```
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Assignment No :06
```


Data Analytics III

1. Implement Simple Naïve Bayes classification algorithm using Python/R on iris.csv dataset.
2. Compute Confusion matrix to find TP, FP, TN, FN, Accuracy, Error rate, Precision, Recall on the given dataset

Step 1: # Import the required libraries

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

Step2: import dataset and convert it to dataframe

In [2]:
```
iris=pd.read_csv("C:\\Users\\alisu\\Desktop\\SIT lonvala\\TE\\6th sem\\DSBD
```

In [3]:
```
iris
```

Out[3]:

	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
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

Step3: data wrangling/preprocessing

In [4]:
```
iris.info() ## to check missing values
```

```
<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]:
```
iris.isnull().sum()
```

Out[5]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

In [6]:
```
iris.Species.value_counts()
```

Out[6]:
```
Species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: count, dtype: int64
```

In [7]:
```
iris.tail(60)
```

Out[7]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
90	91	5.5	2.6	4.4	1.2	Iris-versicolor
91	92	6.1	3.0	4.6	1.4	Iris-versicolor
92	93	5.8	2.6	4.0	1.2	Iris-versicolor
93	94	5.0	2.3	3.3	1.0	Iris-versicolor
94	95	5.6	2.7	4.2	1.3	Iris-versicolor
95	96	5.7	3.0	4.2	1.2	Iris-versicolor
96	97	5.7	2.9	4.2	1.3	Iris-versicolor
97	98	6.2	2.9	4.3	1.3	Iris-versicolor
98	99	5.1	2.5	3.0	1.1	Iris-versicolor
99	100	5.7	2.8	4.1	1.3	Iris-versicolor
100	101	6.3	3.3	6.0	2.5	Iris-virginica
101	102	5.8	2.7	5.1	1.9	Iris-virginica
102	103	7.1	3.0	5.9	2.1	Iris-virginica
103	104	6.3	2.9	5.6	1.8	Iris-virginica
104	105	6.5	3.0	5.8	2.2	Iris-virginica
105	106	7.6	3.0	6.6	2.1	Iris-virginica
106	107	4.9	2.5	4.5	1.7	Iris-virginica
107	108	7.3	2.9	6.3	1.8	Iris-virginica
108	109	6.7	2.5	5.8	1.8	Iris-virginica
109	110	7.2	3.6	6.1	2.5	Iris-virginica
110	111	6.5	3.2	5.1	2.0	Iris-virginica
111	112	6.4	2.7	5.3	1.9	Iris-virginica
