

LetsGrowMore Datascience Internship

Beginner Level -TASK 2 Prediction using

Decision Tree Algorithm:

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Import Libraries

In [5]:

```
import numpy as np
import pandas as pd
import sklearn.metrics as sm
import seaborn as sns
import matplotlib.pyplot as plt
%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
from sklearn import preprocessing
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn import tree
```

In [6]:

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

Out[6]:

	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 [7]: df=pd.read_csv('IRIS.csv')
df
```

```
Out[7]:
```

	sepal_length	sepal_width	petal_length	petal_width	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

```
In [8]: df.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: 5.3+ KB
```

```
In [9]: df.describe()
```

```
Out[9]:
```

	sepal_length	sepal_width	petal_length	petal_width
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

	sepal_length	sepal_width	petal_length	petal_width
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_data.target
```

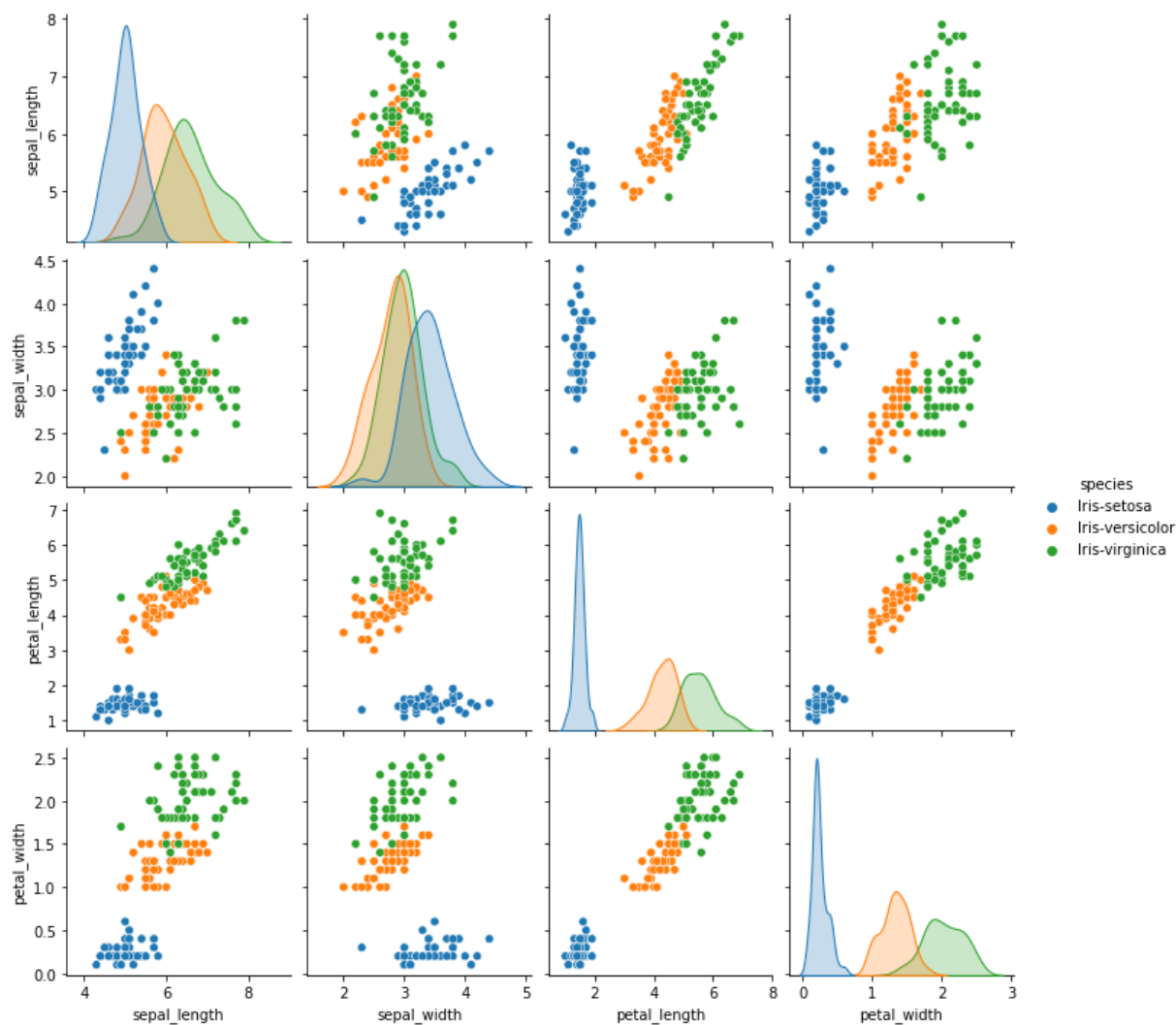
```
Out[13]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 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, 2, 2, 2, 2])
```

```
In [14]: iris_df.isnull().sum()
```

```
Out[14]: sepal length (cm)    0
          sepal width (cm)    0
          petal length (cm)   0
          petal width (cm)    0
          dtype: int64
```

Visialize Dataset

```
In [15]: import matplotlib.pyplot as plt
          sns.pairplot(df, hue='species')
          plt.show()
```



```
In [24]: iris=pd.read_csv("C:/Users/91701/IRIS.csv")
iris
```

Out[24]:

	sepal_length	sepal_width	petal_length	petal_width	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

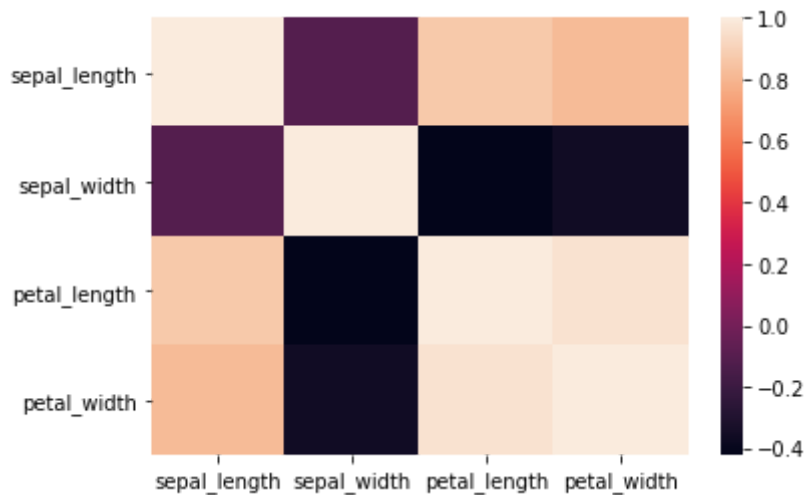
```
In [17]: df.corr()
```

```
Out[17]:
```

	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.109369	0.871754	0.817954
sepal_width	-0.109369	1.000000	-0.420516	-0.356544
petal_length	0.871754	-0.420516	1.000000	0.962757
petal_width	0.817954	-0.356544	0.962757	1.000000

```
In [18]: sns.heatmap(df.corr())
```

```
Out[18]: <AxesSubplot:>
```



Preparation of Data

```
In [29]: y=iris.iloc[:, :-1].values
         z=iris['species']
```

```
In [31]: z
```

```
Out[31]: 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 [35]: y
```

```
Out[35]: 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 [36]:

```
y_train ,y_test ,z_train ,z_test = train_test_split(y, z, test_size=20,random_state=
print("Traingin split:",y_train.shape)
print("Traingin split:",z_test.shape)
```

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

Design and Train the Decision Tree Model

In [37]:

```
dtree = DecisionTreeClassifier()
dtree.fit(y_train,z_train)
print("Decision Tree classifier Created")
```

```
Decision Tree classifier Created
```

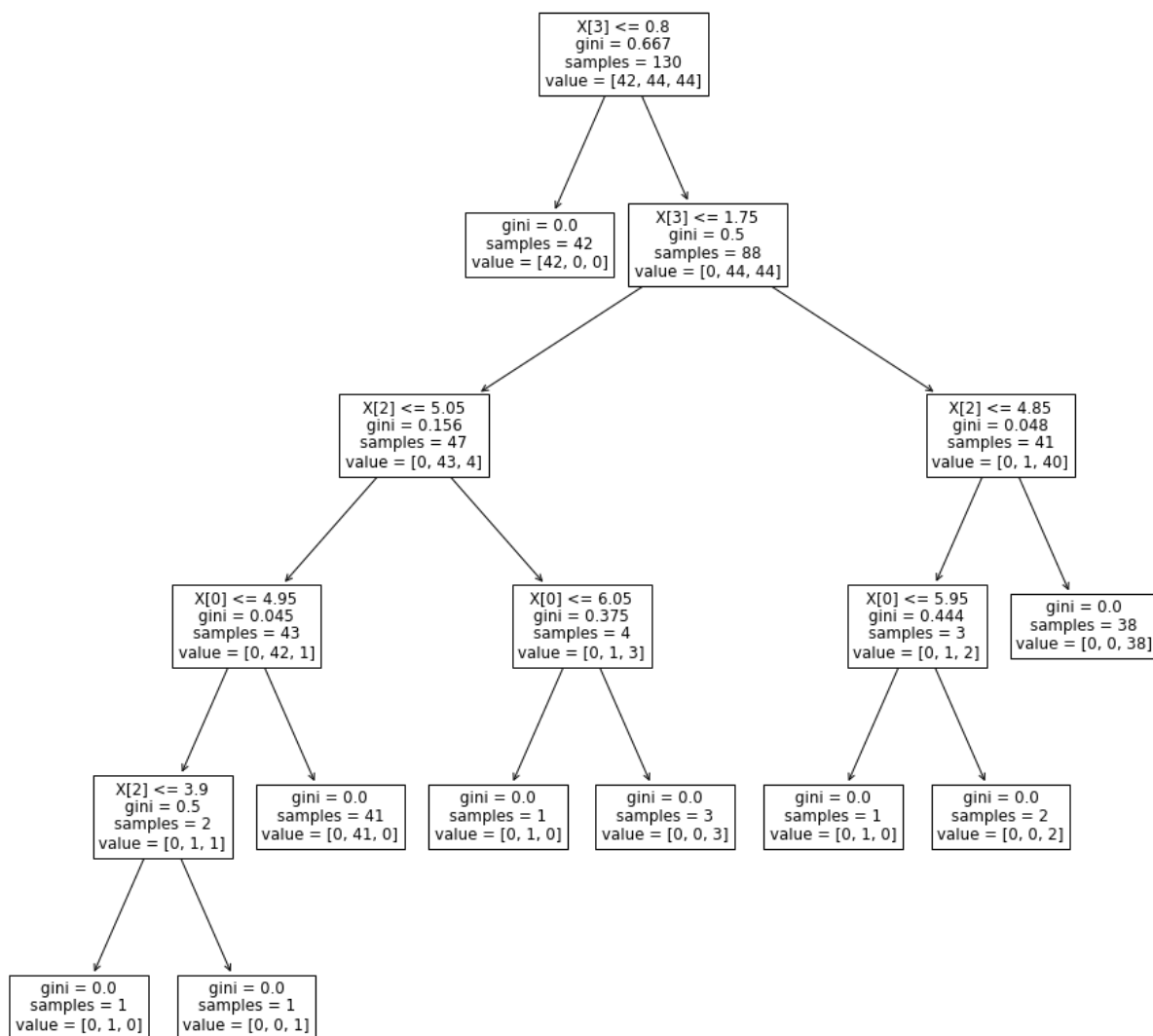
Visualize the Decision Tree Model

In [39]:

```
mt.figure(figsize=(16,16))
tree.plot_tree(dtree)
```

Out[39]:

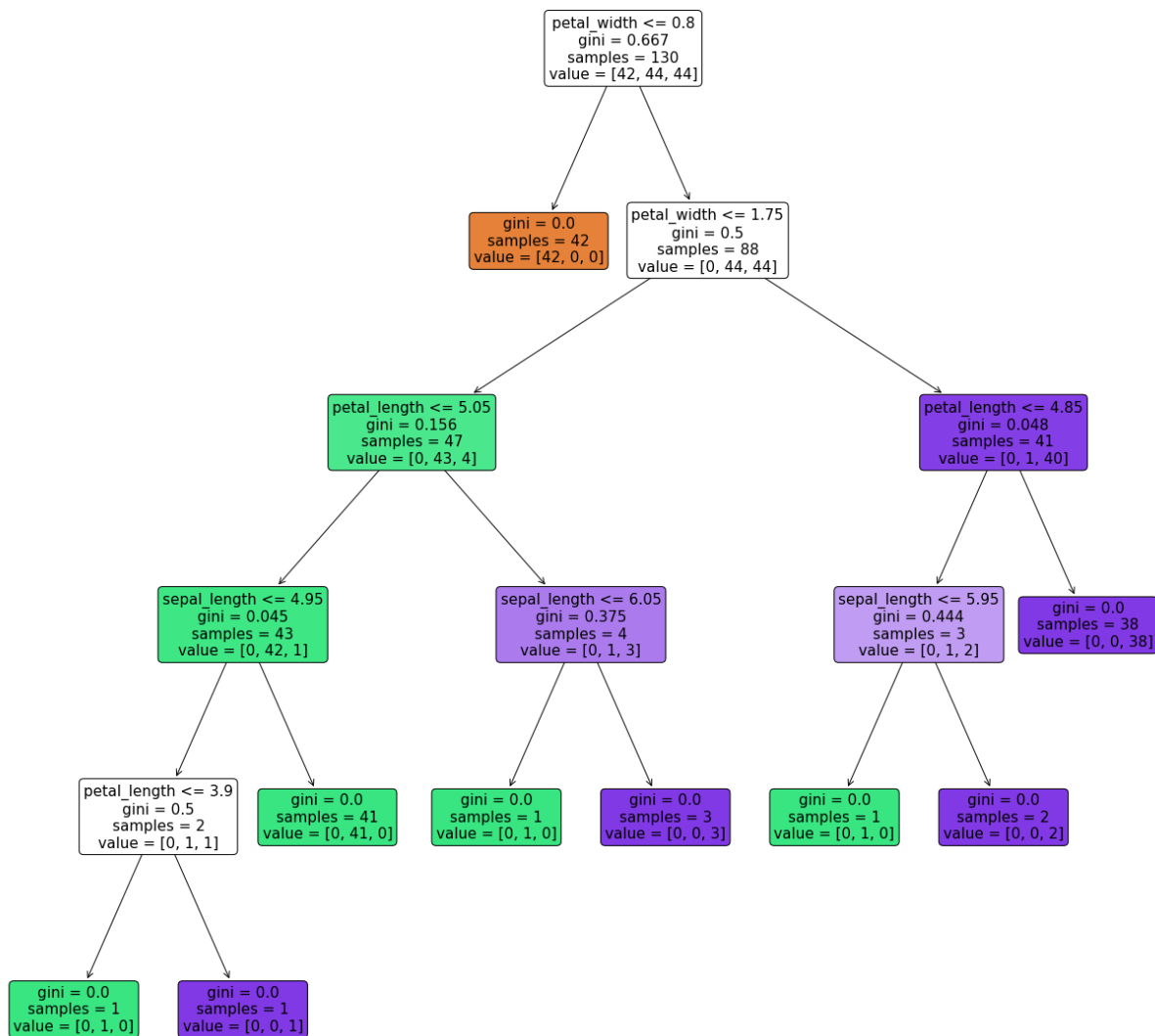
```
[Text(478.2857142857142, 797.28, 'X[3] <= 0.8\ngini = 0.667\nsamples = 130\nvalue =
[42, 44, 44]'),
Text(414.5142857142857, 652.3199999999999, 'gini = 0.0\nsamples = 42\nvalue = [42,
0, 0]'),
Text(542.0571428571428, 652.3199999999999, 'X[3] <= 1.75\ngini = 0.5\nsamples = 88
\nvalue = [0, 44, 44]'),
Text(318.85714285714283, 507.35999999999996, 'X[2] <= 5.05\ngini = 0.156\nsamples =
47\nvalue = [0, 43, 4]'),
Text(191.3142857142857, 362.4, 'X[0] <= 4.95\ngini = 0.045\nsamples = 43\nvalue =
[0, 42, 1]'),
Text(127.54285714285713, 217.43999999999994, 'X[2] <= 3.9\ngini = 0.5\nsamples = 2
\nvalue = [0, 1, 1]'),
Text(63.771428571428565, 72.47999999999999, 'gini = 0.0\nsamples = 1\nvalue = [0, 1,
0]'),
Text(191.3142857142857, 72.47999999999999, 'gini = 0.0\nsamples = 1\nvalue = [0, 0,
1]'),
Text(255.08571428571426, 217.43999999999994, 'gini = 0.0\nsamples = 41\nvalue = [0,
41, 0]'),
Text(446.4, 362.4, 'X[0] <= 6.05\ngini = 0.375\nsamples = 4\nvalue = [0, 1, 3]'),
Text(382.6285714285714, 217.43999999999994, 'gini = 0.0\nsamples = 1\nvalue = [0,
1, 0]'),
Text(510.1714285714285, 217.43999999999994, 'gini = 0.0\nsamples = 3\nvalue = [0,
0, 3]'),
Text(765.2571428571428, 507.35999999999996, 'X[2] <= 4.85\ngini = 0.048\nsamples =
41\nvalue = [0, 1, 40]'),
Text(701.4857142857143, 362.4, 'X[0] <= 5.95\ngini = 0.444\nsamples = 3\nvalue =
[0, 1, 2]'),
Text(637.7142857142857, 217.43999999999994, 'gini = 0.0\nsamples = 1\nvalue = [0,
1, 0]'),
Text(765.2571428571428, 217.43999999999994, 'gini = 0.0\nsamples = 2\nvalue = [0,
0, 2]'),
Text(829.0285714285714, 362.4, 'gini = 0.0\nsamples = 38\nvalue = [0, 0, 38]')]
```

Visualizing the Decision Tree Model filled with colors

In [40]:

```
mt.figure(figsize=(22,22))
tree=plot_tree(dtree,feature_names=df.columns,precision=3,rounded=True,filled=True)
```



Making Prediction

```
In [41]: z_pred = dtree.predict(y_test)
         z_pred
```

```
Out[41]: array(['Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
                'Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
                'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
                'Iris-setosa', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
                'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
                'Iris-virginica', 'Iris-setosa', 'Iris-versicolor'], dtype=object)
```

```
In [42]: label = preprocessing.LabelEncoder()
         z = label.fit_transform(z_pred)
         z
```

```
Out[42]: array([1, 2, 0, 1, 2, 0, 1, 1, 1, 0, 0, 2, 0, 2, 1, 0, 0, 2, 0, 1])
```

Evaluate the model

```
In [43]:
```

```
import sklearn.metrics as sm
print("Accuracy of the model:",sm.accuracy_score(z_test,z_pred))
```

Accuracy of the model: 0.95

In [44]:

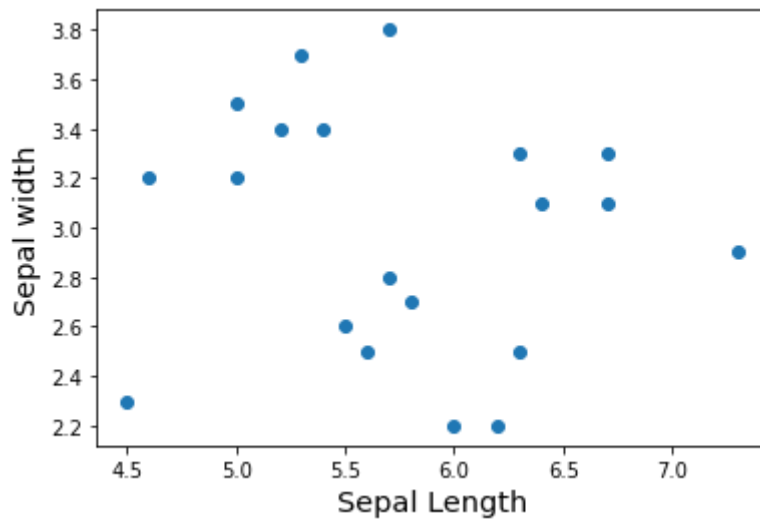
```
#actual vs predicted
result_df = pd.DataFrame({"ACTUAL":z_test,"PREDICTED":z_pred})
result_df
```

Out[44]:

	ACTUAL	PREDICTED
99	Iris-versicolor	Iris-versicolor
137	Iris-virginica	Iris-virginica
20	Iris-setosa	Iris-setosa
56	Iris-versicolor	Iris-versicolor
146	Iris-virginica	Iris-virginica
40	Iris-setosa	Iris-setosa
68	Iris-versicolor	Iris-versicolor
67	Iris-versicolor	Iris-versicolor
69	Iris-versicolor	Iris-versicolor
47	Iris-setosa	Iris-setosa
28	Iris-setosa	Iris-setosa
107	Iris-virginica	Iris-virginica
41	Iris-setosa	Iris-setosa
144	Iris-virginica	Iris-virginica
119	Iris-virginica	Iris-versicolor
35	Iris-setosa	Iris-setosa
18	Iris-setosa	Iris-setosa
140	Iris-virginica	Iris-virginica
48	Iris-setosa	Iris-setosa
90	Iris-versicolor	Iris-versicolor

In [45]:

```
plt.scatter(y_test[:,0],y_test[:,1],cmap='gist_heat')
plt.xlabel('Sepal Length',fontsize=14.5)
plt.ylabel('Sepal width',fontsize=14.5)
plt.show()
```



```
In [46]: print(classification_report (z_test, z_pred))
```

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	8
Iris-versicolor	0.86	1.00	0.92	6
Iris-virginica	1.00	0.83	0.91	6
accuracy			0.95	20
macro avg	0.95	0.94	0.94	20
weighted avg	0.96	0.95	0.95	20

```
In [47]: #confusion matrix alone
conf_matrix=confusion_matrix(z_test,z_pred)
conf_matrix
```

```
Out[47]: array([[8, 0, 0],
               [0, 6, 0],
               [0, 1, 5]], dtype=int64)
```

The Decision Three Classifier is finally created and is finally visualized using graphically.

The Prediction also calculated using decision tree algorithm.

The Accuracy of the model evaluated