## prediction of diabates on medical record data

May 9, 2018

Import required models and layers and libraries

/home/nikhil/anaconda3/lib/python3.6/site-packages/h5py/\_\_init\_\_.py:36: FutureWarning: Conversion from .\_conv import register\_converters as \_register\_converters
Using TensorFlow backend.

Load the data

```
In [9]: dataset = numpy.loadtxt("data/datapima.csv", delimiter=",")
    split the dataset into input variables (X) and the output class variable (Y).
In [10]: X = dataset[:,0:8]
    Y = dataset[:,8]
```

Define the model with required number of layers, activation functions using dense layer and give the shape and dimentions of input data to the first layer

Compile the model by defining the loss function, optimizer and metric

fit our model on our loaded data by calling the fit() function on the model by giving the required number of epochs and batch size.

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Epoch 1/150
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Epoch 2/150
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Epoch 3/150
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Epoch 22/150
768/768 [====================================
Epoch 23/150
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Epoch 24/150
Epoch 25/150
768/768 [=================== ] - 0s 150us/step - loss: 0.5572 - acc: 0.7396
Epoch 26/150
768/768 [================== ] - 0s 142us/step - loss: 0.5700 - acc: 0.7083
Epoch 27/150
768/768 [=================== ] - 0s 153us/step - loss: 0.5551 - acc: 0.7188
Epoch 28/150
Epoch 29/150
Epoch 30/150
Epoch 31/150
Epoch 32/150
Epoch 33/150
768/768 [=================== ] - 0s 155us/step - loss: 0.5529 - acc: 0.7214
Epoch 34/150
Epoch 35/150
Epoch 36/150
768/768 [================= ] - 0s 147us/step - loss: 0.5651 - acc: 0.7031
Epoch 37/150
Epoch 38/150
768/768 [================= ] - 0s 166us/step - loss: 0.5402 - acc: 0.7214
Epoch 39/150
768/768 [================== ] - 0s 150us/step - loss: 0.5464 - acc: 0.7201
Epoch 40/150
768/768 [=================== ] - 0s 161us/step - loss: 0.5455 - acc: 0.7266
Epoch 41/150
768/768 [=================== ] - 0s 165us/step - loss: 0.5440 - acc: 0.7318
Epoch 42/150
Epoch 43/150
Epoch 44/150
Epoch 45/150
Epoch 46/150
Epoch 47/150
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768/768 [=================== ] - 0s 155us/step - loss: 0.5341 - acc: 0.7448
Epoch 48/150
Epoch 49/150
768/768 [=================== ] - 0s 156us/step - loss: 0.5332 - acc: 0.7487
Epoch 50/150
768/768 [=========================== - 0s 159us/step - loss: 0.5277 - acc: 0.7318
Epoch 51/150
Epoch 52/150
768/768 [================== ] - 0s 141us/step - loss: 0.5320 - acc: 0.7435
Epoch 53/150
Epoch 54/150
Epoch 55/150
Epoch 56/150
Epoch 57/150
768/768 [================ ] - 0s 152us/step - loss: 0.5322 - acc: 0.7383
Epoch 58/150
Epoch 59/150
Epoch 60/150
Epoch 61/150
Epoch 62/150
Epoch 63/150
768/768 [================= ] - 0s 146us/step - loss: 0.5430 - acc: 0.7344
Epoch 64/150
768/768 [================= ] - 0s 150us/step - loss: 0.5307 - acc: 0.7461
Epoch 65/150
768/768 [=================== ] - 0s 153us/step - loss: 0.5200 - acc: 0.7539
Epoch 66/150
Epoch 67/150
Epoch 68/150
Epoch 69/150
Epoch 70/150
Epoch 71/150
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Epoch 72/150
768/768 [================== ] - 0s 151us/step - loss: 0.5139 - acc: 0.7578
Epoch 73/150
Epoch 74/150
768/768 [=================== ] - 0s 152us/step - loss: 0.5083 - acc: 0.7656
Epoch 75/150
768/768 [================== ] - 0s 141us/step - loss: 0.5092 - acc: 0.7591
Epoch 76/150
768/768 [=================== ] - 0s 154us/step - loss: 0.5113 - acc: 0.7565
Epoch 77/150
Epoch 78/150
Epoch 79/150
Epoch 80/150
Epoch 81/150
768/768 [================== ] - 0s 152us/step - loss: 0.5011 - acc: 0.7734
Epoch 82/150
Epoch 83/150
Epoch 84/150
768/768 [=================== ] - 0s 154us/step - loss: 0.4944 - acc: 0.7656
Epoch 85/150
Epoch 86/150
Epoch 87/150
Epoch 88/150
768/768 [=================== ] - 0s 150us/step - loss: 0.4977 - acc: 0.7656
Epoch 89/150
768/768 [================== ] - 0s 154us/step - loss: 0.5019 - acc: 0.7747
Epoch 90/150
Epoch 91/150
Epoch 92/150
Epoch 93/150
Epoch 94/150
Epoch 95/150
```

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768/768 [================= ] - 0s 153us/step - loss: 0.5015 - acc: 0.7513
Epoch 96/150
768/768 [=================== ] - 0s 152us/step - loss: 0.4885 - acc: 0.7708
Epoch 97/150
768/768 [=================== ] - 0s 162us/step - loss: 0.4954 - acc: 0.7721
Epoch 98/150
768/768 [==================== ] - 0s 152us/step - loss: 0.4880 - acc: 0.7656
Epoch 99/150
768/768 [=========================== - 0s 155us/step - loss: 0.4887 - acc: 0.7682
Epoch 100/150
Epoch 101/150
Epoch 102/150
Epoch 103/150
Epoch 104/150
Epoch 105/150
Epoch 106/150
Epoch 107/150
Epoch 108/150
768/768 [=================== ] - 0s 151us/step - loss: 0.5013 - acc: 0.7656
Epoch 109/150
768/768 [================= ] - 0s 156us/step - loss: 0.4850 - acc: 0.7604
Epoch 110/150
768/768 [================= ] - 0s 156us/step - loss: 0.4847 - acc: 0.7721
Epoch 111/150
Epoch 112/150
768/768 [================== ] - 0s 160us/step - loss: 0.4864 - acc: 0.7747
Epoch 113/150
768/768 [================== ] - 0s 148us/step - loss: 0.4979 - acc: 0.7565
Epoch 114/150
Epoch 115/150
768/768 [================== ] - 0s 154us/step - loss: 0.4908 - acc: 0.7721
Epoch 116/150
Epoch 117/150
Epoch 118/150
768/768 [================= ] - 0s 154us/step - loss: 0.4844 - acc: 0.7799
Epoch 119/150
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Epoch 120/150
Epoch 121/150
768/768 [================== ] - 0s 148us/step - loss: 0.4900 - acc: 0.7773
Epoch 122/150
768/768 [================== ] - 0s 148us/step - loss: 0.4788 - acc: 0.7865
Epoch 123/150
768/768 [=================== ] - 0s 152us/step - loss: 0.4833 - acc: 0.7682
Epoch 124/150
Epoch 125/150
Epoch 126/150
Epoch 127/150
Epoch 128/150
Epoch 129/150
Epoch 130/150
Epoch 131/150
Epoch 132/150
Epoch 133/150
Epoch 134/150
Epoch 135/150
768/768 [================= ] - 0s 139us/step - loss: 0.4716 - acc: 0.7813
Epoch 136/150
768/768 [================== ] - 0s 150us/step - loss: 0.4691 - acc: 0.7799
Epoch 137/150
768/768 [=================== ] - 0s 142us/step - loss: 0.4655 - acc: 0.7917
Epoch 138/150
Epoch 139/150
Epoch 140/150
Epoch 141/150
Epoch 142/150
Epoch 143/150
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Epoch 144/150
Epoch 145/150
768/768 [=============== ] - 0s 149us/step - loss: 0.4857 - acc: 0.7682
Epoch 146/150
768/768 [=================== ] - 0s 147us/step - loss: 0.4944 - acc: 0.7630
Epoch 147/150
768/768 [================== ] - 0s 147us/step - loss: 0.4799 - acc: 0.7852
Epoch 148/150
768/768 [================== ] - 0s 139us/step - loss: 0.4682 - acc: 0.7799
Epoch 149/150
Epoch 150/150
Out[13]: <keras.callbacks.History at 0x7fb7d6066518>
  Evaluate the model and print the accuracy
In [14]: # evaluate the model
      scores = model.evaluate(X, Y)
      print("\n\%s: \%.2f\%\" \% (model.metrics_names[1], scores[1]*100))
768/768 [========== ] - Os 56us/step
acc: 78.91%
  Now put all the code i.e tie together the code and run it
In [17]: # Create your first MLP in Keras
      from keras.models import Sequential
      from keras.layers import Dense
      import numpy
       # fix random seed for reproducibility
      numpy.random.seed(7)
       # load pima indians dataset
      dataset = numpy.loadtxt("data/datapima.csv", delimiter=",")
       # split into input (X) and output (Y) variables
      X = dataset[:,0:8]
      Y = dataset[:,8]
       # create model
      model = Sequential()
      model.add(Dense(12, input_dim=8, activation='relu'))
      model.add(Dense(8, activation='relu'))
      model.add(Dense(1, activation='sigmoid'))
       # Compile model
```

```
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
   # Fit the model
   model.fit(X, Y, epochs=150, batch_size=10)
   # evaluate the model
   scores = model.evaluate(X, Y)
   print("\n\%s: \%.2f\%\" \% (model.metrics_names[1], scores[1]*100))
Epoch 1/150
Epoch 2/150
768/768 [================= ] - 0s 147us/step - loss: 0.9377 - acc: 0.5924
Epoch 3/150
Epoch 4/150
Epoch 5/150
768/768 [================== ] - 0s 150us/step - loss: 0.6841 - acc: 0.6667
Epoch 6/150
768/768 [================== ] - 0s 146us/step - loss: 0.6521 - acc: 0.6784
Epoch 7/150
Epoch 8/150
Epoch 9/150
768/768 [========================== ] - 0s 152us/step - loss: 0.6250 - acc: 0.6966
Epoch 10/150
768/768 [=================== ] - 0s 157us/step - loss: 0.6315 - acc: 0.6771
Epoch 11/150
Epoch 12/150
Epoch 13/150
Epoch 14/150
Epoch 15/150
Epoch 16/150
Epoch 17/150
Epoch 18/150
Epoch 19/150
Epoch 20/150
Epoch 21/150
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Epoch 22/150
Epoch 23/150
768/768 [================== ] - 0s 142us/step - loss: 0.5731 - acc: 0.7148
Epoch 24/150
768/768 [=================== ] - 0s 142us/step - loss: 0.5672 - acc: 0.7305
Epoch 25/150
768/768 [=========================== - 0s 146us/step - loss: 0.5572 - acc: 0.7370
Epoch 26/150
768/768 [=================== ] - 0s 147us/step - loss: 0.5700 - acc: 0.7005
Epoch 27/150
Epoch 28/150
Epoch 29/150
Epoch 30/150
768/768 [================ ] - 0s 134us/step - loss: 0.5613 - acc: 0.7214
Epoch 31/150
768/768 [================== ] - 0s 139us/step - loss: 0.5688 - acc: 0.7174
Epoch 32/150
Epoch 33/150
768/768 [================ ] - 0s 158us/step - loss: 0.5517 - acc: 0.7214
Epoch 34/150
768/768 [=================== ] - 0s 149us/step - loss: 0.5493 - acc: 0.7318
Epoch 35/150
Epoch 36/150
Epoch 37/150
768/768 [=================== ] - 0s 152us/step - loss: 0.5343 - acc: 0.7370
Epoch 38/150
768/768 [================== ] - 0s 160us/step - loss: 0.5403 - acc: 0.7266
Epoch 39/150
768/768 [==================== ] - 0s 160us/step - loss: 0.5445 - acc: 0.7227
Epoch 40/150
Epoch 41/150
Epoch 42/150
Epoch 43/150
Epoch 44/150
Epoch 45/150
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Epoch 46/150
Epoch 47/150
768/768 [=================== ] - 0s 144us/step - loss: 0.5299 - acc: 0.7370
Epoch 48/150
768/768 [=========================== - 0s 157us/step - loss: 0.5327 - acc: 0.7370
Epoch 49/150
768/768 [================== ] - 0s 160us/step - loss: 0.5321 - acc: 0.7487
Epoch 50/150
Epoch 51/150
Epoch 52/150
Epoch 53/150
Epoch 54/150
Epoch 55/150
Epoch 56/150
Epoch 57/150
Epoch 58/150
Epoch 59/150
Epoch 60/150
768/768 [================= ] - 0s 148us/step - loss: 0.5336 - acc: 0.7331
Epoch 61/150
768/768 [=================== ] - 0s 145us/step - loss: 0.5285 - acc: 0.7422
Epoch 62/150
768/768 [=================== ] - 0s 148us/step - loss: 0.5170 - acc: 0.7539
Epoch 63/150
768/768 [================== ] - 0s 148us/step - loss: 0.5437 - acc: 0.7357
Epoch 64/150
Epoch 65/150
Epoch 66/150
Epoch 67/150
Epoch 68/150
Epoch 69/150
```

```
Epoch 70/150
768/768 [=================== ] - 0s 154us/step - loss: 0.5368 - acc: 0.7227
Epoch 71/150
768/768 [=================== ] - 0s 169us/step - loss: 0.5166 - acc: 0.7435
Epoch 72/150
768/768 [================== ] - 0s 141us/step - loss: 0.5157 - acc: 0.7513
Epoch 73/150
Epoch 74/150
768/768 [================= ] - 0s 145us/step - loss: 0.5091 - acc: 0.7604
Epoch 75/150
Epoch 76/150
Epoch 77/150
Epoch 78/150
768/768 [================ ] - 0s 141us/step - loss: 0.5111 - acc: 0.7474
Epoch 79/150
Epoch 80/150
Epoch 81/150
Epoch 82/150
768/768 [=========================== - 0s 151us/step - loss: 0.5020 - acc: 0.7552
Epoch 83/150
768/768 [================= ] - 0s 152us/step - loss: 0.4979 - acc: 0.7604
Epoch 84/150
Epoch 85/150
768/768 [================== ] - 0s 153us/step - loss: 0.5040 - acc: 0.7513
Epoch 86/150
768/768 [================== ] - 0s 150us/step - loss: 0.5054 - acc: 0.7513
Epoch 87/150
768/768 [==================== ] - 0s 154us/step - loss: 0.4986 - acc: 0.7487
Epoch 88/150
Epoch 89/150
Epoch 90/150
Epoch 91/150
Epoch 92/150
Epoch 93/150
```

```
Epoch 94/150
768/768 [================== ] - 0s 156us/step - loss: 0.4976 - acc: 0.7669
Epoch 95/150
768/768 [=================== ] - 0s 150us/step - loss: 0.5017 - acc: 0.7487
Epoch 96/150
768/768 [================== ] - 0s 147us/step - loss: 0.4899 - acc: 0.7695
Epoch 97/150
768/768 [=================== ] - 0s 143us/step - loss: 0.4961 - acc: 0.7786
Epoch 98/150
Epoch 99/150
Epoch 100/150
Epoch 101/150
Epoch 102/150
768/768 [=================== ] - 0s 142us/step - loss: 0.4977 - acc: 0.7591
Epoch 103/150
Epoch 104/150
Epoch 105/150
Epoch 106/150
768/768 [================== ] - 0s 171us/step - loss: 0.4945 - acc: 0.7708
Epoch 107/150
768/768 [================= ] - 0s 149us/step - loss: 0.4914 - acc: 0.7734
Epoch 108/150
Epoch 109/150
768/768 [=========================== - 0s 166us/step - loss: 0.4850 - acc: 0.7708
Epoch 110/150
768/768 [================== ] - 0s 156us/step - loss: 0.4895 - acc: 0.7682
Epoch 111/150
768/768 [=================== ] - 0s 149us/step - loss: 0.4826 - acc: 0.7812
Epoch 112/150
Epoch 113/150
Epoch 114/150
Epoch 115/150
Epoch 116/150
Epoch 117/150
```

```
Epoch 118/150
Epoch 119/150
768/768 [================== ] - 0s 151us/step - loss: 0.4829 - acc: 0.7708
Epoch 120/150
768/768 [=================== ] - 0s 152us/step - loss: 0.4928 - acc: 0.7773
Epoch 121/150
768/768 [================== ] - 0s 149us/step - loss: 0.4919 - acc: 0.7721
Epoch 122/150
Epoch 123/150
768/768 [=================== ] - 0s 151us/step - loss: 0.4798 - acc: 0.7669
Epoch 124/150
Epoch 125/150
Epoch 126/150
Epoch 127/150
Epoch 128/150
Epoch 129/150
Epoch 130/150
Epoch 131/150
768/768 [================= ] - 0s 154us/step - loss: 0.4796 - acc: 0.7734
Epoch 132/150
Epoch 133/150
Epoch 134/150
768/768 [================ ] - 0s 150us/step - loss: 0.4839 - acc: 0.7734
Epoch 135/150
768/768 [=================== ] - 0s 150us/step - loss: 0.4783 - acc: 0.7786
Epoch 136/150
Epoch 137/150
Epoch 138/150
Epoch 139/150
Epoch 140/150
Epoch 141/150
```

```
Epoch 142/150
768/768 [================= ] - 0s 145us/step - loss: 0.4816 - acc: 0.7734
Epoch 143/150
Epoch 144/150
Epoch 145/150
768/768 [================== ] - 0s 154us/step - loss: 0.4896 - acc: 0.7643
Epoch 146/150
Epoch 147/150
Epoch 148/150
768/768 [================= ] - 0s 153us/step - loss: 0.4718 - acc: 0.7734
Epoch 149/150
Epoch 150/150
768/768 [=========== ] - 0s 71us/step
acc: 80.08%
```

## PREDICTION

We can adapt the above example and use it to generate predictions on the training dataset, pretending it is a new dataset we have not seen before.

Making predictions is as easy as calling model.predict(). We are using a sigmoid activation function on the output layer, so the predictions will be in the range between 0 and 1. We can easily convert them into a crisp binary prediction for this classification task by rounding them.

The complete example that makes predictions for each record in the training data is listed below

```
model.add(Dense(8, init='uniform', activation='relu'))
         model.add(Dense(1, init='uniform', activation='sigmoid'))
         # Compile model
         model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
         # Fit the model
         model.fit(X, Y, epochs=150, batch_size=10, verbose=2)
         # calculate predictions
         predictions = model.predict(X)
         # round predictions
         rounded = [round(x[0]) for x in predictions]
         print(rounded)
/home/nikhil/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:15: UserWarning: Update
  from ipykernel import kernelapp as app
/home/nikhil/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:16: UserWarning: Update
  app.launch_new_instance()
/home/nikhil/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:17: UserWarning: Update
Epoch 1/150
- 0s - loss: 0.6773 - acc: 0.6510
Epoch 2/150
 - 0s - loss: 0.6594 - acc: 0.6510
Epoch 3/150
 - 0s - loss: 0.6476 - acc: 0.6510
Epoch 4/150
 - 0s - loss: 0.6389 - acc: 0.6510
Epoch 5/150
- 0s - loss: 0.6296 - acc: 0.6510
Epoch 6/150
- 0s - loss: 0.6150 - acc: 0.6628
Epoch 7/150
- 0s - loss: 0.6117 - acc: 0.6875
Epoch 8/150
- 0s - loss: 0.6039 - acc: 0.6953
Epoch 9/150
- 0s - loss: 0.5974 - acc: 0.6888
Epoch 10/150
 - 0s - loss: 0.5985 - acc: 0.6940
Epoch 11/150
 - 0s - loss: 0.5931 - acc: 0.6823
Epoch 12/150
 - 0s - loss: 0.5905 - acc: 0.6914
Epoch 13/150
- 0s - loss: 0.5878 - acc: 0.6849
Epoch 14/150
 - 0s - loss: 0.5858 - acc: 0.6940
Epoch 15/150
```

```
- 0s - loss: 0.5812 - acc: 0.6979
Epoch 16/150
 - 0s - loss: 0.5808 - acc: 0.6797
Epoch 17/150
 - 0s - loss: 0.5790 - acc: 0.7083
Epoch 18/150
 - 0s - loss: 0.5833 - acc: 0.7044
Epoch 19/150
- 0s - loss: 0.5756 - acc: 0.7044
Epoch 20/150
 - 0s - loss: 0.5770 - acc: 0.6966
Epoch 21/150
 - 0s - loss: 0.5730 - acc: 0.7122
Epoch 22/150
 - 0s - loss: 0.5765 - acc: 0.6979
Epoch 23/150
 - 0s - loss: 0.5701 - acc: 0.7174
Epoch 24/150
 - 0s - loss: 0.5781 - acc: 0.7005
Epoch 25/150
 - 0s - loss: 0.5656 - acc: 0.7070
Epoch 26/150
- 0s - loss: 0.5781 - acc: 0.6927
Epoch 27/150
- 0s - loss: 0.5715 - acc: 0.7057
Epoch 28/150
- 0s - loss: 0.5636 - acc: 0.7122
Epoch 29/150
 - 0s - loss: 0.5682 - acc: 0.7148
Epoch 30/150
 - 0s - loss: 0.5641 - acc: 0.7122
Epoch 31/150
 - 0s - loss: 0.5631 - acc: 0.7044
Epoch 32/150
 - 0s - loss: 0.5594 - acc: 0.7057
Epoch 33/150
- 0s - loss: 0.5565 - acc: 0.7188
Epoch 34/150
- 0s - loss: 0.5599 - acc: 0.7122
Epoch 35/150
- 0s - loss: 0.5551 - acc: 0.7135
Epoch 36/150
 - 0s - loss: 0.5529 - acc: 0.7044
Epoch 37/150
- 0s - loss: 0.5524 - acc: 0.7253
Epoch 38/150
 - 0s - loss: 0.5590 - acc: 0.7148
Epoch 39/150
```

```
- 0s - loss: 0.5540 - acc: 0.7188
Epoch 40/150
 - 0s - loss: 0.5558 - acc: 0.7201
Epoch 41/150
 - 0s - loss: 0.5496 - acc: 0.7214
Epoch 42/150
 - 0s - loss: 0.5501 - acc: 0.7201
Epoch 43/150
- 0s - loss: 0.5442 - acc: 0.7266
Epoch 44/150
 - 0s - loss: 0.5490 - acc: 0.7318
Epoch 45/150
 - 0s - loss: 0.5457 - acc: 0.7370
Epoch 46/150
 - 0s - loss: 0.5418 - acc: 0.7174
Epoch 47/150
 - 0s - loss: 0.5424 - acc: 0.7266
Epoch 48/150
 - 0s - loss: 0.5401 - acc: 0.7383
Epoch 49/150
 - 0s - loss: 0.5363 - acc: 0.7357
Epoch 50/150
- 0s - loss: 0.5376 - acc: 0.7435
Epoch 51/150
- 0s - loss: 0.5376 - acc: 0.7266
Epoch 52/150
- 0s - loss: 0.5389 - acc: 0.7318
Epoch 53/150
 - 0s - loss: 0.5364 - acc: 0.7292
Epoch 54/150
 - 0s - loss: 0.5348 - acc: 0.7292
Epoch 55/150
 - 0s - loss: 0.5348 - acc: 0.7331
Epoch 56/150
 - Os - loss: 0.5358 - acc: 0.7422
Epoch 57/150
- 0s - loss: 0.5284 - acc: 0.7357
Epoch 58/150
- 0s - loss: 0.5305 - acc: 0.7240
Epoch 59/150
- 0s - loss: 0.5266 - acc: 0.7474
Epoch 60/150
 - 0s - loss: 0.5278 - acc: 0.7409
Epoch 61/150
- 0s - loss: 0.5218 - acc: 0.7396
Epoch 62/150
 - 0s - loss: 0.5255 - acc: 0.7461
Epoch 63/150
```

```
- 0s - loss: 0.5273 - acc: 0.7565
Epoch 64/150
 - 0s - loss: 0.5256 - acc: 0.7409
Epoch 65/150
 - 0s - loss: 0.5198 - acc: 0.7565
Epoch 66/150
 - 0s - loss: 0.5174 - acc: 0.7500
Epoch 67/150
- 0s - loss: 0.5138 - acc: 0.7409
Epoch 68/150
 - 0s - loss: 0.5163 - acc: 0.7474
Epoch 69/150
 - 0s - loss: 0.5119 - acc: 0.7526
Epoch 70/150
 - 0s - loss: 0.5198 - acc: 0.7383
Epoch 71/150
 - 0s - loss: 0.5118 - acc: 0.7526
Epoch 72/150
 - 0s - loss: 0.5111 - acc: 0.7526
Epoch 73/150
 - 0s - loss: 0.5066 - acc: 0.7526
Epoch 74/150
- 0s - loss: 0.5110 - acc: 0.7539
Epoch 75/150
- 0s - loss: 0.5046 - acc: 0.7604
Epoch 76/150
- 0s - loss: 0.5050 - acc: 0.7617
Epoch 77/150
 - 0s - loss: 0.5033 - acc: 0.7604
Epoch 78/150
 - 0s - loss: 0.4993 - acc: 0.7643
Epoch 79/150
 - 0s - loss: 0.5084 - acc: 0.7565
Epoch 80/150
 - 0s - loss: 0.5000 - acc: 0.7643
Epoch 81/150
- 0s - loss: 0.4941 - acc: 0.7578
Epoch 82/150
- 0s - loss: 0.5010 - acc: 0.7617
Epoch 83/150
- 0s - loss: 0.4921 - acc: 0.7565
Epoch 84/150
 - 0s - loss: 0.4916 - acc: 0.7734
Epoch 85/150
 - 0s - loss: 0.4941 - acc: 0.7643
Epoch 86/150
 - 0s - loss: 0.5014 - acc: 0.7500
Epoch 87/150
```

```
- 0s - loss: 0.4960 - acc: 0.7695
Epoch 88/150
 - 0s - loss: 0.4855 - acc: 0.7604
Epoch 89/150
 - 0s - loss: 0.4930 - acc: 0.7643
Epoch 90/150
 - 0s - loss: 0.4878 - acc: 0.7643
Epoch 91/150
- 0s - loss: 0.4823 - acc: 0.7552
Epoch 92/150
 - 0s - loss: 0.4859 - acc: 0.7669
Epoch 93/150
 - 0s - loss: 0.4818 - acc: 0.7617
Epoch 94/150
 - 0s - loss: 0.4865 - acc: 0.7565
Epoch 95/150
 - 0s - loss: 0.4771 - acc: 0.7617
Epoch 96/150
 - 0s - loss: 0.4788 - acc: 0.7721
Epoch 97/150
 - 0s - loss: 0.4798 - acc: 0.7734
Epoch 98/150
- 0s - loss: 0.4776 - acc: 0.7747
Epoch 99/150
- 0s - loss: 0.4721 - acc: 0.7826
Epoch 100/150
- 0s - loss: 0.4744 - acc: 0.7734
Epoch 101/150
 - 0s - loss: 0.4755 - acc: 0.7760
Epoch 102/150
 - 0s - loss: 0.4754 - acc: 0.7669
Epoch 103/150
 - 0s - loss: 0.4783 - acc: 0.7708
Epoch 104/150
 - 0s - loss: 0.4779 - acc: 0.7721
Epoch 105/150
- 0s - loss: 0.4854 - acc: 0.7630
Epoch 106/150
- 0s - loss: 0.4700 - acc: 0.7865
Epoch 107/150
- 0s - loss: 0.4738 - acc: 0.7760
Epoch 108/150
 - 0s - loss: 0.4759 - acc: 0.7839
Epoch 109/150
- 0s - loss: 0.4680 - acc: 0.7786
Epoch 110/150
 - 0s - loss: 0.4678 - acc: 0.7799
Epoch 111/150
```

```
- 0s - loss: 0.4713 - acc: 0.7930
Epoch 112/150
- 0s - loss: 0.4660 - acc: 0.7682
Epoch 113/150
 - 0s - loss: 0.4727 - acc: 0.7669
Epoch 114/150
 - 0s - loss: 0.4739 - acc: 0.7630
Epoch 115/150
- 0s - loss: 0.4650 - acc: 0.7773
Epoch 116/150
- 0s - loss: 0.4714 - acc: 0.7760
Epoch 117/150
 - 0s - loss: 0.4643 - acc: 0.7747
Epoch 118/150
- 0s - loss: 0.4702 - acc: 0.7826
Epoch 119/150
- 0s - loss: 0.4635 - acc: 0.7747
Epoch 120/150
 - 0s - loss: 0.4645 - acc: 0.7721
Epoch 121/150
- 0s - loss: 0.4693 - acc: 0.7982
Epoch 122/150
- 0s - loss: 0.4657 - acc: 0.7891
Epoch 123/150
- 0s - loss: 0.4629 - acc: 0.7708
Epoch 124/150
- 0s - loss: 0.4564 - acc: 0.7812
Epoch 125/150
 - 0s - loss: 0.4608 - acc: 0.7786
Epoch 126/150
- 0s - loss: 0.4584 - acc: 0.7760
Epoch 127/150
 - 0s - loss: 0.4656 - acc: 0.7891
Epoch 128/150
 - 0s - loss: 0.4504 - acc: 0.7852
Epoch 129/150
- 0s - loss: 0.4617 - acc: 0.7878
Epoch 130/150
- 0s - loss: 0.4518 - acc: 0.7826
Epoch 131/150
- 0s - loss: 0.4582 - acc: 0.7826
Epoch 132/150
 - 0s - loss: 0.4539 - acc: 0.7812
Epoch 133/150
- 0s - loss: 0.4643 - acc: 0.7786
Epoch 134/150
- 0s - loss: 0.4573 - acc: 0.7773
Epoch 135/150
```

```
Epoch 137/150
 - 0s - loss: 0.4600 - acc: 0.7917
Epoch 138/150
 - 0s - loss: 0.4583 - acc: 0.7878
Epoch 139/150
- 0s - loss: 0.4452 - acc: 0.7812
Epoch 140/150
- 0s - loss: 0.4575 - acc: 0.7826
Epoch 141/150
 - 0s - loss: 0.4488 - acc: 0.7839
Epoch 142/150
- 0s - loss: 0.4604 - acc: 0.7786
Epoch 143/150
 - 0s - loss: 0.4548 - acc: 0.7760
Epoch 144/150
 - 0s - loss: 0.4560 - acc: 0.7891
Epoch 145/150
- 0s - loss: 0.4598 - acc: 0.7773
Epoch 146/150
- 0s - loss: 0.4505 - acc: 0.7839
Epoch 147/150
- 0s - loss: 0.4536 - acc: 0.7839
Epoch 148/150
- 0s - loss: 0.4523 - acc: 0.7865
Epoch 149/150
 - 0s - loss: 0.4507 - acc: 0.7760
Epoch 150/150
- 0s - loss: 0.4462 - acc: 0.7878
```

- 0s - loss: 0.4545 - acc: 0.7812

- 0s - loss: 0.4534 - acc: 0.7865

Epoch 136/150

Running this modified example now prints the predictions for each input pattern. We could use these predictions directly in our application if needed