```
# Mountage of Google Drive

from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True)
```

```
# Installation of TensorFlow
# Below code is marked as comment. This is required if tensor flow is not installed


#!pip install tensorflow==2.3.0


import tensorflow as tf
print(tf.__version__)
```

```
2.3.0
```

```
# Reading DataSet

import pandas as pd
import numpy as np
import seaborn as sns
% matplotlib inline

bank_data = pd.read_csv('/content/drive/My Drive/Colab Notebooks/bank.csv')
bank_data.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMe
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	

```
# Checking shape of Data
bank_data.shape
```

```
(10000, 14)
```

```
# Checking datatypes of Data
bank_data.dtypes
```

```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

```
# Checking for nulll value in  DataSet
bank_data.isnull().sum()
```

```
RowNumber         0
CustomerId        0
Surname           0
CreditScore       0
```

```
# Checking for no of unique in dataset
bank_data.nunique()
```

```
RowNumber          10000
CustomerId         10000
Surname             2932
CreditScore          460
Geography              3
Gender                 2
Age                   70
Tenure                11
Balance             6382
NumOfProducts          4
HasCrCard              2
IsActiveMember         2
EstimatedSalary     9999
Exited                 2
dtype: int64
```

There are unique Row Number and unique Customer ID. Hence there are no duplicated customer data, However surname may match to many but can be saggregated by customer ID.

```
# Dropping columns which are not required in Analysis
bank_data.drop(columns=['RowNumber', 'CustomerId', 'Surname'],axis=1, inplace=True)
```

```
bank_data.head()
```

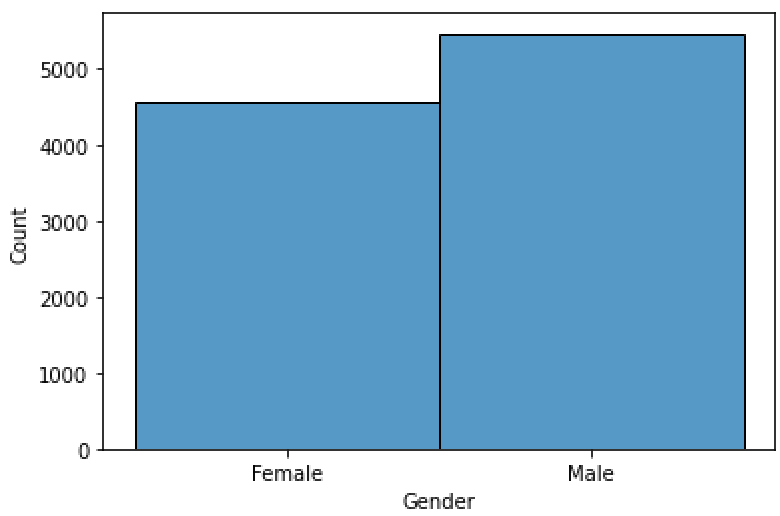
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

```
bank_data['Gender'].value_counts()
```

```
Male      5457
Female    4543
Name: Gender, dtype: int64
```

```
sns.histplot(bank_data['Gender'])

# We can observe that based on Gender, difference in no of Male and Female Customer are not much
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f25cf396668>
```

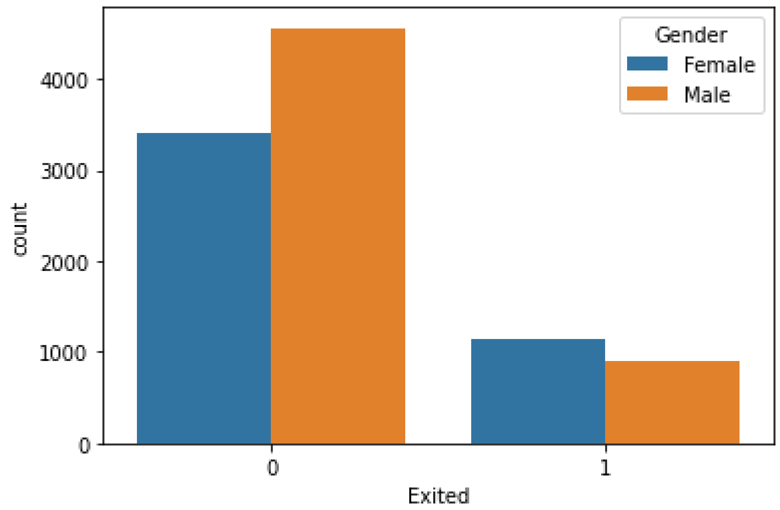



```
bank_data.groupby(by='Gender')['Exited'].value_counts()
```

```
Gender  Exited
Female  0         3404
        1         1139
Male    0         4559
        1          898
Name: Exited, dtype: int64
```

```
sns.countplot(x="Exited", hue="Gender", data=bank_data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f25ce053a58>
```



