The Sparks Foundation - GRIP

Data Science & Business Analytics Intern

Task 6: Prediction using Decision Tree Algorithm

> AIM - Create the Decision Tree classifier and visualize it graphically. The purpose is if we feed any new data to this classifier, it would be able to predict the right class accordingly.

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> Import the required libraries

In [1]:

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report,accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import tree
```

In [2]:

```
iris = pd.read_csv("Iris.csv")
```

In [3]:

```
iris.head(10)
```

Out[3]:

	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
5	6	5.4	3.9	1.7	0.4	Iris-setosa
6	7	4.6	3.4	1.4	0.3	Iris-setosa
7	8	5.0	3.4	1.5	0.2	Iris-setosa
8	9	4.4	2.9	1.4	0.2	Iris-setosa
9	10	4.9	3.1	1.5	0.1	Iris-setosa

In [4]:

```
iris.tail(10)
```

Out[4]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
140	141	6.7	3.1	5.6	2.4	Iris-virginica
141	142	6.9	3.1	5.1	2.3	Iris-virginica
142	143	5.8	2.7	5.1	1.9	Iris-virginica
143	144	6.8	3.2	5.9	2.3	Iris-virginica
144	145	6.7	3.3	5.7	2.5	Iris-virginica
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

In [5]:

```
iris.shape
```

Out[5]:

```
(150, 6)
```

In [6]:

```
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             150 non-null    int64
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [7]:

```
iris.describe()
```

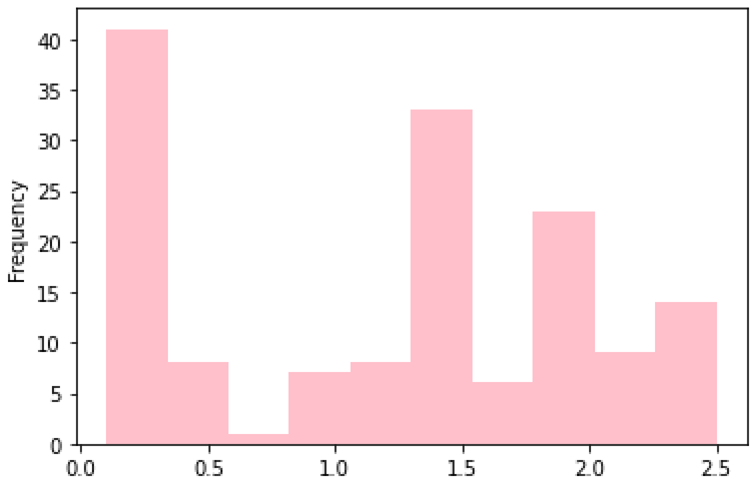
Out[7]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

PetalWidth has a minimum value of 0.1 and maximum of 2.5

In [8]:

```
iris['PetalWidthCm'].plot.hist(color="pink")
plt.show()
```



In [9]:

```
iris.isnull().any()
```

Out[9]:

```
Id               False
SepalLengthCm    False
SepalWidthCm     False
PetalLengthCm    False
PetalWidthCm     False
Species          False
dtype: bool
```

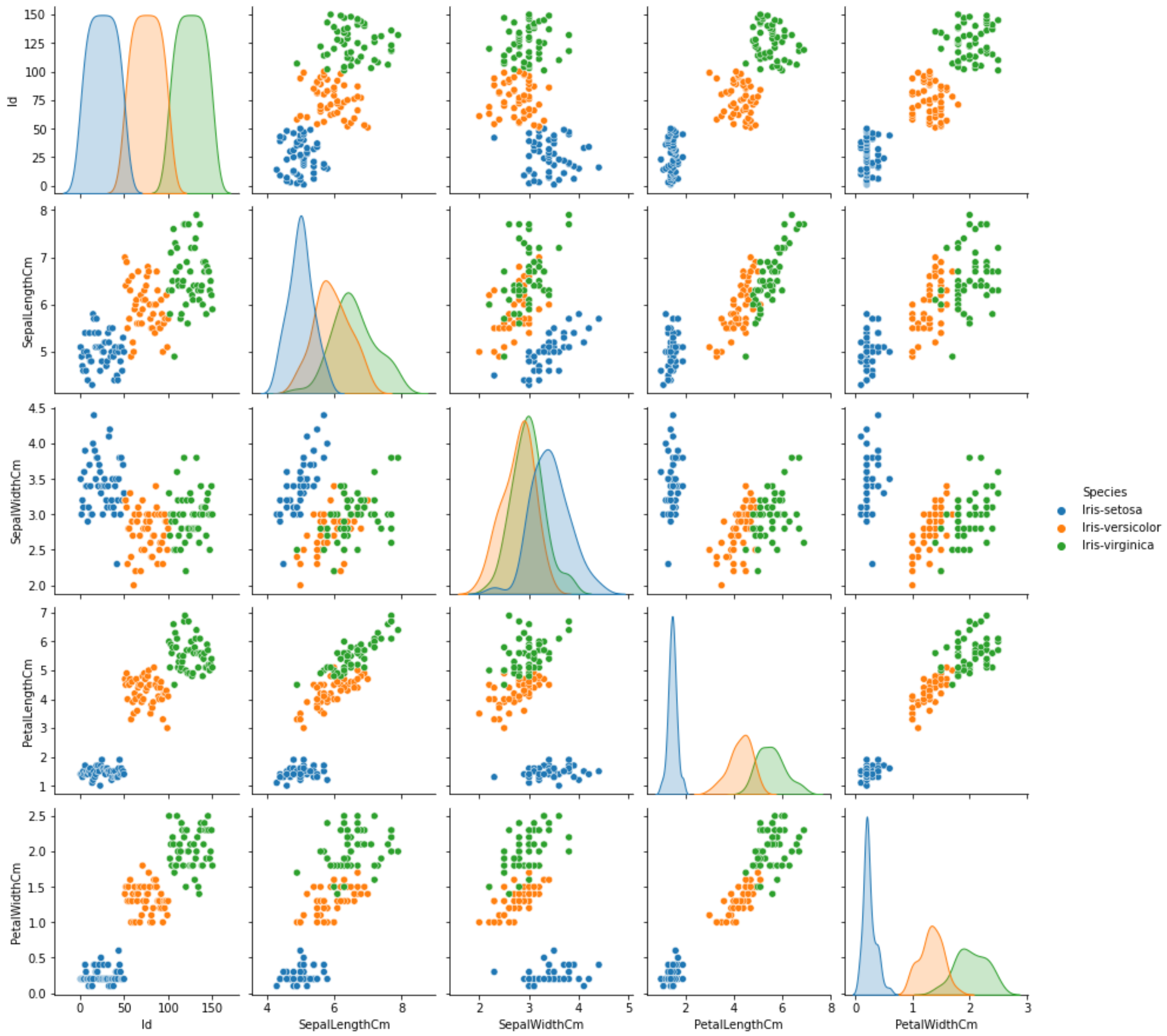
Checking relation between columns

In [10]:

```
sns.pairplot(iris, hue='Species')
```

Out[10]:

```
<seaborn.axisgrid.PairGrid at 0x1cc1caa3430>
```



Iris-versicolor and Iris-virginica are overlapping whereas Iris-Settosa can be easily identified

In [11]:

```
X = iris.iloc[:,1:5]
X.head()
```

Out[11]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
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

In [12]:

```
y = iris['Species']
y.head()
```

Out[12]:

```
0    Iris-setosa
1    Iris-setosa
2    Iris-setosa
3    Iris-setosa
4    Iris-setosa
Name: Species, dtype: object
```

Data visualization

In [13]:

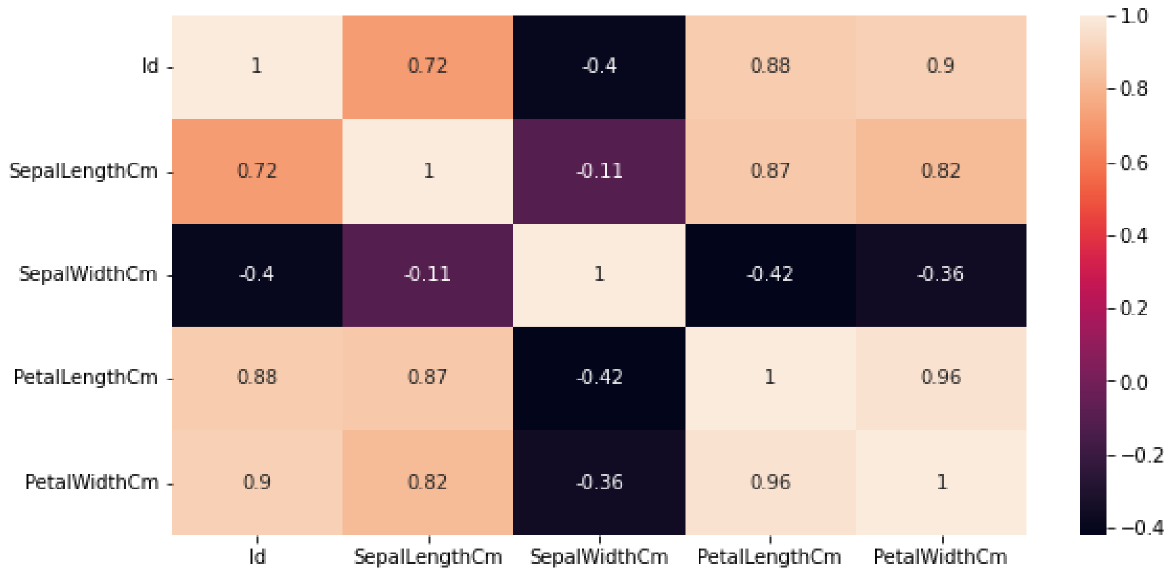
```
#use correalation for quantifying relation
plt.figure(figsize=(10,5))
print(iris.corr())
sns.heatmap(iris.corr(), annot=True)
```

```
                     Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  \
Id             1.000000       0.716676     -0.397729       0.882747
SepalLengthCm  0.716676       1.000000     -0.109369       0.871754
SepalWidthCm  -0.397729      -0.109369      1.000000      -0.420516
PetalLengthCm  0.882747       0.871754     -0.420516       1.000000
PetalWidthCm   0.899759       0.817954     -0.356544       0.962757

               PetalWidthCm
Id                 0.899759
SepalLengthCm      0.817954
SepalWidthCm      -0.356544
PetalLengthCm      0.962757
PetalWidthCm       1.000000
```

Out[13]:

```
<AxesSubplot:>
```



PetalLength and PetalWidth have highest positive correlation

Train Decision Tree Model

In [14]:

```
#train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,random_state=0)
```

In [15]:

```
#Training model
Dt = DecisionTreeClassifier(criterion = "entropy", random_state=0)
model = Dt.fit(X_train, y_train)
print("Training Completed")
```

```
Training Completed
```

In [16]:

```
#predict model
y_predict = Dt.predict(X_test)
print("The predicted values are:\n", y_predict)
print("\n The actual values are:\n",y_test.values.reshape(-1,45)[0])
```

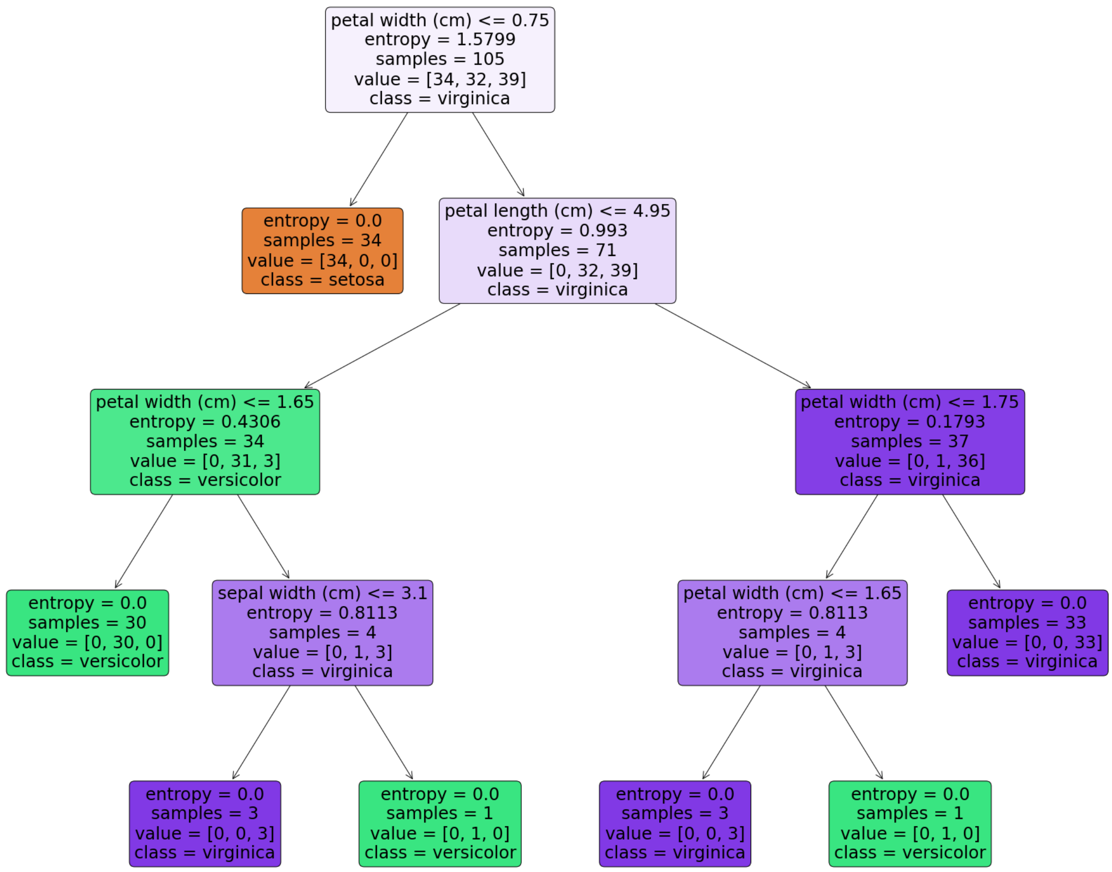
```
The predicted values are:
 ['Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica'
 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-virginica' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor' 'Iris-versicolor'
 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa'
 'Iris-setosa']

 The actual values are:
 ['Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica'
 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-virginica' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor'
 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa'
 'Iris-setosa']
```

Visualization of decision tree

In [17]:

```
#using plot tree
fnames = ['sepal length (cm)','sepal width (cm)','petal length (cm)','petal width (cm)']
cnames = ['setosa','versicolor','virginica']
fig = plt.figure(figsize = (30,25))
tree.plot_tree(Dt,feature_names = fnames, class_names = cnames, filled = True, precision =4
```



Model Evaluation

In [18]:

```
#evaluating performance
print(classification_report(y_test,y_predict))
sns.heatmap(confusion_matrix(y_test,y_predict),annot = True)
```

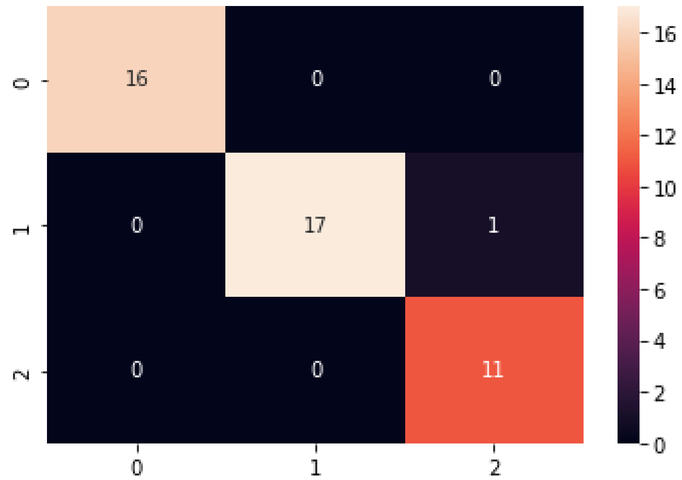
```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        16
Iris-versicolor       1.00      0.94      0.97        18
 Iris-virginica       0.92      1.00      0.96        11

       accuracy                           0.98        45
      macro avg       0.97      0.98      0.98        45
   weighted avg       0.98      0.98      0.98        45
```

Out[18]:

```
<AxesSubplot:>
```



Precision, recall and F1 score are more than 90% - model is fit and predicted with accuracy.