PDL Lab3:. Binary Classification of Heart Disease of Patients using Deep Neural Network

SWETHA JENIFER 225229142

1. load the dataset

```
In [1]:
         import pandas as pd
In [2]: df=pd.read_csv("heart_data.csv")
In [3]: | df.head()
Out[3]:
                  sex cp trestbps chol fbs restecg
                                                      thalach exang
                                                                     oldpeak slope ca
                                                                                        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
          2
              41
                    0
                               130
                                     204
                                           0
                                                   0
                                                          172
                                                                   0
                                                                          1.4
                                                                                  2
                                                                                      0
                                                                                           2
                        1
                                                                                                  1
          3
                               120
                                     236
                                                          178
                                                                   0
                                                                          8.0
                                                                                  2
                                                                                           2
              56
                    1
                                           0
                                                                                      0
                                                                                                  1
              57
                        0
                               120
                                     354
                                           0
                                                   1
                                                          163
                                                                   1
                                                                          0.6
                                                                                  2
                                                                                      0
                                                                                           2
                                                                                                  1
                    0
In [4]: df.shape
Out[4]: (303, 14)
In [5]: df.size
Out[5]: 4242
```

```
In [6]: df.info
```

Out[6]:	<bou< th=""><th>nd me</th><th>thod</th><th>DataF</th><th>rame.info</th><th>of</th><th>age</th><th>sex cp</th><th>trestbps</th><th>chol</th><th>fbs res</th><th>tecg</th></bou<>	nd me	thod	DataF	rame.info	of	age	sex cp	trestbps	chol	fbs res	tecg
	thal	ach	exang	old	peak \							
	0	63	1	3	145	233	1	0	150	0	2.3	
	1	37	1	2	130	250	0	1	187	0	3.5	
	2	41	0	1	130	204	0	0	172	0	1.4	
	3	56	1	1	120	236	0	1	178	0	0.8	
	4	57	0	0	120	354	0	1	1 63	1	0.6	
	• •			• •	• • •		• • •		• • •	• • •	• • •	
	298	57	0	0	140	241	0	1	123	1	0.2	
	299	45	1	3	110	264	0	1	132	0	1.2	
	300	68	1	0	144	193	1	1	141	0	3.4	
	301	57	1	0	130	131	0	1	11 5	1	1.2	
	302	57	0	1	130	236	0	0	174	0	0.0	

	slope	ca	thal	target
0	0	0	1	1
1	0	0	2	1
2	2	0	2	1
3	2	0	2	1
4	2	0	2	1
298	1	0	3	0
299	1	0	3	0
300	1	2	3	0
301	1	1	3	0
302	1	1	2	0

[303 rows x 14 columns]>

In [7]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):

Column	Non-Null Count	Dtype
age	303 non-null	int64
sex	303 non-null	int64
ср	303 non-null	int64
trestbps	303 non-null	int64
chol	303 non-null	int64
fbs	303 non-null	int64
restecg	303 non-null	int64
thalach	303 non-null	int64
exang	303 non-null	int64
oldpeak	303 non-null	float64
slope	303 non-null	int64
ca	303 non-null	int64
thal	303 non-null	int64
target	303 non-null	int64
	age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal	age 303 non-null sex 303 non-null cp 303 non-null trestbps 303 non-null chol 303 non-null fbs 303 non-null restecg 303 non-null thalach 303 non-null exang 303 non-null oldpeak 303 non-null slope 303 non-null ca 303 non-null thal 303 non-null

dtypes: float64(1), int64(13)

memory usage: 33.3 KB

2. Split the dataset

```
In [14]: from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense

In [15]: 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 [16]: from tensorflow import keras
In [17]: optimizer = keras.optimizers.RMSprop(learning_rate=0.001)
```

```
In [18]:
       model.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
       model.fit(X_train, y_train, epochs=10, batch_size=30, verbose=1)
       Epoch 1/10
       9/9 [============= ] - 3s 23ms/step - loss: 0.4504 - accuracy:
       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 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 5/10
       0.5496
       Epoch 6/10
       9/9 [================ ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 7/10
       9/9 [=============== ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 8/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 9/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 10/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.4504 - accuracy:
       0.5496
Out[18]: <keras.callbacks.History at 0x22d50f8d270>
In [19]: model.evaluate(X test, y test)
       0.5246
Out[19]: [0.4754098355770111, 0.5245901346206665]
```

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

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

Trainable params: 121 Non-trainable params: 0

```
model.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
In [21]:
       model.fit(X_train, y_train, epochs=200, batch_size=10, verbose=1)
       Epoch 1/200
       25/25 [============= ] - 1s 1ms/step - loss: 0.4504 - accurac
       y: 0.5496
       Epoch 2/200
       25/25 [============== ] - 0s 1ms/step - loss: 0.4504 - accurac
       y: 0.5496
       Epoch 3/200
       25/25 [================ ] - 0s 11ms/step - loss: 0.4504 - accura
       cy: 0.5496
       Epoch 4/200
       25/25 [============= ] - 0s 1ms/step - loss: 0.4504 - accurac
       y: 0.5496
       Epoch 5/200
       25/25 [============ ] - 0s 1ms/step - loss: 0.4504 - accurac
       y: 0.5496
       Epoch 6/200
       25/25 [============= ] - 0s 1ms/step - loss: 0.4504 - accurac
       y: 0.5496
       Epoch 7/200
        3F/3F F
In [22]: model.evaluate(X_test, y_test)
       0.5246
Out[22]: [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

```
history = model.fit(X train, y train, validation split=0.2, epochs=100, batch size
In [24]:
        Epoch 1/100
        20/20 [============= ] - 0s 6ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 2/100
        20/20 [================= ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val loss: 0.4286 - val accuracy: 0.5714
        20/20 [============ ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 4/100
        20/20 [================ ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 5/100
        20/20 [=========== ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 6/100
        20/20 [================= ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 7/100
        .
.../... [
```

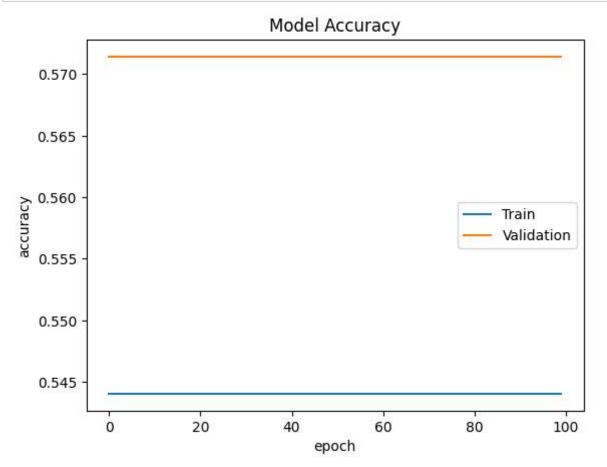
8. Evaluate the trained model to predict the probability values for the test data set (ie., xtest and ytest)

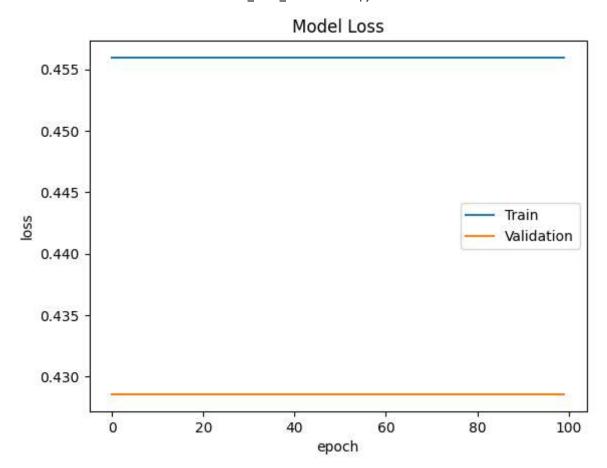
9. Print the model accuracy and model loss as below (Use can use the 'history' object we have saved), Sample code is given below.

```
In [26]: history.history.keys()
Out[26]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
In [28]: import matplotlib.pyplot as plt
```

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

```
In [29]: plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('Model Accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    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 [30]: model1 = Sequential()

model1.add(Dense(16, input_dim=13, activation='relu'))
model1.add(Dense(8, activation='relu'))
model1.add(Dense(1, activation='sigmoid'))
```

```
In [31]:
       model1.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
       model1.fit(X train, y train, epochs=10, batch size=30, verbose=1)
       Epoch 1/10
       0.4504
       Epoch 2/10
       9/9 [=============== ] - 0s 1ms/step - loss: 0.2543 - accuracy:
       0.6198
       Epoch 3/10
       9/9 [============== ] - 0s 1ms/step - loss: 0.2492 - accuracy:
       0.6281
       Epoch 4/10
       9/9 [========== ] - 0s 2ms/step - loss: 0.2566 - accuracy:
       0.6446
       Epoch 5/10
       0.6240
       Epoch 6/10
       9/9 [=============== ] - 0s 1ms/step - loss: 0.2396 - accuracy:
       0.6322
       Epoch 7/10
       9/9 [============ ] - 0s 2ms/step - loss: 0.2450 - accuracy:
       0.6198
       Epoch 8/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.2513 - accuracy:
       0.6157
       Epoch 9/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.2375 - accuracy:
       0.6488
       Epoch 10/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.2347 - accuracy:
       0.6446
Out[31]: <keras.callbacks.History at 0x22d56351240>
In [32]: |model1.evaluate(X_test, y_test)
       2/2 [=========== ] - 0s 3ms/step - loss: 0.1707 - accuracy:
       0.7541
Out[32]: [0.17073306441307068, 0.7540983557701111]
```

```
In [33]: history1 = model.fit(X_train, y_train, validation_split=0.2, epochs=100, batch_s:
        Epoch 1/100
        20/20 [============= ] - 0s 6ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 2/100
        20/20 [============ ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        20/20 [============ ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 4/100
        20/20 [================== ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 5/100
        20/20 [=========== ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 6/100
        20/20 [============== ] - 0s 3ms/step - loss: 0.4560 - accurac
        y: 0.5440 - val_loss: 0.4286 - val_accuracy: 0.5714
        Epoch 7/100
        20/20 5
```

In [34]: 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 [35]: ls = history1.history

```
In [36]: new = pd.DataFrame.from_dict(ls)
new
```

Out[36]:

	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	0.571429

100 rows × 4 columns

```
In [37]: 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 [38]:
       model2.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
       model2.fit(X train, y train, epochs=10, batch size=30, verbose=1)
       Epoch 1/10
       0.4504
       Epoch 2/10
       0.4504
       Epoch 3/10
       9/9 [=============== ] - 0s 1ms/step - loss: 0.5496 - accuracy:
       0.4504
       Epoch 4/10
       9/9 [========== ] - 0s 1ms/step - loss: 0.5455 - accuracy:
       0.4545
       Epoch 5/10
       9/9 [============ ] - 0s 2ms/step - loss: 0.5455 - accuracy:
       0.4545
       Epoch 6/10
       9/9 [================ ] - 0s 2ms/step - loss: 0.5455 - accuracy:
       0.4545
       Epoch 7/10
       9/9 [============ ] - 0s 2ms/step - loss: 0.5494 - accuracy:
       0.4504
       Epoch 8/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.5617 - accuracy:
       0.4339
       Epoch 9/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.5502 - accuracy:
       0.4463
       Epoch 10/10
       9/9 [=============== ] - 0s 2ms/step - loss: 0.5454 - accuracy:
       0.4545
Out[38]: <keras.callbacks.History at 0x22d57637f40>
In [39]: model2.evaluate(X test, y test)
       2/2 [=========== ] - 0s 3ms/step - loss: 0.5246 - accuracy:
       0.4754
Out[39]: [0.5245802402496338, 0.4754098355770111]
```

In [40]: 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 [41]: 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 [42]:
       model3.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
       model3.fit(X train, y train, epochs=10, batch size=30, verbose=1)
       Epoch 1/10
       0.5496
       Epoch 2/10
       9/9 [=============== ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 3/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 4/10
       9/9 [========== ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 5/10
       0.5496
       Epoch 6/10
       9/9 [================ ] - 0s 2ms/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 10ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 9/10
       9/9 [=========== ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
       Epoch 10/10
       9/9 [============== ] - 0s 2ms/step - loss: 0.4504 - accuracy:
       0.5496
Out[42]: <keras.callbacks.History at 0x22d557c2b90>
In [43]: model3.evaluate(X test, y test)
       2/2 [=========== ] - 0s 3ms/step - loss: 0.4754 - accuracy:
       0.5246
Out[43]: [0.4754098355770111, 0.5245901346206665]
```

In [44]: 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