

ROLL NO : 225229105

LAB3: Binary classification of Heart Disease of patients using Deep Neural Network

1.Load the dataset

```
In [15]: ▶ import pandas as pd
df=pd.read_csv("heart_data.csv")
df
```

```
Out[15]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	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 × 14 columns



```
In [5]: ▶ df.shape
```

```
Out[5]: (303, 14)
```

```
In [6]: ▶ df.size
```

```
Out[6]: 4242
```

```
In [7]: df.columns
```

```
Out[7]: Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',  
             'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],  
            dtype='object')
```

2.Split the dataset

```
In [17]: X=df  
        y=df.pop('target')
```

```
In [18]: #!pip install scikit-learn scipy matplotlib numpy
```

```
Requirement already satisfied: scikit-learn in c:\programdata\anaconda3\envs\tf\lib\site-packages (1.3.0)  
Requirement already satisfied: scipy in c:\programdata\anaconda3\envs\tf\lib\site-packages (1.10.1)  
Requirement already satisfied: matplotlib in c:\programdata\anaconda3\envs\tf\lib\site-packages (3.7.2)  
Requirement already satisfied: numpy in c:\programdata\anaconda3\envs\tf\lib\site-packages (1.25.0)  
Requirement already satisfied: joblib>=1.1.1 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from scikit-learn) (1.3.1)  
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from scikit-learn) (3.2.0)  
Requirement already satisfied: contourpy>=1.0.1 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from matplotlib) (1.1.0)  
Requirement already satisfied: cycler>=0.10 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from matplotlib) (0.11.0)  
Requirement already satisfied: fonttools>=4.22.0 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from matplotlib) (4.41.0)  
Requirement already satisfied: kiwisolver>=1.0.1 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from matplotlib) (1.4.4)  
Requirement already satisfied: packaging>=20.0 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from matplotlib) (23.0)  
Requirement already satisfied: pillow>=6.2.0 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from matplotlib) (10.0.0)  
Requirement already satisfied: pyparsing<3.1,>=2.3.1 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from matplotlib) (3.0.9)  
Requirement already satisfied: python-dateutil>=2.7 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from matplotlib) (2.8.2)  
Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\envs\tf\lib\site-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
```

```
In [20]: 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,
```

```
In [21]: ▶ X_train.shape
```

```
Out[21]: (242, 13)
```

```
In [22]: ▶ y_train.shape
```

```
Out[22]: (242,)
```

3.Create a neural network

```
In [23]: ▶ from tensorflow.keras.models import Sequential  
from tensorflow.keras.layers import Dense
```

```
In [24]: ▶ model = Sequential()  
model.add(Dense(8, input_dim=13, activation='relu'))  
model.add(Dense(1, activation='sigmoid'))
```

4.Complie your model

```
In [25]: ▶ from tensorflow import keras
```

```
In [26]: ▶ optimizer = keras.optimizers.RMSprop(learning_rate=0.001)
```

```
In [27]: ▶ 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 [=====] - 2s 15ms/step - loss: 0.5543 - accuracy: 0.4380
Epoch 2/10
9/9 [=====] - 0s 2ms/step - loss: 0.5403 - accuracy: 0.4545
Epoch 3/10
9/9 [=====] - 0s 1ms/step - loss: 0.5403 - accuracy: 0.4545
Epoch 4/10
9/9 [=====] - 0s 1ms/step - loss: 0.5390 - accuracy: 0.4504
Epoch 5/10
9/9 [=====] - 0s 1ms/step - loss: 0.5406 - accuracy: 0.4421
Epoch 6/10
9/9 [=====] - 0s 1ms/step - loss: 0.5370 - accuracy: 0.4628
Epoch 7/10
9/9 [=====] - 0s 1ms/step - loss: 0.5375 - accuracy: 0.4545
Epoch 8/10
9/9 [=====] - 0s 1ms/step - loss: 0.5370 - accuracy: 0.4628
Epoch 9/10
9/9 [=====] - 0s 1ms/step - loss: 0.5410 - accuracy: 0.4504
Epoch 10/10
9/9 [=====] - 0s 3ms/step - loss: 0.5357 - accuracy: 0.4587
```

Out[27]: <keras.callbacks.History at 0x1ba173597e0>

