Iris dataset description:

Iris Dataset Overview:

The Iris dataset is a classic dataset used in machine learning and analysis. It includes measurements of four features from three iris flower species: Iris setosa, Iris versicolor, and Iris virginica.

Features:

1. Sepal Length (cm)
2. Sepal Width (cm)
3. Petal Length (cm)
4. Petal Width (cm)

Species:

1. Iris setosa
2. Iris versicolor
3. Iris virginica

Dataset Summary:

- Samples: 150
- Features: 4
- Feature Types: Floating-point numbers (cm)
- Species: 3

Import necessary modules/libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.metrics import accuracy_score, classification_report
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

Reading the data

In [2]:
```
df=pd.read_csv("Iris.csv")
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

Data information

In [3]:
```
1 df.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
```

Data Descriptive Stats

In [4]:
```
1 df.describe().T
```

Out[4]:

	count	mean	std	min	25%	50%	75%	max
Id	150.0	75.500000	43.445368	1.0	38.25	75.50	112.75	150.0
SepalLengthCm	150.0	5.843333	0.828066	4.3	5.10	5.80	6.40	7.9
SepalWidthCm	150.0	3.054000	0.433594	2.0	2.80	3.00	3.30	4.4
PetalLengthCm	150.0	3.758667	1.764420	1.0	1.60	4.35	5.10	6.9
PetalWidthCm	150.0	1.198667	0.763161	0.1	0.30	1.30	1.80	2.5

Finding the shape (rows,columns) of the dataframe

In [5]:
```
1 print("shape (rows,columns) of the dataframe :",df.shape)
```

```
shape (rows,columns) of the dataframe : (150, 6)
```

Correlation betweem the features

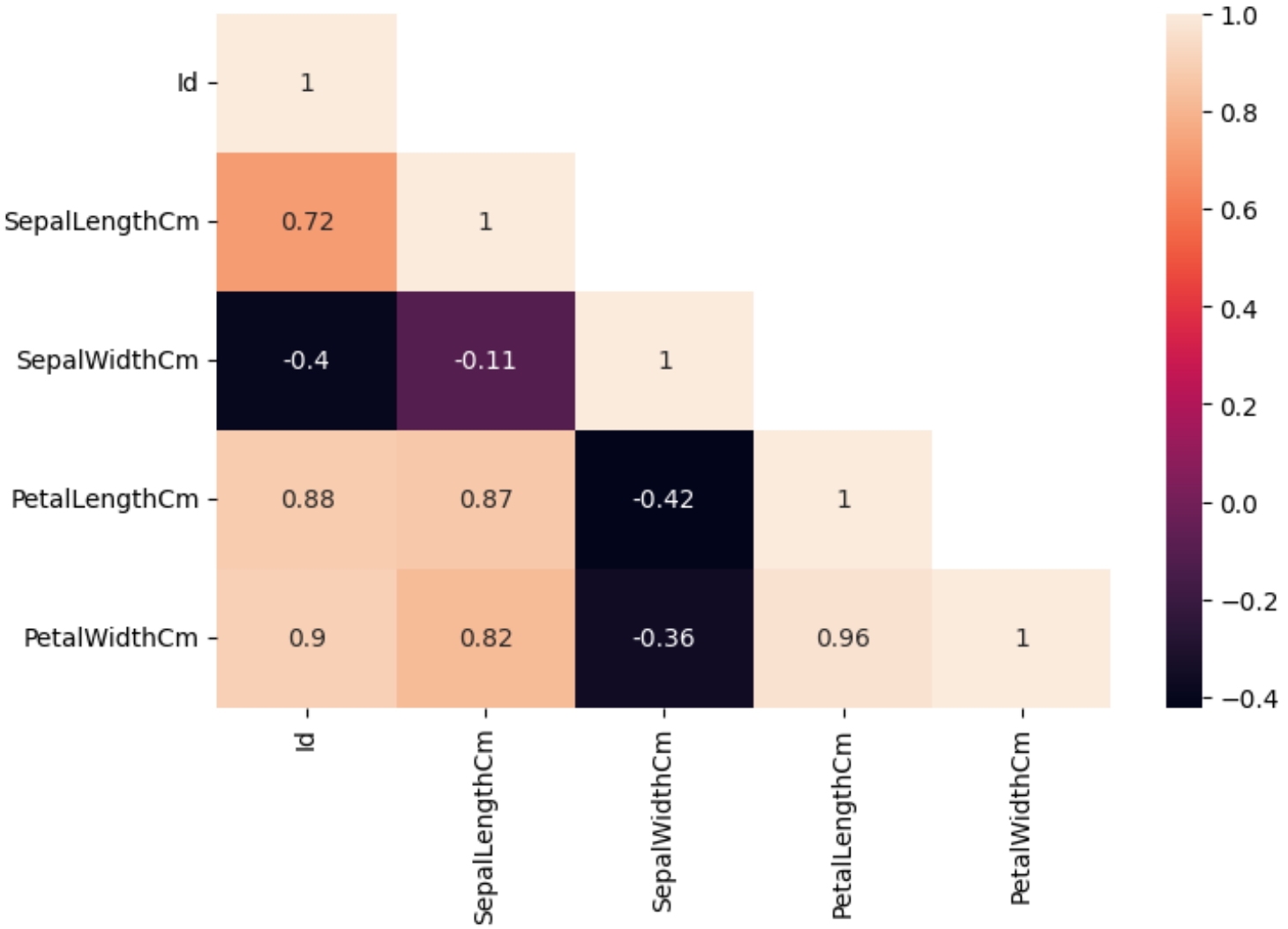
In [6]:
```
1 df.corr()
```

Out[6]:

	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 [7]:

