```
In [2]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
In [3]: df = pd.read_csv('../data/DATA/cancer_classification.csv')
```

## **Exploratory Data Analysis**

```
In [4]: df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 569 entries, 0 to 568
        Data columns (total 31 columns):
         # Column
                                           Non-Null Count Dtype
                                           569 non-null
         0 mean radius
                                                            float64
         1
                                         569 non-null float64
             mean texture
                                        569 non-null float64
         2 mean perimeter
         3 mean area
                                         569 non-null float64
                                        569 non-null float64
569 non-null float64
569 non-null float64
         4
             mean smoothness
         5 mean compactness
6 mean concavity
             mean concave points 569 non-null float64
mean symmetry 569 non-null float64
float64
         7
         9
             mean fractal dimension 569 non-null float64
         10 radius error
                                569 non-null
                                                            float64
                                        569 non-null
569 non-null
         11 texture error
                                                             float64
         12 perimeter error
                                                             float64
                                                             float64
         13 area error
                                         569 non-null
         14smoothness error569 non-null15compactness error569 non-null16concavity error569 non-null17concave points error569 non-null18symmetry error569 non-null
                                                             float64
                                                              float64
                                                              float64
                                                              float64
                                                              float64
         19 fractal dimension error 569 non-null
                                                              float64
                                         569 non-null
                                                              float64
         20 worst radius
         21 worst texture
                                         569 non-null
                                                             float64
                                       569 non-null
         22 worst perimeter
                                                              float64
                                         569 non-null
         23 worst area
                                                              float64
         24 worst smoothness 569 non-null
25 worst compactness 569 non-null
26 worst concavity 569 non-null
27 worst concave points 569 non-null
                                                              float64
                                                              float64
                                                              float64
                                                              float64
                                         569 non-null
                                                              float64
         28 worst symmetry
         29 worst fractal dimension 569 non-null
                                                              float64
         30 benign_0_mal_1
                                           569 non-null
                                                              int64
```

dtypes: float64(30), int64(1)
memory usage: 137.9 KB

In [6]: df.describe().transpose()

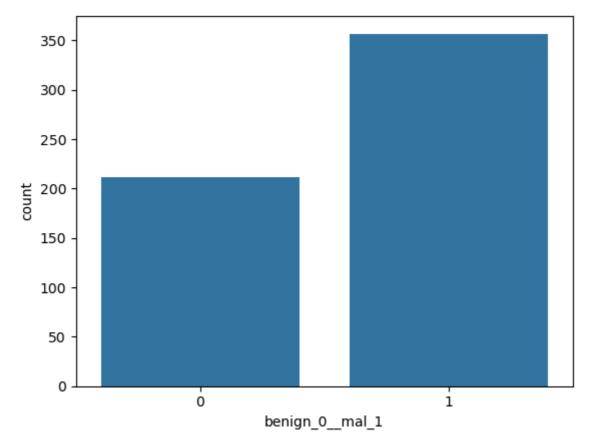
Out[6]:

	count	mean	std	min	25%	50%	
mean radius	569.0	14.127292	3.524049	6.981000	11.700000	13.370000	
mean texture	569.0	19.289649	4.301036	9.710000	16.170000	18.840000	
mean perimeter	569.0	91.969033	24.298981	43.790000	75.170000	86.240000	1
mean area	569.0	654.889104	351.914129	143.500000	420.300000	551.100000	7
mean smoothness	569.0	0.096360	0.014064	0.052630	0.086370	0.095870	
mean compactness	569.0	0.104341	0.052813	0.019380	0.064920	0.092630	
mean concavity	569.0	0.088799	0.079720	0.000000	0.029560	0.061540	
mean concave points	569.0	0.048919	0.038803	0.000000	0.020310	0.033500	
mean symmetry	569.0	0.181162	0.027414	0.106000	0.161900	0.179200	
mean fractal dimension	569.0	0.062798	0.007060	0.049960	0.057700	0.061540	
radius error	569.0	0.405172	0.277313	0.111500	0.232400	0.324200	
texture error	569.0	1.216853	0.551648	0.360200	0.833900	1.108000	
perimeter error	569.0	2.866059	2.021855	0.757000	1.606000	2.287000	
area error	569.0	40.337079	45.491006	6.802000	17.850000	24.530000	
smoothness error	569.0	0.007041	0.003003	0.001713	0.005169	0.006380	
compactness error	569.0	0.025478	0.017908	0.002252	0.013080	0.020450	
concavity error	569.0	0.031894	0.030186	0.000000	0.015090	0.025890	
concave points error	569.0	0.011796	0.006170	0.000000	0.007638	0.010930	
symmetry error	569.0	0.020542	0.008266	0.007882	0.015160	0.018730	
fractal dimension error	569.0	0.003795	0.002646	0.000895	0.002248	0.003187	
worst radius	569.0	16.269190	4.833242	7.930000	13.010000	14.970000	
worst texture	569.0	25.677223	6.146258	12.020000	21.080000	25.410000	
worst perimeter	569.0	107.261213	33.602542	50.410000	84.110000	97.660000	1
worst area	569.0	880.583128	569.356993	185.200000	515.300000	686.500000	10
worst smoothness	569.0	0.132369	0.022832	0.071170	0.116600	0.131300	
worst compactness	569.0	0.254265	0.157336	0.027290	0.147200	0.211900	
worst concavity	569.0	0.272188	0.208624	0.000000	0.114500	0.226700	

	count	mean	std	min	25%	50%
worst concave points	569.0	0.114606	0.065732	0.000000	0.064930	0.099930
worst symmetry	569.0	0.290076	0.061867	0.156500	0.250400	0.282200
worst fractal dimension	569.0	0.083946	0.018061	0.055040	0.071460	0.080040
benign_0mal_1	569.0	0.627417	0.483918	0.000000	0.000000	1.000000

In [7]: sns.countplot(x='benign\_0\_mal\_1', data=df)

Out[7]: <Axes: xlabel='benign\_0\_mal\_1', ylabel='count'>



In [8]: df.corr()['']

Out[8]:

