Churn Modelling

```
import pandas as pd
In [1]:
          import numpy as np
          import tensorflow as tf
          df = pd.read_csv(r"C:\Users\JANHAVI\Desktop\Churn_Modelling.csv")
In [3]:
In [4]:
          df
Out[4]:
                RowNumber
                              CustomerId
                                            Surname
                                                      CreditScore Geography
                                                                               Gender Age
                                                                                             Tenure
                                                                                                       Bala
             0
                                                                                                           C
                                 15634602
                                                                                                  2
                           1
                                                             619
                                                                               Female
                                                                                         42
                                            Hargrave
                                                                       France
                                 15647311
                                                 Hill
                                                             608
                                                                        Spain
                                                                               Female
                                                                                                      83807
             2
                           3
                                                             502
                                15619304
                                               Onio
                                                                                         42
                                                                                                  8
                                                                                                     159660
                                                                       France
                                                                               Female
             3
                                 15701354
                                                Boni
                                                             699
                                                                       France
                                                                               Female
                                                                                         39
                                                                                                           (
             4
                           5
                                15737888
                                             Mitchell
                                                             850
                                                                                         43
                                                                                                  2 125510
                                                                        Spain
                                                                               Female
          9995
                        9996
                                15606229
                                             Obijiaku
                                                             771
                                                                       France
                                                                                         39
                                                                                                  5
                                                                                                           (
                                                                                 Male
          9996
                        9997
                                 15569892
                                           Johnstone
                                                             516
                                                                       France
                                                                                 Male
                                                                                         35
                                                                                                 10
                                                                                                       57369
          9997
                        9998
                                15584532
                                                             709
                                                                                                  7
                                                                       France
                                                                               Female
                                                                                         36
                                                                                                           (
                                                 Liu
          9998
                        9999
                                 15682355
                                            Sabbatini
                                                             772
                                                                     Germany
                                                                                 Male
                                                                                                       75075
          9999
                       10000
                                15628319
                                              Walker
                                                             792
                                                                               Female
                                                                                         28
                                                                                                     130142
                                                                       France
         10000 rows × 14 columns
          df.head(4)
In [5]:
Out[5]:
             RowNumber
                           CustomerId
                                       Surname
                                                 CreditScore
                                                              Geography
                                                                           Gender
                                                                                         Tenure
                                                                                                   Balance
                                                                                   Age
          0
                        1
                             15634602
                                        Hargrave
                                                         619
                                                                   France
                                                                           Female
                                                                                     42
                                                                                              2
                                                                                                       0.00
                        2
          1
                             15647311
                                             Hill
                                                         608
                                                                    Spain
                                                                           Female
                                                                                     41
                                                                                               1
                                                                                                  83807.86
          2
                        3
                             15619304
                                           Onio
                                                         502
                                                                                              8
                                                                                                 159660.80
                                                                   France
                                                                           Female
                                                                                     42
          3
                                                         699
                                                                                                       0.00
                             15701354
                                            Boni
                                                                   France
                                                                           Female
                                                                                     39
In [6]: X = df.iloc[:,3:-1].values
          y = df.iloc[:,-1].values
In [7]:
```

```
array([[619, 'France', 'Female', ..., 1, 1, 101348.88],
Out[7]:
                [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 [8]: from sklearn.preprocessing import LabelEncoder
         le = LabelEncoder()
         X[:,2] = le.fit_transform(X[:,2])
In [9]: X
         array([[619, 'France', 0, ..., 1, 1, 101348.88],
Out[9]:
                [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]: from sklearn.compose import ColumnTransformer
         from sklearn.preprocessing import OneHotEncoder
         ct = ColumnTransformer(transformers=[('encoder',OneHotEncoder(),[1])],remainder='pa
         X = np.array(ct.fit_transform(X))
In [11]: from sklearn.preprocessing import StandardScaler
         sc = StandardScaler()
         X = sc.fit_transform(X)
In [12]: X
         array([[ 0.99720391, -0.57873591, -0.57380915, ..., 0.64609167,
Out[12]:
                  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 [13]: | from sklearn.model_selection import train_test_split
         X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.20, random_state
In [14]: ann = tf.keras.models.Sequential()
         ann.add(tf.keras.layers.Dense(units = 6,activation = 'relu'))
         ann.add(tf.keras.layers.Dense(units = 6,activation = 'relu'))
         ann.add(tf.keras.layers.Dense(units = 5,activation = 'relu'))
         ann.add(tf.keras.layers.Dense(units = 4,activation = 'relu'))
         ann.add(tf.keras.layers.Dense(units = 1,activation = 'sigmoid'))
         ann.compile(optimizer = 'adam',loss = 'binary_crossentropy',metrics = ['accuracy'])
In [15]:
         ann.fit(X_train,y_train,batch_size = 32,epochs = 150,validation_data=(X_test,y_test
In [16]:
```

```
Epoch 1/150
                         --- 3s 3ms/step - accuracy: 0.7879 - loss: 0.5276 - val_a
250/250
ccuracy: 0.7975 - val_loss: 0.4635
Epoch 2/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.7971 - loss: 0.4515 - val a
ccuracy: 0.8145 - val_loss: 0.4325
Epoch 3/150
                       1s 2ms/step - accuracy: 0.8114 - loss: 0.4306 - val_a
250/250 ----
ccuracy: 0.8220 - val loss: 0.4127
Epoch 4/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8165 - loss: 0.4173 - val_a
ccuracy: 0.8355 - val_loss: 0.3995
Epoch 5/150
                           - 0s 2ms/step - accuracy: 0.8298 - loss: 0.4025 - val a
250/250 -
ccuracy: 0.8450 - val loss: 0.3822
Epoch 6/150
                    ______ 1s 2ms/step - accuracy: 0.8400 - loss: 0.3871 - val_a
250/250 ----
ccuracy: 0.8545 - val_loss: 0.3658
Epoch 7/150
                          - 1s 2ms/step - accuracy: 0.8482 - loss: 0.3751 - val_a
250/250 -
ccuracy: 0.8595 - val_loss: 0.3583
Epoch 8/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8505 - loss: 0.3668 - val a
ccuracy: 0.8570 - val loss: 0.3554
Epoch 9/150
250/250 -
                          — 0s 2ms/step - accuracy: 0.8534 - loss: 0.3600 - val_a
ccuracy: 0.8645 - val_loss: 0.3485
Epoch 10/150
                        ---- 0s 2ms/step - accuracy: 0.8550 - loss: 0.3553 - val_a
250/250 -
ccuracy: 0.8615 - val_loss: 0.3476
Epoch 11/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8568 - loss: 0.3531 - val a
ccuracy: 0.8625 - val loss: 0.3441
Epoch 12/150
                           - 1s 2ms/step - accuracy: 0.8570 - loss: 0.3512 - val_a
ccuracy: 0.8555 - val_loss: 0.3490
Epoch 13/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8583 - loss: 0.3501 - val a
ccuracy: 0.8615 - val loss: 0.3439
Epoch 14/150
                      1s 2ms/step - accuracy: 0.8576 - loss: 0.3481 - val a
250/250 -
ccuracy: 0.8625 - val_loss: 0.3421
Epoch 15/150
                           - 0s 2ms/step - accuracy: 0.8566 - loss: 0.3467 - val a
250/250 -
ccuracy: 0.8610 - val_loss: 0.3423
Epoch 16/150
250/250 -
                       —— 0s 2ms/step - accuracy: 0.8585 - loss: 0.3460 - val_a
ccuracy: 0.8630 - val loss: 0.3402
Epoch 17/150
                           - 0s 2ms/step - accuracy: 0.8600 - loss: 0.3446 - val a
250/250 -
ccuracy: 0.8545 - val loss: 0.3484
Epoch 18/150
250/250
                         --- 0s 2ms/step - accuracy: 0.8551 - loss: 0.3444 - val_a
ccuracy: 0.8615 - val_loss: 0.3415
Epoch 19/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8593 - loss: 0.3440 - val_a
ccuracy: 0.8595 - val loss: 0.3410
Epoch 20/150
250/250 -
                      ---- 0s 2ms/step - accuracy: 0.8590 - loss: 0.3437 - val a
ccuracy: 0.8590 - val loss: 0.3391
Epoch 21/150
                           - 0s 2ms/step - accuracy: 0.8596 - loss: 0.3426 - val a
250/250 -
ccuracy: 0.8565 - val_loss: 0.3409
Epoch 22/150
```

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250/250 Os 2ms/step - accuracy: 0.8596 - loss: 0.3423 - val_a
ccuracy: 0.8600 - val_loss: 0.3395
Epoch 23/150
250/250 -
                       ----- 1s 2ms/step - accuracy: 0.8611 - loss: 0.3417 - val_a
ccuracy: 0.8600 - val loss: 0.3382
Epoch 24/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8596 - loss: 0.3417 - val_a
ccuracy: 0.8575 - val_loss: 0.3443
Epoch 25/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8602 - loss: 0.3409 - val_a
ccuracy: 0.8575 - val_loss: 0.3392
Epoch 26/150
                           - 1s 2ms/step - accuracy: 0.8595 - loss: 0.3410 - val_a
250/250 -
ccuracy: 0.8595 - val_loss: 0.3377
Epoch 27/150
250/250 -
                        ---- 1s 2ms/step - accuracy: 0.8609 - loss: 0.3401 - val_a
ccuracy: 0.8580 - val_loss: 0.3419
Epoch 28/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8646 - loss: 0.3400 - val_a
ccuracy: 0.8580 - val_loss: 0.3389
Epoch 29/150
                           - 1s 2ms/step - accuracy: 0.8605 - loss: 0.3396 - val_a
250/250 -
ccuracy: 0.8565 - val_loss: 0.3419
Epoch 30/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8619 - loss: 0.3400 - val_a
ccuracy: 0.8595 - val_loss: 0.3364
Epoch 31/150
                      ---- 0s 2ms/step - accuracy: 0.8606 - loss: 0.3402 - val_a
250/250 -
ccuracy: 0.8605 - val_loss: 0.3378
Epoch 32/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8610 - loss: 0.3389 - val a
ccuracy: 0.8605 - val loss: 0.3380
Epoch 33/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8622 - loss: 0.3382 - val_a
ccuracy: 0.8575 - val_loss: 0.3403
Epoch 34/150
                           - 0s 2ms/step - accuracy: 0.8621 - loss: 0.3383 - val_a
250/250 -
ccuracy: 0.8590 - val loss: 0.3372
Epoch 35/150
                        --- 0s 2ms/step - accuracy: 0.8620 - loss: 0.3385 - val a
250/250
ccuracy: 0.8560 - val loss: 0.3384
Epoch 36/150
250/250 -
                       —— 0s 2ms/step - accuracy: 0.8627 - loss: 0.3381 - val a
ccuracy: 0.8605 - val loss: 0.3375
Epoch 37/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8635 - loss: 0.3378 - val_a
ccuracy: 0.8575 - val_loss: 0.3383
Epoch 38/150
                          - 0s 2ms/step - accuracy: 0.8635 - loss: 0.3377 - val a
250/250 -
ccuracy: 0.8575 - val loss: 0.3383
Epoch 39/150
250/250 ----
                    ----- 0s 2ms/step - accuracy: 0.8626 - loss: 0.3382 - val a
ccuracy: 0.8595 - val_loss: 0.3384
Epoch 40/150
                           - 1s 2ms/step - accuracy: 0.8634 - loss: 0.3369 - val a
ccuracy: 0.8610 - val_loss: 0.3404
Epoch 41/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8643 - loss: 0.3375 - val a
ccuracy: 0.8565 - val_loss: 0.3367
Epoch 42/150
                        --- 0s 2ms/step - accuracy: 0.8640 - loss: 0.3365 - val a
250/250 -
ccuracy: 0.8590 - val_loss: 0.3358
Epoch 43/150
                           - 0s 2ms/step - accuracy: 0.8631 - loss: 0.3367 - val_a
250/250
```

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ccuracy: 0.8595 - val_loss: 0.3364
Epoch 44/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8637 - loss: 0.3362 - val_a
ccuracy: 0.8650 - val_loss: 0.3353
Epoch 45/150
250/250 ----
                    ----- 0s 2ms/step - accuracy: 0.8639 - loss: 0.3362 - val a
ccuracy: 0.8595 - val_loss: 0.3346
Epoch 46/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8637 - loss: 0.3362 - val a
ccuracy: 0.8550 - val_loss: 0.3383
Epoch 47/150
250/250 -
                          - 0s 2ms/step - accuracy: 0.8634 - loss: 0.3363 - val_a
ccuracy: 0.8625 - val_loss: 0.3352
Epoch 48/150
                       ---- 0s 2ms/step - accuracy: 0.8645 - loss: 0.3352 - val_a
250/250 -
ccuracy: 0.8580 - val_loss: 0.3369
Epoch 49/150
250/250
                        --- 0s 2ms/step - accuracy: 0.8630 - loss: 0.3351 - val_a
ccuracy: 0.8635 - val_loss: 0.3354
Epoch 50/150
                           - 0s 2ms/step - accuracy: 0.8650 - loss: 0.3351 - val_a
250/250 -
ccuracy: 0.8565 - val_loss: 0.3356
Epoch 51/150
250/250 -
                       ---- 0s 2ms/step - accuracy: 0.8636 - loss: 0.3350 - val_a
ccuracy: 0.8575 - val_loss: 0.3356
Epoch 52/150
250/250 -
                        ---- 1s 2ms/step - accuracy: 0.8646 - loss: 0.3344 - val_a
ccuracy: 0.8585 - val_loss: 0.3378
Epoch 53/150
                    ______ 1s 2ms/step - accuracy: 0.8637 - loss: 0.3350 - val_a
250/250 -
ccuracy: 0.8585 - val loss: 0.3360
Epoch 54/150
                           - 0s 2ms/step - accuracy: 0.8654 - loss: 0.3340 - val a
250/250 -
ccuracy: 0.8580 - val_loss: 0.3367
Epoch 55/150
250/250 -
                     ----- 0s 2ms/step - accuracy: 0.8639 - loss: 0.3339 - val_a
ccuracy: 0.8620 - val_loss: 0.3359
Epoch 56/150
                    1s 2ms/step - accuracy: 0.8630 - loss: 0.3339 - val a
250/250 ----
ccuracy: 0.8550 - val loss: 0.3397
Epoch 57/150
                      ----- 1s 2ms/step - accuracy: 0.8659 - loss: 0.3334 - val a
250/250 -
ccuracy: 0.8590 - val loss: 0.3357
Epoch 58/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8649 - loss: 0.3332 - val_a
ccuracy: 0.8590 - val_loss: 0.3352
Epoch 59/150
                           - 0s 2ms/step - accuracy: 0.8659 - loss: 0.3331 - val a
250/250 -
ccuracy: 0.8565 - val loss: 0.3361
Epoch 60/150
250/250
                          — 0s 2ms/step - accuracy: 0.8649 - loss: 0.3327 - val a
ccuracy: 0.8625 - val_loss: 0.3365
Epoch 61/150
250/250 -
                    ----- 0s 2ms/step - accuracy: 0.8643 - loss: 0.3333 - val_a
ccuracy: 0.8570 - val loss: 0.3385
Epoch 62/150
                           - 0s 2ms/step - accuracy: 0.8650 - loss: 0.3323 - val a
250/250 -
ccuracy: 0.8575 - val loss: 0.3355
Epoch 63/150
                           - Os 2ms/step - accuracy: 0.8630 - loss: 0.3323 - val a
250/250
ccuracy: 0.8610 - val loss: 0.3360
Epoch 64/150
                       —— 0s 2ms/step - accuracy: 0.8651 - loss: 0.3324 - val_a
250/250 -
ccuracy: 0.8550 - val_loss: 0.3368
```

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Epoch 65/150
                         — 0s 2ms/step - accuracy: 0.8666 - loss: 0.3325 - val_a
250/250
ccuracy: 0.8570 - val_loss: 0.3362
Epoch 66/150
250/250
                           - 1s 2ms/step - accuracy: 0.8641 - loss: 0.3315 - val a
ccuracy: 0.8595 - val_loss: 0.3351
Epoch 67/150
                       —— 0s 2ms/step - accuracy: 0.8646 - loss: 0.3321 - val_a
250/250 ----
ccuracy: 0.8585 - val loss: 0.3356
Epoch 68/150
250/250
                           - 1s 2ms/step - accuracy: 0.8659 - loss: 0.3315 - val_a
ccuracy: 0.8630 - val_loss: 0.3348
Epoch 69/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8661 - loss: 0.3318 - val a
ccuracy: 0.8580 - val loss: 0.3375
Epoch 70/150
                    _____ 0s 2ms/step - accuracy: 0.8645 - loss: 0.3322 - val_a
250/250 -
ccuracy: 0.8580 - val_loss: 0.3391
Epoch 71/150
                          - 0s 2ms/step - accuracy: 0.8659 - loss: 0.3321 - val_a
250/250 -
ccuracy: 0.8620 - val_loss: 0.3354
Epoch 72/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8651 - loss: 0.3315 - val a
ccuracy: 0.8575 - val loss: 0.3389
Epoch 73/150
250/250 -
                         ___ 1s 2ms/step - accuracy: 0.8643 - loss: 0.3317 - val_a
ccuracy: 0.8565 - val_loss: 0.3363
Epoch 74/150
250/250 -
                        ---- 1s 2ms/step - accuracy: 0.8651 - loss: 0.3314 - val_a
ccuracy: 0.8560 - val_loss: 0.3356
Epoch 75/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8660 - loss: 0.3316 - val a
ccuracy: 0.8585 - val loss: 0.3374
Epoch 76/150
                           - 0s 2ms/step - accuracy: 0.8643 - loss: 0.3313 - val_a
ccuracy: 0.8575 - val_loss: 0.3379
Epoch 77/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8654 - loss: 0.3309 - val a
ccuracy: 0.8600 - val loss: 0.3363
Epoch 78/150
                      Os 2ms/step - accuracy: 0.8644 - loss: 0.3313 - val a
250/250 -
ccuracy: 0.8585 - val_loss: 0.3369
Epoch 79/150
                           - 0s 2ms/step - accuracy: 0.8668 - loss: 0.3311 - val a
250/250 -
ccuracy: 0.8555 - val_loss: 0.3385
Epoch 80/150
250/250 -
                       —— 0s 2ms/step - accuracy: 0.8668 - loss: 0.3308 - val_a
ccuracy: 0.8610 - val loss: 0.3362
Epoch 81/150
                           - 0s 2ms/step - accuracy: 0.8669 - loss: 0.3311 - val a
250/250 -
ccuracy: 0.8545 - val loss: 0.3388
Epoch 82/150
250/250 -
                         —— 0s 2ms/step - accuracy: 0.8666 - loss: 0.3311 - val_a
ccuracy: 0.8585 - val_loss: 0.3354
Epoch 83/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8625 - loss: 0.3314 - val_a
ccuracy: 0.8610 - val loss: 0.3353
Epoch 84/150
250/250 -
                      ---- 0s 2ms/step - accuracy: 0.8658 - loss: 0.3310 - val a
ccuracy: 0.8610 - val loss: 0.3362
Epoch 85/150
                           - 0s 2ms/step - accuracy: 0.8664 - loss: 0.3318 - val a
250/250 -
ccuracy: 0.8580 - val_loss: 0.3358
Epoch 86/150
```

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250/250 Os 2ms/step - accuracy: 0.8675 - loss: 0.3311 - val_a
ccuracy: 0.8580 - val_loss: 0.3368
Epoch 87/150
250/250 -
                       ---- 0s 2ms/step - accuracy: 0.8655 - loss: 0.3316 - val_a
ccuracy: 0.8585 - val loss: 0.3367
Epoch 88/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8650 - loss: 0.3311 - val_a
ccuracy: 0.8540 - val_loss: 0.3393
Epoch 89/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8640 - loss: 0.3316 - val_a
ccuracy: 0.8600 - val_loss: 0.3351
Epoch 90/150
                           - 0s 2ms/step - accuracy: 0.8670 - loss: 0.3306 - val_a
250/250 -
ccuracy: 0.8560 - val loss: 0.3367
Epoch 91/150
250/250 -
                        ---- 1s 2ms/step - accuracy: 0.8679 - loss: 0.3311 - val_a
ccuracy: 0.8585 - val_loss: 0.3352
Epoch 92/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8646 - loss: 0.3311 - val_a
ccuracy: 0.8585 - val_loss: 0.3357
Epoch 93/150
                           - 0s 2ms/step - accuracy: 0.8659 - loss: 0.3313 - val_a
250/250 -
ccuracy: 0.8560 - val_loss: 0.3388
Epoch 94/150
                           - 0s 2ms/step - accuracy: 0.8666 - loss: 0.3308 - val_a
250/250 -
ccuracy: 0.8580 - val loss: 0.3355
Epoch 95/150
                      ---- 0s 2ms/step - accuracy: 0.8674 - loss: 0.3306 - val_a
250/250 -
ccuracy: 0.8555 - val_loss: 0.3383
Epoch 96/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8654 - loss: 0.3313 - val a
ccuracy: 0.8575 - val loss: 0.3362
Epoch 97/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8658 - loss: 0.3310 - val_a
ccuracy: 0.8545 - val_loss: 0.3380
Epoch 98/150
                           - 0s 2ms/step - accuracy: 0.8675 - loss: 0.3307 - val_a
250/250 -
ccuracy: 0.8575 - val loss: 0.3351
Epoch 99/150
                        --- 0s 2ms/step - accuracy: 0.8659 - loss: 0.3308 - val a
250/250 -
ccuracy: 0.8560 - val loss: 0.3361
Epoch 100/150
250/250 -
                       1s 2ms/step - accuracy: 0.8687 - loss: 0.3303 - val a
ccuracy: 0.8520 - val loss: 0.3403
Epoch 101/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8670 - loss: 0.3304 - val_a
ccuracy: 0.8540 - val_loss: 0.3397
Epoch 102/150
                          - 0s 2ms/step - accuracy: 0.8659 - loss: 0.3303 - val a
250/250 -
ccuracy: 0.8625 - val loss: 0.3353
Epoch 103/150
250/250 -----
                   ----- 0s 2ms/step - accuracy: 0.8650 - loss: 0.3307 - val a
ccuracy: 0.8575 - val_loss: 0.3379
Epoch 104/150
                           - 0s 2ms/step - accuracy: 0.8658 - loss: 0.3307 - val a
ccuracy: 0.8630 - val_loss: 0.3345
Epoch 105/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8656 - loss: 0.3304 - val a
ccuracy: 0.8605 - val_loss: 0.3345
Epoch 106/150
250/250 -
                        --- 0s 2ms/step - accuracy: 0.8661 - loss: 0.3308 - val a
ccuracy: 0.8595 - val_loss: 0.3366
Epoch 107/150
                           - 0s 2ms/step - accuracy: 0.8651 - loss: 0.3310 - val_a
250/250
```

```
ccuracy: 0.8640 - val_loss: 0.3347
Epoch 108/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8634 - loss: 0.3299 - val_a
ccuracy: 0.8610 - val_loss: 0.3342
Epoch 109/150
250/250 -
                    ______ 1s 2ms/step - accuracy: 0.8658 - loss: 0.3306 - val a
ccuracy: 0.8590 - val_loss: 0.3367
Epoch 110/150
                           - 0s 2ms/step - accuracy: 0.8669 - loss: 0.3305 - val a
250/250
ccuracy: 0.8555 - val_loss: 0.3393
Epoch 111/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8684 - loss: 0.3301 - val_a
ccuracy: 0.8590 - val_loss: 0.3352
Epoch 112/150
                       ---- 0s 2ms/step - accuracy: 0.8656 - loss: 0.3303 - val_a
250/250 -
ccuracy: 0.8565 - val_loss: 0.3386
Epoch 113/150
250/250
                        --- 1s 2ms/step - accuracy: 0.8656 - loss: 0.3298 - val_a
ccuracy: 0.8565 - val_loss: 0.3386
Epoch 114/150
                           - 0s 2ms/step - accuracy: 0.8668 - loss: 0.3301 - val_a
250/250 -
ccuracy: 0.8590 - val_loss: 0.3372
Epoch 115/150
250/250 -
                       —— 0s 2ms/step - accuracy: 0.8662 - loss: 0.3302 - val_a
ccuracy: 0.8595 - val_loss: 0.3363
Epoch 116/150
250/250 -
                        —— 0s 2ms/step - accuracy: 0.8666 - loss: 0.3301 - val_a
ccuracy: 0.8630 - val_loss: 0.3357
Epoch 117/150
                   Os 2ms/step - accuracy: 0.8685 - loss: 0.3302 - val_a
250/250 -
ccuracy: 0.8580 - val loss: 0.3365
Epoch 118/150
                          - 0s 2ms/step - accuracy: 0.8671 - loss: 0.3299 - val a
250/250 -
ccuracy: 0.8610 - val_loss: 0.3356
Epoch 119/150
250/250 -
                      ---- 0s 2ms/step - accuracy: 0.8679 - loss: 0.3299 - val_a
ccuracy: 0.8600 - val_loss: 0.3352
Epoch 120/150
250/250 -----
                     Os 2ms/step - accuracy: 0.8676 - loss: 0.3299 - val a
ccuracy: 0.8625 - val loss: 0.3344
Epoch 121/150
                      —— 0s 2ms/step - accuracy: 0.8650 - loss: 0.3304 - val a
250/250 -
ccuracy: 0.8630 - val loss: 0.3335
Epoch 122/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8674 - loss: 0.3301 - val_a
ccuracy: 0.8585 - val_loss: 0.3345
Epoch 123/150
                           - 0s 2ms/step - accuracy: 0.8656 - loss: 0.3298 - val a
250/250 -
ccuracy: 0.8600 - val loss: 0.3353
Epoch 124/150
250/250
                          — 0s 2ms/step - accuracy: 0.8679 - loss: 0.3298 - val a
ccuracy: 0.8600 - val_loss: 0.3359
Epoch 125/150
250/250 -
                     ----- 0s 2ms/step - accuracy: 0.8655 - loss: 0.3302 - val_a
ccuracy: 0.8600 - val loss: 0.3359
Epoch 126/150
                           - 0s 2ms/step - accuracy: 0.8675 - loss: 0.3300 - val a
250/250 -
ccuracy: 0.8570 - val loss: 0.3378
Epoch 127/150
                           - 1s 2ms/step - accuracy: 0.8655 - loss: 0.3301 - val a
250/250
ccuracy: 0.8615 - val loss: 0.3357
Epoch 128/150
                       —— 0s 2ms/step - accuracy: 0.8648 - loss: 0.3297 - val_a
250/250 -
ccuracy: 0.8645 - val_loss: 0.3351
```

```
Epoch 129/150
                         -- 1s 2ms/step - accuracy: 0.8666 - loss: 0.3299 - val_a
250/250
ccuracy: 0.8615 - val_loss: 0.3343
Epoch 130/150
250/250
                           - 1s 2ms/step - accuracy: 0.8643 - loss: 0.3295 - val a
ccuracy: 0.8590 - val loss: 0.3356
Epoch 131/150
                       1s 2ms/step - accuracy: 0.8665 - loss: 0.3301 - val_a
250/250 ----
ccuracy: 0.8590 - val loss: 0.3355
Epoch 132/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8673 - loss: 0.3308 - val_a
ccuracy: 0.8630 - val_loss: 0.3356
Epoch 133/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8670 - loss: 0.3297 - val a
ccuracy: 0.8590 - val loss: 0.3360
Epoch 134/150
                     1s 2ms/step - accuracy: 0.8673 - loss: 0.3303 - val_a
250/250 ---
ccuracy: 0.8580 - val_loss: 0.3355
Epoch 135/150
250/250 -
                          - 0s 2ms/step - accuracy: 0.8660 - loss: 0.3296 - val_a
ccuracy: 0.8640 - val_loss: 0.3345
Epoch 136/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8679 - loss: 0.3294 - val a
ccuracy: 0.8575 - val loss: 0.3383
Epoch 137/150
                         -- 1s 2ms/step - accuracy: 0.8652 - loss: 0.3303 - val_a
250/250 ---
ccuracy: 0.8585 - val_loss: 0.3395
Epoch 138/150
250/250 -
                        —— 0s 2ms/step - accuracy: 0.8674 - loss: 0.3297 - val_a
ccuracy: 0.8625 - val_loss: 0.3351
Epoch 139/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8664 - loss: 0.3294 - val a
ccuracy: 0.8620 - val loss: 0.3347
Epoch 140/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8673 - loss: 0.3299 - val_a
ccuracy: 0.8605 - val_loss: 0.3351
Epoch 141/150
250/250 -
                           - 0s 2ms/step - accuracy: 0.8661 - loss: 0.3302 - val a
ccuracy: 0.8595 - val loss: 0.3362
Epoch 142/150
                       —— 0s 2ms/step - accuracy: 0.8654 - loss: 0.3295 - val a
250/250 -
ccuracy: 0.8610 - val_loss: 0.3355
Epoch 143/150
                           - 0s 2ms/step - accuracy: 0.8662 - loss: 0.3295 - val a
250/250 -
ccuracy: 0.8615 - val_loss: 0.3338
Epoch 144/150
250/250 -
                       ---- 0s 2ms/step - accuracy: 0.8676 - loss: 0.3296 - val_a
ccuracy: 0.8570 - val loss: 0.3366
Epoch 145/150
                           - 0s 2ms/step - accuracy: 0.8649 - loss: 0.3298 - val a
250/250 -
ccuracy: 0.8645 - val loss: 0.3339
Epoch 146/150
250/250
                        —— 0s 2ms/step - accuracy: 0.8662 - loss: 0.3297 - val_a
ccuracy: 0.8595 - val_loss: 0.3348
Epoch 147/150
250/250 -
                           - 1s 2ms/step - accuracy: 0.8680 - loss: 0.3294 - val_a
ccuracy: 0.8615 - val loss: 0.3341
Epoch 148/150
250/250 -
                       1s 2ms/step - accuracy: 0.8670 - loss: 0.3297 - val a
ccuracy: 0.8605 - val loss: 0.3345
Epoch 149/150
                          - 1s 2ms/step - accuracy: 0.8659 - loss: 0.3293 - val_a
250/250 -
ccuracy: 0.8585 - val_loss: 0.3361
Epoch 150/150
```

```
250/250 — Os 2ms/step - accuracy: 0.8671 - loss: 0.3293 - val_a
         ccuracy: 0.8570 - val_loss: 0.3389
         <keras.src.callbacks.history.History at 0x238cbc2c210>
Out[16]:
In [17]: y_pred = ann.predict(X_test)
         63/63 -
                                  - 0s 4ms/step
In [18]: y_pred = (y_pred > 0.5)
In [19]: print(np.concatenate((y_pred.reshape(len(y_pred),1),y_test.reshape(len(y_test),1)),
         [[0 0]]
          [0 1]
          [0 0]
          . . .
          [0 0]
          [0 0]
          [0 0]]
In [20]: from sklearn.metrics import accuracy_score,confusion_matrix
         ac = accuracy_score(y_test,y_pred)
         ac
         0.857
Out[20]:
         cm = confusion_matrix(y_test,y_pred)
In [21]:
         array([[1495, 100],
Out[21]:
                [ 186, 219]], dtype=int64)
```