

Importing Dependencies

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sklearn.datasets
from sklearn.model_selection import train_test_split
```

Data collection and processing

```
breast_cancer_dataset = sklearn.datasets.load_breast_cancer()
```

```
print(breast_cancer_dataset)
```

[illegible]

```
# creating a dataframe
dataframe = pd.DataFrame(breast_cancer_dataset.data, columns = breast_cancer_dataset.feature_names)
```

```
dataframe.head()
```



	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	sy
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	

5 rows × 30 columns

```
# adding target to the dataframe
# 0 ----> 1---->
dataframe['label'] = breast_cancer_dataset.target
```

```
dataframe.tail()
```



	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000

5 rows × 31 columns

```
dataframe.shape #tells us the no. of columns and rows
```



```
(569, 31)
```

```
dataframe.info() # tells us about each column info. which type of column is that
```



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

```
dataframe.isnull().sum() #tells us about the null values
```

```
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   0
fractal dimension error 0
worst radius     0
worst texture    0
worst perimeter  0
worst area       0
worst smoothness 0
worst compactness 0
worst concavity  0
worst concave points 0
worst symmetry   0
worst fractal dimension 0
label            0
dtype: int64
```

```
dataframe.describe() #tells us about the statistical measures of the data
```

```
count    569.000000  569.000000  569.000000  569.000000  569.000000  569.000000  569.000000
mean      14.127292  19.289649  91.969033  654.889104    0.096360    0.104341    0.086611
std        3.524049   4.301036  24.298981  351.914129    0.014064    0.052813    0.071151
min         6.981000   9.710000  43.790000  143.500000    0.052630    0.019380    0.004600
25%        11.700000  16.170000  75.170000  420.300000    0.086370    0.064920    0.021200
50%        13.370000  18.840000  86.240000  551.100000    0.095870    0.092630    0.061000
75%        15.780000  21.800000  104.100000  782.700000    0.105300    0.130400    0.131000
max        28.110000  39.280000  188.500000 2501.000000    0.163400    0.345400    0.427000

8 rows x 31 columns
```

```
dataframe['label'].value_counts() # checking the distribution of target variable
```

```
label
1     357
0     212
Name: count, dtype: int64
```

1 ----> Benign 0 ----> Malignant

```
dataframe.groupby('label').mean() # groupby helps to show the mean values of the label values separately
```

```
mean radius    mean texture    mean perimeter  mean area    mean smoothness  mean compactness  mean concavity
label
0      17.462830  21.604906  115.365377  978.376415    0.102898    0.145188  0.160771
1      12.146524  17.914762   78.075406  462.790196    0.092478    0.080085  0.046058

2 rows x 30 columns
```

Separating the features and target

```
X = dataframe.drop(columns='label',axis = 1)
Y = dataframe['label']
```

```
print(X)
print(Y)
```

```

564      0.05623 ...      25.450      26.40
565      0.05533 ...      23.690      38.25
566      0.05648 ...      18.980      34.12
567      0.07016 ...      25.740      39.42
568      0.05884 ...       9.456      30.37

      worst perimeter  worst area  worst smoothness  worst compactness \
0      184.60      2019.0      0.16220      0.66560
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
565      155.00      1731.0      0.11660      0.19220
566      126.70      1124.0      0.11390      0.30940
567      184.60      1821.0      0.16500      0.86810
568       59.16       268.6      0.08996      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
3      0.6869      0.2575      0.6638
4      0.4000      0.1625      0.2364
..      ...      ...      ...
564      0.4107      0.2216      0.2060
565      0.3215      0.1628      0.2572
566      0.3403      0.1418      0.2218
567      0.9387      0.2650      0.4087
568      0.0000      0.0000      0.2871

      worst fractal dimension
0      0.11890
1      0.08902
2      0.08758
3      0.17300
4      0.07678
..      ...
564      0.07115
565      0.06637
566      0.07820
567      0.12400
568      0.07039

[569 rows x 30 columns]
0      0
1      0
2      0
3      0
4      0
..
564      0
565      0
566      0
567      0
568      1
Name: label, Length: 569, dtype: int64
```

Splitting the data into training data and Testing data

```
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)
```

Standardize the data

```
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()
```

```
X_train_std = scaler.fit_transform(X_train)
```

```
X_test_std = scaler.transform(X_test)
```

```
print(X_train_std)

→ [[-0.01330339  1.7757658 -0.01491962 ... -0.13236958 -1.08014517
    -0.03527943]
  [-0.8448276 -0.6284278 -0.87702746 ... -1.11552632 -0.85773964
    -0.72098905]
  [ 1.44755936  0.71180168  1.47428816 ...  0.87583964  0.4967602
    0.46321706]
  ...
  [-0.46608541 -1.49375484 -0.53234924 ... -1.32388956 -1.02997851
    -0.75145272]
  [-0.50025764 -1.62161319 -0.527814 ... -0.0987626  0.35796577
    -0.43906159]
  [ 0.96060511  1.21181916  1.00427242 ...  0.8956983 -1.23064515
    0.50697397]]
```

Building The Neural Network

