LetsGrowMore Data Science Internship

Intermediate Level - TASK 2

Prediction using Decision Tree Algorithm:

BY SMRITHIKA ANTONETTE

In [24]:
```
#importing all the required libraries
import numpy as np
import pandas as pd
import sklearn.metrics as sm
import seaborn as sns
import matplotlib.pyplot as mt
%matplotlib inline

import sklearn.datasets as datasets
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.tree import plot_tree
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix, classification_report
```

In [25]:
```
#Loading the Iris dataset
iris_data =datasets.load_iris()

iris_df=pd.DataFrame(iris_data.data,columns=iris_data.feature_names)

iris_df
```

Out[25]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

In [8]:
```
#reading the data
df=pd.read_csv('Iris.csv',index_col=0)
df.head()
```

Out[8]:

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

In [9]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 150 entries, 1 to 150
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: 7.0+ KB
```

In [26]:

```
df.describe()
```

Out[26]:

	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

In [11]:

```
iris_data.feature_names
```

Out[11]:

```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

In [12]:

```
iris_data.target_names
```

Out[12]:

```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

In [13]:

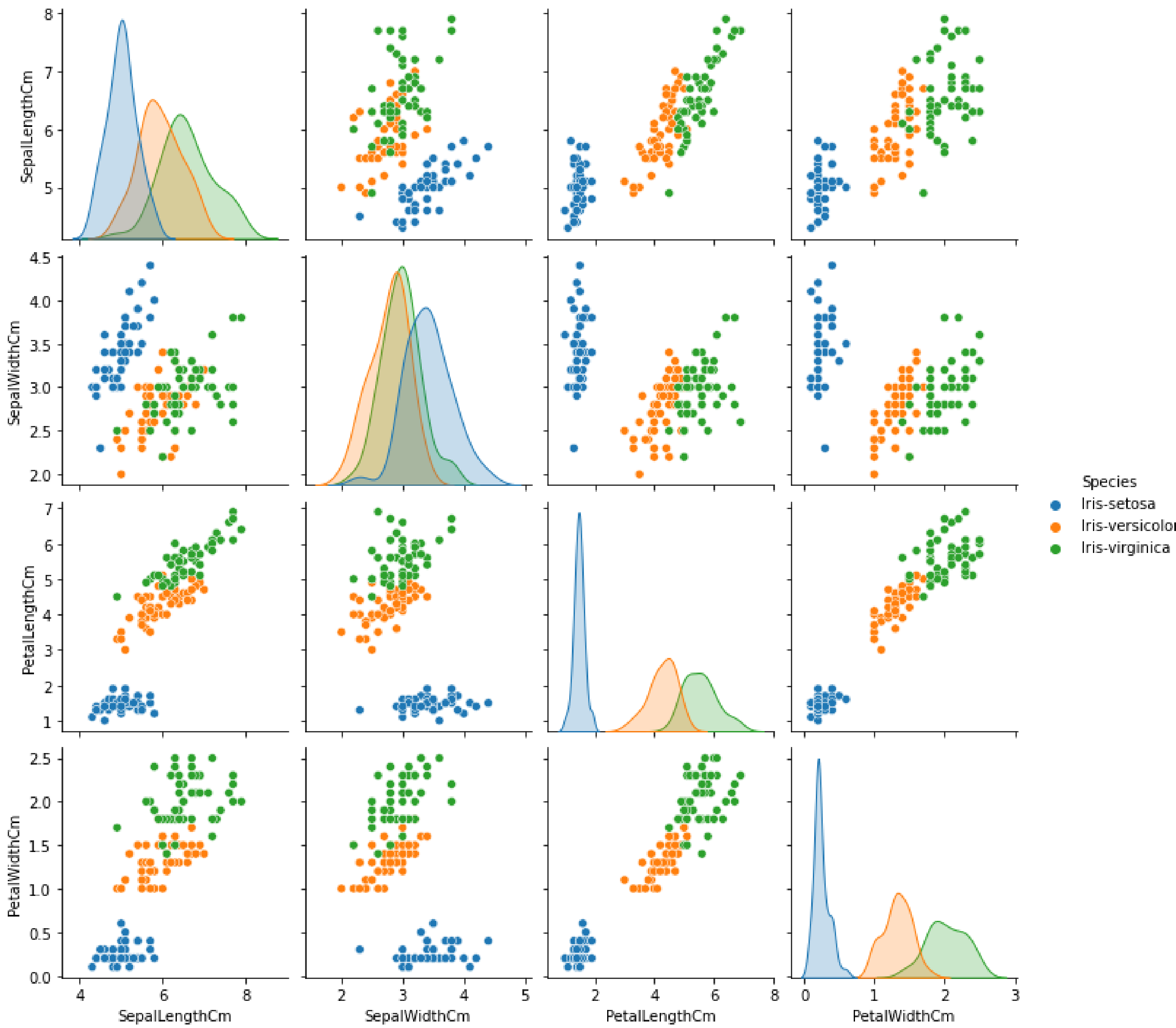
```
iris_df.isnull().sum()
```

Out[13]:

