```
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

2502041956 - Nicholas Javier - LA05 (SOAL UTS NOMOR 1) Link Youtube(ada di 1f): https://youtu.be/GTk\_jg8N2PM

```
df = pd.read_csv('dataset_spine.csv')
df
    Unnamed: 0 Col1 Col2 Col3
                                                Col4
Col5 \
            0 63.027817 22.552586 39.609117 40.475232
98.672917
            1 39.056951 10.060991 25.015378 28.995960
114.405425
            2 68.832021 22.218482 50.092194 46.613539
105.985135
3
            3 69.297008 24.652878 44.311238 44.644130
101.868495
            4 49.712859 9.652075 28.317406 40.060784
108.168725
          ... ... ...
305
          305 47.903565 13.616688 36.000000 34.286877
117.449062
306
          306 53.936748 20.721496 29.220534 33.215251
114.365845
          307 61.446597 22.694968 46.170347 38.751628
307
125.670725
          308 45.252792 8.693157 41.583126 36.559635
308
118.545842
          309 33.841641 5.073991 36.641233 28.767649
309
123.945244
       Col6 Col7 Col8 Col9 Col10 Col11
Col12 \
    -0.254400 0.744503 12.5661 14.5386 15.30468 -28.658501
43.5123
     4.564259 0.415186 12.8874 17.5323 16.78486 -25.530607
16.1102
   -3.530317 0.474889 26.8343 17.4861 16.65897 -29.031888
19.2221
    11.211523 0.369345 23.5603 12.7074 11.42447 -30.470246
18.8329
    7.918501 0.543360 35.4940 15.9546 8.87237 -16.378376
24.9171
         ... ... ... ... ...
```

```
305 -4.245395
               0.129744 7.8433 14.7484
                                            8.51707 -15.728927
11.5472
306 -0.421010
               0.047913
                         19.1986 18.1972
                                            7.08745
                                                      6.013843
43.8693
307 -2.707880
               0.081070
                         16.2059
                                  13.5565
                                            8.89572
                                                      3.564463
18.4151
308
     0.214750
               0.159251
                         14.7334 16.0928
                                            9.75922
                                                      5.767308
33.7192
309 -0.199249 0.674504
                         19.3825 17.6963 13.72929
                                                      1.783007
40.6049
   Class att
0
    Abnormal
1
    Abnormal
2
    Abnormal
3
    Abnormal
4
    Abnormal
305
      Normal
306
      Normal
307
      Normal
308
      Normal
309
      Normal
[310 rows x 14 columns]
```

## #1a

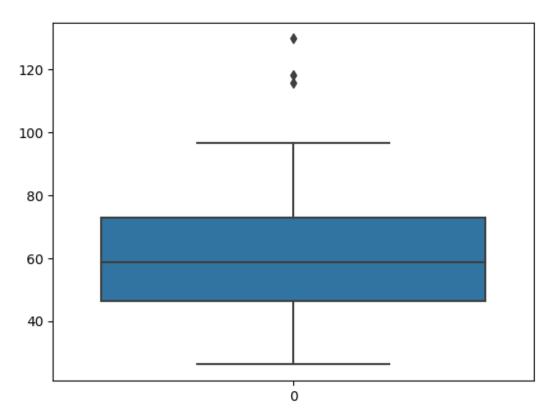
```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 310 entries, 0 to 309
Data columns (total 14 columns):
#
     Column
                 Non-Null Count
                                  Dtype
 0
     Unnamed: 0
                 310 non-null
                                  int64
1
     Col1
                 310 non-null
                                  float64
 2
     Col2
                 310 non-null
                                  float64
 3
     Col3
                 310 non-null
                                  float64
4
     Col4
                 310 non-null
                                  float64
 5
     Col5
                 310 non-null
                                  float64
 6
     Col6
                 310 non-null
                                  float64
 7
                 310 non-null
                                  float64
     Col7
 8
     Col8
                 310 non-null
                                  float64
 9
     Col9
                 310 non-null
                                  float64
    Col10
 10
                 310 non-null
                                  float64
 11
    Coll1
                 310 non-null
                                  float64
 12
    Col12
                 310 non-null
                                  float64
```

13 Class\_att 310 non-null object dtypes: float64(12), int64(1), object(1) memory usage: 34.0+ KB

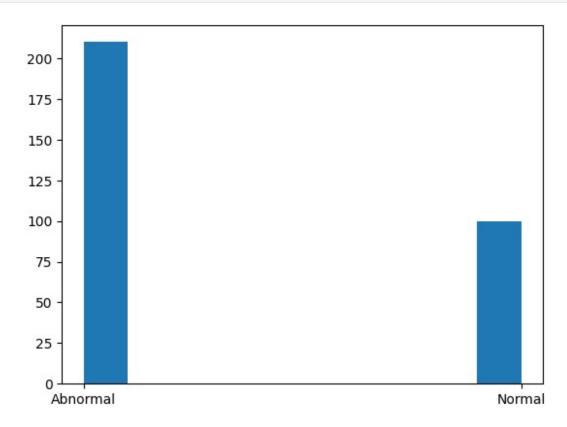
df.describe()

Unnamed: 0	Col1	Col2	Col3	Col4	
Col5 \ count 310.000000 310.000000	310.000000	310.000000	310.000000	310.000000	
mean 154.500000 117.920655	60.496653	17.542822	51.930930	42.953831	
std 89.633513 13.317377	17.236520	10.008330	18.554064	13.423102	
min 0.000000 70.082575	26.147921	-6.554948	14.000000	13.366931	
25% 77.250000 110.709196	46.430294	10.667069	37.000000	33.347122	
50% 154.500000 118.268178	58.691038	16.357689	49.562398	42.404912	
75% 231.750000 125.467674	72.877696	22.120395	63.000000	52.695888	
max 309.000000 163.071041	129.834041	49.431864	125.742385	121.429566	
Col6	Col7	Col8	Col9	Col10	
Coll1 \ count 310.000000	310.000000	310.000000	310.000000	310.000000	
310.000000 mean 26.296694	0.472979	21.321526	13.064511	11.933317	-
14.053139 std 37.559027	0.285787	8.639423	3.399713	2.893265	
12.225582 min -11.058179	0.003220	7.027000	7.037800	7.030600	-
35.287375 25% 1.603727	0.224367	13.054400	10.417800	9.541140	-
24.289522 50% 11.767934	0.475989	21.907150	12.938450	11.953835	-
14.622856 75% 41.287352	0.704846	28.954075	15.889525	14.371810	-
3.497094 max 418.543082	0.998827	36.743900	19.324000	16.821080	
6.972071 Col12					
count 310.000000 mean 25.645981 std 10.450558 min 7.007900 25% 17.189075					

```
50%
        24.931950
75%
        33.979600
max
        44.341200
df.isna().sum()
Unnamed: 0
               0
Col1
               0
Col2
               0
Col3
               0
Col4
               0
Col5
               0
Col6
               0
Col7
               0
Col8
               0
Col9
               0
               0
Col10
Col11
               0
Col12
               0
Class_att
               0
dtype: int64
sns.boxplot(df['Col1'])
<Axes: >
```



```
plt.hist(df['Class_att'])
(array([210., 0., 0., 0., 0., 0., 0., 0., 0., 100.]),
  array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]),
  <BarContainer object of 10 artists>)
```



```
duplicates = df[df.duplicated()]
if not duplicates.empty:
   print("Duplicate rows found:")
   print(duplicates)
else:
   print("No duplicate rows found.")
No duplicate rows found.
df.drop(columns=['Unnamed: 0'],inplace = True)
df
         Col1
                   Col2
                              Col3
                                        Col4
                                                              Col6
                                                    Col5
0
    63.027817 22.552586 39.609117 40.475232 98.672917 -0.254400
    39.056951 10.060991 25.015378 28.995960
                                              114.405425
                                                          4.564259
    68.832021 22.218482 50.092194 46.613539 105.985135 -3.530317
```

```
3
    69.297008 24.652878 44.311238 44.644130 101.868495 11.211523
    49.712859 9.652075 28.317406 40.060784 108.168725 7.918501
.. ... ... ... ... ...
305 47.903565 13.616688 36.000000 34.286877 117.449062 -4.245395
306 53.936748 20.721496 29.220534 33.215251 114.365845 -0.421010
307 61.446597 22.694968 46.170347 38.751628 125.670725 -2.707880
308 45.252792 8.693157 41.583126 36.559635 118.545842 0.214750
309 33.841641 5.073991 36.641233 28.767649 123.945244 -0.199249
       Col7 Col8 Col9 Col10 Col11 Col12
Class att
    0.744503 12.5661 14.5386 15.30468 -28.658501 43.5123
Abnormal
    0.415186 12.8874 17.5323 16.78486 -25.530607 16.1102
1
Abnormal
    0.474889 26.8343 17.4861 16.65897 -29.031888 19.2221
Abnormal
    0.369345 23.5603 12.7074 11.42447 -30.470246 18.8329
Abnormal
    0.543360 35.4940 15.9546 8.87237 -16.378376 24.9171
Abnormal
... ... ... ... ... ... ...
305 0.129744 7.8433 14.7484 8.51707 -15.728927 11.5472
Normal
306 0.047913 19.1986 18.1972 7.08745 6.013843 43.8693
Normal
307 0.081070 16.2059 13.5565 8.89572 3.564463 18.4151
Normal
308 0.159251 14.7334 16.0928 9.75922 5.767308 33.7192
Normal
309 0.674504 19.3825 17.6963 13.72929 1.783007 40.6049
Normal
[310 rows x 13 columns]
# from sklearn.preprocessing import OneHotEncoder
# encoder = OneHotEncoder()
# # df["Class att"] = encoder.fit transform(df["Class att"])
# encoded data = encoder.fit transform(df[["Class att"]])
# print(encoded data)
# column names = encoder.get feature names out(["Class att"])
```

```
# column names
# encoded df = pd.DataFrame(encoded data, columns=column names)
\# a = encoded \ df[0]
\# b = encoded df[1]
# # # Update the original DataFrame by dropping the "Class att" column
and concatenating the one-hot encoded DataFrame
# df = df.drop("Class att", axis=1)
\# df = pd.concat([df, a], axis=1)
\# df = pd.concat([df, b], axis=1)
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 310 entries, 0 to 309
Data columns (total 13 columns):
 #
     Column
                Non-Null Count Dtype
     -----
 0
     Col1
                310 non-null
                                float64
 1
     Col2
                310 non-null
                                float64
 2
     Col3
                310 non-null
                                float64
 3
     Col4
                310 non-null
                                float64
 4
     Col5
                310 non-null
                                float64
 5
     Col6
                310 non-null
                                float64
    Col7
 6
                310 non-null
                                float64
 7
    Col8
                                float64
                310 non-null
 8
    Col9
                310 non-null
                                float64
     Col10
 9
                310 non-null
                                float64
 10 Col11
                310 non-null
                                float64
 11 Col12
                310 non-null
                                float64
 12 Class att 310 non-null
                                object
dtypes: float64(12), object(1)
memory usage: 31.6+ KB
```

Pada dataset\_spine.csv, masalah yang saya temukan adalah adanya kolom 'Unnamed: 0' yang tidak memiliki arti apa2 sehingga saya drop columns tersebut. Selebihnya sudah dapat digunakan

#1b

```
x_val,x_test,y_val,y_test = train_test_split(x_temp,
                                                  y temp,
                                                  test size = 0.5,
                                                  random state = 99)
y_train = pd.get_dummies(y_train)
y val = pd.get dummies(y val)
y test = pd.get dummies(y test)
print("Xtrain: ",len(x_train))
print("Ytrain: ",len(y_train))
print("Xtest: ",len(x_test))
print("Ytest: ",len(y_test))
# print(x train)
print(y train)
Xtrain: 248
Ytrain: 248
Xtest: 31
Ytest: 31
     Abnormal Normal
118
            1
                      0
            1
                      0
207
             1
96
                      0
90
             1
                      0
175
             1
                      0
201
            1
                      0
             1
                      0
168
185
            1
                      0
             1
35
                      0
             1
129
[248 rows x 2 columns]
```

## 1c

```
import tensorflow as tf
from tensorflow import keras

ft = x_train.shape[1]
# category 2 karena abnormal dan normal
cate = 2
neuron1 = 512
#neuron2 : 512 / 2
neuron2 = 256
```

```
#neuron3 : 216 / 2
neuron3 = 128
model neuron = keras.models.Sequential([
   tf.keras.layers.Dense(neuron1,activation = 'sigmoid',
input shape=(ft,)),
   tf.keras.layers.Dense(neuron2,activation = 'sigmoid'),
   tf.keras.layers.Dense(neuron3,activation = 'sigmoid'),
   tf.keras.layers.Dense(cate,activation = 'softmax'),
])
model neuron.compile(optimizer = "adam",
                 loss = "categorical crossentropy",
                 metrics =["accuracy"] )
sum model neur = model neuron.summary()
sum model neur
Model: "sequential"
Layer (type)
                        Output Shape
                                               Param #
dense (Dense)
                        (None, 512)
                                              6656
dense 1 (Dense)
                        (None, 256)
                                              131328
dense 2 (Dense)
                        (None, 128)
                                              32896
dense 3 (Dense)
                        (None, 2)
                                               258
Total params: 171138 (668.51 KB)
Trainable params: 171138 (668.51 KB)
Non-trainable params: 0 (0.00 Byte)
model neuron result = model neuron.fit(x train,
                                 y train,
                                 epochs = 148,
                                 batch size = 20,
                                 validation data=(x val,y val))
Epoch 1/148
accuracy: 0.6492 - val loss: 0.6710 - val accuracy: 0.6452
Epoch 2/148
accuracy: 0.6734 - val loss: 0.5117 - val accuracy: 0.7097
Epoch 3/148
```

```
accuracy: 0.7661 - val loss: 0.4241 - val accuracy: 0.7419
Epoch 4/148
accuracy: 0.7782 - val loss: 0.4112 - val accuracy: 0.7419
Epoch 5/148
accuracy: 0.7581 - val loss: 0.4579 - val accuracy: 0.7097
Epoch 6/148
accuracy: 0.8185 - val loss: 0.5021 - val accuracy: 0.7097
Epoch 7/148
accuracy: 0.8427 - val loss: 0.4687 - val accuracy: 0.7097
Epoch 8/148
accuracy: 0.8185 - val loss: 0.4292 - val accuracy: 0.7742
Epoch 9/148
accuracy: 0.7863 - val loss: 0.3957 - val accuracy: 0.8065
Epoch 10/148
accuracy: 0.8145 - val loss: 0.3871 - val accuracy: 0.8065
Epoch 11/148
accuracy: 0.8387 - val loss: 0.6190 - val accuracy: 0.7097
Epoch 12/148
accuracy: 0.8306 - val loss: 0.4023 - val accuracy: 0.7419
Epoch 13/148
accuracy: 0.8306 - val loss: 0.4616 - val accuracy: 0.7097
Epoch 14/148
accuracy: 0.8589 - val loss: 0.6483 - val accuracy: 0.7097
Epoch 15/148
accuracy: 0.8226 - val loss: 0.4173 - val accuracy: 0.7742
Epoch 16/148
accuracy: 0.8468 - val loss: 0.3742 - val accuracy: 0.7742
Epoch 17/148
accuracy: 0.8266 - val loss: 0.4235 - val accuracy: 0.7742
Epoch 18/148
accuracy: 0.8468 - val_loss: 0.4734 - val_accuracy: 0.7419
Epoch 19/148
accuracy: 0.8669 - val loss: 0.5535 - val accuracy: 0.7419
```

```
Epoch 20/148
accuracy: 0.8548 - val loss: 0.4695 - val accuracy: 0.7419
Epoch 21/148
accuracy: 0.8468 - val loss: 0.5325 - val accuracy: 0.7419
Epoch 22/148
accuracy: 0.8629 - val loss: 0.6518 - val accuracy: 0.7097
Epoch 23/148
accuracy: 0.8589 - val loss: 0.4623 - val accuracy: 0.7419
Epoch 24/148
accuracy: 0.8669 - val loss: 0.3731 - val accuracy: 0.7419
Epoch 25/148
accuracy: 0.8468 - val loss: 0.3559 - val accuracy: 0.7742
Epoch 26/148
accuracy: 0.8831 - val loss: 0.4313 - val accuracy: 0.7419
Epoch 27/148
accuracy: 0.8710 - val loss: 0.4812 - val accuracy: 0.7419
Epoch 28/148
accuracy: 0.8831 - val_loss: 0.3732 - val_accuracy: 0.7419
Epoch 29/148
accuracy: 0.8750 - val loss: 0.3178 - val accuracy: 0.8065
Epoch 30/148
accuracy: 0.8589 - val loss: 0.4641 - val accuracy: 0.7097
Epoch 31/148
accuracy: 0.8750 - val loss: 0.7134 - val accuracy: 0.7097
Epoch 32/148
accuracy: 0.8710 - val loss: 0.3112 - val accuracy: 0.8387
Epoch 33/148
accuracy: 0.8629 - val loss: 0.4120 - val accuracy: 0.7742
Epoch 34/148
accuracy: 0.8710 - val loss: 0.3965 - val accuracy: 0.7742
Epoch 35/148
13/13 [============= ] - 0s 8ms/step - loss: 0.2232 -
accuracy: 0.8871 - val loss: 0.4438 - val accuracy: 0.7742
Epoch 36/148
```

```
accuracy: 0.8831 - val loss: 0.5932 - val accuracy: 0.7419
Epoch 37/148
accuracy: 0.8750 - val loss: 0.3945 - val accuracy: 0.7419
Epoch 38/148
accuracy: 0.8911 - val loss: 0.4639 - val accuracy: 0.7742
Epoch 39/148
accuracy: 0.8871 - val loss: 0.4363 - val accuracy: 0.7419
Epoch 40/148
accuracy: 0.8952 - val loss: 0.6306 - val accuracy: 0.7419
Epoch 41/148
accuracy: 0.8831 - val loss: 0.7578 - val accuracy: 0.7097
Epoch 42/148
accuracy: 0.8992 - val loss: 0.4772 - val accuracy: 0.7742
Epoch 43/148
accuracy: 0.8992 - val loss: 0.4127 - val accuracy: 0.8065
Epoch 44/148
accuracy: 0.9194 - val loss: 0.3774 - val accuracy: 0.8387
Epoch 45/148
accuracy: 0.9073 - val loss: 0.4582 - val accuracy: 0.7742
Epoch 46/148
accuracy: 0.8548 - val loss: 0.5928 - val accuracy: 0.7419
Epoch 47/148
accuracy: 0.8952 - val loss: 0.7454 - val accuracy: 0.7097
Epoch 48/148
accuracy: 0.8871 - val loss: 0.5647 - val accuracy: 0.7419
Epoch 49/148
accuracy: 0.8911 - val loss: 0.4384 - val accuracy: 0.7742
Epoch 50/148
accuracy: 0.9113 - val loss: 0.4458 - val accuracy: 0.7742
Epoch 51/148
accuracy: 0.8992 - val loss: 0.3743 - val accuracy: 0.7742
Epoch 52/148
```

```
accuracy: 0.9113 - val loss: 0.4114 - val accuracy: 0.7742
Epoch 53/148
accuracy: 0.9355 - val loss: 0.4136 - val accuracy: 0.7742
Epoch 54/148
accuracy: 0.9274 - val loss: 0.3687 - val accuracy: 0.7742
Epoch 55/148
accuracy: 0.9073 - val loss: 0.3968 - val accuracy: 0.7742
Epoch 56/148
accuracy: 0.8790 - val loss: 0.4366 - val accuracy: 0.8065
Epoch 57/148
accuracy: 0.8145 - val loss: 0.3973 - val accuracy: 0.7742
Epoch 58/148
accuracy: 0.8629 - val loss: 0.6048 - val accuracy: 0.7097
Epoch 59/148
accuracy: 0.8992 - val loss: 0.4820 - val accuracy: 0.7097
Epoch 60/148
accuracy: 0.9355 - val loss: 0.5061 - val accuracy: 0.7742
Epoch 61/148
accuracy: 0.9194 - val loss: 0.6202 - val accuracy: 0.7742
Epoch 62/148
accuracy: 0.9315 - val loss: 0.6398 - val accuracy: 0.7742
Epoch 63/148
accuracy: 0.9315 - val loss: 0.4723 - val accuracy: 0.8065
Epoch 64/148
accuracy: 0.9395 - val loss: 0.5061 - val accuracy: 0.8065
Epoch 65/148
accuracy: 0.9315 - val loss: 0.4680 - val accuracy: 0.7419
Epoch 66/148
accuracy: 0.8911 - val loss: 0.4870 - val accuracy: 0.8065
Epoch 67/148
13/13 [============== ] - 0s 8ms/step - loss: 0.1469 -
accuracy: 0.9435 - val_loss: 0.4682 - val_accuracy: 0.8065
Epoch 68/148
accuracy: 0.9395 - val loss: 0.5513 - val accuracy: 0.8065
```

```
Epoch 69/148
accuracy: 0.9435 - val loss: 0.4145 - val accuracy: 0.7742
Epoch 70/148
accuracy: 0.9355 - val loss: 0.4527 - val accuracy: 0.7742
Epoch 71/148
accuracy: 0.9435 - val loss: 0.4633 - val accuracy: 0.8065
Epoch 72/148
accuracy: 0.9556 - val loss: 0.5080 - val accuracy: 0.7742
Epoch 73/148
accuracy: 0.9516 - val loss: 0.5144 - val accuracy: 0.8065
Epoch 74/148
accuracy: 0.9597 - val loss: 0.6623 - val accuracy: 0.8387
Epoch 75/148
accuracy: 0.9435 - val loss: 0.5071 - val accuracy: 0.7742
Epoch 76/148
accuracy: 0.9355 - val loss: 0.4543 - val accuracy: 0.7742
Epoch 77/148
13/13 [============== ] - 0s 8ms/step - loss: 0.1098 -
accuracy: 0.9476 - val loss: 0.4708 - val accuracy: 0.8065
Epoch 78/148
accuracy: 0.9597 - val loss: 0.8601 - val accuracy: 0.7742
Epoch 79/148
accuracy: 0.9153 - val loss: 0.7771 - val accuracy: 0.8065
Epoch 80/148
accuracy: 0.9476 - val loss: 0.4837 - val accuracy: 0.8065
Epoch 81/148
accuracy: 0.9395 - val loss: 0.7171 - val accuracy: 0.8065
Epoch 82/148
accuracy: 0.9556 - val loss: 0.5125 - val accuracy: 0.8387
Epoch 83/148
accuracy: 0.9556 - val loss: 0.6077 - val accuracy: 0.7742
Epoch 84/148
13/13 [============== ] - 0s 9ms/step - loss: 0.1431 -
accuracy: 0.9274 - val_loss: 0.6472 - val_accuracy: 0.8065
Epoch 85/148
```

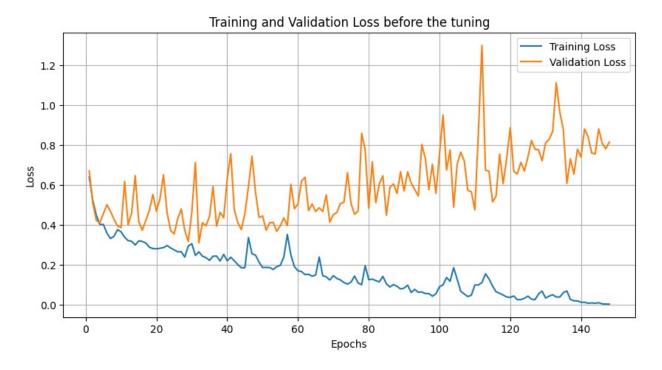
```
accuracy: 0.9597 - val loss: 0.4495 - val accuracy: 0.8710
Epoch 86/148
accuracy: 0.9637 - val loss: 0.5899 - val accuracy: 0.8387
Epoch 87/148
accuracy: 0.9637 - val loss: 0.6064 - val accuracy: 0.7742
Epoch 88/148
accuracy: 0.9556 - val loss: 0.5583 - val accuracy: 0.8387
Epoch 89/148
accuracy: 0.9758 - val loss: 0.6676 - val accuracy: 0.8065
Epoch 90/148
accuracy: 0.9677 - val loss: 0.5713 - val accuracy: 0.8065
Epoch 91/148
accuracy: 0.9677 - val loss: 0.6670 - val accuracy: 0.8065
Epoch 92/148
accuracy: 0.9798 - val_loss: 0.6108 - val_accuracy: 0.8065
Epoch 93/148
accuracy: 0.9758 - val loss: 0.5782 - val accuracy: 0.8387
Epoch 94/148
accuracy: 0.9879 - val loss: 0.5459 - val accuracy: 0.8065
Epoch 95/148
accuracy: 0.9798 - val loss: 0.8041 - val accuracy: 0.8387
Epoch 96/148
accuracy: 0.9839 - val loss: 0.7348 - val accuracy: 0.8065
Epoch 97/148
accuracy: 0.9758 - val loss: 0.5777 - val accuracy: 0.8387
Epoch 98/148
accuracy: 0.9919 - val loss: 0.7052 - val accuracy: 0.8387
Epoch 99/148
accuracy: 0.9758 - val loss: 0.5589 - val accuracy: 0.8065
Epoch 100/148
accuracy: 0.9435 - val loss: 0.7565 - val accuracy: 0.8065
Epoch 101/148
```

```
accuracy: 0.9516 - val loss: 0.9518 - val accuracy: 0.8065
Epoch 102/148
accuracy: 0.9315 - val loss: 0.6765 - val accuracy: 0.8065
Epoch 103/148
accuracy: 0.9516 - val loss: 0.7764 - val accuracy: 0.7419
Epoch 104/148
accuracy: 0.9194 - val loss: 0.4895 - val accuracy: 0.8065
Epoch 105/148
accuracy: 0.9677 - val loss: 0.7054 - val accuracy: 0.7742
Epoch 106/148
accuracy: 0.9758 - val loss: 0.7661 - val accuracy: 0.8065
Epoch 107/148
accuracy: 0.9879 - val loss: 0.7216 - val accuracy: 0.8065
Epoch 108/148
accuracy: 0.9919 - val loss: 0.5746 - val accuracy: 0.8065
Epoch 109/148
accuracy: 0.9798 - val loss: 0.5672 - val accuracy: 0.8710
Epoch 110/148
accuracy: 0.9597 - val loss: 0.4764 - val accuracy: 0.8387
Epoch 111/148
accuracy: 0.9597 - val loss: 0.8651 - val accuracy: 0.8065
Epoch 112/148
accuracy: 0.9395 - val loss: 1.3006 - val accuracy: 0.7742
Epoch 113/148
accuracy: 0.9315 - val loss: 0.6749 - val accuracy: 0.8387
Epoch 114/148
accuracy: 0.9597 - val loss: 0.6706 - val accuracy: 0.7742
Epoch 115/148
accuracy: 0.9556 - val_loss: 0.5164 - val_accuracy: 0.8387
Epoch 116/148
accuracy: 0.9718 - val_loss: 0.5456 - val_accuracy: 0.8065
Epoch 117/148
accuracy: 0.9798 - val loss: 0.7557 - val accuracy: 0.8065
```

```
Epoch 118/148
accuracy: 0.9798 - val loss: 0.6080 - val accuracy: 0.8387
Epoch 119/148
accuracy: 0.9839 - val loss: 0.7362 - val accuracy: 0.8387
Epoch 120/148
accuracy: 0.9879 - val loss: 0.8885 - val accuracy: 0.8065
Epoch 121/148
accuracy: 0.9758 - val loss: 0.6691 - val accuracy: 0.8387
Epoch 122/148
accuracy: 0.9919 - val loss: 0.6562 - val accuracy: 0.8065
Epoch 123/148
accuracy: 0.9919 - val loss: 0.7149 - val accuracy: 0.8065
Epoch 124/148
accuracy: 0.9960 - val loss: 0.6712 - val accuracy: 0.7742
Epoch 125/148
accuracy: 0.9798 - val loss: 0.7412 - val accuracy: 0.8387
Epoch 126/148
accuracy: 0.9879 - val_loss: 0.8239 - val_accuracy: 0.8387
Epoch 127/148
accuracy: 0.9879 - val loss: 0.7801 - val accuracy: 0.8065
Epoch 128/148
accuracy: 0.9798 - val loss: 0.7776 - val accuracy: 0.8387
Epoch 129/148
accuracy: 0.9677 - val loss: 0.7221 - val accuracy: 0.8065
Epoch 130/148
accuracy: 0.9839 - val loss: 0.8132 - val accuracy: 0.8387
Epoch 131/148
accuracy: 0.9798 - val loss: 0.8302 - val accuracy: 0.8065
Epoch 132/148
accuracy: 0.9718 - val loss: 0.8700 - val accuracy: 0.8065
Epoch 133/148
accuracy: 0.9879 - val_loss: 1.1130 - val_accuracy: 0.7742
Epoch 134/148
```

```
accuracy: 0.9798 - val loss: 0.9659 - val accuracy: 0.7742
Epoch 135/148
accuracy: 0.9758 - val loss: 0.8799 - val accuracy: 0.8387
Epoch 136/148
accuracy: 0.9798 - val loss: 0.6087 - val accuracy: 0.8710
Epoch 137/148
accuracy: 0.9879 - val loss: 0.7318 - val accuracy: 0.8387
Epoch 138/148
accuracy: 0.9960 - val loss: 0.6554 - val accuracy: 0.7742
Epoch 139/148
accuracy: 0.9960 - val loss: 0.7804 - val_accuracy: 0.8387
Epoch 140/148
accuracy: 0.9960 - val loss: 0.7410 - val accuracy: 0.8065
Epoch 141/148
accuracy: 1.0000 - val loss: 0.8817 - val accuracy: 0.8065
Epoch 142/148
accuracy: 1.0000 - val loss: 0.8435 - val_accuracy: 0.8065
Epoch 143/148
accuracy: 0.9960 - val loss: 0.7616 - val accuracy: 0.8065
Epoch 144/148
accuracy: 1.0000 - val loss: 0.7565 - val accuracy: 0.8065
Epoch 145/148
accuracy: 0.9960 - val loss: 0.8822 - val accuracy: 0.8387
Epoch 146/148
accuracy: 1.0000 - val loss: 0.8093 - val accuracy: 0.8387
Epoch 147/148
accuracy: 1.0000 - val loss: 0.7826 - val accuracy: 0.8065
Epoch 148/148
accuracy: 1.0000 - val loss: 0.8163 - val accuracy: 0.8387
def plot training history(history):
  train loss = history.history['loss']
  val loss = history.history['val loss']
  epochs = range(1, len(train loss) + 1)
```

```
plt.figure(figsize=(10, 5))
  plt.plot(epochs, train_loss, label='Training Loss')
  plt.plot(epochs, val_loss, label='Validation Loss')
  plt.xlabel('Epochs')
  plt.ylabel('Loss')
  plt.title('Training and Validation Loss before the tuning')
  plt.legend()
  plt.grid(True)
  plt.show()
plot_training_history(model_neuron_result)
```



## 1d

```
metrics =["accuracy"] )
sum model neur = model neuron1.summary()
sum model neur
Model: "sequential 1"
                     Output Shape
Layer (type)
                                         Param #
dense 4 (Dense)
                     (None, 512)
                                         6656
dropout (Dropout)
                     (None, 512)
                                         0
dense 5 (Dense)
                     (None, 256)
                                         131328
dropout 1 (Dropout)
                     (None, 256)
                                         0
dense 6 (Dense)
                                         32896
                     (None, 128)
dropout_2 (Dropout)
                     (None, 128)
                                         0
dense 7 (Dense)
                                         258
                     (None, 2)
Total params: 171138 (668.51 KB)
Trainable params: 171138 (668.51 KB)
Non-trainable params: 0 (0.00 Byte)
model neuron1 result = model neuron1.fit(x train,
                             y train,
                             epochs = 148,
                             batch size = 20,
                             validation data=(x val,y val))
Epoch 1/148
accuracy: 0.5363 - val loss: 0.5977 - val accuracy: 0.7097
Epoch 2/148
accuracy: 0.5968 - val_loss: 0.6108 - val_accuracy: 0.7097
Epoch 3/148
accuracy: 0.6008 - val loss: 0.6012 - val accuracy: 0.7097
Epoch 4/148
accuracy: 0.6048 - val loss: 0.5864 - val accuracy: 0.7097
Epoch 5/148
accuracy: 0.5726 - val loss: 0.5754 - val accuracy: 0.7097
```

```
Epoch 6/148
accuracy: 0.6048 - val loss: 0.5684 - val accuracy: 0.7097
Epoch 7/148
accuracy: 0.5968 - val loss: 0.5601 - val accuracy: 0.7097
Epoch 8/148
accuracy: 0.5806 - val loss: 0.5516 - val accuracy: 0.7097
Epoch 9/148
accuracy: 0.6129 - val loss: 0.5415 - val accuracy: 0.7097
Epoch 10/148
accuracy: 0.6250 - val loss: 0.5350 - val accuracy: 0.7097
Epoch 11/148
accuracy: 0.6694 - val loss: 0.5295 - val accuracy: 0.7097
Epoch 12/148
accuracy: 0.6210 - val loss: 0.5197 - val accuracy: 0.7097
Epoch 13/148
accuracy: 0.6008 - val loss: 0.5125 - val accuracy: 0.7097
Epoch 14/148
accuracy: 0.6008 - val loss: 0.5045 - val accuracy: 0.7097
Epoch 15/148
accuracy: 0.6129 - val loss: 0.4972 - val accuracy: 0.7097
Epoch 16/148
accuracy: 0.6290 - val loss: 0.4893 - val accuracy: 0.7097
Epoch 17/148
accuracy: 0.6976 - val loss: 0.4845 - val accuracy: 0.7097
Epoch 18/148
accuracy: 0.6452 - val loss: 0.4793 - val accuracy: 0.7097
Epoch 19/148
accuracy: 0.6976 - val loss: 0.4726 - val accuracy: 0.7419
Epoch 20/148
accuracy: 0.6532 - val loss: 0.4690 - val accuracy: 0.7097
Epoch 21/148
accuracy: 0.6089 - val loss: 0.4650 - val accuracy: 0.7097
Epoch 22/148
```

```
accuracy: 0.7339 - val loss: 0.4596 - val accuracy: 0.6774
Epoch 23/148
accuracy: 0.7298 - val loss: 0.4609 - val accuracy: 0.7742
Epoch 24/148
accuracy: 0.7097 - val loss: 0.4496 - val accuracy: 0.6774
Epoch 25/148
accuracy: 0.6694 - val loss: 0.4441 - val accuracy: 0.7097
Epoch 26/148
accuracy: 0.6895 - val loss: 0.4445 - val accuracy: 0.7742
Epoch 27/148
accuracy: 0.7258 - val loss: 0.4466 - val accuracy: 0.8065
Epoch 28/148
accuracy: 0.7177 - val loss: 0.4463 - val accuracy: 0.8065
Epoch 29/148
accuracy: 0.6976 - val loss: 0.4514 - val accuracy: 0.6774
Epoch 30/148
accuracy: 0.6895 - val loss: 0.4496 - val accuracy: 0.6774
Epoch 31/148
accuracy: 0.7056 - val loss: 0.4481 - val accuracy: 0.6774
Epoch 32/148
accuracy: 0.7298 - val loss: 0.4422 - val accuracy: 0.7097
Epoch 33/148
accuracy: 0.7177 - val loss: 0.4467 - val accuracy: 0.6774
Epoch 34/148
accuracy: 0.7782 - val loss: 0.4569 - val accuracy: 0.7097
Epoch 35/148
accuracy: 0.7540 - val loss: 0.4534 - val accuracy: 0.7097
Epoch 36/148
accuracy: 0.7419 - val loss: 0.4491 - val accuracy: 0.7097
Epoch 37/148
accuracy: 0.7258 - val loss: 0.4388 - val accuracy: 0.7097
Epoch 38/148
```

```
accuracy: 0.7460 - val loss: 0.4396 - val accuracy: 0.7097
Epoch 39/148
accuracy: 0.7177 - val loss: 0.4420 - val accuracy: 0.7097
Epoch 40/148
accuracy: 0.7500 - val loss: 0.4271 - val accuracy: 0.7419
Epoch 41/148
accuracy: 0.7500 - val loss: 0.4562 - val accuracy: 0.7097
Epoch 42/148
accuracy: 0.7540 - val loss: 0.4480 - val accuracy: 0.7097
Epoch 43/148
accuracy: 0.7742 - val loss: 0.4570 - val accuracy: 0.7097
Epoch 44/148
accuracy: 0.7782 - val loss: 0.4491 - val accuracy: 0.7097
Epoch 45/148
accuracy: 0.7823 - val loss: 0.4481 - val accuracy: 0.7097
Epoch 46/148
accuracy: 0.7782 - val loss: 0.4343 - val accuracy: 0.7419
Epoch 47/148
accuracy: 0.7863 - val loss: 0.4450 - val accuracy: 0.7097
Epoch 48/148
accuracy: 0.7702 - val loss: 0.4412 - val accuracy: 0.7097
Epoch 49/148
accuracy: 0.7702 - val loss: 0.4294 - val accuracy: 0.7097
Epoch 50/148
accuracy: 0.7500 - val loss: 0.4425 - val accuracy: 0.7097
Epoch 51/148
accuracy: 0.7540 - val loss: 0.4544 - val accuracy: 0.7097
Epoch 52/148
accuracy: 0.7903 - val loss: 0.4665 - val accuracy: 0.7097
Epoch 53/148
accuracy: 0.7742 - val_loss: 0.4554 - val_accuracy: 0.7097
Epoch 54/148
accuracy: 0.7863 - val loss: 0.4504 - val accuracy: 0.7097
```

```
Epoch 55/148
accuracy: 0.7782 - val loss: 0.4417 - val accuracy: 0.7097
Epoch 56/148
accuracy: 0.7419 - val loss: 0.4401 - val accuracy: 0.7097
Epoch 57/148
accuracy: 0.7581 - val loss: 0.4471 - val accuracy: 0.7097
Epoch 58/148
accuracy: 0.7540 - val loss: 0.4650 - val accuracy: 0.7097
Epoch 59/148
accuracy: 0.7540 - val loss: 0.4545 - val accuracy: 0.7097
Epoch 60/148
accuracy: 0.8024 - val loss: 0.4545 - val accuracy: 0.7097
Epoch 61/148
accuracy: 0.7782 - val loss: 0.4492 - val accuracy: 0.7097
Epoch 62/148
accuracy: 0.8065 - val loss: 0.4397 - val accuracy: 0.7419
Epoch 63/148
13/13 [============== ] - 0s 9ms/step - loss: 0.4420 -
accuracy: 0.7782 - val loss: 0.4475 - val accuracy: 0.7097
Epoch 64/148
accuracy: 0.7903 - val loss: 0.4645 - val accuracy: 0.7097
Epoch 65/148
accuracy: 0.8065 - val loss: 0.4545 - val accuracy: 0.7097
Epoch 66/148
accuracy: 0.7581 - val loss: 0.4358 - val accuracy: 0.7097
Epoch 67/148
accuracy: 0.7944 - val loss: 0.4503 - val accuracy: 0.7097
Epoch 68/148
accuracy: 0.7661 - val loss: 0.4573 - val accuracy: 0.7097
Epoch 69/148
accuracy: 0.7944 - val loss: 0.4383 - val accuracy: 0.7097
Epoch 70/148
accuracy: 0.8226 - val loss: 0.4436 - val accuracy: 0.7419
Epoch 71/148
```

```
accuracy: 0.7782 - val loss: 0.4533 - val accuracy: 0.7097
Epoch 72/148
accuracy: 0.7944 - val loss: 0.4477 - val accuracy: 0.7419
Epoch 73/148
accuracy: 0.7782 - val loss: 0.4574 - val accuracy: 0.7097
Epoch 74/148
accuracy: 0.7823 - val loss: 0.4466 - val accuracy: 0.7419
Epoch 75/148
accuracy: 0.8226 - val loss: 0.4300 - val accuracy: 0.7419
Epoch 76/148
accuracy: 0.7742 - val loss: 0.4673 - val accuracy: 0.7097
Epoch 77/148
accuracy: 0.7903 - val loss: 0.4397 - val accuracy: 0.7419
Epoch 78/148
accuracy: 0.8226 - val loss: 0.4546 - val accuracy: 0.7419
Epoch 79/148
accuracy: 0.7782 - val loss: 0.4489 - val accuracy: 0.7419
Epoch 80/148
accuracy: 0.8024 - val loss: 0.4586 - val accuracy: 0.7419
Epoch 81/148
accuracy: 0.7984 - val loss: 0.4609 - val accuracy: 0.7419
Epoch 82/148
accuracy: 0.7863 - val loss: 0.4407 - val accuracy: 0.7419
Epoch 83/148
accuracy: 0.8226 - val loss: 0.4430 - val accuracy: 0.7419
Epoch 84/148
13/13 [============= ] - 0s 7ms/step - loss: 0.4264 -
accuracy: 0.7621 - val loss: 0.4473 - val accuracy: 0.7419
Epoch 85/148
accuracy: 0.7782 - val loss: 0.4509 - val accuracy: 0.7419
Epoch 86/148
accuracy: 0.7742 - val loss: 0.4666 - val accuracy: 0.7419
Epoch 87/148
```

```
accuracy: 0.8024 - val loss: 0.4332 - val accuracy: 0.7097
Epoch 88/148
accuracy: 0.8024 - val loss: 0.4454 - val accuracy: 0.7419
Epoch 89/148
accuracy: 0.7863 - val loss: 0.4439 - val accuracy: 0.7419
Epoch 90/148
accuracy: 0.8105 - val loss: 0.4554 - val accuracy: 0.7419
Epoch 91/148
accuracy: 0.7984 - val loss: 0.4539 - val accuracy: 0.7419
Epoch 92/148
accuracy: 0.8145 - val loss: 0.4917 - val accuracy: 0.7097
Epoch 93/148
accuracy: 0.8226 - val loss: 0.4443 - val accuracy: 0.7097
Epoch 94/148
accuracy: 0.8024 - val loss: 0.4353 - val accuracy: 0.7419
Epoch 95/148
accuracy: 0.8065 - val loss: 0.4421 - val accuracy: 0.7097
Epoch 96/148
accuracy: 0.7984 - val loss: 0.4714 - val accuracy: 0.7419
Epoch 97/148
accuracy: 0.8185 - val loss: 0.4641 - val accuracy: 0.7419
Epoch 98/148
accuracy: 0.8427 - val loss: 0.4600 - val accuracy: 0.7419
Epoch 99/148
accuracy: 0.8145 - val loss: 0.4411 - val accuracy: 0.7097
Epoch 100/148
accuracy: 0.8508 - val loss: 0.4582 - val accuracy: 0.7419
Epoch 101/148
accuracy: 0.8226 - val_loss: 0.4557 - val_accuracy: 0.7419
Epoch 102/148
13/13 [============= ] - 0s 9ms/step - loss: 0.3435 -
accuracy: 0.8105 - val_loss: 0.4456 - val_accuracy: 0.7419
Epoch 103/148
accuracy: 0.8266 - val loss: 0.4295 - val accuracy: 0.7097
```

```
Epoch 104/148
accuracy: 0.8226 - val loss: 0.4308 - val accuracy: 0.7097
Epoch 105/148
accuracy: 0.8105 - val loss: 0.4294 - val accuracy: 0.7097
Epoch 106/148
accuracy: 0.7984 - val loss: 0.4481 - val accuracy: 0.7419
Epoch 107/148
accuracy: 0.8024 - val loss: 0.4786 - val accuracy: 0.7419
Epoch 108/148
accuracy: 0.8347 - val loss: 0.4821 - val accuracy: 0.7419
Epoch 109/148
accuracy: 0.8347 - val loss: 0.4910 - val accuracy: 0.7097
Epoch 110/148
accuracy: 0.8105 - val loss: 0.4457 - val accuracy: 0.7097
Epoch 111/148
accuracy: 0.8306 - val loss: 0.4392 - val accuracy: 0.7097
Epoch 112/148
13/13 [============== ] - 0s 8ms/step - loss: 0.3758 -
accuracy: 0.8266 - val_loss: 0.4300 - val_accuracy: 0.7097
Epoch 113/148
accuracy: 0.7944 - val loss: 0.4352 - val accuracy: 0.7097
Epoch 114/148
accuracy: 0.8065 - val loss: 0.4529 - val accuracy: 0.7419
Epoch 115/148
accuracy: 0.7863 - val loss: 0.4593 - val accuracy: 0.7419
Epoch 116/148
accuracy: 0.8387 - val loss: 0.4492 - val accuracy: 0.7419
Epoch 117/148
accuracy: 0.8226 - val loss: 0.4410 - val accuracy: 0.7097
Epoch 118/148
accuracy: 0.8266 - val loss: 0.4425 - val accuracy: 0.7097
Epoch 119/148
13/13 [============== ] - 0s 8ms/step - loss: 0.3590 -
accuracy: 0.7984 - val_loss: 0.4393 - val_accuracy: 0.7097
Epoch 120/148
```

```
accuracy: 0.7944 - val loss: 0.4464 - val accuracy: 0.7097
Epoch 121/148
accuracy: 0.8548 - val loss: 0.4667 - val accuracy: 0.7419
Epoch 122/148
accuracy: 0.8306 - val loss: 0.4496 - val accuracy: 0.7097
Epoch 123/148
accuracy: 0.8266 - val loss: 0.4474 - val accuracy: 0.7097
Epoch 124/148
accuracy: 0.8145 - val loss: 0.4436 - val accuracy: 0.7097
Epoch 125/148
accuracy: 0.8347 - val loss: 0.4398 - val accuracy: 0.7097
Epoch 126/148
accuracy: 0.8065 - val loss: 0.4474 - val accuracy: 0.7419
Epoch 127/148
accuracy: 0.8427 - val loss: 0.4296 - val accuracy: 0.7097
Epoch 128/148
accuracy: 0.8387 - val loss: 0.4265 - val accuracy: 0.7097
Epoch 129/148
accuracy: 0.8145 - val loss: 0.4347 - val accuracy: 0.7097
Epoch 130/148
accuracy: 0.8145 - val loss: 0.4611 - val accuracy: 0.7419
Epoch 131/148
accuracy: 0.8347 - val loss: 0.4572 - val accuracy: 0.7419
Epoch 132/148
accuracy: 0.8266 - val loss: 0.4631 - val accuracy: 0.7419
Epoch 133/148
accuracy: 0.8347 - val loss: 0.4624 - val accuracy: 0.7419
Epoch 134/148
accuracy: 0.8468 - val loss: 0.4376 - val accuracy: 0.7097
Epoch 135/148
accuracy: 0.8347 - val loss: 0.4268 - val accuracy: 0.7097
Epoch 136/148
```

```
accuracy: 0.8306 - val loss: 0.4268 - val accuracy: 0.7097
Epoch 137/148
accuracy: 0.8589 - val loss: 0.4365 - val accuracy: 0.7097
Epoch 138/148
accuracy: 0.8629 - val loss: 0.4342 - val accuracy: 0.7097
Epoch 139/148
accuracy: 0.8266 - val loss: 0.4417 - val accuracy: 0.7419
Epoch 140/148
accuracy: 0.8589 - val loss: 0.4260 - val accuracy: 0.7097
Epoch 141/148
accuracy: 0.8508 - val loss: 0.4307 - val accuracy: 0.7097
Epoch 142/148
accuracy: 0.8468 - val loss: 0.4449 - val accuracy: 0.7419
Epoch 143/148
accuracy: 0.8508 - val loss: 0.4348 - val accuracy: 0.7097
Epoch 144/148
accuracy: 0.8508 - val loss: 0.4673 - val accuracy: 0.7419
Epoch 145/148
accuracy: 0.8266 - val loss: 0.4440 - val accuracy: 0.7419
Epoch 146/148
accuracy: 0.8145 - val loss: 0.4557 - val accuracy: 0.7419
Epoch 147/148
accuracy: 0.8306 - val loss: 0.4661 - val accuracy: 0.7419
Epoch 148/148
accuracy: 0.8145 - val loss: 0.4473 - val accuracy: 0.7419
def plot1 training history(history):
  train loss = history.history['loss']
  val loss = history.history['val loss']
  epochs = range(1, len(train loss) + 1)
  plt.figure(figsize=(10, 5))
  plt.plot(epochs, train loss, label='Training Loss')
  plt.plot(epochs, val loss, label='Validation Loss')
  plt.xlabel('Epochs')
  plt.ylabel('Loss')
  plt.title('Training and Validation Loss after the tuning')
  plt.legend()
```

```
plt.grid(True)
plt.show()

plot1_training_history(model_neuron1_result)
```



## 1e

```
from sklearn.metrics import classification_report
# before being trained
prediction_before = model_neuron.predict(x_test)
print(classification_report(y_test,np.round(prediction_before)))
               ======= ] - 0s 97ms/step
              precision
                           recall f1-score
                                               support
                                                    22
           0
                   0.87
                             0.91
                                        0.89
           1
                                                     9
                   0.75
                             0.67
                                        0.71
                                        0.84
                                                    31
   micro avg
                   0.84
                             0.84
                   0.81
                             0.79
                                        0.80
                                                    31
   macro avg
weighted avg
                   0.83
                             0.84
                                        0.84
                                                    31
 samples avg
                   0.84
                             0.84
                                        0.84
                                                    31
```

```
# after being trained
prediction_after = model_neuron1.predict(x_test)
print(classification_report(y_test,np.round(prediction_after)))
1/1 [=======] - 0s 68ms/step
             precision
                          recall f1-score
                                            support
          0
                  1.00
                            0.86
                                      0.93
                                                 22
          1
                  0.75
                            1.00
                                      0.86
                                                  9
   micro avg
                  0.90
                            0.90
                                      0.90
                                                  31
                  0.88
                            0.93
                                      0.89
                                                  31
   macro avg
                                      0.91
weighted avg
                  0.93
                            0.90
                                                  31
samples avg
                  0.90
                            0.90
                                      0.90
                                                  31
```

Setelah dilakukan tuning dengan perubahan acitvation dan dropping terhadap 1 layer, hasilnya menjadi lebih bagus

#1f

Link Youtube penjelasan: https://youtu.be/GTk\_jg8N2PM