112	113	6.8	3.0	5.5	2.1	Iris-virginica
113	114	5.7	2.5	5.0	2.0	Iris-virginica
114	115	5.8	2.8	5.1	2.4	Iris-virginica
115	116	6.4	3.2	5.3	2.3	Iris-virginica
116	117	6.5	3.0	5.5	1.8	Iris-virginica
117	118	7.7	3.8	6.7	2.2	Iris-virginica
118	119	7.7	2.6	6.9	2.3	Iris-virginica
119	120	6.0	2.2	5.0	1.5	Iris-virginica
120	121	6.9	3.2	5.7	2.3	Iris-virginica
121	122	5.6	2.8	4.9	2.0	Iris-virginica
122	123	7.7	2.8	6.7	2.0	Iris-virginica
123	124	6.3	2.7	4.9	1.8	Iris-virginica
124	125	6.7	3.3	5.7	2.1	Iris-virginica
125	126	7.2	3.2	6.0	1.8	Iris-virginica
126	127	6.2	2.8	4.8	1.8	Iris-virginica
127	128	6.1	3.0	4.9	1.8	Iris-virginica

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
128	129	6.4	2.8	5.6	2.1	Iris-virginica
129	130	7.2	3.0	5.8	1.6	Iris-virginica
130	131	7.4	2.8	6.1	1.9	Iris-virginica
131	132	7.9	3.8	6.4	2.0	Iris-virginica
132	133	6.4	2.8	5.6	2.2	Iris-virginica
133	134	6.3	2.8	5.1	1.5	Iris-virginica
134	135	6.1	2.6	5.6	1.4	Iris-virginica
135	136	7.7	3.0	6.1	2.3	Iris-virginica
136	137	6.3	3.4	5.6	2.4	Iris-virginica
137	138	6.4	3.1	5.5	1.8	Iris-virginica
138	139	6.0	3.0	4.8	1.8	Iris-virginica
139	140	6.9	3.1	5.4	2.1	Iris-virginica
140	141	6.7	3.1	5.6	2.4	Iris-virginica
141	142	6.9	3.1	5.1	2.3	Iris-virginica
142	143	5.8	2.7	5.1	1.9	Iris-virginica
143	144	6.8	3.2	5.9	2.3	Iris-virginica
144	145	6.7	3.3	5.7	2.5	Iris-virginica
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

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

Out[8]:

	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

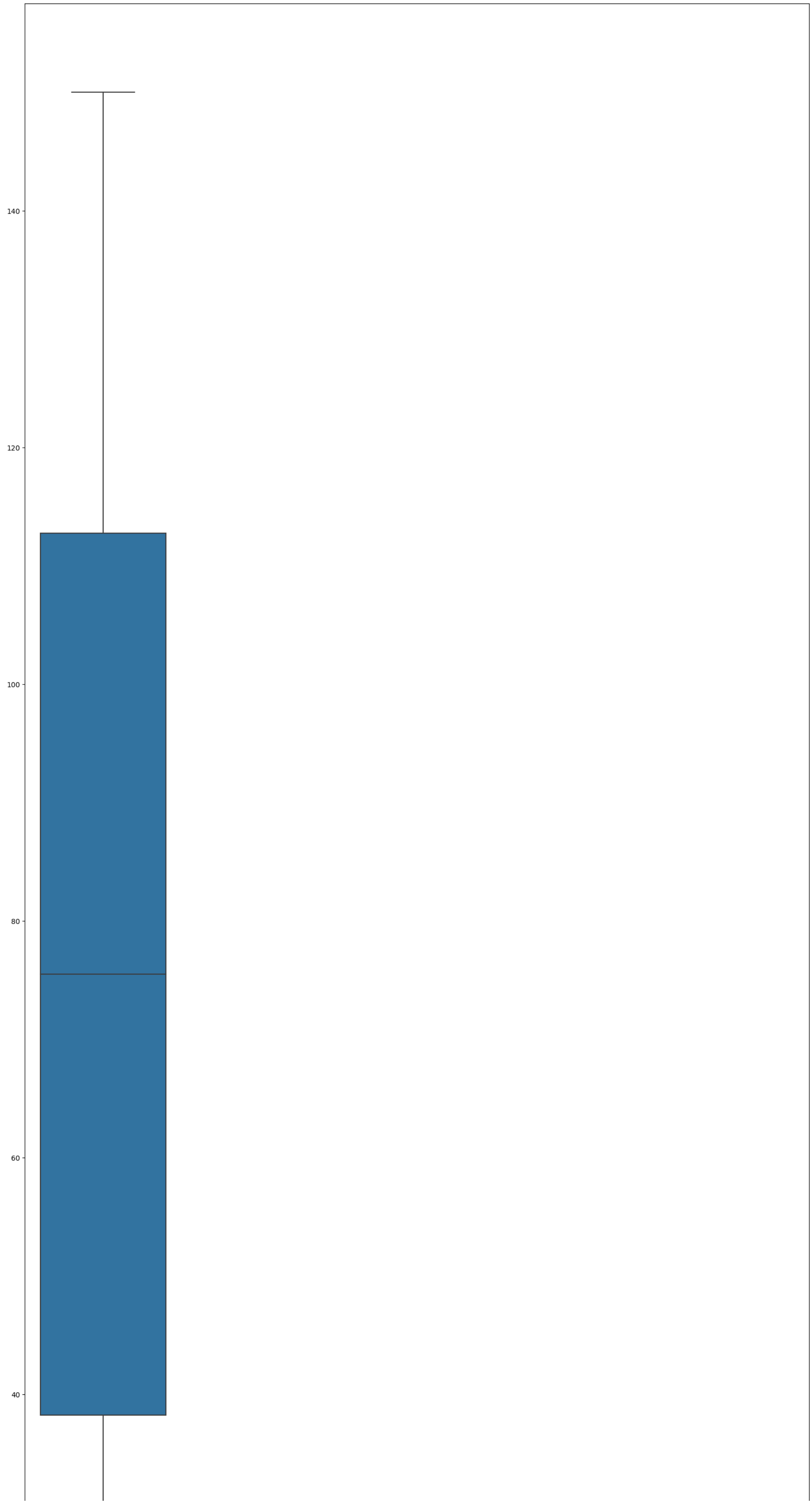
In [9]:
```
iris.duplicated().sum()
```

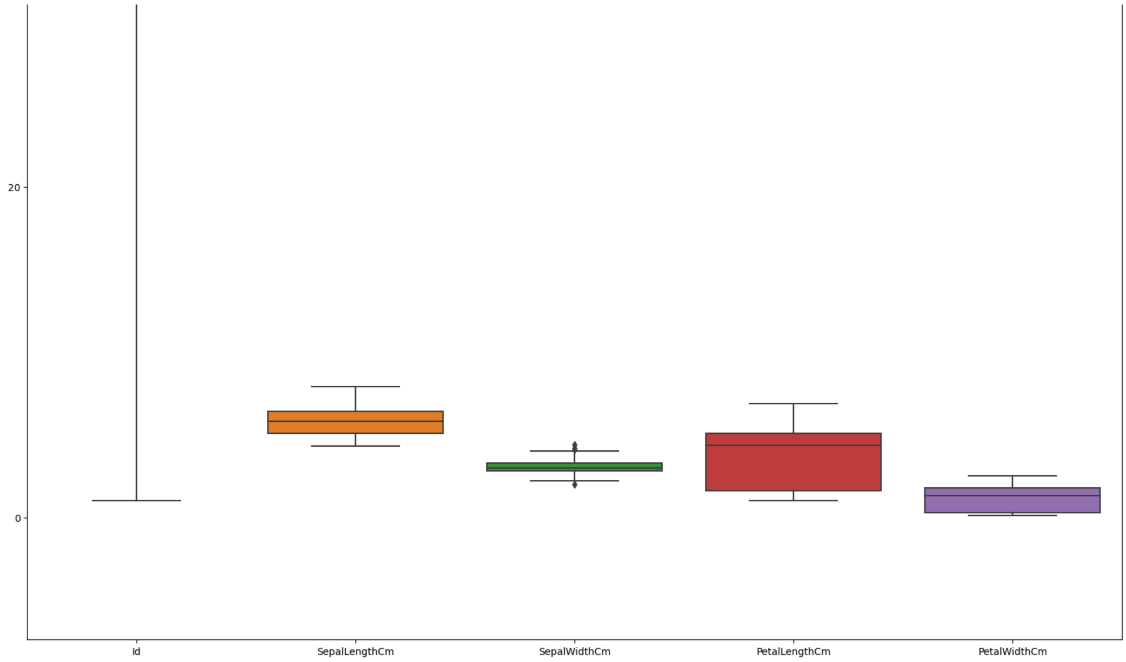
Out[9]: 0

In [10]:
```
##Finding outliers
```

In [11]:
```
plt.figure(figsize=(20,50))
sns.boxplot(iris)
```

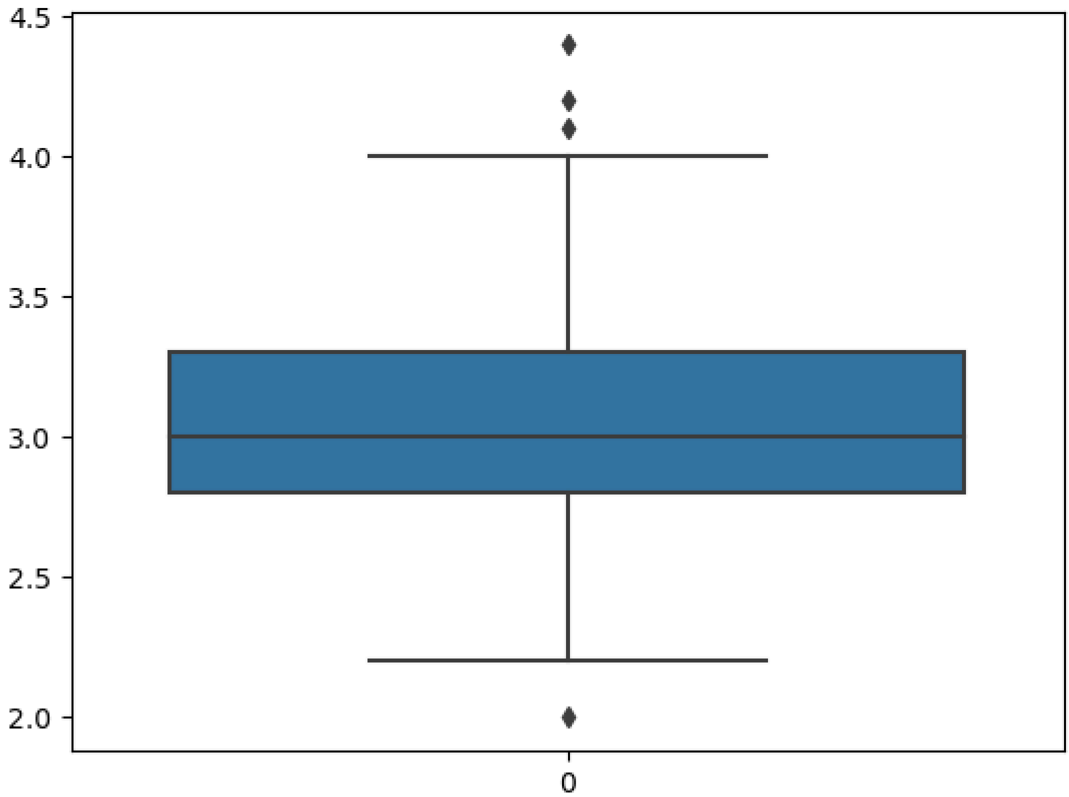
Out[11]: <Axes: >


140
120
100
80
60
40



In [12]:
```
sns.boxplot(iris.SepalWidthCm)
```

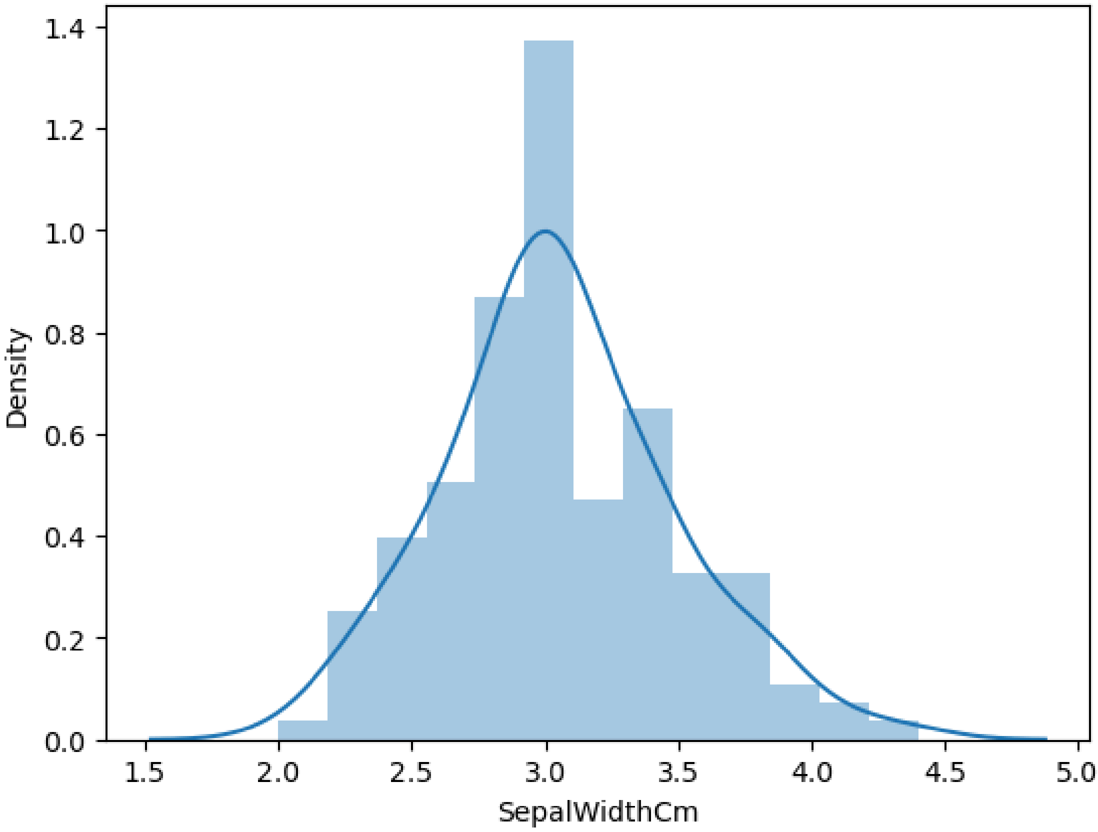
Out[12]: <Axes: >



In [13]:
```
sns.distplot(iris.SepalWidthCm)
```

```
C:\Users\alisu\AppData\Local\Temp\ipykernel_9460\3103411925.py:1: UserWar
ning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.
0.

Please adapt your code to use either `displot` (a figure-level function w
ith
similar flexibility) or `histplot` (an axes-level function for histogram
s).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (http
s://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

  sns.distplot(iris.SepalWidthCm)
```

Out[13]: <Axes: xlabel='SepalWidthCm', ylabel='Density'>



In [14]:
```
#To deal with outliers we can use z-score method as data
#of sepalwidth is normally distributed
```

In [15]:
```
# z-score formula
# zscore= x-mean()/std
```

In [17]:
```
iris["sepalwidth_zscore"] = (iris["SepalWidthCm"] - iris["SepalWidthCm"].me
```

In [18]:
```
iris["sepalwidth_zscore"]
```

Out[18]:
```
0      1.028611
1     -0.124540
2      0.336720
3      0.106090
4      1.259242
         ...
145   -0.124540
146   -1.277692
147   -0.124540
148    0.797981
149   -0.124540
Name: sepalwidth_zscore, Length: 150, dtype: float64
```

In [19]:
```
iris
```

Out[19]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	sepalwidt
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	
...	...	...	...	...	...	...	
145	146	6.7	3.0	5.2	2.3	Iris-virginica	
146	147	6.3	2.5	5.0	1.9	Iris-virginica	
147	148	6.5	3.0	5.2	2.0	Iris-virginica	
148	149	6.2	3.4	5.4	2.3	Iris-virginica	
149	150	5.9	3.0	5.1	1.8	Iris-virginica	

150 rows × 7 columns

In [20]:
```
iris[iris.sepalwidth_zscore>3]
```

Out[20]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	sepalwidth_
15	16	5.7	4.4	1.5	0.4	Iris-setosa	3.

In [22]:
```
iris[iris.sepalwidth_zscore<-3]
```

Out[22]:

Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	sepalwidth_zs

In [23]:
```
iris.sepalwidth_zscore.describe()
```

Out[23]:
```
count    1.500000e+02
mean    -6.158037e-16
std      1.000000e+00
min     -2.430844e+00
25%     -5.858010e-01
50%     -1.245404e-01
75%      5.673506e-01
max      3.104284e+00
Name: sepalwidth_zscore, dtype: float64
```

In [26]:
```
iris = iris.drop(15)
```

In [27]:
```
iris.head(20)
```

Out[27]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	sepalwidth_
0	1	5.1	3.5	1.4	0.2	Iris-setosa	1.
1	2	4.9	3.0	1.4	0.2	Iris-setosa	-0.
2	3	4.7	3.2	1.3	0.2	Iris-setosa	0.
3	4	4.6	3.1	1.5	0.2	Iris-setosa	0.
4	5	5.0	3.6	1.4	0.2	Iris-setosa	1.
5	6	5.4	3.9	1.7	0.4	Iris-setosa	1.
6	7	4.6	3.4	1.4	0.3	Iris-setosa	0.
7	8	5.0	3.4	1.5	0.2	Iris-setosa	0.
8	9	4.4	2.9	1.4	0.2	Iris-setosa	-0.
9	10	4.9	3.1	1.5	0.1	Iris-setosa	0.
10	11	5.4	3.7	1.5	0.2	Iris-setosa	1.
11	12	4.8	3.4	1.6	0.2	Iris-setosa	0.
12	13	4.8	3.0	1.4	0.1	Iris-setosa	-0.
13	14	4.3	3.0	1.1	0.1	Iris-setosa	-0.
14	15	5.8	4.0	1.2	0.2	Iris-setosa	2.
16	17	5.4	3.9	1.3	0.4	Iris-setosa	1.
17	18	5.1	3.5	1.4	0.3	Iris-setosa	1.
18	19	5.7	3.8	1.7	0.3	Iris-setosa	1.
19	20	5.1	3.8	1.5	0.3	Iris-setosa	1.
20	21	5.4	3.4	1.7	0.2	Iris-setosa	0.

In [28]:
```
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 149 entries, 0 to 149
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Id               149 non-null    int64
 1   SepalLengthCm    149 non-null    float64
 2   SepalWidthCm     149 non-null    float64
 3   PetalLengthCm    149 non-null    float64
 4   PetalWidthCm     149 non-null    float64
 5   Species          149 non-null    object
 6   sepalwidth_zscore  149 non-null  float64
dtypes: float64(5), int64(1), object(1)
memory usage: 9.3+ KB
```

In [29]:
```
## to delete unnecessary columns
```

In [30]:
```
iris.drop(["sepalwidth_zscore"],axis='columns')
```

Out[30]:

	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
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

149 rows × 6 columns

In [31]:
```
iris
```

Out[31]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	sepalwidt
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	
...	...	...	...	...	...	...	
145	146	6.7	3.0	5.2	2.3	Iris-virginica	
146	147	6.3	2.5	5.0	1.9	Iris-virginica	
147	148	6.5	3.0	5.2	2.0	Iris-virginica	
148	149	6.2	3.4	5.4	2.3	Iris-virginica	
149	150	5.9	3.0	5.1	1.8	Iris-virginica	

149 rows × 7 columns

In [32]:
```
iris.drop(["sepalwidth_zscore"],axis='columns',inplace=True)
```

In [33]:
```
iris
```

Out[33]:

	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
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

149 rows × 6 columns

In [35]:
```
#  'Species' column contains non-numeric values
# Drop the 'Species' column before computing the correlation matrix
iris_numeric = iris.drop(columns=['Species'])
# Now, compute the correlation matrix
correlation_matrix = iris_numeric.corr()
```

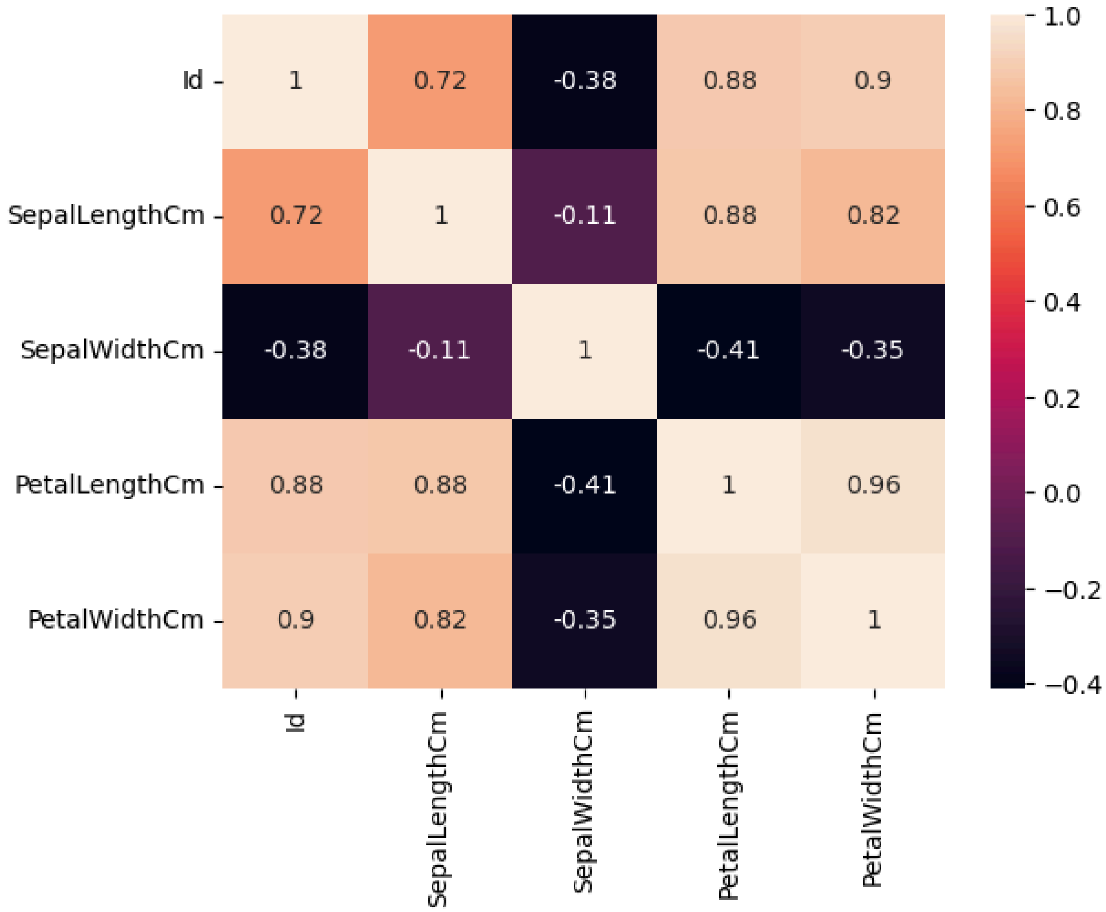
In [36]:
```
correlation_matrix
```

Out[36]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
Id	1.000000	0.719722	-0.384079	0.881366	0.899102
SepalLengthCm	0.719722	1.000000	-0.109370	0.875204	0.819851
SepalWidthCm	-0.384079	-0.109370	1.000000	-0.409417	-0.347337
PetalLengthCm	0.881366	0.875204	-0.409417	1.000000	0.962598
PetalWidthCm	0.899102	0.819851	-0.347337	0.962598	1.000000

In [37]:
```
## to chect corelation of features pictorially we use heatmap
```

In [41]:
```
sns.heatmap(correlation_matrix, annot=True)
plt.show()
```



In [44]:
```
iris.drop(["Id"],axis = "columns" ,inplace =True )
```

In [45]:
```
iris
```

Out[45]:

	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
...	...	...	...	...	...
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

149 rows × 5 columns

Step 4 :

1.divide data frame into x and y ie into input and output feature

2. Split data using train_test_split

In [46]:
```
x=iris.iloc[:,0:4] # iris.iloc[:,:-1]
```

In [47]:
```
x
```

Out[47]:

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

149 rows × 4 columns

In [48]:
```
y= iris.iloc[:,4:5] # iris.iloc[:,-1]
```

In [49]:
```
y
```

Out[49]:

	Species
0	Iris-setosa
1	Iris-setosa
2	Iris-setosa
3	Iris-setosa
4	Iris-setosa
...	...
145	Iris-virginica
146	Iris-virginica
147	Iris-virginica
148	Iris-virginica
149	Iris-virginica

149 rows × 1 columns

In [50]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y, test_size=0.2,random_state=
```

In [51]:
```
xtrain
```

Out[51]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
92	5.8	2.6	4.0	1.2
115	6.4	3.2	5.3	2.3
14	5.8	4.0	1.2	0.2
45	4.8	3.0	1.4	0.3
90	5.5	2.6	4.4	1.2
...	...	...	...	...
76	6.8	2.8	4.8	1.4
44	5.1	3.8	1.9	0.4
23	5.1	3.3	1.7	0.5
73	6.1	2.8	4.7	1.2
16	5.4	3.9	1.3	0.4

119 rows × 4 columns

In [52]:
```
xtest
```

Out[52]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
116	6.5	3.0	5.5	1.8
49	5.0	3.3	1.4	0.2
3	4.6	3.1	1.5	0.2
43	5.0	3.5	1.6	0.6
127	6.1	3.0	4.9	1.8
25	5.0	3.0	1.6	0.2
109	7.2	3.6	6.1	2.5
12	4.8	3.0	1.4	0.1
128	6.4	2.8	5.6	2.1
141	6.9	3.1	5.1	2.3
5	5.4	3.9	1.7	0.4
55	5.7	2.8	4.5	1.3
129	7.2	3.0	5.8	1.6
36	5.5	3.5	1.3	0.2
131	7.9	3.8	6.4	2.0
83	6.0	2.7	5.1	1.6
26	5.0	3.4	1.6	0.4
88	5.6	3.0	4.1	1.3
126	6.2	2.8	4.8	1.8
144	6.7	3.3	5.7	2.5
79	5.7	2.6	3.5	1.0
95	5.7	3.0	4.2	1.2
60	5.0	2.0	3.5	1.0
54	6.5	2.8	4.6	1.5
2	4.7	3.2	1.3	0.2
42	4.4	3.2	1.3	0.2
66	5.6	3.0	4.5	1.5
93	5.0	2.3	3.3	1.0
24	4.8	3.4	1.9	0.2
46	5.1	3.8	1.6	0.2

In [53]:
```
len(xtest)
```

Out[53]: 30

In [54]:
```
ytrain
```

Out[54]:

	Species
92	Iris-versicolor
115	Iris-virginica
14	Iris-setosa
45	Iris-setosa
90	Iris-versicolor
...	...
76	Iris-versicolor
44	Iris-setosa
23	Iris-setosa
73	Iris-versicolor
16	Iris-setosa

119 rows × 1 columns

In [55]:
```
ytest
```

Out[55]:

	Species
116	Iris-virginica
49	Iris-setosa
3	Iris-setosa
43	Iris-setosa
127	Iris-virginica
25	Iris-setosa
109	Iris-virginica
12	Iris-setosa
128	Iris-virginica
141	Iris-virginica
5	Iris-setosa
55	Iris-versicolor
129	Iris-virginica
36	Iris-setosa
131	Iris-virginica
83	Iris-versicolor
26	Iris-setosa
88	Iris-versicolor
126	Iris-virginica
144	Iris-virginica
79	Iris-versicolor
95	Iris-versicolor
60	Iris-versicolor
54	Iris-versicolor
2	Iris-setosa
42	Iris-setosa
66	Iris-versicolor
93	Iris-versicolor
24	Iris-setosa
46	Iris-setosa

In [56]:
```
len(ytest)
```

Out[56]: 30

Step 5: Model selection ie naive bayes

In [57]:
```
from sklearn.naive_bayes import GaussianNB
model=GaussianNB()
```

In [58]:
```
model.fit(xtrain,ytrain)
```

```
C:\Users\alisu\anaconda3\Lib\site-packages\sklearn\utils\validation.py:11
84: DataConversionWarning: A column-vector y was passed when a 1d array w
as expected. Please change the shape of y to (n_samples, ), for example u
sing ravel().
  y = column_or_1d(y, warn=True)
```

Out[58]:
```
▾ GaussianNB
GaussianNB()
```

In [59]:
```
ypredict=model.predict(xtest)
```

In [60]:
```
ypredict
```

Out[60]:
```
array(['Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
       'Iris-virginica', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolo
r',
       'Iris-versicolor', 'Iris-setosa', 'Iris-setosa'], dtype='<U15')
```

In [61]:
```
type(ypredict)
```

Out[61]:
```
numpy.ndarray
```

In [62]:
```
type(ytest)
```

Out[62]:
```
pandas.core.frame.DataFrame
```

In [63]:
```
ytest.values
```

Out[63]:
```
array([['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-setosa'],
       ['Iris-setosa'],
       ['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-virginica'],
       ['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-versicolor'],
       ['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-virginica'],
       ['Iris-versicolor'],
       ['Iris-setosa'],
       ['Iris-versicolor'],
       ['Iris-virginica'],
       ['Iris-virginica'],
       ['Iris-versicolor'],
       ['Iris-versicolor'],
       ['Iris-versicolor'],
       ['Iris-versicolor'],
       ['Iris-setosa'],
       ['Iris-setosa'],
       ['Iris-versicolor'],
       ['Iris-versicolor'],
       ['Iris-setosa'],
       ['Iris-setosa']], dtype=object)
```

Step 6 : Model Evaluation

In [67]:
```
from sklearn.metrics import confusion_matrix,precision_score,recall_score
from sklearn.metrics import f1_score ,classification_report
```

In [68]:
```
matrix= confusion_matrix(ytest,ypredict)
```

In [69]:
```
matrix
```

Out[69]:
```
array([[12,  0,  0],
       [ 0,  9,  0],
       [ 0,  0,  9]], dtype=int64)
```

In [70]:
```
precision=precision_score(ytest,ypredict,average="micro")
```

In [71]:
```
precision
```

Out[71]:
```
1.0
```

In [72]:
```
recall=recall_score(ytest,ypredict,average="micro")
```

In [73]:
```
recall
```

Out[73]:
```
1.0
```

In [74]:
```
f1_score(ytest,ypredict,average="micro")
```

Out[74]:
```
1.0
```

In [76]:
```
print(classification_report(ytest,ypredict))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       1.00      1.00      1.00         9
 Iris-virginica       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 [77]:
```
q=[[4.6,3.1,1.5,0.2]]
```

In [78]:
```
model.predict(q)
```

```
C:\Users\alisu\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarni
ng: X does not have valid feature names, but GaussianNB was fitted with f
eature names
  warnings.warn(
```

Out[78]:
```
array(['Iris-setosa'], dtype='<U15')
```

In [79]:
```
p=[[4.6,3.1,1.5,1.2]]
```

In [80]:
```
model.predict(p)
```

```
C:\Users\alisu\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarni
ng: X does not have valid feature names, but GaussianNB was fitted with f
eature names
  warnings.warn(
```

Out[80]:
```
array(['Iris-versicolor'], dtype='<U15')
```

In [82]:
```
ytest = ytest.values
```

In [84]:
```
ytest
```

Out[84]:
```
array([['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-setosa'],
       ['Iris-setosa'],
       ['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-virginica'],
       ['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-versicolor'],
       ['Iris-virginica'],
       ['Iris-setosa'],
       ['Iris-virginica'],
       ['Iris-versicolor'],
       ['Iris-setosa'],
       ['Iris-versicolor'],
       ['Iris-virginica'],
       ['Iris-virginica'],
       ['Iris-versicolor'],
       ['Iris-versicolor'],
       ['Iris-versicolor'],
       ['Iris-versicolor'],
       ['Iris-setosa'],
       ['Iris-setosa'],
       ['Iris-versicolor'],
       ['Iris-versicolor'],
       ['Iris-setosa'],
       ['Iris-setosa']], dtype=object)
```

In [85]:
```
from sklearn.naive_bayes import MultinomialNB
modelmulti=MultinomialNB()
modelmulti.fit(xtrain,ytrain)
```

```
C:\Users\alisu\anaconda3\Lib\site-packages\sklearn\utils\validation.py:11
84: DataConversionWarning: A column-vector y was passed when a 1d array w
as expected. Please change the shape of y to (n_samples, ), for example u
sing ravel().
  y = column_or_1d(y, warn=True)
```

Out[85]:
```
▾ MultinomialNB
MultinomialNB()
```

In [86]:
```
ypredictmulti=modelmulti.predict(xtest)
```

In [87]:
```
ypredictmulti
```

Out[87]:
```
array(['Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
       'Iris-virginica', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolo
r',
       'Iris-versicolor', 'Iris-setosa', 'Iris-setosa'], dtype='<U15')
```

In [88]:
```
confusion_matrix(ytest,ypredictmulti)
```

Out[88]:
```
array([[12,  0,  0],
       [ 0,  8,  1],
       [ 0,  2,  7]], dtype=int64)
```

In [89]:
```
print(classification_report(ytest,ypredictmulti))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       0.80      0.89      0.84         9
 Iris-virginica       0.88      0.78      0.82         9

       accuracy                           0.90        30
      macro avg       0.89      0.89      0.89        30
   weighted avg       0.90      0.90      0.90        30
```

In [90]:
```
precision_score(ytest,ypredictmulti,average="micro")
```

Out[90]:
```
0.9
```

In [91]:
```
recall_score(ytest,ypredictmulti,average="micro")
```

Out[91]:
```
0.9
```

In [92]:
```
f1_score(ytest,ypredictmulti,average="micro")
```

Out[92]:
```
0.9
```

In [ ]: