```
pip install ucimlrepo
Requirement already satisfied: ucimlrepo in
/usr/local/lib/python3.10/dist-packages (0.0.3)
from ucimlrepo import fetch ucirepo
from sklearn.manifold import TSNE
from sklearn import neighbors
from sklearn import naive bayes
from sklearn.model selection import train test split
from sklearn.model selection import cross val score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion matrix, ConfusionMatrixDisplay,
accuracy score, precision score, recall score
from matplotlib import pyplot as plt
import pandas as pd
import numpy as np
# fetch dataset
breast cancer wisconsin diagnostic = fetch ucirepo(id=17)
# data (as pandas dataframes)
X = breast cancer wisconsin diagnostic.data.features
y = breast cancer wisconsin diagnostic.data.targets
print((len(X) - round(len(X)*0.7))/len(X))
treino = X.iloc[0:round(len(X)*0.7)]
teste = X.iloc[round(len(X)*0.7):len(X)]
target treino = y.iloc[0:round(len(X)*0.7)]
target teste = y.iloc[round(len(X)*0.7):len(X)]
display(treino)
display(teste)
display(target treino)
0.30052724077328646
     radius1 texture1
                        perimeter1
                                            smoothness1
                                                          compactness1
                                     area1
/
0
       17.99
                 10.38
                            122.80
                                    1001.0
                                                 0.11840
                                                               0.27760
       20.57
                 17.77
                            132.90
                                    1326.0
                                                 0.08474
                                                               0.07864
       19.69
                 21.25
                            130.00
                                                 0.10960
                                                               0.15990
                                    1203.0
3
       11.42
                 20.38
                             77.58
                                     386.1
                                                 0.14250
                                                               0.28390
```

4	20.29	14.34	135.10	1297.0	0.10030	0.13280
393	21.61	22.28	144.40	1407.0	0.11670	0.20870
394	12.10	17.72	78.07	446.2	0.10290	0.09758
395	14.06	17.18	89.75	609.1	0.08045	0.05361
396	13.51	18.89	88.10	558.1	0.10590	0.11470
397	12.80	17.46	83.05	508.3	0.08044	0.08895
co radius3	oncavity1 3 \	concave_ <sub>[</sub>	points1	symmetry1	fractal_dimens	sion1
0	0.30010	(	0.14710	0.2419	0.0	7871
25.38 1	0.08690		0.07017	0.1812	Θ. 0	95667
24.99						
2 23.57	0.19740		0.12790	0.2069	0.0	)5999
3	0.24140	(	0.10520	0.2597	0.0	9744
14.91 4	0.19800	(	0.10430	0.1809	0.0	05883
22.54						
			•••			
393 26.23	0.28100		0.15620	0.2162	0.0	06606
394	0.04783	(	0.03326	0.1937	0.0	06161
13.56 395	0.02681		0.03251	0.1641	0.0	95764
14.92						
396 14.80	0.08580		0.05381	0.1806	0.0	06079
397	0.07390		0.04083	0.1574	0.0	)5750
13.74						
	exture3 p ity3 \	erimeter3	area3	smoothness	3 compactness	<b>3</b>
0 0.7119	17.33	184.60	2019.0	0.1622	0 0.665	56
1	23.41	158.80	1956.0	0.1238	0 0.186	56
0.2416	25.53	152.50	1709.0	0.1444	0.424	15
0.4504						
3 0.6869	26.50	98.87	567.7	0.2098	0.866	53

4 0.4000	16.67	152.20	1575.0	0.13740	0.	2050
 393 0.7053	28.74	172.00	2081.0	0.15020	0.	5717
394 0.1603	25.80	88.33	559.5	0.14320	0.	1773
395 0.0846	25.34	96.42	684.5	0.10660	0.	1231
396 0.3438	27.20	97.33	675.2	0.14280	0.	2570
397 0.1901	21.06	90.72	591.0	0.09534	1 0.	1812
0 1 2 3 4  393 394 395 396 397	0. 0. 0. 0. 0.	26540 6 18600 6 24300 6 25750 6 16250 6 24220 6 06266 6 07911 6 14530 6	netry3 fr 0.4601 0.2750 0.3613 0.6638 0.2364  0.3828 0.3049 0.2523 0.2666	0 0 0 0	nsion3 .11890 .08902 .08758 .17300 .07678  .10070 .07081 .06609 .07686	
	adiusl t	exturel pe	erimeter1	areal sr	noothness1	compactness1
\ 398	11.06	14.83	70.31	378.2	0.07741	0.04768
399	11.80	17.26	75.26	431.9	0.09087	0.06232
400	17.91	21.02	124.40	994.0	0.12300	0.25760
401	11.93	10.91	76.14	442.7	0.08872	0.05242
402	12.96	18.29	84.18	525.2	0.07351	0.07899
564	21.56	22.39	142.00	1479.0	0.11100	0.11590
565	20.13	28.25	131.20	1261.0	0.09780	0.10340
566	16.60	28.08	108.30	858.1	0.08455	0.10230
567	20.60	29.33	140.10	1265.0	0.11780	0.27700

568	7.76	24.54	47.92	2 181.0	0.05263	0.04362
co radius3	ncavity1 \	concave_p	oints1	symmetry1	fractal_dimension	1
398 12.680	0.02712	0.0	907246	0.1535	0.0621	4
399 13.450	0.02853	0.0	916380	0.1847	0.0601	9
400 20.800	0.31890	0.	119800	0.2113	0.0711	5
401 13.800	0.02606	0.0	917960	0.1601	0.0554	1
402 14.130	0.04057	0.0	918830	0.1874	0.0589	9
564 25.450	0.24390	0.	138900	0.1726	0.0562	3
565 23.690	0.14400	0.0	997910	0.1752	0.0553	3
566	0.09251	0.0	953020	0.1590	0.0564	8
18.980 567 25.740	0.35140	0.	152000	0.2397	0.0701	6
568 9.456	0.00000	0.0	900000	0.1587	0.0588	4
	xture3 ;	perimeter3	area3	smoothness	3 compactness3	
concavi		80.79	496.7	0.1120	•	
0.2079 399	24.49	86.00	562.0	0.1244	0.17260	
0.1449 400	27.78	149.60	1304.0	0.1873	0.59170	
0.9034 401	20.14	87.64	589.5	0.1374	0.15750	
0.1514 402 0.1604	24.61	96.31	621.9	0.0932	9 0.23180	
 564 0.4107	26.40	166.10	2027.0	0.1410	0.21130	
565	38.25	155.00	1731.0	0.1166	0.19220	
0.3215 566 0.3403	34.12	126.70	1124.0	0.1139	0.30940	
567	39.42	184.60	1821.0	0.1650	0.86810	

```
0.9387
        30.37
                      59.16
                              268.6
                                          0.08996
                                                          0.06444
568
0.0000
                                    fractal dimension3
     concave points3
                        symmetry3
398
              0.05556
                           0.2590
                                                0.09158
399
              0.05356
                           0.2779
                                                0.08121
                                                0.11980
400
              0.19640
                           0.3245
401
              0.06876
                           0.2460
                                                0.07262
402
              0.06608
                           0.3207
                                                0.07247
. .
              0.22160
                           0.2060
                                                0.07115
564
565
              0.16280
                           0.2572
                                                0.06637
566
              0.14180
                           0.2218
                                                0.07820
567
              0.26500
                           0.4087
                                                0.12400
568
              0.00000
                           0.2871
                                                0.07039
[171 rows x 30 columns]
    Diagnosis
0
             M
1
             M
2
             М
3
             M
4
             M
393
             M
394
             В
             В
395
396
             В
             В
397
[398 rows x 1 columns]
```

#### a)

Os valores de média e desvio padrão obtidos mostram uma grande variação entre os parâmetros quanto a escala de valores. Enquanto alguns parâmetros tem valores bem próximos de zero e sem muita variação, há parâmetros com valores na casa das centenas com desvio padrão também na casa das centenas.

```
print('Média e desvio padrão para classe M')
display(treino.loc[target_treino.Diagnosis ==
'M'].describe().loc[['mean','std']])
print('Média e desvio padrão para classe B')
display(treino.loc[target_treino.Diagnosis ==
'B'].describe().loc[['mean','std']])
Média e desvio padrão para classe M
```

