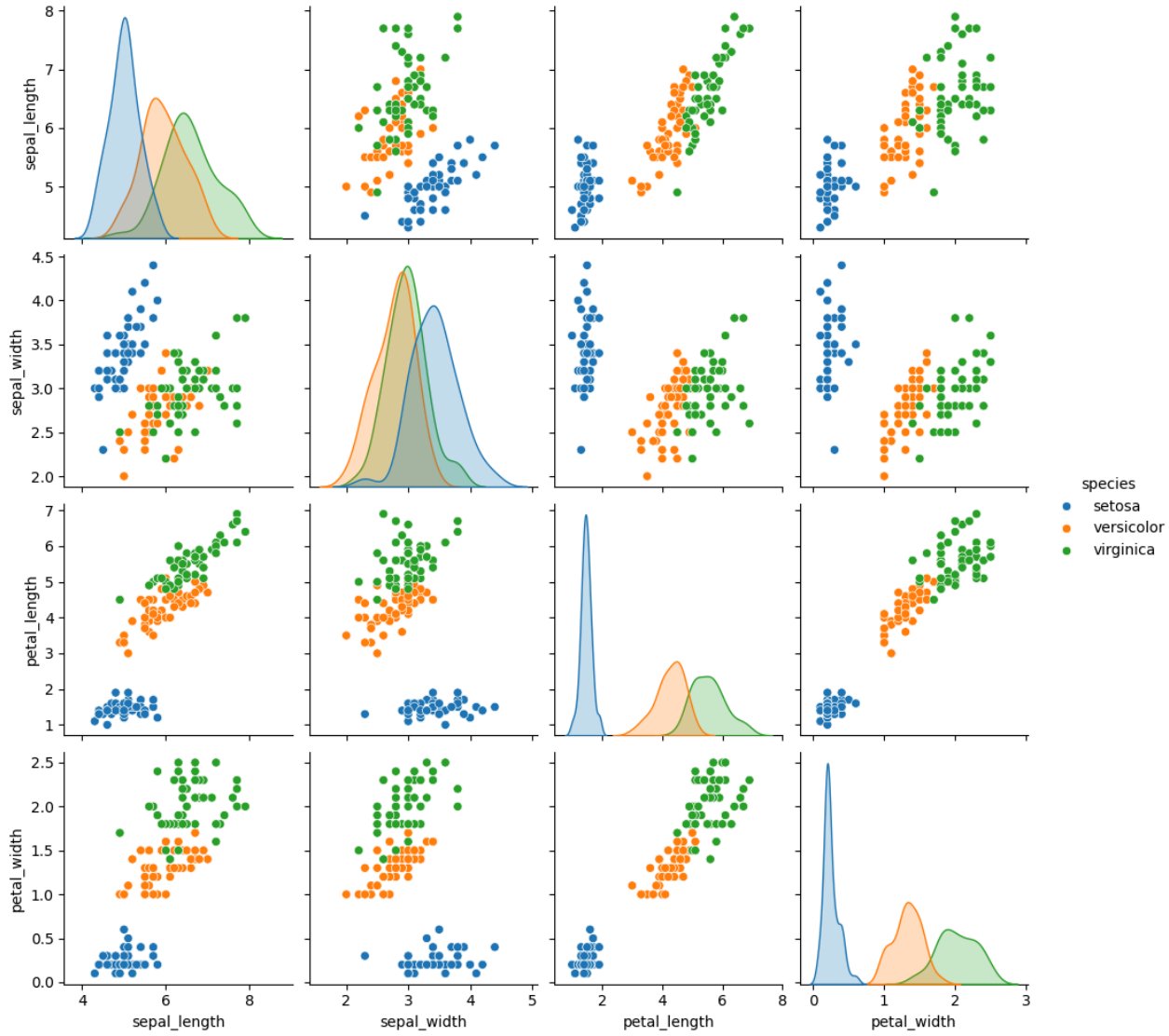
| | 0 |
|---|---|
| **sepal_length** | 0 |
| **sepal_width** | 0 |
| **petal_length** | 0 |
| **petal_width** | 0 |
| **species** | 0 |

**dtype:** int64

### 3. Data Visualization Using Various Attributes

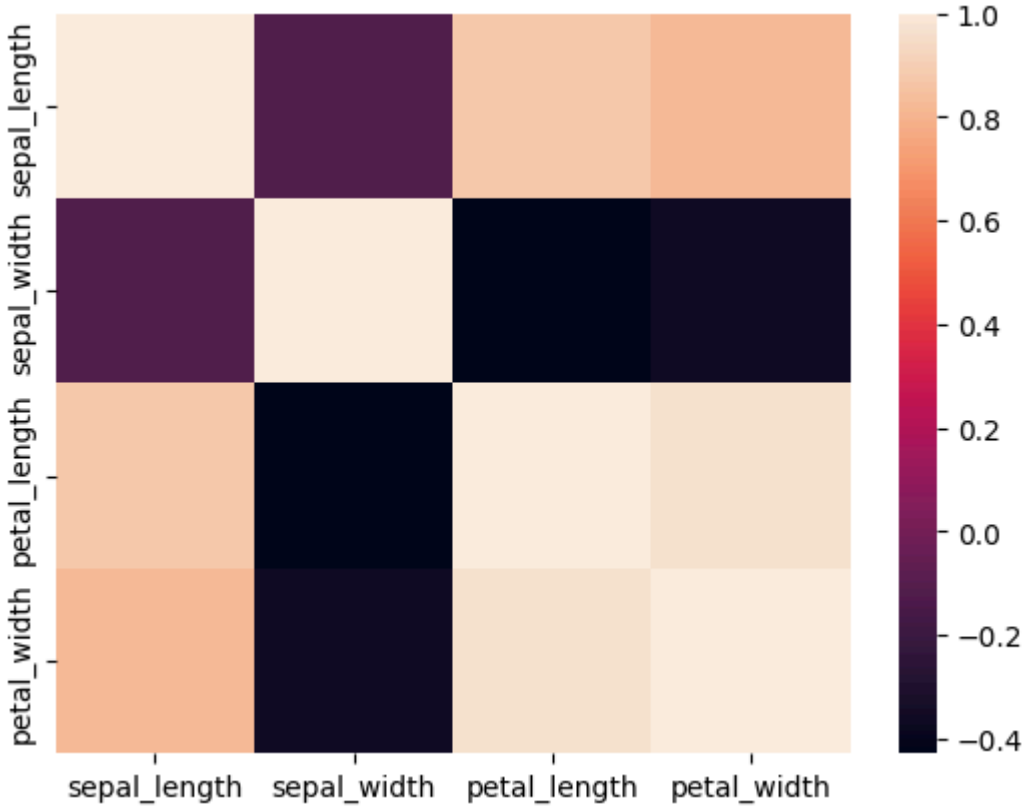
```
# Plotting all the attributes at once using plot pair
sns.pairplot(data=iris,hue ='species')
```

<seaborn.axisgrid.PairGrid at 0x7bbae8f7c090>



```
# Plotting the correlation matrix
data = iris.drop(columns=['species']).corr()
sns.heatmap(data)
```

```
<Axes: >
```




EDA Insights:

- Initial exploration provides an understanding of the dataset's structure and quality.
- Visualization reveals relationships between features and species.

### 4. Predicting Target Variable

```
# Separating target varibale(y) & feature variables (x)
target = iris['species']
data = iris.copy()
data = data.drop('species',axis =1)

x = data # dependent variable

target # independent variable
```

| | species |
|---|---|
| **0** | setosa |
| **1** | setosa |
| **2** | setosa |
| **3** | setosa |
| **4** | setosa |
| **...** | ... |
| **145** | virginica |
| **146** | virginica |
| **147** | virginica |
| **148** | virginica |
| **149** | virginica |

150 rows × 1 columns

**dtype:** object

```
# Label encoding as target variable
le = LabelEncoder()
target = le.fit_transform(target)
target
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

```
y = target
```

Feature and Target Separation:

- Target Variable (y): 'species'
- Feature Variables (x): All other columns except 'species'.

### 5. Training Test Dataset

```
# Splitting the data - 80:20 ratio
x_train,x_test,y_train,y_test = train_test_split ( x,y, test_size = 0.2, random_state = 4
```

### 6. Decision Tree Clasifier

```
# Defining the decision tree alogritham
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
print('Decision Tree Classifier Created')
```

```
Decision Tree Classifier Created
```

```
# Predicting values from test data using confusion matrix and classification report.
y_predt = model.predict(x_test)
from sklearn.metrics import confusion_matrix
print(confusion_matrix(y_test,y_predt))
```

```
[[ 8  0  0]
 [ 0 12  0]
 [ 0  0 10]]
```

```
print('Classification report: \n', classification_report(y_test,y_predt))
```

```
Classification report:
                precision    recall  f1-score   support

             0       1.00      1.00      1.00         8
             1       1.00      1.00      1.00        12
             2       1.00      1.00      1.00        10

      accuracy                           1.00        30
     macro avg       1.00      1.00      1.00        30
  weighted avg       1.00      1.00      1.00        30
```

```
model.feature_importances_
```

```
array([0.02919099, 0.        , 0.06433933, 0.90646968])
```

```
features = pd.DataFrame(model.feature_importances_,index = x.columns)
features.head()
```

| | 0 |
|---|---|
| **sepal_length** | 0.029191 |
| **sepal_width** | 0.000000 |
| **petal_length** | 0.064339 |
| **petal_width** | 0.906470 |

```
model2 = DecisionTreeClassifier(criterion ='entropy',ccp_alpha=0.4)
```

```
model2.fit(x_train,y_train)
```

```
DecisionTreeClassifier(ccp_alpha=0.4, criterion='entropy')
```

```
y_predt2 = model2.predict(x_test)
print(confusion_matrix(y_test,y_predt2))
```

```
[[ 8  0  0]
 [ 0 12  0]
 [ 0  0 10]]
```

```
print('Classification report: \n', classification_report(y_test,y_predt2))
```

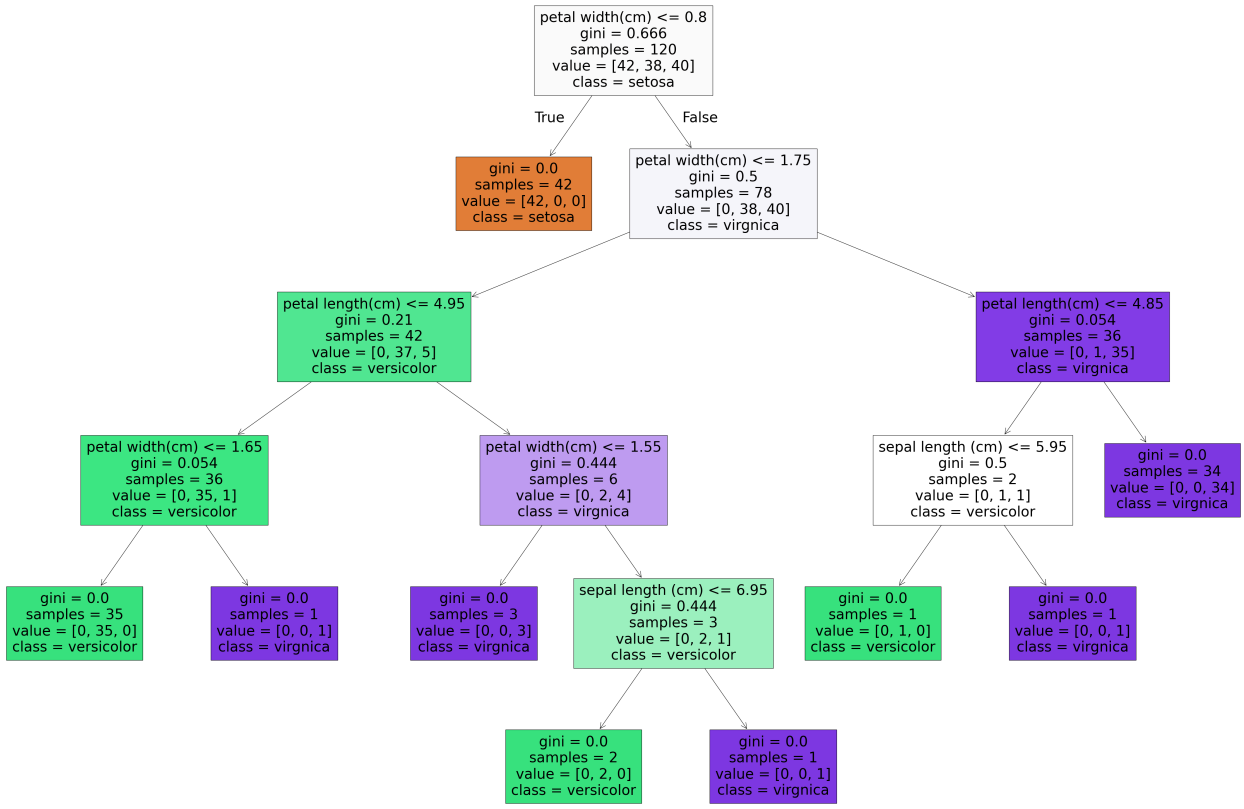
```
Classification report:
                precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       1.00      1.00      1.00        12
           2       1.00      1.00      1.00        10

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

```
features2= pd.DataFrame(model2.feature_importances_,index = x.columns)
features2.head()
```

| | 0 |
|---|---|
| **sepal_length** | 0.000000 |
| **sepal_width** | 0.000000 |
| **petal_length** | 0.694729 |
| **petal_width** | 0.305271 |

## 7. Visualizing the trained model

```
from sklearn import tree
fn = ['sepal length (cm)','sepalwidth (cm)','petal length(cm)','petal width(cm)']
cn =['setosa','versicolor','virgnica']
fig = plt.figure (figsize =(60,40))
tree.plot_tree(model,feature_names = fn,
               class_names = cn ,
               filled = True);
# fig.savefig('imagename.png')
```




Decision Tree Visualization:

- Feature Names: 'sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)'
- Class Names: 'setosa', 'versicolor', 'virginica'

- The decision tree is visualized using tree.plot_tree

### 8. Checking model accuracy

```
# Model Accuracy
import sklearn.metrics as sm
print("Accuracy:",f"{sm.accuracy_score(y_test, y_predt)* 100:.2f}%")
```

```
Accuracy: 100.00%
```

Accuracy Score: The model achieved an accuracy score of 100%, which indicates that all predictions made by the decision tree classifier on the test dataset were correct.