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# Lab-3 Binary Classification of Heart Disease of Patients using Deep Neural Network

## 1. Load the dataset: "heart\_data.csv" and explore the features

```
In [1]: import pandas as pd
In [2]: df = pd.read_csv("heart_data.csv")
In [3]: df.head()
Out[3]:
          age sex cp trestbps chol fbs
                                   restecg thalach exang oldpeak slope ca thal target
        0
           63
                        145
                            233
                                 1
                                            150
                                                         2.3
                                                                  0
                                                                           1
                   3
                                                               0
           37
                  2
                            250
                                            187
                                                                      2
        1
               1
                        130
                                 0
                                                   0
                                                         3.5
                                                               0
                                                                  0
                                                                           1
                                        0
        2
           41
                        130
                            204
                                            172
                                                   0
                                                         1.4
                                                               2 0
                                                                      2
               0
                 1
                                 0
                                                                           1
                                                                      2
           56
               1
                        120
                            236
                                            178
                                                   0
                                                         8.0
                                                               2
                                                                 0
                                                                           1
                                                                      2
           57
               0
                  0
                        120
                           354
                                 0
                                            163
                                                   1
                                                         0.6
                                                               2 0
                                                                           1
In [4]:
        df.shape
Out[4]: (303, 14)
In [5]: df.size
Out[5]: 4242
In [6]: df.columns
dtype='object')
```

# 2. Split the dataset for training and testing (test size = 20%)

```
In [7]: X = df
y = df.pop('target')

In [8]: 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, rando
In [9]: X_train.shape
Out[9]: (242, 13)
In [10]: X_test.shape
Out[10]: (61, 13)
```

### 3. Create a neural network based on the following requirements

```
In [11]: from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense

In [12]: model = Sequential()
    model.add(Dense(8, input_dim=13, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))
```

### 4. Compile your model with learning rate = 0.001, optimizer as 'RMSprop', Mean square error loss and metrics as 'accuracy'.

```
In [13]: from tensorflow import keras
```

```
In [14]: optimizer = keras.optimizers.RMSprop(learning rate=0.001)
       model.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
       model.fit(X_train, y_train, epochs=10, batch_size=30, verbose=1)
       Epoch 1/10
       0.5496
       Epoch 2/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 3/10
       9/9 [============= ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 4/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 5/10
       9/9 [============= ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 6/10
       9/9 [=============== ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 7/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 8/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 9/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 10/10
       0.5496
Out[14]: <keras.callbacks.History at 0x1ecca6e7460>
In [15]: model.evaluate(X_test, y_test)
       0.5246
```

Out[15]: [0.4754098355770111, 0.5245901346206665]

### 5. Print the summary of the model: model.summary()

```
In [16]: model.summary()
      Model: "sequential"
      Layer (type)
                         Output Shape
                                          Param #
      ______
      dense (Dense)
                         (None, 8)
                                          112
      dense_1 (Dense)
                         (None, 1)
                                          9
      ______
      Total params: 121
      Trainable params: 121
      Non-trainable params: 0
```

#### 6. Train the model for 200 epochs and batch size as 10

```
In [17]: model.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
     model.fit(X train, y train, epochs=200, batch size=10, verbose=1)
     Epoch 1/200
     25/25 [=========== ] - 1s 1ms/step - loss: 0.4504 - accu
     racy: 0.5496
     Epoch 2/200
     25/25 [=============== ] - Os 1ms/step - loss: 0.4504 - accu
     racy: 0.5496
     Epoch 3/200
     racy: 0.5496
     Epoch 4/200
     racy: 0.5496
     Epoch 5/200
     25/25 [=============== ] - Os 1ms/step - loss: 0.4504 - accu
     racy: 0.5496
     Epoch 6/200
     racy: 0.5496
     Epoch 7/200
In [18]: model.evaluate(X_test, y_test)
     0.5246
Out[18]: [0.4754098355770111, 0.5245901346206665]
```

# 7. Save the trained model in a variable, such as, history. Also, you can split your training data for validation such as 20% of training data

```
In [19]: history = model.fit(X_train, y_train, validation_split=0.2, epochs=100, batch_
      Epoch 1/100
      97/97 [========= ] - 0s 2ms/step - loss: 0.4560 - accu
      racy: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
      Epoch 2/100
      racy: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
      Epoch 3/100
      racy: 0.5440 - val loss: 0.4286 - val accuracy: 0.5714
      Epoch 4/100
      97/97 [=========== ] - 0s 2ms/step - loss: 0.4560 - accu
      racy: 0.5440 - val loss: 0.4286 - val accuracy: 0.5714
      Epoch 5/100
      97/97 [========== ] - 0s 1ms/step - loss: 0.4560 - accu
      racy: 0.5440 - val loss: 0.4286 - val accuracy: 0.5714
      Epoch 6/100
      racy: 0.5440 - val loss: 0.4286 - val_accuracy: 0.5714
      Epoch 7/100
      07/07 F
```

### 8. Evaluate the trained model to predict the probability values for the test data set (ie., xtest and ytest)

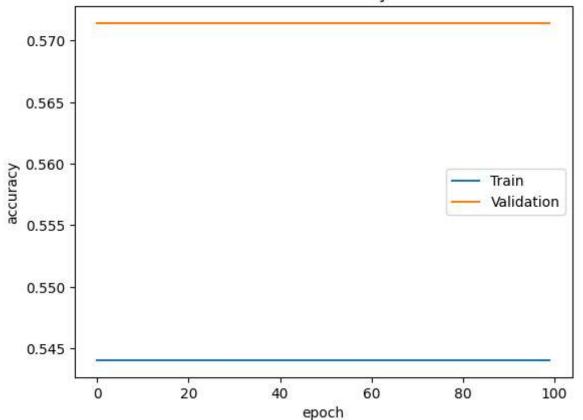
### 9. Print the model accuracy and model loss as below (Use can use the 'history' object we have saved). Sample code is given below.

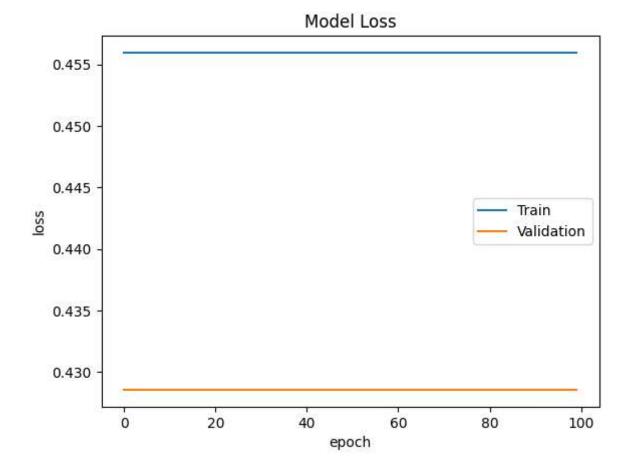
```
In [22]: history.history.keys()
Out[22]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
In [25]: import matplotlib.pyplot as plt
```

Matplotlib is building the font cache; this may take a moment.

```
In [26]: plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('Model Accuracy')
    plt.ylabel('accuracy')
    plt.legend(['Train', 'Validation'])
    plt.show()
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model Loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['Train', 'Validation'])
    plt.show()
```

### Model Accuracy





### 10. Do further experiments

```
In [27]: model1 = Sequential()
    model1.add(Dense(16, input_dim=13, activation='relu'))
    model1.add(Dense(8, activation='relu'))
    model1.add(Dense(1, activation='sigmoid'))
```

```
In [28]: model1.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
     model1.fit(X train, y train, epochs=10, batch size=30, verbose=1)
     Epoch 1/10
     0.5207
     Epoch 2/10
     0.4793
     Epoch 3/10
     0.5165
     Epoch 4/10
     0.5331
     Epoch 5/10
     9/9 [============= ] - 0s 1ms/step - loss: 0.3327 - accuracy:
     0.5496
     Epoch 6/10
     9/9 [============ ] - 0s 1ms/step - loss: 0.3742 - accuracy:
     0.4959
     Epoch 7/10
     9/9 [============== ] - 0s 1ms/step - loss: 0.3223 - accuracy:
     0.5702
     Epoch 8/10
     9/9 [=========== ] - 0s 1ms/step - loss: 0.3172 - accuracy:
     0.5785
     Epoch 9/10
     9/9 [============== ] - 0s 1ms/step - loss: 0.3447 - accuracy:
     0.5455
     Epoch 10/10
     9/9 [========== ] - 0s 1ms/step - loss: 0.3131 - accuracy:
     0.5785
Out[28]: <keras.callbacks.History at 0x1ecd0ca8040>
In [29]: model1.evaluate(X test, y test)
     0.5246
```

Out[29]: [0.4531889259815216, 0.5245901346206665]

```
In [30]: history1 = model.fit(X_train, y_train, validation_split=0.2, epochs=100, batch
     Epoch 1/100
     65/65 [============ ] - 0s 3ms/step - loss: 0.4560 - accu
     racy: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
     Epoch 2/100
     racy: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
     Epoch 3/100
     racy: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
     racy: 0.5440 - val loss: 0.4286 - val accuracy: 0.5714
     Epoch 5/100
     racy: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
     Epoch 6/100
     racy: 0.5440 - val loss: 0.4286 - val accuracy: 0.5714
     Epoch 7/100
```

### In [31]: model1.summary()

#### Model: "sequential\_1"

Layer (type)	Output Shape	Param #
dense_2 (Dense)	(None, 16)	224
dense_3 (Dense)	(None, 8)	136
dense_4 (Dense)	(None, 1)	9

\_\_\_\_\_\_

Total params: 369
Trainable params: 369
Non-trainable params: 0

#### Out[32]: loss accuracy val\_loss val\_accuracy **0** 0.455959 0.544041 0.428571 0.571429 **1** 0.455959 0.544041 0.428571 0.571429 **2** 0.455959 0.544041 0.428571 0.571429 **3** 0.455959 0.544041 0.428571 0.571429 **4** 0.455959 0.544041 0.428571 0.571429 ... **95** 0.455959 0.544041 0.428571 0.571429 **96** 0.455959 0.544041 0.428571 0.571429 **97** 0.455959 0.544041 0.428571 0.571429 **98** 0.455959 0.544041 0.428571 0.571429

**99** 0.455959 0.544041 0.428571

100 rows × 4 columns

```
In [33]: model2 = Sequential()
    model2.add(Dense(32, input_dim=13, activation='relu'))
    model2.add(Dense(16, activation='relu'))
    model2.add(Dense(8, activation='relu'))
    model2.add(Dense(1, activation='sigmoid'))
```

0.571429

```
In [34]: model2.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
     model2.fit(X train, y train, epochs=10, batch size=30, verbose=1)
     Epoch 1/10
     0.5000
     Epoch 2/10
     0.6116
     Epoch 3/10
     0.6157
     Epoch 4/10
     9/9 [============== ] - 0s 2ms/step - loss: 0.2685 - accuracy:
     0.5785
     Epoch 5/10
     9/9 [============ ] - 0s 2ms/step - loss: 0.2583 - accuracy:
     0.6198
     Epoch 6/10
     9/9 [============= ] - 0s 2ms/step - loss: 0.2586 - accuracy:
     0.6033
     Epoch 7/10
     0.6322
     Epoch 8/10
     9/9 [============ ] - 0s 2ms/step - loss: 0.2666 - accuracy:
     0.6198
     Epoch 9/10
     9/9 [============== ] - 0s 2ms/step - loss: 0.2301 - accuracy:
     0.6364
     Epoch 10/10
     9/9 [========== ] - 0s 1ms/step - loss: 0.2305 - accuracy:
     0.6157
Out[34]: <keras.callbacks.History at 0x1ecd1134910>
In [35]: model2.evaluate(X test, y test)
     0.4754
```

Out[35]: [0.3780178129673004, 0.4754098355770111]

### In [36]: model2.summary()

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
dense_5 (Dense)	(None, 32)	448
dense_6 (Dense)	(None, 16)	528
dense_7 (Dense)	(None, 8)	136
dense_8 (Dense)	(None, 1)	9
=======================================	=======================================	===========

Total params: 1,121 Trainable params: 1,121 Non-trainable params: 0

```
In [37]: model3 = Sequential()
         model3.add(Dense(64, input_dim=13, activation='relu'))
         model3.add(Dense(32, activation='relu'))
         model3.add(Dense(16, activation='relu'))
         model3.add(Dense(8, activation='relu'))
         model3.add(Dense(1, activation='sigmoid'))
```

```
In [38]: model3.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
     model3.fit(X train, y train, epochs=10, batch size=30, verbose=1)
     Epoch 1/10
     0.6033
     Epoch 2/10
     0.6281
     Epoch 3/10
     0.6322
     Epoch 4/10
     0.6529
     Epoch 5/10
     0.6364
     Epoch 6/10
     9/9 [============ ] - 0s 2ms/step - loss: 0.2276 - accuracy:
     0.6364
     Epoch 7/10
     9/9 [=============== ] - 0s 2ms/step - loss: 0.2202 - accuracy:
     0.6322
     Epoch 8/10
     9/9 [=========== ] - 0s 1ms/step - loss: 0.2360 - accuracy:
     0.5579
     Epoch 9/10
     9/9 [============== ] - 0s 2ms/step - loss: 0.2829 - accuracy:
     0.6653
     Epoch 10/10
     9/9 [========== ] - 0s 2ms/step - loss: 0.2180 - accuracy:
     0.6405
Out[38]: <keras.callbacks.History at 0x1ecd0f8e710>
In [39]: model3.evaluate(X test, y test)
     0.5082
```

Out[39]: [0.22848190367221832, 0.5081967115402222]

### In [40]: model3.summary()

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
dense_9 (Dense)	(None, 64)	896
dense_10 (Dense)	(None, 32)	2080
dense_11 (Dense)	(None, 16)	528
dense_12 (Dense)	(None, 8)	136
dense_13 (Dense)	(None, 1)	9
dense_13 (Dense)	(None, 1)	9

\_\_\_\_\_\_

Total params: 3,649 Trainable params: 3,649 Non-trainable params: 0