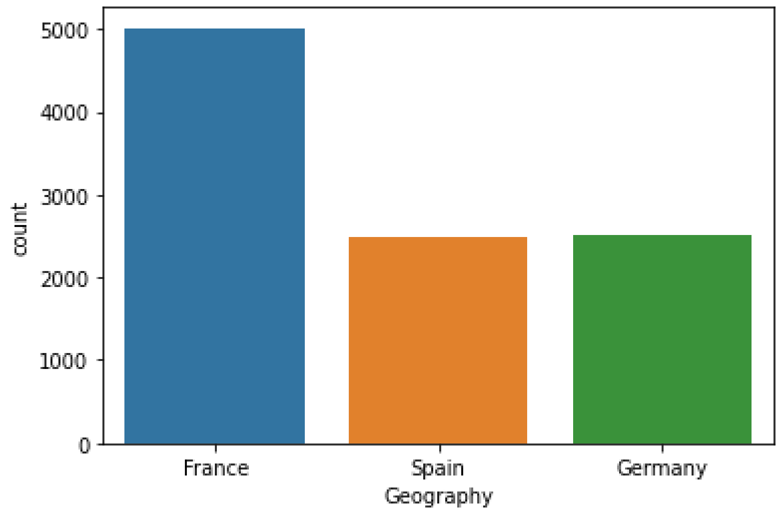

```
Non_Exited=bank_data['Exited'].value_counts()[0]
Exited=bank_data['Exited'].value_counts()[1]

Non_Exited_perc= (Non_Exited/(Non_Exited + Exited))*100
Exited_perc= (Exited/(Non_Exited + Exited))*100

print('Exited Customer     % :' ,Exited_perc)
print('Non Exited Customer % :' ,Non_Exited_perc)
```

```
Exited Customer     % : 20.369999999999997
Non Exited Customer % : 79.63
```

- There are 21% customer out of this complete data set has Exited.

```
sns.countplot(x="Geography", data=bank_data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f25cdb82a20>
```



More Number of customers are there in France in compared to Spain and Germany.

```
bank_data.groupby(by='Geography')['Exited'].value_counts()
```

```
Geography  Exited
France     0         4204
           1          810
Germany    0         1695
           1          814
Spain      0         2064
           1          413
Name: Exited, dtype: int64
```

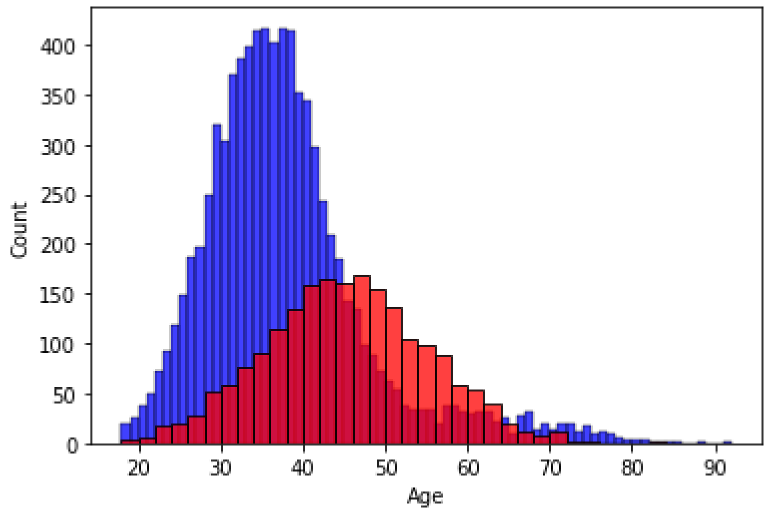
```
sns.countplot(x="Exited", hue="Geography", data=bank_data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f25cdb5ca90>
```

Looking to the ratio of total no of Customer and total no of customer exiting, we can say that more number of customer has exited from Germany

More number of Female Customers have exited Bank in comparison to male customers.

```
import matplotlib.pyplot as plt
sns.histplot(bank_data['Age'][bank_data['Exited']==0],color='blue',label='non-exited')
sns.histplot(bank_data['Age'][bank_data['Exited']==1],color='red',label='exited')
plt.show()
```



- Non Exited Customer graph(Blue Color) is right skewed. There are some customer who are at agemore than 70 and are still customer
- Exited customer graph is like uniform distribution

```
# Statistics of Data

bank_data.describe()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	1000
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	
std	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	
min	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	
25%	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	
max	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	

```
# Distinguish the features and target variable

X= bank_data.drop(columns= 'Exited', axis=1)     # Feature Variable
y= bank_data['Exited']                           # Target Variable


# Converting categorical variable using one Hot Encoding
X= pd.get_dummies(X)
X.head()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Geography_France	Geography_
0	619	42	2	0.00	1	1	1	101348.88	1	
1	608	41	1	83807.86	1	0	1	112542.58	0	
2	502	42	8	159660.80	3	1	0	113931.57	1	
3	699	39	1	0.00	2	0	0	93826.63	1	
4	850	43	2	125510.82	1	1	1	79084.10	0	

```
# Dividing data into Training Set and Testing Set
```

```
# Dividing data into Training Set and Testing Set
#  importing library train test split
from sklearn.model_selection import train_test_split

test_size = 0.20 # taking 80:20 training and testing set
seed = 5  # Random numbmer selection for seeding for reapeatability of code
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, random_state=seed)
```

```
# Checking Shape of training / testing
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((8000, 13), (2000, 13), (8000,), (2000,))
```

```
# Normalization of data
# Now scale the data as features are on different scales. All data must be scaled before modelling
from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()    # MinMaxScalar for scaling

# fitting the Scaler transform on training and testing seperately
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_train
```

```
array([[0.8       , 0.28378378, 0.6       , ..., 1.        , 1.        ,
        0.        ],
       [0.752     , 0.21621622, 0.3       , ..., 0.        , 0.        ,
        1.        ],
       [0.476     , 0.62162162, 0.3       , ..., 0.        , 1.        ,
        0.        ],
       ...,
       [0.466     , 0.17567568, 0.4       , ..., 0.        , 1.        ,
        0.        ],
       [0.658     , 0.24324324, 0.6       , ..., 0.        , 0.        ,
        1.        ],
       [0.278     , 0.45945946, 0.1       , ..., 0.        , 1.        ,
        0.        ]])
```

```
# Convert the data elements into tensors as we need tensors to be fed into different tensorflow based operations

X_train=tf.convert_to_tensor(X_train)
y_train=tf.convert_to_tensor(y_train.values)
X_test=tf.convert_to_tensor(X_test)
y_test=tf.convert_to_tensor(y_test.values)
```

```
X_train.shape, X_test.shape
```

```
(TensorShape([8000, 13]), TensorShape([2000, 13]))
```

Initialize & build the model (2 layers in Hidden layer, activation = Relu)

```
# Initialize Sequential model
model = tf.keras.models.Sequential()
```

```
# Add Input layer to the model
model.add(tf.keras.Input(shape=(13,))) # 13 Features
```

```
# Hidden layers
model.add(tf.keras.layers.Dense(13, activation='relu', name='Layer_1'))
model.add(tf.keras.layers.Dense(10, activation='relu', name='Layer_2'))

#Output layer
model.add(tf.keras.layers.Dense(1, activation='sigmoid', name='Output'))
```

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

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
Layer_1 (Dense)              (None, 13)                182
_________________________________________________________________
Layer_2 (Dense)              (None, 10)                140
_________________________________________________________________
Output (Dense)               (None, 1)                 11
```

```
model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=50,  batch_size = 30)
```

```
Epoch 1/50
267/267 [==============================] - 1s 3ms/step - loss: 0.5616 - accuracy: 0.7251 - val_loss: 0.4873 - val_accuracy: 0.7
Epoch 2/50
267/267 [==============================] - 1s 3ms/step - loss: 0.4811 - accuracy: 0.7960 - val_loss: 0.4712 - val_accuracy: 0.7
Epoch 3/50
267/267 [==============================] - 1s 3ms/step - loss: 0.4660 - accuracy: 0.7971 - val_loss: 0.4589 - val_accuracy: 0.8
Epoch 4/50
267/267 [==============================] - 1s 3ms/step - loss: 0.4516 - accuracy: 0.8048 - val_loss: 0.4468 - val_accuracy: 0.8
Epoch 5/50
267/267 [==============================] - 1s 3ms/step - loss: 0.4377 - accuracy: 0.8120 - val_loss: 0.4372 - val_accuracy: 0.8
Epoch 6/50
267/267 [==============================] - 1s 3ms/step - loss: 0.4245 - accuracy: 0.8185 - val_loss: 0.4240 - val_accuracy: 0.8
Epoch 7/50
267/267 [==============================] - 1s 3ms/step - loss: 0.4118 - accuracy: 0.8211 - val_loss: 0.4112 - val_accuracy: 0.8
Epoch 8/50
267/267 [==============================] - 1s 3ms/step - loss: 0.3995 - accuracy: 0.8275 - val_loss: 0.4043 - val_accuracy: 0.8
Epoch 9/50
267/267 [==============================] - 1s 3ms/step - loss: 0.3893 - accuracy: 0.8320 - val_loss: 0.3993 - val_accuracy: 0.8
Epoch 10/50
267/267 [==============================] - 1s 3ms/step - loss: 0.3827 - accuracy: 0.8379 - val_loss: 0.3877 - val_accuracy: 0.8
Epoch 11/50
267/267 [==============================] - 1s 3ms/step - loss: 0.3754 - accuracy: 0.8410 - val_loss: 0.3819 - val_accuracy: 0.8
Epoch 12/50
267/267 [==============================] - 1s 3ms/step - loss: 0.3695 - accuracy: 0.8430 - val_loss: 0.3766 - val_accuracy: 0.84
Epoch 13/50
```

```
results = model.evaluate(X_test,y_test)
```

```
63/63 [==============================] - 0s 2ms/step - loss: 0.3591 - accuracy: 0.8530
267/267 [==============================] - 1s 3ms/step - loss: 0.3622 - accuracy: 0.8470 - val_loss: 0.3717 - val_accuracy: 0.8
```

```
# Predict the model
predict_arr=model.predict(X_test)
predict_arr[:10]
```

```
array([[0.03385691],
       [0.0595954 ],
       [0.068305  ],
       [0.06269954],
       [0.05250505],
       [0.09442736],
       [0.0081165 ],
       [0.3174991 ],
       [0.00999431],
       [0.9545979 ]], dtype=float32)
267/267 [==============================] - 1s 3ms/step - loss: 0.3493 - accuracy: 0.8530 - val_loss: 0.3631 - val_accuracy: 0.8
```

```
# Predict the results using 0.5 as a threshold

predict_arr_thrshld= predict_arr> 0.5
predict_arr_thrshld
```

```
array([[False],
       [False],
       [False],
       ...,
       [False],
       [False],
       [False]])
267/267 [==============================] - 1s 3ms/step - loss: 0.3457 - accuracy: 0.8576 - val_loss: 0.3609 - val_accuracy: 0.84
```

```
# Confusion matrix with optimal Threshold on test set
from sklearn import metrics
from sklearn.metrics import accuracy_score, recall_score,f1_score, precision_score
metrics.confusion_matrix(y_test, predict_arr_thrshld)
```

```
array([[1545,   50],
       [ 244,  161]])
267/267 [==============================] - 1s 3ms/step - loss: 0.3438 - accuracy: 0.8571 - val_loss: 0.3576 - val_accuracy: 0.8
```

