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BE A Computer

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Given a bank customer, build a neural network-based classifier that can determine whether they will leave or not in the next 6 months. Dataset Description: The case study is from an open-source dataset from Kaggle. The dataset contains 10,000 sample points with 14 distinct features such as CustomerId, CreditScore, Geography, Gender, Age, Tenure, Balance, etc.

Link to the Kaggle project: https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling
Perform following steps:

1. Read the dataset.
2. Distinguish the feature and target set and divide the data set into training and test sets.
3. Normalize the train and test data.
4. Initialize and build the model. Identify the points of improvement and implement the same.
5. Print the accuracy score and confusion matrix (5 points).

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import Dense, Input
from sklearn.metrics import confusion_matrix, accuracy_score, classificatior
```

```
2024-11-06 16:23:11.655811: I tensorflow/core/util/port.cc:153] oneDNN custo
m operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn t
hem off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-11-06 16:23:11.656314: I external/local_xla/xla/tsl/cuda/cudart_stub.c
c:32] Could not find cuda drivers on your machine, GPU will not be used.
2024-11-06 16:23:11.659166: I external/local_xla/xla/tsl/cuda/cudart_stub.c
c:32] Could not find cuda drivers on your machine, GPU will not be used.
2024-11-06 16:23:11.666761: E external/local_xla/xla/stream_executor/cuda/cu
da_fft.cc:485] Unable to register cuFFT factory: Attempting to register fact
ory for plugin cuFFT when one has already been registered
2024-11-06 16:23:11.678891: E external/local_xla/xla/stream_executor/cuda/cu
da_dnn.cc:8454] Unable to register cuDNN factory: Attempting to register fac
tory for plugin cuDNN when one has already been registered
2024-11-06 16:23:11.682973: E external/local_xla/xla/stream_executor/cuda/cu
da_blas.cc:1452] Unable to register cuBLAS factory: Attempting to register f
actory for plugin cuBLAS when one has already been registered
2024-11-06 16:23:11.692873: I tensorflow/core/platform/cpu_feature_guard.cc:
210] This TensorFlow binary is optimized to use available CPU instructions i
n performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other
operations, rebuild TensorFlow with the appropriate compiler flags.
2024-11-06 16:23:12.418863: W tensorflow/compiler/tf2tensorrt/utils/py_util
s.cc:38] TF-TRT Warning: Could not find TensorRT
```

Loading the Dataset

In [2]:
```
df = pd.read_csv('./Datasets/churn_modelling.csv')
df.head()
```

Out[2]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age
0	1	15634602	Hargrave	619	France	Female	42
1	2	15647311	Hill	608	Spain	Female	41
2	3	15619304	Onio	502	France	Female	42
3	4	15701354	Boni	699	France	Female	39
4	5	15737888	Mitchell	850	Spain	Female	43

In [3]:
```
df.shape
```

Out[3]:
```
(10000, 14)
```

In [4]:
```
df.describe
```

Out[4]:

```
<bound method NDFrame.describe of       RowNumber  CustomerId    Surname  CreditScore Geography  Gender  Age  \
0             1    15634602   Hargrave          619    France  Female   42
1             2    15647311       Hill          608     Spain  Female   41
2             3    15619304       Onio          502    France  Female   42
3             4    15701354       Boni          699    France  Female   39
4             5    15737888   Mitchell          850     Spain  Female   43
...         ...         ...        ...          ...       ...     ...  ...
9995       9996    15606229   Obijiaku          771    France    Male   39
9996       9997    15569892  Johnstone          516    France    Male   35
9997       9998    15584532        Liu          709    France  Female   36
9998       9999    15682355  Sabbatini          772   Germany    Male   42
9999      10000    15628319     Walker          792    France  Female   28

      Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0          2       0.00              1          1               1
1          1   83807.86              1          0               1
2          8  159660.80              3          1               0
3          1       0.00              2          0               0
4          2  125510.82              1          1               1
...      ...        ...            ...        ...             ...
9995       5       0.00              2          1               0
9996      10   57369.61              1          1               1
9997       7       0.00              1          0               1
9998       3   75075.31              2          1               0
9999       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
...               ...     ...
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]>
```

Exploratory Data Analysis (EDA)

In [5]:

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

Out[5]:
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [7]:
```
df.dtypes
```

Out[7]:
```
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
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

Data Preprocessing

In [9]:
```
df = df.drop(['RowNumber', 'Surname', 'CustomerId'], axis = 1)
df.head()
```

Out[9]:

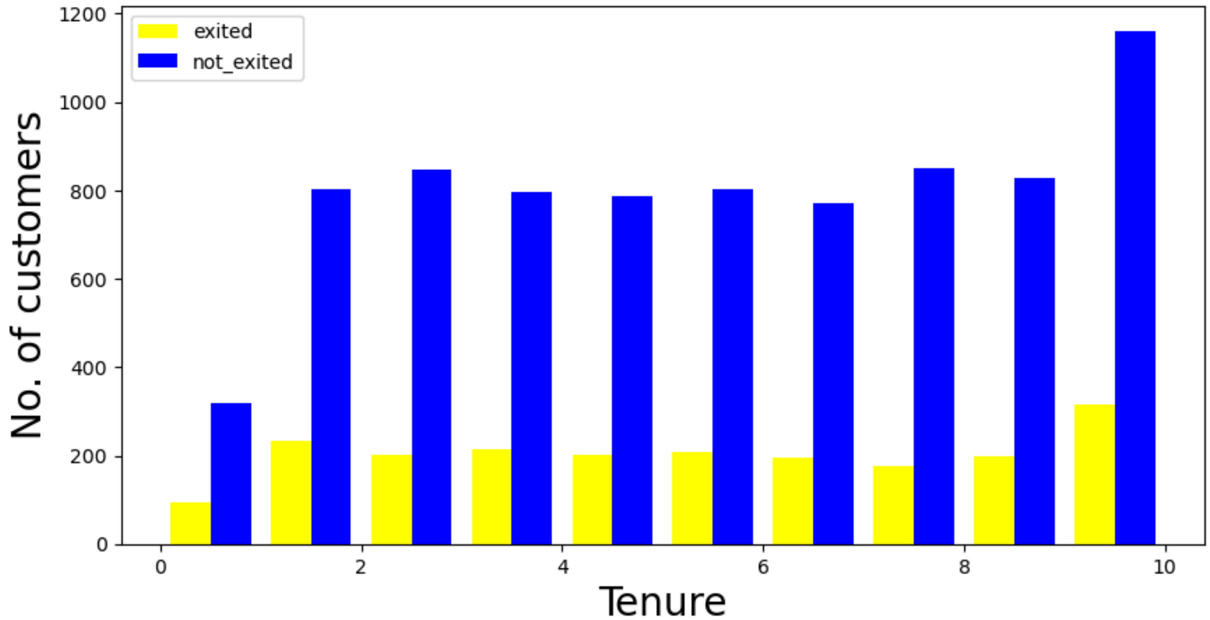
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts
0	619	France	Female	42	2	0.00	1
1	608	Spain	Female	41	1	83807.86	1
2	502	France	Female	42	8	159660.80	3
3	699	France	Female	39	1	0.00	2
4	850	Spain	Female	43	2	125510.82	1

Visualisation

In [10]:
```
def visualization(x, y, xlabel):
    plt.figure(figsize=(10,5))
    plt.hist([x, y], color=['yellow', 'blue'], label = ['exited', 'not_exite
    plt.xlabel(xlabel,fontsize=20)
    plt.ylabel('No. of customers', fontsize=20)
    plt.legend()
```

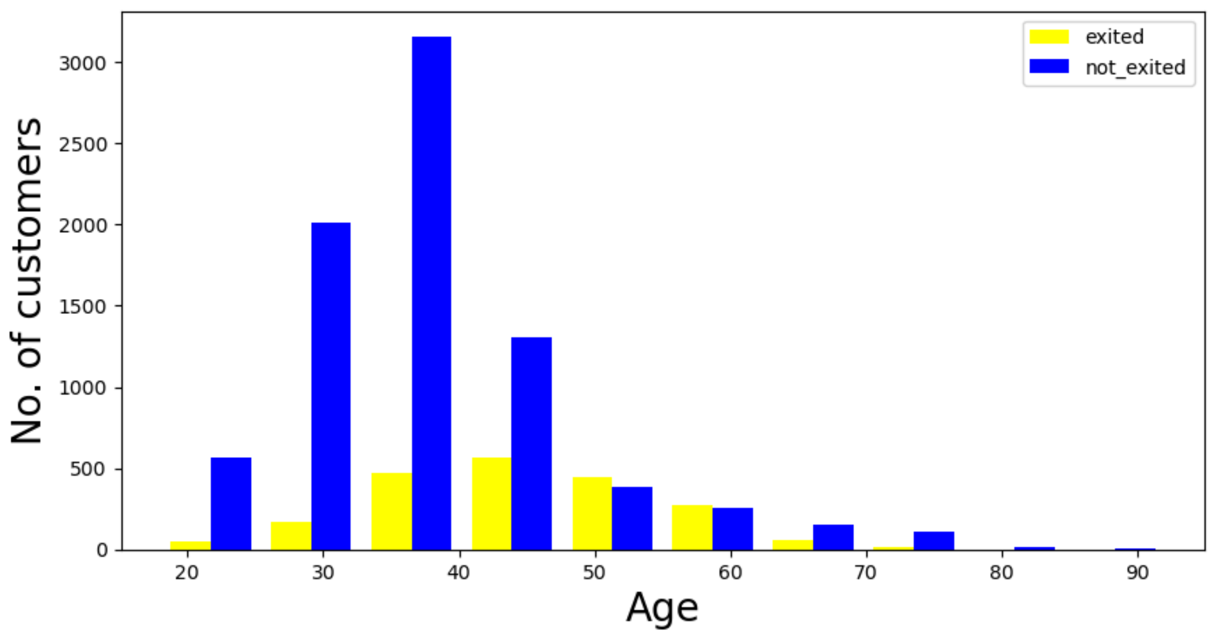
In [11]:
```
df_churn_exited = df[df['Exited']==1]['Tenure']
df_churn_not_exited = df[df['Exited']==0]['Tenure']
```

In [12]:
```
visualization(df_churn_exited, df_churn_not_exited, 'Tenure')
```



In [13]:
```
df_churn_exited2 = df[df['Exited']==1]['Age']
df_churn_not_exited2 = df[df['Exited']==0]['Age']
```

In [14]:
```
visualization(df_churn_exited2, df_churn_not_exited2, 'Age')
```



In [15]:
```
x = df[['CreditScore', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts'
        'HasCrCard', 'IsActiveMember', 'EstimatedSalary']]
states = pd.get_dummies(df['Geography'], drop_first = True)
gender = pd.get_dummies(df['Gender'], drop_first = True)
```

In [16]:
```
df = pd.concat([df,gender,states], axis = 1)
df.head()
```

Out[16]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts
0	619	France	Female	42	2	0.00	1
1	608	Spain	Female	41	1	83807.86	1
2	502	France	Female	42	8	159660.80	3
3	699	France	Female	39	1	0.00	2
4	850	Spain	Female	43	2	125510.82	1

In [17]:
```
x = df[['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'IsActiv
y = df['Exited']
```

Splitting the Dataset

In [18]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3)
```

Normalising the Data

In [19]:
```
sc = StandardScaler()
```

In [20]:
```
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

In [21]:
```
print('Training Data:\n',x_train)
```

```
Training Data:
 [[ 0.96818741 -0.56596928 -1.39661597 ... -1.09823226 -0.57603061
  -0.56789208]
 [ 1.19521436 -0.18753916  0.68426206 ...  0.91055421 -0.57603061
   1.76089794]
 [-0.59004305 -0.37675422 -1.04980297 ...  0.91055421 -0.57603061
  -0.56789208]
 ...
 [ 0.27678714  1.98843404  1.72470107 ... -1.09823226 -0.57603061
  -0.56789208]
 [-0.38365491  1.13696627 -0.70298996 ...  0.91055421 -0.57603061
  -0.56789208]
 [-0.70355653  0.47471356  1.03107506 ... -1.09823226 -0.57603061
  -0.56789208]]
```

In [22]:
```
print('Testing Data:\n',x_test)
```

```
Testing Data:
 [[-2.04507944e+00 -9.29316256e-02  1.03107506e+00 ... -1.09823226e+00
    1.73601886e+00 -5.67892082e-01]
 [-1.15350332e-01 -1.79586717e+00 -3.56176956e-01 ... -1.09823226e+00
   -5.76030610e-01 -5.67892082e-01]
 [-1.66326138e+00  1.67590482e-03 -1.39661597e+00 ...  9.10554206e-01
   -5.76030610e-01 -5.67892082e-01]
 ...
 [ 1.22617258e+00 -1.41743705e+00  1.37788807e+00 ...  9.10554206e-01
   -5.76030610e-01 -5.67892082e-01]
 [ 3.94407736e-02 -9.29316256e-02  1.37788807e+00 ...  9.10554206e-01
   -5.76030610e-01  1.76089794e+00]
 [ 1.25713080e+00  1.23157380e+00 -1.04980297e+00 ...  9.10554206e-01
   -5.76030610e-01  1.76089794e+00]]
```

Building the Neural Network Model

In [23]:
```
classifier = Sequential()
```

In [24]:
```
classifier.add(Input(shape=(10,)))
```

In [25]:
```
classifier.add(Dense(units = 6, kernel_initializer = 'he_uniform', activatic
classifier.add(Dense(units = 6, kernel_initializer = 'he_uniform', activatic
classifier.add(Dense(units = 1, kernel_initializer = 'glorot_uniform', activ
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics
```

In [26]:
```
classifier.summary()
```

Model: "sequential"

Layer (type)	**Output Shape**	**Par**
dense (Dense)	(None, 6)	
dense_1 (Dense)	(None, 6)	
dense_2 (Dense)	(None, 1)	

Total params: 115 (460.00 B)

Trainable params: 115 (460.00 B)

Non-trainable params: 0 (0.00 B)

Training the Model

In [27]:
```
classifier.fit(x_train, y_train, batch_size = 10, epochs = 50)
```

```
Epoch 1/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8044 - loss: 0.4926
Epoch 2/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8125 - loss: 0.4353
Epoch 3/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 984us/step - accuracy: 0.8244 - loss: 0.4096
Epoch 4/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 880us/step - accuracy: 0.8353 - loss: 0.3922
Epoch 5/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 845us/step - accuracy: 0.8432 - loss: 0.3796
Epoch 6/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 856us/step - accuracy: 0.8422 - loss: 0.3821
Epoch 7/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 877us/step - accuracy: 0.8514 - loss: 0.3604
Epoch 8/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 844us/step - accuracy: 0.8516 - loss: 0.3587
Epoch 9/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8466 - loss: 0.3601
Epoch 10/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 903us/step - accuracy: 0.8532 - loss: 0.3516
Epoch 11/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8553 - loss: 0.3512
Epoch 12/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8531 - loss: 0.3550
Epoch 13/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8571 - loss: 0.3474
Epoch 14/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 941us/step - accuracy: 0.8578 - loss: 0.3482
Epoch 15/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 876us/step - accuracy: 0.8645 - loss: 0.3376
Epoch 16/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 946us/step - accuracy: 0.8579 - loss: 0.3509
Epoch 17/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 926us/step - accuracy: 0.8607 - loss: 0.3357
Epoch 18/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 937us/step - accuracy: 0.8558 - loss: 0.3403
Epoch 19/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 905us/step - accuracy: 0.8570 - loss: 0.3469
Epoch 20/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 930us/step - accuracy: 0.8551 - loss: 0.3494
Epoch 21/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 895us/step - accuracy: 0.8600 - loss: 0.3393
Epoch 22/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 958us/step - accuracy: 0.8552 - loss: 0.3418
Epoch 23/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 830us/step - accuracy: 0.8575 - loss: 0.3437
Epoch 24/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 836us/step - accuracy: 0.8582 - loss: 0.3385
Epoch 25/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 836us/step - accuracy: 0.8626 - loss: 0.3301
Epoch 26/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8586 - loss: 0.3398
Epoch 27/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8522 - loss: 0.3455
Epoch 28/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8607 - loss: 0.3337
```

```
Epoch 29/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8582 - loss: 0.3372
Epoch 30/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8584 - loss: 0.3320
Epoch 31/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8602 - loss: 0.3390
Epoch 32/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8622 - loss: 0.3389
Epoch 33/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8631 - loss: 0.3287
Epoch 34/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8557 - loss: 0.3428
Epoch 35/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8612 - loss: 0.3325
Epoch 36/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8590 - loss: 0.3315
Epoch 37/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8608 - loss: 0.3407
Epoch 38/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8584 - loss: 0.3339
Epoch 39/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8550 - loss: 0.3505
Epoch 40/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8572 - loss: 0.3445
Epoch 41/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8500 - loss: 0.3516
Epoch 42/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8657 - loss: 0.3259
Epoch 43/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8583 - loss: 0.3440
Epoch 44/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8632 - loss: 0.3321
Epoch 45/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8620 - loss: 0.3347
Epoch 46/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8565 - loss: 0.3462
Epoch 47/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8512 - loss: 0.3470
Epoch 48/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8602 - loss: 0.3408
Epoch 49/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8549 - loss: 0.3435
Epoch 50/50
700/700 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8623 - loss: 0.3282
```

Out[27]:

```
<keras.src.callbacks.history.History at 0x7f07d9374470>
```

Evaluating the Model

In [28]:

```
y_pred =classifier.predict(x_test)
y_pred = (y_pred > 0.5)
```

```
94/94 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

In [29]:
```
cm = confusion_matrix(y_test, y_pred)
print('Confusion Matrix:\n', cm)
```

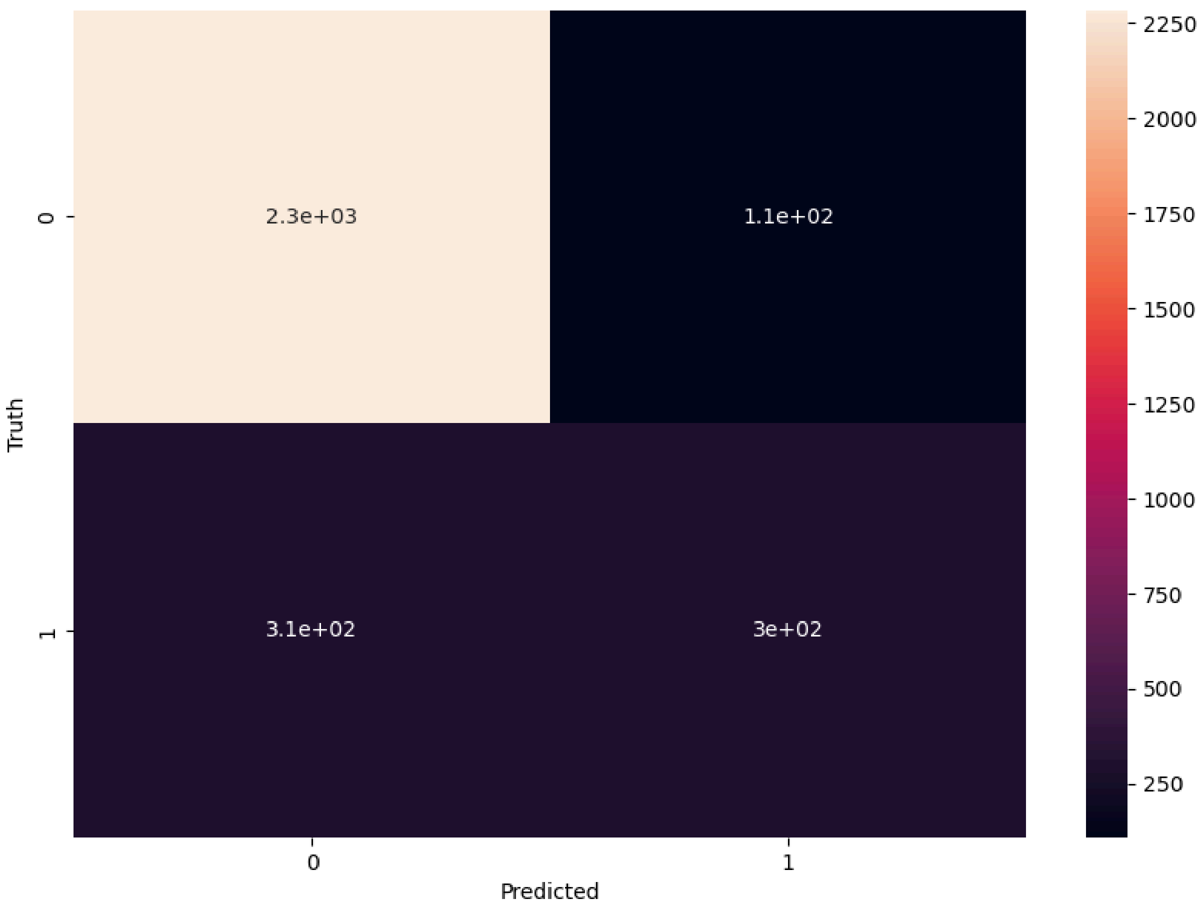
```
Confusion Matrix:
 [[2285  108]
 [ 307  300]]
```

In [30]:
```
acc = accuracy_score(y_test, y_pred)
print('Accuracy Score:', acc)
```

```
Accuracy Score: 0.8616666666666667
```

In [31]:
```
plt.figure(figsize=(10,7))
sns.heatmap(cm, annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[31]:
```
Text(95.72222222222221, 0.5, 'Truth')
```



In [32]:
```
print('Classification Report:\n',classification_report(y_test, y_pred))
```

Classification Report:

	precision	recall	f1-score	support
0	0.88	0.95	0.92	2393
1	0.74	0.49	0.59	607
accuracy			0.86	3000
macro avg	0.81	0.72	0.75	3000
weighted avg	0.85	0.86	0.85	3000