```
#importing tensorflow and keras    <-- developed by google for creating deep learning models
import tensorflow as tf
tf.random.set_seed(3)
from tensorflow import keras
```

```
#setting up the layers of neural network
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(30,)),
    keras.layers.Dense(20,activation='relu'),
    keras.layers.Dense(2,activation='sigmoid')
])
```

```
#compiling the neural networks
```

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

```
#training the model
```

```
history = model.fit(X_train_std,Y_train,validation_split=0.1,epochs=10)
```

```
→ Epoch 1/10
13/13 [=====] - 1s 19ms/step - loss: 0.4866 - accuracy: 0.8020 - val_loss: 0.3797 - val_accuracy: 0.9565
Epoch 2/10
13/13 [=====] - 0s 5ms/step - loss: 0.3194 - accuracy: 0.8924 - val_loss: 0.2560 - val_accuracy: 0.9783
Epoch 3/10
13/13 [=====] - 0s 6ms/step - loss: 0.2439 - accuracy: 0.9242 - val_loss: 0.1995 - val_accuracy: 0.9783
Epoch 4/10
13/13 [=====] - 0s 5ms/step - loss: 0.2030 - accuracy: 0.9340 - val_loss: 0.1686 - val_accuracy: 0.9783
Epoch 5/10
13/13 [=====] - 0s 5ms/step - loss: 0.1762 - accuracy: 0.9413 - val_loss: 0.1496 - val_accuracy: 0.9783
Epoch 6/10
13/13 [=====] - 0s 5ms/step - loss: 0.1575 - accuracy: 0.9462 - val_loss: 0.1360 - val_accuracy: 0.9783
Epoch 7/10
13/13 [=====] - 0s 4ms/step - loss: 0.1430 - accuracy: 0.9487 - val_loss: 0.1258 - val_accuracy: 0.9783
Epoch 8/10
13/13 [=====] - 0s 5ms/step - loss: 0.1313 - accuracy: 0.9560 - val_loss: 0.1181 - val_accuracy: 0.9783
Epoch 9/10
13/13 [=====] - 0s 5ms/step - loss: 0.1217 - accuracy: 0.9658 - val_loss: 0.1110 - val_accuracy: 0.9783
Epoch 10/10
13/13 [=====] - 0s 10ms/step - loss: 0.1131 - accuracy: 0.9682 - val_loss: 0.1066 - val_accuracy: 0.9783
```

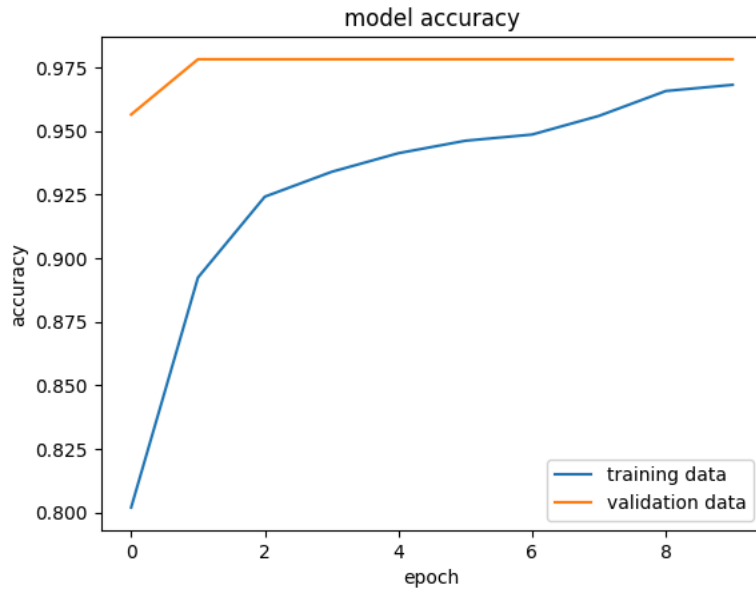
Visualizing accuracy and loss

```
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 0x7e64791ef880>

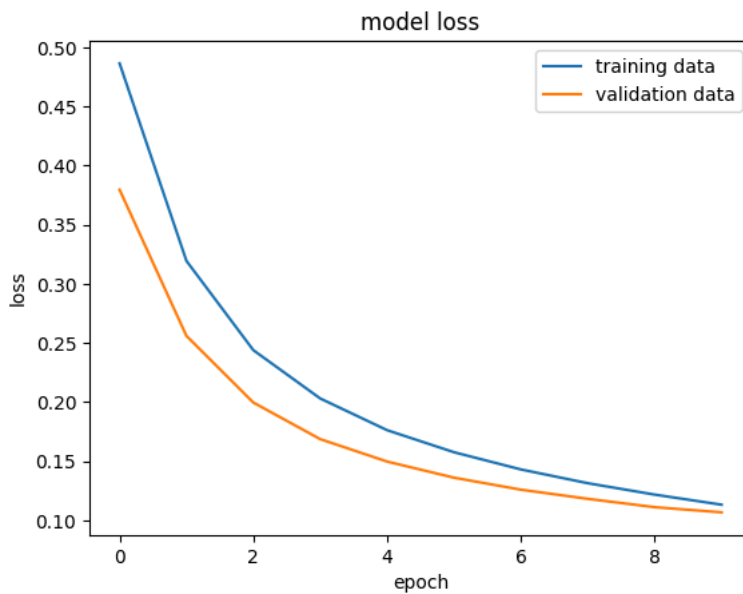


```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

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


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

 <matplotlib.legend.Legend at 0x7e647cd696c0>




Accuracy of the model on test data

```
loss, accuracy = model.evaluate(X_test_std, Y_test)
print(accuracy)
```

 4/4 [=====] - 0s 3ms/step - loss: 0.1164 - accuracy: 0.9386
0.9385964870452881

Build a Predictive System

```
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 0.11405261 1.01246781 0.41126289 0.63848593 2.88971815
-0.41675911 0.74270853 -0.32983699 -1.67435595 -0.36854552 -0.38767294

```
0.32655007 -0.74858917 -0.54689089 -0.18278004 -1.23064515 -0.6268286 ]
```

```
Y_pred = model.predict(X_test_std)
```

```
4/4 [=====] - 0s 3ms/step
```

```
print(Y_pred.shape)
print(Y_pred[0])
```

```
(114, 2)
[0.159299  0.7513883]
```

```
print(Y_pred)
```

```
[2.45191544e-01 9.08973157e-01]
[4.52882946e-02 9.10310149e-01]
[5.23319244e-01 2.35378742e-02]
[2.72058219e-01 9.28914607e-01]
[3.88937235e-01 6.48908556e-01]
[9.18239117e-01 1.03692420e-01]
[1.91242203e-01 9.52847540e-01]
[7.85486937e-01 1.70325059e-02]
[8.13573420e-01 3.63627560e-02]
[5.92141449e-01 7.87646413e-01]
[9.18471038e-01 2.10727402e-03]
[7.23274410e-01 2.61995681e-02]
[6.21686816e-01 6.15288019e-01]
[3.23766828e-01 3.61053884e-01]
[5.83733022e-01 2.14822069e-01]
[8.32518280e-01 9.67573840e-03]
[1.45588398e-01 9.13623810e-01]
[6.71616495e-01 1.39173612e-01]
[1.55286267e-01 9.58647609e-01]
[6.04783535e-01 1.22176632e-01]
[1.49034157e-01 8.74401391e-01]
[1.88912660e-01 9.74478543e-01]
[3.64527762e-01 6.12152040e-01]
[5.74265659e-01 2.73325294e-01]
[8.67894590e-01 1.88622549e-02]
[6.34752631e-01 2.47963086e-01]
[8.27198744e-01 1.38601158e-02]
[2.65208453e-01 8.45021904e-01]
[2.10084021e-01 8.06344211e-01]
[5.08449018e-01 5.54542243e-01]
[1.23695612e-01 9.59269643e-01]
[1.93218455e-01 8.48353505e-01]
[4.20540303e-01 8.25776041e-01]
[9.34040010e-01 1.68232583e-02]
[2.28489354e-01 9.43438649e-01]
[3.82782042e-01 9.00061727e-01]
[2.22888008e-01 9.55945611e-01]
[8.23915243e-01 1.10778555e-01]
[5.57724357e-01 8.70296955e-02]
[2.65221149e-01 8.42225730e-01]
[8.54155481e-01 4.83367452e-03]
[8.51505458e-01 3.37263122e-02]
[1.77255452e-01 8.36346805e-01]
[1.63465813e-01 9.61011887e-01]
[1.61149725e-01 9.88198698e-01]
[5.53071678e-01 1.82995602e-01]
[9.66395378e-01 2.51073536e-04]
[9.50252712e-01 6.19956874e-04]
[2.16956675e-01 8.82590592e-01]
[1.43900380e-01 9.60179210e-01]
[1.02038063e-01 9.81731057e-01]
[2.09759340e-01 9.51954126e-01]
[1.52745489e-02 9.71510172e-01]
[2.43146315e-01 6.91956639e-01]
[9.25043941e-01 4.57590539e-03]
[7.31664360e-01 2.48165708e-03]
[6.49302602e-01 5.24360240e-01]
[8.16598535e-01 4.29233164e-02]]
```

model.predict gives me the probability of each class datapoint

```
#converting probability to label
```

```
Y_pred_label = [np.argmax(i) for i in Y_pred]
print(Y_pred_label)
```

```
[1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1,
```

```

#predictive system

input_data = (17.99,10.38,122.8,1001,0.1184,0.2776,0.3001,0.1471,0.2419,0.07871,1.095,0.9053,8.589,153.4,0.006399,0.04904,0.05373,0.0158)

#change the input data to 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)

#standardize the data
std_data = scaler.transform(input_data_reshaped)


prediction = model.predict(std_data)
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')

```

 1/1 [=====] - 0s 32ms/step
[[8.1881064e-01 3.9951672e-04]]
[0]
The tumor is Malignant
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but StandardScaler was fitted without feature names
warnings.warn(