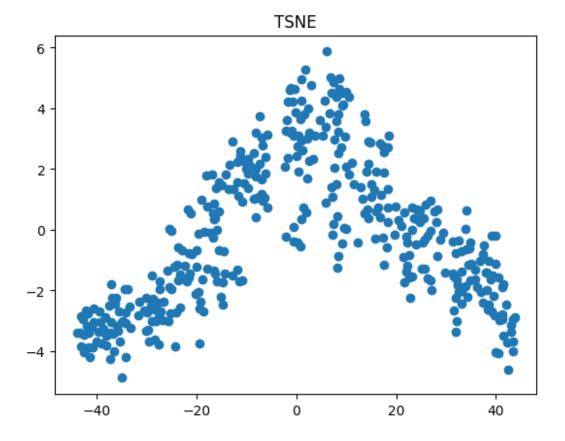
```
radius1 texture1 perimeter1 areal smoothness1
compactness1 \
mean 17.274162 21.360983 114.029653 957.232370
                                               0.103080
0.144564
     3.215195 3.795245 21.882764 362.544383
                                               0.013071
0.054986
     concavity1 concave points1 symmetry1 fractal dimension1 ...
      0.156944
                     0.086749
                               0.193865
                                                0.062774 ...
mean
                     0.034618 0.028619
                                                0.007837 ...
std 0.074200
      radius3 texture3 perimeter3 area3
                                             smoothness3 \
mean 20.980578 29.152312 140.086185 1400.997110
                                                0.145659
std 4.275420 5.519159 29.241505 584.936603
                                                0.022424
     compactness3 concavity3 concave points3 symmetry3
fractal dimension3
      0.376277
                  0.443207 0.181295 0.329265
mean
0.091952
        0.173656 0.174275 0.046430 0.077451
std
0.022062
[2 rows x 30 columns]
Média e desvio padrão para classe B
      radius1 texture1 perimeter1 areal smoothness1
compactness1 \
mean 12.076440 17.127156 77.581689 457.226222
                                               0.092321
0.078284
     1.731315 3.359781 11.437250 128.977373
                                               0.012719
0.033274
     concavity1 concave points1 symmetry1 fractal dimension1 ...
       0.04645
                                                0.062804 ...
                     0.025385 0.175124
mean
                     0.016313 0.025612
std
       0.04925
                                                0.006771 ...
       radius3 texture3 perimeter3 area3 smoothness3
compactness3 \
mean 13.259400 22.408444 86.098978 548.620000
                                               0.123747
0.175684
     1.926465 4.832299 13.132041 156.637776
std
                                               0.019480
0.091804
     concavity3 concave points3 symmetry3 fractal dimension3
```

mean	0.161529	0.072195	0.271338	0.078731
std	0.152275	0.036115	0.043836	0.013912
[2 rows	x 30 columns]			

# b)

Pelo gráfico obtido ao se utilizar o TSNE vemos que há possibilidade de separação das amostras em dois grupos, embora para algumas amostras seja possível uma classificação errada devido a não haver uma separação clara no TSNE 2D.

```
tsne_treino = TSNE().fit_transform(treino)
# display(tsne_treino)
# color = [target_treino.loc[i,['Diagnosis']]['Diagnosis'] for i in
range(len(target_treino))]
# for i in range(len(color)):
    if color[i] == 'M':
#
      color[i] = '#1f77b4'
#
    else:
      color[i] = '#2ca02c'
# display(color)
# plt.scatter(tsne treino[:,0], tsne treino[:,1], c=color)
plt.scatter(tsne treino[:,0], tsne treino[:,1])
plt.title("TSNE")
Text(0.5, 1.0, 'TSNE')
```



```
c)
correl = treino.corr()
# display(correl>0.9)
## display(np.where(correl>0.9))
## display(correl.drop(columns=np.whee(correl>0.9)[0]))
diag ones = (2*np.ones(len(correl)) - np.triu(np.ones(len(correl)))) -
np.tril(np.ones(len(correl)))
# display(diag ones)
non redundant = correl[((diag ones*correl)<=0.9)&((diag ones*correl)!</pre>
=1)1
# display(non redundant)
non redundant = non redundant.dropna(axis=1)
# display(non redundant)
treino non redundant = treino[non redundant.columns]
teste non redundant = teste[non redundant.columns]
display(treino non redundant)
display(teste_non_redundant)
     smoothness1 compactness1 symmetry1 fractal_dimension1
texture2
         0.11840
                       0.27760
                                    0.2419
                                                       0.07871
0
0.9053
         0.08474
                       0.07864
                                    0.1812
                                                       0.05667
```

0.7339 2	0.10960	0.1599	ıa a	2069		0.05999	
0.7869							
3 1.1560	0.14250	0.2839	00 0.	2597		0.09744	
4 0.7813	0.10030	0.1328	80 0.	1809		0.05883	
393	0.11670	0.2087	0 0.	2162		0.06606	j
0.9209 394	0.10290	0.0975	8 0.	1937		0.06161	
1.6520 395	0.08045	0.0536	51 0.	1641		0.05764	
1.6850 396	0.10590	0.1147	'0 O.	1806		0.06079	
1.3320 397 1.2650	0.08044	0.0889	05 0.	1574		0.05750	
	oothness2	compactness	2 conca	avity2	concave	e_points2	symmetry2
0	0.006399	0.0490	0.	05373		0.015870	0.03003
1	0.005225	0.0130	0.	01860		0.013400	0.01389
2	0.006150	0.0400	06 0.	03832		0.020580	0.02250
3	0.009110	0.0745	8 0.	05661		0.018670	0.05963
4	0.011490	0.0246	61 0.	05688		0.018850	0.01756
393	0.005215	0.0372	26 0.	04718		0.012880	0.02045
394	0.008146	0.0163	31 0.	01843		0.007513	0.02015
395	0.005371	0.0127	'3 0.	01132		0.009155	0.01719
396	0.005442	0.0195	57 0.	03304		0.013670	0.01315
397	0.005421	0.0347	77 0.	04545		0.013840	0.01869
	actal_dime	nsion2 smoc	thness3	compa	ctness3	concavity	<b>'</b> 3
symmetr		006193	0.16220		0.6656	0.711	.9
0.4601 1	0.	003532	0.12380		0.1866	0.241	.6

0.2750						
2 0.3613	0.004	4571 0.	14440	0.4245	0.4504	
3	0.009	9208 0.	20980	0.8663	0.6869	
0.6638						
4 0.2364	0.00	5115 0.	13740	0.2050	0.4000	
0.2304						
393 0.3828	0.004	1028 0.	15020	0.5717	0.7053	
394	0.00	1798 0.	14320	0.1773	0.1603	
0.3049						
395 0.2523	0.00	1444 0.	10660	0.1231	0.0846	
396	0.002	2464 0.	14280	0.2570	0.3438	
0.2666						
397	0.004	4067 0.	09534	0.1812	0.1901	
0.1988						
fra 0 1 2 3	0.08 0.08 0.1	ion3 1890 3902 3758 7300 7678				
	0.0					
393 394 395 396 397	0.0 0.0 0.0	9070 7081 5609 7686 7053				
[398 row	s x 16 colur	mns]				
SMO	othness1 c	ompactness1	symmetry1	fractal di	mension1	
texture2	\	·		actat_ar		
398	0.07741	0.04768	0.1535		0.06214	
0.6881 399	0.09087	0.06232	0.1847		0.06019	
1.1400						
400	0.12300	0.25760	0.2113		0.07115	
0.7747 401	0.08872	0.05242	0.1601		0.05541	
1.0450						
402	0.07351	0.07899	0.1874		0.05899	
1.2990						
564	0.11100	0.11590	0.1726		0.05623	

1.2560 565	0.09780	Θ.	10340	0.	1752		0.05533	
2.4630								
566 1.0750	0.08455		10230		1590		0.05648	
567 1.5950	0.11780	0.	27700	0.2	2397		0.07016	
568 1.4280	0.05263	Θ.	04362	0.1	1587		0.05884	
	oothness2	compact	ness2	conca	vity2	concave	e_points2	symmetry2
398	0.004259	0.	01469	0.0	01940		0.004168	0.01191
399	0.005463	0.	01964	0.0	02079		0.005398	0.01477
400	0.007159	0.	03718	0.0	06165		0.010510	0.01591
401	0.006175	0.	01204	0.0	01376		0.005832	0.01096
402	0.003629	0.	03713	0.0	03452		0.010650	0.02632
564	0.010300	0.	02891	0.0	05198		0.024540	0.01114
565	0.005769	0.	02423	0.0	03950		0.016780	0.01898
566	0.005903	0.	03731	0.0	04730		0.015570	0.01318
567	0.006522	0.	06158	0.0	97117		0.016640	0.02324
568	0.007189	0.	00466	0.0	00000		0.000000	0.02676
fr	actal dime	nsion2	smooth	ness3	compa	ctness3	concavity	3
symmetr 398	y3 \	003537		11200		0.18790	0.207	
0.2590								
399 0.2779		003071		12440		0.17260	0.144	
400 0.3245	0.	005099	0.	18730	(	0.59170	0.903	4
401 0.2460	0.	001857	0.	13740	(	0.15750	0.151	4
402 0.3207	0.	003705	0.0	09329	(	9.23180	0.160	4
564	0.	004239	0.	14100	(	0.21130	0.410	7

```
0.2060
                                                            0.3215
                0.002498
                               0.11660
                                              0.19220
565
0.2572
566
                0.003892
                               0.11390
                                              0.30940
                                                            0.3403
0.2218
567
                0.006185
                               0.16500
                                              0.86810
                                                            0.9387
0.4087
568
                0.002783
                               0.08996
                                              0.06444
                                                            0.0000
0.2871
     fractal dimension3
398
                 0.09158
399
                 0.08121
400
                 0.11980
                 0.07262
401
402
                 0.07247
564
                 0.07115
565
                 0.06637
                 0.07820
566
567
                 0.12400
568
                 0.07039
[171 rows x 16 columns]
```

### d)

```
display(treino non redundant.describe())
h = []
p = []
for i in range(len(treino_non_redundant.columns)):
  plt.figure(i)
  n,_{-},_{-} =
plt.hist(treino non redundant[treino non redundant.columns[i]])
  plt.title("Histograma do parâmetro " +
treino non redundant.columns[i])
  plt.ylabel("frequência")
  prob = n/sum(n)
  p.insert(len(p),prob)
  h.insert(len(h), -sum(prob*np.log2((n==0)+prob)))
display(p)
display(h)
       smoothness1
                                    symmetry1 fractal dimension1
                    compactness1
texture2 \
        398,000000
count
                       398,000000
                                   398.000000
                                                        398,000000
398.000000
          0.096998
                         0.107094
                                     0.183271
                                                          0.062791
mean
1.197527
          0.013922
                         0.054926
                                     0.028487
                                                          0.007245
std
```

0.539097 min 0.062510 0.019380 0.116700 0.049960 0.360200 25% 0.086987 0.066713 0.163500 0.057563 0.826875
0.360200 25% 0.086987 0.066713 0.163500 0.057563
0.020073
50% 0.096935 0.095840 0.180950 0.061400
1.067500 75% 0.106175 0.133400 0.196700 0.065975 1.463750
max 0.144700 0.345400 0.304000 0.097440
4.885000
<pre>smoothness2 compactness2 concavity2 concave_points2 symmetry2 \</pre>
count 398.000000 398.000000 398.000000 398.000000
mean 0.007021 0.026282 0.033117 0.012115 0.021205
std 0.003073 0.019225 0.033462 0.006447
0.009067 min 0.001713 0.002252 0.000000 0.000000
0.007882
25% 0.005215 0.013413 0.015522 0.007968 0.015205
50% 0.006301 0.020780 0.026355 0.011220 0.018955
75% 0.008097 0.033687 0.042637 0.015043
0.024047 max 0.031130 0.135400 0.396000 0.052790
0.078950
<pre>fractal_dimension2 smoothness3 compactness3 concavity3</pre>
symmetry3 \ count
398.000000
mean 0.003875 0.133272 0.262877 0.283967
std 0.002896 0.023457 0.166533 0.213983
0.067155 min 0.000895 0.071170 0.027290 0.000000
0.156500 25% 0.002214 0.117025 0.146075 0.112975
0.255175
50% 0.003195 0.132350 0.220200 0.243300 0.285150
75% 0.004560 0.148025 0.354125 0.396500 0.325450
max 0.029840 0.222600 1.058000 1.252000
0.663800

```
fractal dimension3
              398.000000
count
                0.084478
mean
                0.019056
std
min
                0.055040
25%
                0.071165
50%
                0.080195
75%
                0.092560
max
                0.207500
[array([0.02261307, 0.06030151, 0.17085427, 0.21356784, 0.22613065,
       0.15075377, 0.11055276, 0.02512563, 0.01256281, 0.00753769]),
 array([0.11809045, 0.3040201 , 0.22110553, 0.15829146, 0.10301508,
       0.04773869, 0.02763819, 0.00753769, 0.01005025, 0.00251256]),
 array([0.02512563, 0.11557789, 0.23366834, 0.27386935, 0.20603015,
       0.07788945, 0.03517588, 0.02261307, 0.00502513, 0.00502513]),
array([0.07788945, 0.2839196 , 0.29899497, 0.16582915, 0.0879397
       0.05276382, 0.0201005, 0.00502513, 0.00251256, 0.00502513]),
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       0.01005025, 0.00251256, 0.00251256, 0. , 0.00251256]),
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       0.00753769, 0.00251256, 0.00251256, 0.
                                                     , 0.00251256]),
 array([0.35427136, 0.3040201, 0.19849246, 0.06532663, 0.03517588,
       0.01256281, 0.01758794, 0.01005025, 0.
                                                     , 0.00251256]),
 array([0.72361809, 0.2160804 , 0.04271357, 0.01256281, 0.
                 , 0.
                       , 0.00251256, 0. , 0.00251256]),
       0.
 array([0.09045226, 0.36432161, 0.33417085, 0.14070352, 0.04020101,
       0.01507538, 0.00753769, 0.00502513, 0. , 0.00251256]),
 array([0.2361809 , 0.44472362, 0.18090452, 0.07537688, 0.03015075,
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                                                     , 0.002512561),
 array([0.63316583, 0.27135678, 0.06030151, 0.01758794, 0.00753769,
                            , 0.00502513, 0.
       0.00251256, 0.
                                                     , 0.00251256]),
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       0.15075377, 0.0678392 , 0.03517588, 0. , 0.00753769]),
 array([0.21356784, 0.31909548, 0.18844221, 0.14824121, 0.06030151,
       0.03768844, 0.01758794, 0.00502513, 0.00753769, 0.00251256),
 array([0.27889447, 0.23115578, 0.1959799 , 0.13316583, 0.07537688,
       0.06030151, 0.01758794, 0.00251256, 0.00251256, 0.00251256]),
 array([0.04773869, 0.22110553, 0.37939698, 0.2160804, 0.07537688,
       0.02763819, 0.0201005 , 0.00753769, 0.00251256, 0.00251256]),
 array([0.22110553, 0.4120603 , 0.1959799 , 0.10050251, 0.04522613,
       0.01758794, 0.00251256, 0.00251256, 0. , 0.00251256])]
[2.7929232578333147.
 2.620479807449189.
 2.6217788022429174,
 2.4973351593435478,
 2.1194734263842783,
 1.862504305204839,
 2.2129226154839454,
```

```
1.132369147941993,

2.161666780926907,

2.1100475266943577,

1.4098711960976489,

2.6739931582599343,

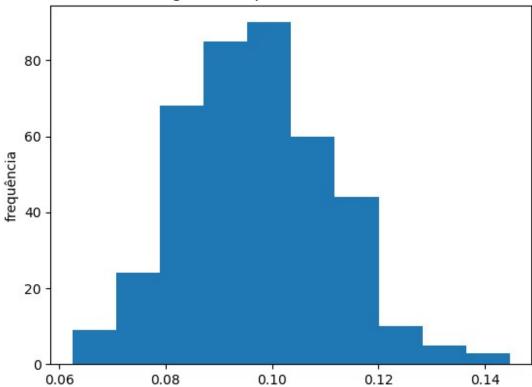
2.501832265268997,

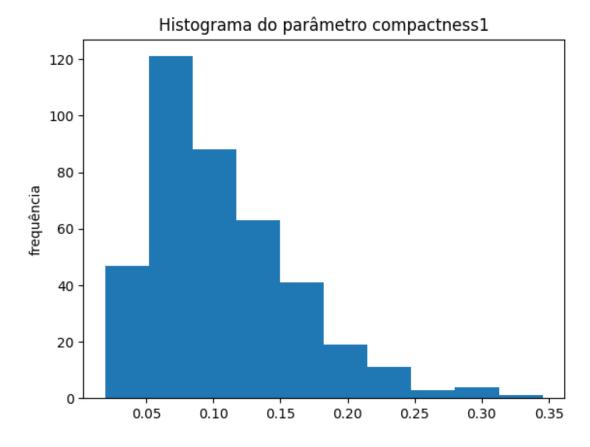
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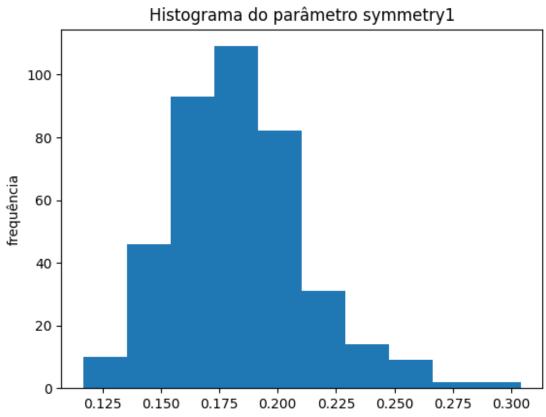
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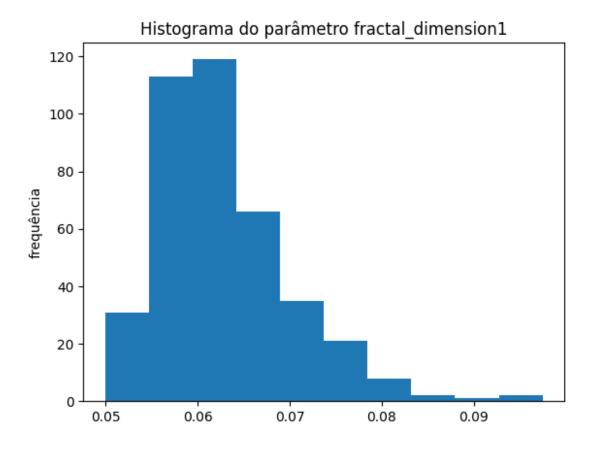
2.172008684502034]
```

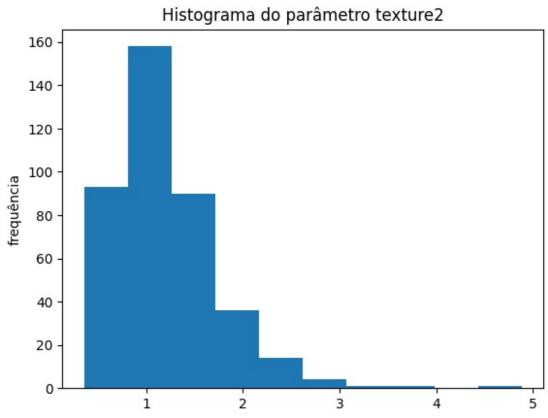


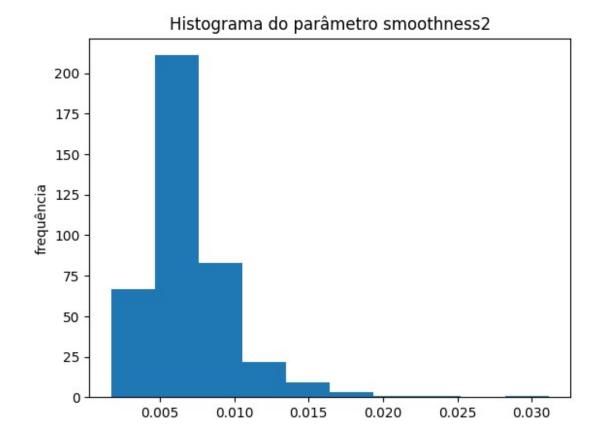


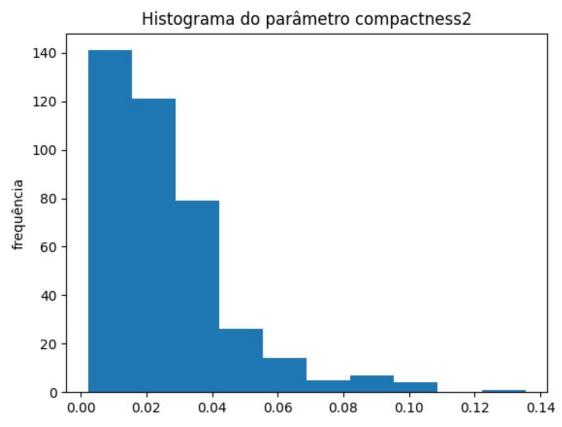


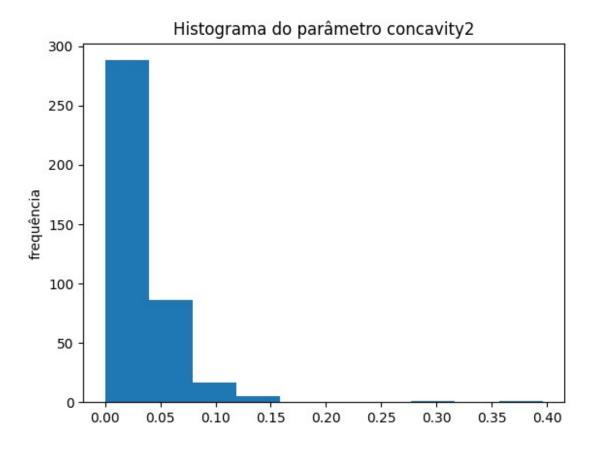


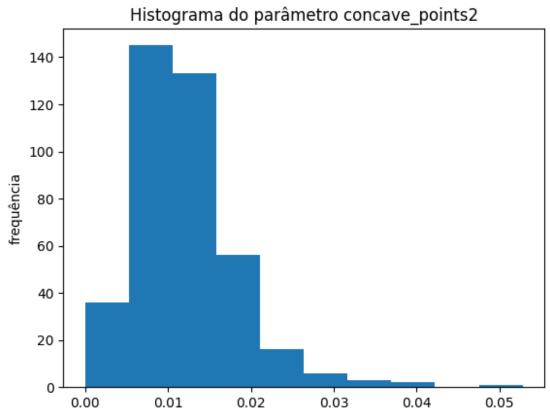


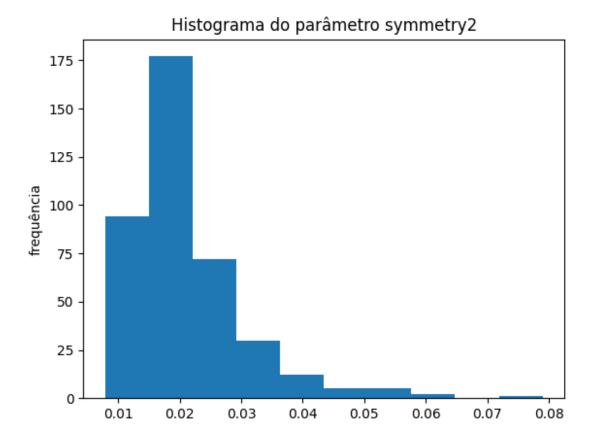


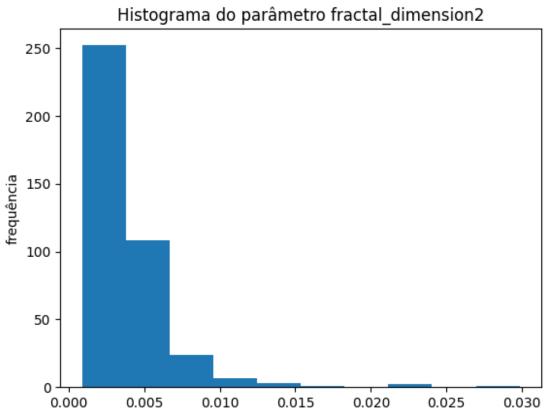


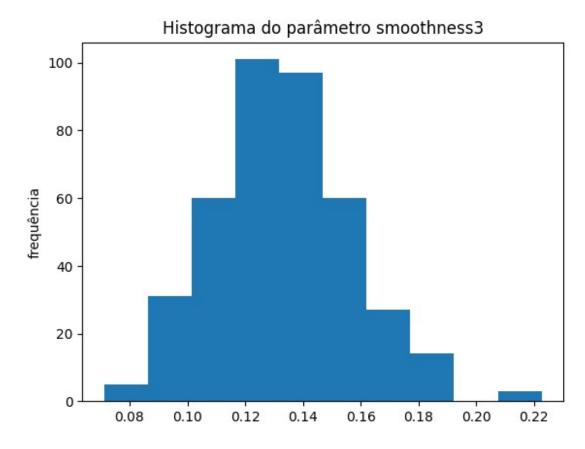


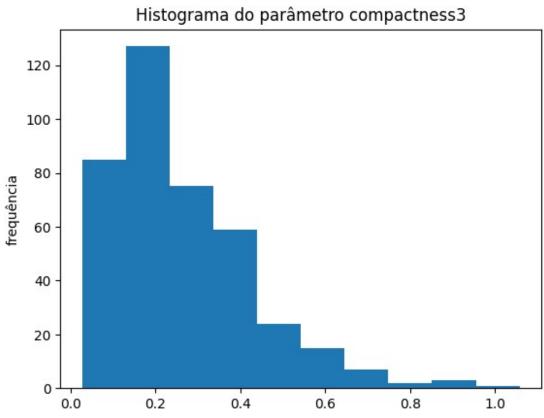


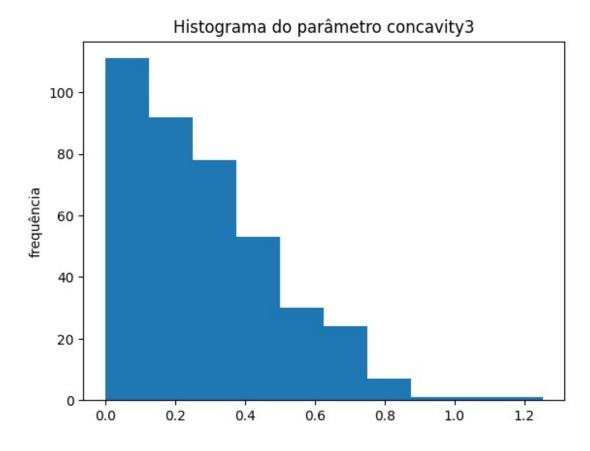


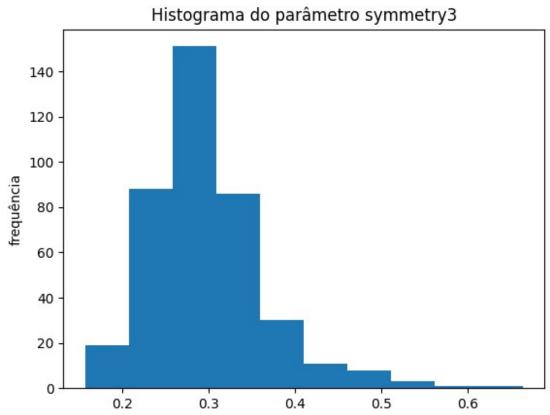


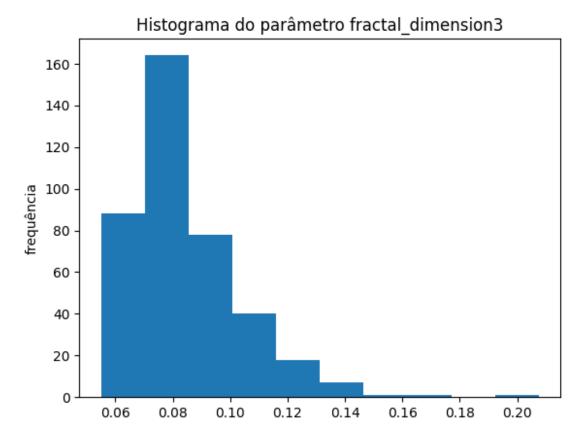






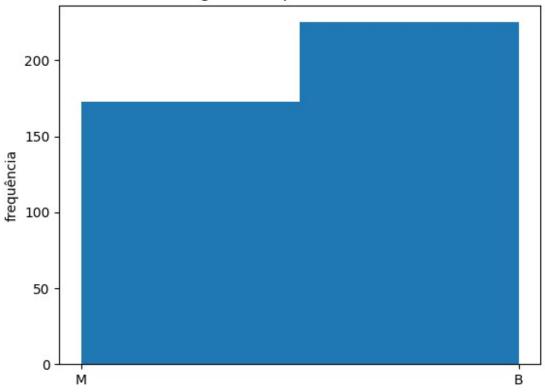






```
plt.figure(100)
n,_,_ = plt.hist(target_treino,len(target_treino.drop_duplicates()))
plt.title("Histograma do parâmetro de saída")
plt.ylabel("frequência")
p_target = n/sum(n)
display(p_target)
h_target = -sum(p_target*np.log2((n==0) + p_target))
display(h_target)
array([0.43467337, 0.56532663])
0.98765112455122
```

## Histograma do parâmetro de saída



```
display(treino non redundant)
display(target_treino)
temp = pd.concat([treino non redundant,target treino], axis=1)
h in2out = []
p = []
freq = []
for i in range(len(treino non redundant.columns)):
  freq.insert(len(freq),
(temp[temp.columns[[i,16]]].value counts()).tolist())
n = sum([sum(freq) for freq in freq])
for i in range(len(treino non redundant.columns)):
  prob = [(freq/n) for freq in freq[i]]
  p.insert(len(p),prob)
  h in2out.insert(len(h in2out),-sum((prob)*np.log2(prob)))
# display(sum([item for row in p for item in row]))
display(h in2out)
     smoothness1 compactness1 symmetry1 fractal dimension1
texture2 \
         0.11840
                       0.27760
                                   0.2419
                                                       0.07871
0.9053
                       0.07864
                                                       0.05667
1
         0.08474
                                   0.1812
```

0.7339 2	0.10960	0.1599	ıa a	2069		0.05999	
0.7869							
3 1.1560	0.14250	0.2839	00 0.	2597		0.09744	
4 0.7813	0.10030	0.1328	80 0.	1809		0.05883	
393	0.11670	0.2087	0 0.	2162		0.06606	j
0.9209 394	0.10290	0.0975	8 0.	1937		0.06161	
1.6520 395	0.08045	0.0536	51 0.	1641		0.05764	
1.6850 396	0.10590	0.1147	'0 O.	1806		0.06079	
1.3320 397 1.2650	0.08044	0.0889	05 0.	1574		0.05750	
	oothness2	compactness	2 conca	avity2	concave	e_points2	symmetry2
0	0.006399	0.0490	0.	05373		0.015870	0.03003
1	0.005225	0.0130	0.	01860		0.013400	0.01389
2	0.006150	0.0400	06 0.	03832		0.020580	0.02250
3	0.009110	0.0745	8 0.	05661		0.018670	0.05963
4	0.011490	0.0246	61 0.	05688		0.018850	0.01756
393	0.005215	0.0372	26 0.	04718		0.012880	0.02045
394	0.008146	0.0163	31 0.	01843		0.007513	0.02015
395	0.005371	0.0127	'3 0.	01132		0.009155	0.01719
396	0.005442	0.0195	57 0.	03304		0.013670	0.01315
397	0.005421	0.0347	77 0.	04545		0.013840	0.01869
	actal_dime	nsion2 smoc	thness3	compa	ctness3	concavity	<b>'</b> 3
symmetr		006193	0.16220		0.6656	0.711	.9
0.4601 1	0.	003532	0.12380		0.1866	0.241	.6

```
0.2750
                0.004571
                               0.14440
                                               0.4245
                                                            0.4504
2
0.3613
                0.009208
                               0.20980
                                               0.8663
                                                            0.6869
0.6638
                0.005115
                               0.13740
                                               0.2050
                                                            0.4000
0.2364
. .
                                                              . . .
393
                0.004028
                               0.15020
                                               0.5717
                                                            0.7053
0.3828
394
                0.001798
                               0.14320
                                               0.1773
                                                            0.1603
0.3049
395
                0.001444
                               0.10660
                                               0.1231
                                                            0.0846
0.2523
396
                0.002464
                               0.14280
                                               0.2570
                                                            0.3438
0.2666
                0.004067
                               0.09534
397
                                               0.1812
                                                            0.1901
0.1988
     fractal_dimension3
                 0.11890
0
1
                 0.08902
2
                 0.08758
3
                 0.17300
4
                 0.07678
                 0.10070
393
394
                 0.07081
395
                 0.06609
                 0.07686
396
                 0.07053
397
[398 rows x 16 columns]
    Diagnosis
0
            M
            M
1
2
            M
3
            M
4
            M
393
            M
394
             В
             В
395
             В
396
             В
397
[398 rows x 1 columns]
```

```
[0.7789505416092561,
0.7866483352663943,
 0.7773801898504621,
 0.7843312989124113.
 0.7863342649146355,
 0.7866483352663943.
 0.7872764759699119,
 0.7835623609488057,
 0.7835623609488057,
 0.7855875803194464,
 0.7872764759699119,
 0.7734928017376854,
 0.7853920538593591,
 0.7851327127075998,
 0.7841357724523239,
 0.7869624056181531]
# display(h target)
# display(h)
# display(h in2out)
m = h target + h - h_in2out
display(m)
display(sorted(m))
display(sorted(np.argsort(m)[(len(m)-10):len(m)]))
treino non redundant =
treino non redundant[treino non redundant.columns[sorted(np.argsort(m)
[(len(m)-10):len(m)]]]
teste non redundant =
teste non redundant[teste non redundant.columns[sorted(np.argsort(m)
[(len(m)-10):len(m)])]]
display(treino non redundant)
display(teste non redundant)
array([3.00162384, 2.8214826 , 2.83204974, 2.70065498, 2.32079029,
       2.06350709, 2.41329726, 1.33645791, 2.36575554, 2.31211107,
       1.61024584, 2.88815148, 2.70409134, 2.74596132, 2.5365876 ,
       2.3726974 ])
[1.3364579115444073,
 1.610245844678957.
 2.0635070944896645,
2.3121110709261314,
2.3207902860208627,
 2.3657555445293212,
 2.372697403435101,
 2.4132972640652537,
 2.536587603513382,
 2.7006549849823567,
 2.704091335960858,
 2.7459613222737556,
```

- 2.8214825967340147, 2.8320497369436755,
- 2.8881514810734688,
- 3.0016238407752787]

## [0, 1, 2, 3, 6, 11, 12, 13, 14, 15]

[0, 1, 2	, 3, 6, 1	1, 12, 13, 14,	15]	
smo compactn	othness1	compactness1	symmetry1	<pre>fractal_dimension1</pre>
0 0.04904	0.11840	0.27760	0.2419	0.07871
1 0.01308	0.08474	0.07864	0.1812	0.05667
2 0.04006	0.10960	0.15990	0.2069	0.05999
3	0.14250	0.28390	0.2597	0.09744
4 0.02461	0.10030	0.13280	0.1809	0.05883
393 0.03726	0.11670	0.20870	0.2162	0.06606
394 0.01631	0.10290	0.09758	0.1937	0.06161
395 0.01273	0.08045	0.05361	0.1641	0.05764
396 0.01957	0.10590	0.11470	0.1806	0.06079
397 0.03477	0.08044	0.08895	0.1574	0.05750
	othness3 dimension	compactness3	concavity3	symmetry3
0 0.11890	0.16220	0.6656	0.7119	0.4601
1 0.08902	0.12380	0.1866	0.2416	0.2750
2 0.08758	0.14440	0.4245	0.4504	0.3613
3 0.17300	0.20980	0.8663	0.6869	0.6638
4 0.07678	0.13740	0.2050	0.4000	0.2364
393 0.10070	0.15020	0.5717	0.7053	0.3828
394 0.07081	0.14320	0.1773	0.1603	0.3049

395 0.06609	0.10660	0.1231	0.0846	0.2523	
396	0.14280	0.2570	0.3438	0.2666	
0.07686 397	0.09534	0.1812	0.1901	0.1988	
0.07053	0.09554	0.1012	0.1901	0.1900	
[398 row	s x 10 co	lumns]			
smo compactn	othness1	compactness1	symmetry1	<pre>fractal_dim</pre>	ension1
398	0.07741	0.04768	0.1535		0.06214
0.01469	0 00007	0.06333	0 1047		0.00010
399 0.01964	0.09087	0.06232	0.1847		0.06019
400	0.12300	0.25760	0.2113		0.07115
0.03718 401	0.08872	0.05242	0.1601		0.05541
0.01204	0.00072	0103242	0.1001		0.03541
402	0.07351	0.07899	0.1874		0.05899
0.03713					
564	0.11100	0.11590	0.1726		0.05623
0.02891 565	0.09780	0.10340	0.1752		0.05533
0.02423	0.09760	0.10340	0.1752		0.05555
566	0.08455	0.10230	0.1590		0.05648
0.03731	0 11700	0 27700	0 2207		0 07016
567 0.06158	0.11780	0.27700	0.2397		0.07016
568	0.05263	0.04362	0.1587		0.05884
0.00466					
	othness3	compactness3	concavity3	symmetry3	
_	dimension		0 2070	0.2500	
398 0.09158	0.11200	0.18790	0.2079	0.2590	
399	0.12440	0.17260	0.1449	0.2779	
0.08121	0 10700	0 50170	0.0024	0 2245	
400 0.11980	0.18730	0.59170	0.9034	0.3245	
401	0.13740	0.15750	0.1514	0.2460	
0.07262					
402 0.07247	0.09329	0.23180	0.1604	0.3207	
0.0/24/					
564	0.14100	0.21130	0.4107	0.2060	
0.07115					

```
565
         0.11660
                        0.19220
                                      0.3215
                                                  0.2572
0.06637
566
         0.11390
                        0.30940
                                      0.3403
                                                  0.2218
0.07820
567
         0.16500
                        0.86810
                                      0.9387
                                                  0.4087
0.12400
568
         0.08996
                        0.06444
                                      0.0000
                                                  0.2871
0.07039
[171 rows x 10 columns]
```

#### e)

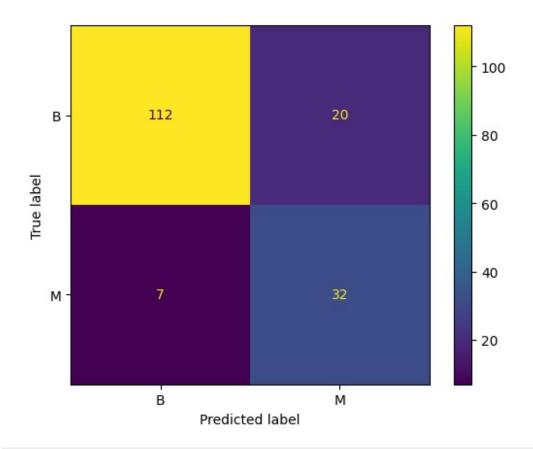
```
### Rocchio
treino treino0, treino validacao0, target treino treino0,
target validacao0 = train test split(treino non redundant,
target treino, test size=0.2,
   random state=1,
stratify = target treino)
model = neighbors.NearestCentroid()
model.fit(treino treino0, np.ravel(target treino treino0))
# print(model.centroids )
target pred0 = model.predict(treino validacao0)
acc = model.score(treino validacao0, target validacao0)
print(f"Acurácia do Rocchio do sklearn para parâmetros selecionados:
{acc*100}%")
Acurácia do Rocchio do sklearn para parâmetros selecionados: 85.0%
### kNN
treino_treino1, treino_validacao1, target_treino_treino1,
target validacao1 = train test split(treino non redundant,
target treino, test size=0.2,
   random state=1,
stratify = target treino)
model = neighbors.KNeighborsClassifier(n neighbors = 3)
model.fit(treino treino1, np.ravel(target treino treino1))
model.predict(treino validacao1)
acc = model.score(treino validacao1, target validacao1)
print(f"Acurácia 3NN: {acc*100}%")
#k-fold
```

```
cv scores = cross val score(model, treino non redundant,
np.ravel(target treino), cv=5, scoring = "accuracy")
print(cv scores)
print("(k-fold cv=5) cv scores médio: {}".format(np.mean(cv scores)))
#Grid Search
model = neighbors.KNeighborsClassifier()
param grid = {"n neighbors": np.arange(1, 10)}
knn_gscv = GridSearchCV(model, param_grid, cv=5)
knn gscv.fit(treino treino1, np.ravel(target treino treino1))
print(f"Melhor valor de k do kNN: {knn gscv.best params } e melhor
resultado: {knn gscv.best score }")
for dicts in knn gscv.best params :
k = knn gscv.best params [dicts]
model = neighbors.KNeighborsClassifier(n neighbors = k)
model.fit(treino treino1, np.ravel(target treino treino1))
target pred1 = model.predict(treino validacao1)
acc = model.score(treino validacao1, np.ravel(target validacao1))
print(f"Acurácia do {k}NN: {acc*100}%")
Acurácia 3NN: 81.25%
[0.85]
            0.9
                       0.8625
                                  0.87341772 0.848101271
(k-fold cv=5) cv scores médio: 0.8668037974683545
Melhor valor de k do kNN: {'n neighbors': 8} e melhor resultado:
0.8898809523809523
Acurácia do 8NN: 83.75%
### Naive Bayes
treino treino2, treino validacao2, target treino treino2,
target validacao2 = train test split(treino non redundant,
target_treino, test size=0.2,
# random state=1,
stratify = target treino)
#considerando atributos com distribuição Gaussiana
model = naive bayes.GaussianNB()
model.fit(treino_treino2, np.ravel(target treino treino2))
target pred2 = model.predict(treino validacao2)
print("Acurácia de %d amostras usando Gaussiana: %d%%"
  % (treino validacao2.shape[0], 100*(np.ravel(target validacao2) ==
target pred2).sum()/treino validacao2.shape[0]))
Acurácia de 80 amostras usando Gaussiana: 78%
```

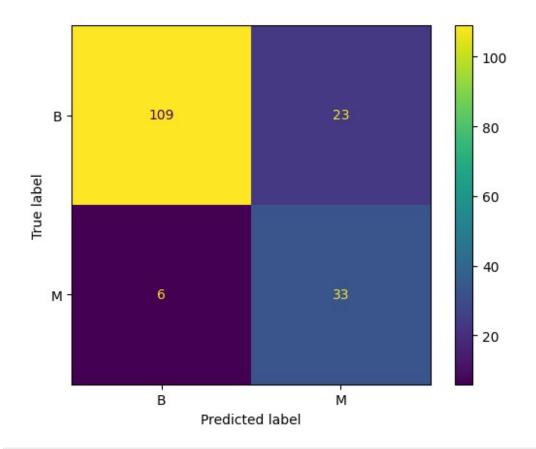
```
f)
```

```
model = neighbors.NearestCentroid()
model.fit(treino treino0, np.ravel(target treino treino0))
target pred0 = model.predict(teste non redundant)
C0 = confusion matrix(target teste, target pred0, labels =
np.unique(target_teste))
recall v = recall score(target teste, target pred0, average=None)
print(f"Recall VN Rocchio: {recall v[0]*100}% \nRecall VP Rocchio:
{recall v[1]*100}%")
precision v = precision score(target teste, target pred0, average=None)
print(f"Precisão VN Rocchio: {precision v[0]*100}% \nPrecisão VP
Rocchio: {precision_v[1]*100}%")
accuracy = accuracy score(target teste, target pred0)
print(f"Acurácia Rocchio: {accuracy*100}%\n")
model = neighbors.KNeighborsClassifier(n neighbors = k)
model.fit(treino treino1, np.ravel(target treino treino1))
target pred1 = model.predict(teste non redundant)
C1 = confusion matrix(target teste, target pred1, labels =
np.unique(target teste))
recall_v = recall_score(target_teste, target_pred1, average=None)
print(f"Recall VN kNN: {recall v[0]*100}%% \nRecall VP kNN:
{recall v[1]*100}%")
precision_v = precision_score(target_teste, target_pred1, average=None)
print(f"Precisão VN kNN: {precision v[0]*100}% \nPrecisão VP kNN:
{precision v[1]*100}%")
accuracy = accuracy score(target teste, target pred1)
print(f"Acurácia kNN: {accuracy*100}%\n")
model = naive bayes.GaussianNB()
model.fit(treino treino2, np.ravel(target treino treino2))
target_pred2 = model.predict(teste non redundant)
C2 = confusion_matrix(target_teste, target_pred2, labels =
np.unique(target teste))
recall v = recall score(target teste, target pred2, average=None)
print(f"Recall VN Naive Bayes distribuição gaussiana:
{recall v[0]*100}% \nRecall VP Naive Bayes distribuição gaussiana:
{recall v[1]*100}%")
precision v = precision score(target teste, target pred2, average=None)
print(f"Precisão VN Naive Bayes distribuição gaussiana:
{precision v[0]*100}% \nPrecisão VP Naive Bayes distribuição
gaussiana: {precision_v[1]*100}%")
accuracy = accuracy score(target teste, target pred2)
print(f"Acurácia Naive Bayes distribuição gaussiana: {accuracy*100}%\\
```

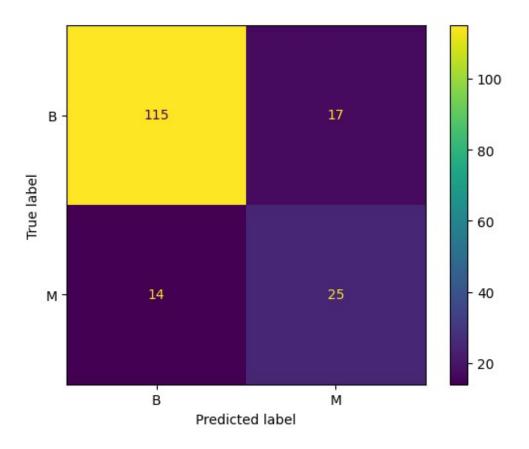
```
n")
plt.figure(1000)
ConfusionMatrixDisplay(confusion matrix=C0, display labels =
np.unique(target validacao0)).plot()
plt.figure(2000)
ConfusionMatrixDisplay(confusion matrix=C1, display labels =
np.unique(target validacao1)).plot()
plt.figure(3000)
ConfusionMatrixDisplay(confusion matrix=C2, display labels =
np.unique(target validacao2)).plot()
Recall VN Rocchio: 84.848484848484848
Recall VP Rocchio: 82.05128205128204%
Precisão VN Rocchio: 94.11764705882352%
Precisão VP Rocchio: 61.53846153846154%
Acurácia Rocchio: 84.21052631578947%
Recall VN kNN: 82.57575757575758%
Recall VP kNN: 84.61538461538461%
Precisão VN kNN: 94.78260869565217%
Precisão VP kNN: 58.92857142857143%
Acurácia kNN: 83.04093567251462%
Recall VN Naive Bayes distribuição gaussiana: 87.12121212121212
Recall VP Naive Bayes distribuição gaussiana: 64.1025641025641%
Precisão VN Naive Bayes distribuição gaussiana: 89.14728682170544%%
Precisão VP Naive Bayes distribuição gaussiana: 59.523809523809526%
Acurácia Naive Bayes distribuição gaussiana: 81.87134502923976%
<sklearn.metrics. plot.confusion matrix.ConfusionMatrixDisplay at</pre>
0x7ac3fa81fe50>
<Figure size 640x480 with 0 Axes>
```



<Figure size 640x480 with 0 Axes>



<Figure size 640x480 with 0 Axes>

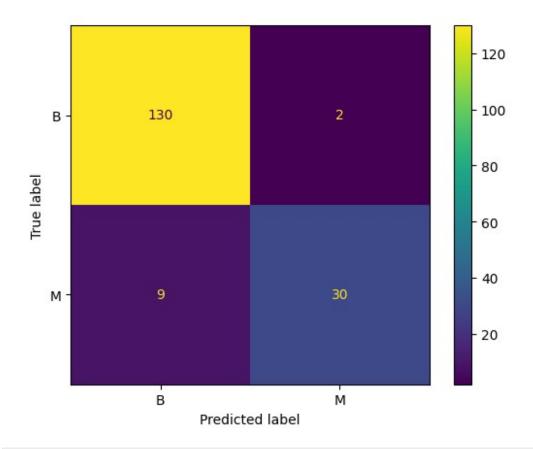


```
g)
### Rocchio
treino treino0, treino validacao0, target treino treino0,
target validacao0 = train test split(treino, target treino,
test_size=0.2,
   random state=1,
stratify = target_treino)
model = neighbors.NearestCentroid()
model.fit(treino_treino0, np.ravel(target_treino_treino0))
# print(model.centroids_)
target pred0 = model.predict(treino validacao0)
acc = model.score(treino validacao0, target validacao0)
print(f"Acurácia do Rocchio do sklearn para todos os parâmetros:
{acc*100}%")
### KNN
treino treinol, treino validacaol, target treino treinol,
target validacao1 = train test split(treino, target treino,
test size=0.2,
```

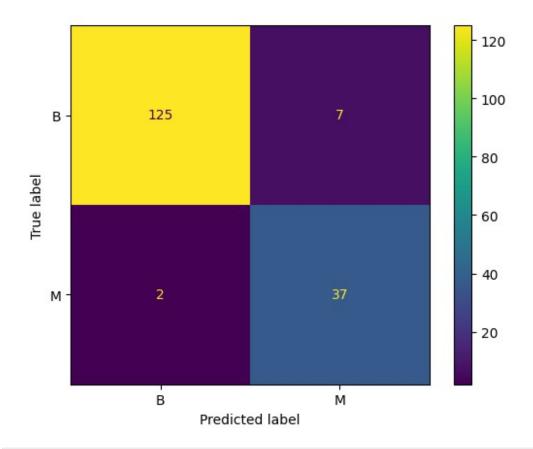
```
random state=1,
stratify = target treino)
model = neighbors.KNeighborsClassifier(n neighbors = 3)
model.fit(treino_treino1, np.ravel(target_treino_treino1))
model.predict(treino validacao1)
acc = model.score(treino validacao1, target validacao1)
print(f"Acurácia 3NN: {acc*100}%")
#k-fold
cv_scores = cross_val_score(model, treino_non_redundant,
np.ravel(target treino), cv=5, scoring = "accuracy")
print(cv scores)
print("(k-fold cv=5) cv scores médio: {}".format(np.mean(cv scores)))
#Grid Search
model = neighbors.KNeighborsClassifier()
param grid = {"n neighbors": np.arange(1, 10)}
knn gscv = GridSearchCV(model, param grid, cv=5)
knn_gscv.fit(treino_treino1, np.ravel(target_treino_treino1))
print(f"Melhor valor de k do kNN: {knn_gscv.best_params_} e melhor
resultado: {knn gscv.best score }")
for dicts in knn gscv.best params :
k = knn_gscv.best_params_[dicts]
model = neighbors.KNeighborsClassifier(n neighbors = k)
model.fit(treino treino1, np.ravel(target treino treino1))
target pred1 = model.predict(treino validacao1)
acc = model.score(treino validacao1, np.ravel(target validacao1))
print(f"Acurácia do {k}NN: {acc*100}%")
### Naive Bayes
treino treino2, treino validacao2, target treino treino2,
target_validacao2 = train_test_split(treino, target_treino,
test size=0.2,
  random state=1,
stratify = target treino)
#considerando atributos com distribuição Gaussiana
model = naive bayes.GaussianNB()
model.fit(treino treino2, np.ravel(target treino treino2))
target_pred2 = model.predict(treino_validacao2)
print("Acurácia de %d amostras usando Gaussiana: %d%%"
  % (treino validacao2.shape[0], 100*(np.ravel(target validacao2) ==
```

```
target pred2).sum()/treino validacao2.shape[0]))
model = neighbors.NearestCentroid()
model.fit(treino treino0, np.ravel(target treino treino0))
target pred0 = model.predict(teste)
C0 = confusion matrix(target teste, target pred0, labels =
np.unique(target teste))
recall v = recall score(target teste, target pred0, average=None)
print(f"Recall VN Rocchio: {recall v[0]*100}%% \nRecall VP Rocchio:
{recall v[1]*100}%")
precision v = precision score(target teste, target pred0, average=None)
print(f"Precisão VN Rocchio: {precision v[0]*100}% \nPrecisão VP
Rocchio: {precision v[1]*100}%")
accuracy = accuracy score(target teste, target pred0)
print(f"Acurácia Rocchio: {accuracy*100}%\n")
model = neighbors.KNeighborsClassifier(n_neighbors = k)
model.fit(treino treino1, np.ravel(target treino treino1))
target pred1 = model.predict(teste)
C1 = confusion matrix(target teste, target pred1, labels =
np.unique(target teste))
recall v = recall score(target teste, target pred1, average=None)
print(f"Recall VN kNN: {recall v[0]*100}% \nRecall VP kNN:
{recall v[1]*100}%%")
precision v = precision score(target teste, target pred1, average=None)
print(f"Precisão VN kNN: {precision_v[0]*100}% \nPrecisão VP kNN:
{precision v[1]*100}%")
accuracy = accuracy score(target teste, target pred1)
print(f"Acurácia kNN: {accuracy*100}%\n")
model = naive bayes.GaussianNB()
model.fit(treino treino2, np.ravel(target treino treino2))
target pred2 = model.predict(teste)
C2 = confusion matrix(target teste, target pred2, labels =
np.unique(target teste))
recall v = recall score(target teste, target pred2, average=None)
print(f"Recall VN Naive Bayes distribuição gaussiana:
{recall v[0]*100}% \nRecall VP Naive Bayes distribuição gaussiana:
{recall v[1]*100}%%")
precision v = precision score(target teste, target pred2, average=None)
print(f"Precisão VN Naive Bayes distribuição gaussiana:
{precision v[0]*100}% \nPrecisão VP Naive Bayes distribuição
qaussiana: {precision v[1]*100}%")
accuracy = accuracy score(target teste, target pred2)
```

```
print(f"Acurácia Naive Bayes distribuição gaussiana: {accuracy*100}%\\
n")
plt.figure(1001)
ConfusionMatrixDisplay(confusion matrix=C0, display labels =
np.unique(target validacao0)).plot()
plt.figure(2001)
ConfusionMatrixDisplay(confusion matrix=C1, display labels =
np.unique(target_validacao1)).plot()
plt.figure(3001)
ConfusionMatrixDisplay(confusion matrix=C2, display labels =
np.unique(target validacao2)).plot()
Acurácia do Rocchio do sklearn para todos os parâmetros: 85.0%
Acurácia 3NN: 92.5%
                       0.8625
                                  0.87341772 0.848101271
            0.9
(k-fold cv=5) cv scores médio: 0.8668037974683545
Melhor valor de k do kNN: {'n neighbors': 7} e melhor resultado:
0.930902777777776
Acurácia do 7NN: 90.0%
Acurácia de 80 amostras usando Gaussiana: 91%
Recall VN Rocchio: 98.48484848484848%
Recall VP Rocchio: 76.92307692307693%
Precisão VN Rocchio: 93.5251798561151%
Precisão VP Rocchio: 93.75%
Acurácia Rocchio: 93.56725146198829%
Recall VN kNN: 94.6969696969697%
Recall VP kNN: 94.87179487179486%
Precisão VN kNN: 98.4251968503937%
Precisão VP kNN: 84.0909090909091%
Acurácia kNN: 94.73684210526315%
Recall VN Naive Bayes distribuição gaussiana: 96.96969696969697%%
Recall VP Naive Bayes distribuição gaussiana: 94.87179487179486%
Precisão VN Naive Bayes distribuição gaussiana: 98.46153846153847%
Precisão VP Naive Bayes distribuição gaussiana: 90.2439024390244%
Acurácia Naive Bayes distribuição gaussiana: 96.49122807017544%
<sklearn.metrics. plot.confusion matrix.ConfusionMatrixDisplay at</pre>
0x7ac3f2faded0>
<Figure size 640x480 with 0 Axes>
```



<Figure size 640x480 with 0 Axes>



<Figure size 640x480 with 0 Axes>

