act uresti

September 8, 2025

1 Actividad Modulo 2

Yose Miguel Sotomayor Carneado A0150908

1.1 Importamos librerias necesarias

1.2 Data

```
[2]: data = load_breast_cancer()

X = data.data
y = data.target
```

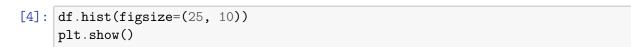
```
[3]: df = pd.DataFrame(X, y, columns=data.feature_names)
df
```

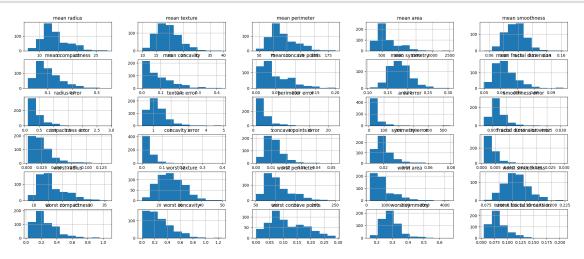
```
[3]: mean radius mean texture mean perimeter mean area mean smoothness \
0 17.99 10.38 122.80 1001.0 0.11840
0 20.57 17.77 132.90 1326.0 0.08474
```

0	19.69	21.25		130.0	00 1	203.0	0.	10960	
0	11.42	20.38		77.5	58	386.1	0.	14250	
0	20.29	14.34		135.1	10 1	297.0	0.	10030	
	***	***			•••		•••		
0	21.56	22.39		142.0	00 1	479.0	0.	11100	
0	20.13	28.25		131.2	20 1	261.0	0.	09780	
0	16.60	28.08		108.3	30	858.1	0.	08455	
0	20.60	29.33		140.1	10 1	265.0	0.	11780	
1	7.76	24.54		47.9	92	181.0	0.	05263	
	mean compactness	s mean cond	avity	mean o	concave	points	mean symm	etry \setminus	
0	0.27760	0.	30010		0	.14710	0.	2419	
0	0.0786	4 0.	08690		0	.07017	0.	1812	
0	0.15990	0.	19740		0	.12790	0.	2069	
0	0.28390	0.	24140		0	.10520	0.	2597	
0	0.13280	0.	19800		0	.10430	0.	1809	
	•••		•••		•••	•			
0	0.11590	0.	24390		0	.13890	0.	1726	
0	0.10340	0.	14400		0	.09791	0.	1752	
0	0.10230	0.	09251		0	.05302	0.	1590	
0	0.27700	0.	35140		0	.15200	0.	2397	
1	0.04362	2 0.	00000		0	.00000	0.	1587	
	mean fractal dir	mension	worst	radius	worst	texture	worst pe	rimeter	. /
0	(0.07871	2	25.380		17.33		184.60)
0	(0.05667	2	24.990		23.41		158.80)
0	(0.05999	2	23.570		25.53		152.50)
0	(0.09744	-	14.910		26.50		98.87	•
0	(0.05883	2	22.540		16.67		152.20)
		•••		•••			•••		
0	(0.05623	2	25.450		26.40		166.10)
0	(0.05533	2	23.690		38.25		155.00)
0	(0.05648		18.980		34.12		126.70)
0	(0.07016	4	25.740		39.42		184.60)
1	(0.05884		9.456		30.37		59.16	5
	worst area wors	st smoothnes	s wor	st comp	actness	worst	concavity	\	
0	2019.0	0.1622	20		0.66560)	0.7119)	
0	1956.0	0.1238	30		0.18660)	0.2416	3	
0	1709.0	0.1444	ŁO		0.42450)	0.4504	Ŀ	
0	567.7	0.2098	30		0.86630)	0.6869)	
0	1575.0	0.1374	ŁO		0.20500)	0.4000)	
	•••	•••					•••		
0	2027.0	0.1410	00		0.21130)	0.4107	•	
0	1731.0	0.1166	30		0.19220)	0.3215	·	
0	1124.0	0.1139	90		0.30940)	0.3403	3	
0	1821.0	0.1650	00		0.86810)	0.9387	•	

1	268.6	0.08996	0.06444	0.0000
	worst concave point	s worst symmetry	worst fractal	dimension
0	0.265	0.4601		0.11890
0	0.186	0.2750		0.08902
0	0.243	0.3613		0.08758
0	0.257	0.6638		0.17300
0	0.162	0.2364		0.07678
		•••		•••
0	0.221	.6 0.2060		0.07115
0	0.162	0.2572		0.06637
0	0.141	.8 0.2218		0.07820
0	0.265	0.4087		0.12400
1	0.000	0.2871		0.07039

[569 rows x 30 columns]





vemos que las distribuciones son bastante validas, y no hay inconsistencia en los datos.

1.2.1 Train-Test Split

1.2.2 Scale the data

se escalan los datos para que la red neuronal no tenga problemas con numeros grandes

```
[6]: X_test_scaled = transform_standardizer(X_test, *fit_standardizer(X_train))
X_train_scaled = transform_standardizer(X_train, *fit_standardizer(X_train))
```

1.3 Neural Network Configuration

```
[7]: input_size = X_test_scaled.shape[1]
  output_size = len(np.unique(y))
  layers = 64

  layer_sizes = [input_size] + [layers] + [output_size]

  nn = NNMultiClass(layer_sizes=layer_sizes, hidden_activation="relu", seed=42,u=1r=3e-1)
  nn.show_weights()
  y_pred = nn.predict(X_test_scaled)
```

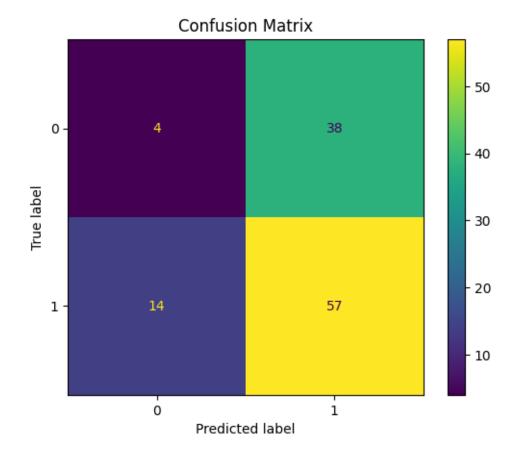
```
Pesos capa 0 (30 \rightarrow 64):
0.15136196]
[0.18363791 \quad 0.20484138 \quad -0.09004043 \dots \quad 0.09214371 \quad 0.37782318
 -0.3069373 ]
 [-0.16518314 -0.23924088 -0.10064846 ... 0.42626776 0.44504858
 -0.04635166]
 [0.0189196 \quad 0.00968846 \quad -0.02346277 \quad ... \quad 0.2622049 \quad -0.4281804
 -0.00204094]
 [0.0707058 -0.07765708 -0.47822613 ... 0.17353917 0.12267754
 -0.17865651]
 -0.37856759]]
Pesos capa 1 (64 → 2):
[[-0.13671713 0.12836322]
[-0.24018807 0.14112389]
[-0.00688776 -0.14904942]
[-0.07288938 -0.12715304]
[ 0.10827815  0.09155348]
 [-0.21489514 -0.05044901]
 [-0.10789821 0.16168875]
[-0.16876239 0.20052864]
 [-0.00416184 -0.1452418 ]
[-0.08465927 -0.10020236]
```

- [-0.1593273 0.01185336]
- [-0.15348944 -0.27254578]
- [-0.04745956 -0.22535702]
- [-0.09402011 -0.11363786]
- [-0.10890201 0.25012039]
- [0.00705145 0.03067138]
- [-0.22204979 -0.08174539]
- [0.02691283 -0.12806611]
- [0.11350786 -0.15033707]
- [-0.03579577 -0.07325645]
- [0.02054008 -0.08006126]
- [-0.0338617 -0.02951626]
- [-0.09179847 0.06063673]
- [0.02979855 -0.01107674]
- [-0.05380729 0.099568]
- [-0.02947928 -0.03833716]
- [0.01308625 0.21207334]
- [-0.16754453 0.09623211]
- 5 ------
- [-0.2366464 0.02715914]
- [0.02132813 -0.07005618]
- [0.0038809 -0.03150785]
- [-0.09824708 -0.03623445]
- [0.02479765 -0.09590213]
- [-0.10078523 -0.17003043]
- [0.04884063 0.06816541]
- [0.02895756 0.12064631]
- [0.01098345 0.04900137]
- [0.03797968 -0.0114425]
- [-0.06635273 0.27676908]
- [-0.05649387 -0.08323471]
- [0.05425123 0.0314818]
- [-0.17559894 0.14033478]
- [-0.01177432 -0.13886639]
- [0.14859801 0.07820945]
- [-0.15806775 0.22214786]
- [0.08234967 -0.00127451]
- [0.19877735 0.01991222]
- [-0.00351038 -0.08253751]
- [0.00183502 -0.09874829] [0.01624123 -0.00872485]
- [-0.16668429 -0.18397654]
- [0.07064417 -0.32523604]
- [0.02567632 -0.05976038]
- [0.16353083 -0.06168353]

1.4 Pre - Backpropagation Prediction

1.4.1 Confusion Matrix

[8]: ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
 plt.title("Confusion Matrix")
 plt.show()



1.4.2 Classification Report

[9]: print(classification_report(y_test, y_pred))

	precision	recall	f1-score	support
0	0.22	0.10 0.80	0.13 0.69	42 71
1	0.00	0.00	0.00	, ,
accuracy			0.54	113
macro avg	0.41	0.45	0.41	113
weighted avg	0.46	0.54	0.48	113

Al tener la red neuronal con pesos aleatorios, nos damos cuenta que el modelo es muy malo, no acertando en nada excepto en el caso del recall para cuando si hay cancer.

1.5 Post - Backpropagation Prediction

```
[10]: nn.fit(X_train_scaled, y_train, epochs=100, verbose=True, batch_size=12)
     nn.show_weights()
     y_pred_back = nn.predict(X_test_scaled)
             1 | loss=0.0754 | acc=0.9627
     Epoch
     Epoch
            10 | loss=0.0118 | acc=0.9978
     Epoch
            20 | loss=0.0044 | acc=1.0000
     Epoch
            30 | loss=0.0025 | acc=1.0000
     Epoch
            40 | loss=0.0018 | acc=1.0000
     Epoch
            50 | loss=0.0012 | acc=1.0000
     Epoch
            60 | loss=0.0010 | acc=1.0000
     Epoch
            70 | loss=0.0008 | acc=1.0000
     Epoch
            80 | loss=0.0007 | acc=1.0000
     Epoch
            90 | loss=0.0006 | acc=1.0000
     Epoch 100 | loss=0.0005 | acc=1.0000
     Pesos capa 0 (30 \rightarrow 64):
     [[0.09582232 - 0.24182964 \ 0.1429559 \ ... - 0.00692755 - 0.0270322]
       0.09307529]
      -0.33071288]
```

[-0.16502683 -0.20602504 -0.1481132 ... 0.50929718 0.377776

 $[-0.10474993 -0.13614516 \ 0.02158844 ... \ 0.35400317 -0.34604035$

[0.01184807 -0.22272733 -0.46169803 ... 0.12743401 0.16537303

-0.10055337]

0.04677166]

-0.12167377]

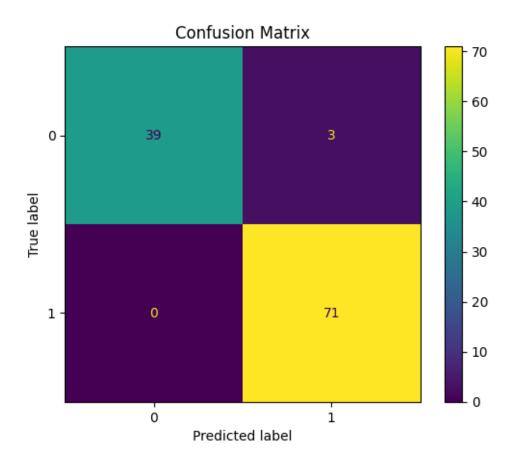
[-0.37771899 0.34937802 0.18190729 ... 0.37980639 0.04488426 -0.30202109]]

```
Pesos capa 1 (64 \rightarrow 2):
[[-0.4238707
               0.415516787
 [-0.46451026 0.36544608]
 [ 0.26965039 -0.42558757]
 [-0.06563598 -0.13440645]
 [ 0.75524641 -0.55541478]
 [-0.11586743 -0.14947673]
 [-0.26339052 0.31718106]
 [-0.30631175 0.338078 ]
 [ 0.68701407 -0.83641771]
 [ 0.17469264 -0.35955427]
 [ 0.38974796 -0.5372219 ]
 [-0.05085441 -0.37518081]
 [-0.22963684 -0.04317975]
 [-0.5455276
             0.33786963]
 [ 0.31542774 -0.17420936]
 [ 0.00232824  0.03539458]
 [-0.66155474 0.35775956]
 [ 0.05576089 -0.15691418]
 [ 0.09044808 -0.1272773 ]
 [ 0.38257371 -0.49162593]
 [ 0.11920511 -0.17872628]
 [-0.11949055 0.05611259]
 [-0.11667327 0.08551153]
 [-0.13493247 0.15365427]
 [-0.3141884
               0.35994911]
 [-0.20827038 0.14045394]
 [-0.93786824 1.16302783]
 [-0.52375069 0.45243828]
 [-0.54494272 0.33545547]
 [-0.30694987 0.56491879]
 [-0.34925877 0.30053072]
 [ 0.30763542 -0.33526237]
 [-0.57051047 0.43602894]
 [ 0.47927616 -0.55038065]
 [-0.32807945 0.0572638 ]
 [ 0.9033696 -0.78636357]
 [ 0.57043922 -0.42083536]
 [-0.10346656 0.16345138]
 [ 0.24143225 -0.21489507]
 [-0.16817483 0.37859118]
 [-0.72486934 0.58514076]
 [ 0.77407554 -0.68834251]
 [-0.52308219 0.48781802]
 [-0.41996018 0.26931947]
```

```
[-0.37516139 0.60196885]
[-0.48078672 0.54486682]
[ 0.07780546  0.00326969]
[ 0.37527923 -0.15658965]
[-0.17469371 0.08864581]
[-0.2435533
              0.37585998]
[-0.24643117 0.1495179]
[-0.03237395 0.03989033]
[ 0.47911329 -0.82977412]
[ 0.44209931 -0.69669117]
[-0.02922146 -0.00486261]
[-0.23066274 0.33251004]
[-0.02470126 0.05752256]
[ 0.1993498 -0.09302672]
[ 0.60658938 -0.53983948]
[-0.02558089 -0.06180724]
[ 0.24890958 -0.05107493]
[ 0.25264623 -0.10852054]
[ 0.12279248 -0.41947803]
[ 0.36010641 -0.21531072]]
```

1.5.1 Confusion Matrix

```
[11]: ConfusionMatrixDisplay.from_predictions(y_test, y_pred_back)
    plt.title("Confusion Matrix")
    plt.show()
```



1.5.2 Classification Report

[12]: print(classification_report(y_test, y_pred_back))

	precision	recall	f1-score	support
0	1.00	0.93	0.96	42
1	0.96	1.00	0.98	71
accuracy			0.97	113
macro avg	0.98	0.96	0.97	113
weighted avg	0.97	0.97	0.97	113

Al aplicar el algoritmo de backpropagation observamos que el modelo funciona muy bien, dandonos resultados consistentes y válidos, dandonos a entender que el modelo aprendio bien los datos y se comporta bien con los datos de prueba.

2 Conclusiones

En resumen, el trabajo realizado permitió consolidar aprendizajes clave, demostrar avances técnicos y prácticos, y fortalecer la capacidad de análisis y adaptación.

Aunque se identificaron áreas de mejora que servirán de guía para el perfeccionamiento futuro, se cuenta ya con una base sólida que permitirá afrontar con mayor claridad y seguridad los retos de las siguientes etapas.

11