

Importing Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Reading Data

```
df = pd.read_csv("/content/breast-cancer.csv",index_col=0)
df.head()
```

	concavity_mean	concave points_mean	symmetry_mean	...	radius_worst	texture_worst	perimeter_worst	area_worst	smoothness_worst	compactness_worst	concavity_worst
0	0.3001	0.14710	0.2419	...	25.38	17.33	184.60	2019.0	0.1622	0.6656	0.2575
1	0.0869	0.07017	0.1812	...	24.99	23.41	158.80	1956.0	0.1238	0.1866	0.1616
2	0.1974	0.12790	0.2069	...	23.57	25.53	152.50	1709.0	0.1444	0.4245	0.2439
3	0.2414	0.10520	0.2597	...	14.91	26.50	98.87	567.7	0.2098	0.8663	0.4388
4	0.1980	0.10430	0.1809	...	22.54	16.67	152.20	1575.0	0.1374	0.2050	0.1723

Understanding Data

```
df.diagnosis.value_counts()
```

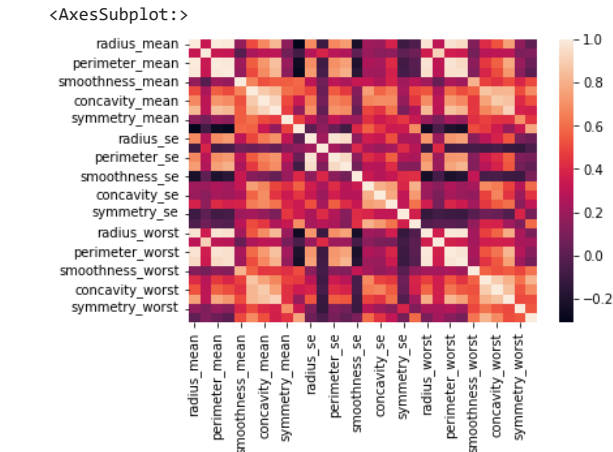
```
B    357
M    212
Name: diagnosis, dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 569 entries, 842302 to 92751
Data columns (total 31 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   diagnosis                             569 non-null    object
1   radius_mean                           569 non-null    float64
2   texture_mean                           569 non-null    float64
3   perimeter_mean                         569 non-null    float64
4   area_mean                             569 non-null    float64
5   smoothness_mean                       569 non-null    float64
6   compactness_mean                      569 non-null    float64
7   concavity_mean                        569 non-null    float64
8   concave points_mean                   569 non-null    float64
9   symmetry_mean                         569 non-null    float64
10  fractal_dimension_mean                569 non-null    float64
11  radius_se                             569 non-null    float64
12  texture_se                             569 non-null    float64
13  perimeter_se                           569 non-null    float64
14  area_se                               569 non-null    float64
15  smoothness_se                         569 non-null    float64
16  compactness_se                        569 non-null    float64
17  concavity_se                          569 non-null    float64
18  concave points_se                     569 non-null    float64
19  symmetry_se                           569 non-null    float64
20  fractal_dimension_se                  569 non-null    float64
21  radius_worst                          569 non-null    float64
22  texture_worst                         569 non-null    float64
23  perimeter_worst                       569 non-null    float64
24  area_worst                            569 non-null    float64
25  smoothness_worst                     569 non-null    float64
26  compactness_worst                     569 non-null    float64
27  concavity_worst                       569 non-null    float64
28  concave points_worst                  569 non-null    float64
29  symmetry_worst                        569 non-null    float64
30  fractal_dimension_worst               569 non-null    float64
dtypes: float64(30), object(1)
memory usage: 142.2+ KB
```

Checking Correlation

```
sns.heatmap(df.corr())
```



Standardization

```
from sklearn.preprocessing import StandardScaler,LabelEncoder
SS = StandardScaler()
LE = LabelEncoder()
```

```
X = df.iloc[:,1:]
X = SS.fit_transform(X)
X
```

```
array([[ 1.09706398, -2.07333501,  1.26993369, ...,  2.29607613,
        2.75062224,  1.93701461],
       [ 1.82982061, -0.35363241,  1.68595471, ...,  1.0870843 ,
       -0.24388967,  0.28118999],
       [ 1.57988811,  0.45618695,  1.56650313, ...,  1.95500035,
        1.152255  ,  0.20139121],
       ...,
       [ 0.70228425,  2.0455738 ,  0.67267578, ...,  0.41406869,
       -1.10454895, -0.31840916],
       [ 1.83834103,  2.33645719,  1.98252415, ...,  2.28998549,
        1.91908301,  2.21963528],
```

```
[-1.80840125, 1.22179204, -1.81438851, ..., -1.74506282,
-0.04813821, -0.75120669]]])
```

```
Y = df.diagnosis
Y = LE.fit_transform(Y)
Y
```

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1,
0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1,
0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0,
0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1,
1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0,
0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1,
1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1,
0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0,
0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1,
1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1,
1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1,
0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0,
0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0,
0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0,
0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0,
0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0])
```

```
LE.classes_

array(['B', 'M'], dtype=object)
```

Splitting the Data

```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.3,random_state=1)
```

```
import tensorflow as tf
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
```

EarlyStopping to save resources

```
ES = EarlyStopping(monitor="val_loss",mode="min",verbose=1,patience=8)
```

Building Model

```
# step1 :- initialize the Model
ann = Sequential()

# step2 :- Add Layers into model
ann.add( Dense(units = 20, activation = "relu") )
ann.add( Dense(units = 20, activation = "relu") )

ann.add( Dense(units = 1, activation="sigmoid") )      # Output Layer

# step3 :- Establihing connection
ann.compile(optimizer='adam', loss = 'binary_crossentropy' , metrics=["accuracy"])

# step4 :- Fit the model
ann.fit(X_train, Y_train, batch_size = 15, epochs = 800,validation_data=(X_test,Y_test),callbacks=[ES])

Epoch 1/800
27/27 [=====] - 1s 11ms/step - loss: 0.5787 - accuracy: 0.7085 - val_loss: 0.4808 - val_accuracy: 0.9006
Epoch 2/800
27/27 [=====] - 0s 4ms/step - loss: 0.3251 - accuracy: 0.9347 - val_loss: 0.3009 - val_accuracy: 0.9298
Epoch 3/800
27/27 [=====] - 0s 4ms/step - loss: 0.2023 - accuracy: 0.9497 - val_loss: 0.2122 - val_accuracy: 0.9474
Epoch 4/800
27/27 [=====] - 0s 5ms/step - loss: 0.1434 - accuracy: 0.9673 - val_loss: 0.1723 - val_accuracy: 0.9532
Epoch 5/800
27/27 [=====] - 0s 4ms/step - loss: 0.1126 - accuracy: 0.9724 - val_loss: 0.1488 - val_accuracy: 0.9649
Epoch 6/800
27/27 [=====] - 0s 4ms/step - loss: 0.0937 - accuracy: 0.9749 - val_loss: 0.1357 - val_accuracy: 0.9649
Epoch 7/800
27/27 [=====] - 0s 4ms/step - loss: 0.0807 - accuracy: 0.9824 - val_loss: 0.1274 - val_accuracy: 0.9649
Epoch 8/800
27/27 [=====] - 0s 4ms/step - loss: 0.0718 - accuracy: 0.9849 - val_loss: 0.1221 - val_accuracy: 0.9649
Epoch 9/800
27/27 [=====] - 0s 4ms/step - loss: 0.0655 - accuracy: 0.9874 - val_loss: 0.1201 - val_accuracy: 0.9649
Epoch 10/800
27/27 [=====] - 0s 4ms/step - loss: 0.0603 - accuracy: 0.9849 - val_loss: 0.1164 - val_accuracy: 0.9649
Epoch 11/800
27/27 [=====] - 0s 4ms/step - loss: 0.0563 - accuracy: 0.9849 - val_loss: 0.1159 - val_accuracy: 0.9474
Epoch 12/800
27/27 [=====] - 0s 4ms/step - loss: 0.0524 - accuracy: 0.9874 - val_loss: 0.1164 - val_accuracy: 0.9474
Epoch 13/800
27/27 [=====] - 0s 4ms/step - loss: 0.0497 - accuracy: 0.9874 - val_loss: 0.1143 - val_accuracy: 0.9474
Epoch 14/800
27/27 [=====] - 0s 4ms/step - loss: 0.0466 - accuracy: 0.9899 - val_loss: 0.1151 - val_accuracy: 0.9474
Epoch 15/800
27/27 [=====] - 0s 6ms/step - loss: 0.0441 - accuracy: 0.9899 - val_loss: 0.1147 - val_accuracy: 0.9474
Epoch 16/800
27/27 [=====] - 0s 8ms/step - loss: 0.0423 - accuracy: 0.9899 - val_loss: 0.1155 - val_accuracy: 0.9474
Epoch 17/800
27/27 [=====] - 0s 8ms/step - loss: 0.0409 - accuracy: 0.9899 - val_loss: 0.1154 - val_accuracy: 0.9474
Epoch 18/800
27/27 [=====] - 0s 6ms/step - loss: 0.0382 - accuracy: 0.9925 - val_loss: 0.1153 - val_accuracy: 0.9474
Epoch 19/800
27/27 [=====] - 0s 11ms/step - loss: 0.0369 - accuracy: 0.9899 - val_loss: 0.1151 - val_accuracy: 0.9474
Epoch 20/800
27/27 [=====] - 0s 7ms/step - loss: 0.0353 - accuracy: 0.9899 - val_loss: 0.1170 - val_accuracy: 0.9474
Epoch 21/800
27/27 [=====] - 0s 9ms/step - loss: 0.0342 - accuracy: 0.9925 - val_loss: 0.1156 - val_accuracy: 0.9474
Epoch 21: early stopping
<keras.callbacks.History at 0x7fd7b42357f0>
```

```
ann.history.history
```

## Visualising the loss

The plot displays the following data series:

- loss** (blue line): Starts at approximately 0.58 and decreases to about 0.04 by epoch 20.
- accuracy** (orange line): Starts at approximately 0.70 and increases to about 0.99 by epoch 20.
- val\_loss** (green line): Starts at approximately 0.48 and decreases to about 0.12 by epoch 20.
- val\_accuracy** (red line): Starts at approximately 0.90 and increases to about 0.96 by epoch 20.

6/6 [=====] - 0s 3ms/step

## Evaluation

	precision	recall	f1-score	support
0	0.95	0.96	0.96	108
1	0.94	0.92	0.93	63
accuracy			0.95	171
macro avg	0.94	0.94	0.94	171
weighted avg	0.95	0.95	0.95	171