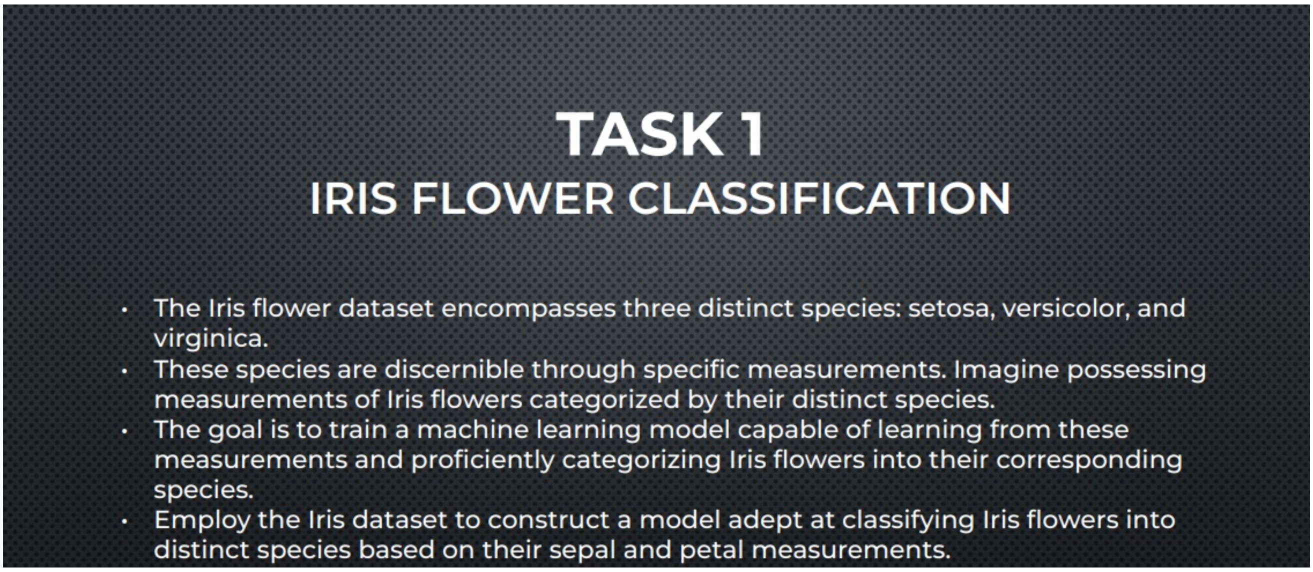


Import Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
import warnings
warnings.filterwarnings('ignore')
```

Load the Iris Dataset

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

Out[2]:

	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
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

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 [4]:
```
df.tail()
```

Out[4]:

	sepal_length	sepal_width	petal_length	petal_width	species
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

In [5]:

```
df.shape
```

Out[5]:

```
(150, 5)
```

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   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [7]:

```
df.describe()
```

Out[7]:

	sepal_length	sepal_width	petal_length	petal_width
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 [8]:

```
df.isnull().sum()
```

Out[8]:

```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

In [9]:

```
df.columns
```

Out[9]:

```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',
       'species'],
      dtype='object')
```

In [10]:

```
df['species'].value_counts()
```

Out[10]:

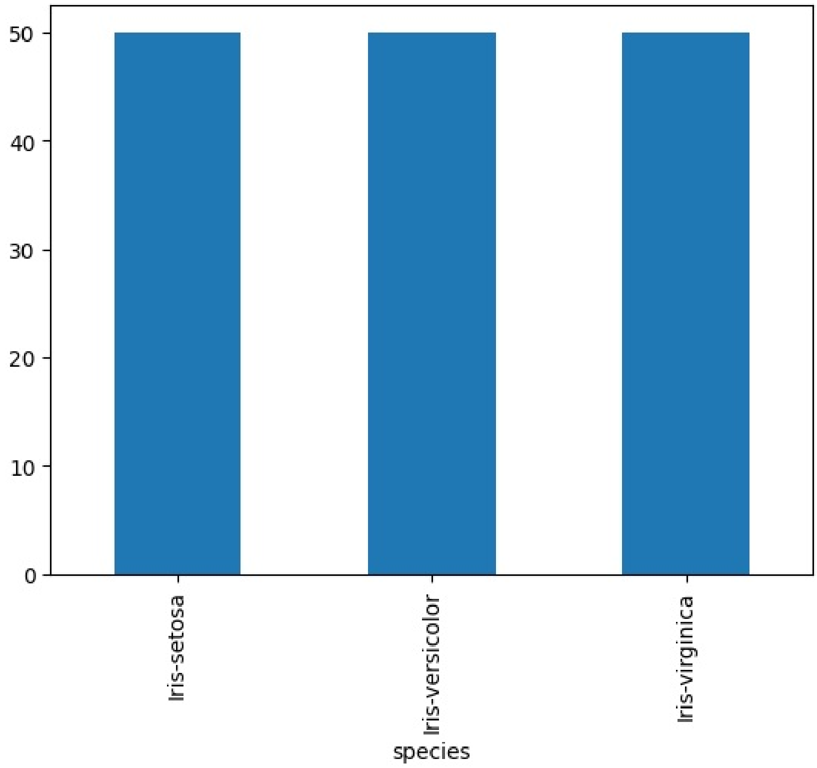
```
species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: count, dtype: int64
```

In [11]:

```
df['species'].value_counts().plot(kind='bar')
```

Out[11]:

```
<Axes: xlabel='species'>
```



In [12]:

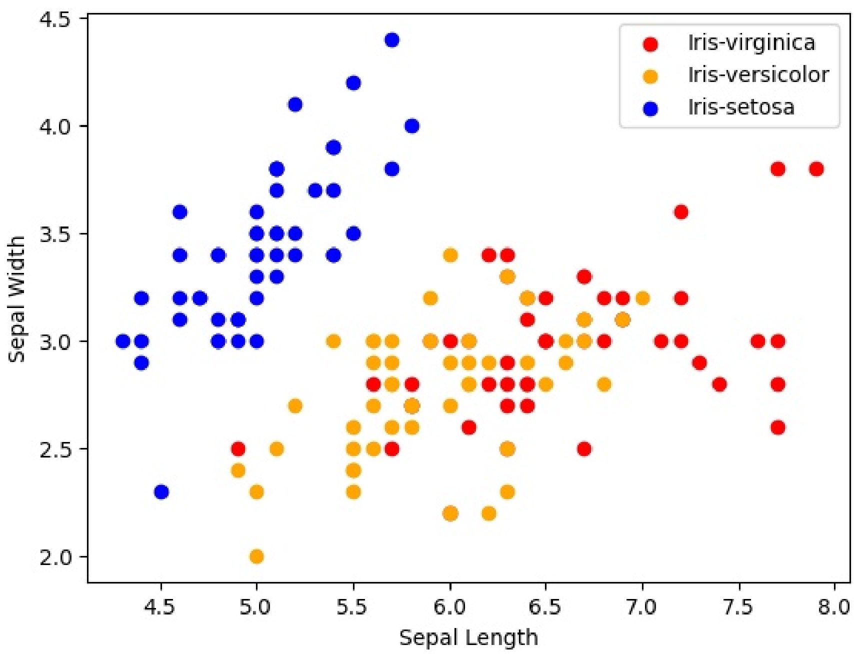
```
# scatterplot
colors = ['red', 'orange', 'blue']
species = ['Iris-virginica','Iris-versicolor','Iris-setosa']
```

In [13]:

```
for i in range(3):
    x = df[df['species'] == species[i]]
    plt.scatter(x['sepal_length'], x['sepal_width'], c = colors[i], label=species[i])
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.legend()
```

Out[13]:

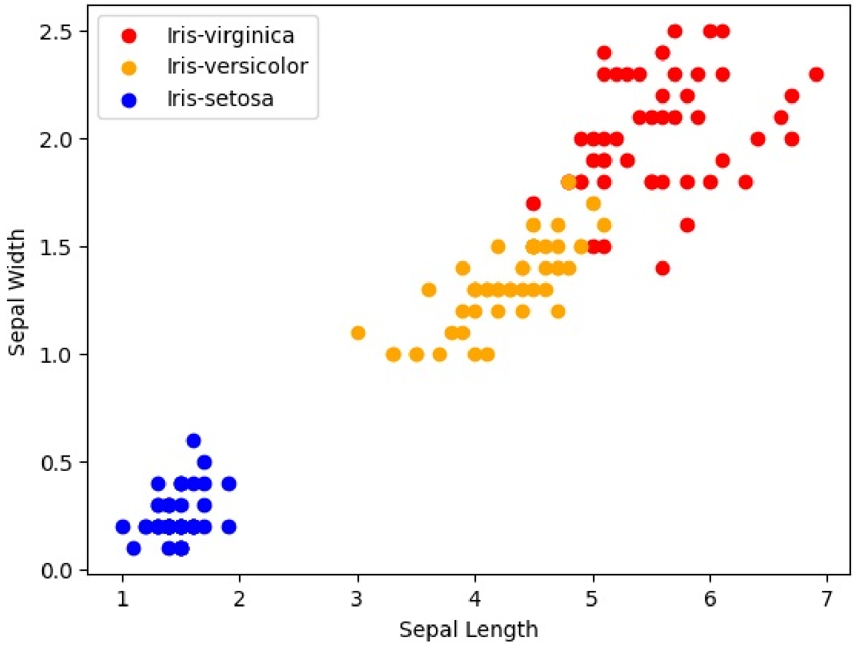
```
<matplotlib.legend.Legend at 0x1cf5e8a3790>
```



```
In [14]: # scatterplot
colors = ['red', 'orange', 'blue']
species = ['Iris-virginica','Iris-versicolor','Iris-setosa']
```

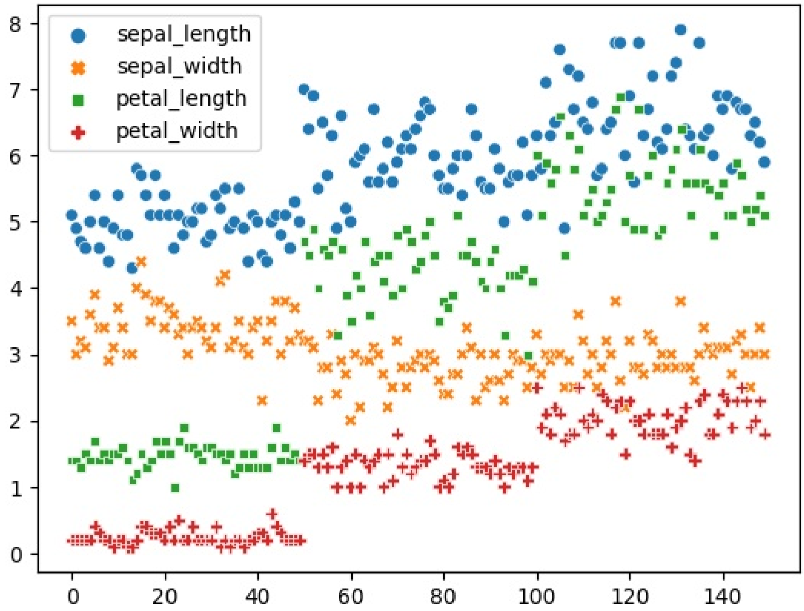
```
In [15]: for i in range(3):
    x = df[df['species'] == species[i]]
    plt.scatter(x['petal_length'], x['petal_width'], c = colors[i], label=species[i])
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.legend()
```

```
Out[15]: &lt;matplotlib.legend.Legend at 0x1cf60c77ed0&gt;
```




```
In [16]: sns.scatterplot(df)
```

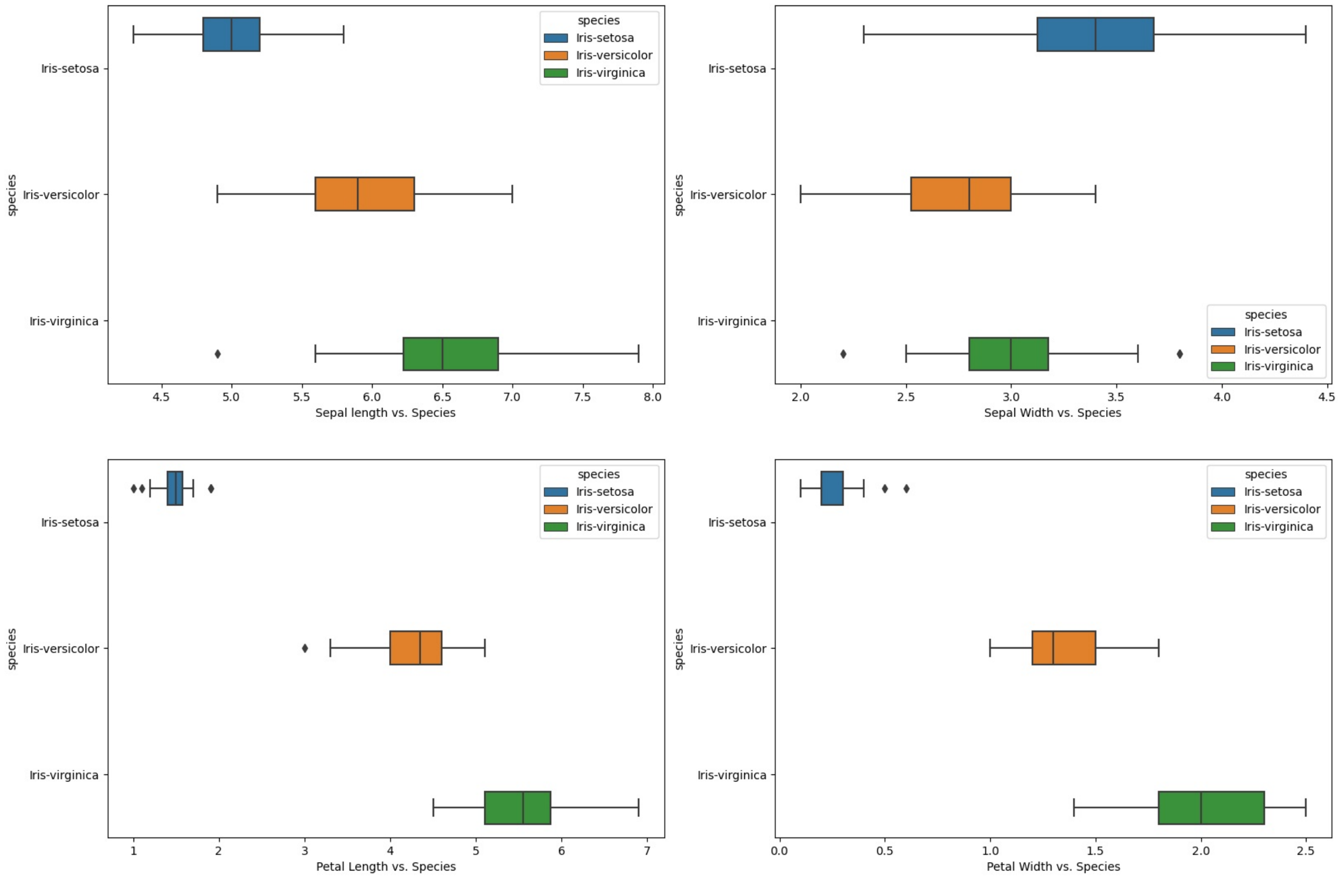
```
Out[16]: <Axes: >
```



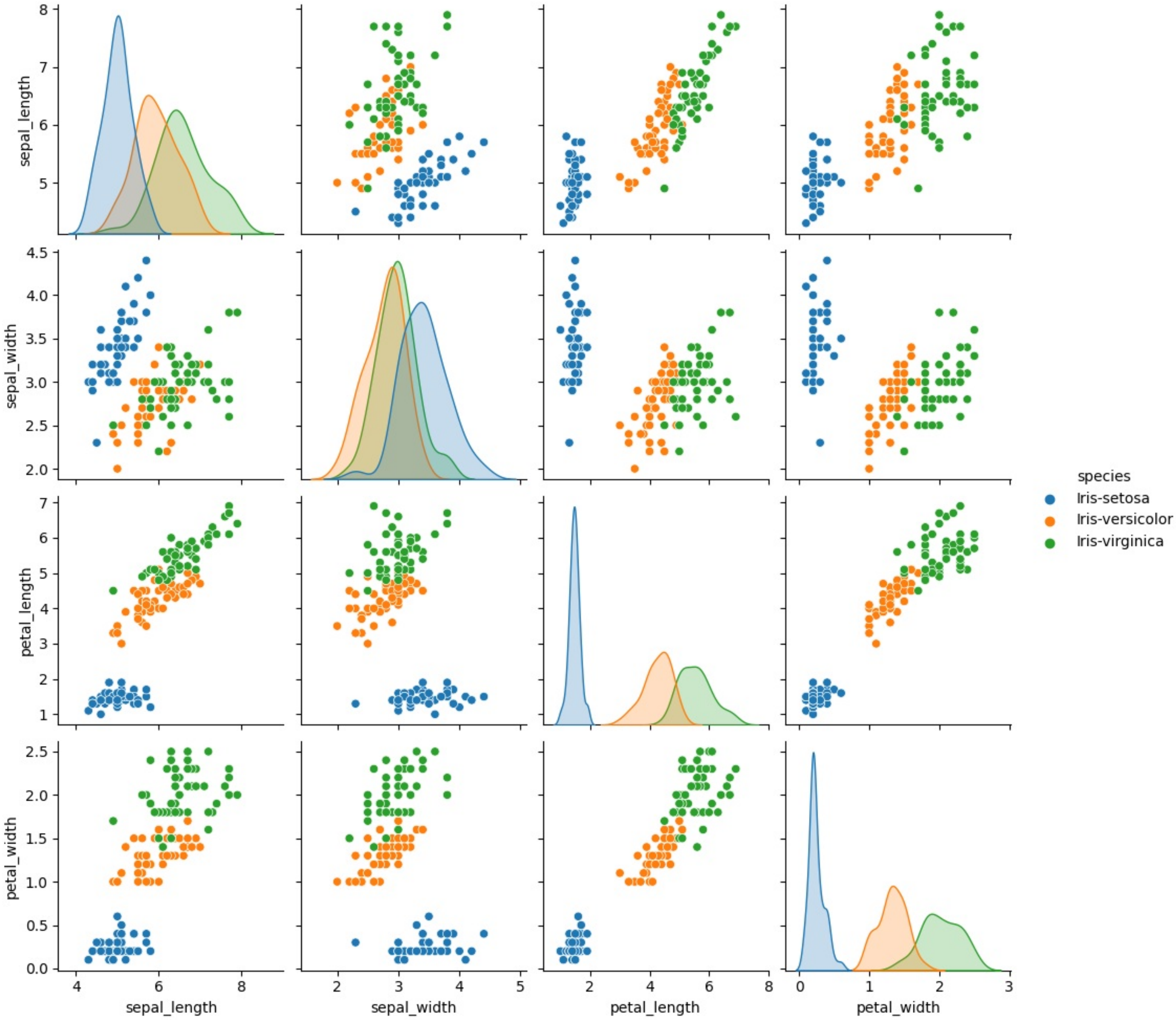

```
In [17]: #Using boxplot visualization.
plt.figure(figsize=(19,13))

plt.subplot(2,2,1)
sns.boxplot(x=df['sepal_length'], y=df['species'], hue=df['species'])
plt.xlabel('Sepal length vs. Species')


plt.subplot(2,2,2)
sns.boxplot(x=df['sepal_width'], y=df['species'], hue=df['species'])
plt.xlabel('Sepal Width vs. Species')


plt.subplot(2,2,3)
sns.boxplot(x=df['petal_length'], y=df['species'], hue=df['species'])
plt.xlabel('Petal Length vs. Species')
```

```
plt.subplot(2,2,4)
sns.boxplot(x=df['petal_width'], y=df['species'], hue=df['species'])
plt.xlabel('Petal Width vs. Species')
```

Out[17]: Text(0.5, 0, 'Petal Width vs. Species')



In [18]:
```
sns.pairplot(df, hue='species')
plt.savefig('species.jpg')
```



Insight

1. Iris-setosa forms distinct clusters, while Iris-versicolor and Iris-virginica overlap slightly with linear trends.
2. Petal Length and Width:Clear separation; Iris-setosa is smallest, followed by Iris-versicolor, then Iris-virginica.
3. Sepal Length and Width:More overlap, especially between Iris-versicolor and Iris-virginica.

In [19]:
```
df.iloc[1:50]
```

Out[19]:

	sepal_length	sepal_width	petal_length	petal_width	species
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
5	5.4	3.9	1.7	0.4	Iris-setosa
6	4.6	3.4	1.4	0.3	Iris-setosa
7	5.0	3.4	1.5	0.2	Iris-setosa
8	4.4	2.9	1.4	0.2	Iris-setosa
9	4.9	3.1	1.5	0.1	Iris-setosa
10	5.4	3.7	1.5	0.2	Iris-setosa
11	4.8	3.4	1.6	0.2	Iris-setosa
12	4.8	3.0	1.4	0.1	Iris-setosa
13	4.3	3.0	1.1	0.1	Iris-setosa
14	5.8	4.0	1.2	0.2	Iris-setosa
15	5.7	4.4	1.5	0.4	Iris-setosa
16	5.4	3.9	1.3	0.4	Iris-setosa
17	5.1	3.5	1.4	0.3	Iris-setosa
18	5.7	3.8	1.7	0.3	Iris-setosa
19	5.1	3.8	1.5	0.3	Iris-setosa
20	5.4	3.4	1.7	0.2	Iris-setosa
21	5.1	3.7	1.5	0.4	Iris-setosa
22	4.6	3.6	1.0	0.2	Iris-setosa
23	5.1	3.3	1.7	0.5	Iris-setosa
24	4.8	3.4	1.9	0.2	Iris-setosa
25	5.0	3.0	1.6	0.2	Iris-setosa
26	5.0	3.4	1.6	0.4	Iris-setosa
27	5.2	3.5	1.5	0.2	Iris-setosa
28	5.2	3.4	1.4	0.2	Iris-setosa
29	4.7	3.2	1.6	0.2	Iris-setosa
30	4.8	3.1	1.6	0.2	Iris-setosa
31	5.4	3.4	1.5	0.4	Iris-setosa
32	5.2	4.1	1.5	0.1	Iris-setosa
33	5.5	4.2	1.4	0.2	Iris-setosa
34	4.9	3.1	1.5	0.1	Iris-setosa
35	5.0	3.2	1.2	0.2	Iris-setosa
36	5.5	3.5	1.3	0.2	Iris-setosa
37	4.9	3.1	1.5	0.1	Iris-setosa
38	4.4	3.0	1.3	0.2	Iris-setosa
39	5.1	3.4	1.5	0.2	Iris-setosa
40	5.0	3.5	1.3	0.3	Iris-setosa
41	4.5	2.3	1.3	0.3	Iris-setosa
42	4.4	3.2	1.3	0.2	Iris-setosa
43	5.0	3.5	1.6	0.6	Iris-setosa
44	5.1	3.8	1.9	0.4	Iris-setosa
45	4.8	3.0	1.4	0.3	Iris-setosa
46	5.1	3.8	1.6	0.2	Iris-setosa
47	4.6	3.2	1.4	0.2	Iris-setosa
48	5.3	3.7	1.5	0.2	Iris-setosa
49	5.0	3.3	1.4	0.2	Iris-setosa

In [20]:

```
df.iloc[51:100]
```

Out[20]:

	sepal_length	sepal_width	petal_length	petal_width	species
51	6.4	3.2	4.5	1.5	Iris-versicolor
52	6.9	3.1	4.9	1.5	Iris-versicolor
53	5.5	2.3	4.0	1.3	Iris-versicolor
54	6.5	2.8	4.6	1.5	Iris-versicolor
55	5.7	2.8	4.5	1.3	Iris-versicolor
56	6.3	3.3	4.7	1.6	Iris-versicolor
57	4.9	2.4	3.3	1.0	Iris-versicolor
58	6.6	2.9	4.6	1.3	Iris-versicolor
59	5.2	2.7	3.9	1.4	Iris-versicolor
60	5.0	2.0	3.5	1.0	Iris-versicolor
61	5.9	3.0	4.2	1.5	Iris-versicolor
62	6.0	2.2	4.0	1.0	Iris-versicolor
63	6.1	2.9	4.7	1.4	Iris-versicolor
64	5.6	2.9	3.6	1.3	Iris-versicolor
65	6.7	3.1	4.4	1.4	Iris-versicolor
66	5.6	3.0	4.5	1.5	Iris-versicolor
67	5.8	2.7	4.1	1.0	Iris-versicolor
68	6.2	2.2	4.5	1.5	Iris-versicolor
69	5.6	2.5	3.9	1.1	Iris-versicolor
70	5.9	3.2	4.8	1.8	Iris-versicolor
71	6.1	2.8	4.0	1.3	Iris-versicolor
72	6.3	2.5	4.9	1.5	Iris-versicolor
73	6.1	2.8	4.7	1.2	Iris-versicolor
74	6.4	2.9	4.3	1.3	Iris-versicolor
75	6.6	3.0	4.4	1.4	Iris-versicolor
76	6.8	2.8	4.8	1.4	Iris-versicolor
77	6.7	3.0	5.0	1.7	Iris-versicolor
78	6.0	2.9	4.5	1.5	Iris-versicolor
79	5.7	2.6	3.5	1.0	Iris-versicolor
80	5.5	2.4	3.8	1.1	Iris-versicolor
81	5.5	2.4	3.7	1.0	Iris-versicolor
82	5.8	2.7	3.9	1.2	Iris-versicolor
83	6.0	2.7	5.1	1.6	Iris-versicolor
84	5.4	3.0	4.5	1.5	Iris-versicolor
85	6.0	3.4	4.5	1.6	Iris-versicolor
86	6.7	3.1	4.7	1.5	Iris-versicolor
87	6.3	2.3	4.4	1.3	Iris-versicolor
88	5.6	3.0	4.1	1.3	Iris-versicolor
89	5.5	2.5	4.0	1.3	Iris-versicolor
90	5.5	2.6	4.4	1.2	Iris-versicolor
91	6.1	3.0	4.6	1.4	Iris-versicolor
92	5.8	2.6	4.0	1.2	Iris-versicolor
93	5.0	2.3	3.3	1.0	Iris-versicolor
94	5.6	2.7	4.2	1.3	Iris-versicolor
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

In [21]:

```
df.iloc[100:150]
```

Out[21]:

	sepal_length	sepal_width	petal_length	petal_width	species
100	6.3	3.3	6.0	2.5	Iris-virginica
101	5.8	2.7	5.1	1.9	Iris-virginica
102	7.1	3.0	5.9	2.1	Iris-virginica
103	6.3	2.9	5.6	1.8	Iris-virginica
104	6.5	3.0	5.8	2.2	Iris-virginica
105	7.6	3.0	6.6	2.1	Iris-virginica
106	4.9	2.5	4.5	1.7	Iris-virginica
107	7.3	2.9	6.3	1.8	Iris-virginica
108	6.7	2.5	5.8	1.8	Iris-virginica
109	7.2	3.6	6.1	2.5	Iris-virginica
110	6.5	3.2	5.1	2.0	Iris-virginica
111	6.4	2.7	5.3	1.9	Iris-virginica
112	6.8	3.0	5.5	2.1	Iris-virginica
113	5.7	2.5	5.0	2.0	Iris-virginica
114	5.8	2.8	5.1	2.4	Iris-virginica
115	6.4	3.2	5.3	2.3	Iris-virginica
116	6.5	3.0	5.5	1.8	Iris-virginica
117	7.7	3.8	6.7	2.2	Iris-virginica
118	7.7	2.6	6.9	2.3	Iris-virginica
119	6.0	2.2	5.0	1.5	Iris-virginica
120	6.9	3.2	5.7	2.3	Iris-virginica
121	5.6	2.8	4.9	2.0	Iris-virginica
122	7.7	2.8	6.7	2.0	Iris-virginica
123	6.3	2.7	4.9	1.8	Iris-virginica
124	6.7	3.3	5.7	2.1	Iris-virginica
125	7.2	3.2	6.0	1.8	Iris-virginica
126	6.2	2.8	4.8	1.8	Iris-virginica
127	6.1	3.0	4.9	1.8	Iris-virginica
128	6.4	2.8	5.6	2.1	Iris-virginica
129	7.2	3.0	5.8	1.6	Iris-virginica
130	7.4	2.8	6.1	1.9	Iris-virginica
131	7.9	3.8	6.4	2.0	Iris-virginica
132	6.4	2.8	5.6	2.2	Iris-virginica
133	6.3	2.8	5.1	1.5	Iris-virginica
134	6.1	2.6	5.6	1.4	Iris-virginica
135	7.7	3.0	6.1	2.3	Iris-virginica
136	6.3	3.4	5.6	2.4	Iris-virginica
137	6.4	3.1	5.5	1.8	Iris-virginica
138	6.0	3.0	4.8	1.8	Iris-virginica
139	6.9	3.1	5.4	2.1	Iris-virginica
140	6.7	3.1	5.6	2.4	Iris-virginica
141	6.9	3.1	5.1	2.3	Iris-virginica
142	5.8	2.7	5.1	1.9	Iris-virginica
143	6.8	3.2	5.9	2.3	Iris-virginica
144	6.7	3.3	5.7	2.5	Iris-virginica
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

In [22]:
```
x=df.drop('species',axis=1)
```

In [23]:
```
x.head()
```

Out[23]:

	sepal_length	sepal_width	petal_length	petal_width
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 [24]:
```
y=df['species']
```

In [25]:
```
y.head()
```

Out[25]:
```
0    Iris-setosa
1    Iris-setosa
2    Iris-setosa
3    Iris-setosa
4    Iris-setosa
Name: species, dtype: object
```

In [26]:
```
x.shape,y.shape
```

Out[26]:
```
((150, 4), (150,))
```

In [27]:
```
# Split the data to train and test dataset
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3,random_state=42)
```

In [28]:
```
x_train
```

Out[28]:

	sepal_length	sepal_width	petal_length	petal_width
81	5.5	2.4	3.7	1.0
133	6.3	2.8	5.1	1.5
137	6.4	3.1	5.5	1.8
75	6.6	3.0	4.4	1.4
109	7.2	3.6	6.1	2.5
...	...	...	...	...
71	6.1	2.8	4.0	1.3
106	4.9	2.5	4.5	1.7
14	5.8	4.0	1.2	0.2
92	5.8	2.6	4.0	1.2
102	7.1	3.0	5.9	2.1

105 rows × 4 columns

In [29]:
```
y_train.shape, y_test.shape
```

Out[29]:
```
((105,), (45,))
```

In [30]:
```
# Create the Model (Classification)
model=LogisticRegression()
model.fit(x_train,y_train)
```

Out[30]:
```
▾ LogisticRegression
LogisticRegression()
```

In [31]:
```
# Prediction
y_pred=model.predict(x_test)
```

In [32]:
```
y_pred
```

Out[32]:
```
array(['Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-virginica',
       'Iris-setosa', 'Iris-virginica', 'Iris-setosa', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa', 'Iris-setosa'], dtype=object)
```

In [33]:
```
y_test
```

Out[33]:
```
73     Iris-versicolor
18         Iris-setosa
118     Iris-virginica
78     Iris-versicolor
76     Iris-versicolor
31         Iris-setosa
64     Iris-versicolor
141     Iris-virginica
68     Iris-versicolor
82     Iris-versicolor
110     Iris-virginica
12         Iris-setosa
36         Iris-setosa
9          Iris-setosa
19         Iris-setosa
56     Iris-versicolor
104     Iris-virginica
69     Iris-versicolor
55     Iris-versicolor
132     Iris-virginica
29         Iris-setosa
127     Iris-virginica
26         Iris-setosa
128     Iris-virginica
131     Iris-virginica
145     Iris-virginica
108     Iris-virginica
143     Iris-virginica
45         Iris-setosa
30         Iris-setosa
22         Iris-setosa
15         Iris-setosa
65     Iris-versicolor
11         Iris-setosa
42         Iris-setosa
146     Iris-virginica
51     Iris-versicolor
27         Iris-setosa
4          Iris-setosa
32         Iris-setosa
142     Iris-virginica
85     Iris-versicolor
86     Iris-versicolor
16         Iris-setosa
10         Iris-setosa
Name: species, dtype: object
```

In [34]:
```
accuracy=accuracy_score(y_test,y_pred)
accuracy
```

Out[34]:
```
1.0
```

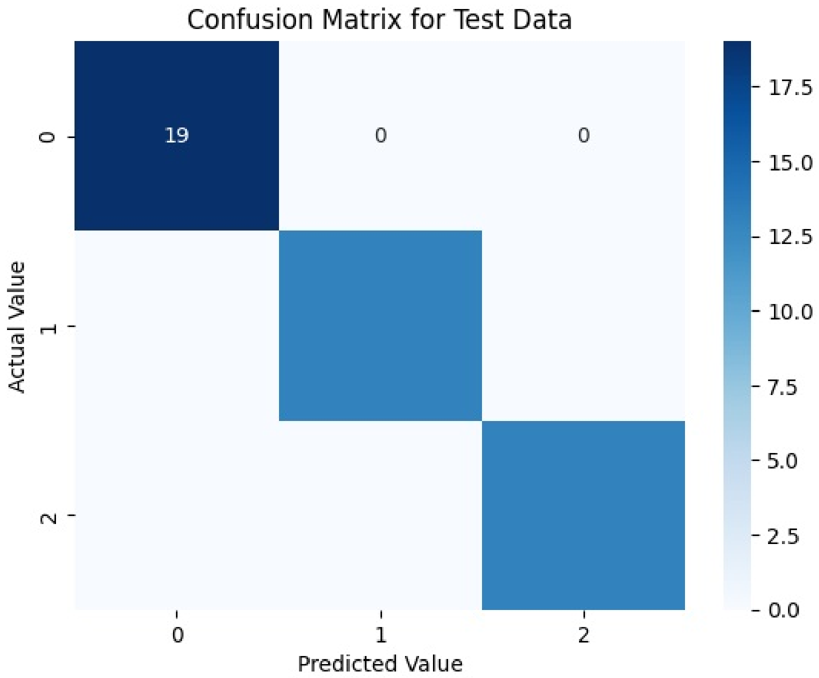
In [35]:
```
# A detailed classification report
print(classification_report(y_test, y_pred))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        19
Iris-versicolor       1.00      1.00      1.00        13
 Iris-virginica       1.00      1.00      1.00        13

       accuracy                           1.00        45
      macro avg       1.00      1.00      1.00        45
   weighted avg       1.00      1.00      1.00        45
```

In [36]:
```
confusion_matrix(y_test,y_pred)
```

Out[36]:
```
array([[19,  0,  0],
       [ 0, 13,  0],
       [ 0,  0, 13]], dtype=int64)
```

In [37]:
```
# Confusion matrix
conf_matrix = confusion_matrix(y_test,y_pred )
sns.heatmap(conf_matrix, annot=True, cmap='Blues', fmt='d')
plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix for Test Data')
plt.show()
```



In [38]:
```
#Take new datasempal and test accuracy of  model.
```

In [39]:
```
x_newdata=pd.DataFrame({"sepal_length":[6.5,4.3,4.1],
                        "sepal_width":[3.7,3.3,3.9],
                        "petal_length":[4.9, 2.2, 3.8],
                        "petal_width":[2.7, 0.6, 1.2],
                       })
x_newdata
```

Out[39]:

	sepal_length	sepal_width	petal_length	petal_width
0	6.5	3.7	4.9	2.7
1	4.3	3.3	2.2	0.6
2	4.1	3.9	3.8	1.2

In [40]:
```
accuracy = model.predict(x_newdata)
accuracy
```

Out[40]:
```
array(['Iris-virginica', 'Iris-setosa', 'Iris-versicolor'], dtype=object)
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

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