

```
In [1]: import numpy as np
import pandas as pd
import tensorflow as tf
```

```
In [2]: tf.__version__
```

```
Out[2]: '2.16.2'
```

```
In [4]: dataset=pd.read_csv(r"D:\Data Science with AI\Data Science With AI\6th, 7th-octo
x=dataset.iloc[:,3:-1].values
y=dataset.iloc[:, -1].values
```

```
In [5]: x
```

```
Out[5]: array([[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]], dtype=object)
```

```
In [6]: y
```

```
Out[6]: array([1, 0, 1, ..., 1, 1, 0], dtype=int64)
```

```
In [7]: dataset
```

```
Out[7]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
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	

10000 rows × 14 columns



```
In [8]: from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
x[:,2]=le.fit_transform(x[:,2])
```

In [9]: x

```
Out[9]: array([[619, 'France', 0, ..., 1, 1, 101348.88],
               [608, 'Spain', 0, ..., 0, 1, 112542.58],
               [502, 'France', 0, ..., 1, 0, 113931.57],
               ...,
               [709, 'France', 0, ..., 0, 1, 42085.58],
               [772, 'Germany', 1, ..., 1, 0, 92888.52],
               [792, 'France', 0, ..., 1, 0, 38190.78]], dtype=object)
```

In [10]: print(x)

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

In [11]: dataset

Out[11]:

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

10000 rows × 14 columns



```
In [13]: from sklearn.compose import ColumnTransformer
          from sklearn.preprocessing import OneHotEncoder
          ct=ColumnTransformer(transformers=[('encoder',OneHotEncoder(),[1])],remainder='passthrough')
          x=np.array(ct.fit_transform(x))
```

In [14]: print(x)

```
[[1.0 0.0 0.0 ... 1 1 101348.88]
 [0.0 0.0 1.0 ... 0 1 112542.58]
 [1.0 0.0 0.0 ... 1 0 113931.57]
 ...
 [1.0 0.0 0.0 ... 0 1 42085.58]
 [0.0 1.0 0.0 ... 1 0 92888.52]
 [1.0 0.0 0.0 ... 1 0 38190.78]]
```

```
In [15]: from sklearn.preprocessing import StandardScaler
         sc=StandardScaler()
         x=sc.fit_transform(x)
```

```
In [16]: print(x)
```

```
[[ 0.99720391 -0.57873591 -0.57380915 ... 0.64609167 0.97024255
  0.02188649]
 [-1.00280393 -0.57873591 1.74273971 ... -1.54776799 0.97024255
  0.21653375]
 [ 0.99720391 -0.57873591 -0.57380915 ... 0.64609167 -1.03067011
  0.2406869 ]
 ...
 [ 0.99720391 -0.57873591 -0.57380915 ... -1.54776799 0.97024255
 -1.00864308]
 [-1.00280393 1.72790383 -0.57380915 ... 0.64609167 -1.03067011
 -0.12523071]
 [ 0.99720391 -0.57873591 -0.57380915 ... 0.64609167 -1.03067011
 -1.07636976]]
```

