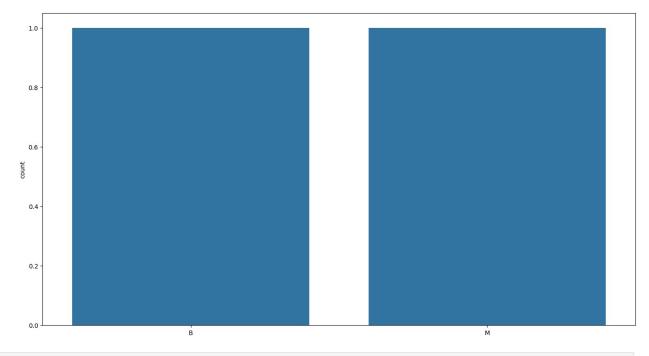
```
#import pandas
import pandas as pd
#import numpy
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
import tensorflow as tf
import keras
df = pd.read_csv("/content/breast-cancer.csv")
print(df)
           id diagnosis radius mean texture mean perimeter mean
area mean \
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                                              10.38
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                                                              122.80
1001.0
       842517
                                20.57
                                              17.77
                                                              132.90
1326.0
     84300903
                                19.69
                                              21.25
                                                              130.00
1203.0
     84348301
                                11.42
                                              20.38
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386.1
     84358402
                                20.29
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. .
       926424
                      М
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1479.0
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       926682
                                20.13
                                              28.25
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1261.0
566
       926954
                                16.60
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                                                              108.30
858.1
                                20.60
                                              29.33
                                                              140.10
567
       927241
1265.0
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                                              24.54
                                                               47.92
568
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     smoothness mean compactness mean concavity mean
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points mean
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             0.11840
                                0.27760
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                                                0.08690
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                                0.15990
                                                0.19740
0.12790
             0.14250
                                0.28390
                                                0.24140
0.10520
             0.10030
                                0.13280
                                                0.19800
0.10430
```

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0.13896		0.11390	0.24390	
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0.09791				
566	0.08455	0.10230	0.09251	
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567 568	0.2650 0.0000	0.4087 0.2871		0.12400 0.07039
200	0.0000	0.20/1		0.07039

```
[569 rows x 32 columns]
# counting values of variables in 'diagnosis'
df['diagnosis'].value_counts()

B    357
M    212
Name: diagnosis, dtype: int64

plt.figure(figsize=[17,9])
sb.countplot(df['diagnosis'].value_counts())
plt.show()
```



```
df.isnull().sum()
id
                            0
                            0
diagnosis
radius mean
                            0
texture_mean
                            0
                            0
perimeter_mean
                            0
area_mean
smoothness mean
                            0
compactness_mean
                            0
concavity mean
                            0
concave points mean
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symmetry_mean
                            0
fractal dimension mean
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                            0
radius se
                            0
texture_se
```

```
0
perimeter se
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area se
smoothness se
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compactness se
concavity se
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concave points se
                           0
symmetry se
fractal dimension se
                           0
                           0
radius worst
texture worst
                           0
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perimeter worst
area worst
                           0
                           0
smoothness worst
                           0
compactness_worst
concavity worst
                           0
                           0
concave points worst
symmetry_worst
fractal dimension worst
dtype: int64
# independent variables
x = df.drop('diagnosis',axis=1)
#dependent variables
y = df.diagnosis
from sklearn.preprocessing import LabelEncoder
#creating the object
lb = LabelEncoder()
y = lb.fit transform(y)
from sklearn.model selection import train test split
xtrain, xtest, ytrain, ytest =
train test split(x,y,test size=0.3,random state=40)
#importing StandardScaler
from sklearn.preprocessing import StandardScaler
#creating object
sc = StandardScaler()
xtrain = sc.fit_transform(xtrain)
xtest = sc.transform(xtest)
#importing keras
import keras
#importing sequential module
from keras.models import Sequential
# import dense module for hidden layers
from keras.layers import Dense
#importing activation functions
from keras.layers import LeakyReLU,PReLU,ELU
from keras.layers import Dropout
```


#taking summary of layers

classifier.summary()

Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_12 (Dense)	(None, 9)	288
dense_13 (Dense)	(None, 9)	90
dense_14 (Dense)	(None, 1)	10

Total params: 388 (1.52 KB)
Trainable params: 388 (1.52 KB)
Non-trainable params: 0 (0.00 Byte)

#taking summary of layers

classifier.summary()

Model: "sequential 2"

Layer (type)	Output Shape	Param #
dense_12 (Dense)	(None, 9)	288
dense_13 (Dense)	(None, 9)	90
dense_14 (Dense)	(None, 1)	10

Total params: 388 (1.52 KB)
Trainable params: 388 (1.52 KB)
Non-trainable params: 0 (0.00 Byte)

```
#compiling the ANN
classifier.compile(optimizer='adam',loss='binary crossentropy',metrics
=['accuracy'])
#fitting the ANN to the training set
model = classifier.fit(xtrain,ytrain,batch size=100,epochs=100)
Epoch 1/100
accuracy: 0.2362
Epoch 2/100
4/4 [============= ] - Os 5ms/step - loss: 1.1396 -
accuracy: 0.2764
Epoch 3/100
accuracy: 0.3367
Epoch 4/100
accuracy: 0.3769
Epoch 5/100
accuracy: 0.4397
Epoch 6/100
accuracy: 0.4925
Epoch 7/100
accuracy: 0.5503
Epoch 8/100
accuracy: 0.6080
Epoch 9/100
accuracy: 0.6482
Epoch 10/100
accuracy: 0.6884
Epoch 11/100
accuracy: 0.7111
Epoch 12/100
accuracy: 0.7387
Epoch 13/100
4/4 [============= ] - 0s 6ms/step - loss: 0.5283 -
accuracy: 0.7688
Epoch 14/100
4/4 [============= ] - Os 5ms/step - loss: 0.5045 -
accuracy: 0.7764
Epoch 15/100
```

```
accuracy: 0.7889
Epoch 16/100
accuracy: 0.8040
Epoch 17/100
accuracy: 0.8090
Epoch 18/100
accuracy: 0.8241
Epoch 19/100
4/4 [============== ] - Os 5ms/step - loss: 0.4200 -
accuracy: 0.8317
Epoch 20/100
accuracy: 0.8417
Epoch 21/100
4/4 [============= ] - Os 4ms/step - loss: 0.3953 -
accuracy: 0.8518
Epoch 22/100
accuracy: 0.8568
Epoch 23/100
accuracy: 0.8618
Epoch 24/100
accuracy: 0.8668
Epoch 25/100
accuracy: 0.8744
Epoch 26/100
accuracy: 0.8794
Epoch 27/100
accuracy: 0.8869
Epoch 28/100
accuracy: 0.8869
Epoch 29/100
accuracy: 0.8894
Epoch 30/100
accuracy: 0.8920
Epoch 31/100
```

```
accuracy: 0.8945
Epoch 32/100
accuracy: 0.8995
Epoch 33/100
accuracy: 0.8995
Epoch 34/100
accuracy: 0.9020
Epoch 35/100
accuracy: 0.9020
Epoch 36/100
accuracy: 0.9070
Epoch 37/100
accuracy: 0.9070
Epoch 38/100
accuracy: 0.9095
Epoch 39/100
accuracy: 0.9146
Epoch 40/100
accuracy: 0.9171
Epoch 41/100
4/4 [============= ] - Os 6ms/step - loss: 0.2454 -
accuracy: 0.9171
Epoch 42/100
4/4 [============= ] - Os 4ms/step - loss: 0.2405 -
accuracy: 0.9171
Epoch 43/100
accuracy: 0.9171
Epoch 44/100
accuracy: 0.9171
Epoch 45/100
accuracy: 0.9171
Epoch 46/100
accuracy: 0.9196
Epoch 47/100
accuracy: 0.9221
```

```
Epoch 48/100
accuracy: 0.9246
Epoch 49/100
4/4 [============= ] - Os 4ms/step - loss: 0.2096 -
accuracy: 0.9246
Epoch 50/100
accuracy: 0.9271
Epoch 51/100
accuracy: 0.9296
Epoch 52/100
accuracy: 0.9296
Epoch 53/100
accuracy: 0.9296
Epoch 54/100
4/4 [============= ] - Os 5ms/step - loss: 0.1912 -
accuracy: 0.9296
Epoch 55/100
accuracy: 0.9347
Epoch 56/100
accuracy: 0.9372
Epoch 57/100
accuracy: 0.9397
Epoch 58/100
accuracy: 0.9397
Epoch 59/100
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Epoch 60/100
accuracy: 0.9397
Epoch 61/100
accuracy: 0.9397
Epoch 62/100
accuracy: 0.9397
Epoch 63/100
4/4 [========= ] - 0s 10ms/step - loss: 0.1640 -
accuracy: 0.9397
Epoch 64/100
```

```
accuracy: 0.9422
Epoch 65/100
accuracy: 0.9447
Epoch 66/100
accuracy: 0.9497
Epoch 67/100
accuracy: 0.9497
Epoch 68/100
4/4 [============== ] - Os 6ms/step - loss: 0.1517 -
accuracy: 0.9548
Epoch 69/100
4/4 [============= ] - Os 6ms/step - loss: 0.1496 -
accuracy: 0.9548
Epoch 70/100
4/4 [============= ] - 0s 6ms/step - loss: 0.1474 -
accuracy: 0.9548
Epoch 71/100
accuracy: 0.9548
Epoch 72/100
accuracy: 0.9548
Epoch 73/100
accuracy: 0.9548
Epoch 74/100
accuracy: 0.9573
Epoch 75/100
4/4 [============= ] - 0s 5ms/step - loss: 0.1374 -
accuracy: 0.9573
Epoch 76/100
accuracy: 0.9573
Epoch 77/100
accuracy: 0.9573
Epoch 78/100
4/4 [============ ] - Os 7ms/step - loss: 0.1319 -
accuracy: 0.9598
Epoch 79/100
4/4 [============== ] - Os 6ms/step - loss: 0.1302 -
accuracy: 0.9623
Epoch 80/100
```

```
accuracy: 0.9673
Epoch 81/100
4/4 [============= ] - Os 8ms/step - loss: 0.1269 -
accuracy: 0.9673
Epoch 82/100
accuracy: 0.9698
Epoch 83/100
accuracy: 0.9673
Epoch 84/100
accuracy: 0.9673
Epoch 85/100
accuracy: 0.9673
Epoch 86/100
accuracy: 0.9673
Epoch 87/100
accuracy: 0.9673
Epoch 88/100
accuracy: 0.9673
Epoch 89/100
accuracy: 0.9673
Epoch 90/100
4/4 [============= ] - Os 6ms/step - loss: 0.1139 -
accuracy: 0.9673
Epoch 91/100
accuracy: 0.9673
Epoch 92/100
accuracy: 0.9673
Epoch 93/100
accuracy: 0.9673
Epoch 94/100
accuracy: 0.9673
Epoch 95/100
accuracy: 0.9724
Epoch 96/100
accuracy: 0.9724
```

```
Epoch 97/100
accuracy: 0.9724
Epoch 98/100
accuracy: 0.9724
Epoch 99/100
4/4 [============= ] - Os 5ms/step - loss: 0.1028 -
accuracy: 0.9724
Epoch 100/100
4/4 [============= ] - Os 6ms/step - loss: 0.1016 -
accuracy: 0.9724
#now testing for Test data
y pred = classifier.predict(xtest)
6/6 [=======] - 0s 4ms/step
#converting values
y_pred = (y_pred>0.5)
print(y pred)
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from sklearn.metrics import confusion matrix
from sklearn.metrics import accuracy_score
cm = confusion matrix(ytest,y pred)
score = accuracy_score(ytest,y_pred)
```

```
print(cm)
print('score is:',score)

[[109 6]
  [ 1 55]]
score is: 0.9590643274853801
```