

Tensorflow

```
In [7]: from numpy import loadtxt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

Pregnancies,Glucose,BloodPressure,SkinThickness,Insulin,BMI,DiabetesPedigreeFunction,Age,Out

```
In [9]: dataset=loadtxt('diabetes.csv',delimiter=',')
x = dataset[:, 0:8]
y = dataset[:, 8]
```

```
In [11]: print(type(x))
print(type(y))
```

```
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
```

```
In [12]: model = Sequential()
model.add(Dense(12, input_shape=(8,), activation='relu'))
model.add(Dense(8, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model.fit(x, y, epochs=150, batch_size=10)
```

C:\Users\bonde\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Epoch 1/150
77/77 3s 3ms/step - accuracy: 0.3689 - loss: 19.6261
Epoch 2/150
77/77 0s 2ms/step - accuracy: 0.5580 - loss: 2.9622
Epoch 3/150
77/77 0s 2ms/step - accuracy: 0.5966 - loss: 1.7193
Epoch 4/150
77/77 0s 2ms/step - accuracy: 0.6603 - loss: 1.2587
Epoch 5/150
77/77 0s 3ms/step - accuracy: 0.6653 - loss: 0.9877
Epoch 6/150
77/77 0s 2ms/step - accuracy: 0.6571 - loss: 0.8183
Epoch 7/150
77/77 0s 3ms/step - accuracy: 0.6241 - loss: 0.7967
Epoch 8/150
77/77 0s 3ms/step - accuracy: 0.6101 - loss: 0.7679
Epoch 9/150
77/77 0s 3ms/step - accuracy: 0.6553 - loss: 0.7152
Epoch 10/150
77/77 0s 2ms/step - accuracy: 0.6453 - loss: 0.6528
Epoch 11/150
77/77 0s 2ms/step - accuracy: 0.6977 - loss: 0.6113
Epoch 12/150
77/77 0s 2ms/step - accuracy: 0.6870 - loss: 0.5919
Epoch 13/150
77/77 0s 2ms/step - accuracy: 0.6575 - loss: 0.6568
Epoch 14/150
77/77 0s 2ms/step - accuracy: 0.6820 - loss: 0.5931
Epoch 15/150
77/77 0s 2ms/step - accuracy: 0.7294 - loss: 0.6136
Epoch 16/150
77/77 0s 2ms/step - accuracy: 0.7023 - loss: 0.5914
Epoch 17/150
77/77 0s 2ms/step - accuracy: 0.7040 - loss: 0.5634
Epoch 18/150
77/77 0s 3ms/step - accuracy: 0.7222 - loss: 0.5727
Epoch 19/150
77/77 0s 3ms/step - accuracy: 0.7246 - loss: 0.5562
Epoch 20/150
77/77 0s 2ms/step - accuracy: 0.6944 - loss: 0.5844
Epoch 21/150
77/77 0s 2ms/step - accuracy: 0.7298 - loss: 0.5455
Epoch 22/150
77/77 0s 2ms/step - accuracy: 0.7459 - loss: 0.5479
Epoch 23/150
77/77 0s 3ms/step - accuracy: 0.7177 - loss: 0.5415
Epoch 24/150
77/77 0s 3ms/step - accuracy: 0.7273 - loss: 0.5729
Epoch 25/150
77/77 0s 3ms/step - accuracy: 0.7337 - loss: 0.5531
Epoch 26/150
77/77 0s 3ms/step - accuracy: 0.6853 - loss: 0.5961
Epoch 27/150
77/77 0s 3ms/step - accuracy: 0.7014 - loss: 0.5934
Epoch 28/150
77/77 0s 3ms/step - accuracy: 0.7348 - loss: 0.5613

Epoch 29/150
77/77 0s 2ms/step - accuracy: 0.7257 - loss: 0.5383
Epoch 30/150
77/77 0s 2ms/step - accuracy: 0.7671 - loss: 0.5237
Epoch 31/150
77/77 0s 2ms/step - accuracy: 0.7255 - loss: 0.5607
Epoch 32/150
77/77 0s 2ms/step - accuracy: 0.7203 - loss: 0.5354
Epoch 33/150
77/77 0s 2ms/step - accuracy: 0.6851 - loss: 0.5882
Epoch 34/150
77/77 0s 2ms/step - accuracy: 0.7471 - loss: 0.5247
Epoch 35/150
77/77 0s 3ms/step - accuracy: 0.7485 - loss: 0.5408
Epoch 36/150
77/77 0s 2ms/step - accuracy: 0.7124 - loss: 0.5617
Epoch 37/150
77/77 0s 2ms/step - accuracy: 0.7237 - loss: 0.5443
Epoch 38/150
77/77 0s 2ms/step - accuracy: 0.7373 - loss: 0.5287
Epoch 39/150
77/77 0s 2ms/step - accuracy: 0.7136 - loss: 0.5325
Epoch 40/150
77/77 0s 3ms/step - accuracy: 0.7513 - loss: 0.5135
Epoch 41/150
77/77 0s 3ms/step - accuracy: 0.7246 - loss: 0.5290
Epoch 42/150
77/77 0s 3ms/step - accuracy: 0.6983 - loss: 0.5564
Epoch 43/150
77/77 0s 3ms/step - accuracy: 0.6981 - loss: 0.5707
Epoch 44/150
77/77 0s 3ms/step - accuracy: 0.7248 - loss: 0.5352
Epoch 45/150
77/77 0s 3ms/step - accuracy: 0.7222 - loss: 0.5557
Epoch 46/150
77/77 0s 3ms/step - accuracy: 0.7449 - loss: 0.5173
Epoch 47/150
77/77 0s 2ms/step - accuracy: 0.7600 - loss: 0.4890
Epoch 48/150
77/77 0s 3ms/step - accuracy: 0.7451 - loss: 0.5290
Epoch 49/150
77/77 0s 3ms/step - accuracy: 0.7402 - loss: 0.5174
Epoch 50/150
77/77 0s 3ms/step - accuracy: 0.7257 - loss: 0.5420
Epoch 51/150
77/77 0s 3ms/step - accuracy: 0.7501 - loss: 0.5421
Epoch 52/150
77/77 0s 2ms/step - accuracy: 0.7461 - loss: 0.5381
Epoch 53/150
77/77 0s 3ms/step - accuracy: 0.7545 - loss: 0.5264
Epoch 54/150
77/77 0s 3ms/step - accuracy: 0.7527 - loss: 0.5151
Epoch 55/150
77/77 0s 2ms/step - accuracy: 0.7314 - loss: 0.5261
Epoch 56/150
77/77 0s 3ms/step - accuracy: 0.7465 - loss: 0.5064

Epoch 57/150
77/77 0s 3ms/step - accuracy: 0.7539 - loss: 0.5275
Epoch 58/150
77/77 0s 2ms/step - accuracy: 0.7000 - loss: 0.5942
Epoch 59/150
77/77 0s 3ms/step - accuracy: 0.7424 - loss: 0.5348
Epoch 60/150
77/77 0s 3ms/step - accuracy: 0.7446 - loss: 0.5107
Epoch 61/150
77/77 0s 2ms/step - accuracy: 0.7751 - loss: 0.4940
Epoch 62/150
77/77 0s 3ms/step - accuracy: 0.7590 - loss: 0.5129
Epoch 63/150
77/77 0s 3ms/step - accuracy: 0.7626 - loss: 0.5236
Epoch 64/150
77/77 0s 3ms/step - accuracy: 0.7372 - loss: 0.5161
Epoch 65/150
77/77 0s 3ms/step - accuracy: 0.7661 - loss: 0.4997
Epoch 66/150
77/77 0s 3ms/step - accuracy: 0.7422 - loss: 0.5194
Epoch 67/150
77/77 0s 3ms/step - accuracy: 0.7345 - loss: 0.5175
Epoch 68/150
77/77 0s 3ms/step - accuracy: 0.7298 - loss: 0.5145
Epoch 69/150
77/77 0s 3ms/step - accuracy: 0.7593 - loss: 0.5087
Epoch 70/150
77/77 0s 2ms/step - accuracy: 0.7462 - loss: 0.5289
Epoch 71/150
77/77 0s 3ms/step - accuracy: 0.7943 - loss: 0.4730
Epoch 72/150
77/77 0s 3ms/step - accuracy: 0.7659 - loss: 0.4978
Epoch 73/150
77/77 0s 3ms/step - accuracy: 0.7550 - loss: 0.4989
Epoch 74/150
77/77 0s 3ms/step - accuracy: 0.7853 - loss: 0.4827
Epoch 75/150
77/77 0s 2ms/step - accuracy: 0.7589 - loss: 0.5171
Epoch 76/150
77/77 0s 3ms/step - accuracy: 0.7813 - loss: 0.4851
Epoch 77/150
77/77 0s 3ms/step - accuracy: 0.7413 - loss: 0.5189
Epoch 78/150
77/77 0s 2ms/step - accuracy: 0.7774 - loss: 0.4803
Epoch 79/150
77/77 0s 3ms/step - accuracy: 0.7775 - loss: 0.5079
Epoch 80/150
77/77 0s 3ms/step - accuracy: 0.7557 - loss: 0.4965
Epoch 81/150
77/77 0s 3ms/step - accuracy: 0.7676 - loss: 0.4975
Epoch 82/150
77/77 0s 3ms/step - accuracy: 0.7624 - loss: 0.5010
Epoch 83/150
77/77 0s 2ms/step - accuracy: 0.7503 - loss: 0.5006
Epoch 84/150
77/77 0s 3ms/step - accuracy: 0.7606 - loss: 0.4884

Epoch 85/150
77/77 0s 3ms/step - accuracy: 0.7694 - loss: 0.4943
Epoch 86/150
77/77 0s 3ms/step - accuracy: 0.7674 - loss: 0.4895
Epoch 87/150
77/77 0s 3ms/step - accuracy: 0.7626 - loss: 0.4946
Epoch 88/150
77/77 0s 3ms/step - accuracy: 0.7541 - loss: 0.4916
Epoch 89/150
77/77 0s 2ms/step - accuracy: 0.7544 - loss: 0.5106
Epoch 90/150
77/77 0s 2ms/step - accuracy: 0.7850 - loss: 0.4734
Epoch 91/150
77/77 0s 2ms/step - accuracy: 0.7597 - loss: 0.4783
Epoch 92/150
77/77 0s 2ms/step - accuracy: 0.7932 - loss: 0.4692
Epoch 93/150
77/77 0s 3ms/step - accuracy: 0.7810 - loss: 0.4740
Epoch 94/150
77/77 0s 2ms/step - accuracy: 0.7661 - loss: 0.4980
Epoch 95/150
77/77 0s 3ms/step - accuracy: 0.7943 - loss: 0.4684
Epoch 96/150
77/77 0s 2ms/step - accuracy: 0.7900 - loss: 0.4783
Epoch 97/150
77/77 0s 2ms/step - accuracy: 0.7654 - loss: 0.4834
Epoch 98/150
77/77 0s 2ms/step - accuracy: 0.7660 - loss: 0.4806
Epoch 99/150
77/77 0s 2ms/step - accuracy: 0.7573 - loss: 0.5278
Epoch 100/150
77/77 0s 4ms/step - accuracy: 0.7660 - loss: 0.4853
Epoch 101/150
77/77 0s 3ms/step - accuracy: 0.7920 - loss: 0.4687
Epoch 102/150
77/77 0s 2ms/step - accuracy: 0.7589 - loss: 0.4889
Epoch 103/150
77/77 0s 3ms/step - accuracy: 0.7662 - loss: 0.5083
Epoch 104/150
77/77 0s 3ms/step - accuracy: 0.7641 - loss: 0.4776
Epoch 105/150
77/77 0s 4ms/step - accuracy: 0.7909 - loss: 0.4637
Epoch 106/150
77/77 0s 3ms/step - accuracy: 0.7450 - loss: 0.5270
Epoch 107/150
77/77 0s 3ms/step - accuracy: 0.7756 - loss: 0.4945
Epoch 108/150
77/77 0s 2ms/step - accuracy: 0.7747 - loss: 0.4636
Epoch 109/150
77/77 0s 3ms/step - accuracy: 0.7576 - loss: 0.5233
Epoch 110/150
77/77 0s 2ms/step - accuracy: 0.7450 - loss: 0.4953
Epoch 111/150
77/77 0s 3ms/step - accuracy: 0.7610 - loss: 0.5053
Epoch 112/150
77/77 0s 3ms/step - accuracy: 0.7576 - loss: 0.5038

Epoch 113/150
77/77 0s 3ms/step - accuracy: 0.7831 - loss: 0.4770
Epoch 114/150
77/77 0s 3ms/step - accuracy: 0.7709 - loss: 0.4716
Epoch 115/150
77/77 0s 3ms/step - accuracy: 0.7921 - loss: 0.4389
Epoch 116/150
77/77 0s 3ms/step - accuracy: 0.8250 - loss: 0.4502
Epoch 117/150
77/77 0s 3ms/step - accuracy: 0.7595 - loss: 0.4824
Epoch 118/150
77/77 0s 3ms/step - accuracy: 0.8125 - loss: 0.4493
Epoch 119/150
77/77 0s 3ms/step - accuracy: 0.7678 - loss: 0.4938
Epoch 120/150
77/77 0s 3ms/step - accuracy: 0.7912 - loss: 0.4701
Epoch 121/150
77/77 0s 3ms/step - accuracy: 0.7803 - loss: 0.4915
Epoch 122/150
77/77 0s 3ms/step - accuracy: 0.7808 - loss: 0.4759
Epoch 123/150
77/77 0s 3ms/step - accuracy: 0.7889 - loss: 0.4485
Epoch 124/150
77/77 0s 3ms/step - accuracy: 0.7626 - loss: 0.4879
Epoch 125/150
77/77 0s 2ms/step - accuracy: 0.7557 - loss: 0.4978
Epoch 126/150
77/77 0s 3ms/step - accuracy: 0.7855 - loss: 0.4754
Epoch 127/150
77/77 0s 3ms/step - accuracy: 0.7826 - loss: 0.4562
Epoch 128/150
77/77 0s 3ms/step - accuracy: 0.7686 - loss: 0.4734
Epoch 129/150
77/77 0s 3ms/step - accuracy: 0.7895 - loss: 0.4595
Epoch 130/150
77/77 0s 3ms/step - accuracy: 0.7675 - loss: 0.4781
Epoch 131/150
77/77 0s 2ms/step - accuracy: 0.7617 - loss: 0.4890
Epoch 132/150
77/77 0s 3ms/step - accuracy: 0.7725 - loss: 0.4658
Epoch 133/150
77/77 0s 3ms/step - accuracy: 0.7874 - loss: 0.4824
Epoch 134/150
77/77 0s 3ms/step - accuracy: 0.7693 - loss: 0.4904
Epoch 135/150
77/77 0s 3ms/step - accuracy: 0.7620 - loss: 0.5013
Epoch 136/150
77/77 0s 3ms/step - accuracy: 0.7821 - loss: 0.4532
Epoch 137/150
77/77 0s 3ms/step - accuracy: 0.7896 - loss: 0.4330
Epoch 138/150
77/77 0s 3ms/step - accuracy: 0.8026 - loss: 0.4526
Epoch 139/150
77/77 0s 4ms/step - accuracy: 0.7676 - loss: 0.4554
Epoch 140/150
77/77 0s 2ms/step - accuracy: 0.7926 - loss: 0.4597

```
Epoch 141/150
77/77 0s 3ms/step - accuracy: 0.7812 - loss: 0.4717
Epoch 142/150
77/77 0s 3ms/step - accuracy: 0.7914 - loss: 0.4415
Epoch 143/150
77/77 0s 4ms/step - accuracy: 0.7940 - loss: 0.4572
Epoch 144/150
77/77 0s 3ms/step - accuracy: 0.7547 - loss: 0.4979
Epoch 145/150
77/77 0s 2ms/step - accuracy: 0.7779 - loss: 0.4667
Epoch 146/150
77/77 0s 2ms/step - accuracy: 0.7755 - loss: 0.4698
Epoch 147/150
77/77 0s 3ms/step - accuracy: 0.7966 - loss: 0.4506
Epoch 148/150
77/77 0s 2ms/step - accuracy: 0.7772 - loss: 0.4873
Epoch 149/150
77/77 0s 2ms/step - accuracy: 0.7730 - loss: 0.4644
Epoch 150/150
77/77 0s 3ms/step - accuracy: 0.7709 - loss: 0.4830
```

```
Out[12]: <keras.src.callbacks.history.History at 0x262f0613150>
```

```
In [13]: loss, accuracy = model.evaluate(x, y)
print(f"Model accuracy: {accuracy * 100:.2f}%")
```

```
24/24 0s 1ms/step - accuracy: 0.7666 - loss: 0.4938
Model accuracy: 80.73%
```

```
In [14]: predicted_probabilities = model.predict(x)

predicted_classes = (predicted_probabilities > 0.5).astype(int)
# Print the first 10 actual and predicted values
print("Actual values:", y[:10])
print("Predicted probabilities:", predicted_probabilities[:10])
print("Predicted classes:", predicted_classes[:10])
```

```
24/24 ----- 0s 3ms/step
Actual values: [1. 0. 1. 0. 1. 0. 1. 0. 1. 1.]
Predicted probabilities: [[0.8793448 ]
 [0.11715838]
 [0.68718874]
 [0.09204928]
 [0.6513829 ]
 [0.24935585]
 [0.16379377]
 [0.653388 ]
 [0.9338086 ]
 [0.11915239]]
Predicted classes: [[1]
 [0]
 [1]
 [0]
 [1]
 [0]
 [0]
 [1]
 [1]
 [0]]
```

Pytorch

```
In [15]: import torch
import numpy as np
```

```
In [16]: data = [
[1,2],
[3,4]
]
x = torch.tensor(data)
print(type(x))
```

```
<class 'torch.Tensor'>
```

```
In [17]: np_array = np.array(data)
x_np = torch.from_numpy(np_array)
print(x_np)
print(type(x_np))
```

```
tensor([[1, 2],
       [3, 4]], dtype=torch.int32)
<class 'torch.Tensor'>
```

```
In [18]: x_ones = torch.ones_like(x)
print("One Tensor: \n",x_ones)
x_rand = torch.rand_like(x,dtype=torch.float)
print(x_rand)
```

```
One Tensor:
tensor([[1, 1],
       [1, 1]])
tensor([[0.7958, 0.9639],
       [0.7413, 0.6462]])
```

```
In [19]: shape = (2,3)
random_tensor = torch.rand(shape)
print(random_tensor)
print(type(random_tensor))
```

```
tensor([[0.9549, 0.9309, 0.4621],
        [0.5212, 0.4073, 0.2761]])
<class 'torch.Tensor'>
```

```
In [20]: ones_tensor = torch.ones(shape)
print(ones_tensor)
print(type(ones_tensor))
```

```
tensor([[1., 1., 1.],
        [1., 1., 1.]])
<class 'torch.Tensor'>
```

```
In [21]: zeros_tensor = torch.zeros(shape)
print(zeros_tensor)
print(type(zeros_tensor))
```

```
tensor([[0., 0., 0.],
        [0., 0., 0.]])
<class 'torch.Tensor'>
```

```
In [22]: tensor = torch.rand(3,4)
print(tensor)
print(tensor.shape)
print(tensor.dtype)
print(tensor.device)
```

```
tensor([[0.2989, 0.0897, 0.8760, 0.7776],
        [0.5551, 0.1710, 0.7330, 0.5732],
        [0.6748, 0.2287, 0.9280, 0.2634]])
torch.Size([3, 4])
torch.float32
cpu
```

```
In [23]: if torch.cuda.is_available():
    tensor = tensor.to('cuda')
    print("Device tensor is stored in ", tensor.device)
```

```
In [24]: # Indexing, Slicing
tensor = torch.ones(4,4)
print(tensor)
print(tensor)
tensor1 = torch.zeros(4,4)
print(tensor1)
tensor2 = torch.cat([tensor,tensor1])
print(tensor2)

tensor.mul(tensor1)
tensor * tensor1
tensor.T
```

```
tensor.add_(3)
print(tensor)

tensor([[1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.]])
tensor([[1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.]])
tensor([[0., 0., 0., 0.],
       [0., 0., 0., 0.],
       [0., 0., 0., 0.],
       [0., 0., 0., 0.]])
tensor([[1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [0., 0., 0., 0.],
       [0., 0., 0., 0.],
       [0., 0., 0., 0.],
       [0., 0., 0., 0.]])
tensor([[4., 4., 4., 4.],
       [4., 4., 4., 4.],
       [4., 4., 4., 4.],
       [4., 4., 4., 4.]])
```

```
In [25]: # from tensor to numpy
t = torch.ones(5)
print(t)
n = t.numpy()
print(n)
print(type(n))

tensor([1., 1., 1., 1., 1.])
[1. 1. 1. 1. 1.]
<class 'numpy.ndarray'>
```

```
In [ ]:
```