```
In [29]: ▶ model.evaluate(X_test, y_test)
```

```
2/2 [=====] - 0s 3ms/step - loss: 0.4934 - accuracy: 0.4918
```

Out[29]: [0.49344146251678467, 0.49180328845977783]

6. Train the model

In [30]: `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		

In [31]: `model.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])`
`model.fit(X_train, y_train, epochs=200, batch_size=10, verbose=1)`

```
Epoch 46/200
25/25 [=====] - 0s 1ms/step - loss: 0.3869
- accuracy: 0.4959
Epoch 47/200
25/25 [=====] - 0s 1ms/step - loss: 0.3658
- accuracy: 0.5537
Epoch 48/200
25/25 [=====] - 0s 1ms/step - loss: 0.3709
- accuracy: 0.5124
Epoch 49/200
25/25 [=====] - 0s 1ms/step - loss: 0.3288
- accuracy: 0.5413
Epoch 50/200
25/25 [=====] - 0s 1ms/step - loss: 0.3215
- accuracy: 0.5909
Epoch 51/200
25/25 [=====] - 0s 1ms/step - loss: 0.2856
- accuracy: 0.5992
Epoch 52/200
25/25 [=====] - 0s 1ms/step - loss: 0.2726
```

In [32]: `model.evaluate(X_test, y_test)`

```
2/2 [=====] - 0s 3ms/step - loss: 0.1094 - accuracy: 0.8689
```

Out[32]: [0.1093633845448494, 0.868852436542511]

7. Save the trained Model

In [34]: `history = model.fit(X_train, y_train, validation_split=0.2, epochs=100, b`

```
Epoch 1/100
20/20 [=====] - 0s 6ms/step - loss: 0.1319
- accuracy: 0.8187 - val_loss: 0.1160 - val_accuracy: 0.8571
Epoch 2/100
20/20 [=====] - 0s 3ms/step - loss: 0.1332
- accuracy: 0.8238 - val_loss: 0.1081 - val_accuracy: 0.8776
Epoch 3/100
20/20 [=====] - 0s 3ms/step - loss: 0.1270
- accuracy: 0.8135 - val_loss: 0.1093 - val_accuracy: 0.8367
Epoch 4/100
20/20 [=====] - 0s 3ms/step - loss: 0.1195
- accuracy: 0.8342 - val_loss: 0.1752 - val_accuracy: 0.7959
Epoch 5/100
20/20 [=====] - 0s 3ms/step - loss: 0.1399
- accuracy: 0.7876 - val_loss: 0.1224 - val_accuracy: 0.8163
Epoch 6/100
20/20 [=====] - 0s 3ms/step - loss: 0.1215
- accuracy: 0.8290 - val_loss: 0.1248 - val_accuracy: 0.7755
Epoch 7/100
20/20 [=====] - 0s 3ms/step - loss: 0.1110
- accuracy: 0.8410 - val_loss: 0.1110 - val_accuracy: 0.8410
```

8.Evaluate

In [36]: `model.evaluate(X_test, y_test)`

```
2/2 [=====] - 0s 3ms/step - loss: 0.1222 - accuracy: 0.8525
```

Out[36]: `[0.12221997231245041, 0.8524590134620667]`

9.Print the model accuracy

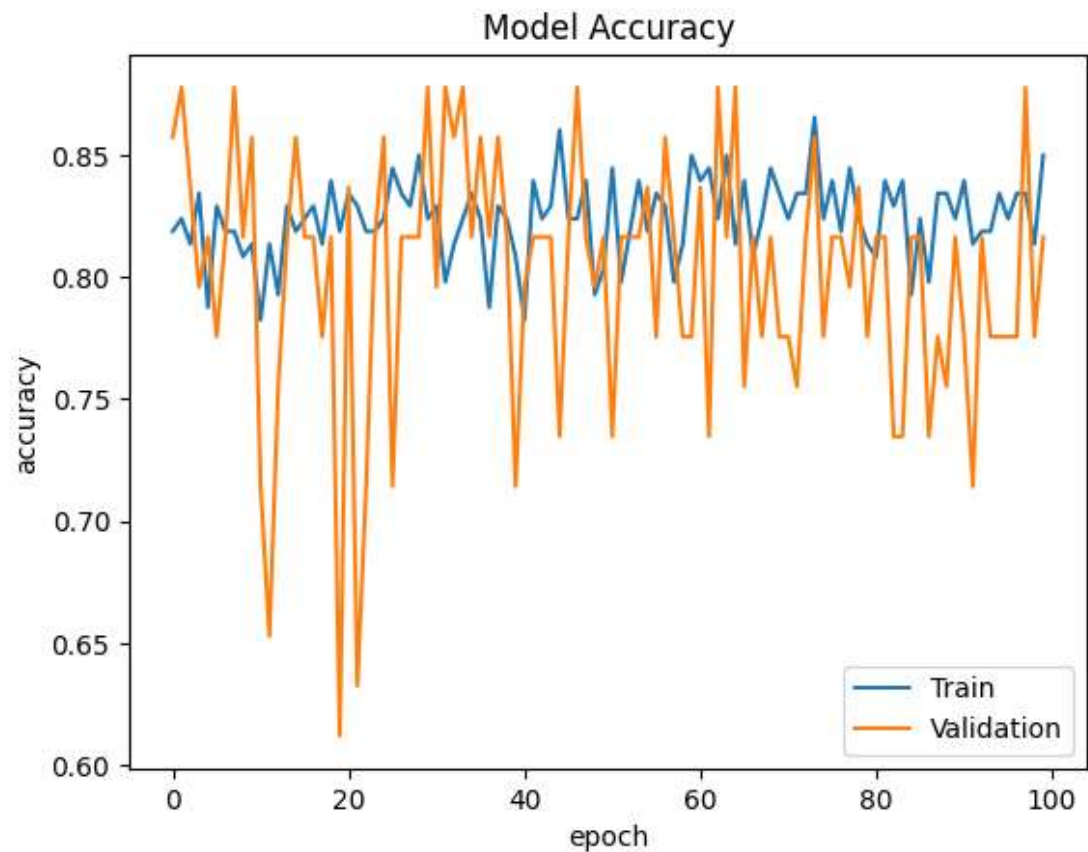
In [38]: `history.history.keys()`

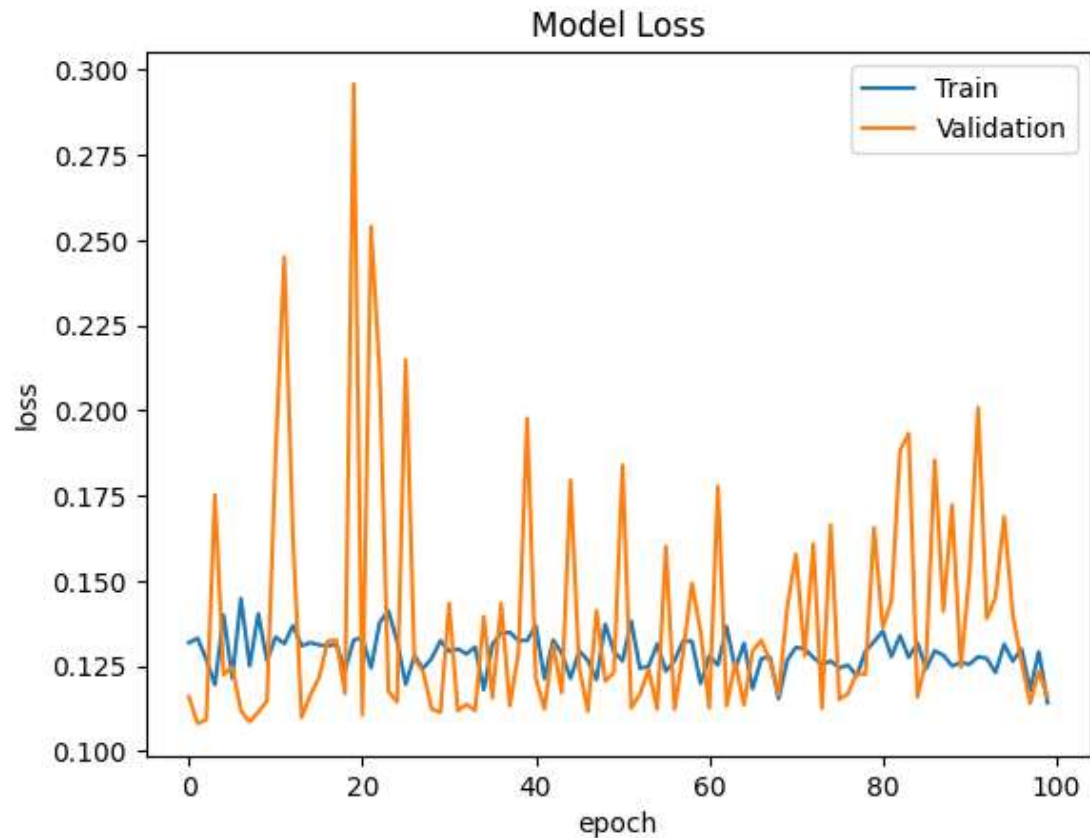
Out[38]: `dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])`

In [39]: `import matplotlib.pyplot as plt`

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

```
In [40]: ▶ 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

1. Add a hidden layer with 16 nodes and Relu activation function. Note that now this Dense layer should be the first hidden layer, which is followed by the previous Dense layer with 8 nodes. Now retrain your model, evaluate and print the accuracy and loss chart using matplotlib.
2. Add a hidden layer with 32 nodes and Relu activation function. Note that now this Dense layer should be the first hidden layer. Now retrain your model, evaluate and print the accuracy and loss chart using matplotlib.
3. Now, increase the nodes 64, 32, 16 for the three hidden layers. Now retrain your model, evaluate and print the accuracy and loss chart using matplotlib.
4. Now, increase number of epochs as 150, 200, 300 and batch size as 15 and 20. Now retrain your model, evaluate and print the accuracy and loss chart using matplotlib.
5. Now use binary_crossentropy loss function instead of mean square error loss function. Now, compare the accuracy and loss function values. Draw a bar chart and compare the performance.


```
In [42]: model1 = Sequential()

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

```
In [43]: model1.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
model1.fit(X_train, y_train, epochs=10, batch_size=30, verbose=1)
```

```
Epoch 1/10
9/9 [=====] - 1s 2ms/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
9/9 [=====] - 0s 1ms/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 2ms/step - loss: 0.4504 - accuracy: 0.5496
Epoch 10/10
9/9 [=====] - 0s 1ms/step - loss: 0.4504 - accuracy: 0.5496
```

```
Out[43]: <keras.callbacks.History at 0x1ba1cf39120>
```

```
In [44]: history1 = model.fit(X_train, y_train, validation_split=0.2, epochs=100,
Epoch 27/100
20/20 [=====] - 0s 3ms/step - loss: 0.1300
- accuracy: 0.8290 - val_loss: 0.1310 - val_accuracy: 0.7755
Epoch 30/100
20/20 [=====] - 0s 3ms/step - loss: 0.1210
- accuracy: 0.8394 - val_loss: 0.1181 - val_accuracy: 0.8163
Epoch 31/100
20/20 [=====] - 0s 3ms/step - loss: 0.1298
- accuracy: 0.8187 - val_loss: 0.1336 - val_accuracy: 0.8163
Epoch 32/100
20/20 [=====] - 0s 3ms/step - loss: 0.1304
- accuracy: 0.8238 - val_loss: 0.1147 - val_accuracy: 0.8571
Epoch 33/100
20/20 [=====] - 0s 3ms/step - loss: 0.1229
- accuracy: 0.8394 - val_loss: 0.1308 - val_accuracy: 0.8163
Epoch 34/100
20/20 [=====] - 0s 3ms/step - loss: 0.1226
- accuracy: 0.8290 - val_loss: 0.1627 - val_accuracy: 0.7755
Epoch 35/100
20/20 [=====] - 0s 3ms/step - loss: 0.1309
- accuracy: 0.8125 - val_loss: 0.1146 - val_accuracy: 0.8571
```

```
In [45]: 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 [51]: ls=history1.history
```

```
In [52]: new = pd.DataFrame.from_dict(ls)
new
```

```
Out[52]:
```

	loss	accuracy	val_loss	val_accuracy
0	0.131734	0.818653	0.134154	0.816327
1	0.127754	0.829016	0.119010	0.857143
2	0.127098	0.839378	0.118809	0.836735
3	0.130912	0.818653	0.114429	0.877551
4	0.130033	0.823834	0.114726	0.857143
...
95	0.126855	0.839378	0.115113	0.877551
96	0.124219	0.823834	0.115173	0.816327
97	0.127046	0.829016	0.120731	0.857143
98	0.123939	0.829016	0.143220	0.755102
99	0.128357	0.823834	0.147119	0.816327

100 rows × 4 columns

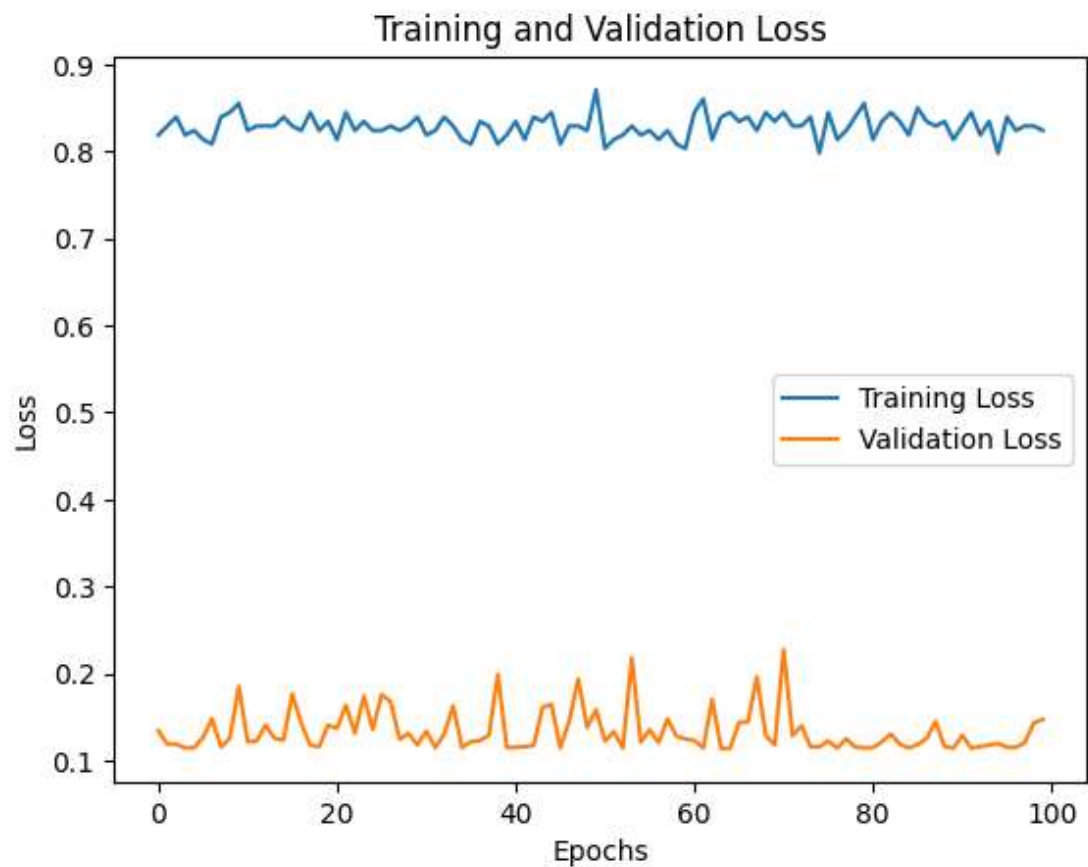
```
In [73]: history1.history.keys()
```

```
Out[73]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
In [74]: ▶ import matplotlib.pyplot as plt

# Accessing loss values from the history object
loss = history1.history['accuracy']
val_loss = history1.history['val_loss']

# Creating the Loss chart
plt.plot(loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
In [53]: ▶ 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 [54]: ▶ model2.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])  
model2.fit(X_train, y_train, epochs=10, batch_size=30, verbose=1)
```

```
Epoch 1/10  
9/9 [=====] - 1s 2ms/step - loss: 0.5496 - accu  
racy: 0.4504  
Epoch 2/10  
9/9 [=====] - 0s 2ms/step - loss: 0.4040 - accu  
racy: 0.4959  
Epoch 3/10  
9/9 [=====] - 0s 2ms/step - loss: 0.2635 - accu  
racy: 0.5868  
Epoch 4/10  
9/9 [=====] - 0s 1ms/step - loss: 0.2468 - accu  
racy: 0.6116  
Epoch 5/10  
9/9 [=====] - 0s 1ms/step - loss: 0.2408 - accu  
racy: 0.6281  
Epoch 6/10  
9/9 [=====] - 0s 1ms/step - loss: 0.2369 - accu  
racy: 0.6570  
Epoch 7/10  
9/9 [=====] - 0s 1ms/step - loss: 0.2271 - accu  
racy: 0.6322  
Epoch 8/10  
9/9 [=====] - 0s 1ms/step - loss: 0.2662 - accu  
racy: 0.6033  
Epoch 9/10  
9/9 [=====] - 0s 2ms/step - loss: 0.2431 - accu  
racy: 0.6322  
Epoch 10/10  
9/9 [=====] - 0s 2ms/step - loss: 0.2355 - accu  
racy: 0.6281
```

```
Out[54]: <keras.callbacks.History at 0x1ba1d865450>
```

```
In [55]: ▶ model2.evaluate(X_test, y_test)
```

```
2/2 [=====] - 0s 3ms/step - loss: 0.2544 - accu  
racy: 0.6230
```

```
Out[55]: [0.2543584704399109, 0.6229507923126221]
```

In [56]: `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 [57]: `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 [58]: `model3.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])
 model3.fit(X_train, y_train, epochs=10, batch_size=30, verbose=1)`

Epoch 1/10
 9/9 [=====] - 1s 2ms/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 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
 9/9 [=====] - 0s 2ms/step - loss: 0.4504 - accuracy: 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

In [59]: `model3.evaluate(X_test, y_test)`

2/2 [=====] - 0s 3ms/step - loss: 0.4754 - accuracy: 0.5246

Out[59]: [0.4754098355770111, 0.5245901346206665]

In [60]: `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 [61]: `model4 = Sequential()
model4.add(Dense(150, input_dim=13, activation='relu'))
model4.add(Dense(200, activation='relu'))
model4.add(Dense(300, activation='relu'))
model4.add(Dense(8, activation='relu'))
model4.add(Dense(1, activation='sigmoid'))`

```
In [66]: ▶ model4.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])  
model4.fit(X_train, y_train, epochs=10, batch_size=15, verbose=1)
```

```
Epoch 1/10  
17/17 [=====] - 1s 2ms/step - loss: 0.5286 - ac  
curacy: 0.4711  
Epoch 2/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 3/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 4/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 5/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 6/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 7/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 8/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 9/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 10/10  
17/17 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504
```

```
Out[66]: <keras.callbacks.History at 0x1ba2364b580>
```



```
In [67]: ► model4.compile(loss='mse', optimizer=optimizer, metrics=['accuracy'])  
model4.fit(X_train, y_train, epochs=10, batch_size=20, verbose=1)
```


```
Epoch 1/10  
13/13 [=====] - 1s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 2/10  
13/13 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 3/10  
13/13 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 4/10  
13/13 [=====] - 0s 3ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 5/10  
13/13 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 6/10  
13/13 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 7/10  
13/13 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 8/10  
13/13 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 9/10  
13/13 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504  
Epoch 10/10  
13/13 [=====] - 0s 2ms/step - loss: 0.5496 - ac  
curacy: 0.4504
```

Out[67]: <keras.callbacks.History at 0x1ba23b0a1d0>

```
In [68]: ► model4.evaluate(X_test, y_test)
```

```
2/2 [=====] - 0s 3ms/step - loss: 0.5246 - accu  
racy: 0.4754
```

Out[68]: [0.5245901346206665, 0.4754098355770111]

In [69]:  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 []: 