```
sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
dtype: int64
```

Visualize the Dataset

In [14]:
```
import matplotlib.pyplot as plt
sns.pairplot(df, hue='Species')
plt.show()
```



In [27]:
```
#Reading the data from the computer location
iris=pd.read_csv("C:/Users/SMRITHIKA/Iris.csv")
iris
```

Out[27]:

	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
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

In [28]:

```
iris.drop('Id',inplace=True,axis=1)
iris
```

Out[28]:

	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 × 5 columns

Find the Correlation matrix

In [18]:

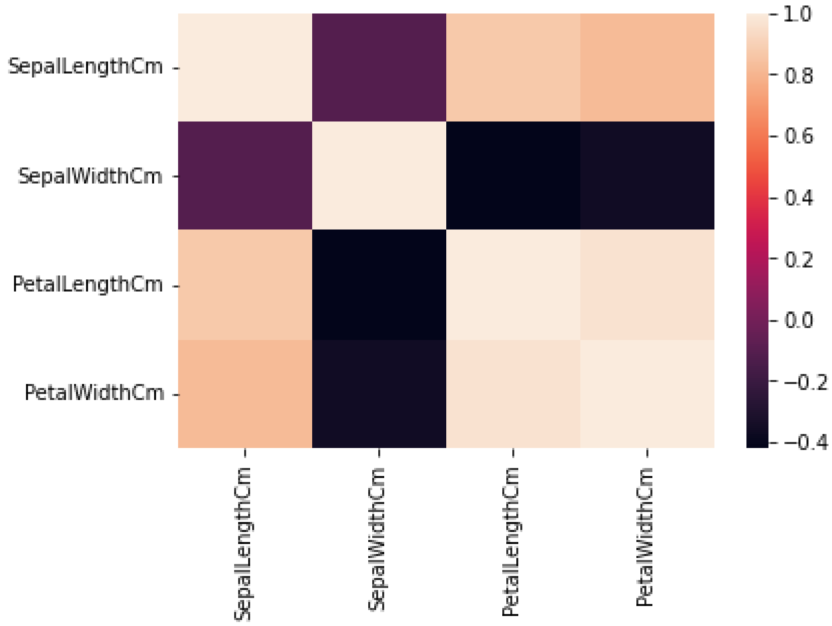
```
df.corr()
```

Out[18]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
SepalLengthCm	1.000000	-0.109369	0.871754	0.817954
SepalWidthCm	-0.109369	1.000000	-0.420516	-0.356544
PetalLengthCm	0.871754	-0.420516	1.000000	0.962757
PetalWidthCm	0.817954	-0.356544	0.962757	1.000000

In [13]:
```
sns.heatmap(df.corr())
```

Out[13]:
```
<AxesSubplot:>
```



Prepare the Data

In [19]:
```
a=iris.iloc[:,:-1].values
b=iris['Species']
a
```