```
# Printing Metrics

print('Neural Network Metrics')
print('Accuracy  :' ,accuracy_score(y_test, predict_arr_thrshld))
print('Precision :',precision_score(y_test, predict_arr_thrshld))
print('Recall    :',recall_score(y_test, predict_arr_thrshld))
print('F1 Score  :',f1_score(y_test, predict_arr_thrshld))
```

```
Neural Network Metrics
Accuracy  : 0.853
Precision : 0.7630331753554502
Recall    : 0.39753086419753086
F1 Score  : 0.5227272727272727
Epoch 45/50
267/267 [==============================] - 1s 3ms/step - loss: 0.3404 - accuracy: 0.8590 - val_loss: 0.3552 - val_accuracy: 0.8
```

```
# Rebuilding Model by changing Hyper parameters as improvement points
# using tanh as activation function
# using 3 layers in hidden layer
# using different optimizer
```

Epoch 48/50

Initialize & build the model (3 layers in Hidden layer, activation = tanh)

```
267/267 [==============================] - 1s 3ms/step - loss: 0.3392 - accuracy: 0.8602 - val_loss: 0.3583 - val_accuracy: 0.8
```

```
# Initialize Sequential model
model = tf.keras.models.Sequential()


# Add Input layer to the model
model.add(tf.keras.Input(shape=(13,))) # 13 Features


# Hidden layers
model.add(tf.keras.layers.Dense(20, activation='tanh', name='Layer_1'))
model.add(tf.keras.layers.Dense(10, activation='tanh', name='Layer_2'))
model.add(tf.keras.layers.Dense(5, activation='tanh', name='Layer_3'))

#Output layer
model.add(tf.keras.layers.Dense(1, activation='sigmoid', name='Output'))


# model compilation
from tensorflow.keras import optimizers
sgd = optimizers.Adam(lr = 0.01)
model.compile(optimizer=sgd, loss='binary_crossentropy', metrics=['accuracy'])



model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
Layer_1 (Dense)              (None, 20)                280
_________________________________________________________________
Layer_2 (Dense)              (None, 10)                210
_________________________________________________________________
Layer_3 (Dense)              (None, 5)                 55
_________________________________________________________________
Output (Dense)               (None, 1)                 6
=================================================================
Total params: 551
Trainable params: 551
Non-trainable params: 0
_________________________________________________________________
```

```
model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=50, batch_size = 32)
```

```
Epoch 1/50
250/250 [==============================] - 1s 3ms/step - loss: 0.4630 - accuracy: 0.8026 - val_loss: 0.4333 - val_accuracy: 0.8
Epoch 2/50
250/250 [==============================] - 1s 2ms/step - loss: 0.4183 - accuracy: 0.8282 - val_loss: 0.4288 - val_accuracy: 0.8
Epoch 3/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3998 - accuracy: 0.8309 - val_loss: 0.3892 - val_accuracy: 0.84
Epoch 4/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3708 - accuracy: 0.8491 - val_loss: 0.3906 - val_accuracy: 0.84
Epoch 5/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3617 - accuracy: 0.8506 - val_loss: 0.3805 - val_accuracy: 0.84
Epoch 6/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3572 - accuracy: 0.8526 - val_loss: 0.3781 - val_accuracy: 0.84
Epoch 7/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3570 - accuracy: 0.8541 - val_loss: 0.3673 - val_accuracy: 0.84
Epoch 8/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3540 - accuracy: 0.8544 - val_loss: 0.3683 - val_accuracy: 0.8
Epoch 9/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3503 - accuracy: 0.8594 - val_loss: 0.3605 - val_accuracy: 0.8
Epoch 10/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3478 - accuracy: 0.8606 - val_loss: 0.3670 - val_accuracy: 0.8
Epoch 11/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3454 - accuracy: 0.8595 - val_loss: 0.3509 - val_accuracy: 0.8
Epoch 12/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3394 - accuracy: 0.8631 - val_loss: 0.3618 - val_accuracy: 0.8
Epoch 13/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3406 - accuracy: 0.8609 - val_loss: 0.3620 - val_accuracy: 0.8
Epoch 14/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3415 - accuracy: 0.8586 - val_loss: 0.3552 - val_accuracy: 0.8
Epoch 15/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3377 - accuracy: 0.8627 - val_loss: 0.3540 - val_accuracy: 0.8
Epoch 16/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3354 - accuracy: 0.8621 - val_loss: 0.3581 - val_accuracy: 0.8
Epoch 17/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3348 - accuracy: 0.8650 - val_loss: 0.3559 - val_accuracy: 0.8
Epoch 18/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3383 - accuracy: 0.8626 - val_loss: 0.3586 - val_accuracy: 0.8
Epoch 19/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3345 - accuracy: 0.8636 - val_loss: 0.3562 - val_accuracy: 0.8
Epoch 20/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3367 - accuracy: 0.8596 - val_loss: 0.3527 - val_accuracy: 0.8
Epoch 21/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3357 - accuracy: 0.8609 - val_loss: 0.3482 - val_accuracy: 0.8
Epoch 22/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3332 - accuracy: 0.8662 - val_loss: 0.3570 - val_accuracy: 0.8
Epoch 23/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3346 - accuracy: 0.8636 - val_loss: 0.3633 - val_accuracy: 0.84
Epoch 24/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3315 - accuracy: 0.8649 - val_loss: 0.3609 - val_accuracy: 0.84
Epoch 25/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3334 - accuracy: 0.8624 - val_loss: 0.3689 - val_accuracy: 0.84
Epoch 26/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3300 - accuracy: 0.8659 - val_loss: 0.3567 - val_accuracy: 0.8
Epoch 27/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3294 - accuracy: 0.8651 - val_loss: 0.3586 - val_accuracy: 0.84
Epoch 28/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3301 - accuracy: 0.8631 - val_loss: 0.3530 - val_accuracy: 0.8
Epoch 29/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3341 - accuracy: 0.8646 - val_loss: 0.3661 - val_accuracy: 0.84
Epoch 30/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3275 - accuracy: 0.8665 - val_loss: 0.3619 - val_accuracy: 0.8
Epoch 31/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3288 - accuracy: 0.8656 - val_loss: 0.3636 - val_accuracy: 0.84
Epoch 32/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3279 - accuracy: 0.8656 - val_loss: 0.3613 - val_accuracy: 0.8
Epoch 33/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3261 - accuracy: 0.8666 - val_loss: 0.3595 - val_accuracy: 0.8
Epoch 34/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3267 - accuracy: 0.8677 - val_loss: 0.3691 - val_accuracy: 0.84
Epoch 35/50
250/250 [==============================] - 1s 2ms/step - loss: 0.3248 - accuracy: 0.8665 - val_loss: 0.3700 - val_accuracy: 0.84
Epoch 36/50
```

```
results = model.evaluate(X_test,y_test)
```

```
63/63 [==============================] - 0s 2ms/step - loss: 0.3665 - accuracy: 0.8500
250/250 [==============================] - 1s 2ms/step - loss: 0.3248 - accuracy: 0.8684 - val_loss: 0.3605 - val_accuracy: 0.8
```

```
predict_arr=model.predict(X_test)
predict_arr[:10]
```

```
array([[0.02159878],
       [0.04477165],
```

```
predict_arr_thrshld= predict_arr> 0.5
predict_arr_thrshld
```

```
array([[False],
       [False],
       [False],
       ...,
       [False],
       [False],
       [False]])
```

```
# Confusion matrix with optimal Threshold on test set
from sklearn import metrics
from sklearn.metrics import accuracy_score, recall_score,f1_score, precision_score
metrics.confusion_matrix(y_test, predict_arr_thrshld)
```

```
array([[1545,   50],
       [ 250,  155]])
```

```
# printing matrix

print('Neural Network Metrics')
print('Accuracy  :' ,accuracy_score(y_test, predict_arr_thrshld))
print('Precision :',precision_score(y_test, predict_arr_thrshld))
print('Recall    :',recall_score(y_test, predict_arr_thrshld))
print('F1 Score  :',f1_score(y_test, predict_arr_thrshld))
```

```
Neural Network Metrics
Accuracy  : 0.85
Precision : 0.7560975609756098
Recall    : 0.38271604938271603
F1 Score  : 0.5081967213114754
```