

# DS640 Assignment 5

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## 1 Manav Patel

### 1.1 Introduction

Repeat customers are the most valuable customers you have.

Repeat customers:

- Are loyal and satisfied
- Make multiple purchases
- Talk about your brand
- Refer your brand to their friends

However, maintaining your relationship with loyal customers can be tricky. These relationships need to be maintained with a consistent and rewarding customer experience. When your customers are happy, your business will prosper.

What is Churn ? Customers that have churned are customers that have cut ties with a business or brand.

What is Churn Rate used for ? Churn rate is a measurement of the health of your business. Churn measures:

- The success of increasing customer retention for a company
- The changes that affect customer retention
- Customer Lifetime Value
- The type of customers that have the highest retention rate with your company
- Much more!

Today, we are going to analyse a customer dataset of a bank to provide them with valuable insights for their ongoing customer retention issue. We would apply the ANN(Artificial Neural Networks) to classify the dataset and provide the bank with the best fit model. The problem statement is mentioned in detail below.

### 1.2 Problem Statement

The bank has been seen unusual churn rates for their customers (churn is when people leave the company). They want to understand the problem for this unusual high churn rates. Here we have been provided with a sample of their, last six months customers whose characteristics like

- credit score

- geography
- gender
- age
- tenure (how many years a customer is with the bank)
- balance
- number of products a customer had with the bank
- if he/she had a credit card
- if he/she is an active member
- estimated salary (the bank has estimated the salary based of the data they had)
- exited (if a customer has left the bank or not within the last six months)

Our task is to create a classification model for predicting customers at risk of churning. From this classification model the bank could gain useful insights and can take relevant actions to prevent further unusual churn rate and improve the overall customer experience.

### 1.3 Data Preprocessing

In [89]: *# Importing the required libraries*

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

In [90]: *#Reading the dataset*

```
dataset = pd.read_csv('/Users/Lenovo/Desktop/Churn_Modelling.csv')
dataset
```

Out [90]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	\
0	1	15634602	Hargrave	619	France	Female	
1	2	15647311	Hill	608	Spain	Female	
2	3	15619304	Onio	502	France	Female	
3	4	15701354	Boni	699	France	Female	
4	5	15737888	Mitchell	850	Spain	Female	
5	6	15574012	Chu	645	Spain	Male	
6	7	15592531	Bartlett	822	France	Male	
7	8	15656148	Obinna	376	Germany	Female	
8	9	15792365	He	501	France	Male	
9	10	15592389	H?	684	France	Male	
10	11	15767821	Bearce	528	France	Male	
11	12	15737173	Andrews	497	Spain	Male	
12	13	15632264	Kay	476	France	Female	
13	14	15691483	Chin	549	France	Female	
14	15	15600882	Scott	635	Spain	Female	
15	16	15643966	Goforth	616	Germany	Male	
16	17	15737452	Romeo	653	Germany	Male	
17	18	15788218	Henderson	549	Spain	Female	
18	19	15661507	Muldrow	587	Spain	Male	
19	20	15568982	Hao	726	France	Female	
20	21	15577657	McDonald	732	France	Male	
21	22	15597945	Dellucci	636	Spain	Female	

22	23	15699309	Gerasimov	510	Spain	Female
23	24	15725737	Mosman	669	France	Male
24	25	15625047	Yen	846	France	Female
25	26	15738191	Maclean	577	France	Male
26	27	15736816	Young	756	Germany	Male
27	28	15700772	Nebechi	571	France	Male
28	29	15728693	McWilliams	574	Germany	Female
29	30	15656300	Lucciano	411	France	Male
...	...	...	...	...	...	...
9970	9971	15587133	Thompson	518	France	Male
9971	9972	15721377	Chou	833	France	Female
9972	9973	15747927	Ch'in	758	France	Male
9973	9974	15806455	Miller	611	France	Male
9974	9975	15695474	Barker	583	France	Male
9975	9976	15666295	Smith	610	Germany	Male
9976	9977	15656062	Azikiwe	637	France	Female
9977	9978	15579969	Mancini	683	France	Female
9978	9979	15703563	P'eng	774	France	Male
9979	9980	15692664	Diribe	677	France	Female
9980	9981	15719276	T'ao	741	Spain	Male
9981	9982	15672754	Burbidge	498	Germany	Male
9982	9983	15768163	Griffin	655	Germany	Female
9983	9984	15656710	Cocci	613	France	Male
9984	9985	15696175	Echezonachukwu	602	Germany	Male
9985	9986	15586914	Nepean	659	France	Male
9986	9987	15581736	Bartlett	673	Germany	Male
9987	9988	15588839	Mancini	606	Spain	Male
9988	9989	15589329	Pirozzi	775	France	Male
9989	9990	15605622	McMillan	841	Spain	Male
9990	9991	15798964	Nkemakonam	714	Germany	Male
9991	9992	15769959	Ajuluchukwu	597	France	Female
9992	9993	15657105	Chukwualuka	726	Spain	Male
9993	9994	15569266	Rahman	644	France	Male
9994	9995	15719294	Wood	800	France	Female
9995	9996	15606229	Obijiaku	771	France	Male
9996	9997	15569892	Johnstone	516	France	Male
9997	9998	15584532	Liu	709	France	Female
9998	9999	15682355	Sabbatini	772	Germany	Male
9999	10000	15628319	Walker	792	France	Female

	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	\
0	42	2	0.00	1	1	1	
1	41	1	83807.86	1	0	1	
2	42	8	159660.80	3	1	0	
3	39	1	0.00	2	0	0	
4	43	2	125510.82	1	1	1	
5	44	8	113755.78	2	1	0	
6	50	7	0.00	2	1	1	

7	29	4	115046.74	4	1	0
8	44	4	142051.07	2	0	1
9	27	2	134603.88	1	1	1
10	31	6	102016.72	2	0	0
11	24	3	0.00	2	1	0
12	34	10	0.00	2	1	0
13	25	5	0.00	2	0	0
14	35	7	0.00	2	1	1
15	45	3	143129.41	2	0	1
16	58	1	132602.88	1	1	0
17	24	9	0.00	2	1	1
18	45	6	0.00	1	0	0
19	24	6	0.00	2	1	1
20	41	8	0.00	2	1	1
21	32	8	0.00	2	1	0
22	38	4	0.00	1	1	0
23	46	3	0.00	2	0	1
24	38	5	0.00	1	1	1
25	25	3	0.00	2	0	1
26	36	2	136815.64	1	1	1
27	44	9	0.00	2	0	0
28	43	3	141349.43	1	1	1
29	29	0	59697.17	2	1	1
...	...	...	...	...	...	...
9970	42	7	151027.05	2	1	0
9971	34	3	144751.81	1	0	0
9972	26	4	155739.76	1	1	0
9973	27	7	0.00	2	1	1
9974	33	7	122531.86	1	1	0
9975	50	1	113957.01	2	1	0
9976	33	7	103377.81	1	1	0
9977	32	9	0.00	2	1	1
9978	40	9	93017.47	2	1	0
9979	58	1	90022.85	1	0	1
9980	35	6	74371.49	1	0	0
9981	42	3	152039.70	1	1	1
9982	46	7	137145.12	1	1	0
9983	40	4	0.00	1	0	0
9984	35	7	90602.42	2	1	1
9985	36	6	123841.49	2	1	0
9986	47	1	183579.54	2	0	1
9987	30	8	180307.73	2	1	1
9988	30	4	0.00	2	1	0
9989	28	4	0.00	2	1	1
9990	33	3	35016.60	1	1	0
9991	53	4	88381.21	1	1	0
9992	36	2	0.00	1	1	0
9993	28	7	155060.41	1	1	0

9994	29	2	0.00	2	0	0
9995	39	5	0.00	2	1	0
9996	35	10	57369.61	1	1	1
9997	36	7	0.00	1	0	1
9998	42	3	75075.31	2	1	0
9999	28	4	130142.79	1	1	0

	EstimatedSalary	Exited
0	101348.88	1
1	112542.58	0
2	113931.57	1
3	93826.63	0
4	79084.10	0
5	149756.71	1
6	10062.80	0
7	119346.88	1
8	74940.50	0
9	71725.73	0
10	80181.12	0
11	76390.01	0
12	26260.98	0
13	190857.79	0
14	65951.65	0
15	64327.26	0
16	5097.67	1
17	14406.41	0
18	158684.81	0
19	54724.03	0
20	170886.17	0
21	138555.46	0
22	118913.53	1
23	8487.75	0
24	187616.16	0
25	124508.29	0
26	170041.95	0
27	38433.35	0
28	100187.43	0
29	53483.21	0
...	...	...
9970	119377.36	0
9971	166472.81	0
9972	171552.02	0
9973	157474.10	0
9974	13549.24	0
9975	196526.55	1
9976	84419.78	0
9977	24991.92	0
9978	191608.97	0

9979	2988.28	0
9980	99595.67	0
9981	53445.17	1
9982	115146.40	1
9983	151325.24	0
9984	51695.41	0
9985	96833.00	0
9986	34047.54	0
9987	1914.41	0
9988	49337.84	0
9989	179436.60	0
9990	53667.08	0
9991	69384.71	1
9992	195192.40	0
9993	29179.52	0
9994	167773.55	0
9995	96270.64	0
9996	101699.77	0
9997	42085.58	1
9998	92888.52	1
9999	38190.78	0

[10000 rows x 14 columns]

In [91]: *#Summary of the dataset*  
dataset.describe()

Out [91]:

	RowNumber	CustomerId	CreditScore	Age	Tenure \
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000

  

	Balance	NumOfProducts	HasCrCard	IsActiveMember \
count	10000.000000	10000.000000	10000.00000	10000.000000
mean	76485.889288	1.530200	0.70550	0.515100
std	62397.405202	0.581654	0.45584	0.499797
min	0.000000	1.000000	0.00000	0.000000
25%	0.000000	1.000000	0.00000	0.000000
50%	97198.540000	1.000000	1.00000	1.000000
75%	127644.240000	2.000000	1.00000	1.000000
max	250898.090000	4.000000	1.00000	1.000000

  

EstimatedSalary	Exited
-----------------	--------

count	10000.000000	10000.000000
mean	100090.239881	0.203700
std	57510.492818	0.402769
min	11.580000	0.000000
25%	51002.110000	0.000000
50%	100193.915000	0.000000
75%	149388.247500	0.000000
max	199992.480000	1.000000

We can see that there is no missing value in the dataset as the size of the dataset is 10000x14 and all the attributes have a count of 10000.

We do not consider the row number, the customer id and the surname as independent variables as they would have no impact on our dependent variable. Hence we trim the dataset and divide the dataset as follows:

```
In [92]: X = dataset.iloc[:, 3:13].values #Feature Variable
        y = dataset.iloc[:, 13].values #Target Variable
```

```
In [93]: print(X)
        print(y)
```

```
[[619 'France' 'Female' ... 1 1 101348.88]
 [608 'Spain' 'Female' ... 0 1 112542.58]
 [502 'France' 'Female' ... 1 0 113931.57]
 ...
 [709 'France' 'Female' ... 0 1 42085.58]
 [772 'Germany' 'Male' ... 1 0 92888.52]
 [792 'France' 'Female' ... 1 0 38190.78]]
[1 0 1 ... 1 1 0]
```

Our model needs in input numerical data, so, we need to encode categorical data into numerical data. In This case we have Geography (France, Spain and Germany) and Gender (Male and Female). For Geography we will have 0,1,2 instead of France, Spain and Germany and 0,1 instead of Gender.

```
In [94]: #Converting to Variables
        from sklearn.preprocessing import LabelEncoder, OneHotEncoder
        labelencoder_X_1 = LabelEncoder()
        X[:, 1] = labelencoder_X_1.fit_transform(X[:, 1])
        labelencoder_X_2 = LabelEncoder()
        X[:, 2] = labelencoder_X_2.fit_transform(X[:, 2])
```

We have a binary value for the column 'Gender' hence we don't have issues with the encoding.

But, for the column 'Geography', we have 3 possible values and considering that our categorical values have no comparison (for example, Germany is not higher than France), we need to create dummy variables, so we will create 3 columns, one for each country where we will have 1 if the customer is from that country and 0 if not. And to avoid the dummy variable trap, we will also delete 1 of the 3 columns:

```
In [95]: #Creating a dummy variable
onehotencoder = OneHotEncoder(categorical_features = [1])
X = onehotencoder.fit_transform(X).toarray()
X = X[:, 1:]
```

We now split the dataset into training and testing sets.

```
In [96]: #Splitting the dataset into Training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

We need to apply feature scaling to the dataset to standardize the dataset to convert them into same scale for faster computation of results.

```
In [97]: #Feature scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

## 1.4 Artificial Neural Network Clustering

```
In [98]: #Importing the required libraries
import keras
from keras.models import Sequential
from keras.layers import Dense
```

### 1.4.1 Model 1

We now create the ANN with one hidden layer and having 6 nodes (Half of feature and target variables) with activation function of the hidden and the input layer as 'relu' (rectified linear units) and the output layer 'sigmoid' as we need binary result for our classification model. Then we compile the model with SGD 'adam' as its the best which can be used in this case.

```
In [99]: #Creating a Neural network
classifier = Sequential()
classifier.add(Dense(output_dim = 6, init = 'uniform', activation = 'relu', input_dim = 13))
classifier.add(Dense(output_dim = 6, init = 'uniform', activation = 'relu'))#The hidden layer
classifier.add(Dense(output_dim = 1, init = 'uniform', activation = 'sigmoid'))#The output layer
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

```
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: UserWarning: Update your jupyterlab
This is separate from the ipykernel package so we can avoid doing imports until
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: UserWarning: Update your jupyterlab
after removing the cwd from sys.path.
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:5: UserWarning: Update your jupyterlab
"""
```



```
In [100]: #Fitting the Neural network model on the testing data
          classifier.fit(X_train, y_train, batch_size = 10, nb_epoch = 100)
```

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:2: UserWarning: The `nb\_epoch`

```
Epoch 1/100
8000/8000 [=====] - 4s 499us/step - loss: 0.4931 - acc: 0.7954
Epoch 2/100
8000/8000 [=====] - 2s 265us/step - loss: 0.4302 - acc: 0.7960
Epoch 3/100
8000/8000 [=====] - 2s 255us/step - loss: 0.4255 - acc: 0.7960
Epoch 4/100
8000/8000 [=====] - 2s 221us/step - loss: 0.4210 - acc: 0.7999
Epoch 5/100
8000/8000 [=====] - 2s 233us/step - loss: 0.4182 - acc: 0.8226
Epoch 6/100
8000/8000 [=====] - 2s 220us/step - loss: 0.4161 - acc: 0.8262
Epoch 7/100
8000/8000 [=====] - 2s 228us/step - loss: 0.4144 - acc: 0.8294
Epoch 8/100
8000/8000 [=====] - 1s 184us/step - loss: 0.4132 - acc: 0.8292
Epoch 9/100
8000/8000 [=====] - 1s 178us/step - loss: 0.4125 - acc: 0.8312
Epoch 10/100
8000/8000 [=====] - 2s 200us/step - loss: 0.4113 - acc: 0.8317
Epoch 11/100
8000/8000 [=====] - 2s 280us/step - loss: 0.4103 - acc: 0.8336
Epoch 12/100
8000/8000 [=====] - 2s 245us/step - loss: 0.4094 - acc: 0.8326
Epoch 13/100
8000/8000 [=====] - 2s 226us/step - loss: 0.4088 - acc: 0.8324
Epoch 14/100
8000/8000 [=====] - 2s 227us/step - loss: 0.4086 - acc: 0.8350
Epoch 15/100
8000/8000 [=====] - 2s 225us/step - loss: 0.4079 - acc: 0.8349
Epoch 16/100
8000/8000 [=====] - 2s 225us/step - loss: 0.4074 - acc: 0.8335
Epoch 17/100
8000/8000 [=====] - 2s 231us/step - loss: 0.4068 - acc: 0.8341
Epoch 18/100
8000/8000 [=====] - 2s 216us/step - loss: 0.4065 - acc: 0.8340
Epoch 19/100
8000/8000 [=====] - 2s 273us/step - loss: 0.4059 - acc: 0.8341
Epoch 20/100
8000/8000 [=====] - 2s 285us/step - loss: 0.4056 - acc: 0.8346
Epoch 21/100
```

8000/8000 [=====] - 2s 256us/step - loss: 0.4056 - acc: 0.8347  
 Epoch 22/100  
 8000/8000 [=====] - 2s 210us/step - loss: 0.4049 - acc: 0.8350  
 Epoch 23/100  
 8000/8000 [=====] - 1s 186us/step - loss: 0.4047 - acc: 0.8325  
 Epoch 24/100  
 8000/8000 [=====] - 1s 171us/step - loss: 0.4045 - acc: 0.8350  
 Epoch 25/100  
 8000/8000 [=====] - 1s 173us/step - loss: 0.4039 - acc: 0.8336  
 Epoch 26/100  
 8000/8000 [=====] - 1s 165us/step - loss: 0.4038 - acc: 0.8365  
 Epoch 27/100  
 8000/8000 [=====] - 1s 168us/step - loss: 0.4038 - acc: 0.8352  
 Epoch 28/100  
 8000/8000 [=====] - 2s 193us/step - loss: 0.4033 - acc: 0.8342  
 Epoch 29/100  
 8000/8000 [=====] - 2s 271us/step - loss: 0.4038 - acc: 0.8341  
 Epoch 30/100  
 8000/8000 [=====] - 2s 261us/step - loss: 0.4034 - acc: 0.8345  
 Epoch 31/100  
 8000/8000 [=====] - 2s 244us/step - loss: 0.4031 - acc: 0.8354  
 Epoch 32/100  
 8000/8000 [=====] - 2s 224us/step - loss: 0.4027 - acc: 0.8346  
 Epoch 33/100  
 8000/8000 [=====] - 2s 230us/step - loss: 0.4028 - acc: 0.8371  
 Epoch 34/100  
 8000/8000 [=====] - 2s 232us/step - loss: 0.4024 - acc: 0.8341  
 Epoch 35/100  
 8000/8000 [=====] - 2s 213us/step - loss: 0.4019 - acc: 0.8336  
 Epoch 36/100  
 8000/8000 [=====] - 2s 225us/step - loss: 0.4019 - acc: 0.8347  
 Epoch 37/100  
 8000/8000 [=====] - 2s 239us/step - loss: 0.4022 - acc: 0.8360  
 Epoch 38/100  
 8000/8000 [=====] - 2s 208us/step - loss: 0.4019 - acc: 0.8345  
 Epoch 39/100  
 8000/8000 [=====] - 2s 193us/step - loss: 0.4020 - acc: 0.8372  
 Epoch 40/100  
 8000/8000 [=====] - 1s 169us/step - loss: 0.4025 - acc: 0.8351  
 Epoch 41/100  
 8000/8000 [=====] - 2s 191us/step - loss: 0.4018 - acc: 0.8361  
 Epoch 42/100  
 8000/8000 [=====] - 1s 169us/step - loss: 0.4015 - acc: 0.8337  
 Epoch 43/100  
 8000/8000 [=====] - 2s 192us/step - loss: 0.4019 - acc: 0.8360  
 Epoch 44/100  
 8000/8000 [=====] - 2s 255us/step - loss: 0.4017 - acc: 0.8344  
 Epoch 45/100

8000/8000 [=====] - 2s 245us/step - loss: 0.4015 - acc: 0.8350  
 Epoch 46/100  
 8000/8000 [=====] - 2s 223us/step - loss: 0.4017 - acc: 0.8334  
 Epoch 47/100  
 8000/8000 [=====] - 2s 254us/step - loss: 0.4017 - acc: 0.8349  
 Epoch 48/100  
 8000/8000 [=====] - 2s 250us/step - loss: 0.4012 - acc: 0.8362  
 Epoch 49/100  
 8000/8000 [=====] - 2s 249us/step - loss: 0.4015 - acc: 0.8365  
 Epoch 50/100  
 8000/8000 [=====] - 2s 258us/step - loss: 0.4013 - acc: 0.8345  
 Epoch 51/100  
 8000/8000 [=====] - 2s 237us/step - loss: 0.4016 - acc: 0.8349  
 Epoch 52/100  
 8000/8000 [=====] - 2s 232us/step - loss: 0.4012 - acc: 0.8360  
 Epoch 53/100  
 8000/8000 [=====] - 2s 220us/step - loss: 0.4009 - acc: 0.8354  
 Epoch 54/100  
 8000/8000 [=====] - 2s 221us/step - loss: 0.4011 - acc: 0.8346  
 Epoch 55/100  
 8000/8000 [=====] - 2s 254us/step - loss: 0.4011 - acc: 0.8342  
 Epoch 56/100  
 8000/8000 [=====] - 2s 250us/step - loss: 0.4009 - acc: 0.8351  
 Epoch 57/100  
 8000/8000 [=====] - 2s 243us/step - loss: 0.4011 - acc: 0.8342  
 Epoch 58/100  
 8000/8000 [=====] - 2s 219us/step - loss: 0.4005 - acc: 0.8350  
 Epoch 59/100  
 8000/8000 [=====] - 2s 220us/step - loss: 0.4004 - acc: 0.8339  
 Epoch 60/100  
 8000/8000 [=====] - 2s 214us/step - loss: 0.4008 - acc: 0.8330  
 Epoch 61/100  
 8000/8000 [=====] - 2s 214us/step - loss: 0.4010 - acc: 0.8346  
 Epoch 62/100  
 8000/8000 [=====] - 2s 217us/step - loss: 0.4007 - acc: 0.8347  
 Epoch 63/100  
 8000/8000 [=====] - 2s 224us/step - loss: 0.4005 - acc: 0.8346  
 Epoch 64/100  
 8000/8000 [=====] - 2s 222us/step - loss: 0.4007 - acc: 0.8354  
 Epoch 65/100  
 8000/8000 [=====] - 2s 209us/step - loss: 0.4008 - acc: 0.8344  
 Epoch 66/100  
 8000/8000 [=====] - 2s 195us/step - loss: 0.4010 - acc: 0.8345  
 Epoch 67/100  
 8000/8000 [=====] - 2s 220us/step - loss: 0.4003 - acc: 0.8349  
 Epoch 68/100  
 8000/8000 [=====] - 2s 222us/step - loss: 0.4003 - acc: 0.8342  
 Epoch 69/100

```

8000/8000 [=====] - 2s 224us/step - loss: 0.4005 - acc: 0.8359
Epoch 70/100
8000/8000 [=====] - 2s 219us/step - loss: 0.4006 - acc: 0.8346
Epoch 71/100
8000/8000 [=====] - 2s 212us/step - loss: 0.4001 - acc: 0.8349
Epoch 72/100
8000/8000 [=====] - 2s 219us/step - loss: 0.4003 - acc: 0.8347
Epoch 73/100
8000/8000 [=====] - 2s 256us/step - loss: 0.4005 - acc: 0.8359
Epoch 74/100
8000/8000 [=====] - 2s 249us/step - loss: 0.4004 - acc: 0.8340
Epoch 75/100
8000/8000 [=====] - 2s 242us/step - loss: 0.4007 - acc: 0.8342
Epoch 76/100
8000/8000 [=====] - 2s 239us/step - loss: 0.4005 - acc: 0.8361
Epoch 77/100
8000/8000 [=====] - 2s 198us/step - loss: 0.3999 - acc: 0.8357
Epoch 78/100
8000/8000 [=====] - 2s 200us/step - loss: 0.4004 - acc: 0.8345 1s - 1
Epoch 79/100
8000/8000 [=====] - 1s 166us/step - loss: 0.4000 - acc: 0.8342
Epoch 80/100
8000/8000 [=====] - 1s 173us/step - loss: 0.4003 - acc: 0.8364
Epoch 81/100
8000/8000 [=====] - 2s 193us/step - loss: 0.4005 - acc: 0.8345
Epoch 82/100
8000/8000 [=====] - 2s 199us/step - loss: 0.4003 - acc: 0.8362
Epoch 83/100
8000/8000 [=====] - 2s 218us/step - loss: 0.4003 - acc: 0.8349
Epoch 84/100
8000/8000 [=====] - 2s 201us/step - loss: 0.4002 - acc: 0.8355
Epoch 85/100
8000/8000 [=====] - 1s 178us/step - loss: 0.3999 - acc: 0.8346
Epoch 86/100
8000/8000 [=====] - 1s 179us/step - loss: 0.4000 - acc: 0.8341
Epoch 87/100
8000/8000 [=====] - 2s 196us/step - loss: 0.3997 - acc: 0.8364 0s - 1
Epoch 88/100
8000/8000 [=====] - 2s 239us/step - loss: 0.4002 - acc: 0.8355
Epoch 89/100
8000/8000 [=====] - 2s 213us/step - loss: 0.3996 - acc: 0.8359
Epoch 90/100
8000/8000 [=====] - 2s 208us/step - loss: 0.3996 - acc: 0.8342
Epoch 91/100
8000/8000 [=====] - 2s 209us/step - loss: 0.3996 - acc: 0.8336
Epoch 92/100
8000/8000 [=====] - 2s 238us/step - loss: 0.3998 - acc: 0.8351
Epoch 93/100

```

```

8000/8000 [=====] - 2s 248us/step - loss: 0.3999 - acc: 0.8364
Epoch 94/100
8000/8000 [=====] - 2s 254us/step - loss: 0.3999 - acc: 0.8351
Epoch 95/100
8000/8000 [=====] - 2s 212us/step - loss: 0.3998 - acc: 0.8365
Epoch 96/100
8000/8000 [=====] - 2s 212us/step - loss: 0.3997 - acc: 0.8369
Epoch 97/100
8000/8000 [=====] - 2s 222us/step - loss: 0.3995 - acc: 0.8342
Epoch 98/100
8000/8000 [=====] - 2s 213us/step - loss: 0.3995 - acc: 0.8359
Epoch 99/100
8000/8000 [=====] - 2s 204us/step - loss: 0.3992 - acc: 0.8347
Epoch 100/100
8000/8000 [=====] - 2s 206us/step - loss: 0.3995 - acc: 0.8369

```

```
Out[100]: <keras.callbacks.History at 0x1a082447278>
```

```
In [101]: #Predicting the testing set results
y_pred = classifier.predict(X_test)
y_pred = (y_pred > 0.5)
```

```
In [102]: #Creating the confusion matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[1539  56]
 [ 256 149]]
```

```
In [103]: #Calculating the accuracy of the model
accuracy_ANN = (cm[0,0]+cm[1,1]) / (cm[0,0]+cm[0,1]+cm[1,0]+cm[1,1])
accuracy_ANN
```

```
Out[103]: 0.844
```

What is Specificity ?

Specificity (also called the true negative rate) measures the proportion of actual negatives that are correctly identified. Specificity relates to the test's ability to correctly reject customers who did not churn and actually didn't churn.

```
In [104]: #Calculating the specificity of the model
specificity_ANN = (cm[1,1] / (cm[1,1]+cm[0,1]))
specificity_ANN
```

```
Out[104]: 0.7268292682926829
```

What is Sensitivity ?

Sensitivity (also called the true positive rate) measures the proportion of actual positives that are correctly identified. Sensitivity refers to the test's ability to correctly detect people who are going to churn and actually do churn.

```
In [105]: #Calculating the sensitivity of the model
          sensitivity_ANN =(cm[0,0]/(cm[0,0]+cm[1,0]))
          sensitivity_ANN
```

```
Out[105]: 0.8573816155988858
```

```
In [125]: #loss function
          classifier_1.evaluate(X_test,y_pred1, verbose=1)
```

```
2000/2000 [=====] - 0s 38us/step
```

```
Out[125]: [0.17338521599769594, 1.0]
```

### 1.4.2 Model 2

We now create the ANN with one hidden layer and having 6 nodes (Half of feature and target variables) with activation function of the hidden and the input layer as 'tanh' (hyperbolic tangent) and the output layer 'sigmoid' as we need binary result for our classification model. Then we compile the model with SGD 'adam' as its the best which can be used in this case.

```
In [106]: #Creating a Neural Network model
          classifier_1 = Sequential()
          classifier_1.add(Dense(output_dim = 6, init = 'uniform', activation = 'tanh', input_dim = 12))
          classifier_1.add(Dense(output_dim = 6, init = 'uniform', activation = 'tanh'))
          classifier_1.add(Dense(output_dim = 1, init = 'uniform', activation = 'sigmoid'))
          classifier_1.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

```
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: UserWarning: Update your `ipykernel` package to
This is separate from the ipykernel package so we can avoid doing imports until
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: UserWarning: Update your `ipykernel` package to
after removing the cwd from sys.path.
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:5: UserWarning: Update your `ipykernel` package to
"""
```

```
In [107]: #Fitting the model on testing data
          classifier_1.fit(X_train, y_train, batch_size = 10, nb_epoch = 100)
```

```
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: UserWarning: The `nb_epoch` parameter has been
deprecated in favor of `epochs`.
```

Epoch 1/100  
8000/8000 [=====] - 3s 344us/step - loss: 0.4769 - acc: 0.8085  
Epoch 2/100  
8000/8000 [=====] - 2s 212us/step - loss: 0.4335 - acc: 0.8121  
Epoch 3/100  
8000/8000 [=====] - 2s 264us/step - loss: 0.4322 - acc: 0.8102  
Epoch 4/100  
8000/8000 [=====] - 2s 258us/step - loss: 0.4293 - acc: 0.8116  
Epoch 5/100  
8000/8000 [=====] - 2s 241us/step - loss: 0.4202 - acc: 0.8144  
Epoch 6/100  
8000/8000 [=====] - 2s 213us/step - loss: 0.4023 - acc: 0.8306  
Epoch 7/100  
8000/8000 [=====] - 2s 217us/step - loss: 0.3820 - acc: 0.8391  
Epoch 8/100  
8000/8000 [=====] - 2s 221us/step - loss: 0.3660 - acc: 0.8510  
Epoch 9/100  
8000/8000 [=====] - 2s 218us/step - loss: 0.3565 - acc: 0.8545  
Epoch 10/100  
8000/8000 [=====] - 2s 242us/step - loss: 0.3520 - acc: 0.8579  
Epoch 11/100  
8000/8000 [=====] - 2s 244us/step - loss: 0.3489 - acc: 0.8584  
Epoch 12/100  
8000/8000 [=====] - 2s 263us/step - loss: 0.3490 - acc: 0.8579  
Epoch 13/100  
8000/8000 [=====] - 2s 259us/step - loss: 0.3475 - acc: 0.8599  
Epoch 14/100  
8000/8000 [=====] - 2s 230us/step - loss: 0.3476 - acc: 0.8584  
Epoch 15/100  
8000/8000 [=====] - 2s 221us/step - loss: 0.3464 - acc: 0.8570  
Epoch 16/100  
8000/8000 [=====] - 2s 211us/step - loss: 0.3460 - acc: 0.8584  
Epoch 17/100  
8000/8000 [=====] - 2s 224us/step - loss: 0.3458 - acc: 0.8584  
Epoch 18/100  
8000/8000 [=====] - 2s 218us/step - loss: 0.3454 - acc: 0.8605  
Epoch 19/100  
8000/8000 [=====] - 2s 218us/step - loss: 0.3449 - acc: 0.8604  
Epoch 20/100  
8000/8000 [=====] - 2s 246us/step - loss: 0.3449 - acc: 0.8600  
Epoch 21/100  
8000/8000 [=====] - 2s 269us/step - loss: 0.3447 - acc: 0.8591  
Epoch 22/100  
8000/8000 [=====] - 2s 261us/step - loss: 0.3443 - acc: 0.8565  
Epoch 23/100  
8000/8000 [=====] - 2s 231us/step - loss: 0.3431 - acc: 0.8580  
Epoch 24/100  
8000/8000 [=====] - 2s 220us/step - loss: 0.3432 - acc: 0.8571

Epoch 25/100  
8000/8000 [=====] - 2s 222us/step - loss: 0.3442 - acc: 0.8586  
Epoch 26/100  
8000/8000 [=====] - 2s 212us/step - loss: 0.3427 - acc: 0.8589  
Epoch 27/100  
8000/8000 [=====] - 2s 229us/step - loss: 0.3423 - acc: 0.8577  
Epoch 28/100  
8000/8000 [=====] - 2s 214us/step - loss: 0.3426 - acc: 0.8579  
Epoch 29/100  
8000/8000 [=====] - 2s 284us/step - loss: 0.3425 - acc: 0.8592  
Epoch 30/100  
8000/8000 [=====] - 2s 260us/step - loss: 0.3418 - acc: 0.8569  
Epoch 31/100  
8000/8000 [=====] - 2s 244us/step - loss: 0.3410 - acc: 0.8582  
Epoch 32/100  
8000/8000 [=====] - 2s 227us/step - loss: 0.3403 - acc: 0.8587  
Epoch 33/100  
8000/8000 [=====] - 2s 226us/step - loss: 0.3399 - acc: 0.8604  
Epoch 34/100  
8000/8000 [=====] - 2s 230us/step - loss: 0.3393 - acc: 0.8619  
Epoch 35/100  
8000/8000 [=====] - 2s 232us/step - loss: 0.3394 - acc: 0.8599  
Epoch 36/100  
8000/8000 [=====] - 2s 226us/step - loss: 0.3387 - acc: 0.8601  
Epoch 37/100  
8000/8000 [=====] - 2s 269us/step - loss: 0.3378 - acc: 0.8590  
Epoch 38/100  
8000/8000 [=====] - 2s 269us/step - loss: 0.3385 - acc: 0.8607  
Epoch 39/100  
8000/8000 [=====] - 2s 274us/step - loss: 0.3370 - acc: 0.8591  
Epoch 40/100  
8000/8000 [=====] - 2s 251us/step - loss: 0.3369 - acc: 0.8605  
Epoch 41/100  
8000/8000 [=====] - 2s 248us/step - loss: 0.3372 - acc: 0.8595  
Epoch 42/100  
8000/8000 [=====] - 2s 242us/step - loss: 0.3358 - acc: 0.8612  
Epoch 43/100  
8000/8000 [=====] - 2s 241us/step - loss: 0.3372 - acc: 0.8602  
Epoch 44/100  
8000/8000 [=====] - 2s 225us/step - loss: 0.3361 - acc: 0.8622  
Epoch 45/100  
8000/8000 [=====] - 2s 258us/step - loss: 0.3365 - acc: 0.8619  
Epoch 46/100  
8000/8000 [=====] - 2s 274us/step - loss: 0.3357 - acc: 0.8614  
Epoch 47/100  
8000/8000 [=====] - 2s 244us/step - loss: 0.3360 - acc: 0.8605  
Epoch 48/100  
8000/8000 [=====] - 2s 232us/step - loss: 0.3352 - acc: 0.8605 1s - 1



Epoch 49/100  
8000/8000 [=====] - 2s 236us/step - loss: 0.3357 - acc: 0.8614  
Epoch 50/100  
8000/8000 [=====] - 2s 224us/step - loss: 0.3350 - acc: 0.8632  
Epoch 51/100  
8000/8000 [=====] - 2s 226us/step - loss: 0.3358 - acc: 0.8619  
Epoch 52/100  
8000/8000 [=====] - 2s 229us/step - loss: 0.3353 - acc: 0.8616  
Epoch 53/100  
8000/8000 [=====] - 2s 243us/step - loss: 0.3348 - acc: 0.8614  
Epoch 54/100  
8000/8000 [=====] - 2s 261us/step - loss: 0.3348 - acc: 0.8635  
Epoch 55/100  
8000/8000 [=====] - 2s 255us/step - loss: 0.3351 - acc: 0.8624  
Epoch 56/100  
8000/8000 [=====] - 2s 221us/step - loss: 0.3344 - acc: 0.8621  
Epoch 57/100  
8000/8000 [=====] - 2s 216us/step - loss: 0.3346 - acc: 0.8624  
Epoch 58/100  
8000/8000 [=====] - 2s 223us/step - loss: 0.3337 - acc: 0.8602  
Epoch 59/100  
8000/8000 [=====] - 2s 220us/step - loss: 0.3327 - acc: 0.8625  
Epoch 60/100  
8000/8000 [=====] - 2s 222us/step - loss: 0.3338 - acc: 0.8624  
Epoch 61/100  
8000/8000 [=====] - 2s 226us/step - loss: 0.3339 - acc: 0.8624  
Epoch 62/100  
8000/8000 [=====] - 2s 264us/step - loss: 0.3335 - acc: 0.8614  
Epoch 63/100  
8000/8000 [=====] - 2s 243us/step - loss: 0.3332 - acc: 0.8642  
Epoch 64/100  
8000/8000 [=====] - 2s 240us/step - loss: 0.3335 - acc: 0.8627  
Epoch 65/100  
8000/8000 [=====] - 2s 217us/step - loss: 0.3328 - acc: 0.8646  
Epoch 66/100  
8000/8000 [=====] - 2s 227us/step - loss: 0.3332 - acc: 0.8621  
Epoch 67/100  
8000/8000 [=====] - 2s 220us/step - loss: 0.3332 - acc: 0.8635  
Epoch 68/100  
8000/8000 [=====] - 2s 224us/step - loss: 0.3332 - acc: 0.8630  
Epoch 69/100  
8000/8000 [=====] - 2s 216us/step - loss: 0.3320 - acc: 0.8640  
Epoch 70/100  
8000/8000 [=====] - 2s 236us/step - loss: 0.3330 - acc: 0.8626  
Epoch 71/100  
8000/8000 [=====] - 2s 260us/step - loss: 0.3327 - acc: 0.8644  
Epoch 72/100  
8000/8000 [=====] - 2s 252us/step - loss: 0.3328 - acc: 0.8612

Epoch 73/100  
8000/8000 [=====] - 2s 231us/step - loss: 0.3330 - acc: 0.8621  
Epoch 74/100  
8000/8000 [=====] - 2s 229us/step - loss: 0.3321 - acc: 0.8619  
Epoch 75/100  
8000/8000 [=====] - 2s 217us/step - loss: 0.3326 - acc: 0.8619  
Epoch 76/100  
8000/8000 [=====] - 2s 231us/step - loss: 0.3328 - acc: 0.8630  
Epoch 77/100  
8000/8000 [=====] - 2s 219us/step - loss: 0.3327 - acc: 0.8631  
Epoch 78/100  
8000/8000 [=====] - 2s 219us/step - loss: 0.3317 - acc: 0.8634  
Epoch 79/100  
8000/8000 [=====] - 2s 248us/step - loss: 0.3326 - acc: 0.8651  
Epoch 80/100  
8000/8000 [=====] - 2s 251us/step - loss: 0.3325 - acc: 0.8631  
Epoch 81/100  
8000/8000 [=====] - 2s 247us/step - loss: 0.3327 - acc: 0.8611  
Epoch 82/100  
8000/8000 [=====] - 2s 209us/step - loss: 0.3325 - acc: 0.8639  
Epoch 83/100  
8000/8000 [=====] - 2s 222us/step - loss: 0.3328 - acc: 0.8631  
Epoch 84/100  
8000/8000 [=====] - 2s 224us/step - loss: 0.3318 - acc: 0.8665  
Epoch 85/100  
8000/8000 [=====] - 2s 243us/step - loss: 0.3328 - acc: 0.8631  
Epoch 86/100  
8000/8000 [=====] - 2s 221us/step - loss: 0.3323 - acc: 0.8635  
Epoch 87/100  
8000/8000 [=====] - 2s 215us/step - loss: 0.3325 - acc: 0.8637  
Epoch 88/100  
8000/8000 [=====] - 2s 269us/step - loss: 0.3321 - acc: 0.8654  
Epoch 89/100  
8000/8000 [=====] - 2s 251us/step - loss: 0.3328 - acc: 0.8629  
Epoch 90/100  
8000/8000 [=====] - 2s 240us/step - loss: 0.3326 - acc: 0.8630  
Epoch 91/100  
8000/8000 [=====] - 2s 214us/step - loss: 0.3317 - acc: 0.8647  
Epoch 92/100  
8000/8000 [=====] - 2s 221us/step - loss: 0.3325 - acc: 0.8615  
Epoch 93/100  
8000/8000 [=====] - 2s 216us/step - loss: 0.3319 - acc: 0.8651  
Epoch 94/100  
8000/8000 [=====] - 2s 216us/step - loss: 0.3323 - acc: 0.8646  
Epoch 95/100  
8000/8000 [=====] - 2s 209us/step - loss: 0.3324 - acc: 0.8630  
Epoch 96/100  
8000/8000 [=====] - 2s 241us/step - loss: 0.3325 - acc: 0.8647

```
Epoch 97/100
8000/8000 [=====] - 2s 257us/step - loss: 0.3318 - acc: 0.8632
Epoch 98/100
8000/8000 [=====] - 2s 260us/step - loss: 0.3326 - acc: 0.8620
Epoch 99/100
8000/8000 [=====] - 2s 222us/step - loss: 0.3320 - acc: 0.8631
Epoch 100/100
8000/8000 [=====] - 2s 222us/step - loss: 0.3321 - acc: 0.8635
```

```
Out[107]: <keras.callbacks.History at 0x1a0821e3ef0>
```

```
In [108]: #Predicting the target values using the model on testing data
y_pred1 = classifier_1.predict(X_test)
y_pred1 = (y_pred1 > 0.5)
```

```
In [109]: #Creating the confusion matrix
from sklearn.metrics import confusion_matrix
cm1 = confusion_matrix(y_test, y_pred1)
print(cm1)
```

```
[[1513  82]
 [ 194 211]]
```

```
In [110]: #Calculating the accuracy of the model
accuracy_ANN1 = (cm1[0,0]+cm1[1,1])/ (cm1[0,0]+cm1[0,1]+cm1[1,0]+cm1[1,1])
accuracy_ANN1
```

```
Out[110]: 0.862
```

```
In [111]: #Calculating the specificity of the model
specificity_ANN1 =(cm1[1,1]/(cm1[1,1]+cm1[0,1]))
specificity_ANN1
```

```
Out[111]: 0.7201365187713311
```

```
In [112]: #Calculating the sensitivity of the model
sensitivity_ANN1 =(cm1[0,0]/(cm1[0,0]+cm1[1,0]))
sensitivity_ANN1
```

```
Out[112]: 0.8863503222026948
```

```
In [113]: #Calculating the loss function of the model
classifier_1.evaluate(X_test,y_pred1, verbose=1)
```

```
2000/2000 [=====] - 0s 181us/step
```

```
Out[113]: [0.17338521599769594, 1.0]
```

### 1.4.3 Model 3

We now create the ANN with two hidden layer and having 6 nodes (Half of feature and target variables) with activation function of the hidden and the input layers as 'tanh' (hyperbolic tangent) and the output layer 'sigmoid' as we need binary result for our classification model. Then we compile the model with SGD 'adam' as its the best which can be used in this case.

```
In [115]: #Creating a Neural Network model
classifier_2 = Sequential()
classifier_2.add(Dense(output_dim = 6, init = 'uniform', activation = 'tanh', input_dim = 12))
classifier_2.add(Dense(output_dim = 6, init = 'uniform', activation = 'tanh'))
classifier_2.add(Dense(output_dim = 6, init = 'uniform', activation = 'tanh'))
classifier_2.add(Dense(output_dim = 1, init = 'uniform', activation = 'sigmoid'))
classifier_2.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
classifier_2.fit(X_train, y_train, batch_size = 10, nb_epoch = 100)
```

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:2: UserWarning: Update your jupyterlab to 0.35.2 or later to avoid this warning.

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:3: UserWarning: Update your jupyterlab to 0.35.2 or later to avoid this warning.

This is separate from the ipykernel package so we can avoid doing imports until

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:4: UserWarning: Update your jupyterlab to 0.35.2 or later to avoid this warning.

after removing the cwd from sys.path.

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:5: UserWarning: Update your jupyterlab to 0.35.2 or later to avoid this warning.

"""

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:7: UserWarning: The `nb\_epoch` argument in `fit` has been deprecated and will be removed in a future version. Use `epochs` instead.

import sys

Epoch 1/100

8000/8000 [=====] - 8s 986us/step - loss: 0.4787 - acc: 0.8046

Epoch 2/100

8000/8000 [=====] - 2s 272us/step - loss: 0.4353 - acc: 0.8164

Epoch 3/100

8000/8000 [=====] - 2s 228us/step - loss: 0.4341 - acc: 0.8129

Epoch 4/100

8000/8000 [=====] - 2s 227us/step - loss: 0.4310 - acc: 0.8129

Epoch 5/100

8000/8000 [=====] - 2s 223us/step - loss: 0.4257 - acc: 0.8171

Epoch 6/100

8000/8000 [=====] - 2s 232us/step - loss: 0.4179 - acc: 0.8239

Epoch 7/100

8000/8000 [=====] - 2s 237us/step - loss: 0.4103 - acc: 0.8301

Epoch 8/100

8000/8000 [=====] - 2s 231us/step - loss: 0.3993 - acc: 0.8360

Epoch 9/100

8000/8000 [=====] - 2s 286us/step - loss: 0.3805 - acc: 0.8436

Epoch 10/100

8000/8000 [=====] - 2s 285us/step - loss: 0.3644 - acc: 0.8511

Epoch 11/100

8000/8000 [=====] - 2s 258us/step - loss: 0.3541 - acc: 0.8560  
 Epoch 12/100  
 8000/8000 [=====] - 2s 244us/step - loss: 0.3523 - acc: 0.8549  
 Epoch 13/100  
 8000/8000 [=====] - 2s 247us/step - loss: 0.3511 - acc: 0.8590  
 Epoch 14/100  
 8000/8000 [=====] - 2s 233us/step - loss: 0.3488 - acc: 0.8582  
 Epoch 15/100  
 8000/8000 [=====] - 2s 245us/step - loss: 0.3490 - acc: 0.8596  
 Epoch 16/100  
 8000/8000 [=====] - 2s 250us/step - loss: 0.3478 - acc: 0.8609  
 Epoch 17/100  
 8000/8000 [=====] - 2s 281us/step - loss: 0.3477 - acc: 0.8587  
 Epoch 18/100  
 8000/8000 [=====] - 2s 281us/step - loss: 0.3478 - acc: 0.8606  
 Epoch 19/100  
 8000/8000 [=====] - 2s 251us/step - loss: 0.3477 - acc: 0.8565  
 Epoch 20/100  
 8000/8000 [=====] - 2s 233us/step - loss: 0.3464 - acc: 0.8601  
 Epoch 21/100  
 8000/8000 [=====] - 2s 228us/step - loss: 0.3467 - acc: 0.8597  
 Epoch 22/100  
 8000/8000 [=====] - 2s 228us/step - loss: 0.3468 - acc: 0.8610  
 Epoch 23/100  
 8000/8000 [=====] - 2s 238us/step - loss: 0.3459 - acc: 0.8594  
 Epoch 24/100  
 8000/8000 [=====] - 2s 251us/step - loss: 0.3455 - acc: 0.8589  
 Epoch 25/100  
 8000/8000 [=====] - 2s 287us/step - loss: 0.3454 - acc: 0.8595  
 Epoch 26/100  
 8000/8000 [=====] - 2s 280us/step - loss: 0.3451 - acc: 0.8595  
 Epoch 27/100  
 8000/8000 [=====] - 2s 248us/step - loss: 0.3434 - acc: 0.8612  
 Epoch 28/100  
 8000/8000 [=====] - 2s 245us/step - loss: 0.3442 - acc: 0.8605  
 Epoch 29/100  
 8000/8000 [=====] - 2s 232us/step - loss: 0.3438 - acc: 0.8622  
 Epoch 30/100  
 8000/8000 [=====] - 2s 252us/step - loss: 0.3438 - acc: 0.8587  
 Epoch 31/100  
 8000/8000 [=====] - 2s 252us/step - loss: 0.3450 - acc: 0.8587  
 Epoch 32/100  
 8000/8000 [=====] - 2s 282us/step - loss: 0.3440 - acc: 0.8586  
 Epoch 33/100  
 8000/8000 [=====] - 2s 279us/step - loss: 0.3434 - acc: 0.8622  
 Epoch 34/100  
 8000/8000 [=====] - 2s 267us/step - loss: 0.3424 - acc: 0.8630  
 Epoch 35/100

8000/8000 [=====] - 2s 240us/step - loss: 0.3435 - acc: 0.8596  
 Epoch 36/100  
 8000/8000 [=====] - 2s 237us/step - loss: 0.3420 - acc: 0.8607  
 Epoch 37/100  
 8000/8000 [=====] - 2s 234us/step - loss: 0.3441 - acc: 0.8615  
 Epoch 38/100  
 8000/8000 [=====] - 2s 241us/step - loss: 0.3432 - acc: 0.8626  
 Epoch 39/100  
 8000/8000 [=====] - 2s 237us/step - loss: 0.3428 - acc: 0.8621  
 Epoch 40/100  
 8000/8000 [=====] - 2s 277us/step - loss: 0.3423 - acc: 0.8614  
 Epoch 41/100  
 8000/8000 [=====] - 3s 316us/step - loss: 0.3427 - acc: 0.8627  
 Epoch 42/100  
 8000/8000 [=====] - 2s 292us/step - loss: 0.3423 - acc: 0.8635  
 Epoch 43/100  
 8000/8000 [=====] - 2s 219us/step - loss: 0.3415 - acc: 0.8610 1s - 1  
 Epoch 44/100  
 8000/8000 [=====] - 2s 220us/step - loss: 0.3429 - acc: 0.8612  
 Epoch 45/100  
 8000/8000 [=====] - ETA: 0s - loss: 0.3418 - acc: 0.861 - 2s 251us/st  
 Epoch 46/100  
 8000/8000 [=====] - 2s 272us/step - loss: 0.3417 - acc: 0.8609  
 Epoch 47/100  
 8000/8000 [=====] - 2s 241us/step - loss: 0.3417 - acc: 0.8617  
 Epoch 48/100  
 8000/8000 [=====] - 2s 274us/step - loss: 0.3422 - acc: 0.8637  
 Epoch 49/100  
 8000/8000 [=====] - 2s 223us/step - loss: 0.3419 - acc: 0.8610  
 Epoch 50/100  
 8000/8000 [=====] - 2s 202us/step - loss: 0.3421 - acc: 0.8605  
 Epoch 51/100  
 8000/8000 [=====] - 1s 177us/step - loss: 0.3401 - acc: 0.8620  
 Epoch 52/100  
 8000/8000 [=====] - 1s 177us/step - loss: 0.3404 - acc: 0.8625  
 Epoch 53/100  
 8000/8000 [=====] - 2s 197us/step - loss: 0.3415 - acc: 0.8616  
 Epoch 54/100  
 8000/8000 [=====] - 2s 262us/step - loss: 0.3407 - acc: 0.8614  
 Epoch 55/100  
 8000/8000 [=====] - 2s 232us/step - loss: 0.3407 - acc: 0.8615  
 Epoch 56/100  
 8000/8000 [=====] - 2s 230us/step - loss: 0.3405 - acc: 0.8611  
 Epoch 57/100  
 8000/8000 [=====] - 2s 268us/step - loss: 0.3402 - acc: 0.8612  
 Epoch 58/100  
 8000/8000 [=====] - 2s 279us/step - loss: 0.3404 - acc: 0.8617  
 Epoch 59/100

8000/8000 [=====] - 2s 255us/step - loss: 0.3397 - acc: 0.8641  
 Epoch 60/100  
 8000/8000 [=====] - 2s 231us/step - loss: 0.3392 - acc: 0.8611  
 Epoch 61/100  
 8000/8000 [=====] - 2s 235us/step - loss: 0.3393 - acc: 0.8634  
 Epoch 62/100  
 8000/8000 [=====] - 2s 228us/step - loss: 0.3395 - acc: 0.8637  
 Epoch 63/100  
 8000/8000 [=====] - 2s 231us/step - loss: 0.3382 - acc: 0.8637  
 Epoch 64/100  
 8000/8000 [=====] - 2s 229us/step - loss: 0.3382 - acc: 0.8639  
 Epoch 65/100  
 8000/8000 [=====] - 2s 265us/step - loss: 0.3381 - acc: 0.8616  
 Epoch 66/100  
 8000/8000 [=====] - 2s 266us/step - loss: 0.3382 - acc: 0.8605  
 Epoch 67/100  
 8000/8000 [=====] - 2s 250us/step - loss: 0.3378 - acc: 0.8617  
 Epoch 68/100  
 8000/8000 [=====] - 2s 229us/step - loss: 0.3379 - acc: 0.8611  
 Epoch 69/100  
 8000/8000 [=====] - 2s 235us/step - loss: 0.3374 - acc: 0.8636  
 Epoch 70/100  
 8000/8000 [=====] - 2s 233us/step - loss: 0.3368 - acc: 0.8611  
 Epoch 71/100  
 8000/8000 [=====] - 2s 231us/step - loss: 0.3369 - acc: 0.8610  
 Epoch 72/100  
 8000/8000 [=====] - 2s 237us/step - loss: 0.3368 - acc: 0.8611  
 Epoch 73/100  
 8000/8000 [=====] - 3s 342us/step - loss: 0.3365 - acc: 0.8627  
 Epoch 74/100  
 8000/8000 [=====] - 2s 276us/step - loss: 0.3356 - acc: 0.8620  
 Epoch 75/100  
 8000/8000 [=====] - 2s 258us/step - loss: 0.3364 - acc: 0.8607  
 Epoch 76/100  
 8000/8000 [=====] - 2s 229us/step - loss: 0.3361 - acc: 0.8615  
 Epoch 77/100  
 8000/8000 [=====] - 2s 231us/step - loss: 0.3354 - acc: 0.8639  
 Epoch 78/100  
 8000/8000 [=====] - 2s 228us/step - loss: 0.3355 - acc: 0.8629  
 Epoch 79/100  
 8000/8000 [=====] - 2s 225us/step - loss: 0.3349 - acc: 0.8635  
 Epoch 80/100  
 8000/8000 [=====] - 2s 225us/step - loss: 0.3351 - acc: 0.8617  
 Epoch 81/100  
 8000/8000 [=====] - 2s 241us/step - loss: 0.3348 - acc: 0.8627  
 Epoch 82/100  
 8000/8000 [=====] - 2s 275us/step - loss: 0.3348 - acc: 0.8627  
 Epoch 83/100

```

8000/8000 [=====] - 2s 277us/step - loss: 0.3355 - acc: 0.8626
Epoch 84/100
8000/8000 [=====] - 2s 235us/step - loss: 0.3353 - acc: 0.8631
Epoch 85/100
8000/8000 [=====] - 2s 226us/step - loss: 0.3339 - acc: 0.8641
Epoch 86/100
8000/8000 [=====] - 2s 252us/step - loss: 0.3343 - acc: 0.8652
Epoch 87/100
8000/8000 [=====] - 2s 231us/step - loss: 0.3348 - acc: 0.8634
Epoch 88/100
8000/8000 [=====] - 2s 231us/step - loss: 0.3331 - acc: 0.8636
Epoch 89/100
8000/8000 [=====] - 2s 254us/step - loss: 0.3347 - acc: 0.8627
Epoch 90/100
8000/8000 [=====] - 2s 281us/step - loss: 0.3341 - acc: 0.8651
Epoch 91/100
8000/8000 [=====] - 2s 262us/step - loss: 0.3330 - acc: 0.8656
Epoch 92/100
8000/8000 [=====] - 2s 225us/step - loss: 0.3335 - acc: 0.8656
Epoch 93/100
8000/8000 [=====] - 2s 227us/step - loss: 0.3340 - acc: 0.8642
Epoch 94/100
8000/8000 [=====] - 2s 224us/step - loss: 0.3338 - acc: 0.8626
Epoch 95/100
8000/8000 [=====] - 2s 228us/step - loss: 0.3341 - acc: 0.8615
Epoch 96/100
8000/8000 [=====] - 2s 248us/step - loss: 0.3336 - acc: 0.8626
Epoch 97/100
8000/8000 [=====] - 2s 239us/step - loss: 0.3326 - acc: 0.8641
Epoch 98/100
8000/8000 [=====] - 2s 296us/step - loss: 0.3334 - acc: 0.8636
Epoch 99/100
8000/8000 [=====] - 2s 271us/step - loss: 0.3333 - acc: 0.8626
Epoch 100/100
8000/8000 [=====] - 2s 232us/step - loss: 0.3321 - acc: 0.8654

```

```
Out[115]: <keras.callbacks.History at 0x1a083c03d68>
```

```

In [116]: #Predicting the model with test set
          y_pred2 = classifier_2.predict(X_test)
          y_pred2 = (y_pred2 > 0.5)
          y_pred2

```

```

Out[116]: array([[False],
                  [False],
                  [False],
                  ...,

```



```

[False],
[False],
[False]])

```

```

In [117]: #Creating the confusion matrix
          cm2 = confusion_matrix(y_test, y_pred2)
          print(cm2)

          #Accuracy of the model
          accuracy_ANN2 = (cm2[0,0]+cm2[1,1])/ (cm2[0,0]+cm2[0,1]+cm2[1,0]+cm2[1,1])
          accuracy_ANN2

```

```

[[1521  74]
 [ 203 202]]

```

Out[117]: 0.8615

```

In [118]: #Calculating the specificity of the model
          specificity_ANN2 =(cm2[1,1]/(cm2[1,1]+cm2[0,1]))
          specificity_ANN2

```

Out[118]: 0.7318840579710145

```

In [119]: #Calculating the sensitivity of the model
          sensitivity_ANN2 =(cm2[0,0]/(cm2[0,0]+cm2[1,0]))
          sensitivity_ANN2

```

Out[119]: 0.8822505800464037

#### 1.4.4 Model 4

```

In [120]: #Creating the Neural Network model
          classifier_2 = Sequential()
          classifier_2.add(Dense(output_dim = 6, init = 'uniform', activation = 'tanh', input_dim = 6))
          classifier_2.add(Dense(output_dim = 6, init = 'uniform', activation = 'relu'))
          classifier_2.add(Dense(output_dim = 6, init = 'uniform', activation = 'tanh'))
          classifier_2.add(Dense(output_dim = 1, init = 'uniform', activation = 'sigmoid'))
          classifier_2.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])

          #Fitting the model on testing data
          classifier_2.fit(X_train, y_train, batch_size = 10, nb_epoch = 100)

```

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:3: UserWarning: Update your Jupyter kernel to match the current Python environment. This is separate from the ipykernel package so we can avoid doing imports until the kernel is updated.

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:4: UserWarning: Update your Jupyter kernel to match the current Python environment. This is separate from the ipykernel package so we can avoid doing imports until the kernel is updated.

C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel\_launcher.py:5: UserWarning: Update your Jupyter kernel to match the current Python environment. This is separate from the ipykernel package so we can avoid doing imports until the kernel is updated.

"""

```
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: UserWarning: Update your
C:\Users\Lenovo\Anaconda3\lib\site-packages\ipykernel_launcher.py:10: UserWarning: The `nb_epo
# Remove the CWD from sys.path while we load stuff.
```

```
Epoch 1/100
8000/8000 [=====] - 3s 393us/step - loss: 0.4793 - acc: 0.7941
Epoch 2/100
8000/8000 [=====] - 2s 249us/step - loss: 0.4314 - acc: 0.7951
Epoch 3/100
8000/8000 [=====] - 2s 261us/step - loss: 0.4301 - acc: 0.7974
Epoch 4/100
8000/8000 [=====] - 2s 233us/step - loss: 0.4278 - acc: 0.8022
Epoch 5/100
8000/8000 [=====] - 2s 270us/step - loss: 0.4226 - acc: 0.8131
Epoch 6/100
8000/8000 [=====] - 2s 282us/step - loss: 0.4153 - acc: 0.8211
Epoch 7/100
8000/8000 [=====] - 2s 273us/step - loss: 0.4006 - acc: 0.8326
Epoch 8/100
8000/8000 [=====] - 2s 234us/step - loss: 0.3702 - acc: 0.8511
Epoch 9/100
8000/8000 [=====] - 2s 243us/step - loss: 0.3553 - acc: 0.8579
Epoch 10/100
8000/8000 [=====] - 2s 243us/step - loss: 0.3501 - acc: 0.8595
Epoch 11/100
8000/8000 [=====] - 2s 281us/step - loss: 0.3487 - acc: 0.8587
Epoch 12/100
8000/8000 [=====] - 2s 278us/step - loss: 0.3475 - acc: 0.8596
Epoch 13/100
8000/8000 [=====] - 3s 317us/step - loss: 0.3459 - acc: 0.8595
Epoch 14/100
8000/8000 [=====] - 2s 290us/step - loss: 0.3461 - acc: 0.8600
Epoch 15/100
8000/8000 [=====] - 2s 270us/step - loss: 0.3453 - acc: 0.8584
Epoch 16/100
8000/8000 [=====] - 2s 244us/step - loss: 0.3451 - acc: 0.8594
Epoch 17/100
8000/8000 [=====] - 2s 230us/step - loss: 0.3444 - acc: 0.8605
Epoch 18/100
8000/8000 [=====] - 2s 236us/step - loss: 0.3437 - acc: 0.8602
Epoch 19/100
8000/8000 [=====] - 2s 234us/step - loss: 0.3437 - acc: 0.8610
Epoch 20/100
8000/8000 [=====] - 2s 256us/step - loss: 0.3439 - acc: 0.8620
Epoch 21/100
8000/8000 [=====] - 2s 293us/step - loss: 0.3420 - acc: 0.8625
```

Epoch 22/100  
8000/8000 [=====] - 2s 273us/step - loss: 0.3426 - acc: 0.8615  
Epoch 23/100  
8000/8000 [=====] - 2s 241us/step - loss: 0.3424 - acc: 0.8605  
Epoch 24/100  
8000/8000 [=====] - 2s 238us/step - loss: 0.3410 - acc: 0.8605  
Epoch 25/100  
8000/8000 [=====] - 2s 237us/step - loss: 0.3411 - acc: 0.8624  
Epoch 26/100  
8000/8000 [=====] - 2s 248us/step - loss: 0.3408 - acc: 0.8607  
Epoch 27/100  
8000/8000 [=====] - 2s 238us/step - loss: 0.3400 - acc: 0.8610  
Epoch 28/100  
8000/8000 [=====] - 2s 248us/step - loss: 0.3397 - acc: 0.8610  
Epoch 29/100  
8000/8000 [=====] - 2s 282us/step - loss: 0.3400 - acc: 0.8587  
Epoch 30/100  
8000/8000 [=====] - 2s 276us/step - loss: 0.3392 - acc: 0.8614  
Epoch 31/100  
8000/8000 [=====] - 2s 243us/step - loss: 0.3390 - acc: 0.8630  
Epoch 32/100  
8000/8000 [=====] - 2s 243us/step - loss: 0.3389 - acc: 0.8600  
Epoch 33/100  
8000/8000 [=====] - 2s 257us/step - loss: 0.3388 - acc: 0.8635  
Epoch 34/100  
8000/8000 [=====] - 2s 246us/step - loss: 0.3381 - acc: 0.8601  
Epoch 35/100  
8000/8000 [=====] - 2s 239us/step - loss: 0.3372 - acc: 0.8627  
Epoch 36/100  
8000/8000 [=====] - 2s 287us/step - loss: 0.3379 - acc: 0.8621  
Epoch 37/100  
8000/8000 [=====] - 2s 282us/step - loss: 0.3378 - acc: 0.8626  
Epoch 38/100  
8000/8000 [=====] - 2s 269us/step - loss: 0.3372 - acc: 0.8605  
Epoch 39/100  
8000/8000 [=====] - 2s 242us/step - loss: 0.3377 - acc: 0.8626  
Epoch 40/100  
8000/8000 [=====] - 2s 253us/step - loss: 0.3362 - acc: 0.8621  
Epoch 41/100  
8000/8000 [=====] - 2s 242us/step - loss: 0.3370 - acc: 0.8614  
Epoch 42/100  
8000/8000 [=====] - 2s 249us/step - loss: 0.3366 - acc: 0.8634  
Epoch 43/100  
8000/8000 [=====] - 2s 249us/step - loss: 0.3356 - acc: 0.8640  
Epoch 44/100  
8000/8000 [=====] - 2s 283us/step - loss: 0.3362 - acc: 0.8621  
Epoch 45/100  
8000/8000 [=====] - 2s 275us/step - loss: 0.3358 - acc: 0.8616

Epoch 46/100  
8000/8000 [=====] - 2s 260us/step - loss: 0.3351 - acc: 0.8639  
Epoch 47/100  
8000/8000 [=====] - 2s 249us/step - loss: 0.3358 - acc: 0.8631  
Epoch 48/100  
8000/8000 [=====] - 2s 254us/step - loss: 0.3359 - acc: 0.8611  
Epoch 49/100  
8000/8000 [=====] - 2s 264us/step - loss: 0.3357 - acc: 0.8620  
Epoch 50/100  
8000/8000 [=====] - 2s 257us/step - loss: 0.3354 - acc: 0.8635  
Epoch 51/100  
8000/8000 [=====] - 2s 257us/step - loss: 0.3356 - acc: 0.8631  
Epoch 52/100  
8000/8000 [=====] - 2s 282us/step - loss: 0.3354 - acc: 0.8619  
Epoch 53/100  
8000/8000 [=====] - 2s 273us/step - loss: 0.3344 - acc: 0.8624  
Epoch 54/100  
8000/8000 [=====] - 2s 249us/step - loss: 0.3348 - acc: 0.8619  
Epoch 55/100  
8000/8000 [=====] - 2s 244us/step - loss: 0.3347 - acc: 0.8634  
Epoch 56/100  
8000/8000 [=====] - 2s 246us/step - loss: 0.3345 - acc: 0.8636  
Epoch 57/100  
8000/8000 [=====] - 2s 244us/step - loss: 0.3345 - acc: 0.8616  
Epoch 58/100  
8000/8000 [=====] - 2s 251us/step - loss: 0.3347 - acc: 0.8615  
Epoch 59/100  
8000/8000 [=====] - 2s 253us/step - loss: 0.3334 - acc: 0.8634  
Epoch 60/100  
8000/8000 [=====] - 2s 280us/step - loss: 0.3343 - acc: 0.8612  
Epoch 61/100  
8000/8000 [=====] - 2s 273us/step - loss: 0.3345 - acc: 0.8622  
Epoch 62/100  
8000/8000 [=====] - 2s 240us/step - loss: 0.3341 - acc: 0.8612  
Epoch 63/100  
8000/8000 [=====] - 2s 240us/step - loss: 0.3342 - acc: 0.8619  
Epoch 64/100  
8000/8000 [=====] - 2s 234us/step - loss: 0.3337 - acc: 0.8642  
Epoch 65/100  
8000/8000 [=====] - 2s 237us/step - loss: 0.3334 - acc: 0.8614  
Epoch 66/100  
8000/8000 [=====] - 2s 236us/step - loss: 0.3332 - acc: 0.8625  
Epoch 67/100  
8000/8000 [=====] - 2s 249us/step - loss: 0.3333 - acc: 0.8655  
Epoch 68/100  
8000/8000 [=====] - 2s 275us/step - loss: 0.3338 - acc: 0.8630  
Epoch 69/100  
8000/8000 [=====] - 2s 281us/step - loss: 0.3338 - acc: 0.8626

Epoch 70/100  
8000/8000 [=====] - 2s 234us/step - loss: 0.3336 - acc: 0.8637  
Epoch 71/100  
8000/8000 [=====] - 2s 241us/step - loss: 0.3338 - acc: 0.8625  
Epoch 72/100  
8000/8000 [=====] - 2s 243us/step - loss: 0.3333 - acc: 0.8637  
Epoch 73/100  
8000/8000 [=====] - 2s 239us/step - loss: 0.3333 - acc: 0.8640  
Epoch 74/100  
8000/8000 [=====] - 2s 236us/step - loss: 0.3335 - acc: 0.8612  
Epoch 75/100  
8000/8000 [=====] - 2s 251us/step - loss: 0.3336 - acc: 0.8609  
Epoch 76/100  
8000/8000 [=====] - 2s 276us/step - loss: 0.3329 - acc: 0.8624  
Epoch 77/100  
8000/8000 [=====] - 2s 269us/step - loss: 0.3337 - acc: 0.8619  
Epoch 78/100  
8000/8000 [=====] - 2s 236us/step - loss: 0.3327 - acc: 0.8626  
Epoch 79/100  
8000/8000 [=====] - 2s 251us/step - loss: 0.3331 - acc: 0.8629  
Epoch 80/100  
8000/8000 [=====] - 2s 241us/step - loss: 0.3328 - acc: 0.8644  
Epoch 81/100  
8000/8000 [=====] - 2s 253us/step - loss: 0.3325 - acc: 0.8615  
Epoch 82/100  
8000/8000 [=====] - 2s 274us/step - loss: 0.3333 - acc: 0.8634  
Epoch 83/100  
8000/8000 [=====] - 2s 253us/step - loss: 0.3327 - acc: 0.8639  
Epoch 84/100  
8000/8000 [=====] - 2s 274us/step - loss: 0.3334 - acc: 0.8640  
Epoch 85/100  
8000/8000 [=====] - 2s 281us/step - loss: 0.3327 - acc: 0.8632  
Epoch 86/100  
8000/8000 [=====] - 2s 236us/step - loss: 0.3328 - acc: 0.8625  
Epoch 87/100  
8000/8000 [=====] - 2s 226us/step - loss: 0.3323 - acc: 0.8634  
Epoch 88/100  
8000/8000 [=====] - 2s 221us/step - loss: 0.3324 - acc: 0.8647  
Epoch 89/100  
8000/8000 [=====] - 2s 243us/step - loss: 0.3317 - acc: 0.8646  
Epoch 90/100  
8000/8000 [=====] - 2s 240us/step - loss: 0.3325 - acc: 0.8630  
Epoch 91/100  
8000/8000 [=====] - 2s 263us/step - loss: 0.3322 - acc: 0.8656  
Epoch 92/100  
8000/8000 [=====] - 2s 297us/step - loss: 0.3325 - acc: 0.8635  
Epoch 93/100  
8000/8000 [=====] - 2s 268us/step - loss: 0.3319 - acc: 0.8622

```

Epoch 94/100
8000/8000 [=====] - 2s 249us/step - loss: 0.3319 - acc: 0.8627
Epoch 95/100
8000/8000 [=====] - 2s 248us/step - loss: 0.3323 - acc: 0.8612
Epoch 96/100
8000/8000 [=====] - 2s 236us/step - loss: 0.3322 - acc: 0.8630
Epoch 97/100
8000/8000 [=====] - 2s 240us/step - loss: 0.3324 - acc: 0.8632
Epoch 98/100
8000/8000 [=====] - 2s 247us/step - loss: 0.3316 - acc: 0.8630
Epoch 99/100
8000/8000 [=====] - 2s 293us/step - loss: 0.3316 - acc: 0.8636
Epoch 100/100
8000/8000 [=====] - 2s 278us/step - loss: 0.3314 - acc: 0.8636

```

```
Out[120]: <keras.callbacks.History at 0x1a084107a20>
```

```
In [121]: #Predicting the target value using the model on testing data
```

```

y_pred3 = classifier_2.predict(X_test)
y_pred3 = (y_pred3 > 0.5)

```

```
In [122]: #Creating the confusion matrix
```

```

cm3 = confusion_matrix(y_test, y_pred3)
print(cm3)
#Calculating the accuracy of the model
accuracy_ANN3 = (cm3[0,0]+cm3[1,1]) / (cm3[0,0]+cm3[0,1]+cm3[1,0]+cm3[1,1])
accuracy_ANN3

```

```

[[1515   80]
 [ 201  204]]

```

```
Out[122]: 0.8595
```

```
In [123]: #Calculating the Specificity of the model
```

```

specificity_ANN3 =(cm3[1,1]/(cm3[1,1]+cm3[0,1]))
specificity_ANN3

```

```
Out[123]: 0.7183098591549296
```

```
In [124]: ##Calculating the Sensitivity of the model
```

```

sensitivity_ANN3 =(cm3[0,0]/(cm3[0,0]+cm3[1,0]))
sensitivity_ANN3

```

```
Out[124]: 0.8828671328671329
```

## 1.5 Conclusion

The model 2 has the accurate representation of the churn rate of bank customers as we achieved highest accuracy among all the ANN models with varying activation functions and number of hidden layers. It has better accuracy of 86.2% with specificity 72.01% and 88.6% sensitivity and low loss function of 0.173.

The model 2 can provide most accurate classification to the bank for their customers at risk of churning. From that data the bank can analyse the customer's requirement and problems to cater the customers in a better manner and to avoid churn.