

```
In [1]: import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classification_
from sklearn.preprocessing import LabelEncoder
```

```
In [2]: data = pd.read_csv("IRIS.csv")
```

```
In [3]: data
```

```
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
...
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 [4]: data.head(5)
```

```
Out[4]:
```

	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]: data.tail()
```

```
Out[5]:
```

	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 [6]: data.describe(include = 'all')
```

```
Out[6]:
```

	sepal_length	sepal_width	petal_length	petal_width	species
count	150.000000	150.000000	150.000000	150.000000	150
unique	NaN	NaN	NaN	NaN	3
top	NaN	NaN	NaN	NaN	Iris-setosa
freq	NaN	NaN	NaN	NaN	50
mean	5.843333	3.054000	3.758667	1.198667	NaN
std	0.828066	0.433594	1.764420	0.763161	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	4.350000	1.300000	NaN
75%	6.400000	3.300000	5.100000	1.800000	NaN
max	7.900000	4.400000	6.900000	2.500000	NaN

```
In [7]: data.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 [9]: print(data.shape)
data['species'].unique()
```

```
(150, 5)
```

```
Out[9]: array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

```
In [10]: data.isnull().sum()
```

```
Out[10]: sepal_length    0
          sepal_width    0
          petal_length    0
          petal_width    0
          species        0
          dtype: int64
```

```
In [14]: x = data.iloc[:,0:4]
          y = data.iloc[:,4]
```

```
In [15]: encode = LabelEncoder()
          y = encode.fit_transform(y)
```

```
In [16]: x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state =
```

```
In [17]: naive_bayes = GaussianNB()
          naive_bayes.fit(x_train,y_train)
          pred = naive_bayes.predict(x_test)
```

```
In [18]: pred
```

```
Out[18]: array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1,
                0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 2, 1, 0, 1, 1, 1, 2, 0, 2, 0,
                0])
```

```
In [19]: y_test
```

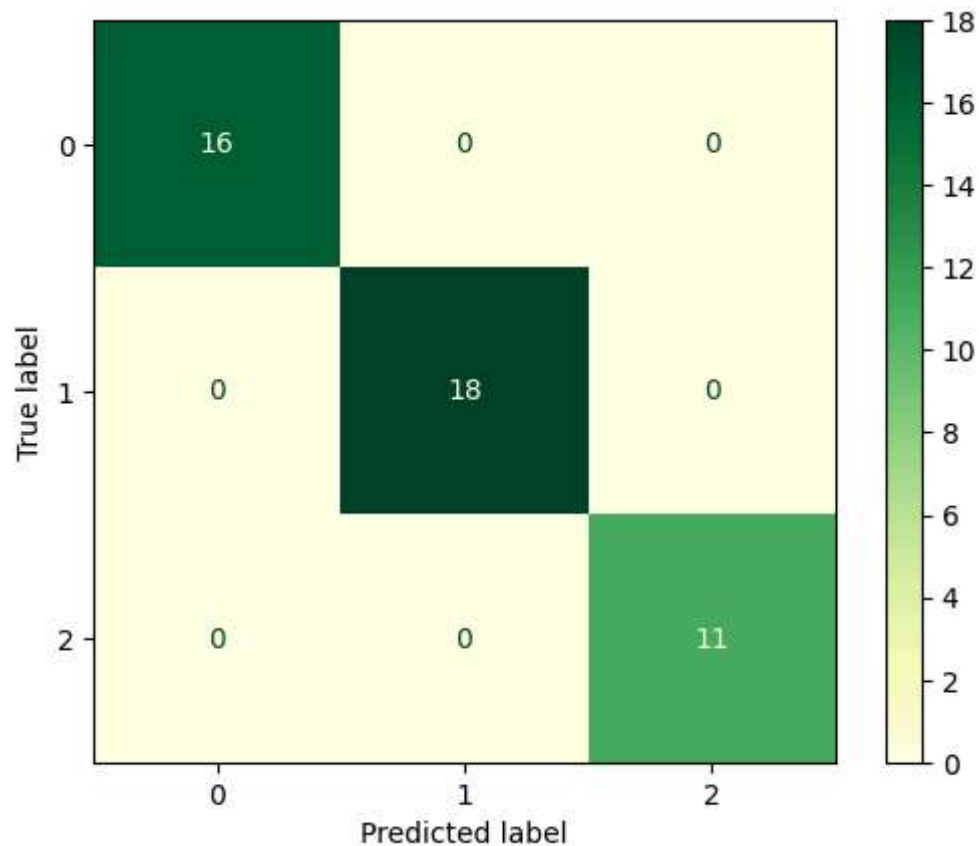
```
Out[19]: array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1,
                0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 2, 1, 0, 1, 1, 1, 2, 0, 2, 0,
                0])
```

```
In [20]: matrix = confusion_matrix(y_test,pred,labels = naive_bayes.classes_)
          print(matrix)
```

```
tp, fn, fp, tn = confusion_matrix(y_test,pred,labels=[1,0]).reshape(-1)

[[16  0  0]
 [ 0 18  0]
 [ 0  0 11]]
```

```
In [21]: conf_matrix = ConfusionMatrixDisplay(confusion_matrix=matrix,display_labels=naive_b
          conf_matrix.plot(cmap=plt.cm.YlGn)
          plt.show())
```



```
In [22]: print(classification_report(y_test,pred))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	16
1	1.00	1.00	1.00	18
2	1.00	1.00	1.00	11
accuracy			1.00	45
macro avg	1.00	1.00	1.00	45
weighted avg	1.00	1.00	1.00	45

```
In [23]: print('\nAccuracy: {:.2f}'.format(accuracy_score(y_test,pred)))
print('Error Rate: ',(fp+fn)/(tp+tn+fn+fp))
print('Sensitivity (Recall or True positive rate) :',tp/(tp+fn))
print('Specificity (True negative rate) :',tn/(fp+tn))
print('Precision (Positive predictive value) :',tp/(tp+fp))
print('False Positive Rate :',fp/(tn+fp))
```

```
Accuracy: 1.00
Error Rate: 0.0
Sensitivity (Recall or True positive rate) : 1.0
Specificity (True negative rate) : 1.0
Precision (Positive predictive value) : 1.0
False Positive Rate : 0.0
```

```
In [ ]:
```