```
1 plt.figure(figsize=(8,5))
2 sns.heatmap(df.corr(),annot=True,mask=np.triu(df.corr(),+1))
3 plt.show()
```



Finding the missing values using heatmap

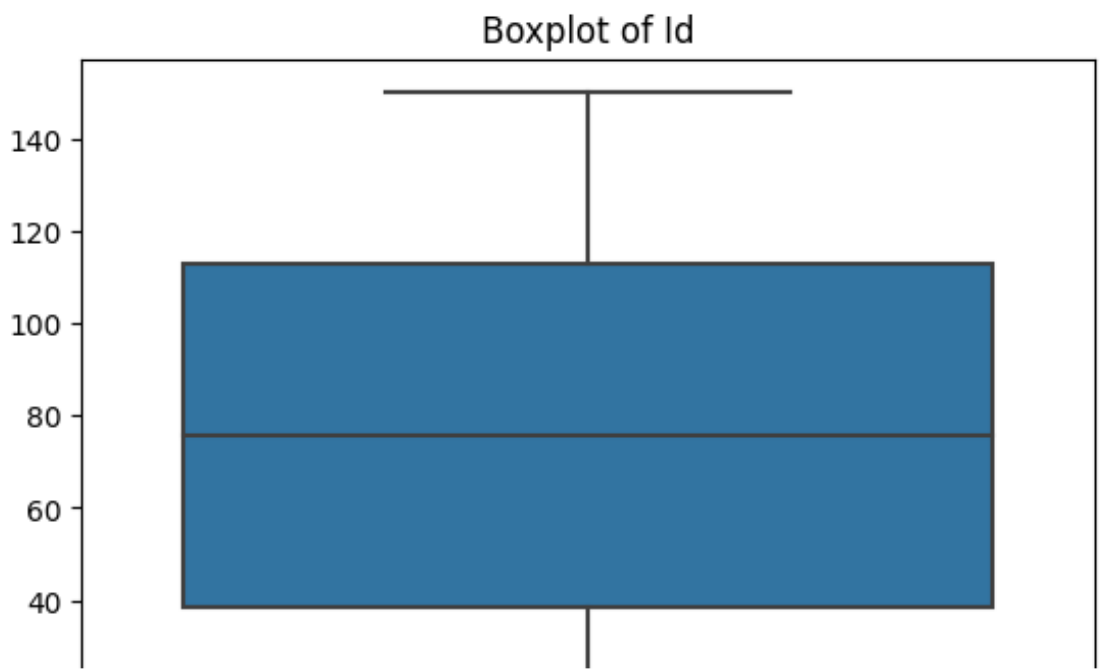
In [8]:
```
1 sns.heatmap(df.isnull())
```

Out[8]: <AxesSubplot: >

Outliers

Checking the outliers using the visualization (Boxplot).

In [9]:
```
for col in df.select_dtypes(exclude='object').columns:
    sns.boxplot(df[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```



Outliers Detection

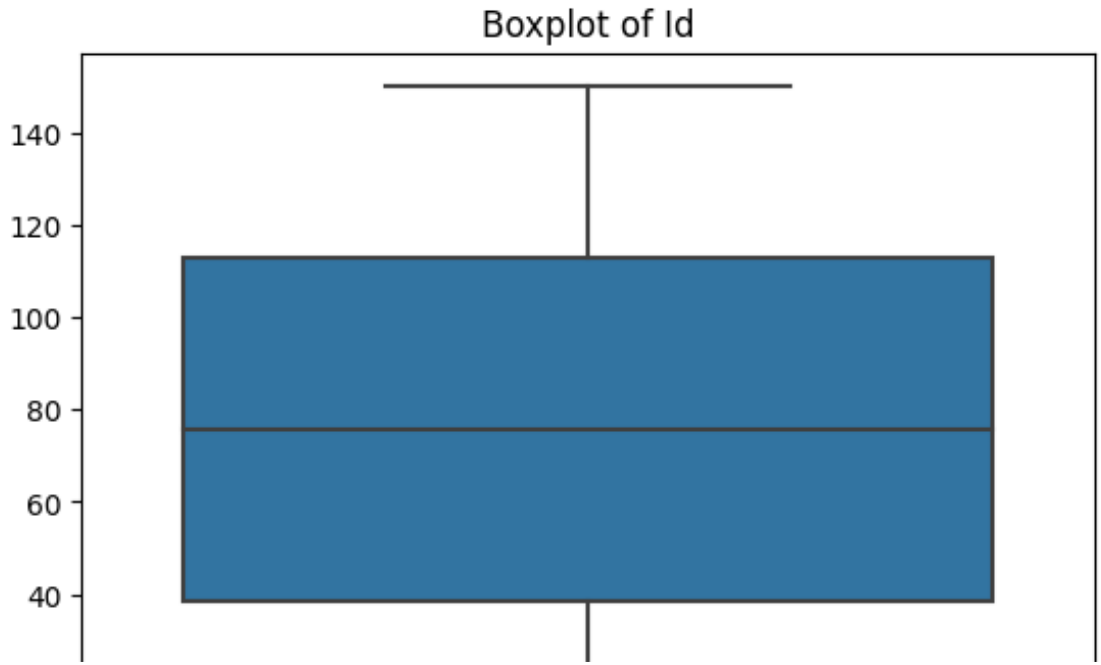
In [10]:
```
def outliers(col):
    Q1=np.quantile(col,.25)
    Q3=np.quantile(col,.75)
    IQR=Q3-Q1
    lr=Q1-(1.5*IQR)
    ur=Q3+(1.5*IQR)
    return lr,ur

```

Treatment of outliers

In [11]:
```
for col in df.select_dtypes(exclude='object').columns:
    lr,ur=outliers(df[col])
    df[col]=np.where(df[col]>ur,ur,df[col])
    df[col]=np.where(df[col]<lr,lr,df[col])
```

In [12]:

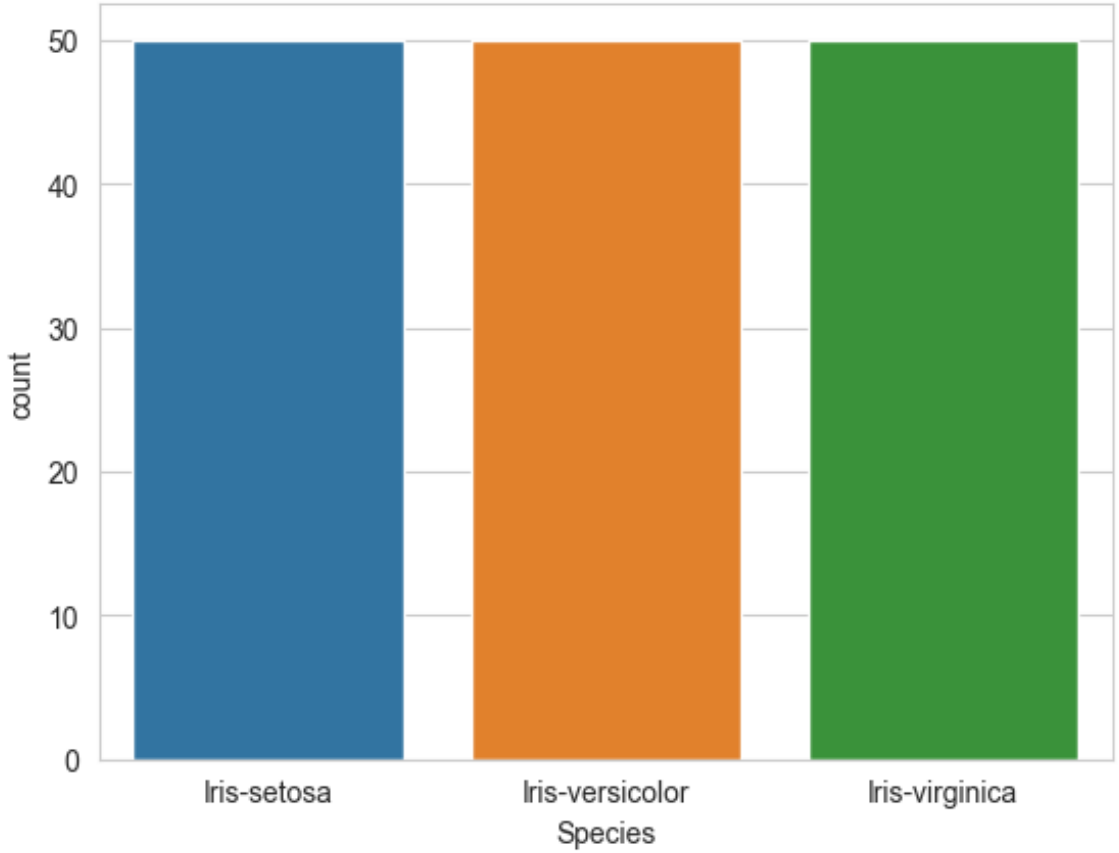
```
for col in df.select_dtypes(exclude='object').columns:
    sns.boxplot(df[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```



Count the types of Species

In [13]:
```
1 sns.set_style('whitegrid')
2 sns.countplot(x='Species',data=df)
```

Out[13]: <AxesSubplot: xlabel='Species', ylabel='count'>



In [14]:
```
1 df['Species'].unique()
```

Out[14]: array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)

In [15]:
```
1 df['Species'].value_counts()
```

Out[15]:
```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: Species, dtype: int64
```

In [16]:
```
1 df.columns
```

Out[16]:
```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

Using LabelEncoder we convert categorical data into numerical data

In [17]:
```
1 le=LabelEncoder()
```

In [18]:
```
df.drop('Id',axis=1,inplace=True)
df.head(100)
```

Out[18]:

	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
...	...	...	...	...	...
95	5.7	3.0	4.2	1.2	Iris-versicolor
96	5.7	2.9	4.2	1.3	Iris-versicolor
97	6.2	2.9	4.3	1.3	Iris-versicolor
98	5.1	2.5	3.0	1.1	Iris-versicolor
99	5.7	2.8	4.1	1.3	Iris-versicolor

100 rows × 5 columns

In [19]:
```
dfle=df
dfle.Species=le.fit_transform(dfle.Species)
dfle.head(5)
```

Out[19]:

	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 [20]:
```
1 df['Species'].unique()
```

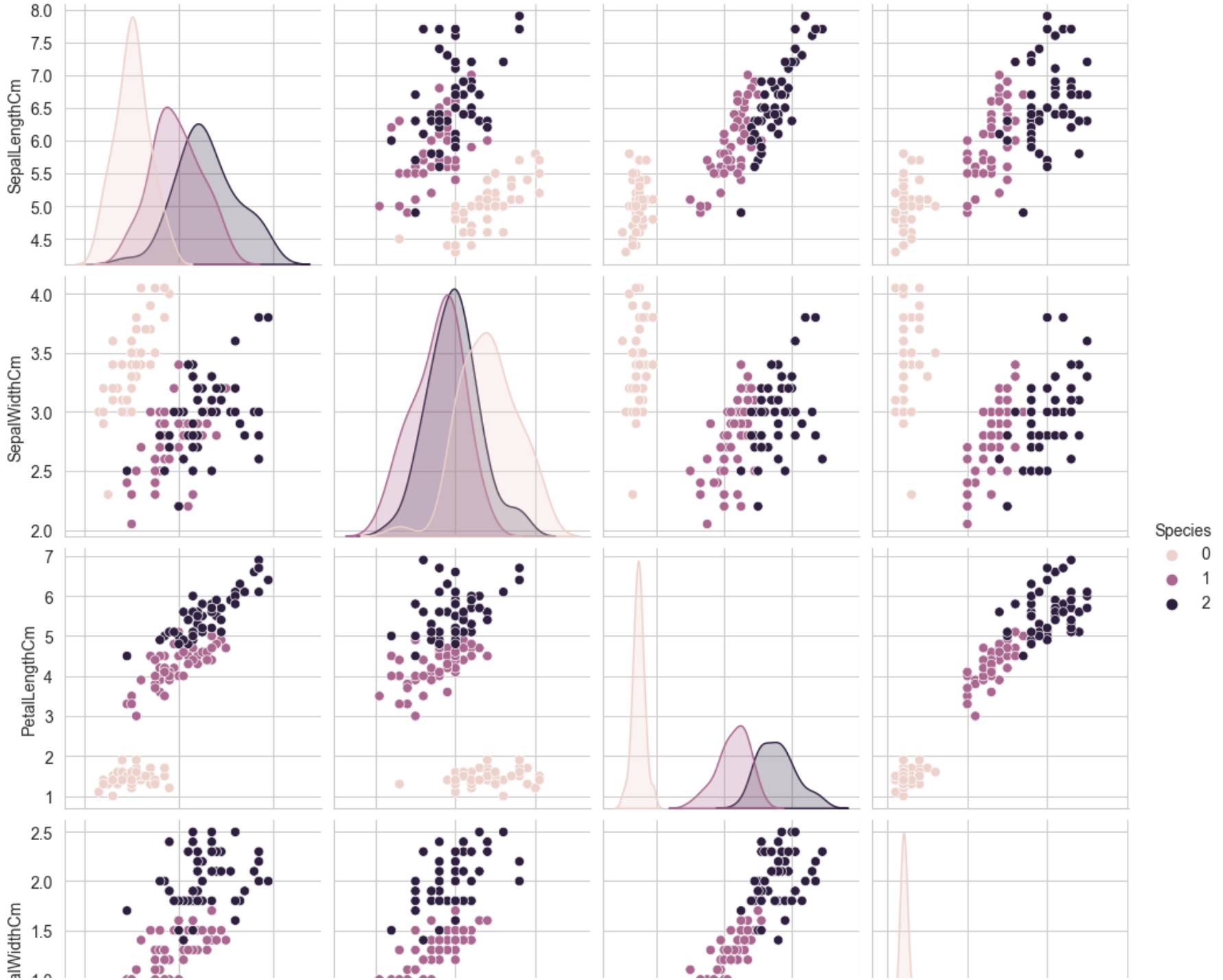
Out[20]:
```
array([0, 1, 2])
```

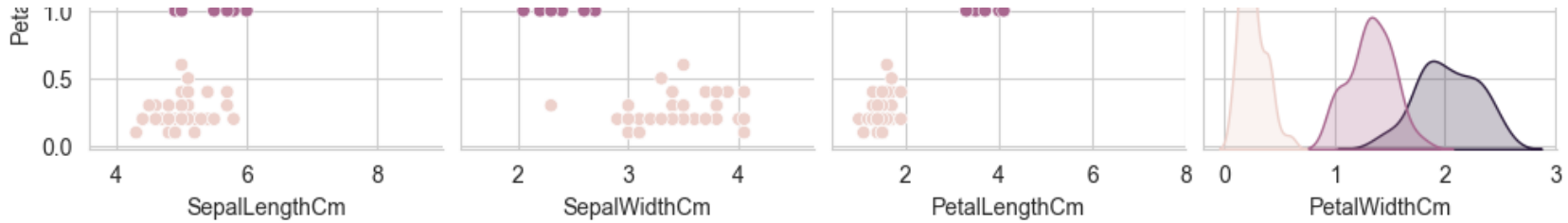
EDA-Pairplot

In [21]:

```
plt.figure(figsize=(16,9))
sns.pairplot(df,hue='Species')
plt.show()
```

```
<Figure size 1600x900 with 0 Axes>
```


SepalLengthCm
SepalWidthCm
PetalLengthCm
Species
0
1
2



Decision Tree (Machine Learning Algorithm)

In [22]:
```
1 df.columns
```

Out[22]:
```
Index(['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

In [23]:
```
1 inputs=df.drop(['Species'],axis=1)
2 target=df['Species']
```

Splitting the data into train & test.

In [24]:
```
1 X_train,X_test,y_train,y_test=train_test_split(inputs,target,train_size=0.8,random_state=35)
```

In [25]:
```
1 model=tree.DecisionTreeClassifier()
```

Model Fitting.

In [26]:
```
1 model.fit(X_train,y_train)
```

Out[26]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

Model Prediction

In [27]:
```
y_pred=model.predict(X_test)
```

In [28]:
```
Accuracy=model.score(X_test,y_test)*100
```

In [29]:
```
round(Accuracy,2)
```

Out[29]: 100.0

Accuracy of this model is equal 100.0 %

In [30]:
```
print(classification_report(y_pred,y_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        11
           1       1.00      1.00      1.00        10
           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
```