```
In [17]: 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=0)
```

```
In [18]: ann = tf.keras.models.Sequential()
```































```
In [19]: ann.add(tf.keras.layers.Dense(units=6,activation='relu'))
```


```
In [20]: ann.add(tf.keras.layers.Dense(units=6,activation='relu'))
```


```
In [21]: ann.add(tf.keras.layers.Dense(units=1,activation='sigmoid'))
```


```
In [22]: ann.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])
```


```
In [23]: ann.fit(x_train,y_train,batch_size=32,epochs=100)
```


Epoch 1/100			
250/250		2s 2ms/step	- accuracy: 0.7665 - loss: 0.5525
Epoch 2/100			
250/250		0s 2ms/step	- accuracy: 0.7996 - loss: 0.4524
Epoch 3/100			
250/250		0s 2ms/step	- accuracy: 0.8013 - loss: 0.4371
Epoch 4/100			
250/250		0s 2ms/step	- accuracy: 0.7998 - loss: 0.4418
Epoch 5/100			
250/250		1s 2ms/step	- accuracy: 0.8097 - loss: 0.4323
Epoch 6/100			
250/250		0s 2ms/step	- accuracy: 0.8113 - loss: 0.4253
Epoch 7/100			
250/250		0s 2ms/step	- accuracy: 0.8165 - loss: 0.4227
Epoch 8/100			
250/250		1s 2ms/step	- accuracy: 0.8150 - loss: 0.4189
Epoch 9/100			
250/250		0s 2ms/step	- accuracy: 0.8285 - loss: 0.4050
Epoch 10/100			
250/250		0s 2ms/step	- accuracy: 0.8292 - loss: 0.4066
Epoch 11/100			
250/250		0s 2ms/step	- accuracy: 0.8262 - loss: 0.4099
Epoch 12/100			
250/250		0s 2ms/step	- accuracy: 0.8320 - loss: 0.3984
Epoch 13/100			
250/250		0s 2ms/step	- accuracy: 0.8428 - loss: 0.3774
Epoch 14/100			
250/250		0s 2ms/step	- accuracy: 0.8441 - loss: 0.3753
Epoch 15/100			
250/250		0s 2ms/step	- accuracy: 0.8559 - loss: 0.3607
Epoch 16/100			
250/250		0s 2ms/step	- accuracy: 0.8593 - loss: 0.3535
Epoch 17/100			
250/250		1s 2ms/step	- accuracy: 0.8552 - loss: 0.3572
Epoch 18/100			
250/250		1s 2ms/step	- accuracy: 0.8561 - loss: 0.3486
Epoch 19/100			
250/250		1s 2ms/step	- accuracy: 0.8535 - loss: 0.3494
Epoch 20/100			
250/250		1s 2ms/step	- accuracy: 0.8649 - loss: 0.3357
Epoch 21/100			
250/250		1s 3ms/step	- accuracy: 0.8564 - loss: 0.3406
Epoch 22/100			
250/250		1s 2ms/step	- accuracy: 0.8621 - loss: 0.3364
Epoch 23/100			
250/250		1s 2ms/step	- accuracy: 0.8666 - loss: 0.3301
Epoch 24/100			
250/250		1s 2ms/step	- accuracy: 0.8635 - loss: 0.3365
Epoch 25/100			
250/250		0s 2ms/step	- accuracy: 0.8612 - loss: 0.3415
Epoch 26/100			
250/250		0s 2ms/step	- accuracy: 0.8701 - loss: 0.3319
Epoch 27/100			
250/250		1s 2ms/step	- accuracy: 0.8632 - loss: 0.3358
Epoch 28/100			
250/250		0s 2ms/step	- accuracy: 0.8654 - loss: 0.3341
Epoch 29/100			
250/250		1s 2ms/step	- accuracy: 0.8638 - loss: 0.3354
Epoch 30/100			
250/250		0s 2ms/step	- accuracy: 0.8592 - loss: 0.3354


Epoch 31/100  
250/250  0s 2ms/step - accuracy: 0.8668 - loss: 0.3310


Epoch 32/100  
250/250  1s 2ms/step - accuracy: 0.8654 - loss: 0.3308


Epoch 33/100  
250/250  0s 2ms/step - accuracy: 0.8735 - loss: 0.3196


Epoch 34/100  
250/250  0s 2ms/step - accuracy: 0.8595 - loss: 0.3453


Epoch 35/100  
250/250  1s 2ms/step - accuracy: 0.8670 - loss: 0.3268


Epoch 36/100  
250/250  0s 2ms/step - accuracy: 0.8655 - loss: 0.3326


Epoch 37/100  
250/250  0s 2ms/step - accuracy: 0.8656 - loss: 0.3325


Epoch 38/100  
250/250  0s 2ms/step - accuracy: 0.8715 - loss: 0.3211


Epoch 39/100  
250/250  1s 2ms/step - accuracy: 0.8647 - loss: 0.3311


Epoch 40/100  
250/250  0s 2ms/step - accuracy: 0.8649 - loss: 0.3308


Epoch 41/100  
250/250  1s 2ms/step - accuracy: 0.8687 - loss: 0.3305


Epoch 42/100  
250/250  0s 2ms/step - accuracy: 0.8645 - loss: 0.3335


Epoch 43/100  
250/250  0s 2ms/step - accuracy: 0.8674 - loss: 0.3287


Epoch 44/100  
250/250  0s 2ms/step - accuracy: 0.8634 - loss: 0.3259


Epoch 45/100  
250/250  0s 2ms/step - accuracy: 0.8669 - loss: 0.3253


Epoch 46/100  
250/250  1s 2ms/step - accuracy: 0.8549 - loss: 0.3451


Epoch 47/100  
250/250  1s 2ms/step - accuracy: 0.8618 - loss: 0.3275


Epoch 48/100  
250/250  0s 2ms/step - accuracy: 0.8601 - loss: 0.3384


Epoch 49/100  
250/250  1s 2ms/step - accuracy: 0.8663 - loss: 0.3251


Epoch 50/100  
250/250  1s 2ms/step - accuracy: 0.8563 - loss: 0.3478


Epoch 51/100  
250/250  1s 2ms/step - accuracy: 0.8676 - loss: 0.3308


Epoch 52/100  
250/250  1s 2ms/step - accuracy: 0.8655 - loss: 0.3365


Epoch 53/100  
250/250  1s 3ms/step - accuracy: 0.8639 - loss: 0.3285


Epoch 54/100  
250/250  1s 2ms/step - accuracy: 0.8628 - loss: 0.3351


Epoch 55/100  
250/250  1s 2ms/step - accuracy: 0.8582 - loss: 0.3365































Epoch 56/100  
250/250  1s 2ms/step - accuracy: 0.8616 - loss: 0.3375

Epoch 57/100  
250/250  1s 2ms/step - accuracy: 0.8687 - loss: 0.3240

Epoch 58/100  
250/250  1s 2ms/step - accuracy: 0.8556 - loss: 0.3485

Epoch 59/100  
250/250  1s 2ms/step - accuracy: 0.8705 - loss: 0.3233

Epoch 60/100  
250/250  0s 2ms/step - accuracy: 0.8701 - loss: 0.3261

Epoch 61/100  
250/250  1s 2ms/step - accuracy: 0.8668 - loss: 0.3255  
Epoch 62/100  
250/250  1s 2ms/step - accuracy: 0.8635 - loss: 0.3309  
Epoch 63/100  
250/250  1s 2ms/step - accuracy: 0.8657 - loss: 0.3291  
Epoch 64/100  
250/250  1s 2ms/step - accuracy: 0.8660 - loss: 0.3304  
Epoch 65/100  
250/250  1s 2ms/step - accuracy: 0.8644 - loss: 0.3292  
Epoch 66/100  
250/250  1s 2ms/step - accuracy: 0.8605 - loss: 0.3307  
Epoch 67/100  
250/250  1s 2ms/step - accuracy: 0.8707 - loss: 0.3185  
Epoch 68/100  
250/250  1s 2ms/step - accuracy: 0.8627 - loss: 0.3300  
Epoch 69/100  
250/250  1s 2ms/step - accuracy: 0.8651 - loss: 0.3294  
Epoch 70/100  
250/250  0s 2ms/step - accuracy: 0.8649 - loss: 0.3300  
Epoch 71/100  
250/250  1s 2ms/step - accuracy: 0.8667 - loss: 0.3262  
Epoch 72/100  
250/250  1s 2ms/step - accuracy: 0.8656 - loss: 0.3267  
Epoch 73/100  
250/250  1s 2ms/step - accuracy: 0.8632 - loss: 0.3353  
Epoch 74/100  
250/250  1s 2ms/step - accuracy: 0.8637 - loss: 0.3328  
Epoch 75/100  
250/250  1s 2ms/step - accuracy: 0.8652 - loss: 0.3296  
Epoch 76/100  
250/250  1s 2ms/step - accuracy: 0.8667 - loss: 0.3271  
Epoch 77/100  
250/250  1s 2ms/step - accuracy: 0.8614 - loss: 0.3419  
Epoch 78/100  
250/250  1s 2ms/step - accuracy: 0.8630 - loss: 0.3278  
Epoch 79/100  
250/250  1s 2ms/step - accuracy: 0.8648 - loss: 0.3310  
Epoch 80/100  
250/250  1s 2ms/step - accuracy: 0.8642 - loss: 0.3234  
Epoch 81/100  
250/250  1s 3ms/step - accuracy: 0.8616 - loss: 0.3351  
Epoch 82/100  
250/250  1s 2ms/step - accuracy: 0.8643 - loss: 0.3295  
Epoch 83/100  
250/250  1s 2ms/step - accuracy: 0.8639 - loss: 0.3347  
Epoch 84/100  
250/250  1s 2ms/step - accuracy: 0.8597 - loss: 0.3342  
Epoch 85/100  
250/250  1s 2ms/step - accuracy: 0.8724 - loss: 0.3189  
Epoch 86/100  
250/250  1s 2ms/step - accuracy: 0.8689 - loss: 0.3308  
Epoch 87/100  
250/250  1s 2ms/step - accuracy: 0.8645 - loss: 0.3245  
Epoch 88/100  
250/250  1s 2ms/step - accuracy: 0.8587 - loss: 0.3383  
Epoch 89/100  
250/250  0s 2ms/step - accuracy: 0.8709 - loss: 0.3259  
Epoch 90/100  
250/250  1s 2ms/step - accuracy: 0.8684 - loss: 0.3328

```

Epoch 91/100
250/250 ————— 1s 2ms/step - accuracy: 0.8698 - loss: 0.3148
Epoch 92/100
250/250 ————— 1s 2ms/step - accuracy: 0.8703 - loss: 0.3199
Epoch 93/100
250/250 ————— 0s 2ms/step - accuracy: 0.8638 - loss: 0.3314
Epoch 94/100
250/250 ————— 0s 2ms/step - accuracy: 0.8634 - loss: 0.3306
Epoch 95/100
250/250 ————— 1s 2ms/step - accuracy: 0.8626 - loss: 0.3334
Epoch 96/100
250/250 ————— 1s 2ms/step - accuracy: 0.8637 - loss: 0.3356
Epoch 97/100
250/250 ————— 0s 2ms/step - accuracy: 0.8628 - loss: 0.3310
Epoch 98/100
250/250 ————— 1s 2ms/step - accuracy: 0.8651 - loss: 0.3336
Epoch 99/100
250/250 ————— 1s 2ms/step - accuracy: 0.8639 - loss: 0.3314
Epoch 100/100
250/250 ————— 1s 3ms/step - accuracy: 0.8712 - loss: 0.3250

```

Out[23]: <keras.src.callbacks.history.History at 0x1ec2e0dfe30>

```

In [24]: y_pred=ann.predict(x_test)
         y_pred=(y_pred>0.5)
         print(np.concatenate((y_pred.reshape(len(y_pred),1),y_test.reshape(len(y_test),1)

```

```

63/63 ————— 0s 2ms/step
[[0 0]
 [0 1]
 [0 0]
 ...
 [0 0]
 [0 0]
 [0 0]]

```

```

In [25]: from sklearn.metrics import confusion_matrix
         cm=confusion_matrix(y_test,y_pred)
         print(cm)

```

```

[[1504  91]
 [ 189 216]]

```

In [ ]: