Experiment 3:

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.

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).

Link to the Kaggle project: [https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling (https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling)](https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling)

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt #Importing the libraries
```

In [2]:
```
df = pd.read_csv("Churn_Modelling.csv")
```

Preprocessing

In [3]:
```
df.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Bala
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	8380
2	3	15619304	Onio	502	France	Female	42	8	15966
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	12551

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

Out[4]:
```
(10000, 14)
```

In [5]:
```
df.describe()
```

Out[5]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000

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

Out[6]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	B
0	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	
9995	False	False	False	False	False	False	False	False	
9996	False	False	False	False	False	False	False	False	
9997	False	False	False	False	False	False	False	False	
9998	False	False	False	False	False	False	False	False	
9999	False	False	False	False	False	False	False	False	

10000 rows × 14 columns

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
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 [8]:
```
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 [9]:
```
df.dtypes
```

Out[9]:
```
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 [10]:
```
df.columns
```

Out[10]:
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

In [11]:
```
df = df.drop(['RowNumber', 'Surname', 'CustomerId'], axis= 1) #Dropping the
```

In [50]:
```
df.head()
```

Out[50]:

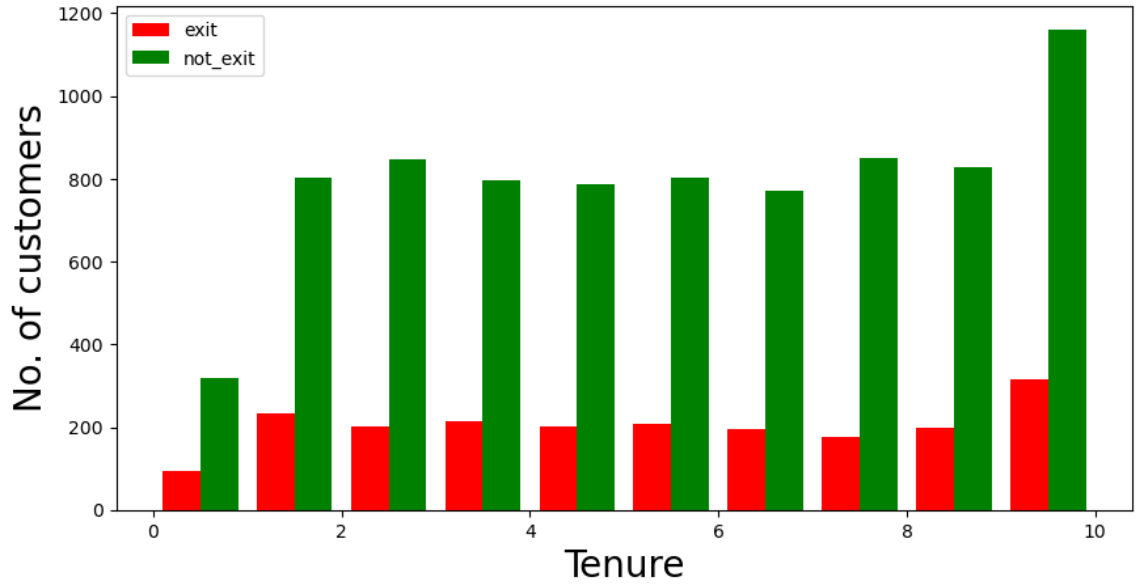
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	Is
0	619	France	Female	42	2	0.00	1	1	
1	608	Spain	Female	41	1	83807.86	1	0	
2	502	France	Female	42	8	159660.80	3	1	
3	699	France	Female	39	1	0.00	2	0	
4	850	Spain	Female	43	2	125510.82	1	1	

Visualization

In [13]:
```
def visualization(x, y, xlabel):
    plt.figure(figsize=(10,5))
    plt.hist([x, y], color=['red', 'green'], label = ['exit', 'not_exit'])
    plt.xlabel(xlabel,fontsize=20)
    plt.ylabel("No. of customers", fontsize=20)
    plt.legend()
```

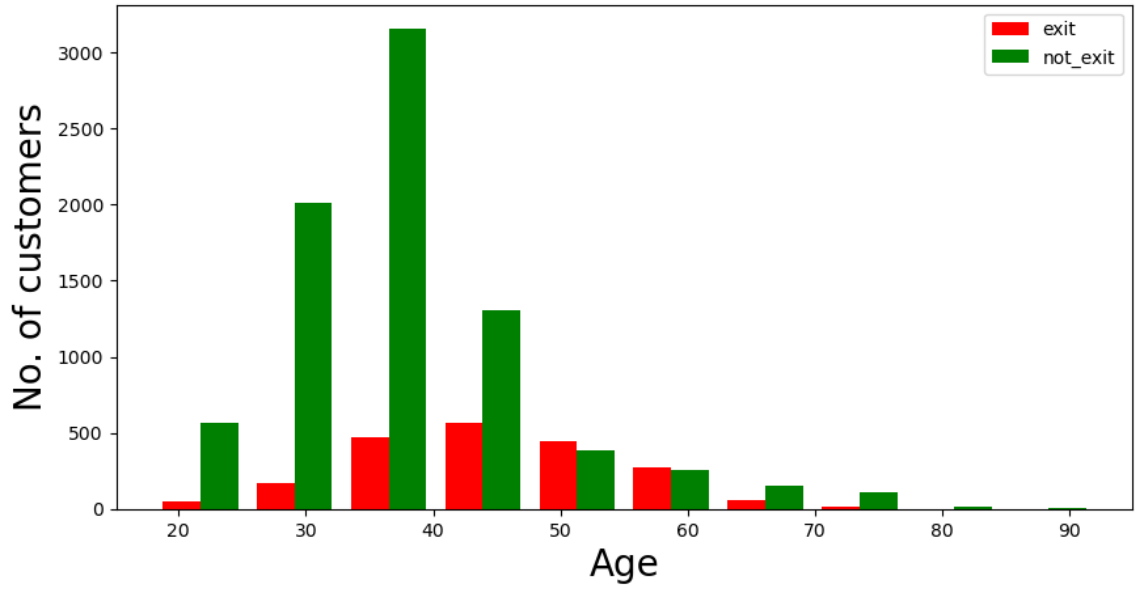
In [15]:
```
df_churn_exited = df[df['Exited']==1]['Tenure']
df_churn_not_exited = df[df['Exited']==0]['Tenure']
```

In [16]:
```
visualization(df_churn_exited, df_churn_not_exited, "Tenure")
```



In [17]:
```
df_churn_exited2 = df[df['Exited']==1]['Age']
df_churn_not_exited2 = df[df['Exited']==0]['Age']
```

In [18]:
```
visualization(df_churn_exited2, df_churn_not_exited2, "Age")
```



Converting the Categorical Variables

In [19]:
```
X = df[['CreditScore','Gender','Age','Tenure','Balance','NumOfProducts','Ha
states = pd.get_dummies(df['Geography'],drop_first = True)
gender = pd.get_dummies(df['Gender'],drop_first = True)
```

In [20]:
```
df = pd.concat([df,gender,states], axis = 1)
```

Splitting the training and testing Dataset

In [21]:
```
df.head()
```

Out[21]:

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

In [22]:
```
X = df[['CreditScore','Age','Tenure','Balance','NumOfProducts','HasCrCard',
        'Germany','Spain']]
```

In [23]:
```
y = df['Exited']
```

In [24]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.30)
```

Normalizing the values with mean as 0 and Standard Deviation as 1

In [25]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

In [26]:
```
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [27]:
```
X_train
```

Out[27]:
```
array([[-1.72344949,  0.19202639, -0.01511572, ...,  0.91318178,
        -0.57954971, -0.56877202],
       [ 0.44336207, -0.85655401,  1.36802225, ..., -1.09507222,
        -0.57954971, -0.56877202],
       [ 1.11404185,  0.19202639,  1.36802225, ...,  0.91318178,
        -0.57954971, -0.56877202],
       ...,
       [-0.21699955, -0.28460106,  1.02223775, ..., -1.09507222,
        -0.57954971, -0.56877202],
       [ 0.68067953,  2.38451269,  1.71380674, ..., -1.09507222,
         1.72547754, -0.56877202],
       [ 1.85694867,  0.47800287,  1.71380674, ..., -1.09507222,
        -0.57954971,  1.7581737 ]])
```

In [28]:
```
X_test
```

Out[28]:
```
array([[ 1.05213294e+00,  4.78002867e-01, -7.06684706e-01, ...,
         9.13181783e-01,  1.72547754e+00, -5.68772017e-01],
       [ 1.29976855e+00, -9.51879501e-01,  1.36802225e+00, ...,
        -1.09507222e+00, -5.79549707e-01, -5.68772017e-01],
       [ 2.05299352e+00,  1.37541066e-03,  3.30668770e-01, ...,
         9.13181783e-01, -5.79549707e-01,  1.75817370e+00],
       ...,
       [-2.22903886e+00, -1.89275572e-01,  1.02223775e+00, ...,
         9.13181783e-01,  1.72547754e+00, -5.68772017e-01],
       [ 1.15531445e+00, -6.65903028e-01,  1.71380674e+00, ...,
        -1.09507222e+00, -5.79549707e-01,  1.75817370e+00],
       [ 8.87042538e-01,  1.37541066e-03,  6.76453262e-01, ...,
        -1.09507222e+00, -5.79549707e-01,  1.75817370e+00]])
```

Building the Classifier Model using Keras

In [29]:
```
import keras #Keras is the wrapper on the top of tenserflow
#Can use Tenserflow as well but won't be able to understand the errors init
```

In [30]:
```
from keras.models import Sequential #To create sequential neural network
from keras.layers import Dense #To create hidden layers
```

In [31]:
```
classifier = Sequential()
```

In [32]:
```
 #To add the layers
#Dense helps to contruct the neurons
#Input Dimension means we have 11 features
# Units is to create the hidden layers
#Uniform helps to distribute the weight uniformly
classifier.add(Dense(activation = "relu",input_dim = 11,units = 6,kernel_in
```

In [33]:
```
classifier.add(Dense(activation = "relu",units = 6,kernel_initializer = "un
```

In [34]:
```
classifier.add(Dense(activation = "sigmoid",units = 1,kernel_initializer =
```

In [35]:
```
classifier.compile(optimizer="adam",loss = 'binary_crossentropy',metrics =
```

In [36]:
```
classifier.summary() #3 layers created. 6 neurons in 1st,6neurons in 2nd la
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 6)                 72

 dense_1 (Dense)             (None, 6)                 42

 dense_2 (Dense)             (None, 1)                 7

=================================================================
Total params: 121 (484.00 Byte)
Trainable params: 121 (484.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [51]:
```
classifier.fit(X_train,y_train,batch_size=10,epochs=50) #Fitting the ANN to
```

```
Epoch 1/50
700/700 [==============================] - 2s 3ms/step - loss: 0.3915 - ac
curacy: 0.8376
Epoch 2/50
700/700 [==============================] - 2s 3ms/step - loss: 0.3917 - ac
curacy: 0.8399
Epoch 3/50
700/700 [==============================] - 2s 2ms/step - loss: 0.3911 - ac
curacy: 0.8404
Epoch 4/50
700/700 [==============================] - 2s 2ms/step - loss: 0.3913 - ac
curacy: 0.8411
Epoch 5/50
700/700 [==============================] - 2s 2ms/step - loss: 0.3915 - ac
curacy: 0.8411
...
Epoch 45/50
700/700 [==============================] - 2s 3ms/step - loss: 0.3901 - ac
curacy: 0.8420
Epoch 46/50
700/700 [==============================] - 2s 2ms/step - loss: 0.3895 - ac
curacy: 0.8404
Epoch 47/50
700/700 [==============================] - 2s 2ms/step - loss: 0.3898 - ac
curacy: 0.8397
Epoch 48/50
700/700 [==============================] - 2s 2ms/step - loss: 0.3906 - ac
curacy: 0.8431
Epoch 49/50
700/700 [==============================] - 2s 2ms/step - loss: 0.3895 - ac
curacy: 0.8426
Epoch 50/50
700/700 [==============================] - 2s 3ms/step - loss: 0.3893 - ac
curacy: 0.8411
```

Out[51]:
```
<keras.src.callbacks.History at 0x240208e9310>
```

In [38]:
```
y_pred =classifier.predict(X_test)
y_pred = (y_pred > 0.5) #Predicting the result
```

```
94/94 [==============================] - 1s 2ms/step
```

In [43]:
```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_
```

In [44]:
```
cm = confusion_matrix(y_test,y_pred)
```

In [45]:
```
cm
```

Out[45]:
```
array([[2310,   74],
       [ 429,  187]], dtype=int64)
```

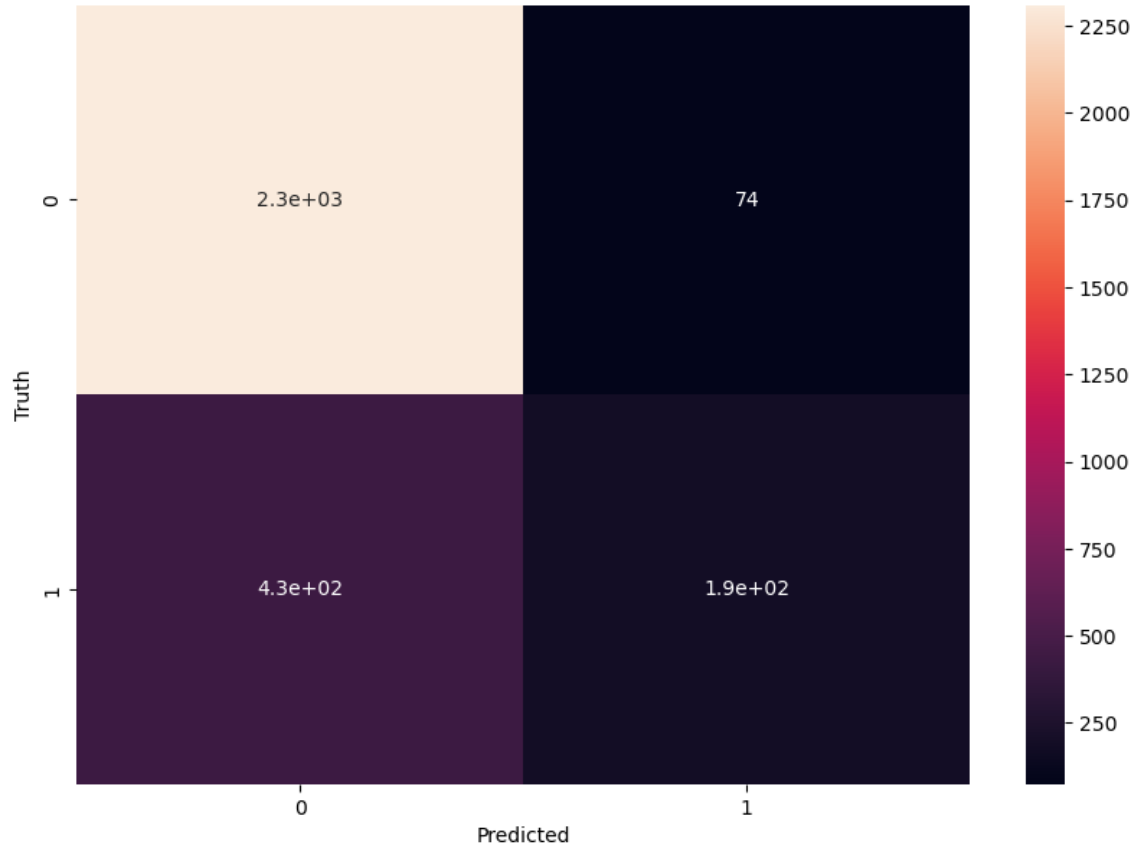
In [46]:
```
accuracy = accuracy_score(y_test,y_pred)
```

In [47]:
```
accuracy
```

Out[47]:
```
0.8323333333333334
```

In [48]:
```
plt.figure(figsize = (10,7))
sns.heatmap(cm,annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[48]:
```
Text(95.72222222222221, 0.5, 'Truth')
```



In [49]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.97      0.90      2384
           1       0.72      0.30      0.43       616

    accuracy                           0.83      3000
   macro avg       0.78      0.64      0.66      3000
weighted avg       0.82      0.83      0.80      3000
```