LAB3: BINARY CLASSIOFICATION OF HEART DISEASE OF PATIENTS USING DEEP NEURAL NETWORK

```
In [1]: import pandas as pd
In [2]: | df = pd.read_csv("heart_data.csv")
         df.head(10)
Out[2]:
                          trestbps chol fbs restecg thalach exang
                                                                       oldpeak slope ca
             age
                  sex
                       ср
                                                                                           thal target
          0
              63
                     1
                         3
                                145
                                     233
                                            1
                                                     0
                                                           150
                                                                    0
                                                                            2.3
                                                                                    0
                                                                                        0
                                                                                             1
                                                                                                    1
           1
              37
                     1
                         2
                                130
                                     250
                                            0
                                                     1
                                                           187
                                                                    0
                                                                            3.5
                                                                                    0
                                                                                        0
                                                                                             2
                                                                                                    1
                                130
                                     204
                                                                    0
          2
              41
                    0
                         1
                                            0
                                                     0
                                                           172
                                                                            1.4
                                                                                    2
                                                                                        0
                                                                                             2
                                                                                                    1
           3
              56
                                120
                                     236
                                            0
                                                     1
                                                           178
                                                                    0
                                                                            8.0
                                                                                    2
                                                                                        0
                                                                                             2
                                                                                                    1
                     1
                         1
              57
                     0
                                120
                                     354
                                                     1
                                                           163
                                                                    1
                                                                            0.6
                                                                                    2
                                                                                             2
                                                                                                    1
          5
              57
                         0
                                140
                                     192
                                            0
                                                     1
                                                           148
                                                                    0
                                                                            0.4
                                                                                    1
                                                                                        0
                                                                                             1
                                                                                                    1
                    1
                                     294
              56
                                            0
                                                     0
                                                           153
                                                                    0
                                                                            1.3
                                                                                             2
           6
                    0
                         1
                                140
                                                                                    1
                                                                                        0
                                                                                                    1
          7
              44
                                120
                                     263
                                                           173
                                                                    0
                                                                            0.0
                                                                                             3
                     1
                         1
                                            0
                                                     1
                                                                                    2
                                                                                        0
                                                                                                    1
                         2
                                172
                                                                    0
                                                                            0.5
                                                                                    2
          8
              52
                     1
                                     199
                                            1
                                                     1
                                                           162
                                                                                        0
                                                                                             3
                                                                                                    1
              57
                     1
                         2
                                150
                                     168
                                            0
                                                     1
                                                           174
                                                                    0
                                                                            1.6
                                                                                    2
                                                                                        0
                                                                                             2
                                                                                                    1
In [3]: df.shape
Out[3]: (303, 14)
In [4]: df.size
Out[4]: 4242
In [5]: | df.columns
Out[5]: Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
                  'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
                dtype='object')
         2. Split the dataset for training and testing (test size = 20%)
In [6]: X = df.drop('target',axis=1)
         y = df['target']
```

In [8]: X

Out[8]:

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	са	thal
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2

303 rows × 13 columns

```
In [13]: y
Out[13]: 0
                 1
         1
                 1
         2
                 1
         3
                 1
                 1
         298
         299
                 0
         300
                 0
         301
                 0
         302
         Name: target, Length: 303, dtype: int64
In [14]: 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_s
In [15]: X_train.shape
Out[15]: (242, 13)
In [12]: X_test.shape
Out[12]: (61, 13)
```

3. Create a neural network based on the following requirements

```
In [16]: from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense

In [17]: 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 [18]: |from tensorflow import keras
In [19]: optimizer = keras.optimizers.RMSprop(learning rate=0.001)
       model.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
In [20]:
       model.fit(X_train, y_train, epochs=10, batch_size=30, verbose=1)
       Epoch 1/10
       9/9 [========== ] - 3s 9ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 2/10
       9/9 [=========== ] - 0s 2ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 3/10
       9/9 [=========== ] - 0s 2ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 4/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 5/10
       9/9 [========== ] - 0s 1ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 6/10
       9/9 [=========== ] - 0s 1ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 7/10
       9/9 [========== ] - 0s 1ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 8/10
       9/9 [============ ] - 0s 2ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 9/10
       0.4504
       Epoch 10/10
       9/9 [============= ] - 0s 2ms/step - loss: 0.5496 - accuracy:
       0.4504
Out[20]: <keras.callbacks.History at 0x1d7869cf0d0>
```

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

In [22]: 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 [23]: model.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
      model.fit(X train, y train, epochs=200, batch size=10, verbose=1)
      --/-- L
      y: 0.4504
      Epoch 13/200
      25/25 [=========== ] - 0s 1ms/step - loss: 0.5496 - accurac
      v: 0.4504
      Epoch 14/200
      25/25 [=========== ] - 0s 1ms/step - loss: 0.5496 - accurac
      v: 0.4504
      Epoch 15/200
      y: 0.4504
      Epoch 16/200
      25/25 [============= ] - 0s 1ms/step - loss: 0.5496 - accurac
      y: 0.4504
      Epoch 17/200
      y: 0.4504
      Epoch 18/200
      25/25 [============= ] - 0s 1ms/step - loss: 0.5496 - accurac
      y: 0.4504
       Facab 10/200
```

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.

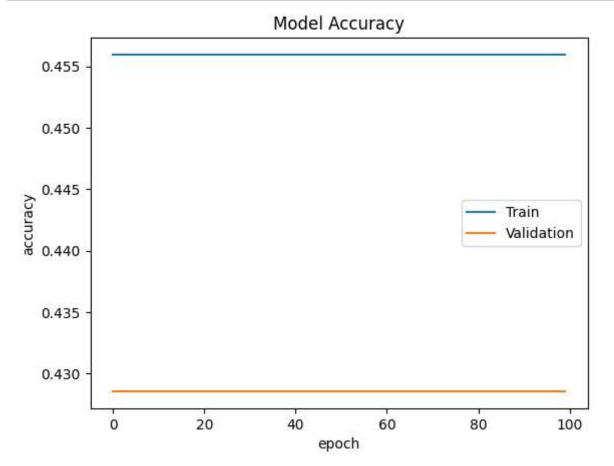
```
history = model.fit(X_train, y_train, validation_split=0.2, epochs=100, batch_siz
In [26]:
        20/20 [================ ] - 0s 6ms/step - loss: 0.5440 - accurac
        y: 0.4560 - val loss: 0.5714 - val accuracy: 0.4286
        Epoch 2/100
        20/20 [================= ] - 0s 3ms/step - loss: 0.5440 - accurac
        y: 0.4560 - val loss: 0.5714 - val accuracy: 0.4286
        Epoch 3/100
        20/20 [============ ] - 0s 3ms/step - loss: 0.5440 - accurac
        y: 0.4560 - val_loss: 0.5714 - val_accuracy: 0.4286
        Epoch 4/100
        20/20 [============= ] - 0s 3ms/step - loss: 0.5440 - accurac
        y: 0.4560 - val_loss: 0.5714 - val_accuracy: 0.4286
        Epoch 5/100
        20/20 [============ ] - 0s 3ms/step - loss: 0.5440 - accurac
        y: 0.4560 - val loss: 0.5714 - val accuracy: 0.4286
        Epoch 6/100
        20/20 [============ ] - 0s 3ms/step - loss: 0.5440 - accurac
        y: 0.4560 - val loss: 0.5714 - val accuracy: 0.4286
        Epoch 7/100
        20/20 F
```

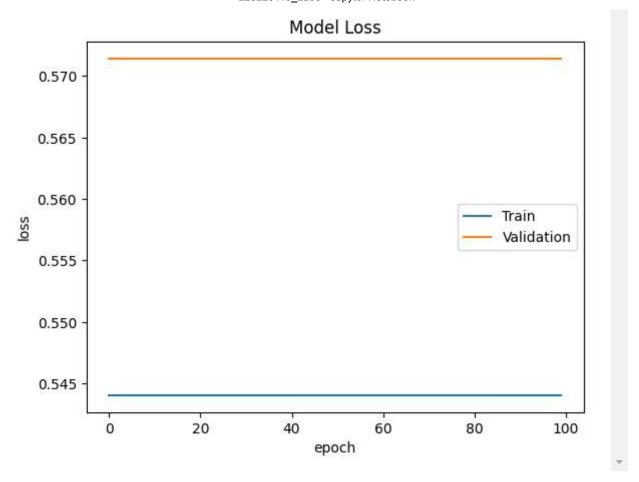
8. Evaluate the trained model to predict the probability values for the test data set (ie., xtest and ytest)

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 [28]: history.history.keys()
Out[28]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
In [31]: import matplotlib.pyplot as plt
```

```
In [32]: 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()
```





10. Do further experiments

```
In [33]: model1 = Sequential()
    model1.add(Dense(16, input_dim=13, activation='relu'))
    model1.add(Dense(8, activation='relu'))
    model1.add(Dense(1, activation='sigmoid'))
```

```
In [34]:
      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
       9/9 [=============== ] - 0s 1ms/step - loss: 0.3482 - accuracy:
       0.5868
       Epoch 3/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.3434 - accuracy:
       0.5992
       Epoch 4/10
       0.5992
       Epoch 5/10
       0.6157
       Epoch 6/10
       9/9 [=============== ] - 0s 1ms/step - loss: 0.3256 - accuracy:
       0.6198
       Epoch 7/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.3232 - accuracy:
       0.6157
       Epoch 8/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.3080 - accuracy:
       0.6446
       Epoch 9/10
       9/9 [============= ] - 0s 1ms/step - loss: 0.2986 - accuracy:
       0.6612
       Epoch 10/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.3306 - accuracy:
       0.6198
Out[34]: <keras.callbacks.History at 0x1d78bda9d80>
In [35]: model1.evaluate(X test, y test)
       2/2 [=========== ] - 0s 3ms/step - loss: 0.2617 - accuracy:
       0.7049
Out[35]: [0.26170825958251953, 0.7049180269241333]
```

```
In [36]: history1 = model.fit(X train, y train, validation split=0.2, epochs=100, batch si
     ช.4560 - vai_ioss: ช.5/14 - vai_accuracy: ช.4286
     Epoch 5/100
     0.4560 - val_loss: 0.5714 - val_accuracy: 0.4286
     Epoch 6/100
     0.4560 - val loss: 0.5714 - val accuracy: 0.4286
     Epoch 7/100
     0.4560 - val loss: 0.5714 - val accuracy: 0.4286
     Epoch 8/100
     0.4560 - val_loss: 0.5714 - val_accuracy: 0.4286
     Epoch 9/100
     0.4560 - val_loss: 0.5714 - val_accuracy: 0.4286
     Epoch 10/100
     7/7 [=============== ] - 0s 6ms/step - loss: 0.5440 - accuracy:
     0.4560 - val loss: 0.5714 - val accuracy: 0.4286
     Epoch 11/100
```

In [37]: 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

In [38]: ls = history1.history

```
In [39]:    new = pd.DataFrame.from_dict(ls)
    new
```

Out[39]:

loss	accuracy	val_loss	val_accuracy
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
0.544041	0.455959	0.571429	0.428571
	0.544041 0.544041 0.544041 0.544041 0.544041 0.544041 0.544041 0.544041	0.544041 0.455959 0.544041 0.455959 0.544041 0.455959 0.544041 0.455959 0.544041 0.455959 0.544041 0.455959 0.544041 0.455959 0.544041 0.455959 0.544041 0.455959	0.544041 0.455959 0.571429 0.544041 0.455959 0.571429 0.544041 0.455959 0.571429 0.544041 0.455959 0.571429 0.544041 0.455959 0.571429 0.544041 0.455959 0.571429 0.544041 0.455959 0.571429 0.544041 0.455959 0.571429 0.544041 0.455959 0.571429

100 rows × 4 columns

```
In [40]: 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'))
```

```
In [41]:
      model2.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
       model2.fit(X train, y train, epochs=10, batch size=30, verbose=1)
       Epoch 1/10
       0.4711
       Epoch 2/10
       9/9 [=============== ] - 0s 2ms/step - loss: 0.3643 - accuracy:
       0.4463
       Epoch 3/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.3247 - accuracy:
       0.4421
       Epoch 4/10
       0.5083
       Epoch 5/10
       0.5083
       Epoch 6/10
       9/9 [=============== ] - 0s 2ms/step - loss: 0.2606 - accuracy:
       0.5289
       Epoch 7/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.2603 - accuracy:
       0.5248
       Epoch 8/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.2560 - accuracy:
       0.6074
       Epoch 9/10
       9/9 [========== ] - 0s 2ms/step - loss: 0.2442 - accuracy:
       0.5992
       Epoch 10/10
       9/9 [============= ] - 0s 2ms/step - loss: 0.2316 - accuracy:
       0.6281
Out[41]: <keras.callbacks.History at 0x1d78d06ed70>
In [42]: model2.evaluate(X test, y test)
       2/2 [=========== ] - 0s 3ms/step - loss: 0.2314 - accuracy:
       0.6066
Out[42]: [0.23137971758842468, 0.6065573692321777]
```

In [43]: 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 [44]: 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 [45]:
      model3.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
       model3.fit(X train, y train, epochs=10, batch size=30, verbose=1)
       Epoch 1/10
       0.4917
       Epoch 2/10
       9/9 [=============== ] - 0s 2ms/step - loss: 0.3186 - accuracy:
       0.5702
       Epoch 3/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.2737 - accuracy:
       0.6281
       Epoch 4/10
       0.5868
       Epoch 5/10
       0.5289
       Epoch 6/10
       9/9 [================ ] - 0s 2ms/step - loss: 0.2845 - accuracy:
       0.5537
       Epoch 7/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.2123 - accuracy:
       0.6736
       Epoch 8/10
       9/9 [============= ] - 0s 2ms/step - loss: 0.3161 - accuracy:
       0.5992
       Epoch 9/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.2393 - accuracy:
       0.6612
       Epoch 10/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.2566 - accuracy:
       0.5661
Out[45]: <keras.callbacks.History at 0x1d78cf7ace0>
In [46]: model3.evaluate(X test, y test)
       2/2 [=========== ] - 0s 4ms/step - loss: 0.3637 - accuracy:
       0.4918
Out[46]: [0.36367374658584595, 0.49180328845977783]
```

In [47]: 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

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

In []: