#### Breast Cancer Classification with a simple Neural Network (NN)

```
import numpy as np
import pandas as pd
{\tt import\ matplotlib.pyplot\ as\ plt}
import sklearn.datasets
from sklearn.model selection import train test split
breast_cancer_dataset = sklearn.datasets.load_breast_cancer()
print(breast cancer dataset)
→▼ {'data': array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
           [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
            8.902e-02],
           [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
            8.758e-02],
           [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
            7.820e-02],
           [2.060e+01, 2.933e+01, 1.401e+02, ..., 2.650e-01, 4.087e-01,
            1.240e-01],
           [7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 2.871e-01,
            0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0,
           1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0,
           1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
           1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
           0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
           1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
           1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
           0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
           1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1,
           1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
           0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1,
           1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
           1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0,
           0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
           0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0,
           1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1,
           1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0,
           1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
           1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
           1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
           1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,
           'mean smoothness', 'mean compactness', 'mean concavity', 'mean concave points', 'mean symmetry', 'mean fractal dimension',
           'radius error', 'texture error', 'perimeter error', 'area error',
           'smoothness error', 'compactness error', 'concavity error',
           'concave points error', 'symmetry error',
'fractal dimension error', 'worst radius', 'worst texture',
           'worst perimeter', 'worst area', 'worst smoothness',
           'worst compactness', 'worst concavity', 'worst concave points', 'worst symmetry', 'worst fractal dimension'], dtype='<U23'), 'filename': 'breast_cancer.csv', 'data_module': 'sklearn.dataset
data_frame = pd.DataFrame(breast_cancer_dataset.data, columns = breast_cancer_dataset.feature_names)
```

data frame.head()

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-		~
٠	_	_

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	•••	worst radius	worst texture	woı perime
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871		25.38	17.33	184
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667		24.99	23.41	158
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999		23.57	25.53	152
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744		14.91	26.50	98
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883		22.54	16.67	152

5 rows × 30 columns

4

data\_frame.tail()

•	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	 worst texture	worst perimeter	W
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	 26.40	166.10	20
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	 38.25	155.00	11
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	 34.12	126.70	1.
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397	0.07016	 39.42	184.60	18
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	 30.37	59.16	1

4

5 rows × 31 columns

data\_frame.shape

**→** (569, 31)

data\_frame.info()

<<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):

#	Column	Non-Null Count	Dtype
0	mean radius	569 non-null	float64
1	mean texture	569 non-null	float64
2	mean perimeter	569 non-null	float64
3	mean area	569 non-null	float64
4	mean smoothness	569 non-null	float64
5	mean compactness	569 non-null	float64
6	mean concavity	569 non-null	float64
7	mean concave points	569 non-null	float64
8	mean symmetry	569 non-null	float64
9	mean fractal dimension	569 non-null	float64
10	radius error	569 non-null	float64
11	texture error	569 non-null	float64
12	perimeter error	569 non-null	float64
13	area error	569 non-null	float64
14	smoothness error	569 non-null	float64
15	compactness error	569 non-null	float64
16	concavity error	569 non-null	float64
17	concave points error	569 non-null	float64
18	symmetry error	569 non-null	float64
19	fractal dimension error	569 non-null	float64
20	worst radius	569 non-null	float64
21	worst texture	569 non-null	float64
22	worst perimeter	569 non-null	float64
23	worst area	569 non-null	float64
24	worst smoothness	569 non-null	float64
25	worst compactness	569 non-null	float64
26	worst concavity	569 non-null	float64
27	worst concave points	569 non-null	float64
28	worst symmetry	569 non-null	float64
29	worst fractal dimension	569 non-null	float64
30	label	569 non-null	int64
d+vn	$ac \cdot float64(30) int64(1)$		

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

# data\_frame.isnull().sum()

→ ▼	mean radius	0
	mean texture	0
	mean perimeter	0
	mean area	0
	mean smoothness	0
	mean compactness	0
	mean concavity	0
	mean concave points	0
	mean symmetry	0
	mean fractal dimension	0
	radius error	0
	texture error	0
	perimeter error	0
	area error	0
	smoothness error	0
	compactness error	0
	concavity error	0
	concave points error	0

```
symmetry error
     fractal dimension error
                                 0
     worst radius
                                 0
     worst texture
     worst perimeter
     worst area
                                 0
     worst smoothness
     worst compactness
                                 0
     worst concavity
     worst concave points
                                 0
     worst symmetry
     worst fractal dimension
                                 0
     label
     dtype: int64
data_frame.describe()
₹
                                                                                                         mean
                                                                                                                                 mean
                   mean
                               mean
                                          mean
                                                                    mean
                                                                                 mean
                                                                                             mean
                                                                                                                     mean
                                                  mean area
                                                                                                      concave
                                                                                                                              fractal
                 radius
                                     perimeter
                                                              smoothness compactness
                                                                                                                 symmetry
                           texture
                                                                                        concavity
                                                                                                       points
                                                                                                                            dimension
      count 569.000000
                         569.000000
                                    569.000000
                                                  569.000000
                                                              569.000000
                                                                           569.000000
                                                                                       569.000000 569.000000 569.000000
                                                                                                                           569.000000
                                                                                                                                            56
              14.127292
                          19.289649
                                      91.969033
                                                  654.889104
                                                                0.096360
                                                                              0.104341
                                                                                         0.088799
                                                                                                     0.048919
                                                                                                                  0.181162
                                                                                                                             0.062798
      mean
       std
               3.524049
                           4.301036
                                      24.298981
                                                  351.914129
                                                                0.014064
                                                                              0.052813
                                                                                         0.079720
                                                                                                     0.038803
                                                                                                                 0.027414
                                                                                                                             0.007060
      min
               6.981000
                           9.710000
                                      43.790000
                                                  143.500000
                                                                0.052630
                                                                              0.019380
                                                                                         0.000000
                                                                                                     0.000000
                                                                                                                 0.106000
                                                                                                                             0.049960
      25%
              11.700000
                          16.170000
                                      75.170000
                                                  420.300000
                                                                0.086370
                                                                              0.064920
                                                                                         0.029560
                                                                                                     0.020310
                                                                                                                 0.161900
                                                                                                                             0.057700
                                                                                                     0.033500
      50%
              13 370000
                          18 840000
                                      86 240000
                                                  551 100000
                                                                0.095870
                                                                             0.092630
                                                                                         0.061540
                                                                                                                 0.179200
                                                                                                                             0.061540
      75%
              15.780000
                          21.800000
                                     104.100000
                                                  782.700000
                                                                0.105300
                                                                              0.130400
                                                                                         0.130700
                                                                                                     0.074000
                                                                                                                 0.195700
                                                                                                                             0.066120
      max
              28.110000
                          39.280000 188.500000 2501.000000
                                                                0.163400
                                                                              0.345400
                                                                                         0.426800
                                                                                                     0.201200
                                                                                                                 0.304000
                                                                                                                             0.097440
     8 rows × 31 columns
data_frame['label'].value_counts()
₹
     Name: label, dtype: int64
data_frame.groupby('label').mean()
\overline{\Rightarrow}
                 mean
                            mean
                                        mean
                                                                 mean
                                                                              mean
                                                                                         mean
                                                                                                             mean
                                                                                                                                       worst
                                                                                                concave
                                                                                                                      fractal
                                               mean area
                radius
                         texture
                                   perimeter
                                                          smoothness compactness concavity
                                                                                                         symmetry
                                                                                                                                       radius
                                                                                                                   dimension
                                                                                                 points
      label
        0
             17.462830 21.604906 115.365377 978.376415
                                                                                      0.160775 0.087990 0.192909
                                                             0.102898
                                                                          0.145188
                                                                                                                     0.062680
                                                                                                                                    21.134811
        1
             12.146524 17.914762
                                  78.075406 462.790196
                                                             0.092478
                                                                          0.080085
                                                                                      0.046058 0.025717
                                                                                                          0.174186
                                                                                                                     0.062867
                                                                                                                                    13.379801
     2 rows × 30 columns
    4
X = data_frame.drop(columns='label', axis=1)
Y = data frame['label']
print(X)
          mean radius mean texture mean perimeter mean area mean smoothness \
     0
                17.99
                               10.38
                                              122.80
                                                          1001.0
                                                                           0.11840
                20.57
                               17.77
                                               132.90
                                                                           0.08474
                                                          1326.0
     2
                19.69
                               21.25
                                               130.00
                                                          1203.0
                                                                           0.10960
     3
                11.42
                               20.38
                                               77.58
                                                           386.1
                                                                           0.14250
     4
                20.29
                               14.34
                                               135.10
                                                          1297.0
                                                                           0.10030
                               22.39
                                               142.00
                                                          1479.0
     564
                21.56
                                                                           0.11100
                                                                           0.09780
     565
                20.13
                               28.25
                                               131,20
                                                          1261.0
                                                                           0.08455
     566
                16.60
                               28.08
                                               108.30
                                                           858.1
     567
                20.60
                               29.33
                                               140.10
                                                          1265.0
                                                                           0.11780
     568
                 7.76
                               24.54
                                               47.92
                                                           181.0
                                                                           0.05263
          mean compactness mean concavity mean concave points mean symmetry
     0
                                    0.30010
                   0.27760
                                                          0.14710
                                                                           0.2419
                   0.07864
                                    0.08690
                                                          0.07017
                                                                           0.1812
     1
```

₹

2

3

4

0.15990

0.28390

0.13280

0.19740

0.24140

0.19800

0.12790

0.10520

0.10430

0.2069

0.2597

0.1809

2

2

4

```
565
                   0.10340
                                   0.14400
                                                         0.09791
                                                                          0.1752
     566
                   0.10230
                                   0.09251
                                                         0.05302
                                                                          0.1590
                   0.27700
                                    0.35140
                                                         0.15200
                                                                          0.2397
     568
                   0.04362
                                    0.00000
                                                         0.00000
                                                                          0.1587
          mean fractal dimension ... worst radius worst texture ∖
     0
                         0.07871 ...
                                             25.380
                                                              17.33
                         0.05667
                                              24,990
                                                              23,41
     1
                                  . . .
                         0.05999 ...
     2
                                              23,570
                                                              25.53
                         0.09744 ...
     3
                                             14.910
                                                              26.50
     4
                         0.05883
                                             22.540
                                                              16.67
                         0.05623 ...
                                              25.450
                                                              26.40
                         0.05533 ...
                                              23.690
                                                              38.25
                         0.05648 ...
     566
                                              18.980
                                                              34.12
     567
                         0.07016 ...
                                             25.740
                                                              39.42
                         0.05884 ...
                                              9.456
                                                              30.37
     568
          worst perimeter worst area worst smoothness worst compactness \
     a
                               2019.0
                                                                    0.66560
                   184.60
                                                 0.16220
     1
                   158.80
                               1956.0
                                                 0.12380
                                                                    0.18660
     2
                   152.50
                               1709.0
                                                 0.14440
                                                                    0.42450
     3
                    98.87
                                567.7
                                                 0.20980
                                                                    0.86630
     4
                   152.20
                               1575.0
                                                 0.13740
                                                                    0.20500
     564
                   166.10
                               2027.0
                                                 0.14100
                                                                    0.21130
                   155.00
                               1731.0
                                                 0.11660
                                                                    0.19220
     565
                   126.70
                                                 0.11390
                                                                    0.30940
     566
                               1124.0
     567
                   184.60
                               1821.0
                                                 0.16500
                                                                    0.86810
                                                 0.08996
     568
                    59.16
                                268.6
                                                                    0.06444
          worst concavity worst concave points worst symmetry \
     0
                   0.7119
                                          0.2654
                                                          0.4601
     1
                   0.2416
                                          0.1860
                                                          0.2750
     2
                   0.4504
                                          0.2430
                                                          0.3613
                   0.6869
                                          0.2575
                                                          0.6638
     4
                   0.4000
                                          0.1625
                                                          0.2364
print(Y)
\overline{\Rightarrow}
    0
            0
     1
     2
            0
     3
            a
     4
            0
     564
            0
     566
     568
            1
     Name: label, Length: 569, dtype: int64
X train, X test, Y train, Y test = train test split(X, Y, test size=0.2, random state=2)
print(X.shape, X_train.shape, X_test.shape)
→ (569, 30) (455, 30) (114, 30)
from \ sklearn.preprocessing \ import \ StandardScaler
scaler = StandardScaler()
X_train_std = scaler.fit_transform(X_train)
X test std = scaler.transform(X test)
import tensorflow as tf
tf.random.set_seed(3)
from tensorflow import keras
model = keras.Sequential([
                          keras.layers.Flatten(input_shape=(30,)),
                          keras.layers.Dense(20, activation='relu'),
                          keras.layers.Dense(2, activation='sigmoid')
])
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

564

0.11590

0.24390

0.13890

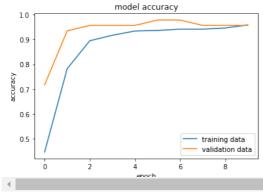
0.1726

```
→ Epoch 1/10
  13/13 [====
          Epoch 2/10
  Epoch 3/10
  13/13 [===
                 :=======] - 0s 5ms/step - loss: 0.3243 - accuracy: 0.8826 - val_loss: 0.2706 - val_accuracy: 0.8913
  Epoch 4/10
  Epoch 5/10
  13/13 [====
                :========] - 0s 6ms/step - loss: 0.2281 - accuracy: 0.9267 - val_loss: 0.2001 - val_accuracy: 0.9130
  Epoch 6/10
  13/13 [====
                 :========] - 0s 6ms/step - loss: 0.2010 - accuracy: 0.9315 - val_loss: 0.1795 - val_accuracy: 0.9565
  Epoch 7/10
  13/13 [====
                ========] - 0s 5ms/step - loss: 0.1793 - accuracy: 0.9413 - val_loss: 0.1632 - val_accuracy: 0.9565
  Epoch 8/10
  13/13 [====
                ========] - 0s 5ms/step - loss: 0.1627 - accuracy: 0.9438 - val_loss: 0.1493 - val_accuracy: 0.9565
  Epoch 9/10
  13/13 [=====
             Epoch 10/10
               ==========] - 0s 6ms/step - loss: 0.1362 - accuracy: 0.9560 - val_loss: 0.1292 - val_accuracy: 0.9565
  13/13 [=====
```

### Visualizing accuracy and loss

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training data', 'validation data'], loc = 'lower right')
```

## <matplotlib.legend.Legend at 0x7fcf3ff52450>

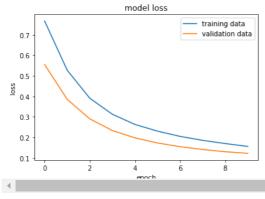


```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')

plt.legend(['training data', 'validation data'], loc = 'upper right')
```

### <matplotlib.legend.Legend at 0x7fcf409fbcd0>



```
loss, accuracy = model.evaluate(X_test_std, Y_test)
print(accuracy)
0.9385964870452881
print(X_test_std.shape)
print(X_test_std[0])
→ (114, 30)
     [-0.04462793 -1.41612656 -0.05903514 -0.16234067 2.0202457 -0.11323672 0.18500609 0.47102419 0.63336386 0.26335737 0.53209124 2.62763999
       0.62351167 \quad 0.11405261 \quad 1.01246781 \quad 0.41126289 \quad 0.63848593 \quad 2.88971815
      \hbox{-0.41675911} \quad \hbox{0.74270853} \ \hbox{-0.32983699} \ \hbox{-1.67435595} \ \hbox{-0.36854552} \ \hbox{-0.38767294}
       0.32655007 -0.74858917 -0.54689089 -0.18278004 -1.23064515 -0.6268286 ]
Y_pred = model.predict(X_test_std)
print(Y_pred.shape)
print(Y_pred[0])
→ (114, 2)
     [0.24822891 0.537705 ]
print(X_test_std)
→ [[-0.04462793 -1.41612656 -0.05903514 ... -0.18278004 -1.23064515
       -0.6268286 1
      [ 0.24583601 -0.06219797 0.21802678 ... 0.54129749 0.11047691
       0.0483572 ]
      [-1.26115925 \ -0.29051645 \ -1.26499659 \ \dots \ -1.35138617 \ \ 0.269338
       -0.28231213]
      [ 0.72709489  0.45836817  0.75277276  ...  1.46701686  1.19909344
      -1.595573441
      [ 0.84100232 -0.06676434 0.8929529 ... 2.15137705 0.35629355
        0.37459546]]
print(Y_pred)
→ [[2.48228908e-01 5.37705004e-01]
      [5.04756272e-01 5.95336974e-01]
      [3.67398351e-01 9.86996770e-01]
      [9.29620504e-01 2.29299068e-04]
      [5.93764186e-01 4.93302941e-01]
      [8.53436947e-01 1.02660358e-02]
      [2.81091124e-01 6.12119973e-01]
      [4.79383349e-01 9.91485417e-01]
      [4.34603453e-01 9.51259434e-01]
      [6.34022474e-01 9.53936636e-01]
      [4.83262986e-01 6.63963675e-01]
      [3.86232853e-01 9.23828781e-01]
      [2.77723640e-01 7.82129407e-01]
      [3.78485560e-01 8.21216226e-01]
      [4.91592646e-01 9.53726530e-01]
      [7.36154735e-01 1.57864958e-01]
      [4.71651524e-01 9.74555612e-01]
      [2.54375935e-01 8.85443091e-01]
      [5.75661778e-01 9.49565291e-01]
      [8.55701387e-01 1.94370747e-02]
      [1.90429598e-01 1.22809112e-02]
      [4.47704107e-01 9.82434034e-01]
      [5.11266708e-01 9.58328366e-01]
      [5.38256645e-01 9.74644005e-01]
      [5.29228508e-01 8.16611886e-01]
      [7.13969886e-01 6.25776052e-02]
      [4.54092264e-01 9.09015238e-01]
      [5.10061681e-01 7.40805507e-01]
      [6.70265079e-01 1.68987542e-01]
      [6.56581044e-01 1.18384689e-01]
      [5.91236949e-01 9.38910842e-01]
      [4.20632422e-01 9.19608235e-01]
```

[5.11391044e-01 9.51588750e-01] [8.78562212e-01 1.91476941e-03] [8.40861440e-01 3.40589881e-02] [5.59490383e-01 7.92683899e-01] [4.08323050e-01 9.93038535e-01] [5.17861009e-01 8.50202918e-01] [3.98939788e-01 9.78648603e-01] [3.16001832e-01 9.14353132e-01] [9.31815386e-01 1.04099512e-03] [5.36973536e-01 2.56363392e-01] [3.96728277e-01 9.79030609e-01]

```
[7.01928675e-01 1.99133068e-01]
             [4.22424793e-01 9.64499712e-01]
             [2.93639600e-01 9.86928105e-01]
             [4.57987458e-01 9.43145216e-01]
             [8.21546316e-01 1.38805807e-02]
             [7.11578608e-01 1.09298050e-01]
             [6.50350690e-01 9.58284259e-01]
             [6.42665863e-01 3.17812234e-01]
             [5.54926872e-01 6.52379811e-01]
             [4.63142991e-01 9.63462353e-01]
             [3.21405470e-01 9.79116678e-01]
             [5.65109372e-01 6.47464037e-01]
             [4.16883409e-01 8.96000743e-01]
             [2.26916492e-01 9.79369640e-01]
model.predict() gives the prediction probability of each class for that data point
# argmax function
my_list = [0.25, 0.56]
index_of_max_value = np.argmax(my_list)
print(my_list)
print(index_of_max_value)
→ [0.25, 0.56]
# converting the prediction probability to class labels
Y_pred_labels = [np.argmax(i) for i in Y_pred]
print(Y_pred_labels)
Building the predictive system
input\_data = (11.76, 21.6, 74.72, 427.9, 0.08637, 0.04966, 0.01657, 0.01115, 0.1495, 0.05888, 0.4062, 1.21, 2.635, 28.47, 0.005857, 0.009758, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01168, 0.01684, 0.01168, 0.0168, 0.0168, 0.0168, 0.0168, 0.0168, 0.0168, 0.0168, 0.0168, 0.0168, 0.0
# change the input_data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)
# reshape the numpy array as we are predicting for one data point
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)
# standardizing the input data
input_data_std = scaler.transform(input_data_reshaped)
prediction = model.predict(input_data_std)
print(prediction)
prediction_label = [np.argmax(prediction)]
print(prediction_label)
if(prediction_label[0] == 0):
   print('The tumor is Malignant')
else:
    print('The tumor is Benign')
```

/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feature names, but StandardScaler was

Start coding or generate with AI.

[[0.42537233 0.9805447 ]]

"X does not have valid feature names, but"

The tumor is Benign

[1]

[2.11794227e-01 8.85924697e-01]

