Classification algorithms

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```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score,
ConfusionMatrixDisplay
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
```

```
df = pd.read_csv("./Iris.csv")
```

```
df.head()
```

```
   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
```

```
df.drop(["Id"], axis = 1, inplace=True)
```

```
categories = dict(zip(set(df.Species), range(3)))
categories
```

```
{'Iris-versicolor': 0, 'Iris-setosa': 1, 'Iris-virginica': 2}
```

```
species_num = df.Species.map(lambda x: categories[x])
species_num.head()
```

```
0    1
1    1
2    1
3    1
4    1
Name: Species, dtype: int64
```

Regresión Logística

```
setosa = df[df.Species == "Iris-setosa"]
versicolor = df[df.Species == "Iris-versicolor"]
virginica = df[df.Species == "Iris-virginica"]

setosa
```

	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
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

versicolor

    SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm
Species
50              7.0           3.2            4.7           1.4  Iris-
versicolor
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
```

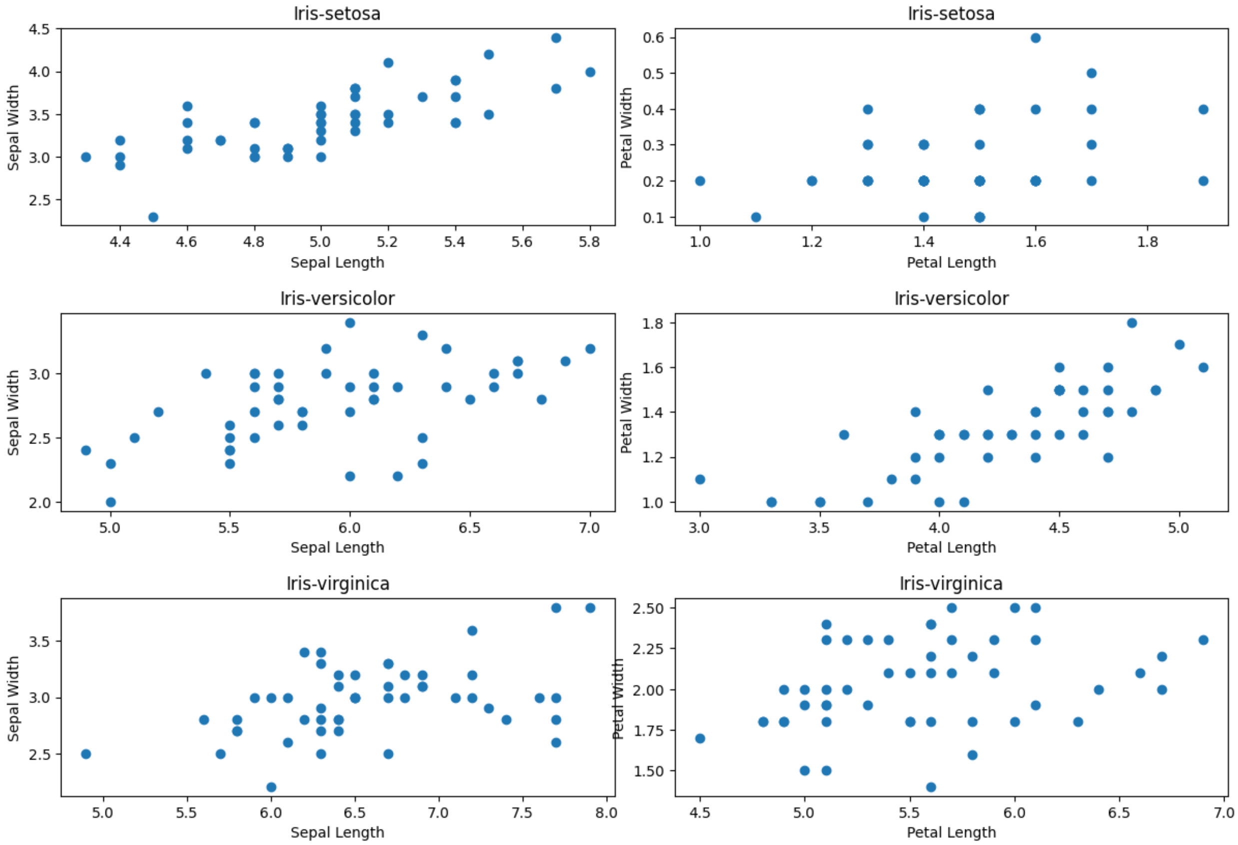
67	5.8	2.7	4.1	1.0	Iris-versicolor
68	6.2	2.2	4.5	1.5	Iris-versicolor
69	5.6	2.5	3.9	1.1	Iris-versicolor
70	5.9	3.2	4.8	1.8	Iris-versicolor
71	6.1	2.8	4.0	1.3	Iris-versicolor
72	6.3	2.5	4.9	1.5	Iris-versicolor
73	6.1	2.8	4.7	1.2	Iris-versicolor
74	6.4	2.9	4.3	1.3	Iris-versicolor
75	6.6	3.0	4.4	1.4	Iris-versicolor
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
```

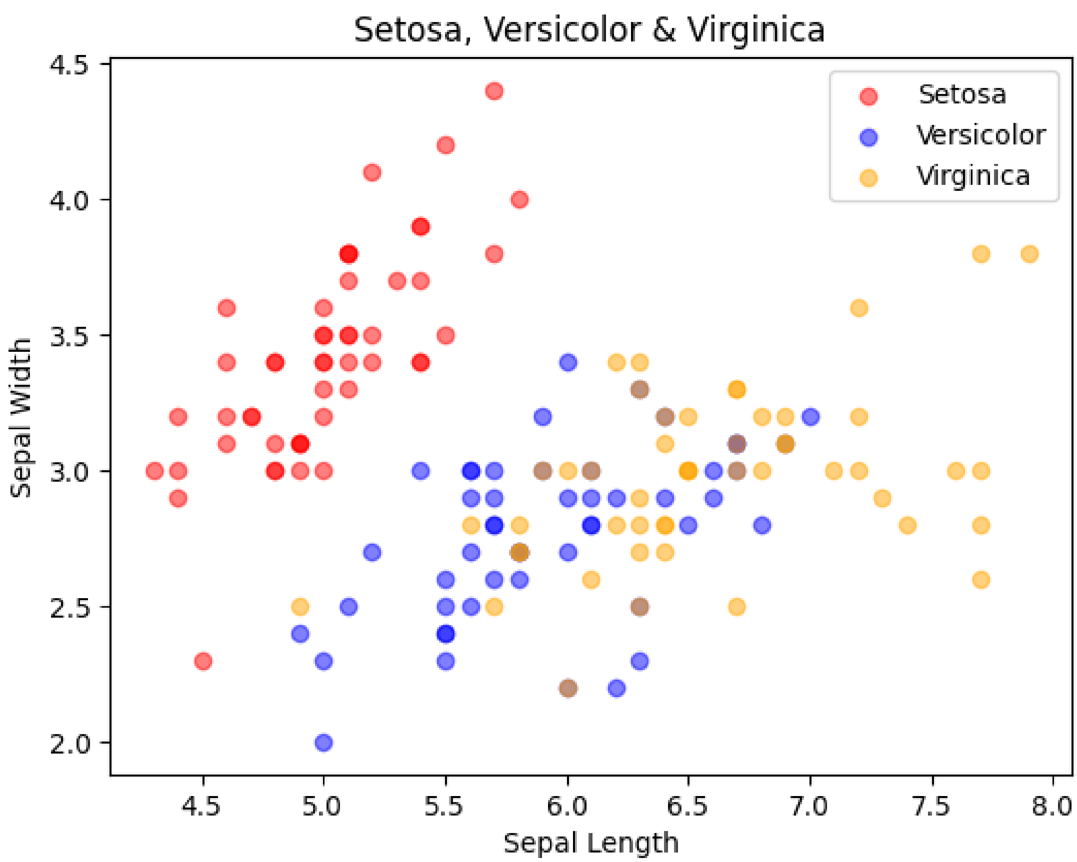
```
virginica.head()
```

```
     SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm
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
```

```
fig, axes = plt.subplots(3, 2, figsize=(12, 8))
fig.tight_layout(h_pad=4)
fig.suptitle("")

for i, iris in enumerate([setosa, versicolor, virginica]):
    axes[i][0].set_title(f"{iris.iloc[0, -1].capitalize()}")
    axes[i][0].scatter(iris.SepalLengthCm, iris.SepalWidthCm)
    axes[i][0].set_ylabel("Sepal Width")
    axes[i][0].set_xlabel("Sepal Length")


    axes[i][1].set_title(f"{iris.iloc[0, -1].capitalize()}")
    axes[i][1].scatter(iris.PetalLengthCm, iris.PetalWidthCm)
    axes[i][1].set_ylabel("Petal Width")
    axes[i][1].set_xlabel("Petal Length")
```



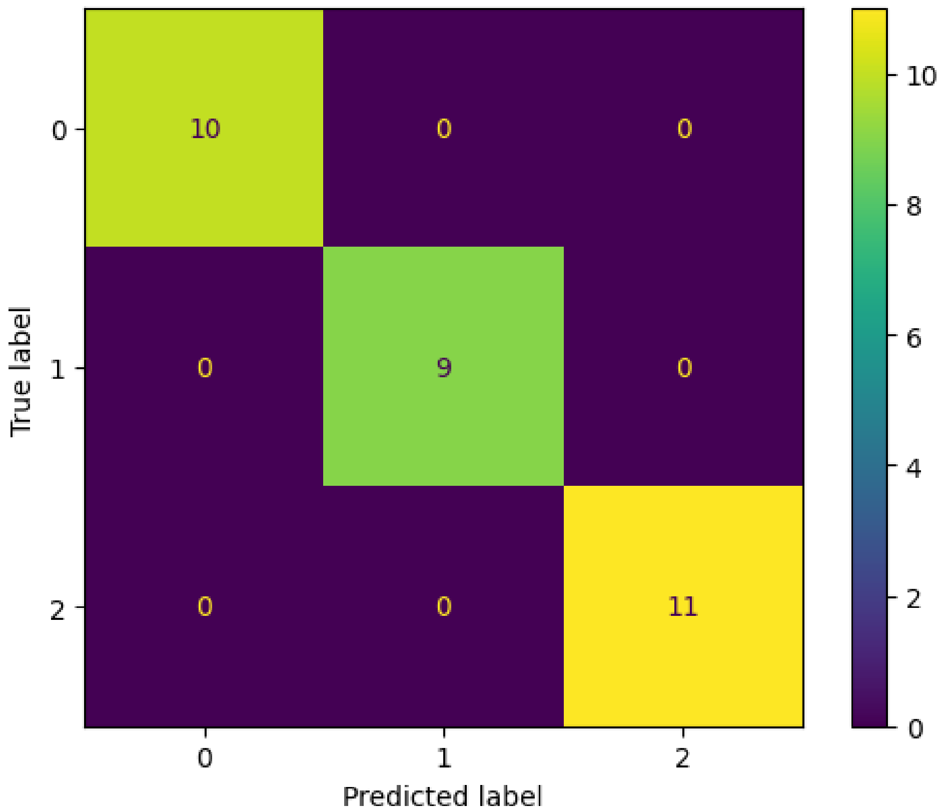

```
plt.title("Setosa, Versicolor & Virginica")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(setosa.SepalLengthCm,setosa.SepalWidthCm,
color='red',label = "Setosa", alpha = 0.5)
plt.scatter(versicolor.SepalLengthCm, versicolor.SepalWidthCm, color =
"blue",label = "Versicolor", alpha = 0.5)
plt.scatter(virginica.SepalLengthCm, virginica.SepalWidthCm, color =
"orange",label = "Virginica", alpha = 0.5)
plt.legend()
plt.show()
```




```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1]

X_train, X_test, y_train,
y_test=train_test_split(X,y,test_size=0.2,random_state=42)

logistic_model = LogisticRegression()
logistic_model.fit(X_train, y_train)

y_hat_logistic_train = logistic_model.predict(X_train)
y_hat_logistic_test = logistic_model.predict(X_test)

logistic_train_acc = accuracy_score(y_train, y_hat_logistic_train)
logistic_test_acc = accuracy_score(y_test, y_hat_logistic_test)
print(f"Training accurancy: {logistic_train_acc:.4f}\nTest accurancy:
{logistic_test_acc:.4f}")
```

```
Training accurancy: 0.9750
Test accurancy: 1.0000
```

```
test_conf_matrix = confusion_matrix(y_test, y_hat_logistic_test)
test_cm_disp = ConfusionMatrixDisplay(test_conf_matrix)
test_cm_disp.plot()
plt.show()
```

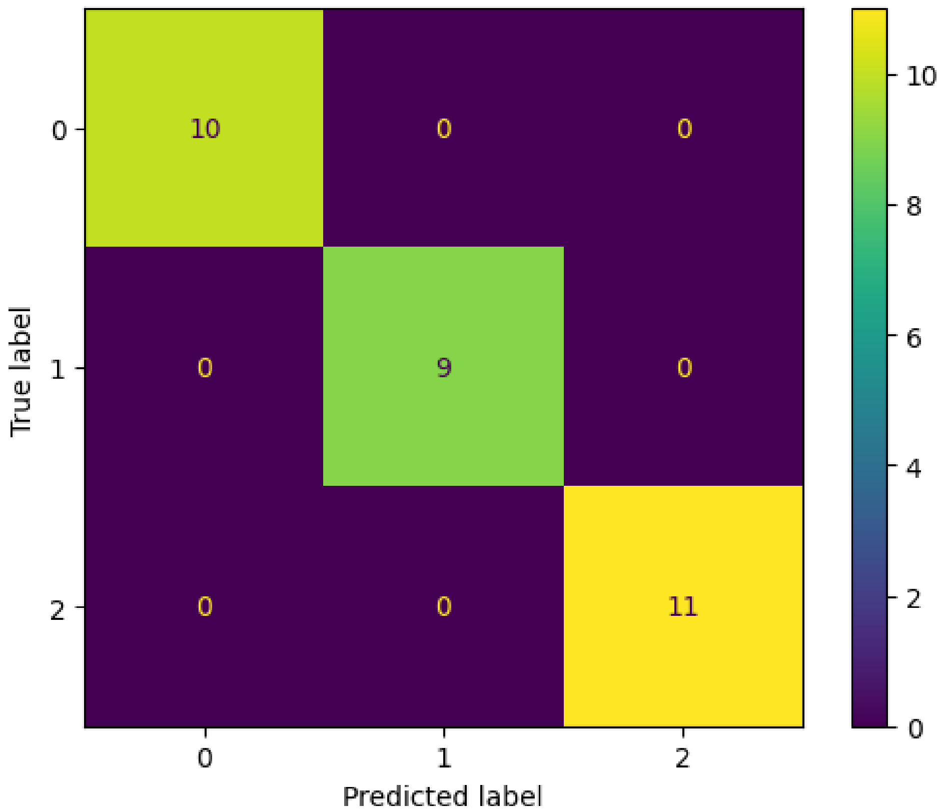


Bayes

```
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

y_hat_nb_train = nb_model.predict(X_train)
y_hat_nb_test = nb_model.predict(X_test)

nb_train_acc = accuracy_score(y_train, y_hat_nb_train)
nb_test_acc = accuracy_score(y_test, y_hat_nb_test)
print(f"Training accurancy: {nb_train_acc:.4f}\nTest accurancy:
{nb_test_acc:.4f}")
```

```
Training accurancy: 0.9500
Test accurancy: 1.0000
```

```
test_conf_matrix = confusion_matrix(y_test, y_hat_nb_test)
test_cm_disp = ConfusionMatrixDisplay(test_conf_matrix)
test_cm_disp.plot()
plt.show()
```

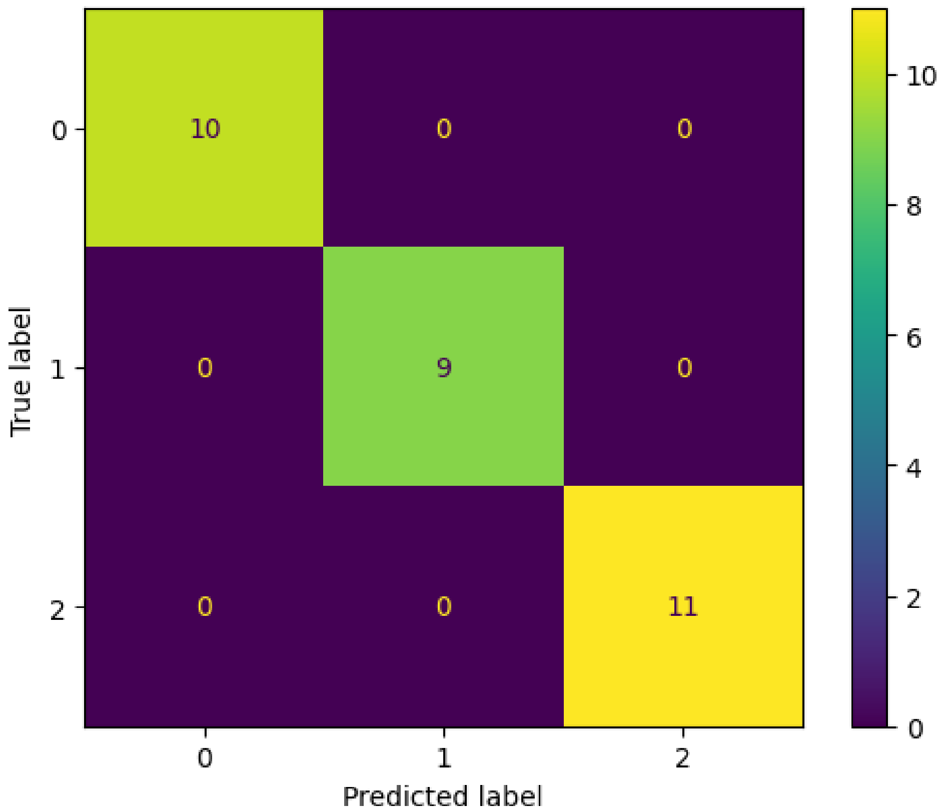


Análisis de discriminate

```
disc_model = LinearDiscriminantAnalysis()
disc_model.fit(X_train, y_train)

y_hat_disc_train = disc_model.predict(X_train)
y_hat_disc_test = disc_model.predict(X_test)

disc_train_acc = accuracy_score(y_train, y_hat_disc_train)
disc_test_acc = accuracy_score(y_test, y_hat_disc_test)
print(f"Training accurancy: {disc_train_acc:.4f}\nTest accurancy:
{disc_test_acc:.4f}")
```

```
Training accurancy: 0.9750
Test accurancy: 1.0000
```

```
test_conf_matrix = confusion_matrix(y_test, y_hat_disc_test)
test_cm_disp = ConfusionMatrixDisplay(test_conf_matrix)
test_cm_disp.plot()
plt.show()
```



¿Qué modelo fue el méjor? ¿Por qué crees que se suceda esto?

Logistica por que al tener los mismos resultados que el discriminante es más facil de interpretar los resultados.

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