Importing Necessary Libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

Importing dataset

In [2]:
```
iris=pd.read_csv("D:\\Career\\Unified_Mentor_Intenship\\iris.csv")
iris.head(5)
```

Out[2]:

	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

Data Exploration

In [3]:
```
iris.duplicated().sum()
```

Out[3]:
```
3
```

In [5]:
```
iris.drop_duplicates(inplace=True)
```

In [6]:
```
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 147 entries, 0 to 149
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   SepalLengthCm  147 non-null    float64
 1   SepalWidthCm   147 non-null    float64
 2   PetalLengthCm  147 non-null    float64
 3   PetalWidthCm   147 non-null    float64
 4   Species        147 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.9+ KB
```

In [7]:
```
iris.describe(include="all")
```

Out[7]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
count	147.000000	147.000000	147.000000	147.000000	147
unique	NaN	NaN	NaN	NaN	3
top	NaN	NaN	NaN	NaN	Iris-versicolor
freq	NaN	NaN	NaN	NaN	50
mean	5.856463	3.055782	3.780272	1.208844	NaN
std	0.829100	0.437009	1.759111	0.757874	NaN
min	4.300000	2.000000	1.000000	0.100000	NaN
25%	5.100000	2.800000	1.600000	0.300000	NaN
50%	5.800000	3.000000	4.400000	1.300000	NaN
75%	6.400000	3.300000	5.100000	1.800000	NaN
max	7.900000	4.400000	6.900000	2.500000	NaN

In [8]:
```
iris.nunique()
```

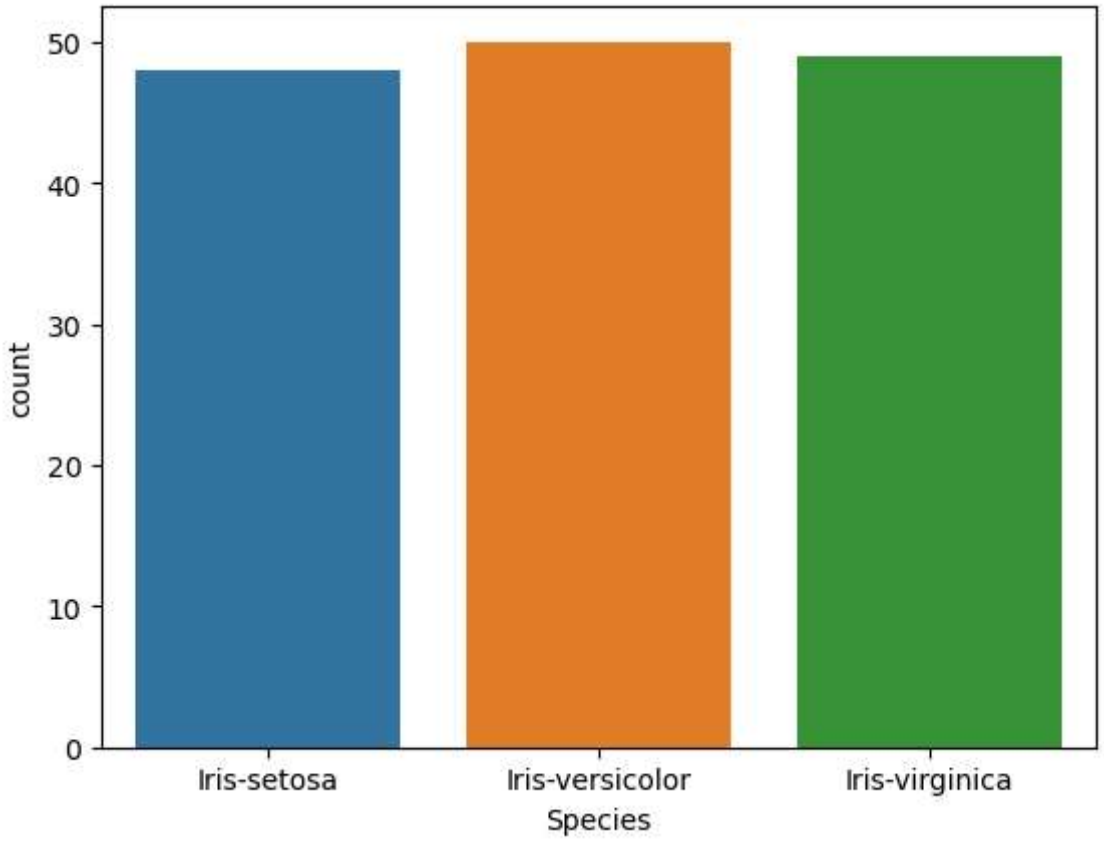
Out[8]:
```
SepalLengthCm    35
SepalWidthCm     23
PetalLengthCm    43
PetalWidthCm     22
Species           3
dtype: int64
```

Therefore this indicates 4 continuous column and one (the target feature) categorical column. This indicates a classification problem

Exploratory Data Analysis

In [9]:
```
#Checking imbalance in target feature
sns.countplot(x='Species',data=iris)
```

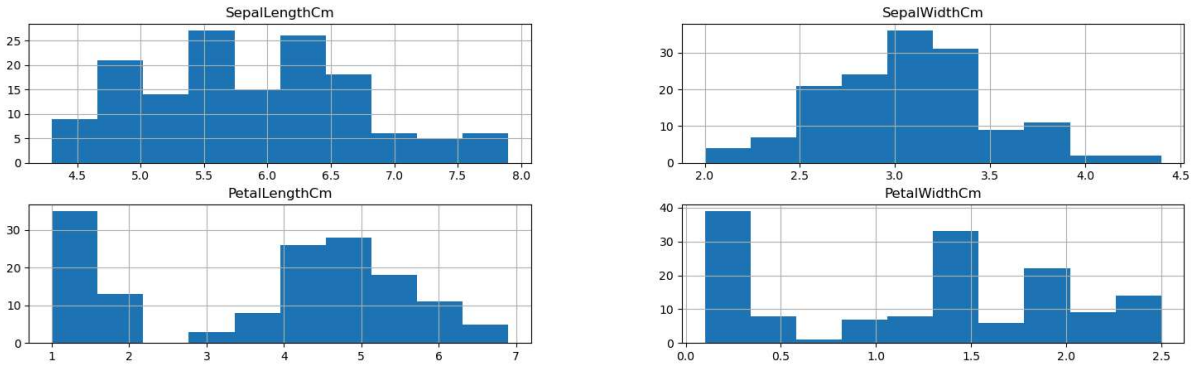
Out[9]:
```
<Axes: xlabel='Species', ylabel='count'>
```



This plot indicates there is a fine distribution between all variables in the target feature, there is no significant imbalance present in that

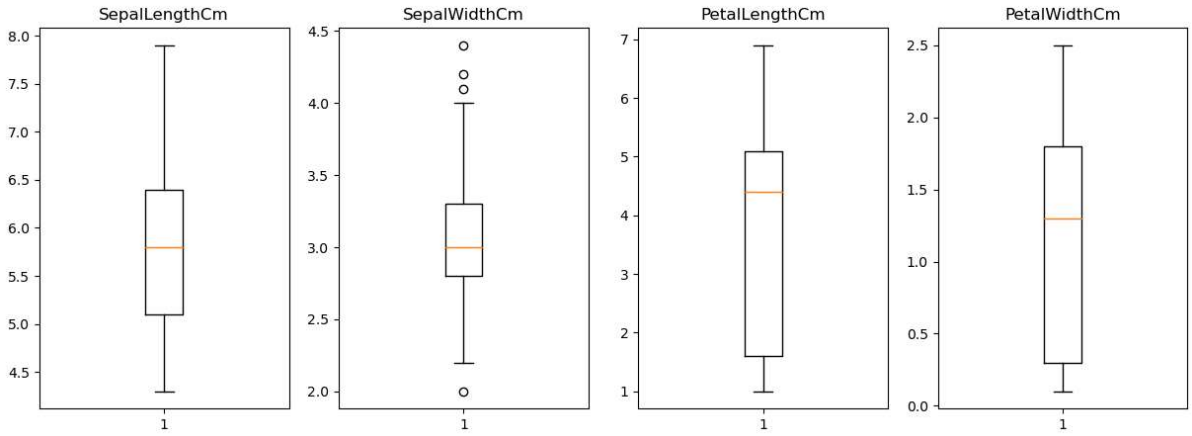
In [11]:
```
#Checking distributions
iris.hist(['SepalLengthCm','SepalWidthCm','PetalLengthCm','PetalWidthCm'],figsi
```

Out[11]:
```
array([[<Axes: title={'center': 'SepalLengthCm'}>,
        <Axes: title={'center': 'SepalWidthCm'}>],
       [<Axes: title={'center': 'PetalLengthCm'}>,
        <Axes: title={'center': 'PetalWidthCm'}>]], dtype=object)
```



From Histogram plot, in PetalLengthCm, there is a significant gap present in the distribution which may possibly indicates the presence of outliers

In [12]:
```
#Checking possibility in outliers with boxplot
ColforBox=['SepalLengthCm','SepalWidthCm','PetalLengthCm','PetalWidthCm']
fig,axs=plt.subplots(1,len(ColforBox),figsize=(15,5))
for i, column in enumerate(ColforBox):
    axs[i].boxplot(iris[column])
    axs[i].set_title(column)
plt.show()
```



The SeplaWidthCm has some outliers, but as the outliers are very close to their respective limmit value then these outliers can be considered for further approach

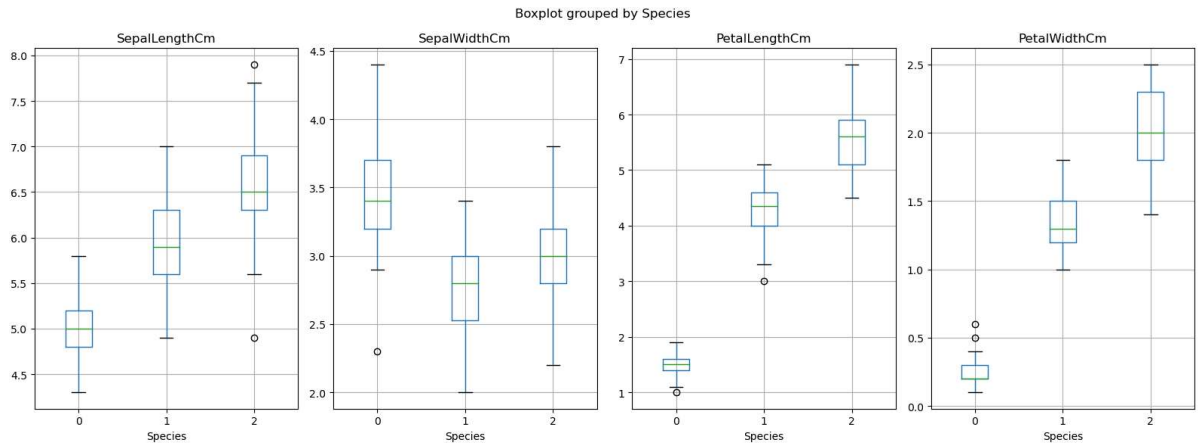
In [13]:
```
#Encoding target feature for fitting values in the model
from sklearn.preprocessing import LabelEncoder
```

In [14]:
```
Species=LabelEncoder()
iris['Species']=Species.fit_transform(iris['Species'])
iris.head(5)
```

Out[14]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

In [15]:
```
#Investigating relationship of these contineous feature with the target feature
fig,axs=plt.subplots(nrows=1,ncols=len(ColforBox),figsize=(16,6))
for i, col in enumerate(ColforBox):
    iris.boxplot(column=col,by='Species',ax=axs[i])
fig.tight_layout()
```



The above plot indicates signifcant relationship presence of all continuous variables with the target feature

In [16]:
```
#Conducting statistical approch (Anova) for more assurance in relationship
def FunctionAnova(inpData, TargetVariable, ContinuousPredictorList):
    from scipy.stats import f_oneway

    # Creating an empty list of final selected predictors
    SelectedPredictors=[]

    print('##### ANOVA Results ##### \n')
    for predictor in ContinuousPredictorList:
        CategoryGroupLists=inpData.groupby(TargetVariable)[predictor].apply(lis
        AnovaResults = f_oneway(*CategoryGroupLists)

        # If the ANOVA P-Value is <0.05, that means we reject H0
        if (AnovaResults[1] < 0.05):
            print(predictor, 'is correlated with', TargetVariable, '| P-Value:'
            SelectedPredictors.append(predictor)
        else:
            print(predictor, 'is NOT correlated with', TargetVariable, '| P-Val

    return(SelectedPredictors)
```

In [17]:
```
# Calling the function to check which categorical variables are correlated with
ContinuousVariables=ColforBox
FunctionAnova(inpData=iris, TargetVariable='Species', ContinuousPredictorList=C
```

```
##### ANOVA Results #####

SepalLengthCm is correlated with Species | P-Value: 7.530911607751589e-31
SepalWidthCm is correlated with Species | P-Value: 1.150337645778676e-16
PetalLengthCm is correlated with Species | P-Value: 8.180545708674455e-89
PetalWidthCm is correlated with Species | P-Value: 1.3529729471552313e-82
```

Out[17]:
```
['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']
```

Model Building for Prediction

In [18]:
```
x=iris.drop('Species',axis=1)
x.head(5)
```

Out[18]:

	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 [19]:
```
#80% training data and 20% testing data
y = iris['Species']
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)
```

In [20]:
```
lr = LogisticRegression()
lr.fit(x_train,y_train)
```

Out[20]:
```
LogisticRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [21]:
```
lr.predict(x_test)
```

Out[21]:
```
array([1, 2, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 2, 2, 1, 0, 1, 1, 1, 1, 0,
       2, 2, 1, 2, 2, 1, 2, 2])
```

In [22]:
```
from sklearn import metrics
print(metrics.confusion_matrix(y_test, lr.predict(x_test)))
```

```
[[ 9  0  0]
 [ 0 12  0]
 [ 0  0  9]]
```

In [23]:
```
print(metrics.classification_report(y_test, lr.predict(x_test)))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         9
           1       1.00      1.00      1.00        12
           2       1.00      1.00      1.00         9

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

In [24]:
```
print("Accuracy Score: ",lr.score(x_test,y_test))
```

```
Accuracy Score:  1.0
```

In [ ]:
```

```