Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
```

In [2]:
```
Data = pd.read_csv("C:\\Users\\EXCELL  COMPUTERS\\Programming_Data_Science\\CSV_Files\\Churn_Modelling_deep_lea
```

In [3]:
```
pd.options.display.max_rows = 120000
```

In [4]:
```
Data.head(5)
```

Out[4]:

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

Data type checking

In [5]:
```
Data.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
```

Null data checking

In [6]:
```
Data.isnull().sum()
```

Out[6]:
```
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
```

Converting categorical data

In [7]:
```
Data['Geography'].unique()
```

Out[7]:
```
array(['France', 'Spain', 'Germany'], dtype=object)
```

In [8]:
```
Data['Surname'].unique()
```

Out[8]:
```
array(['Hargrave', 'Hill', 'Onio', ..., 'Kashiwagi', 'Aldridge',
       'Burbidge'], dtype=object)
```

In [9]:
```
C_gender = pd.get_dummies(Data['Gender'],dtype=int)
```

In [10]:
```
C_gender.head(5)
```

Out[10]:

	Female	Male
0	1	0
1	1	0
2	1	0
3	1	0
4	1	0

In [11]:
```
Data = pd.concat([Data,C_gender],axis=1)
```

In [12]:
```
Data = Data.drop(['Gender'],axis=1)
```

In [13]:
```
Data.head(5)
```

Out[13]:

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

In [14]:
```
columns = ['RowNumber','CustomerId','Surname']
Data = Data.drop(columns,axis=1)
```

In [15]:
```
Data.head(5)
```

Out[15]:

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

In [16]:
```
mapp = {'France':1,'Spain':2,'Germany':3}
Data['Geography'] = Data['Geography'].map(mapp)
```

In [17]:
```
Data.head(5)
```

Out[17]:

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

In [18]:
```
Data['Categorical_Salary'] = pd.qcut(Data['EstimatedSalary'],5)
```

In [19]:
```
Data.head(5)
```

Out[19]:

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

In [20]:

```
Data['Categorical_Salary'].unique()
```

Out[20]:

```
[(80238.34, 119710.038], (41050.736, 80238.34], (119710.038, 159836.726], (11.579, 41050.736], (159836.726, 199
992.48]]
Categories (5, interval[float64, right]): [(11.579, 41050.736] < (41050.736, 80238.34] < (80238.34, 119710.038]
< (119710.038, 159836.726] < (159836.726, 199992.48]]
```

In [21]:

```
Iteration = [Data]
for dataset in Iteration:
    dataset.loc[(dataset['EstimatedSalary'] <= 41050.736), 'EstimatedSalary'] = 1
    dataset.loc[(dataset['EstimatedSalary'] > 41050.736) & (dataset['EstimatedSalary'] <= 80238.34) , 'Estimate
    dataset.loc[(dataset['EstimatedSalary'] > 80238.34) & (dataset['EstimatedSalary'] <= 119710.038) , 'Estimat
    dataset.loc[(dataset['EstimatedSalary'] > 119710.038) & (dataset['EstimatedSalary'] <= 159836.729) , 'Estim
    dataset.loc[(dataset['EstimatedSalary'] > 159836.726) ,'EstimatedSalary'] = 5
```

In [22]:

```
Data = Data.drop(['Categorical_Salary'],axis=1)
```

In [23]:

```
Data.head(5)
```

Out[23]:

	CreditScore	Geography	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Female	Male
0	619	1	42	2	0.00	1	1	1	3.0	1	1	0
1	608	2	41	1	83807.86	1	0	1	3.0	0	1	0
2	502	1	42	8	159660.80	3	1	0	3.0	1	1	0
3	699	1	39	1	0.00	2	0	0	3.0	0	1	0
4	850	2	43	2	125510.82	1	1	1	2.0	0	1	0

In [24]:

```
Data['Catergorical_Balance'] = pd.qcut(Data['Balance'],5 , duplicates= 'drop')
```

In [25]:

```
Data.head(5)
```

Out[25]:

	CreditScore	Geography	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Female	Male	Ca
0	619	1	42	2	0.00	1	1	1	3.0	1	1	0	
1	608	2	41	1	83807.86	1	0	1	3.0	0	1	0	
2	502	1	42	8	159660.80	3	1	0	3.0	1	1	0	
3	699	1	39	1	0.00	2	0	0	3.0	0	1	0	
4	850	2	43	2	125510.82	1	1	1	2.0	0	1	0	

In [26]:

```
Data['Catergorical_Balance'].unique()
```

Out[26]:

```
[(-0.001, 73080.908], (73080.908, 110138.926], (133710.358, 250898.09], (110138.926, 133710.358]]
Categories (4, interval[float64, right]): [(-0.001, 73080.908] < (73080.908, 110138.926] < (110138.926, 133710.
358] < (133710.358, 250898.09]]
```

In [27]:

```
Iteration2 = [Data]
for dataset in Iteration2:
    dataset.loc[(dataset['Balance'] <= 73080.908) , 'Balance'] = 1
    dataset.loc[(dataset['Balance'] > 73080.908) & (dataset['Balance'] <= 110138.926) , 'Balance'] = 2
    dataset.loc[(dataset['Balance'] > 110138.926) & (dataset['Balance'] <= 133710.358) , 'Balance'] = 3
    dataset.loc[(dataset['Balance'] >= 133710.358) , 'Balance'] = 4
```

In [28]:

```
Data = Data.drop(['Catergorical_Balance'] , axis=1)
```

In [29]:

```
Data.head(5)
```

Out[29]:

	CreditScore	Geography	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Female	Male
0	619	1	42	2	1.0	1	1	1	3.0	1	1	0
1	608	2	41	1	2.0	1	0	1	3.0	0	1	0
2	502	1	42	8	4.0	3	1	0	3.0	1	1	0
3	699	1	39	1	1.0	2	0	0	3.0	0	1	0
4	850	2	43	2	3.0	1	1	1	2.0	0	1	0

In [30]:

```
'''Iteration3 = [Data]
for dataset in Iteration3:
    dataset.loc[(dataset['Age'] <= 32.8) , ' Age'] = 1
    dataset.loc[(dataset['Age'] > 32.8) & (dataset['Age'] <= 47.6) , 'Age'] = 2
    dataset.loc[(dataset['Age'] > 47.6) & (dataset['Age'] <= 62.4) , 'Age'] = 3
    dataset.loc[(dataset['Age'] > 62.4) & (dataset['Age'] <= 77.2) , 'Age'] = 4
    dataset.loc[(dataset['Age'] > 77.2) & (dataset['Age'] <= 92.0) , 'Age'] = 5'''
```

Out[30]:

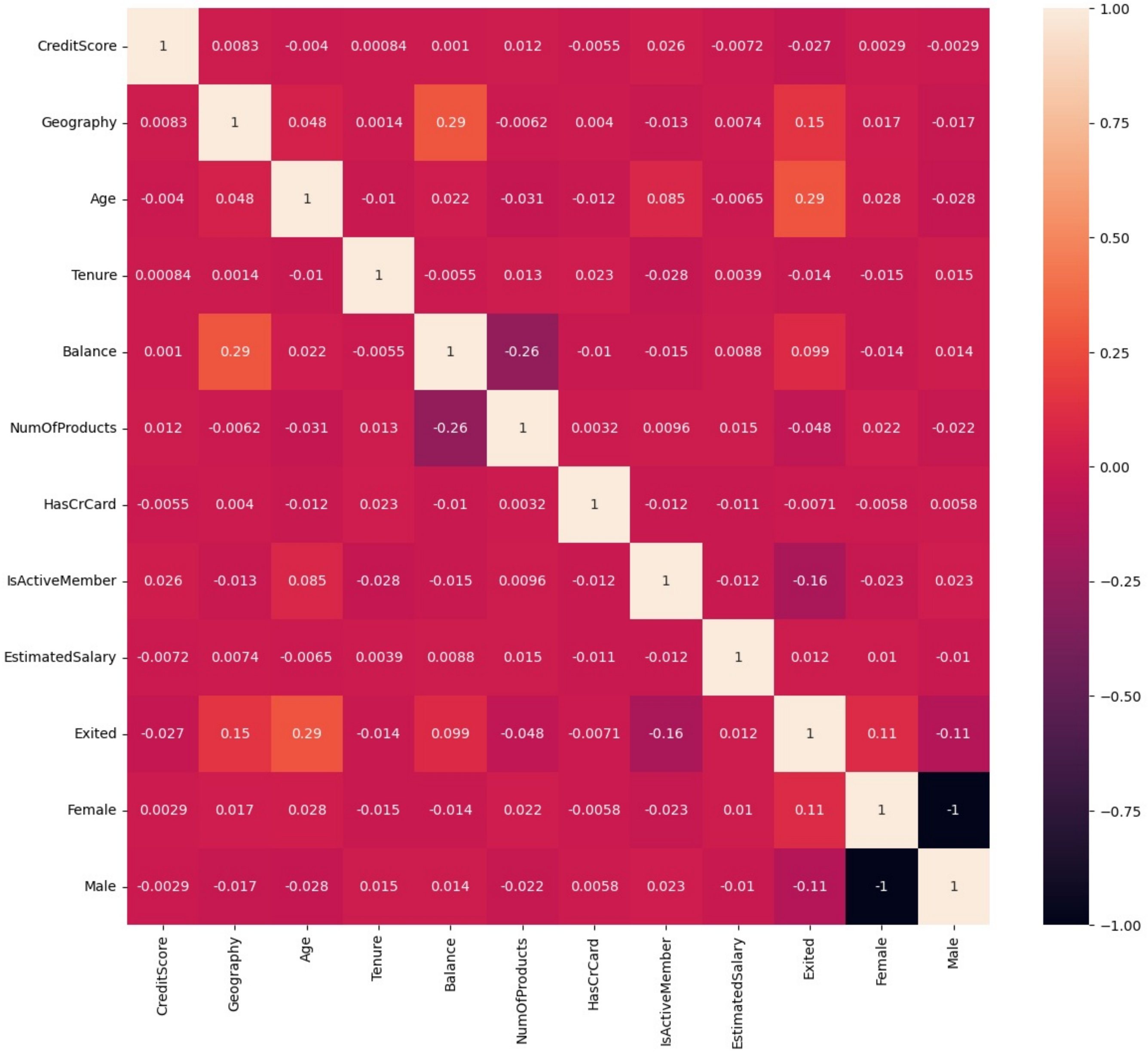
```
"Iteration3 = [Data]\nfor dataset in Iteration3:\n    dataset.loc[(dataset['Age'] <= 32.8) , ' Age'] = 1\n    d
ataset.loc[(dataset['Age'] > 32.8) & (dataset['Age'] <= 47.6) , 'Age'] = 2\n    dataset.loc[(dataset['Age'] > 4
7.6) & (dataset['Age'] <= 62.4) , 'Age'] = 3\n    dataset.loc[(dataset['Age'] > 62.4) & (dataset['Age'] <= 77.2
) , 'Age'] = 4\n    dataset.loc[(dataset['Age'] > 77.2) & (dataset['Age'] <= 92.0) , 'Age'] = 5"
```

Checking correlation

In [31]:

```
plt.figure(figsize=(14,12))
sns.heatmap(Data.corr(),annot=True)
```

Out[31]: <AxesSubplot:>



In [32]:

```
x  = Data.iloc[:,[1,2,7,10,11]].values
y = Data.iloc[:,9].values
```

In [33]:

```
from sklearn.model_selection import train_test_split
x_train , x_test , y_train , y_test = train_test_split(x,y, test_size = 0.25)
```

In [34]:
```
x_train.shape
```
Out[34]:
```
(7500, 5)
```
In [35]:
```
x_test.shape
```
Out[35]:
```
(2500, 5)
```
In [36]:
```
import keras_tuner
from tensorflow import keras
from tensorflow.keras.losses import BinaryCrossentropy
```
In [43]:
```
def build_model(hp):
    model = keras.Sequential()
    hp_units = hp.Int('units', min_value = 5 , max_value = 100 ,step = 10)
    #model.add(keras.layers.Dense(hp.Choice('units',[5,10,15,20,25,30,35,40]),activation='relu'))
    model.add(keras.layers.Dense(units=hp_units , activation = 'relu'))
    model.add(keras.layers.Dense(1 , activation= 'sigmoid'))

    hp_learning_rate = hp.Choice('learning_rate', values = [1e-2 , 1e-3 , 1e-4])

    model.compile(optimizer=keras.optimizers.Adam(learning_rate=hp_learning_rate) , loss = keras.losses.BinaryC
                  metrics=['accuracy'])
    return model;
```
In [38]:
```
#tuner = keras_tuner.Hyperband(build_model, max_epochs= 10)
```
In [39]:
```
#tuner.search(x_train , y_train , epochs = 50 , validation_split = 0.2 )
```
In [46]:
```
tuner = keras_tuner.RandomSearch(hypermodel=build_model ,objective='val_loss',max_trials=5,
                                executions_per_trial = 3, directory = 'document',project_name = 'Ai churn class
```
In [47]:
```
tuner.search(x_train,y_train,epochs = 10 ,validation_data = (x_test , y_test))
```
```
Trial 5 Complete [00h 00m 14s]
val_loss: 0.4459363321463267

Best val_loss So Far: 0.44340654214223224
Total elapsed time: 00h 01m 15s
INFO:tensorflow:Oracle triggered exit
```
In [48]:
```
tuner.results_summary()
```
```
Results summary
Results in document\Ai churn classification
Showing 10 best trials
Objective(name="val_loss", direction="min")

Trial 3 summary
Hyperparameters:
units: 95
learning_rate: 0.01
Score: 0.44340654214223224

Trial 1 summary
Hyperparameters:
units: 45
learning_rate: 0.001
Score: 0.44464991490046185

Trial 2 summary
Hyperparameters:
units: 65
learning_rate: 0.01
Score: 0.4454662303129832

Trial 4 summary
Hyperparameters:
units: 65
learning_rate: 0.001
Score: 0.4459363321463267

Trial 0 summary
Hyperparameters:
units: 25
learning_rate: 0.001
Score: 0.46053119500478107
```
In [49]:
```
best_hp = tuner.get_best_hyperparameters(num_trials = 1)[0]
```
In [52]:
```
print(f"""
The hyperparameter search is complete. The optimal number of units in the first densely-connected
layer is {best_hp.get('units')} and the optimal learning rate for the optimizer
is {best_hp.get('learning_rate')}.
```

```
""")
```

```
The hyperparameter search is complete. The optimal number of units in the first densely-connected
layer is 95 and the optimal learning rate for the optimizer
is 0.01.
```

In [53]:
```
model1 = tuner.hypermodel.build(best_hp)
```

In [54]:
```
history = model1.fit(x_train,y_train,epochs = 50 ,validation_split=0.2)
```

```
Epoch 1/50
188/188 [==============================] - 1s 2ms/step - loss: 0.5438 - accuracy: 0.7760 - val_loss: 0.4814 - v
al_accuracy: 0.7867
Epoch 2/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4833 - accuracy: 0.7957 - val_loss: 0.4248 - v
al_accuracy: 0.8173
Epoch 3/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4590 - accuracy: 0.7983 - val_loss: 0.4231 - v
al_accuracy: 0.8173
Epoch 4/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4503 - accuracy: 0.8042 - val_loss: 0.4493 - v
al_accuracy: 0.8100
Epoch 5/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4458 - accuracy: 0.8057 - val_loss: 0.4226 - v
al_accuracy: 0.8207
Epoch 6/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4470 - accuracy: 0.8068 - val_loss: 0.4214 - v
al_accuracy: 0.8193
Epoch 7/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4493 - accuracy: 0.8087 - val_loss: 0.4253 - v
al_accuracy: 0.8173
Epoch 8/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4458 - accuracy: 0.8028 - val_loss: 0.4221 - v
al_accuracy: 0.8167
Epoch 9/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4414 - accuracy: 0.8085 - val_loss: 0.4235 - v
al_accuracy: 0.8160
Epoch 10/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4418 - accuracy: 0.8085 - val_loss: 0.4272 - v
al_accuracy: 0.8140
Epoch 11/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4384 - accuracy: 0.8083 - val_loss: 0.4307 - v
al_accuracy: 0.8160
Epoch 12/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4450 - accuracy: 0.8072 - val_loss: 0.4241 - v
al_accuracy: 0.8173
Epoch 13/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4448 - accuracy: 0.8105 - val_loss: 0.4368 - v
al_accuracy: 0.8160
Epoch 14/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4434 - accuracy: 0.8108 - val_loss: 0.4470 - v
al_accuracy: 0.8087
Epoch 15/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4369 - accuracy: 0.8105 - val_loss: 0.4219 - v
al_accuracy: 0.8147
Epoch 16/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4402 - accuracy: 0.8100 - val_loss: 0.4341 - v
al_accuracy: 0.8167
Epoch 17/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4383 - accuracy: 0.8107 - val_loss: 0.4265 - v
al_accuracy: 0.8133
Epoch 18/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4402 - accuracy: 0.8075 - val_loss: 0.4263 - v
al_accuracy: 0.8133
Epoch 19/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4361 - accuracy: 0.8127 - val_loss: 0.4398 - v
al_accuracy: 0.8100
Epoch 20/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4396 - accuracy: 0.8102 - val_loss: 0.4225 - v
al_accuracy: 0.8193
Epoch 21/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4377 - accuracy: 0.8110 - val_loss: 0.4206 - v
al_accuracy: 0.8193
Epoch 22/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4351 - accuracy: 0.8145 - val_loss: 0.4309 - v
al_accuracy: 0.8073
Epoch 23/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4335 - accuracy: 0.8162 - val_loss: 0.4163 - v
al_accuracy: 0.8227
Epoch 24/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4333 - accuracy: 0.8187 - val_loss: 0.4469 - v
al_accuracy: 0.8080
Epoch 25/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4384 - accuracy: 0.8075 - val_loss: 0.4199 - v
al_accuracy: 0.8140
Epoch 26/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4346 - accuracy: 0.8103 - val_loss: 0.4240 - v
al_accuracy: 0.8167
```

```
Epoch 27/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4351 - accuracy: 0.8120 - val_loss: 0.4402 - v
al_accuracy: 0.8040
Epoch 28/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4392 - accuracy: 0.8065 - val_loss: 0.4211 - v
al_accuracy: 0.8193
Epoch 29/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4362 - accuracy: 0.8108 - val_loss: 0.4188 - v
al_accuracy: 0.8180
Epoch 30/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4357 - accuracy: 0.8140 - val_loss: 0.4223 - v
al_accuracy: 0.8200
Epoch 31/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4326 - accuracy: 0.8135 - val_loss: 0.4227 - v
al_accuracy: 0.8160
Epoch 32/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4361 - accuracy: 0.8147 - val_loss: 0.4246 - v
al_accuracy: 0.8167
Epoch 33/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4319 - accuracy: 0.8187 - val_loss: 0.4206 - v
al_accuracy: 0.8280
Epoch 34/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4314 - accuracy: 0.8193 - val_loss: 0.4121 - v
al_accuracy: 0.8280
Epoch 35/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4253 - accuracy: 0.8267 - val_loss: 0.4224 - v
al_accuracy: 0.8180
Epoch 36/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4380 - accuracy: 0.8075 - val_loss: 0.4451 - v
al_accuracy: 0.8007
Epoch 37/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4366 - accuracy: 0.8102 - val_loss: 0.4212 - v
al_accuracy: 0.8160
Epoch 38/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4345 - accuracy: 0.8128 - val_loss: 0.4386 - v
al_accuracy: 0.8067
Epoch 39/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4331 - accuracy: 0.8107 - val_loss: 0.4214 - v
al_accuracy: 0.8160
Epoch 40/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4351 - accuracy: 0.8112 - val_loss: 0.4215 - v
al_accuracy: 0.8167
Epoch 41/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4354 - accuracy: 0.8120 - val_loss: 0.4225 - v
al_accuracy: 0.8160
Epoch 42/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4344 - accuracy: 0.8125 - val_loss: 0.4220 - v
al_accuracy: 0.8167
Epoch 43/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4346 - accuracy: 0.8123 - val_loss: 0.4318 - v
al_accuracy: 0.8107
Epoch 44/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4349 - accuracy: 0.8110 - val_loss: 0.4319 - v
al_accuracy: 0.8027
Epoch 45/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4353 - accuracy: 0.8105 - val_loss: 0.4229 - v
al_accuracy: 0.8120
Epoch 46/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4359 - accuracy: 0.8088 - val_loss: 0.4215 - v
al_accuracy: 0.8173
Epoch 47/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4338 - accuracy: 0.8135 - val_loss: 0.4226 - v
al_accuracy: 0.8147
Epoch 48/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4348 - accuracy: 0.8073 - val_loss: 0.4231 - v
al_accuracy: 0.8160
Epoch 49/50
188/188 [==============================] - 0s 1ms/step - loss: 0.4327 - accuracy: 0.8157 - val_loss: 0.4521 - v
al_accuracy: 0.8007
Epoch 50/50
188/188 [==============================] - 0s 2ms/step - loss: 0.4336 - accuracy: 0.8128 - val_loss: 0.4290 - v
al_accuracy: 0.8127
```

In [55]:

```
val_acc_per_epoch = history.history['val_accuracy']
best_epoch = val_acc_per_epoch.index(max(val_acc_per_epoch)) + 1
```

In [56]:

```
best_epoch
```

Out[56]:

```
33
```

In [57]:

```
hypermodel = tuner.hypermodel.build(best_hp)
hypermodel.fit(x_train , y_train, epochs = best_epoch, validation_split = 0.2)
```

```
Epoch 1/33
188/188 [==============================] - 1s 2ms/step - loss: 0.5295 - accuracy: 0.7838 - val_loss: 0.5607 - v
al_accuracy: 0.7293
Epoch 2/33
188/188 [==============================] - 0s 2ms/step - loss: 0.5231 - accuracy: 0.7777 - val_loss: 0.4248 - v
```

```
al_accuracy: 0.8240
Epoch 3/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4589 - accuracy: 0.8015 - val_loss: 0.6212 - v
al_accuracy: 0.6987
Epoch 4/33
188/188 [==============================] - 0s 2ms/step - loss: 0.4545 - accuracy: 0.8007 - val_loss: 0.4808 - v
al_accuracy: 0.8080
Epoch 5/33
188/188 [==============================] - 0s 2ms/step - loss: 0.4533 - accuracy: 0.8108 - val_loss: 0.4577 - v
al_accuracy: 0.8087
Epoch 6/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4516 - accuracy: 0.8032 - val_loss: 0.4252 - v
al_accuracy: 0.8173
Epoch 7/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4502 - accuracy: 0.8023 - val_loss: 0.4270 - v
al_accuracy: 0.8113
Epoch 8/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4386 - accuracy: 0.8138 - val_loss: 0.4282 - v
al_accuracy: 0.8167
Epoch 9/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4415 - accuracy: 0.8105 - val_loss: 0.4463 - v
al_accuracy: 0.8013
Epoch 10/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4432 - accuracy: 0.8080 - val_loss: 0.4847 - v
al_accuracy: 0.7740
Epoch 11/33
188/188 [==============================] - 0s 2ms/step - loss: 0.4411 - accuracy: 0.8093 - val_loss: 0.4229 - v
al_accuracy: 0.8173
Epoch 12/33
188/188 [==============================] - 0s 2ms/step - loss: 0.4423 - accuracy: 0.8098 - val_loss: 0.4218 - v
al_accuracy: 0.8187
Epoch 13/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4440 - accuracy: 0.8070 - val_loss: 0.4458 - v
al_accuracy: 0.8020
Epoch 14/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4416 - accuracy: 0.8082 - val_loss: 0.4611 - v
al_accuracy: 0.7993
Epoch 15/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4382 - accuracy: 0.8075 - val_loss: 0.4433 - v
al_accuracy: 0.8027
Epoch 16/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4390 - accuracy: 0.8078 - val_loss: 0.4207 - v
al_accuracy: 0.8173
Epoch 17/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4378 - accuracy: 0.8110 - val_loss: 0.4643 - v
al_accuracy: 0.7980
Epoch 18/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4383 - accuracy: 0.8107 - val_loss: 0.4231 - v
al_accuracy: 0.8140
Epoch 19/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4376 - accuracy: 0.8082 - val_loss: 0.4264 - v
al_accuracy: 0.8133
Epoch 20/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4389 - accuracy: 0.8093 - val_loss: 0.4290 - v
al_accuracy: 0.8180
Epoch 21/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4436 - accuracy: 0.8093 - val_loss: 0.4340 - v
al_accuracy: 0.8047
Epoch 22/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4382 - accuracy: 0.8070 - val_loss: 0.4200 - v
al_accuracy: 0.8207
Epoch 23/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4333 - accuracy: 0.8133 - val_loss: 0.4267 - v
al_accuracy: 0.8100
Epoch 24/33
188/188 [==============================] - 0s 2ms/step - loss: 0.4444 - accuracy: 0.8110 - val_loss: 0.4378 - v
al_accuracy: 0.8047
Epoch 25/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4365 - accuracy: 0.8113 - val_loss: 0.4238 - v
al_accuracy: 0.8180
Epoch 26/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4372 - accuracy: 0.8125 - val_loss: 0.4194 - v
al_accuracy: 0.8187
Epoch 27/33
188/188 [==============================] - 0s 2ms/step - loss: 0.4375 - accuracy: 0.8052 - val_loss: 0.4192 - v
al_accuracy: 0.8140
Epoch 28/33
188/188 [==============================] - 0s 2ms/step - loss: 0.4394 - accuracy: 0.8080 - val_loss: 0.4214 - v
al_accuracy: 0.8187
Epoch 29/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4359 - accuracy: 0.8112 - val_loss: 0.4167 - v
al_accuracy: 0.8140
Epoch 30/33
188/188 [==============================] - 0s 2ms/step - loss: 0.4378 - accuracy: 0.8092 - val_loss: 0.4210 - v
al_accuracy: 0.8167
Epoch 31/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4366 - accuracy: 0.8115 - val_loss: 0.4451 - v
al_accuracy: 0.8100
Epoch 32/33
```

```
188/188 [==============================] - 0s 1ms/step - loss: 0.4363 - accuracy: 0.8120 - val_loss: 0.4318 - v
al_accuracy: 0.8047
Epoch 33/33
188/188 [==============================] - 0s 1ms/step - loss: 0.4347 - accuracy: 0.8150 - val_loss: 0.4175 - v
al_accuracy: 0.8227
```

Out[57]:

```
<keras.src.callbacks.History at 0x1d24d4ac700>
```

In [58]:

```
eval_result = hypermodel.evaluate(x_test,y_test)
```

```
79/79 [==============================] - 0s 984us/step - loss: 0.4446 - accuracy: 0.8124
```

In [63]:

```
prediction = hypermodel.predict(x_test)
prediction = (prediction > 0.5).astype(np.float32)
```

```
79/79 [==============================] - 0s 889us/step
```

In [68]:

```
from sklearn.metrics import accuracy_score
print(accuracy_score(prediction,y_test)*100,'%')
```

```
81.24 %
```

In [ ]: