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

In [2]:
```
df = pd.read_csv('iris.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	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

In [5]:
```
df.columns = ('SL', 'SW', 'PL', 'PW', 'Species')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   SL       150 non-null    float64
 1   SW       150 non-null    float64
 2   PL       150 non-null    float64
 3   PW       150 non-null    float64
 4   Species  150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [7]:
```
df.size
```

Out[7]:
```
750
```

In [10]:
```
print('Total Number of Null Values in Dataset:')
df.isnull().sum()
```

```
Total Number of Null Values in Dataset:
```

Out[10]:
```
SL         0
SW         0
PL         0
PW         0
Species    0
dtype: int64
```

In [11]:
```
print('Statistical information of Numerical Columns:')
df.describe()
```

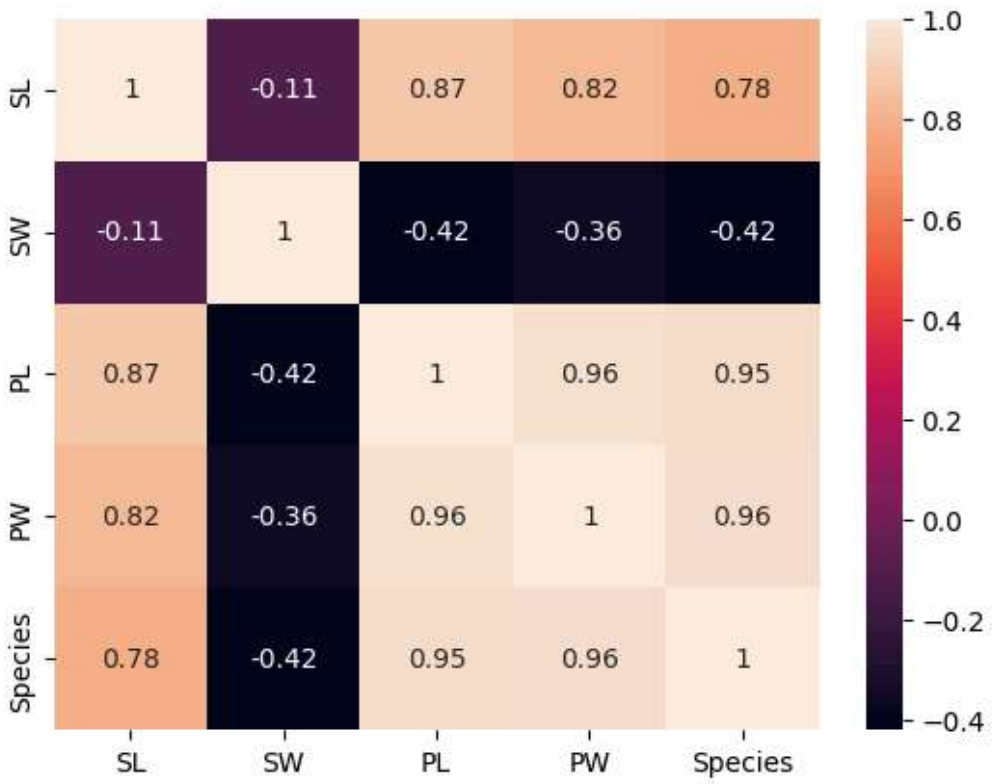
```
Statistical information of Numerical Columns:
```

Out[11]:

	SL	SW	PL	PW
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
max	7.900000	4.400000	6.900000	2.500000

In [12]:
```
# Label encoding
df['Species']=df['Species'].astype('category')
df['Species']=df['Species'].cat.codes
```

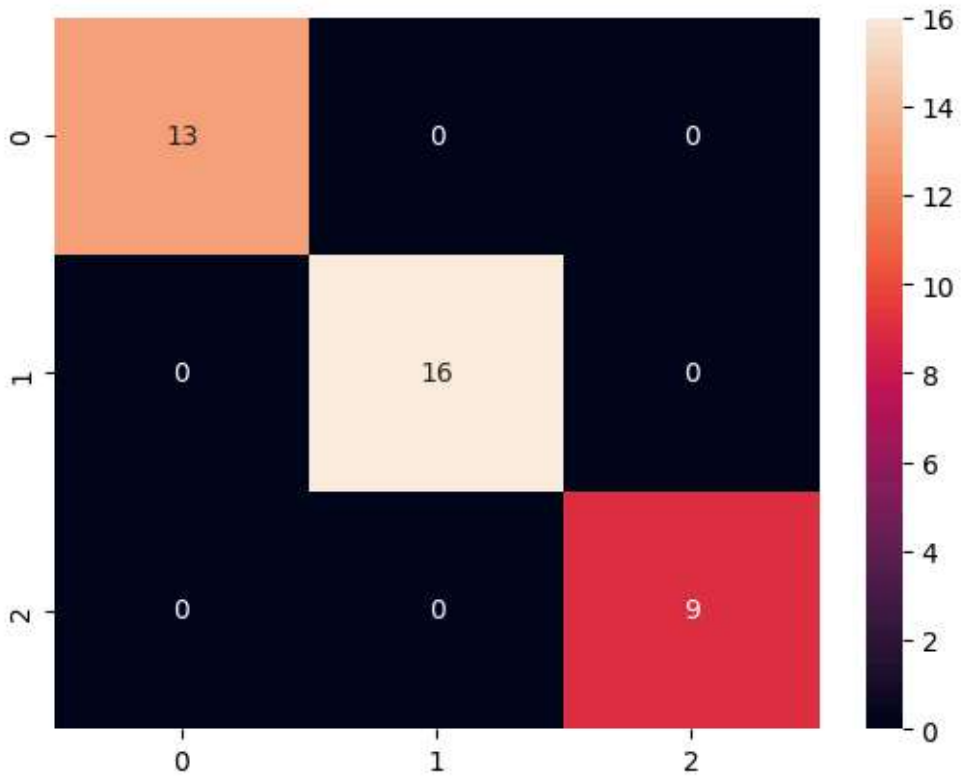
In [13]:
```
sns.heatmap(df.corr(),annot=True)
plt.show()
```



In [15]:
```
def BuildModel(X, Y):
# Training and testing data
    from sklearn.model_selection import train_test_split
# Assign test data size 20%
    xtrain, xtest, ytrain, ytest =train_test_split(X,Y,test_size= 0.25, random_state
# from sklearn.linear_model import LogisticRegression
# model = LogisticRegression(solver = 'lbfgs')
    from sklearn.naive_bayes import GaussianNB
    model = GaussianNB()
    model = model.fit(xtrain,ytrain)
    ypred = model.predict(xtest)
    from sklearn.metrics import confusion_matrix
```

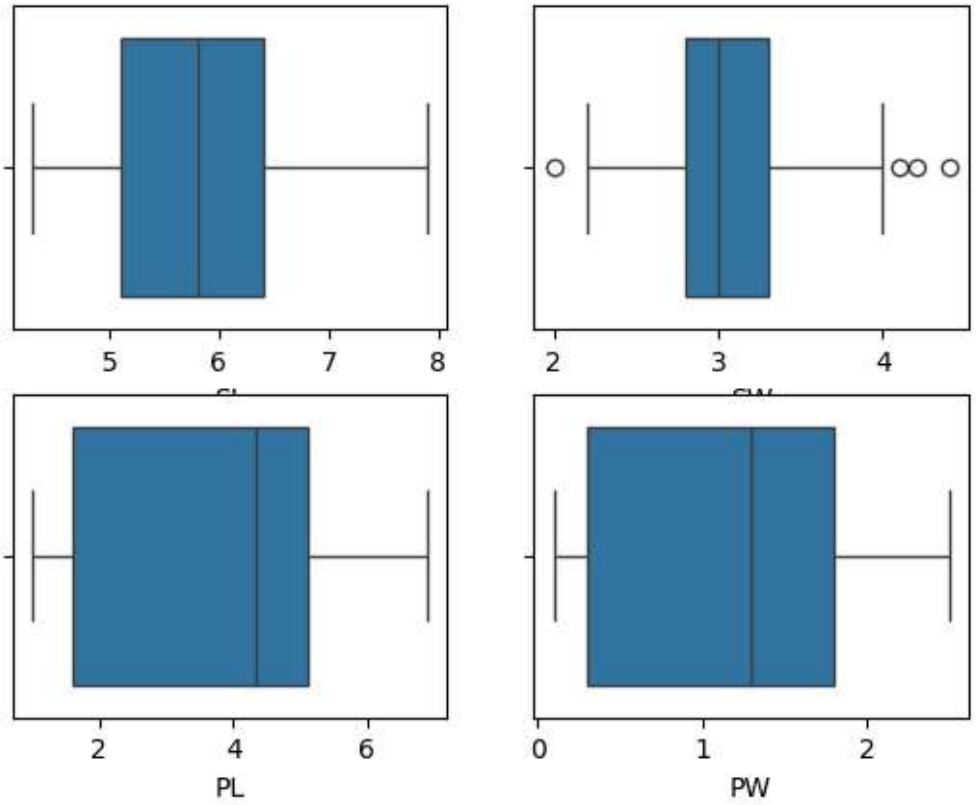
```
    cm = confusion_matrix(ytest, ypred)
    sns.heatmap(cm, annot=True)
    plt.show()
    from sklearn.metrics import classification_report
    print(classification_report(ytest, ypred))
```

In [16]:
```
X = df[['SL','SW', 'PL', 'PW']]
Y = df['Species']
BuildModel(X, Y)
```



	precision	recall	f1-score	support
0	1.00	1.00	1.00	13
1	1.00	1.00	1.00	16
2	1.00	1.00	1.00	9
accuracy			1.00	38
macro avg	1.00	1.00	1.00	38
weighted avg	1.00	1.00	1.00	38

In [17]:
```
# Checking model score after removing outliers
fig, axes = plt.subplots(2,2)
sns.boxplot(data = df, x ='SL', ax=axes[0,0])
sns.boxplot(data = df, x ='SW', ax=axes[0,1])
sns.boxplot(data = df, x ='PL', ax=axes[1,0])
sns.boxplot(data = df, x ='PW', ax=axes[1,1])
plt.show()
```

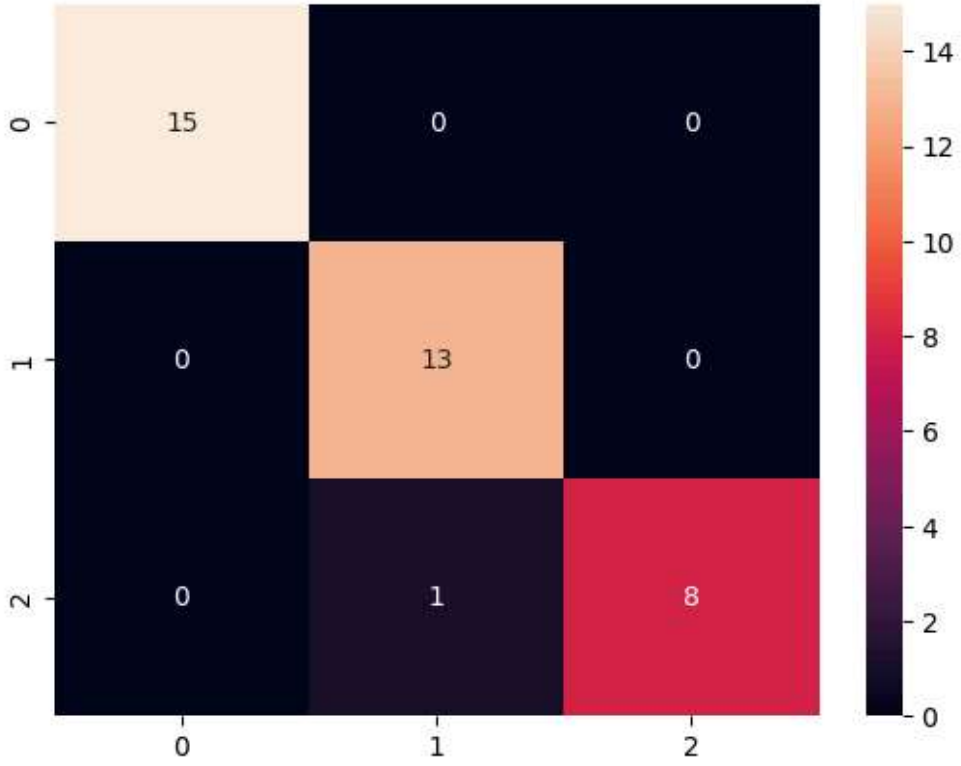


In [18]:
```
def RemoveOutlier(df,var):
    Q1 = df[var].quantile(0.25)
    Q3 = df[var].quantile(0.75)
    IQR = Q3 - Q1
    high, low = Q3+1.5*IQR, Q1-1.5*IQR
    print("Highest allowed in variable:", var, high)
    print("lowest allowed in variable:", var, low)
    count = df[(df[var] > high) | (df[var] < low)][var].count()
    print('Total outliers in:',var,':',count)
    df = df[((df[var] >= low) & (df[var] <= high))]
    return df
```

In [19]:
```
df = RemoveOutlier(df, 'SW')
```

```
Highest allowed in variable: SW 4.05
lowest allowed in variable: SW 2.05
Total outliers in: SW : 4
```

In [20]:
```
# Choosing input and output variables from correlation matrix
X = df[['SL','SW', 'PL', 'PW']]
Y = df['Species']
BuildModel(X, Y)
```



	precision	recall	f1-score	support
0	1.00	1.00	1.00	15
1	0.93	1.00	0.96	13
2	1.00	0.89	0.94	9
accuracy			0.97	37
macro avg	0.98	0.96	0.97	37
weighted avg	0.97	0.97	0.97	37