```
Out[19]: array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
       [5.1, 3.8, 1.5, 0.3],
       [5.4, 3.4, 1.7, 0.2],
       [5.1, 3.7, 1.5, 0.4],
       [4.6, 3.6, 1. , 0.2],
       [5.1, 3.3, 1.7, 0.5],
       [4.8, 3.4, 1.9, 0.2],
       [5. , 3. , 1.6, 0.2],
       [5. , 3.4, 1.6, 0.4],
       [5.2, 3.5, 1.5, 0.2],
       [5.2, 3.4, 1.4, 0.2],
       [4.7, 3.2, 1.6, 0.2],
       [4.8, 3.1, 1.6, 0.2],
       [5.4, 3.4, 1.5, 0.4],
       [5.2, 4.1, 1.5, 0.1],
       [5.5, 4.2, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5. , 3.2, 1.2, 0.2],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [4.4, 3. , 1.3, 0.2],
       [5.1, 3.4, 1.5, 0.2],
       [5. , 3.5, 1.3, 0.3],
       [4.5, 2.3, 1.3, 0.3],
       [4.4, 3.2, 1.3, 0.2],
       [5. , 3.5, 1.6, 0.6],
       [5.1, 3.8, 1.9, 0.4],
       [4.8, 3. , 1.4, 0.3],
       [5.1, 3.8, 1.6, 0.2],
       [4.6, 3.2, 1.4, 0.2],
       [5.3, 3.7, 1.5, 0.2],
       [5. , 3.3, 1.4, 0.2],
       [7. , 3.2, 4.7, 1.4],
       [6.4, 3.2, 4.5, 1.5],
       [6.9, 3.1, 4.9, 1.5],
       [5.5, 2.3, 4. , 1.3],
       [6.5, 2.8, 4.6, 1.5],
       [5.7, 2.8, 4.5, 1.3],
       [6.3, 3.3, 4.7, 1.6],
       [4.9, 2.4, 3.3, 1. ],
       [6.6, 2.9, 4.6, 1.3],
       [5.2, 2.7, 3.9, 1.4],
       [5. , 2. , 3.5, 1. ],
       [5.9, 3. , 4.2, 1.5],
       [6. , 2.2, 4. , 1. ],
       [6.1, 2.9, 4.7, 1.4],
```

```
[5.6, 2.9, 3.6, 1.3],
[6.7, 3.1, 4.4, 1.4],
[5.6, 3. , 4.5, 1.5],
[5.8, 2.7, 4.1, 1. ],
[6.2, 2.2, 4.5, 1.5],
[5.6, 2.5, 3.9, 1.1],
[5.9, 3.2, 4.8, 1.8],
[6.1, 2.8, 4. , 1.3],
[6.3, 2.5, 4.9, 1.5],
[6.1, 2.8, 4.7, 1.2],
[6.4, 2.9, 4.3, 1.3],
[6.6, 3. , 4.4, 1.4],
[6.8, 2.8, 4.8, 1.4],
[6.7, 3. , 5. , 1.7],
[6. , 2.9, 4.5, 1.5],
[5.7, 2.6, 3.5, 1. ],
[5.5, 2.4, 3.8, 1.1],
[5.5, 2.4, 3.7, 1. ],
[5.8, 2.7, 3.9, 1.2],
[6. , 2.7, 5.1, 1.6],
[5.4, 3. , 4.5, 1.5],
[6. , 3.4, 4.5, 1.6],
[6.7, 3.1, 4.7, 1.5],
[6.3, 2.3, 4.4, 1.3],
[5.6, 3. , 4.1, 1.3],
[5.5, 2.5, 4. , 1.3],
[5.5, 2.6, 4.4, 1.2],
[6.1, 3. , 4.6, 1.4],
[5.8, 2.6, 4. , 1.2],
[5. , 2.3, 3.3, 1. ],
[5.6, 2.7, 4.2, 1.3],
[5.7, 3. , 4.2, 1.2],
[5.7, 2.9, 4.2, 1.3],
[6.2, 2.9, 4.3, 1.3],
[5.1, 2.5, 3. , 1.1],
[5.7, 2.8, 4.1, 1.3],
[6.3, 3.3, 6. , 2.5],
[5.8, 2.7, 5.1, 1.9],
[7.1, 3. , 5.9, 2.1],
[6.3, 2.9, 5.6, 1.8],
[6.5, 3. , 5.8, 2.2],
[7.6, 3. , 6.6, 2.1],
[4.9, 2.5, 4.5, 1.7],
[7.3, 2.9, 6.3, 1.8],
[6.7, 2.5, 5.8, 1.8],
[7.2, 3.6, 6.1, 2.5],
[6.5, 3.2, 5.1, 2. ],
[6.4, 2.7, 5.3, 1.9],
[6.8, 3. , 5.5, 2.1],
[5.7, 2.5, 5. , 2. ],
[5.8, 2.8, 5.1, 2.4],
[6.4, 3.2, 5.3, 2.3],
[6.5, 3. , 5.5, 1.8],
[7.7, 3.8, 6.7, 2.2],
[7.7, 2.6, 6.9, 2.3],
[6. , 2.2, 5. , 1.5],
[6.9, 3.2, 5.7, 2.3],
[5.6, 2.8, 4.9, 2. ],
[7.7, 2.8, 6.7, 2. ],
[6.3, 2.7, 4.9, 1.8],
[6.7, 3.3, 5.7, 2.1],
[7.2, 3.2, 6. , 1.8],
[6.2, 2.8, 4.8, 1.8],
[6.1, 3. , 4.9, 1.8],
```

```
       [6.4, 2.8, 5.6, 2.1],
       [7.2, 3. , 5.8, 1.6],
       [7.4, 2.8, 6.1, 1.9],
       [7.9, 3.8, 6.4, 2. ],
       [6.4, 2.8, 5.6, 2.2],
       [6.3, 2.8, 5.1, 1.5],
       [6.1, 2.6, 5.6, 1.4],
       [7.7, 3. , 6.1, 2.3],
       [6.3, 3.4, 5.6, 2.4],
       [6.4, 3.1, 5.5, 1.8],
       [6. , 3. , 4.8, 1.8],
       [6.9, 3.1, 5.4, 2.1],
       [6.7, 3.1, 5.6, 2.4],
       [6.9, 3.1, 5.1, 2.3],
       [5.8, 2.7, 5.1, 1.9],
       [6.8, 3.2, 5.9, 2.3],
       [6.7, 3.3, 5.7, 2.5],
       [6.7, 3. , 5.2, 2.3],
       [6.3, 2.5, 5. , 1.9],
       [6.5, 3. , 5.2, 2. ],
       [6.2, 3.4, 5.4, 2.3],
       [5.9, 3. , 5.1, 1.8]])
```

In [15]:

```
b
```

Out[15]:

```
0         Iris-setosa
1         Iris-setosa
2         Iris-setosa
3         Iris-setosa
4         Iris-setosa
            ...
145    Iris-virginica
146    Iris-virginica
147    Iris-virginica
148    Iris-virginica
149    Iris-virginica
Name: Species, Length: 150, dtype: object
```

In [20]:

```
a_train ,a_test ,b_train ,b_test = train_test_split(a, b, test_size=20,random_state=200)
print("Traingin split:",a_train.shape)
print("Testin spllit:",b_test.shape)
```

```
Traingin split: (130, 4)
Testin spllit: (20,)
```

Design and Train the Decision Tree Model

In [21]:

```
from sklearn.tree import DecisionTreeClassifier,export_graphviz
from sklearn import tree
dtree = DecisionTreeClassifier()
dtree.fit(a_train,b_train)
print("Decision Tree classifier Created")
```

```
Decision Tree classifier Created
```

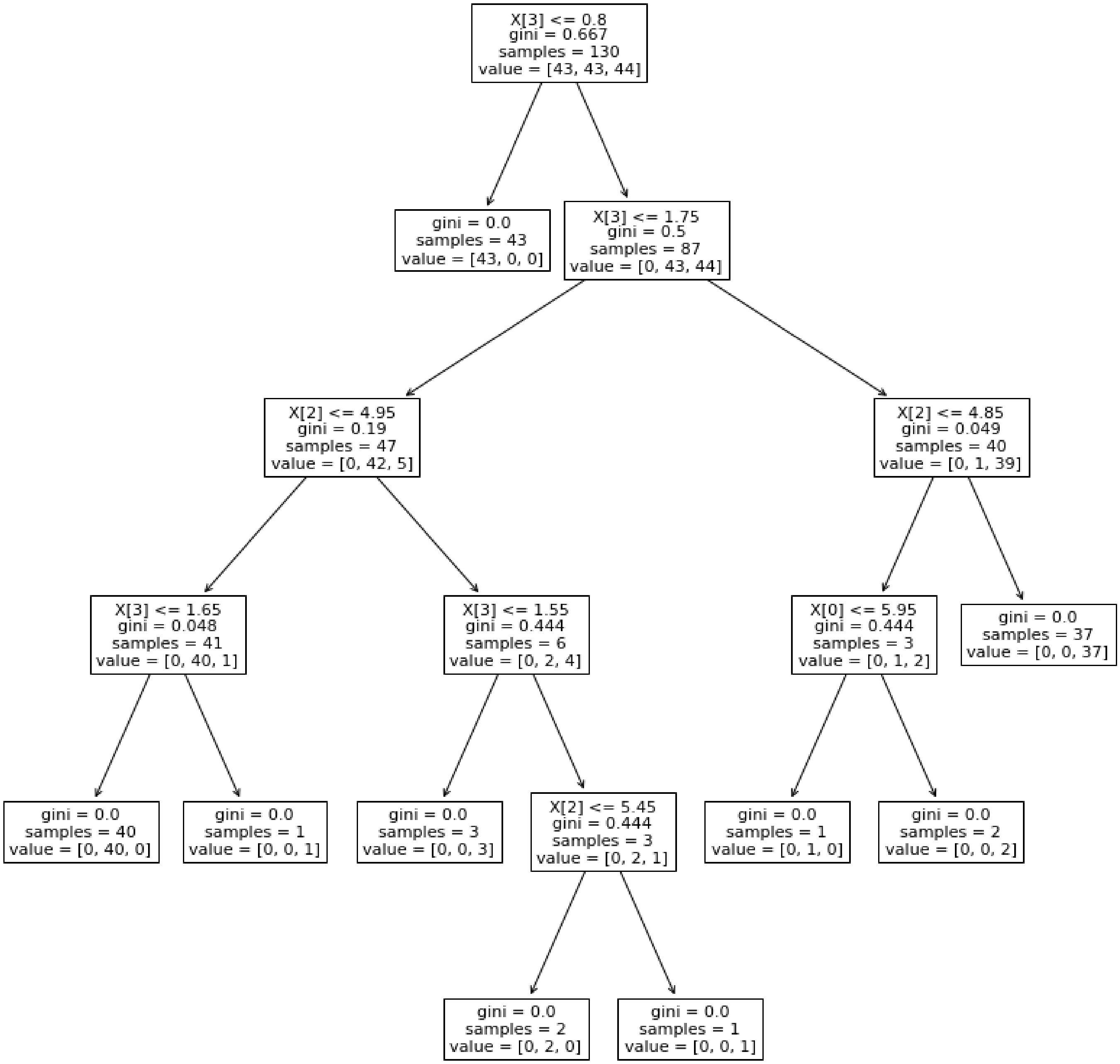
Visualize the Decision Tree Model

In [19]:

```
mt.figure(figsize=(14,15))
tree.plot_tree(dtree)
```

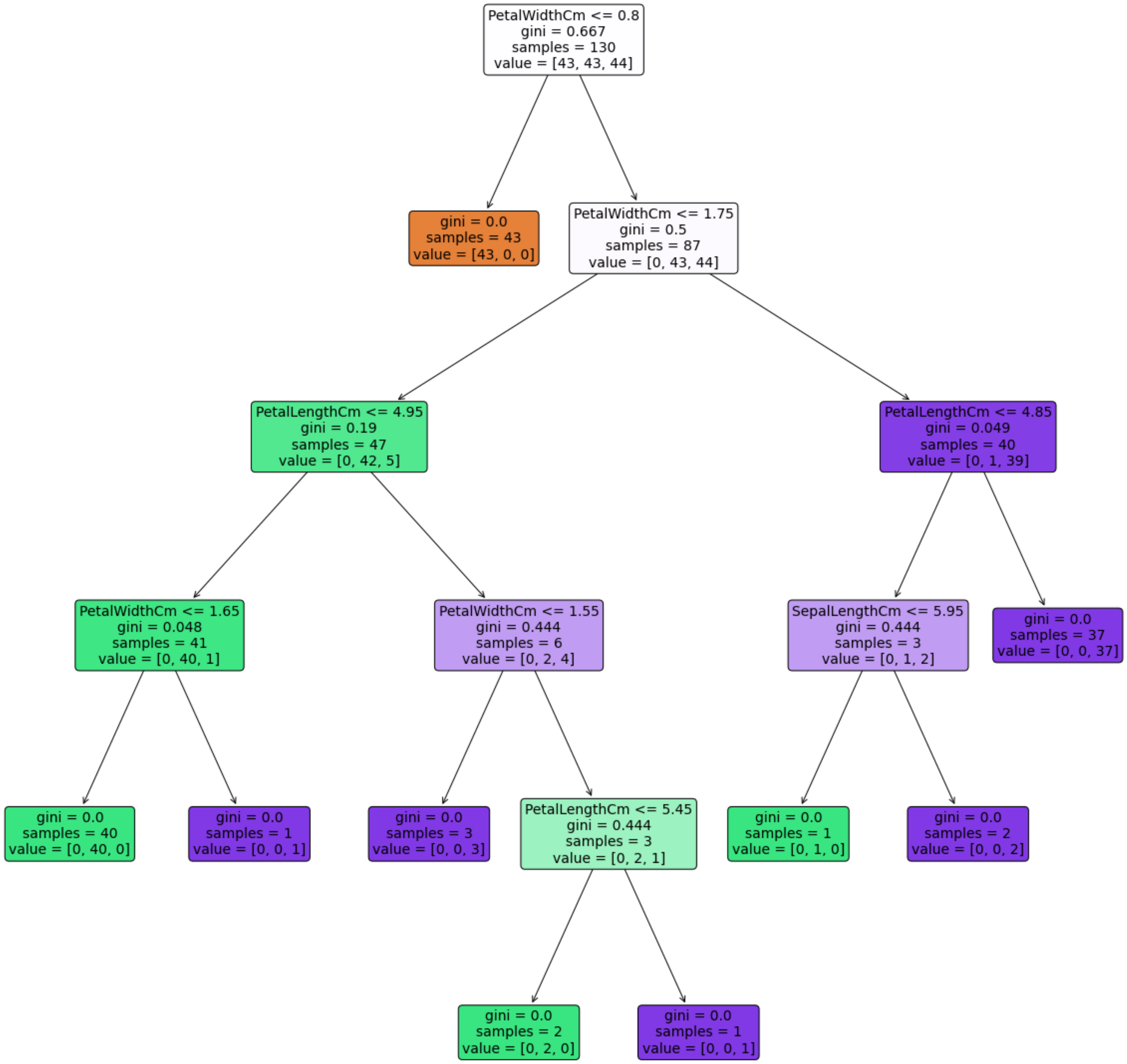
Out[19]:

```
[Text(0.5, 0.9166666666666666, 'X[3] <= 0.8\ngini = 0.667\nsamples = 130\nvalue = [43, 4
3, 44]'),
 Text(0.4230769230769231, 0.75, 'gini = 0.0\nsamples = 43\nvalue = [43, 0, 0]'),
 Text(0.5769230769230769, 0.75, 'X[3] <= 1.75\ngini = 0.5\nsamples = 87\nvalue = [0, 43,
44]'),
 Text(0.3076923076923077, 0.5833333333333334, 'X[2] <= 4.95\ngini = 0.19\nsamples = 47\n
value = [0, 42, 5]'),
 Text(0.15384615384615385, 0.4166666666666667, 'X[3] <= 1.65\ngini = 0.048\nsamples = 41
\nvalue = [0, 40, 1]'),
 Text(0.07692307692307693, 0.25, 'gini = 0.0\nsamples = 40\nvalue = [0, 40, 0]'),
 Text(0.23076923076923078, 0.25, 'gini = 0.0\nsamples = 1\nvalue = [0, 0, 1]'),
 Text(0.46153846153846156, 0.4166666666666667, 'X[3] <= 1.55\ngini = 0.444\nsamples = 6
\nvalue = [0, 2, 4]'),
 Text(0.38461538461538464, 0.25, 'gini = 0.0\nsamples = 3\nvalue = [0, 0, 3]'),
 Text(0.5384615384615384, 0.25, 'X[2] <= 5.45\ngini = 0.444\nsamples = 3\nvalue = [0, 2,
1]'),
 Text(0.46153846153846156, 0.08333333333333333, 'gini = 0.0\nsamples = 2\nvalue = [0, 2,
0]'),
 Text(0.6153846153846154, 0.08333333333333333, 'gini = 0.0\nsamples = 1\nvalue = [0, 0,
1]'),
 Text(0.8461538461538461, 0.5833333333333334, 'X[2] <= 4.85\ngini = 0.049\nsamples = 40
\nvalue = [0, 1, 39]'),
 Text(0.7692307692307693, 0.4166666666666667, 'X[0] <= 5.95\ngini = 0.444\nsamples = 3\n
value = [0, 1, 2]'),
 Text(0.6923076923076923, 0.25, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0]'),
 Text(0.8461538461538461, 0.25, 'gini = 0.0\nsamples = 2\nvalue = [0, 0, 2]'),
 Text(0.9230769230769231, 0.4166666666666667, 'gini = 0.0\nsamples = 37\nvalue = [0, 0,
37]')]
```



Visualizing the Decision Tree Model filled with colors

In [20]:
```
mt.figure(figsize=(21,22))
tree=plot_tree(dtree,feature_names=df.columns,precision=3,rounded=True,filled=True)
```



Making Prediction

In [22]:
```
b_pred= dtree.predict(a_test)
b_pred
```

Out[22]:
```
array(['Iris-versicolor', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-virginica',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

In [22]:
```
from sklearn import preprocessing

label = preprocessing.LabelEncoder()

b = label.fit_transform(b_pred)
b
```

Out[22]:
```
array([1, 2, 0, 0, 1, 2, 1, 1, 1, 2, 2, 0, 0, 0, 2, 0, 1, 0, 1, 2])
```

Evaluate the model

In [23]:
```
import sklearn.metrics as sm
print("Accuracy of the model:",sm.accuracy_score(b_test,b_pred))
```

```
Accuracy of the model: 1.0
```

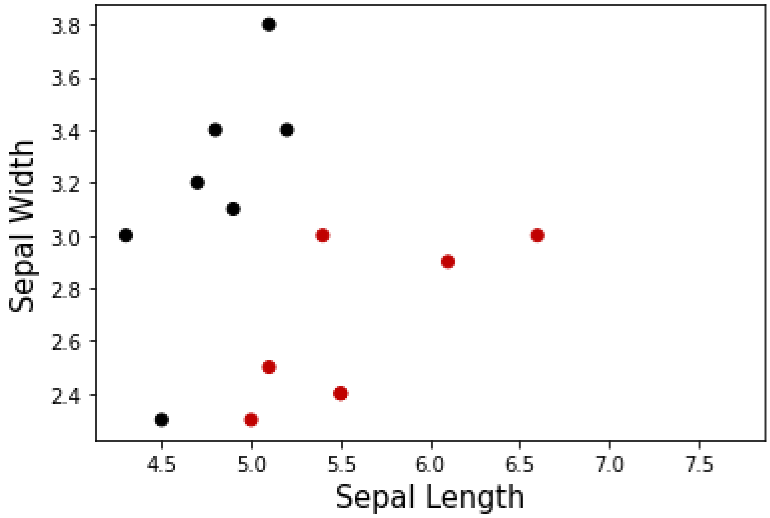
In [29]:
```
#comparing the actutal vs predicted

result_df = pd.DataFrame({"ACTUAL":b_test,"PREDICTED":b_pred})
result_df
```

Out[29]:

	ACTUAL	PREDICTED
84	Iris-versicolor	Iris-versicolor
122	Iris-virginica	Iris-virginica
28	Iris-setosa	Iris-setosa
24	Iris-setosa	Iris-setosa
75	Iris-versicolor	Iris-versicolor
109	Iris-virginica	Iris-virginica
81	Iris-versicolor	Iris-versicolor
98	Iris-versicolor	Iris-versicolor
80	Iris-versicolor	Iris-versicolor
100	Iris-virginica	Iris-virginica
124	Iris-virginica	Iris-virginica
2	Iris-setosa	Iris-setosa
34	Iris-setosa	Iris-setosa
44	Iris-setosa	Iris-setosa
128	Iris-virginica	Iris-virginica
13	Iris-setosa	Iris-setosa
93	Iris-versicolor	Iris-versicolor
41	Iris-setosa	Iris-setosa
63	Iris-versicolor	Iris-versicolor
137	Iris-virginica	Iris-virginica

In [25]:
```
plt.scatter(a_test[:,0],a_test[:,1],c=b , cmap='gist_heat')
plt.xlabel('Sepal Length',fontsize=14.5)
plt.ylabel('Sepal Width',fontsize=14.5)
plt.show()
```



In [26]:
```
print(classification_report (b_test, b_pred))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       1.00      1.00      1.00         7
 Iris-virginica       1.00      1.00      1.00         6

       accuracy                           1.00        20
      macro avg       1.00      1.00      1.00        20
   weighted avg       1.00      1.00      1.00        20
```

In [27]:
```
#confusion matrix alone
conf_matrix=confusion_matrix(b_test,b_pred)
conf_matrix
```

Out[27]:
```
array([[7, 0, 0],
       [0, 7, 0],
       [0, 0, 6]], dtype=int64)
```

The Decision Tree Classifier is finally created and is finally visaulized graphically.

The Prediction also calculated using decision tree algorithm.

The Accuracy of the model evaluated