

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OrdinalEncoder
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
sns.set_style('darkgrid')

```

Import the data

```
df=pd.read_csv('data.csv')
```

Examine first few rows

```
df.head()
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean
area_mean \					
0	842302	M	17.99	10.38	122.80
1001.0					
1	842517	M	20.57	17.77	132.90
1326.0					
2	84300903	M	19.69	21.25	130.00
1203.0					
3	84348301	M	11.42	20.38	77.58
386.1					
4	84358402	M	20.29	14.34	135.10
1297.0					

	smoothness_mean	compactness_mean	concavity_mean	concave
points_mean \				
0	0.11840	0.27760	0.3001	
0.14710				
1	0.08474	0.07864	0.0869	
0.07017				
2	0.10960	0.15990	0.1974	
0.12790				
3	0.14250	0.28390	0.2414	
0.10520				
4	0.10030	0.13280	0.1980	
0.10430				

	... texture_worst	perimeter_worst	area_worst
smoothness_worst \			

0	...	17.33	184.60	2019.0	0.1622
1	...	23.41	158.80	1956.0	0.1238
2	...	25.53	152.50	1709.0	0.1444
3	...	26.50	98.87	567.7	0.2098
4	...	16.67	152.20	1575.0	0.1374

	compactness_worst	concavity_worst	concave points_worst
0	0.6656	0.7119	0.2654
1	0.1866	0.2416	0.1860
2	0.4245	0.4504	0.2430
3	0.8663	0.6869	0.2575
4	0.2050	0.4000	0.1625

	fractal_dimension_worst	Unnamed: 32
0	0.11890	NaN
1	0.08902	NaN
2	0.08758	NaN
3	0.17300	NaN
4	0.07678	NaN

[5 rows x 33 columns]

df.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 569 entries, 0 to 568

Data columns (total 33 columns):

#	Column	Non-Null Count	Dtype
0	id	569 non-null	int64
1	diagnosis	569 non-null	object
2	radius_mean	569 non-null	float64
3	texture_mean	569 non-null	float64
4	perimeter_mean	569 non-null	float64
5	area_mean	569 non-null	float64
6	smoothness_mean	569 non-null	float64
7	compactness_mean	569 non-null	float64
8	concavity_mean	569 non-null	float64
9	concave points_mean	569 non-null	float64

```

10 symmetry_mean          569 non-null    float64
11 fractal_dimension_mean  569 non-null    float64
12 radius_se              569 non-null    float64
13 texture_se             569 non-null    float64
14 perimeter_se           569 non-null    float64
15 area_se                569 non-null    float64
16 smoothness_se          569 non-null    float64
17 compactness_se         569 non-null    float64
18 concavity_se           569 non-null    float64
19 concave points_se      569 non-null    float64
20 symmetry_se            569 non-null    float64
21 fractal_dimension_se   569 non-null    float64
22 radius_worst           569 non-null    float64
23 texture_worst          569 non-null    float64
24 perimeter_worst        569 non-null    float64
25 area_worst             569 non-null    float64
26 smoothness_worst       569 non-null    float64
27 compactness_worst      569 non-null    float64
28 concavity_worst        569 non-null    float64
29 concave points_worst   569 non-null    float64
30 symmetry_worst         569 non-null    float64
31 fractal_dimension_worst 569 non-null    float64
32 Unnamed: 32            0 non-null    float64
dtypes: float64(31), int64(1), object(1)
memory usage: 146.8+ KB

```

Attribute Information: ID number Diagnosis (M = malignant, B = benign) Ten real-valued features are computed for each cell nucleus: radius (mean of distances from center to points on the perimeter) texture (standard deviation of gray-scale values) perimeter area smoothness (local variation in radius lengths) compactness (perimeter² / area - 1.0) concavity (severity of concave portions of the contour) concave points (number of concave portions of the contour) symmetry fractal dimension ("coastline approximation" - 1)

Total 569 entries and 33 columns. column consist of values with float, object and integer datatype.

```
#Dropped unnamed:32 and id column
```

```
df.drop(['Unnamed: 32', 'id'], axis=1, inplace=True) #Dropped unnamed:32 and id column
```

```
#No of rows and columns
```

```
df.shape
```

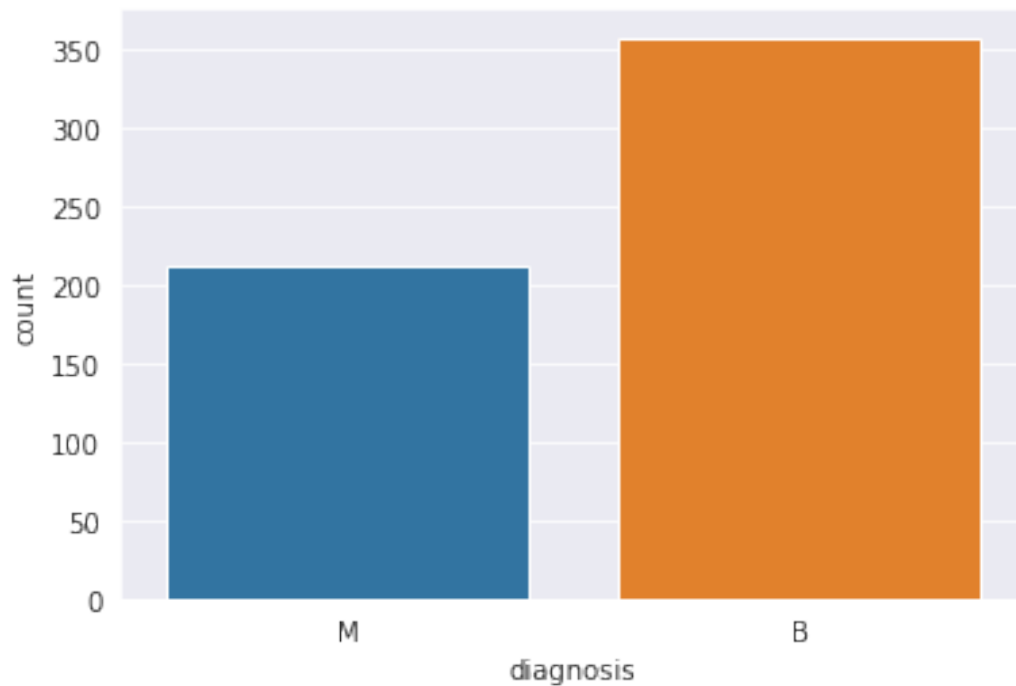
```
(569, 31)
```

```
#Target class(diagnosis) distribution
```

```
sns.countplot(df["diagnosis"])
```

```
print(df['diagnosis'].value_counts())
```

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



The dataset is mildly imbalanced

#Missing attribute values

```
df.isnull().sum()
```

diagnosis	0
radius_mean	0
texture_mean	0
perimeter_mean	0
area_mean	0
smoothness_mean	0
compactness_mean	0
concavity_mean	0
concave points_mean	0
symmetry_mean	0
fractal_dimension_mean	0
radius_se	0
texture_se	0
perimeter_se	0
area_se	0
smoothness_se	0
compactness_se	0
concavity_se	0
concave points_se	0
symmetry_se	0

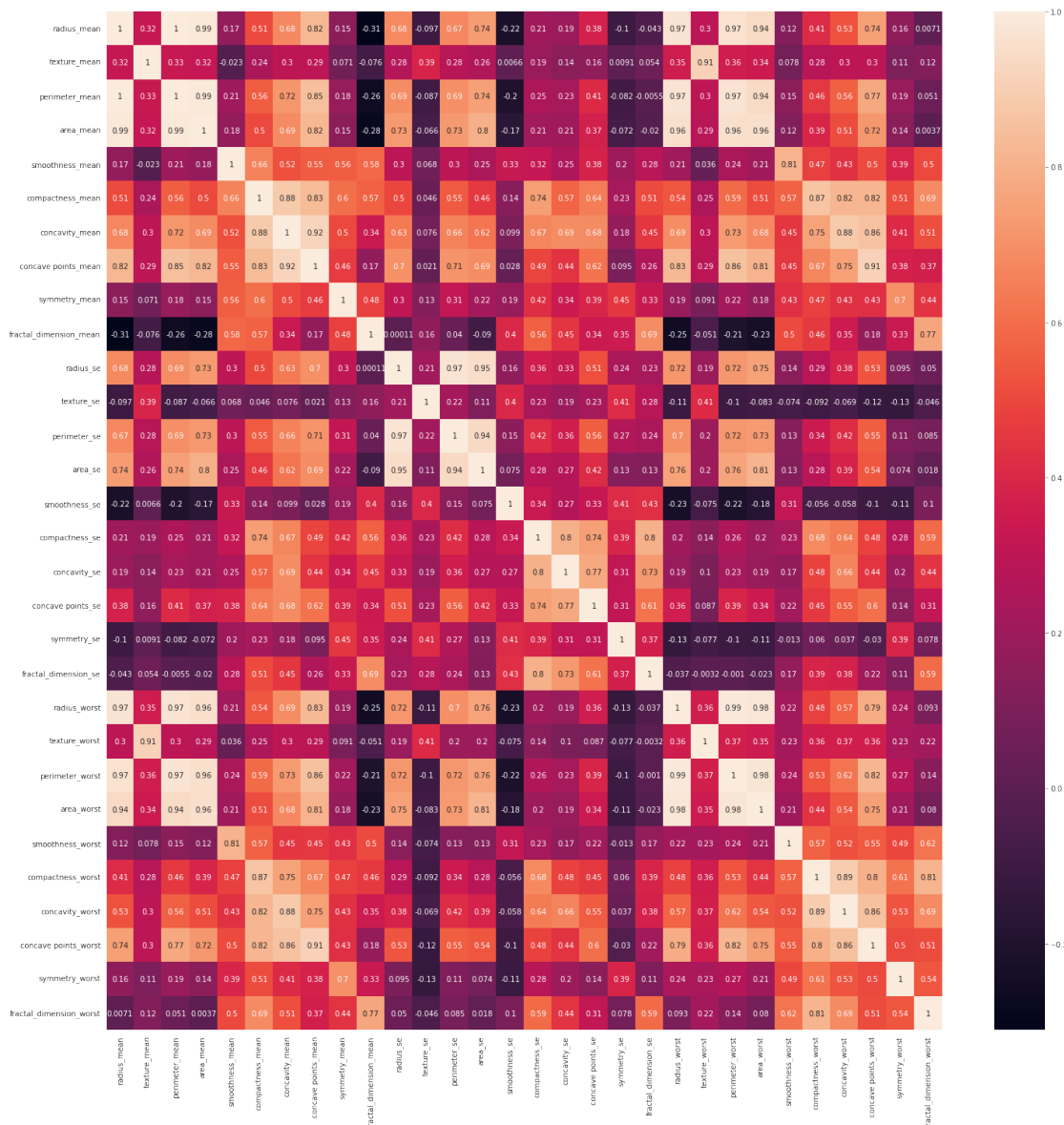
```
fractal_dimension_se      0
radius_worst              0
texture_worst             0
perimeter_worst          0
area_worst                0
smoothness_worst          0
compactness_worst         0
concavity_worst           0
concave points_worst      0
symmetry_worst            0
fractal_dimension_worst   0
dtype: int64
```

No Missing values

#Visualising using heatmap: Helps to understand correlation between features

```
plt.figure(figsize=(25,25))
sns.heatmap(df.corr(),annot=True)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fd819fccb90>



```
#Replacing string values of diagnosis column into 0&1
df['diagnosis']= df['diagnosis'].apply(lambda x: 1 if x=='M' else 0) #
B with 0 and M with 1
```

```
#Most 10 correlated attributes with diagnosis
df.corr()['diagnosis'][:].sort_values()[:10]
```

```
smoothness_se          -0.067016
fractal_dimension_mean -0.012838
texture_se             -0.008303
symmetry_se           -0.006522
fractal_dimension_se   0.077972
concavity_se           0.253730
compactness_se         0.292999
fractal_dimension_worst 0.323872
```

```

symmetry_mean          0.330499
smoothness_mean        0.358560
Name: diagnosis, dtype: float64

```

#Selecting only highly correlated data

```

df_corr = df[['smoothness_se', 'fractal_dimension_mean',
'texture_se', 'symmetry_se', 'fractal_dimension_se',

```

```

'concavity_se', 'compactness_se', 'fractal_dimension_worst', 'symmetry_me
an', 'smoothness_mean', 'diagnosis']]

```

#First 5 samples of df_corr

```

df_corr.head()

```

	smoothness_se	fractal_dimension_mean	texture_se	symmetry_se \
0	0.006399	0.07871	0.9053	0.03003
1	0.005225	0.05667	0.7339	0.01389
2	0.006150	0.05999	0.7869	0.02250
3	0.009110	0.09744	1.1560	0.05963
4	0.011490	0.05883	0.7813	0.01756

	fractal_dimension_se	concavity_se	compactness_se \
0	0.006193	0.05373	0.04904
1	0.003532	0.01860	0.01308
2	0.004571	0.03832	0.04006
3	0.009208	0.05661	0.07458
4	0.005115	0.05688	0.02461

	fractal_dimension_worst	symmetry_mean	smoothness_mean	diagnosis
0	0.11890	0.2419	0.11840	1
1	0.08902	0.1812	0.08474	1
2	0.08758	0.2069	0.10960	1
3	0.17300	0.2597	0.14250	1
4	0.07678	0.1809	0.10030	1

#Descriptive statistics

```

df_corr.describe()

```

	smoothness_se	fractal_dimension_mean	texture_se	symmetry_se
\ count	569.000000	569.000000	569.000000	569.000000
mean	0.007041	0.062798	1.216853	0.020542
std	0.003003	0.007060	0.551648	0.008266

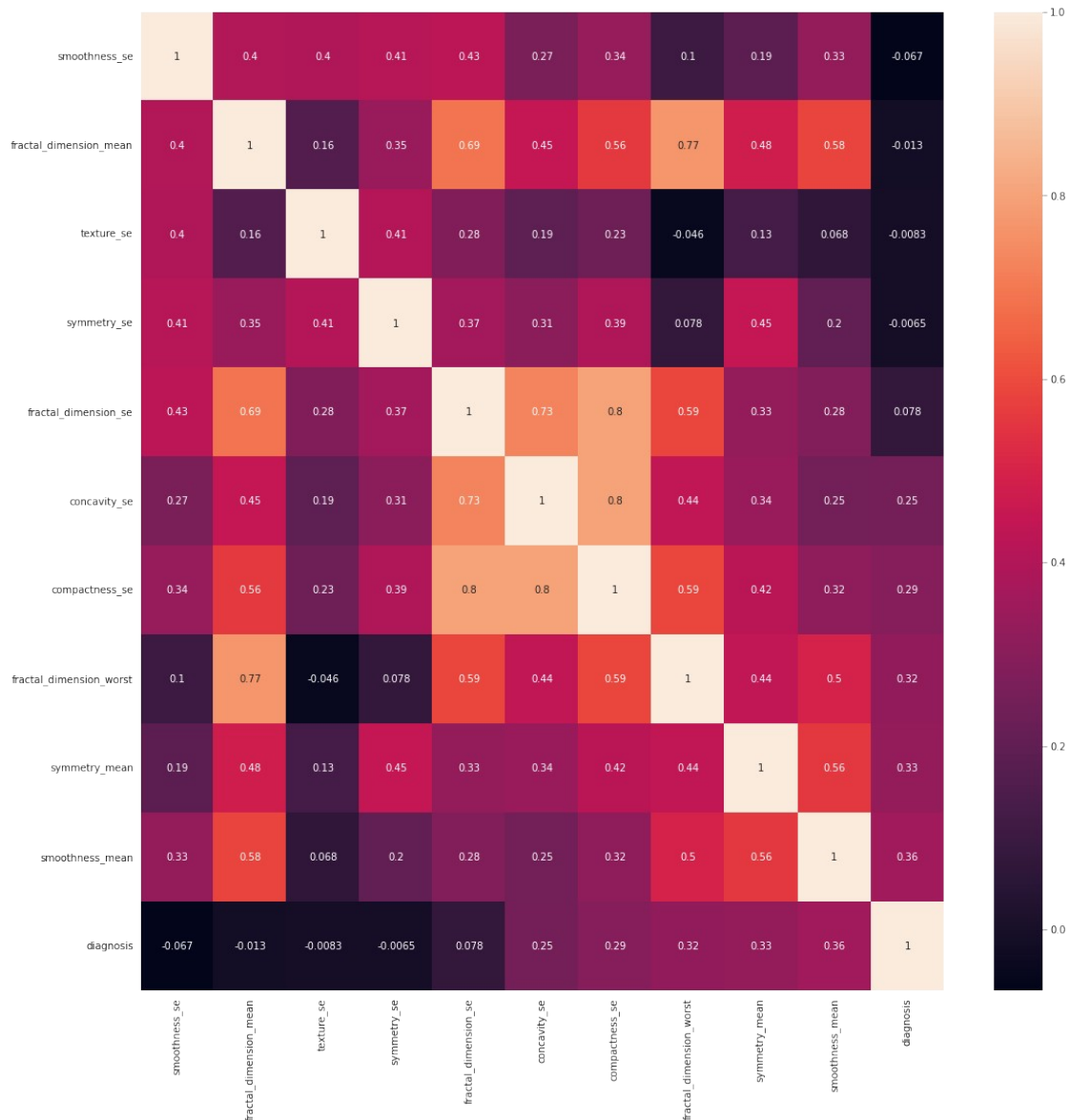
min	0.001713	0.049960	0.360200	0.007882
25%	0.005169	0.057700	0.833900	0.015160
50%	0.006380	0.061540	1.108000	0.018730
75%	0.008146	0.066120	1.474000	0.023480
max	0.031130	0.097440	4.885000	0.078950

	fractal_dimension_se	concavity_se	compactness_se	\
count	569.000000	569.000000	569.000000	
mean	0.003795	0.031894	0.025478	
std	0.002646	0.030186	0.017908	
min	0.000895	0.000000	0.002252	
25%	0.002248	0.015090	0.013080	
50%	0.003187	0.025890	0.020450	
75%	0.004558	0.042050	0.032450	
max	0.029840	0.396000	0.135400	

	fractal_dimension_worst	symmetry_mean	smoothness_mean
diagnosis			
count	569.000000	569.000000	569.000000
569.000000			
mean	0.083946	0.181162	0.096360
0.372583			
std	0.018061	0.027414	0.014064
0.483918			
min	0.055040	0.106000	0.052630
0.000000			
25%	0.071460	0.161900	0.086370
0.000000			
50%	0.080040	0.179200	0.095870
0.000000			
75%	0.092080	0.195700	0.105300
1.000000			
max	0.207500	0.304000	0.163400
1.000000			

```
plt.figure(figsize=(18,18))
sns.heatmap(df_corr.corr(),annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd81a0d6810>
```

#Splitting X & Y for model building

x=df.drop(['diagnosis'],axis=1)

x

	radius_mean	texture_mean	perimeter_mean	area_mean
smoothness_mean \				
0	17.99	10.38	122.80	1001.0
0.11840				
1	20.57	17.77	132.90	1326.0
0.08474				
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				
..
...				
564	21.56	22.39	142.00	1479.0
0.11100				
565	20.13	28.25	131.20	1261.0
0.09780				
566	16.60	28.08	108.30	858.1
0.08455				
567	20.60	29.33	140.10	1265.0
0.11780				
568	7.76	24.54	47.92	181.0
0.05263				

	compactness_mean	concavity_mean	concave	points_mean
symmetry_mean \				
0	0.27760	0.30010		0.14710
0.2419				
1	0.07864	0.08690		0.07017
0.1812				
2	0.15990	0.19740		0.12790
0.2069				
3	0.28390	0.24140		0.10520
0.2597				
4	0.13280	0.19800		0.10430
0.1809				
..
...				
564	0.11590	0.24390		0.13890
0.1726				
565	0.10340	0.14400		0.09791
0.1752				
566	0.10230	0.09251		0.05302
0.1590				
567	0.27700	0.35140		0.15200
0.2397				
568	0.04362	0.00000		0.00000
0.1587				

	fractal_dimension_mean	...	radius_worst	texture_worst	\
0	0.07871	...	25.380	17.33	
1	0.05667	...	24.990	23.41	
2	0.05999	...	23.570	25.53	
3	0.09744	...	14.910	26.50	
4	0.05883	...	22.540	16.67	
..	
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
	perimeter_worst	area_worst	smoothness_worst	compactness_worst
\				
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

	concavity_worst	concave points_worst	symmetry_worst	\
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	

	fractal_dimension_worst
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]
```

```
y=df['diagnosis']
y
```

```
0      1
1      1
2      1
3      1
4      1
```

```
..
564    1
565    1
566    1
567    1
568    0
```

```
Name: diagnosis, Length: 569, dtype: int64
```

```
#Splitting data using inbuilt function train_test_split to get training and testing values of x & y
```

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=1)
```

```
#Scaled features values between 0-1 using standardization.
```

```
#Standardization use standard normal distribution to scale down values
```

```
ss=StandardScaler()
xtrain=ss.fit_transform(xtrain)
xtest=ss.transform(xtest)
```

```
from tensorflow.keras.layers import Dropout #Dropout library is imported to overcome the overfitting of model
```

```
ann=Sequential()
ann.add(Dense(units=9,activation="relu")) #Input layers with 9 neurons
ann.add(Dropout(0.3)) #Dropout rate
ann.add(Dense(units=9,activation="relu")) #Hidden layer with 9 neuron
ann.add(Dense(units=1,activation="sigmoid")) #output layer
ann.compile(optimizer='adam',loss="binary_crossentropy")
ann.fit(xtrain,ytrain, epochs=95,validation_data=(xtest,ytest))
```

```
Epoch 1/95
```

```
13/13 [=====] - 2s 52ms/step - loss: 0.7085 -
```

```
val_loss: 0.6715
```

```
Epoch 2/95
```

```
13/13 [=====] - 0s 14ms/step - loss: 0.6184 -
```

```
val_loss: 0.6073
```

```
Epoch 3/95
```

```
13/13 [=====] - 0s 10ms/step - loss: 0.5569 -  
val_loss: 0.5506  
Epoch 4/95  
13/13 [=====] - 0s 9ms/step - loss: 0.5198 -  
val_loss: 0.4991  
Epoch 5/95  
13/13 [=====] - 0s 10ms/step - loss: 0.4677 -  
val_loss: 0.4479  
Epoch 6/95  
13/13 [=====] - 0s 14ms/step - loss: 0.4091 -  
val_loss: 0.3987  
Epoch 7/95  
13/13 [=====] - 0s 10ms/step - loss: 0.3796 -  
val_loss: 0.3529  
Epoch 8/95  
13/13 [=====] - 0s 12ms/step - loss: 0.3227 -  
val_loss: 0.3150  
Epoch 9/95  
13/13 [=====] - 0s 16ms/step - loss: 0.3077 -  
val_loss: 0.2830  
Epoch 10/95  
13/13 [=====] - 0s 13ms/step - loss: 0.2786 -  
val_loss: 0.2534  
Epoch 11/95  
13/13 [=====] - 0s 9ms/step - loss: 0.2407 -  
val_loss: 0.2302  
Epoch 12/95  
13/13 [=====] - 0s 8ms/step - loss: 0.2248 -  
val_loss: 0.2108  
Epoch 13/95  
13/13 [=====] - 0s 9ms/step - loss: 0.2061 -  
val_loss: 0.1941  
Epoch 14/95  
13/13 [=====] - 0s 8ms/step - loss: 0.1889 -  
val_loss: 0.1811  
Epoch 15/95  
13/13 [=====] - 0s 9ms/step - loss: 0.1618 -  
val_loss: 0.1712  
Epoch 16/95  
13/13 [=====] - 0s 14ms/step - loss: 0.1520 -  
val_loss: 0.1631  
Epoch 17/95  
13/13 [=====] - 0s 14ms/step - loss: 0.1559 -  
val_loss: 0.1562  
Epoch 18/95  
13/13 [=====] - 0s 16ms/step - loss: 0.1640 -  
val_loss: 0.1500  
Epoch 19/95  
13/13 [=====] - 0s 9ms/step - loss: 0.1578 -  
val_loss: 0.1442
```

```
Epoch 20/95
13/13 [=====] - 0s 13ms/step - loss: 0.1415 -
val_loss: 0.1397
Epoch 21/95
13/13 [=====] - 0s 14ms/step - loss: 0.1304 -
val_loss: 0.1362
Epoch 22/95
13/13 [=====] - 0s 13ms/step - loss: 0.1307 -
val_loss: 0.1331
Epoch 23/95
13/13 [=====] - 0s 21ms/step - loss: 0.1140 -
val_loss: 0.1305
Epoch 24/95
13/13 [=====] - 0s 22ms/step - loss: 0.1220 -
val_loss: 0.1281
Epoch 25/95
13/13 [=====] - 0s 14ms/step - loss: 0.1082 -
val_loss: 0.1262
Epoch 26/95
13/13 [=====] - 0s 18ms/step - loss: 0.1052 -
val_loss: 0.1245
Epoch 27/95
13/13 [=====] - 0s 18ms/step - loss: 0.0892 -
val_loss: 0.1230
Epoch 28/95
13/13 [=====] - 0s 16ms/step - loss: 0.1139 -
val_loss: 0.1220
Epoch 29/95
13/13 [=====] - 0s 10ms/step - loss: 0.1073 -
val_loss: 0.1218
Epoch 30/95
13/13 [=====] - 0s 13ms/step - loss: 0.1043 -
val_loss: 0.1218
Epoch 31/95
13/13 [=====] - 0s 14ms/step - loss: 0.1105 -
val_loss: 0.1218
Epoch 32/95
13/13 [=====] - 0s 9ms/step - loss: 0.0849 -
val_loss: 0.1218
Epoch 33/95
13/13 [=====] - 0s 8ms/step - loss: 0.0852 -
val_loss: 0.1208
Epoch 34/95
13/13 [=====] - 0s 9ms/step - loss: 0.0830 -
val_loss: 0.1205
Epoch 35/95
13/13 [=====] - 0s 13ms/step - loss: 0.0981 -
val_loss: 0.1201
Epoch 36/95
13/13 [=====] - 0s 9ms/step - loss: 0.0700 -
```

```
val_loss: 0.1198
Epoch 37/95
13/13 [=====] - 0s 11ms/step - loss: 0.0838 -
val_loss: 0.1195
Epoch 38/95
13/13 [=====] - 0s 17ms/step - loss: 0.0860 -
val_loss: 0.1195
Epoch 39/95
13/13 [=====] - 0s 12ms/step - loss: 0.0803 -
val_loss: 0.1190
Epoch 40/95
13/13 [=====] - 0s 8ms/step - loss: 0.0802 -
val_loss: 0.1186
Epoch 41/95
13/13 [=====] - 0s 8ms/step - loss: 0.0733 -
val_loss: 0.1187
Epoch 42/95
13/13 [=====] - 0s 7ms/step - loss: 0.0789 -
val_loss: 0.1192
Epoch 43/95
13/13 [=====] - 0s 11ms/step - loss: 0.0740 -
val_loss: 0.1194
Epoch 44/95
13/13 [=====] - 0s 21ms/step - loss: 0.0766 -
val_loss: 0.1194
Epoch 45/95
13/13 [=====] - 0s 15ms/step - loss: 0.0683 -
val_loss: 0.1192
Epoch 46/95
13/13 [=====] - 0s 12ms/step - loss: 0.0854 -
val_loss: 0.1192
Epoch 47/95
13/13 [=====] - 0s 12ms/step - loss: 0.0702 -
val_loss: 0.1199
Epoch 48/95
13/13 [=====] - 0s 12ms/step - loss: 0.0700 -
val_loss: 0.1200
Epoch 49/95
13/13 [=====] - 0s 9ms/step - loss: 0.0778 -
val_loss: 0.1196
Epoch 50/95
13/13 [=====] - 0s 8ms/step - loss: 0.0713 -
val_loss: 0.1199
Epoch 51/95
13/13 [=====] - 0s 8ms/step - loss: 0.0690 -
val_loss: 0.1203
Epoch 52/95
13/13 [=====] - 0s 16ms/step - loss: 0.0675 -
val_loss: 0.1209
Epoch 53/95
```

```
13/13 [=====] - 0s 19ms/step - loss: 0.0567 -  
val_loss: 0.1216  
Epoch 54/95  
13/13 [=====] - 0s 8ms/step - loss: 0.0720 -  
val_loss: 0.1249  
Epoch 55/95  
13/13 [=====] - 0s 18ms/step - loss: 0.0606 -  
val_loss: 0.1237  
Epoch 56/95  
13/13 [=====] - 0s 19ms/step - loss: 0.0617 -  
val_loss: 0.1241  
Epoch 57/95  
13/13 [=====] - 0s 23ms/step - loss: 0.0532 -  
val_loss: 0.1245  
Epoch 58/95  
13/13 [=====] - 0s 19ms/step - loss: 0.0444 -  
val_loss: 0.1243  
Epoch 59/95  
13/13 [=====] - 0s 19ms/step - loss: 0.0756 -  
val_loss: 0.1230  
Epoch 60/95  
13/13 [=====] - 0s 7ms/step - loss: 0.0516 -  
val_loss: 0.1244  
Epoch 61/95  
13/13 [=====] - 0s 16ms/step - loss: 0.0697 -  
val_loss: 0.1248  
Epoch 62/95  
13/13 [=====] - 0s 11ms/step - loss: 0.0722 -  
val_loss: 0.1245  
Epoch 63/95  
13/13 [=====] - 0s 8ms/step - loss: 0.0554 -  
val_loss: 0.1250  
Epoch 64/95  
13/13 [=====] - 0s 14ms/step - loss: 0.0642 -  
val_loss: 0.1249  
Epoch 65/95  
13/13 [=====] - 0s 15ms/step - loss: 0.0623 -  
val_loss: 0.1250  
Epoch 66/95  
13/13 [=====] - 0s 13ms/step - loss: 0.0585 -  
val_loss: 0.1254  
Epoch 67/95  
13/13 [=====] - 0s 16ms/step - loss: 0.0572 -  
val_loss: 0.1251  
Epoch 68/95  
13/13 [=====] - 0s 13ms/step - loss: 0.0532 -  
val_loss: 0.1255  
Epoch 69/95  
13/13 [=====] - 0s 12ms/step - loss: 0.0574 -  
val_loss: 0.1259
```


Epoch 70/95
13/13 [=====] - 0s 9ms/step - loss: 0.0382 -
val_loss: 0.1263
Epoch 71/95
13/13 [=====] - 0s 10ms/step - loss: 0.0480 -
val_loss: 0.1262
Epoch 72/95
13/13 [=====] - 0s 12ms/step - loss: 0.0488 -
val_loss: 0.1256
Epoch 73/95
13/13 [=====] - 0s 14ms/step - loss: 0.0573 -
val_loss: 0.1267
Epoch 74/95
13/13 [=====] - 0s 10ms/step - loss: 0.0490 -
val_loss: 0.1273
Epoch 75/95
13/13 [=====] - 0s 13ms/step - loss: 0.0483 -
val_loss: 0.1278
Epoch 76/95
13/13 [=====] - 0s 11ms/step - loss: 0.0465 -
val_loss: 0.1285
Epoch 77/95
13/13 [=====] - 0s 12ms/step - loss: 0.0560 -
val_loss: 0.1285
Epoch 78/95
13/13 [=====] - 0s 10ms/step - loss: 0.0317 -
val_loss: 0.1294
Epoch 79/95
13/13 [=====] - 0s 8ms/step - loss: 0.0409 -
val_loss: 0.1294
Epoch 80/95
13/13 [=====] - 0s 9ms/step - loss: 0.0463 -
val_loss: 0.1312
Epoch 81/95
13/13 [=====] - 0s 11ms/step - loss: 0.0493 -
val_loss: 0.1319
Epoch 82/95
13/13 [=====] - 0s 13ms/step - loss: 0.0508 -
val_loss: 0.1317
Epoch 83/95
13/13 [=====] - 0s 9ms/step - loss: 0.0451 -
val_loss: 0.1354
Epoch 84/95
13/13 [=====] - 0s 8ms/step - loss: 0.0480 -
val_loss: 0.1339
Epoch 85/95
13/13 [=====] - 0s 11ms/step - loss: 0.0501 -
val_loss: 0.1314
Epoch 86/95
13/13 [=====] - 0s 7ms/step - loss: 0.0511 -

```
val_loss: 0.1310
Epoch 87/95
13/13 [=====] - 0s 7ms/step - loss: 0.0484 -
val_loss: 0.1324
Epoch 88/95
13/13 [=====] - 0s 9ms/step - loss: 0.0455 -
val_loss: 0.1329
Epoch 89/95
13/13 [=====] - 0s 11ms/step - loss: 0.0404 -
val_loss: 0.1337
Epoch 90/95
13/13 [=====] - 0s 8ms/step - loss: 0.0523 -
val_loss: 0.1337
Epoch 91/95
13/13 [=====] - 0s 12ms/step - loss: 0.0382 -
val_loss: 0.1352
Epoch 92/95
13/13 [=====] - 0s 15ms/step - loss: 0.0408 -
val_loss: 0.1348
Epoch 93/95
13/13 [=====] - 0s 16ms/step - loss: 0.0438 -
val_loss: 0.1350
Epoch 94/95
13/13 [=====] - 0s 13ms/step - loss: 0.0346 -
val_loss: 0.1337
Epoch 95/95
13/13 [=====] - 0s 18ms/step - loss: 0.0395 -
val_loss: 0.1347
```

<keras.callbacks.History at 0x7fd811385290>

ann.history.history *#Stores the values of accuracy and loss*

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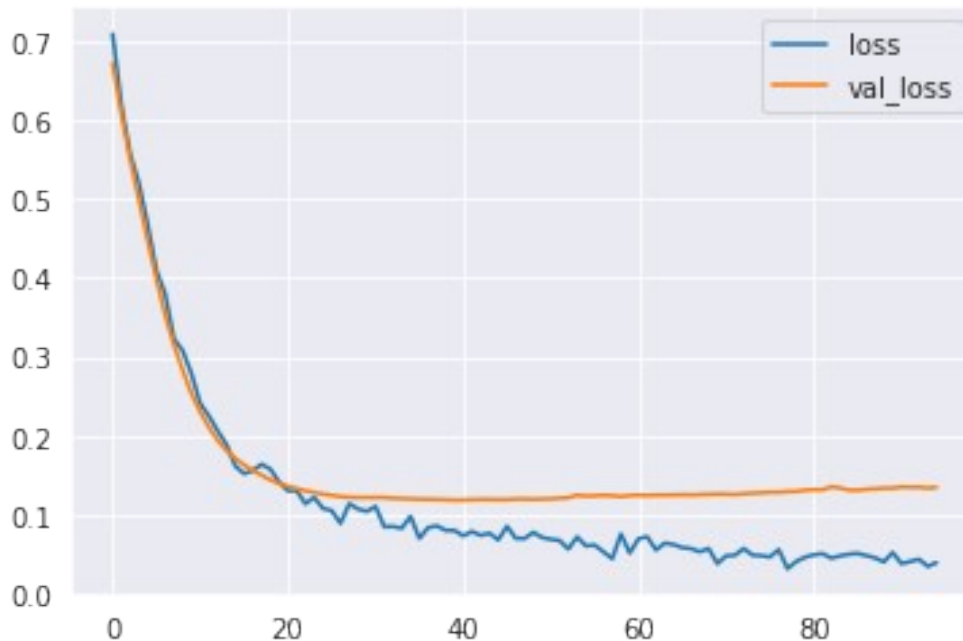
```

```

lossdf=pd.DataFrame(ann.history.history)
lossdf.plot()
print('

```

Loss Vs Validation loss



```
ypred=ann.predict(xtest)
ypred=ypred>0.4 #Set threshold to 0.4

from sklearn.metrics import classification_report,confusion_matrix
print(classification_report(ytest,ypred))
```

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

CLASSIFICATION REPORT : It helps to interpret the precision,recall, f1_score, support and accuracy.

```
print(confusion_matrix(ytest,ypred))
```

```
[[104  4]
 [ 4 59]]
```

CONFUSION MATRIX: It helps to interpret the values such as True Negative(104), False positive(4), False Negative(3) and True Positive(60).

#Graphically representation of confusion matrix

```
from mlxtend.plotting import plot_confusion_matrix
fig, ax = plot_confusion_matrix(confusion_matrix(ytest,ypred),
figsize=(6, 6), cmap=plt.cm.Greens)
```

