GRIP: The Spark Foundation

Data Science and Bussiness Analyti Intern

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Task 6: Prediction Using Decision Tree

Importing the libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Reading Data

In [2]:
```
Iris_df=pd.read_csv("C:/Users/DELL/Desktop/Iris Data.csv")
Iris_df.head()
```

Out[2]:

	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

In [3]:
```
Iris_df.shape
```

Out[3]:
```
(150, 6)
```

In [4]:
```
Iris_df.info()
```

Out[4]:
```
<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 [5]:
```
# Unique value in each columns
for i in Iris_df.columns:
    print(i,':',len(Iris_df[i].unique()))
```

Out[5]:
```
Id : 150
SepalLengthCm : 35
SepalWidthCm : 23
PetalLengthCm : 43
PetalWidthCm : 22
Species : 3
```

In [6]:
```
list_columns=Iris_df.columns
list_columns
```

Out[6]:
```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

Find Average Min-Max etc... for Continuves Variable

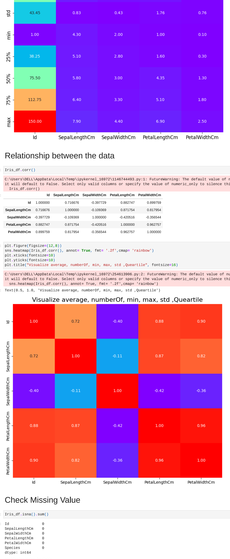
In [7]:
```
Iris_df.describe()
```

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

In [8]:
```
plt.figure(figsize=(12,8))
sns.heatmap(Iris_df.describe(),annot= True, fmt= '.2f',cmap='rainbow')
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.title("Visualize average, numberOf, min, max, std, Quaertile")
```

Out[8]:
```
Text(0.5, 1.0, 'Visualize average, numberOf, min, max, std, Quaertile')
```



Relationship between the data

In [9]:
```
Iris_df.corr()
```

Out[9]:
```
C:\Users\DELL\AppData\Local\Temp\ipykernel_10872\1140744683.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  Iris_df.corr()
```

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

In [10]:
```
plt.figure(figsize=(12,8))
sns.heatmap(Iris_df.corr(), annot= True, fmt= '.2f',cmap='rainbow')
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.title("Visualize average, numberOf, min, max, std ,Quaertile")
```

Out[10]:
```
C:\Users\DELL\AppData\Local\Temp\ipykernel_10872\3401390.py:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(Iris_df.corr(), annot= True, fmt= '.2f',cmap='rainbow')
Text(0.5, 1.0, 'Visualize average, numberOf, min, max, std ,Quaertile')
```

Check Missing Value

In [11]:
```
Iris_df.isna().sum()
```

Out[11]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

No Missing Value Available

Encoding Categorical Variable

In [12]:
```
Iris_df.dtypes
```

Out[12]:
```
Id               int64
SepalLengthCm  float64
SepalWidthCm   float64
PetalLengthCm  float64
PetalWidthCm   float64
Species         object
dtype: object
```

In [13]:
```
from sklearn import preprocessing

Iris_df['Species'] = preprocessing.LabelEncoder().fit_transform(Iris_df['Species'])
```

In [14]:
```
Iris_df.dtypes
```

Out[14]:
```
Id               int64
SepalLengthCm  float64
SepalWidthCm   float64
PetalLengthCm  float64
PetalWidthCm   float64
Species          int32
dtype: object
```

Split Dependent and Independent Data

In [15]:
```
X= Iris_df.iloc[:, 1:5].values
y = Iris_df.iloc[:, -1].values
```

Splitting the dataset into the Training set and Test set

In [16]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =1/3,random_state = 0)
```

In [17]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

The Decision Tree Algorithm

Training the Decision Tree Classification model on the Training set

In [18]:
```
from sklearn.tree import DecisionTreeClassifier

classifier = DecisionTreeClassifier(criterion = 'entropy',random_state = 0)
classifier.fit(X_train,y_train)

print("The Decision Tree Classification model trained")
```

```
The Decision Tree Classification model trained
```

Visualize the Decision Tree

In [19]:
```
from sklearn import tree

classifier_tree = tree.DecisionTreeClassifier()
classifier_tree = classifier_tree.fit(X_train, y_train)
```

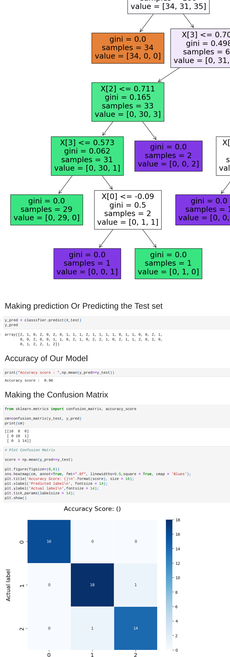
In [20]:
```
# Text Graph representation

text_representation = tree.export_text(classifier_tree)
print(text_representation)
```

```
|--- feature_2 <= 0.58
|   |--- class: 0
|--- feature_2 >  0.58
|   |--- feature_3 <= 0.70
|   |   |--- feature_2 <= 0.71
|   |   |   |--- feature_0 <= 0.57
|   |   |   |   |--- class: 1
|   |   |   |--- feature_0 >  0.57
|   |   |   |   |--- feature_0 <= -0.09
|   |   |   |   |   |--- class: 2
|   |   |   |   |--- feature_0 >  -0.09
|   |   |   |   |   |--- class: 1
|   |   |--- feature_2 >  0.71
|   |   |   |--- class: 2
|   |--- feature_3 >  0.70
|   |   |--- feature_2 <= 0.66
|   |   |   |--- class: 1
|   |   |--- feature_2 >  0.66
|   |   |   |--- class: 2
```

In [21]:
```
# Decision Tree Plot
plt.figure(figsize=(20, 16))
tree.plot_tree(classifier_tree, filled=True, impurity=True);
```

Out[21]:
```
[Text(0.4444444444444444, 0.9166666666666666, 'X[3] <= -0.579\ngini = 0.666\nsamples = 100\nvalue = [34, 31, 35]'),
 Text(0.3333333333333333, 0.75, 'gini = 0.0\nsamples = 34\nvalue = [34, 0, 0]'),
 Text(0.5555555555555556, 0.75, 'X[3] <= 0.701\ngini = 0.498\nsamples = 66\nvalue = [0, 31, 35]'),
 Text(0.3333333333333333, 0.5833333333333334, 'X[2] <= 0.711\ngini = 0.165\nsamples = 33\nvalue = [0, 30, 3]'),
 Text(0.2222222222222222, 0.4166666666666667, 'X[3] <= 0.573\ngini = 0.062\nsamples = 31\nvalue = [0, 30, 1]'),
 Text(0.1111111111111111, 0.25, 'X[0] <= -0.09\ngini = 0.5\nsamples = 2\nvalue = [0, 1, 1]'),
 Text(0.05555555555555555, 0.08333333333333333, 'gini = 0.0\nsamples = 1\nvalue = [0, 0, 1]'),
 Text(0.16666666666666666, 0.08333333333333333, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0]'),
 Text(0.3333333333333333, 0.25, 'gini = 0.0\nsamples = 29\nvalue = [0, 29, 0]'),
 Text(0.4444444444444444, 0.4166666666666667, 'gini = 0.0\nsamples = 2\nvalue = [0, 0, 2]'),
 Text(0.7777777777777778, 0.5833333333333334, 'X[2] <= 0.6\ngini = 0.059\nsamples = 33\nvalue = [0, 1, 32]'),
 Text(0.6666666666666666, 0.4166666666666667, 'X[1] <= 0.078\ngini = 0.5\nsamples = 2\nvalue = [0, 1, 1]'),
 Text(0.5555555555555556, 0.25, 'gini = 0.0\nsamples = 1\nvalue = [0, 0, 1]'),
 Text(0.7777777777777778, 0.25, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0]'),
 Text(0.8888888888888888, 0.4166666666666667, 'gini = 0.0\nsamples = 31\nvalue = [0, 0, 31]')]
```



Making prediction Or Predicting the Test set

In [22]:
```
y_pred = classifier.predict(X_test)
y_pred
```

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

Accuracy of Our Model

In [23]:
```
print("Accuracy score : ",sp.mean(y_pred==y_test))
```

```
Accuracy score :  0.96
```

Making the Confusion Matrix

In [24]:
```
from sklearn.metrics import confusion_matrix, accuracy_score

cm=confusion_matrix(y_test, y_pred)
print("Confusion Matrix")
print(cm)
```

Out[24]:
```
Confusion Matrix
[[16  0  0]
 [ 0 18  1]
 [ 0  1 14]]
```

In [25]:
```
# Plot Confusion Matrix

score = sp.mean(y_pred==y_test)

plt.figure(figsize=(6,6))
sns.heatmap(cm, annot=True, fmt='.0f', linewidths=0.5,square = True, cmap = 'Blues');
plt.title('Accuracy Score: {}'.format(score), size = 15);
plt.xlabel('Predicted labels',fontsize = 14);
plt.ylabel('Actual labels',fontsize = 14);
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.show()
```


In [26]:
```
ok_accuracy = accuracy_score(y_test,y_pred)
print("Accuracy of model : ",ok_accuracy)
```

```
Accuracy of model :  0.96
```

Classification Report

In [27]:
```
from sklearn import metrics

print (metrics.classification_report(y_test, classifier.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        16
           1       0.95      0.95      0.95        19
           2       0.93      0.93      0.93        15

    accuracy                           0.96        50
   macro avg       0.96      0.96      0.96        50
weighted avg       0.96      0.96      0.96        50
```

Conclusion

This classifier model can predict the Species of the flower with 96 % Accuracy Score.