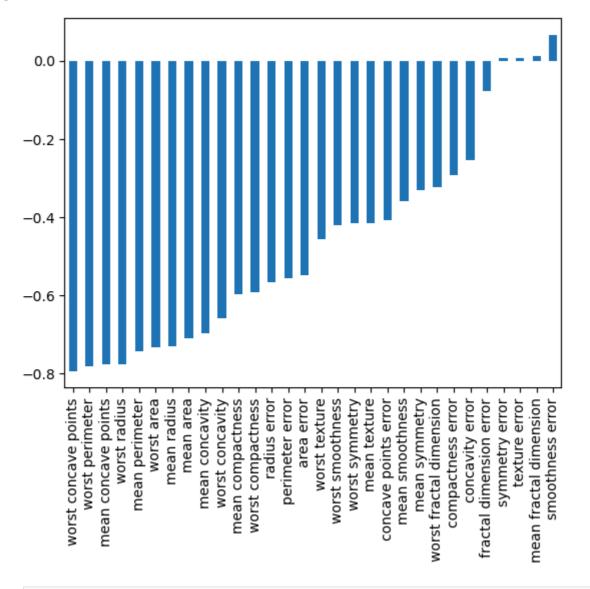
	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness
mean radius	1.000000	0.323782	0.997855	0.987357	0.170581	0.506124
mean texture	0.323782	1.000000	0.329533	0.321086	-0.023389	0.236702
mean perimeter	0.997855	0.329533	1.000000	0.986507	0.207278	0.556936
mean area	0.987357	0.321086	0.986507	1.000000	0.177028	0.498502
mean smoothness	0.170581	-0.023389	0.207278	0.177028	1.000000	0.659123
mean compactness	0.506124	0.236702	0.556936	0.498502	0.659123	1.000000
mean concavity	0.676764	0.302418	0.716136	0.685983	0.521984	0.883121
mean concave points	0.822529	0.293464	0.850977	0.823269	0.553695	0.831135
mean symmetry	0.147741	0.071401	0.183027	0.151293	0.557775	0.602641
mean fractal dimension	-0.311631	-0.076437	-0.261477	-0.283110	0.584792	0.565369
radius error	0.679090	0.275869	0.691765	0.732562	0.301467	0.497473
texture error	-0.097317	0.386358	-0.086761	-0.066280	0.068406	0.046205
perimeter error	0.674172	0.281673	0.693135	0.726628	0.296092	0.548905
area error	0.735864	0.259845	0.744983	0.800086	0.246552	0.455653
smoothness error	-0.222600	0.006614	-0.202694	-0.166777	0.332375	0.135299
compactness error	0.206000	0.191975	0.250744	0.212583	0.318943	0.738722
concavity error	0.194204	0.143293	0.228082	0.207660	0.248396	0.570517
concave points error	0.376169	0.163851	0.407217	0.372320	0.380676	0.642262
symmetry error	-0.104321	0.009127	-0.081629	-0.072497	0.200774	0.229977
fractal dimension error	-0.042641	0.054458	-0.005523	-0.019887	0.283607	0.507318
worst radius	0.969539	0.352573	0.969476	0.962746	0.213120	0.535315
worst texture	0.297008	0.912045	0.303038	0.287489	0.036072	0.248133
worst perimeter	0.965137	0.358040	0.970387	0.959120	0.238853	0.590210
worst area	0.941082	0.343546	0.941550	0.959213	0.206718	0.509604
worst smoothness	0.119616	0.077503	0.150549	0.123523	0.805324	0.565541
worst compactness	0.413463	0.277830	0.455774	0.390410	0.472468	0.865809

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness
worst concavity	0.526911	0.301025	0.563879	0.512606	0.434926	0.816275
worst concave points	0.744214	0.295316	0.771241	0.722017	0.503053	0.815573
worst symmetry	0.163953	0.105008	0.189115	0.143570	0.394309	0.510223
worst fractal dimension	0.007066	0.119205	0.051019	0.003738	0.499316	0.687382
benign_0mal_1	-0.730029	-0.415185	-0.742636	-0.708984	-0.358560	-0.596534

31 rows × 31 columns

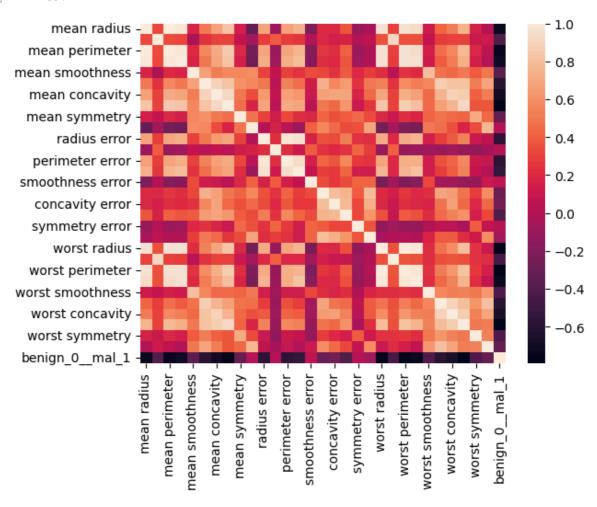


Out[14]: <Axes: >



In [15]: sns.heatmap(df.corr())

Out[15]: <Axes: >



```
In [17]: X= df.drop('benign_0_mal_1', axis=1).values
In [18]: y= df['benign_0_mal_1'].values
In [19]: from sklearn.model_selection import train_test_split
In [20]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random
In [21]:
        from sklearn.preprocessing import MinMaxScaler
In [22]:
         scaler = MinMaxScaler()
In [23]: X_train = scaler.fit_transform(X_train)
         X test = scaler.fit transform(X test)
In [26]:
         X_test.max()
Out[26]: 1.0000000000000000
In [28]:
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Dense, Dropout
In [29]: X_train.shape
Out[29]: (426, 30)
```

```
In [30]: model = Sequential()

In [31]: model.add(Dense(30, activation='relu'))
    model.add(Dense(15, activation='relu'))
    # BINARY CLASSIFICATION PROBLEM we will use sigmoid
    model.add(Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer='adam')

In [32]: model.fit(x=X_train, y=y_train, epochs=600, validation_data=(X_test, y_test))
```

```
Epoch 1/600
0.6472
Epoch 2/600
14/14 [============= ] - 0s 11ms/step - loss: 0.6431 - val_loss:
0.6111
Epoch 3/600
0.5727
Epoch 4/600
0.5328
Epoch 5/600
14/14 [============== ] - 0s 10ms/step - loss: 0.5310 - val_loss:
0.4923
Epoch 6/600
14/14 [============== ] - 0s 11ms/step - loss: 0.4870 - val_loss:
0.4441
Epoch 7/600
0.4000
Epoch 8/600
14/14 [=============] - 0s 11ms/step - loss: 0.4002 - val_loss:
0.3606
Epoch 9/600
14/14 [============== ] - 0s 12ms/step - loss: 0.3566 - val_loss:
0.3178
Epoch 10/600
14/14 [============= ] - 0s 10ms/step - loss: 0.3229 - val_loss:
0.2910
Epoch 11/600
14/14 [============== ] - 0s 6ms/step - loss: 0.2913 - val loss:
0.2662
Epoch 12/600
0.2465
Epoch 13/600
0.2237
Epoch 14/600
0.2167
Epoch 15/600
0.1979
Epoch 16/600
0.1990
Epoch 17/600
0.1865
Epoch 18/600
0.1907
Epoch 19/600
0.1817
Epoch 20/600
0.1636
```

```
Epoch 21/600
0.1735
Epoch 22/600
0.1632
Epoch 23/600
0.1654
Epoch 24/600
14/14 [============= ] - 0s 12ms/step - loss: 0.1305 - val_loss:
0.1563
Epoch 25/600
0.1534
Epoch 26/600
0.1620
Epoch 27/600
0.1664
Epoch 28/600
14/14 [============= ] - 0s 10ms/step - loss: 0.1079 - val_loss:
0.1548
Epoch 29/600
0.1607
Epoch 30/600
0.1678
Epoch 31/600
14/14 [============== ] - 0s 5ms/step - loss: 0.0960 - val loss:
0.1589
Epoch 32/600
0.1472
Epoch 33/600
0.1700
Epoch 34/600
0.1518
Epoch 35/600
0.1657
Epoch 36/600
0.1655
Epoch 37/600
0.1626
Epoch 38/600
0.1789
Epoch 39/600
0.1629
Epoch 40/600
0.1652
```

```
Epoch 41/600
0.1654
Epoch 42/600
14/14 [============= ] - 0s 15ms/step - loss: 0.0709 - val_loss:
0.1781
Epoch 43/600
0.1629
Epoch 44/600
14/14 [============= ] - 0s 19ms/step - loss: 0.0728 - val_loss:
0.1991
Epoch 45/600
0.1647
Epoch 46/600
14/14 [============== ] - 0s 15ms/step - loss: 0.0680 - val_loss:
0.1825
Epoch 47/600
14/14 [============== ] - 0s 13ms/step - loss: 0.0659 - val_loss:
0.1893
Epoch 48/600
0.1779
Epoch 49/600
0.1805
Epoch 50/600
0.1969
Epoch 51/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0615 - val loss:
0.1780
Epoch 52/600
0.2110
Epoch 53/600
0.1894
Epoch 54/600
0.2036
Epoch 55/600
0.1721
Epoch 56/600
0.2127
Epoch 57/600
0.1920
Epoch 58/600
0.2120
Epoch 59/600
0.1946
Epoch 60/600
0.1916
```

```
Epoch 61/600
0.2044
Epoch 62/600
0.1908
Epoch 63/600
14/14 [============== ] - 0s 7ms/step - loss: 0.0561 - val loss:
0.2252
Epoch 64/600
0.1913
Epoch 65/600
0.2479
Epoch 66/600
0.1872
Epoch 67/600
0.2047
Epoch 68/600
0.2151
Epoch 69/600
0.2137
Epoch 70/600
0.2195
Epoch 71/600
14/14 [============== ] - 0s 8ms/step - loss: 0.0542 - val loss:
0.2191
Epoch 72/600
0.2311
Epoch 73/600
14/14 [============== ] - 0s 22ms/step - loss: 0.0532 - val_loss:
0.1844
Epoch 74/600
14/14 [============= ] - 0s 20ms/step - loss: 0.0520 - val loss:
0.2446
Epoch 75/600
0.2163
Epoch 76/600
14/14 [============= ] - 0s 20ms/step - loss: 0.0549 - val loss:
0.2148
Epoch 77/600
0.2457
Epoch 78/600
0.2246
Epoch 79/600
0.2418
Epoch 80/600
0.2246
```

```
Epoch 81/600
0.2343
Epoch 82/600
0.2081
Epoch 83/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0508 - val loss:
0.2482
Epoch 84/600
0.2103
Epoch 85/600
0.2420
Epoch 86/600
0.2234
Epoch 87/600
0.2523
Epoch 88/600
0.2282
Epoch 89/600
0.2465
Epoch 90/600
0.2200
Epoch 91/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0491 - val loss:
0.2456
Epoch 92/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0498 - val loss:
0.2396
Epoch 93/600
0.2424
Epoch 94/600
0.2334
Epoch 95/600
0.2584
Epoch 96/600
0.2286
Epoch 97/600
0.2872
Epoch 98/600
14/14 [============= ] - 0s 16ms/step - loss: 0.0500 - val loss:
0.2121
Epoch 99/600
14/14 [============= ] - 0s 14ms/step - loss: 0.0486 - val loss:
0.2671
Epoch 100/600
14/14 [============== ] - 0s 13ms/step - loss: 0.0471 - val_loss:
0.2390
```

```
Epoch 101/600
0.2454
Epoch 102/600
14/14 [============= ] - 0s 34ms/step - loss: 0.0481 - val_loss:
0.2631
Epoch 103/600
0.2297
Epoch 104/600
14/14 [============= ] - 0s 14ms/step - loss: 0.0494 - val_loss:
0.2853
Epoch 105/600
14/14 [============== ] - 0s 13ms/step - loss: 0.0479 - val_loss:
0.2510
Epoch 106/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0514 - val_loss:
0.2824
Epoch 107/600
0.2424
Epoch 108/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0518 - val_loss:
0.2802
Epoch 109/600
14/14 [============== ] - 0s 13ms/step - loss: 0.0450 - val_loss:
0.2370
Epoch 110/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0467 - val_loss:
0.2962
Epoch 111/600
0.2670
Epoch 112/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0440 - val loss:
0.2832
Epoch 113/600
14/14 [==============] - 0s 11ms/step - loss: 0.0445 - val_loss:
Epoch 114/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0465 - val loss:
0.2399
Epoch 115/600
0.3305
Epoch 116/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0467 - val loss:
0.2564
Epoch 117/600
0.2907
Epoch 118/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0448 - val loss:
0.2887
Epoch 119/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0459 - val loss:
0.3029
Epoch 120/600
0.2943
```

```
Epoch 121/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0459 - val_loss:
0.2651
Epoch 122/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0439 - val_loss:
0.2982
Epoch 123/600
0.2724
Epoch 124/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0431 - val_loss:
0.2709
Epoch 125/600
0.2729
Epoch 126/600
0.3522
Epoch 127/600
0.2578
Epoch 128/600
0.2991
Epoch 129/600
0.2945
Epoch 130/600
0.3227
Epoch 131/600
14/14 [============== ] - 0s 8ms/step - loss: 0.0452 - val loss:
0.3078
Epoch 132/600
0.2869
Epoch 133/600
0.2819
Epoch 134/600
0.3191
Epoch 135/600
0.3004
Epoch 136/600
0.3274
Epoch 137/600
0.2523
Epoch 138/600
0.3150
Epoch 139/600
0.2988
Epoch 140/600
0.3088
```

```
Epoch 141/600
0.3082
Epoch 142/600
0.3298
Epoch 143/600
14/14 [============== ] - 0s 7ms/step - loss: 0.0417 - val loss:
0.3041
Epoch 144/600
0.3163
Epoch 145/600
0.3386
Epoch 146/600
0.3334
Epoch 147/600
0.3410
Epoch 148/600
0.3358
Epoch 149/600
0.3421
Epoch 150/600
0.3293
Epoch 151/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0385 - val loss:
0.3481
Epoch 152/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0391 - val loss:
0.3093
Epoch 153/600
0.3368
Epoch 154/600
0.3442
Epoch 155/600
0.3178
Epoch 156/600
0.3460
Epoch 157/600
0.3462
Epoch 158/600
0.3580
Epoch 159/600
0.3348
Epoch 160/600
0.3701
```

```
Epoch 161/600
0.3250
Epoch 162/600
0.3593
Epoch 163/600
14/14 [============== ] - 0s 7ms/step - loss: 0.0384 - val loss:
0.3615
Epoch 164/600
0.3366
Epoch 165/600
0.3611
Epoch 166/600
0.3851
Epoch 167/600
0.3310
Epoch 168/600
0.3687
Epoch 169/600
0.3561
Epoch 170/600
0.3361
Epoch 171/600
14/14 [============== ] - 0s 7ms/step - loss: 0.0424 - val loss:
0.4062
Epoch 172/600
0.3237
Epoch 173/600
0.4132
Epoch 174/600
0.3431
Epoch 175/600
0.4007
Epoch 176/600
0.3699
Epoch 177/600
0.3846
Epoch 178/600
0.3846
Epoch 179/600
0.3651
Epoch 180/600
0.4069
```

```
Epoch 181/600
0.3954
Epoch 182/600
0.4018
Epoch 183/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0343 - val loss:
0.3613
Epoch 184/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0345 - val_loss:
0.4002
Epoch 185/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0359 - val_loss:
0.4121
Epoch 186/600
0.3555
Epoch 187/600
0.4182
Epoch 188/600
14/14 [============= ] - 0s 13ms/step - loss: 0.0352 - val_loss:
0.3426
Epoch 189/600
14/14 [============== ] - 0s 18ms/step - loss: 0.0357 - val_loss:
0.4212
Epoch 190/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0346 - val_loss:
0.4054
Epoch 191/600
14/14 [============== ] - 0s 14ms/step - loss: 0.0337 - val_loss:
0.4109
Epoch 192/600
14/14 [============= ] - 0s 15ms/step - loss: 0.0369 - val loss:
0.4268
Epoch 193/600
0.3600
Epoch 194/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0350 - val loss:
0.3862
Epoch 195/600
0.4147
Epoch 196/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0329 - val loss:
0.4215
Epoch 197/600
0.3835
Epoch 198/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0411 - val loss:
0.4209
Epoch 199/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0327 - val loss:
0.4196
Epoch 200/600
0.3967
```

```
Epoch 201/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0362 - val_loss:
0.4741
Epoch 202/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0399 - val_loss:
0.3921
Epoch 203/600
0.4672
Epoch 204/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0313 - val_loss:
0.3689
Epoch 205/600
0.4731
Epoch 206/600
14/14 [============== ] - 0s 18ms/step - loss: 0.0353 - val_loss:
0.4624
Epoch 207/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0333 - val_loss:
0.3995
Epoch 208/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0347 - val_loss:
0.4454
Epoch 209/600
0.4236
Epoch 210/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0419 - val_loss:
0.4080
Epoch 211/600
0.4253
Epoch 212/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0343 - val loss:
0.4379
Epoch 213/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0310 - val_loss:
0.3990
Epoch 214/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0309 - val loss:
0.4538
Epoch 215/600
0.4309
Epoch 216/600
0.4600
Epoch 217/600
0.4735
Epoch 218/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0315 - val loss:
0.4407
Epoch 219/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0316 - val loss:
0.4506
Epoch 220/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0333 - val_loss:
0.4736
```

```
Epoch 221/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0311 - val_loss:
0.4631
Epoch 222/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0323 - val_loss:
0.4850
Epoch 223/600
0.3830
Epoch 224/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0356 - val_loss:
0.5299
Epoch 225/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0339 - val_loss:
0.4288
Epoch 226/600
0.4516
Epoch 227/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0336 - val_loss:
0.4371
Epoch 228/600
0.4757
Epoch 229/600
0.5046
Epoch 230/600
0.3778
Epoch 231/600
0.5399
Epoch 232/600
0.4033
Epoch 233/600
14/14 [============= ] - 0s 14ms/step - loss: 0.0304 - val loss:
0.5143
Epoch 234/600
14/14 [============= ] - 0s 13ms/step - loss: 0.0297 - val loss:
0.4466
Epoch 235/600
0.5351
Epoch 236/600
14/14 [============= ] - 0s 16ms/step - loss: 0.0362 - val loss:
0.4416
Epoch 237/600
0.4522
Epoch 238/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0311 - val loss:
0.5549
Epoch 239/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0309 - val loss:
0.5128
Epoch 240/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0289 - val_loss:
0.4587
```

```
Epoch 241/600
0.5027
Epoch 242/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0288 - val_loss:
0.4713
Epoch 243/600
0.5557
Epoch 244/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0298 - val_loss:
0.4492
Epoch 245/600
0.4990
Epoch 246/600
0.4473
Epoch 247/600
0.5551
Epoch 248/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0264 - val_loss:
0.4195
Epoch 249/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0377 - val_loss:
0.5709
Epoch 250/600
0.4240
Epoch 251/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0269 - val loss:
0.5389
Epoch 252/600
0.4723
Epoch 253/600
0.4881
Epoch 254/600
0.4964
Epoch 255/600
0.4471
Epoch 256/600
0.4737
Epoch 257/600
0.4775
Epoch 258/600
0.4881
Epoch 259/600
0.5289
Epoch 260/600
0.5374
```

```
Epoch 261/600
0.5184
Epoch 262/600
0.5029
Epoch 263/600
14/14 [============== ] - 0s 8ms/step - loss: 0.0279 - val loss:
0.5334
Epoch 264/600
0.5156
Epoch 265/600
0.5038
Epoch 266/600
0.5577
Epoch 267/600
0.5192
Epoch 268/600
0.5352
Epoch 269/600
0.5065
Epoch 270/600
0.6129
Epoch 271/600
14/14 [============== ] - 0s 8ms/step - loss: 0.0329 - val loss:
0.5702
Epoch 272/600
0.4735
Epoch 273/600
0.6440
Epoch 274/600
0.4936
Epoch 275/600
0.5618
Epoch 276/600
0.4999
Epoch 277/600
0.5478
Epoch 278/600
0.5308
Epoch 279/600
0.5575
Epoch 280/600
0.5400
```

```
Epoch 281/600
0.5615
Epoch 282/600
0.5527
Epoch 283/600
14/14 [============== ] - 0s 6ms/step - loss: 0.0235 - val loss:
0.5365
Epoch 284/600
0.5941
Epoch 285/600
0.5330
Epoch 286/600
0.5384
Epoch 287/600
0.5566
Epoch 288/600
0.5414
Epoch 289/600
0.6256
Epoch 290/600
0.5706
Epoch 291/600
14/14 [============== ] - 0s 8ms/step - loss: 0.0240 - val loss:
0.5372
Epoch 292/600
0.6186
Epoch 293/600
0.5473
Epoch 294/600
0.5904
Epoch 295/600
0.5950
Epoch 296/600
0.5479
Epoch 297/600
0.5987
Epoch 298/600
0.5737
Epoch 299/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0222 - val loss:
0.5772
Epoch 300/600
0.6287
```

```
Epoch 301/600
0.5486
Epoch 302/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0251 - val_loss:
0.5746
Epoch 303/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0270 - val loss:
0.6323
Epoch 304/600
0.4709
Epoch 305/600
0.6556
Epoch 306/600
0.4915
Epoch 307/600
0.6993
Epoch 308/600
0.5529
Epoch 309/600
0.6148
Epoch 310/600
0.6164
Epoch 311/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0215 - val loss:
0.6004
Epoch 312/600
0.5975
Epoch 313/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0224 - val_loss:
0.6089
Epoch 314/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0225 - val loss:
0.6420
Epoch 315/600
0.5337
Epoch 316/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0267 - val loss:
0.6899
Epoch 317/600
0.4977
Epoch 318/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0249 - val loss:
0.7055
Epoch 319/600
14/14 [============= ] - 0s 13ms/step - loss: 0.0248 - val loss:
0.5971
Epoch 320/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0232 - val_loss:
0.6404
```

```
Epoch 321/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0220 - val_loss:
0.6124
Epoch 322/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0219 - val_loss:
0.5983
Epoch 323/600
0.6348
Epoch 324/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0207 - val_loss:
0.6123
Epoch 325/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0219 - val_loss:
0.6042
Epoch 326/600
0.6287
Epoch 327/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0202 - val_loss:
0.5891
Epoch 328/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0261 - val_loss:
0.6933
Epoch 329/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0215 - val_loss:
0.6206
Epoch 330/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0201 - val_loss:
0.6086
Epoch 331/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0252 - val_loss:
0.7147
Epoch 332/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0251 - val loss:
0.6291
Epoch 333/600
14/14 [==============] - 0s 11ms/step - loss: 0.0198 - val_loss:
0.6358
Epoch 334/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0209 - val loss:
0.6485
Epoch 335/600
0.5829
Epoch 336/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0205 - val loss:
0.6559
Epoch 337/600
0.7180
Epoch 338/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0236 - val loss:
0.6350
Epoch 339/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0202 - val loss:
0.6526
Epoch 340/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0201 - val_loss:
0.7106
```

```
Epoch 341/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0190 - val_loss:
0.6220
Epoch 342/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0203 - val_loss:
0.6882
Epoch 343/600
0.5947
Epoch 344/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0234 - val_loss:
0.7651
Epoch 345/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0223 - val_loss:
0.6023
Epoch 346/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0202 - val_loss:
0.6619
Epoch 347/600
0.6856
Epoch 348/600
0.6682
Epoch 349/600
0.7046
Epoch 350/600
0.6609
Epoch 351/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0196 - val_loss:
0.6420
Epoch 352/600
0.7941
Epoch 353/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0206 - val loss:
0.6502
Epoch 354/600
0.7181
Epoch 355/600
0.6598
Epoch 356/600
0.6494
Epoch 357/600
0.7212
Epoch 358/600
0.6253
Epoch 359/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0226 - val loss:
0.7475
Epoch 360/600
0.6385
```

```
Epoch 361/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0192 - val_loss:
0.6777
Epoch 362/600
0.7115
Epoch 363/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0192 - val loss:
0.6412
Epoch 364/600
0.7938
Epoch 365/600
0.6853
Epoch 366/600
0.7444
Epoch 367/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0187 - val_loss:
0.7233
Epoch 368/600
0.7178
Epoch 369/600
0.7052
Epoch 370/600
0.6809
Epoch 371/600
14/14 [============== ] - 0s 8ms/step - loss: 0.0176 - val loss:
0.7052
Epoch 372/600
0.7079
Epoch 373/600
0.7682
Epoch 374/600
0.6350
Epoch 375/600
0.7183
Epoch 376/600
0.7547
Epoch 377/600
0.6839
Epoch 378/600
0.7488
Epoch 379/600
0.6462
Epoch 380/600
0.7829
```

```
Epoch 381/600
0.7216
Epoch 382/600
0.7178
Epoch 383/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0181 - val loss:
0.7496
Epoch 384/600
0.7298
Epoch 385/600
0.7151
Epoch 386/600
0.7430
Epoch 387/600
0.7199
Epoch 388/600
0.7667
Epoch 389/600
0.7838
Epoch 390/600
0.7403
Epoch 391/600
14/14 [============== ] - 0s 8ms/step - loss: 0.0171 - val loss:
0.7264
Epoch 392/600
0.8047
Epoch 393/600
0.6865
Epoch 394/600
0.7188
Epoch 395/600
0.8610
Epoch 396/600
0.7246
Epoch 397/600
14/14 [=============== ] - 0s 9ms/step - loss: 0.0183 - val loss:
0.7807
Epoch 398/600
0.7659
Epoch 399/600
0.7092
Epoch 400/600
0.7720
```

```
Epoch 401/600
0.7059
Epoch 402/600
0.8668
Epoch 403/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0224 - val loss:
0.6528
Epoch 404/600
0.8091
Epoch 405/600
0.7248
Epoch 406/600
0.7957
Epoch 407/600
0.7061
Epoch 408/600
0.7960
Epoch 409/600
0.7794
Epoch 410/600
0.7824
Epoch 411/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0146 - val_loss:
0.7381
Epoch 412/600
0.8760
Epoch 413/600
0.7805
Epoch 414/600
0.7375
Epoch 415/600
0.8726
Epoch 416/600
0.7268
Epoch 417/600
0.8547
Epoch 418/600
0.7738
Epoch 419/600
0.7800
Epoch 420/600
0.8329
```

```
Epoch 421/600
0.8371
Epoch 422/600
0.7446
Epoch 423/600
14/14 [============== ] - 0s 8ms/step - loss: 0.0147 - val loss:
0.8768
Epoch 424/600
0.7953
Epoch 425/600
0.7685
Epoch 426/600
0.8417
Epoch 427/600
0.7407
Epoch 428/600
0.8837
Epoch 429/600
0.7923
Epoch 430/600
14/14 [============= ] - 0s 13ms/step - loss: 0.0127 - val_loss:
0.8404
Epoch 431/600
14/14 [============== ] - 0s 13ms/step - loss: 0.0134 - val_loss:
0.8256
Epoch 432/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0129 - val loss:
0.7938
Epoch 433/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0124 - val loss:
0.8441
Epoch 434/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0127 - val loss:
0.8204
Epoch 435/600
0.8194
Epoch 436/600
14/14 [============= ] - 0s 13ms/step - loss: 0.0120 - val loss:
0.8545
Epoch 437/600
0.7966
Epoch 438/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0134 - val loss:
0.9156
Epoch 439/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0162 - val loss:
0.7992
Epoch 440/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0137 - val_loss:
0.8150
```

```
Epoch 441/600
0.8896
Epoch 442/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0119 - val_loss:
0.8014
Epoch 443/600
0.8638
Epoch 444/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0138 - val_loss:
0.7688
Epoch 445/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0145 - val_loss:
0.8649
Epoch 446/600
0.9176
Epoch 447/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0134 - val_loss:
0.8331
Epoch 448/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0140 - val_loss:
0.8409
Epoch 449/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0140 - val_loss:
0.9333
Epoch 450/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0118 - val_loss:
0.8129
Epoch 451/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0116 - val_loss:
0.9340
Epoch 452/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0118 - val loss:
0.8558
Epoch 453/600
14/14 [============== ] - 0s 13ms/step - loss: 0.0111 - val_loss:
0.8966
Epoch 454/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0108 - val loss:
0.8681
Epoch 455/600
1.0131
Epoch 456/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0146 - val loss:
0.8447
Epoch 457/600
0.9416
Epoch 458/600
0.8640
Epoch 459/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0143 - val loss:
0.8050
Epoch 460/600
0.9466
```

```
Epoch 461/600
0.8800
Epoch 462/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0108 - val_loss:
0.9128
Epoch 463/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0102 - val loss:
0.8962
Epoch 464/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0106 - val_loss:
0.9462
Epoch 465/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0124 - val_loss:
0.8547
Epoch 466/600
0.9464
Epoch 467/600
0.9583
Epoch 468/600
0.9088
Epoch 469/600
0.9809
Epoch 470/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0111 - val_loss:
0.9123
Epoch 471/600
0.9062
Epoch 472/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0145 - val loss:
0.8450
Epoch 473/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0149 - val loss:
0.9884
Epoch 474/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0136 - val loss:
0.9687
Epoch 475/600
0.9490
Epoch 476/600
14/14 [============= ] - 0s 13ms/step - loss: 0.0155 - val loss:
0.8567
Epoch 477/600
0.9853
Epoch 478/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0108 - val loss:
0.8444
Epoch 479/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0106 - val loss:
1.0295
Epoch 480/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0099 - val_loss:
0.9058
```

```
Epoch 481/600
0.9618
Epoch 482/600
14/14 [============= ] - 0s 13ms/step - loss: 0.0098 - val_loss:
0.9898
Epoch 483/600
0.9010
Epoch 484/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0118 - val_loss:
0.9754
Epoch 485/600
14/14 [============== ] - 0s 16ms/step - loss: 0.0104 - val_loss:
0.9676
Epoch 486/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0096 - val_loss:
0.9609
Epoch 487/600
14/14 [============== ] - 0s 14ms/step - loss: 0.0096 - val_loss:
0.9707
Epoch 488/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0097 - val_loss:
0.9688
Epoch 489/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0097 - val_loss:
0.9110
Epoch 490/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0100 - val_loss:
0.9773
Epoch 491/600
14/14 [============== ] - 0s 13ms/step - loss: 0.0091 - val_loss:
0.9313
Epoch 492/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0091 - val loss:
0.9501
Epoch 493/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0108 - val_loss:
0.9935
Epoch 494/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0090 - val loss:
0.9212
Epoch 495/600
0.9851
Epoch 496/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0111 - val loss:
1.0460
Epoch 497/600
0.9548
Epoch 498/600
14/14 [============= ] - 0s 13ms/step - loss: 0.0089 - val loss:
1.0392
Epoch 499/600
14/14 [============= ] - 0s 14ms/step - loss: 0.0084 - val loss:
0.9115
Epoch 500/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0113 - val_loss:
0.9304
```

```
Epoch 501/600
1.0480
Epoch 502/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0086 - val_loss:
0.9765
Epoch 503/600
0.9213
Epoch 504/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0103 - val_loss:
1.1067
Epoch 505/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0118 - val_loss:
0.9269
Epoch 506/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0098 - val_loss:
1.0733
Epoch 507/600
14/14 [============== ] - 0s 14ms/step - loss: 0.0125 - val_loss:
1.0584
Epoch 508/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0130 - val_loss:
0.9522
Epoch 509/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0107 - val_loss:
0.9668
Epoch 510/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0104 - val_loss:
1.0044
Epoch 511/600
0.9919
Epoch 512/600
1.0550
Epoch 513/600
0.9761
Epoch 514/600
1.0286
Epoch 515/600
0.9960
Epoch 516/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0076 - val loss:
1.0070
Epoch 517/600
1.0653
Epoch 518/600
0.9949
Epoch 519/600
1.0336
Epoch 520/600
0.9505
```

```
Epoch 521/600
1.1282
Epoch 522/600
0.9612
Epoch 523/600
14/14 [============== ] - 0s 7ms/step - loss: 0.0085 - val loss:
1.0952
Epoch 524/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0088 - val_loss:
1.0342
Epoch 525/600
1.0480
Epoch 526/600
0.9697
Epoch 527/600
1.0843
Epoch 528/600
1.0964
Epoch 529/600
1.0532
Epoch 530/600
0.8690
Epoch 531/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0189 - val loss:
1.1023
Epoch 532/600
1,2006
Epoch 533/600
0.9232
Epoch 534/600
1.1752
Epoch 535/600
1.0410
Epoch 536/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0106 - val loss:
0.9476
Epoch 537/600
1.1062
Epoch 538/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0070 - val loss:
1.0358
Epoch 539/600
1.1123
Epoch 540/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0077 - val_loss:
1.0074
```

```
Epoch 541/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0075 - val_loss:
1.0556
Epoch 542/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0071 - val_loss:
1.0903
Epoch 543/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0070 - val loss:
1.0560
Epoch 544/600
1.1002
Epoch 545/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0094 - val_loss:
0.9488
Epoch 546/600
1.2166
Epoch 547/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0156 - val_loss:
0.8844
Epoch 548/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0150 - val_loss:
1.3800
Epoch 549/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0243 - val_loss:
0.7983
Epoch 550/600
1.2114
Epoch 551/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0144 - val loss:
1.1410
Epoch 552/600
1.0955
Epoch 553/600
1.0812
Epoch 554/600
1.0899
Epoch 555/600
1.0906
Epoch 556/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0071 - val loss:
1.0459
Epoch 557/600
1.1298
Epoch 558/600
1.0269
Epoch 559/600
1.1490
Epoch 560/600
1.0760
```

```
Epoch 561/600
1.1285
Epoch 562/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0066 - val_loss:
1.1069
Epoch 563/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0061 - val loss:
1.0957
Epoch 564/600
1.1100
Epoch 565/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0062 - val_loss:
1.1206
Epoch 566/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0059 - val_loss:
1.0785
Epoch 567/600
1.1418
Epoch 568/600
1.0690
Epoch 569/600
1,1201
Epoch 570/600
1.1450
Epoch 571/600
14/14 [============== ] - 0s 9ms/step - loss: 0.0061 - val loss:
1.0656
Epoch 572/600
1.1547
Epoch 573/600
1.0828
Epoch 574/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0075 - val loss:
1.1890
Epoch 575/600
1.1241
Epoch 576/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0065 - val loss:
1.0944
Epoch 577/600
1.1563
Epoch 578/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0057 - val loss:
1.1732
Epoch 579/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0061 - val loss:
1.0641
Epoch 580/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0055 - val_loss:
1,2347
```

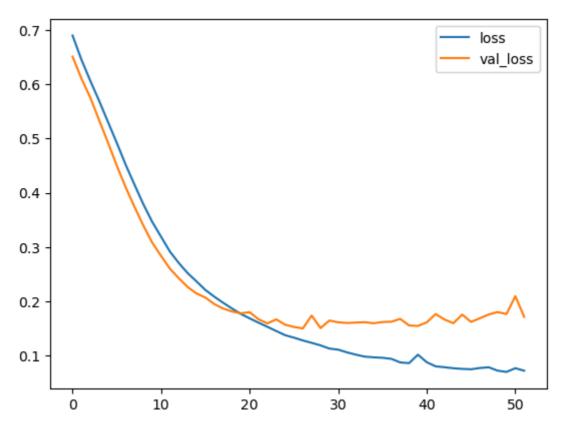
```
Epoch 581/600
14/14 [============== ] - 0s 15ms/step - loss: 0.0094 - val_loss:
1.0477
Epoch 582/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0059 - val_loss:
1.3149
Epoch 583/600
1.1223
Epoch 584/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0091 - val_loss:
1.0827
Epoch 585/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0071 - val_loss:
1.1905
Epoch 586/600
14/14 [============== ] - 0s 13ms/step - loss: 0.0057 - val_loss:
1.1365
Epoch 587/600
1.1415
Epoch 588/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0071 - val_loss:
1.1859
Epoch 589/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0057 - val_loss:
1.1559
Epoch 590/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0053 - val_loss:
1.1236
Epoch 591/600
14/14 [============== ] - 0s 11ms/step - loss: 0.0074 - val_loss:
1.2649
Epoch 592/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0056 - val loss:
1.1206
Epoch 593/600
14/14 [============== ] - 0s 12ms/step - loss: 0.0053 - val_loss:
1.1901
Epoch 594/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0053 - val loss:
1.1732
Epoch 595/600
1.2259
Epoch 596/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0068 - val loss:
1.1611
Epoch 597/600
1.1861
Epoch 598/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0048 - val loss:
1.1255
Epoch 599/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0051 - val loss:
1.2346
Epoch 600/600
14/14 [============== ] - 0s 10ms/step - loss: 0.0055 - val_loss:
1.1116
```

```
Out[32]: <keras.callbacks.History at 0x1f1d246e5b0>
In [34]:
         losses = pd.DataFrame(model.history.history)
In [35]:
        losses.plot()
Out[35]: <Axes: >
        1.4
                    loss
                     val loss
        1.2
        1.0
        0.8
        0.6
        0.4
        0.2
        0.0
                0
                         100
                                    200
                                               300
                                                         400
                                                                    500
                                                                               600
         # This is the perfect example of overfitting, during the first few epochs both L
In [36]:
In [37]:
         #however at certain point our loss is decreasing vs val loss is increasing; this
In [39]:
         # we need to try early stopping
In [43]:
         model_v1 = Sequential()
         model_v1.add(Dense(30, activation='relu'))
         model v1.add(Dense(15, activation='relu'))
         # BINARY CLASSIFICATION PROBLEM we will use sigmoid
         model_v1.add(Dense(1, activation='sigmoid'))
         model_v1.compile(loss='binary_crossentropy', optimizer='adam')
In [44]: from tensorflow.keras.callbacks import EarlyStopping
         earlyStop = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=25
In [45]:
In [46]: model_v1.fit(x=X_train, y=y_train, epochs=600, validation_data=(X_test, y_test),
```

```
Epoch 1/600
0.6509
Epoch 2/600
0.6105
Epoch 3/600
14/14 [============== ] - 0s 7ms/step - loss: 0.6064 - val loss:
0.5755
Epoch 4/600
0.5338
Epoch 5/600
0.4925
Epoch 6/600
0.4498
Epoch 7/600
0.4100
Epoch 8/600
14/14 [============== ] - 0s 12ms/step - loss: 0.4148 - val_loss:
0.3738
Epoch 9/600
0.3395
Epoch 10/600
0.3082
Epoch 11/600
14/14 [============== ] - 0s 5ms/step - loss: 0.3190 - val loss:
0.2837
Epoch 12/600
0.2601
Epoch 13/600
0.2426
Epoch 14/600
0.2264
Epoch 15/600
0.2146
Epoch 16/600
0.2071
Epoch 17/600
0.1951
Epoch 18/600
0.1870
Epoch 19/600
0.1814
Epoch 20/600
0.1781
```

```
Epoch 21/600
0.1801
Epoch 22/600
0.1671
Epoch 23/600
14/14 [============== ] - 0s 7ms/step - loss: 0.1533 - val loss:
0.1595
Epoch 24/600
14/14 [============= ] - 0s 11ms/step - loss: 0.1455 - val_loss:
0.1669
Epoch 25/600
0.1571
Epoch 26/600
0.1530
Epoch 27/600
0.1502
Epoch 28/600
0.1739
Epoch 29/600
0.1508
Epoch 30/600
0.1648
Epoch 31/600
0.1615
Epoch 32/600
0.1603
Epoch 33/600
14/14 [============== ] - 0s 12ms/step - loss: 0.1019 - val_loss:
0.1610
Epoch 34/600
14/14 [============= ] - 0s 11ms/step - loss: 0.0983 - val loss:
0.1617
Epoch 35/600
0.1597
Epoch 36/600
14/14 [============= ] - 0s 12ms/step - loss: 0.0962 - val loss:
0.1621
Epoch 37/600
0.1626
Epoch 38/600
14/14 [============= ] - 0s 10ms/step - loss: 0.0876 - val loss:
0.1679
Epoch 39/600
0.1557
Epoch 40/600
0.1548
```

```
Epoch 41/600
    0.1615
    Epoch 42/600
    0.1767
    Epoch 43/600
    14/14 [============== ] - 0s 6ms/step - loss: 0.0788 - val loss:
    0.1666
    Epoch 44/600
    0.1599
    Epoch 45/600
    0.1758
    Epoch 46/600
    0.1622
    Epoch 47/600
    0.1690
    Epoch 48/600
    14/14 [============= ] - 0s 13ms/step - loss: 0.0787 - val_loss:
    0.1760
    Epoch 49/600
    0.1804
    Epoch 50/600
    14/14 [============= ] - 0s 13ms/step - loss: 0.0701 - val_loss:
    0.1767
    Epoch 51/600
    14/14 [============== ] - 0s 13ms/step - loss: 0.0770 - val_loss:
    0.2098
    Epoch 52/600
    0.1715
    Epoch 52: early stopping
Out[46]: <keras.callbacks.History at 0x1f1d6e62c40>
In [47]: model_v1_loss = pd.DataFrame(model_v1.history.history)
In [48]: model v1 loss.plot()
Out[48]: <Axes: >
```



In [49]: # Let's try Dropout Layers ; this will drop percentage of neurons randomly

In [78]: model\_v2 = Sequential()
 model\_v2.add(Dense(30, activation='relu'))
 model\_v2.add(Dropout(0.5))
 model\_v2.add(Dense(15, activation='relu'))
 model\_v2.add(Dropout(0.5))
 # BINARY CLASSIFICATION PROBLEM we will use sigmoid
 model\_v2.add(Dense(1, activation='sigmoid'))
 model\_v2.compile(loss='binary\_crossentropy', optimizer='adam')

In [79]: model\_v2.fit(x=X\_train, y=y\_train, epochs=600, validation\_data=(X\_test, y\_test),

```
Epoch 1/600
0.6833
Epoch 2/600
0.6679
Epoch 3/600
14/14 [============== ] - 0s 7ms/step - loss: 0.6551 - val loss:
0.6537
Epoch 4/600
0.6374
Epoch 5/600
0.6184
Epoch 6/600
0.5951
Epoch 7/600
14/14 [============== ] - 0s 10ms/step - loss: 0.6096 - val_loss:
0.5719
Epoch 8/600
0.5393
Epoch 9/600
0.5075
Epoch 10/600
0.4809
Epoch 11/600
14/14 [============== ] - 0s 9ms/step - loss: 0.5089 - val loss:
0.4537
Epoch 12/600
0.4245
Epoch 13/600
0.3885
Epoch 14/600
0.3604
Epoch 15/600
0.3346
Epoch 16/600
0.3098
Epoch 17/600
0.3030
Epoch 18/600
0.2845
Epoch 19/600
14/14 [============= ] - 0s 10ms/step - loss: 0.3738 - val loss:
0.2673
Epoch 20/600
0.2575
```

```
Epoch 21/600
0.2493
Epoch 22/600
0.2363
Epoch 23/600
14/14 [============== ] - 0s 9ms/step - loss: 0.3292 - val loss:
0.2228
Epoch 24/600
14/14 [============== ] - 0s 10ms/step - loss: 0.2978 - val_loss:
0.2241
Epoch 25/600
0.2030
Epoch 26/600
0.1949
Epoch 27/600
0.1890
Epoch 28/600
0.1820
Epoch 29/600
0.1830
Epoch 30/600
0.1906
Epoch 31/600
14/14 [============== ] - 0s 7ms/step - loss: 0.2300 - val loss:
0.1634
Epoch 32/600
0.1789
Epoch 33/600
0.1701
Epoch 34/600
0.1679
Epoch 35/600
0.1672
Epoch 36/600
0.1822
Epoch 37/600
0.1575
Epoch 38/600
0.1628
Epoch 39/600
0.1644
Epoch 40/600
0.1684
```

```
Epoch 41/600
14/14 [============== ] - 0s 11ms/step - loss: 0.2209 - val_loss:
0.1469
Epoch 42/600
14/14 [============= ] - 0s 11ms/step - loss: 0.2101 - val_loss:
0.1586
Epoch 43/600
14/14 [============== ] - 0s 8ms/step - loss: 0.2141 - val loss:
0.1571
Epoch 44/600
0.1402
Epoch 45/600
14/14 [============== ] - 0s 11ms/step - loss: 0.1873 - val_loss:
0.1437
Epoch 46/600
0.1692
Epoch 47/600
14/14 [============== ] - 0s 14ms/step - loss: 0.1940 - val_loss:
0.1524
Epoch 48/600
14/14 [============= ] - 0s 12ms/step - loss: 0.1849 - val_loss:
0.1545
Epoch 49/600
14/14 [============== ] - 0s 11ms/step - loss: 0.1913 - val_loss:
0.1617
Epoch 50/600
14/14 [============= ] - 0s 15ms/step - loss: 0.1842 - val_loss:
0.1565
Epoch 51/600
14/14 [============== ] - 0s 17ms/step - loss: 0.1740 - val_loss:
0.1442
Epoch 52/600
14/14 [============= ] - 0s 16ms/step - loss: 0.1588 - val_loss:
0.1497
Epoch 53/600
14/14 [============== ] - 0s 15ms/step - loss: 0.1792 - val_loss:
0.2009
Epoch 54/600
14/14 [============= ] - 0s 13ms/step - loss: 0.1621 - val loss:
0.1525
Epoch 55/600
0.1424
Epoch 56/600
14/14 [============= ] - 0s 15ms/step - loss: 0.1453 - val loss:
0.1340
Epoch 57/600
0.1648
Epoch 58/600
0.1423
Epoch 59/600
0.1603
Epoch 60/600
0.1398
```

```
Epoch 61/600
0.1616
Epoch 62/600
0.1544
Epoch 63/600
14/14 [============== ] - 0s 9ms/step - loss: 0.1668 - val loss:
0.1497
Epoch 64/600
0.1744
Epoch 65/600
14/14 [============== ] - 0s 16ms/step - loss: 0.1396 - val_loss:
0.1588
Epoch 66/600
0.1409
Epoch 67/600
0.1568
Epoch 68/600
14/14 [============= ] - 0s 15ms/step - loss: 0.1250 - val_loss:
0.1778
Epoch 69/600
0.1538
Epoch 70/600
14/14 [============= ] - 0s 14ms/step - loss: 0.1361 - val_loss:
0.1645
Epoch 71/600
14/14 [============== ] - 0s 15ms/step - loss: 0.1230 - val_loss:
0.1696
Epoch 72/600
0.1472
Epoch 73/600
14/14 [============= ] - 0s 14ms/step - loss: 0.1337 - val loss:
0.1521
Epoch 74/600
14/14 [============= ] - 0s 13ms/step - loss: 0.1167 - val loss:
0.1698
Epoch 75/600
0.1801
Epoch 76/600
0.1582
Epoch 77/600
0.1565
Epoch 78/600
14/14 [============= ] - 0s 10ms/step - loss: 0.1300 - val loss:
0.1363
Epoch 79/600
0.1902
Epoch 80/600
0.1663
```

```
Epoch 81/600
                            ========= ] - 0s 10ms/step - loss: 0.1098 - val_loss:
        14/14 [=======
        0.1509
        Epoch 81: early stopping
Out[79]: <keras.callbacks.History at 0x1f1d2da1220>
In [82]: losses = pd.DataFrame(model_v2.history.history)
         losses.plot()
Out[82]: <Axes: >
                                                                        loss
        0.7
                                                                        val loss
        0.6
        0.5
        0.4
        0.3
        0.2
        0.1
               0
                      10
                              20
                                      30
                                              40
                                                      50
                                                             60
                                                                     70
                                                                             80
         # Notice that the training los and val loss both are quickly going down in same
In [56]:
In [90]:
         predicted_classes = model_v2.predict(X_test)
         predicted_classes = (predicted_classes > 0.5).astype(int)
        5/5 [======] - 0s 3ms/step
In [91]:
         from sklearn.metrics import classification_report, confusion_matrix
         print(classification_report(y_test, predicted_classes))
In [92]:
                      precision
                                  recall f1-score
                                                     support
                   0
                           0.84
                                    0.98
                                              0.91
                                                          55
                   1
                                                          88
                           0.99
                                    0.89
                                              0.93
                                              0.92
                                                         143
            accuracy
                           0.92
                                    0.93
                                              0.92
                                                         143
           macro avg
                                              0.92
        weighted avg
                           0.93
                                    0.92
                                                         143
In [93]:
         print(confusion_matrix(y_test, predicted_classes))
```

[[54 1] [10 78]]

In [94]: # Overall we should got performance precision and recall

In [ ]: