

## ffnn\_trial\_2

Python - Digit Recognizer

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Competition Notebook  
Digit RecognizerRun  
598.0s - CPUPublic Score  
0.87707Best Score  
0.87707 V6

Version 4 of 4

CPU



## FFNN

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```

1 # Importing necessary libraries
2 import pandas as pd
3 import numpy as np
4 from tensorflow import keras
5 from keras.layers import Dense, Reshape, Conv2D, Dropout, Flatten
6 from keras.models import Sequential
7 from keras.utils import np_utils
8 from keras.datasets import mnist
9 from sklearn import metrics
10 import numpy
11 from matplotlib import pyplot as plt
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13 import tensorflow as tf
14 from keras.preprocessing.image import ImageDataGenerator
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```

20-110 test_dataset_y

20-111 array([[ 1.,  0.],
        [ 1.,  0.],
        [ 1.,  0.],
        ...,
        [27999,  0.],
        [27999,  0.],
        [28000,  0.]])

20-112 print(train_dataset.shape)
print(test_dataset_x.shape)
print(test_dataset_y.shape)

(40000, 784)
(10000, 784)
(10000, 2)

20-113 x0 = test_dataset_y[:,0]
x0.shape = (10000,1)

20-114 test_dataset = np.hstack((test_dataset_x[:, :3], x0, test_dataset_x[:, 3:]))

20-115 X_train = train_dataset[:, 1:] .reshape(train_dataset.shape[0],28,28, 1).astype('float32')
X_train = X_train / 255.0

y_train = train_dataset[:,0]

X_test = test_dataset[:, 1:] .reshape(test_dataset.shape[0],28,28, 1).astype('float32')
X_test = X_test / 255.0

y_test = test_dataset[:,0]

20-116 print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)

(40000, 28, 28, 1)
(10000, 28, 28, 1)
(40000,)
(10000,)

20-117 # y_train = np.where(is_categorical(y_train))
# y_test_copy = y_test #for future use
# y_test = np.where(is_categorical(y_test, max_classes = 10))
# print(y_train.shape)
# print(y_test.shape)

20-118 model=tf.keras.models.Sequential()
model.add(tf.keras.layers.Flatten(input_shape=(28,28,1)))
model.add(tf.keras.layers.Dense(512,activation='relu'))
model.add(tf.keras.layers.Dense(256,activation='relu'))
model.add(tf.keras.layers.Dense(128,activation='relu'))
model.add(tf.keras.layers.Dense(64,activation='relu'))
model.add(tf.keras.layers.Dense(32,activation='relu'))
model.add(tf.keras.layers.Dense(16,activation='relu'))
model.add(tf.keras.layers.Dense(8,activation='softmax'))

```

```

model.fit(x=x_train, y=y_train, batch_size=10, epochs=100)
model.summary()

```

```

2022-05-12 00:01:19.700342: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:19.800347: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:19.810446: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:19.811700: I tensorflow/core/platforms/cpu_feature_guard.cc:142] This
TensorFlow binary is optimized with openCL Deep Neural Network Library (nnl) to use
the following CPU instructions in performance-critical operations: 4002 400132 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate compiler f
lags.
2022-05-12 00:01:19.812707: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:19.813467: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:19.814008: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:21.406872: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:21.406888: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:21.407479: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:91
7] successful NvML node read from SysFS had negative value (-1), but there must be at
least one NvML node, so returning NvML node zero
2022-05-12 00:01:21.408040: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1519] C
reated device /job:localhost/replica:0/task:0/device:GPU:0 with 15480 MB memory: -- d
evice: 0, name: Tesla P100-PCIE-16GB, pci bus id: 0000:00:04:0, compute capability: 6.
0
2022-05-12 00:01:22.408061: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.c
c:105] None of the MLIR Optimization Passes are enabled (registered 2)

```

```

Epoch 1/100
2100/2100 [#####] - 3s 200ms/step - Loss: 0.2782 - accuracy: 0.
0100
Epoch 2/100
2100/2100 [#####] - 3s 200ms/step - Loss: 0.1227 - accuracy: 0.
0641
Epoch 3/100
2100/2100 [#####] - 4s 200ms/step - Loss: 0.0905 - accuracy: 0.
0745
Epoch 4/100
2100/2100 [#####] - 4s 200ms/step - Loss: 0.0706 - accuracy: 0.
0793
Epoch 5/100
2100/2100 [#####] - 5s 200ms/step - Loss: 0.0603 - accuracy: 0.
0829
Epoch 6/100
2100/2100 [#####] - 5s 200ms/step - Loss: 0.0461 - accuracy: 0.
0907
Epoch 7/100
2100/2100 [#####] - 5s 200ms/step - Loss: 0.0472 - accuracy: 0.
0881
Epoch 8/100
2100/2100 [#####] - 4s 200ms/step - Loss: 0.0399 - accuracy: 0.
0906
Epoch 9/100
2100/2100 [#####] - 4s 200ms/step - Loss: 0.0377 - accuracy: 0.
0916
Epoch 10/100

```

2100/2100 [.....] - 4s 20m/step - loss: 0.8287 - accuracy: 0.9928  
 Epoch 11/100  
 2100/2100 [.....] - 4s 20m/step - loss: 0.8229 - accuracy: 0.9936  
 Epoch 12/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8332 - accuracy: 0.9921  
 Epoch 13/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8318 - accuracy: 0.9941  
 Epoch 14/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8338 - accuracy: 0.9923  
 Epoch 15/100  
 2100/2100 [.....] - 4s 20m/step - loss: 0.8191 - accuracy: 0.9951  
 Epoch 16/100  
 2100/2100 [.....] - 4s 20m/step - loss: 0.8199 - accuracy: 0.9949  
 Epoch 17/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8189 - accuracy: 0.9954  
 Epoch 18/100  
 2100/2100 [.....] - 4s 20m/step - loss: 0.8199 - accuracy: 0.9956  
 Epoch 19/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8182 - accuracy: 0.9953  
 Epoch 20/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8156 - accuracy: 0.9963  
 Epoch 21/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8148 - accuracy: 0.9968  
 Epoch 22/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8153 - accuracy: 0.9966  
 Epoch 23/100  
 2100/2100 [.....] - 4s 20m/step - loss: 0.8131 - accuracy: 0.9968  
 Epoch 24/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8154 - accuracy: 0.9964  
 Epoch 25/100  
 2100/2100 [.....] - 4s 20m/step - loss: 0.8146 - accuracy: 0.9967  
 Epoch 26/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8132 - accuracy: 0.9971  
 Epoch 27/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8139 - accuracy: 0.9969  
 Epoch 28/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8129 - accuracy: 0.9974  
 Epoch 29/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8143 - accuracy: 0.9971  
 Epoch 30/100  
 2100/2100 [.....] - 4s 20m/step - loss: 0.8118 - accuracy: 0.9979  
 Epoch 31/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8121 - accuracy: 0.9976  
 Epoch 32/100  
 2100/2100 [.....] - 4s 20m/step - loss: 0.8085 - accuracy: 0.9982  
 Epoch 33/100  
 2100/2100 [.....] - 5s 20m/step - loss: 0.8109 - accuracy: 0.9972  
 Epoch 34/100

2100/2100 [.....] - 5s 2m/step - loss: 0.0121 - accuracy: 0.9977  
 Epoch 35/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0098 - accuracy: 0.9982  
 Epoch 36/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0139 - accuracy: 0.9974  
 Epoch 37/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0093 - accuracy: 0.9983  
 Epoch 38/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0102 - accuracy: 0.9981  
 Epoch 39/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0107 - accuracy: 0.9977  
 Epoch 40/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0109 - accuracy: 0.9979  
 Epoch 41/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0093 - accuracy: 0.9983  
 Epoch 42/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0137 - accuracy: 0.9983  
 Epoch 43/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0177 - accuracy: 0.9973  
 Epoch 44/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0142 - accuracy: 0.9974  
 Epoch 45/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0112 - accuracy: 0.9979  
 Epoch 46/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0084 - accuracy: 0.9985  
 Epoch 47/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0072 - accuracy: 0.9988  
 Epoch 48/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0107 - accuracy: 0.9971  
 Epoch 49/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0069 - accuracy: 0.9988  
 Epoch 50/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0075 - accuracy: 0.9984  
 Epoch 51/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0103 - accuracy: 0.9981  
 Epoch 52/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0068 - accuracy: 0.9988  
 Epoch 53/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0117 - accuracy: 0.9977  
 Epoch 54/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0098 - accuracy: 0.9983  
 Epoch 55/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0139 - accuracy: 0.9982  
 Epoch 56/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0098 - accuracy: 0.9984  
 Epoch 57/100  
 2100/2100 [.....] - 5s 2m/step - loss: 0.0098 - accuracy: 0.9986  
 Epoch 58/100  
 2100/2100 [.....] - 4s 2m/step - loss: 0.0100 - accuracy: 0.9988

```

9378
Epoch 50/100
2100/2100 [#####] - 4s 200/step - loss: 0.0000 - accuracy: 0.9989

Epoch 51/100
2100/2100 [#####] - 5s 200/step - loss: 0.0000 - accuracy: 0.9989

Epoch 52/100
2100/2100 [#####] - 4s 200/step - loss: 0.0129 - accuracy: 0.9989

Epoch 53/100
2100/2100 [#####] - 5s 200/step - loss: 0.0000 - accuracy: 0.9992

Epoch 54/100
2100/2100 [#####] - 5s 200/step - loss: 0.0179 - accuracy: 0.9979

Epoch 55/100
2100/2100 [#####] - 5s 200/step - loss: 0.0123 - accuracy: 0.9988

Epoch 56/100
2100/2100 [#####] - 4s 200/step - loss: 0.0000 - accuracy: 0.9992

Epoch 57/100
2100/2100 [#####] - 4s 200/step - loss: 0.0000 - accuracy: 0.9996

Epoch 58/100
2100/2100 [#####] - 5s 200/step - loss: 0.0109 - accuracy: 0.9992

Epoch 59/100
2100/2100 [#####] - 4s 200/step - loss: 0.0000 - accuracy: 0.9996

Epoch 60/100
2100/2100 [#####] - 5s 200/step - loss: 0.0040 - accuracy: 0.9999

Epoch 61/100
2100/2100 [#####] - 4s 200/step - loss: 0.0100 - accuracy: 0.9974

Epoch 62/100
2100/2100 [#####] - 5s 200/step - loss: 0.0000 - accuracy: 0.9984

Epoch 63/100
2100/2100 [#####] - 4s 200/step - loss: 0.0004 - accuracy: 0.9985

Epoch 64/100
2100/2100 [#####] - 4s 200/step - loss: 0.0000 - accuracy: 0.9984

Epoch 65/100
2100/2100 [#####] - 5s 200/step - loss: 0.0000 - accuracy: 0.9993

Epoch 66/100
2100/2100 [#####] - 4s 200/step - loss: 0.0000 - accuracy: 0.9995

Epoch 67/100
2100/2100 [#####] - 5s 200/step - loss: 0.0100 - accuracy: 0.9983

Epoch 68/100
2100/2100 [#####] - 5s 200/step - loss: 0.0000 - accuracy: 0.9994

Epoch 69/100
2100/2100 [#####] - 5s 200/step - loss: 0.0223 - accuracy: 0.9987

Epoch 70/100
2100/2100 [#####] - 4s 200/step - loss: 0.0113 - accuracy: 0.9989

Epoch 71/100
2100/2100 [#####] - 4s 200/step - loss: 0.0000 - accuracy: 0.9986

Epoch 72/100
2100/2100 [#####] - 4s 200/step - loss: 0.0107 - accuracy: 0.9987

Epoch 73/100
2100/2100 [#####] - 5s 200/step - loss: 0.0000 - accuracy: 0.9990

```

```

9991
Epoch 51/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8115 - accuracy: 0.
9993
Epoch 52/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8129 - accuracy: 0.
9993
Epoch 53/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8102 - accuracy: 0.
9994
Epoch 54/100
2100/2100 [#####] - 4s 200ms/step - loss: 0.8106 - accuracy: 0.
9992
Epoch 55/100
2100/2100 [#####] - 4s 200ms/step - loss: 0.8133 - accuracy: 0.
9994
Epoch 56/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8138 - accuracy: 0.
9993
Epoch 57/100
2100/2100 [#####] - 4s 200ms/step - loss: 0.8067 - accuracy: 0.
9995
Epoch 58/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8081 - accuracy: 0.
9995
Epoch 59/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8103 - accuracy: 0.
9993
Epoch 60/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8120 - accuracy: 0.
9993
Epoch 61/100
2100/2100 [#####] - 4s 200ms/step - loss: 0.8085 - accuracy: 0.
9996
Epoch 62/100
2100/2100 [#####] - 4s 200ms/step - loss: 0.8221 - accuracy: 0.
9998
Epoch 63/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8098 - accuracy: 0.
9997
Epoch 64/100
2100/2100 [#####] - 4s 200ms/step - loss: 0.8095 - accuracy: 0.
9993
Epoch 65/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8187 - accuracy: 0.
9995
Epoch 66/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8144 - accuracy: 0.
9996
Epoch 67/100
2100/2100 [#####] - 5s 200ms/step - loss: 0.8113 - accuracy: 0.
9992
Epoch 68/100
2100/2100 [#####] - 4s 200ms/step - loss: 0.8175 - accuracy: 0.
9979
Model: "sequential"

```

Layer (Type)	Output Shape	Param #
Flatten (Flatten)	(None, 784)	0
Dense (Dense)	(None, 512)	401920
Dense_1 (Dense)	(None, 256)	131200
Dense_2 (Dense)	(None, 128)	32768
Dense_3 (Dense)	(None, 64)	8200
Dense_4 (Dense)	(None, 32)	2048
Dense_5 (Dense)	(None, 10)	320

```
dense_8 (dense) (None, 10) 170
-----
Total params: 577,178
Trainable params: 577,178
Non-trainable params: 0
-----
```

```
In [141]: y_pred = model.predict(X_test)
          y_pred = y_pred.argmax(axis=-1)
          y_pred
```

```
Out[141]: array([2, 9, 9, ..., 9, 9, 2])
```

```
In [142]: #submitting predictions
          sub=pd.read_csv('/kaggle/input/digit-recognizer/sample_submission.csv', header='infer')
          sub['label']=y_pred
          sub.to_csv('submission.csv', index=False)
```

```
In [143]: # prediction = model.predict(X_test)
          # prediction = prediction.argmax(axis=-1)
          # prediction
```

```
In [144]: # print('accuracy score for the MNIST classification of the dataset is :',metrics.accuracy_
          score(y_test, prediction, normalize = True))
          # print(metrics.classification_report(y_test, prediction))
          # print(metrics.confusion_matrix(y_test, prediction))
```

```
In [ ]:
```

```
In [145]: # output = pd.DataFrame({"imageId": [i for i in range(1,len(prediction)+1)], "label": predi
          ction})
          # print(output)
          # output.to_csv('1802240_01_FPM.csv', index=False)
```

#### License

This Notebook has been released under the Apache 2.0 open source license.

## Continue exploring



Data  
1 input and 1 output



Logs  
588.0 second run - successful



Comments  
0 comments

