

Digit Recognizer Summary
Nicholas Bergeland
MSDS 422, Dr. Fulton

Summary:

This week for our assignment I built an algorithm trained to recognize images of numerical digits 1-10. The model I built tested at 99.175% recognition, which was good enough for 378 / 1806 (top 21%).

The model was built and trained with a combination of matplotlib, numpy, seaborn, tensorflow, SKlearn, and Keras. I first read in the testing and training datasets for the various models to work with. From this point, I began understanding the dataset with some basic EDA.

To perform the basic analysis, I used a graph within matplotlib to see the occurrence of different numbers. Is the dataset normally distributed? After observing the normality (shape) of the dataset, I got to work. The work involved some simple encoding, then creation of different layers of the CNN model.














The thing I was not prepared for was how time intensive the model was. Each different visualization model took 45-60 minutes to run through all of the sequences of testing. I found it fascinating to watch the model simulate through “epochs” of data and continually improve itself with no guidance provided by me.

The result was just as impressive. With no structure provided by me, the model was recognizing nearly every number it was presented with. One could argue the 99 + % success rate may be below a human, which would likely get all of the numbers. However, with no prior

learning and in such a short period, it is truly shocking the success the model was able to develop given the timeframe.

Despite placing in the top 25% of this challenge, I will look to improve my model moving forward to next week. Having seen scores testing at 100% recognition, I will set my sights on this mark as I develop my models further.

Kaggle Score:

Overview	Data	Code	Discussion	Leaderboard	Rules	Team	My Submissions	Submit Predictions	...	
363	Harper Corpus							0.99189	1	1mo
364	Kittitouchfah							0.99189	6	20d
365	Qaiser Rafiq							0.99182	4	2mo
366	Yuhang Wei							0.99182	4	21d
367	Pratik Hadiya							0.99182	5	3d
368	Maiols							0.99178	1	2mo
369	ANUJ KUMAR RONIYAR							0.99178	1	1mo
370	Diego Little							0.99178	2	13d
371	Murlocy							0.99175	1	2mo
372	newdm2000							0.99175	1	1mo
373	nick bergeland							0.99175	1	1s
Your First Entry 										
Welcome to the leaderboard!										
374	HARRY7307							0.99171	1	1mo

Appendix:

Out[2]:

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import tensorflow as tf
```

```
In [2]: train = pd.read_csv ( "train2.csv" )
test = pd.read_csv ( "test2.csv" )
train . head ()
```

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	...	pixel774	pixel775
0	1	0	0	0	0	0	0	0	0	0	...		
		0	0										
1	0	0	0	0	0	0	0	0	0	0	...		
		0	0										
2	1	0	0	0	0	0	0	0	0	0	...		
		0	0										
3	4	0	0	0	0	0	0	0	0	0	...		
		0	0										
4	0	0	0	0	0	0	0	0	0	0	...		
		0	0										

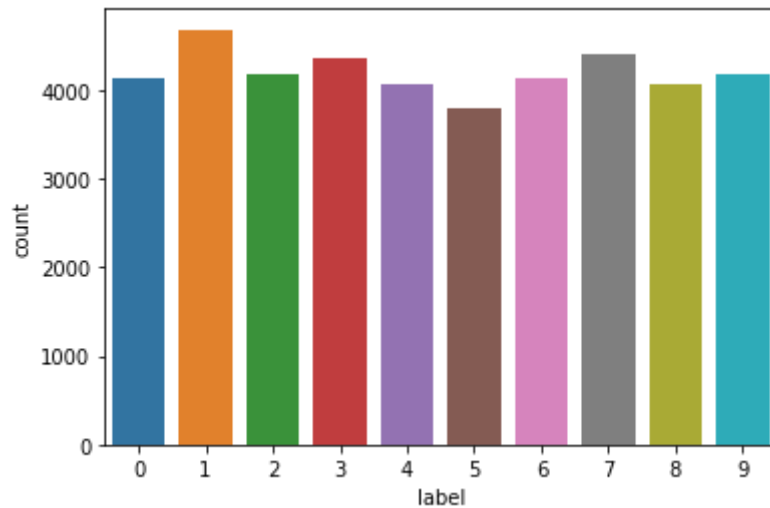
5 rows x 785 columns

```
In [3]: y_train = train['label'].astype('float32')
X_train = train.drop(['label'], axis=1).astype('int32')
X_test = test.astype('float32')
X_train.shape, y_train.shape, X_test.shape
```

Out[3]: ((42000, 784), (42000,), (28000, 784))

In [4]:

```
sns . countplot ( x='label' , data =train );
```



In [5]:

```
# Data normalization  
X_train = X_train / 255  
X_test = X_test / 255
```

In [6]: `X_train = X_train.values.reshape(-1,28,28,1)`
`X_test = X_test.values.reshape(-1,28,28,1)`
`X_train.shape, X_test.shape`

Out[6]: ((42000, 28, 28, 1), (28000, 28, 28, 1))

In [7]: `# one-hot encoding from keras.utils.np_utils`
`import to_categorical y_train = to_categorical(y_train,`
`num_classes = 10) y_train.shape`

Using TensorFlow backend.

Out[7]: (42000, 10)

In [8]:

```
print ( train [ 'label' ] . head ())  
y_train [ 0: 5,:]
```

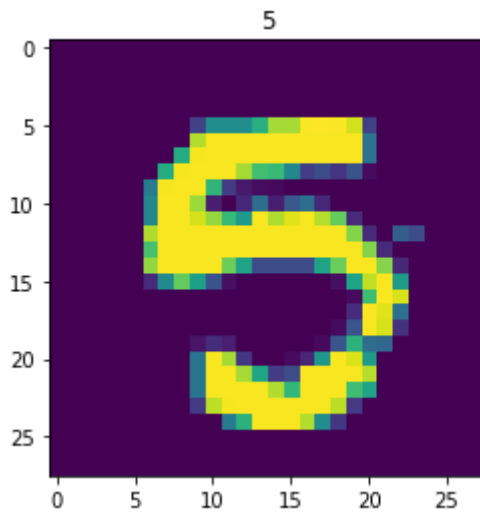
```
0    1  
1    0  
2    1  
3    4  
4    0
```

Name: label, dtype: int64

```
Out[8]: array([[0., 1., 0., 0., 0., 0., 0., 0., 0., 0.], [1., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
               [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
               [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.],
               [1., 0., 0., 0., 0., 0., 0., 0., 0., 0.]], dtype=float32)
```

```
In [9]: from sklearn.model_selection import train_test_split
X_train , X_cv , y_train , y_cv = train_test_split ( X_train , y_train , test_s
ize = 0.1 , random_state = 42 )
```

```
In [10]: plt . imshow ( X_train [ 1][:, :, 0])
plt . title ( y_train [ 1] . argmax ()) ;
```



```
In [11]: from keras.layers import Input, InputLayer, Dense, Activation, ZeroPadding2D,
BatchNormalization, Flatten, Conv2D
from keras.layers import AveragePooling2D, MaxPooling2D, Dropout
from keras.models import Sequential, Model from keras.optimizers
import SGD
from keras.callbacks import ModelCheckpoint, LearningRateScheduler import
keras
from keras import backend as K
```

In [12]: # Building a CNN model

```
input_shape = (28,28,1) X_input =
Input(input_shape)

# layer 1
x = Conv2D(64,(3,3),strides=(1,1),name='layer_conv1',padding='same')(X_input)
x = BatchNormalization()(x) x =
Activation('relu')(x)
x = MaxPooling2D((2,2),name='maxPool1')(x)
# layer 2
x = Conv2D(32,(3,3),strides=(1,1),name='layer_conv2',padding='same')(x) x =
BatchNormalization()(x) x = Activation('relu')(x)
x = MaxPooling2D((2,2),name='maxPool2')(x)
# layer 3
x = Conv2D(32,(3,3),strides=(1,1),name='conv3',padding='same')(x) x =
BatchNormalization()(x) x = Activation('relu')(x)
x = MaxPooling2D((2,2), name='maxPool3')(x)
# fc x =
Flatten()(x)
x = Dense(64,activation='relu',name='fc0')(x) x =
Dropout(0.25)(x)
x = Dense(32,activation='relu',name='fc1')(x) x =
Dropout(0.25)(x)
x = Dense(10,activation='softmax',name='fc2')(x)

conv_model = Model(inputs=X_input, outputs=x, name='Predict') conv_model.summary()
Model: "Predict"
```

Layer (type)	Output Shape	Param #
===== input_1 (InputLayer)	(None, 28, 28, 1)	0
_____ layer_conv1 (Conv2D)	(None, 28, 28, 64)	640
_____ batch_normalization_1 (Batch Normalization)	(None, 28, 28, 64)	256
_____ activation_1 (Activation)	(None, 28, 28, 64)	0
_____ maxPool1 (MaxPooling2D)	(None, 14, 14, 64)	0
_____ layer_conv2 (Conv2D)	(None, 14, 14, 32)	18464
_____ batch_normalization_2 (Batch Normalization)	(None, 14, 14, 32)	128
_____ activation_2 (Activation)	(None, 14, 14, 32)	0

_____	maxPool2 (MaxPooling2D)	(None, 7, 7, 32)	0
_____	conv3 (Conv2D)	(None, 7, 7, 32)	9248
_____	batch_normalization_3 (Batch Normalization)	(None, 7, 7, 32)	128
_____	activation_3 (Activation)	(None, 7, 7, 32)	0
_____	maxPool3 (MaxPooling2D)	(None, 3, 3, 32)	0
_____	flatten_1 (Flatten)	(None, 288)	0
_____	fc0 (Dense)	(None, 64)	18496
_____	dropout_1 (Dropout)	(None, 64)	0
_____	fc1 (Dense)	(None, 32)	2080
_____	dropout_2 (Dropout)	(None, 32)	0
_____	fc2 (Dense)	(None, 10)	330

=====

=====

Total params: 49,770
Trainable params: 49,514
Non-trainable params: 256

In [13]: # Adam optimizer

```
conv_model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
conv_model.fit(X_train, y_train, epochs=10, batch_size=100, validation_data=(X_cv,y_cv))
```

Train on 37800 samples, validate on 4200 samples

Epoch 1/10

37800/37800 [=====] - 144s 4ms/step - loss: 0.4887 - accuracy: 0.8468 - val_loss: 0.6940 - val_accuracy: 0.8188

Epoch 2/10

37800/37800 [=====] - 138s 4ms/step - loss: 0.1349 - accuracy: 0.9610 - val_loss: 0.0763 - val_accuracy: 0.9776

Epoch 3/10

37800/37800 [=====] - 138s 4ms/step - loss: 0.0911 - accuracy: 0.9744 - val_loss: 0.0541 - val_accuracy: 0.9857

Epoch 4/10

37800/37800 [=====] - 138s 4ms/step - loss: 0.

0760 - accuracy: 0.9791 - val_loss: 0.0640 - val_accuracy: 0.9840
Epoch 5/10
37800/37800 [=====] - 138s 4ms/step - loss: 0.
0629 - accuracy: 0.9824 - val_loss: 0.0658 - val_accuracy: 0.9795
Epoch 6/10
37800/37800 [=====] - 142s 4ms/step - loss: 0.
0566 - accuracy: 0.9845 - val_loss: 0.0549 - val_accuracy: 0.9838
Epoch 7/10
37800/37800 [=====] - 139s 4ms/step - loss: 0.
0471 - accuracy: 0.9872 - val_loss: 0.0378 - val_accuracy: 0.9902
Epoch 8/10
37800/37800 [=====] - 139s 4ms/step - loss: 0.
0460 - accuracy: 0.9872 - val_loss: 0.0558 - val_accuracy: 0.9864
Epoch 9/10
37800/37800 [=====] - 139s 4ms/step - loss: 0.
0363 - accuracy: 0.9893 - val_loss: 0.0427 - val_accuracy: 0.9888
Epoch 10/10
37800/37800 [=====] - 140s 4ms/step - loss: 0.
0366 - accuracy: 0.9899 - val_loss: 0.0680 - val_accuracy: 0.9850

Out[13]: <keras.callbacks.callbacks.History at 0x7f8bee1d2850>

```
In [14]: # SGD optimizer sgd = SGD(lr=0.0005, momentum=0.5, decay=0.0, nesterov=False)
conv_model.compile(optimizer=sgd,loss='categorical_crossentropy',metrics
=['accuracy'])
conv_model.fit(X_train, y_train, epochs=30, validation_data=(X_cv, y_cv
))
```


Train on 37800 samples, validate on 4200 samples

Epoch 1/30

37800/37800 [=====] - 173s 5ms/step - loss: 0.0288 - accuracy: 0.9922 - val_loss: 0.0345 - val_accuracy: 0.9929

Epoch 2/30

37800/37800 [=====] - 170s 5ms/step - loss: 0.0237 - accuracy: 0.9937 - val_loss: 0.0337 - val_accuracy: 0.9929

Epoch 3/30

37800/37800 [=====] - 172s 5ms/step - loss: 0.0208 - accuracy: 0.9943 - val_loss: 0.0327 - val_accuracy: 0.9929

Epoch 4/30

37800/37800 [=====] - 1599s 42ms/step - loss: 0.0188 - accuracy: 0.9949 - val_loss: 0.0327 - val_accuracy: 0.9938

Epoch 5/30

37800/37800 [=====] - 1359s 36ms/step - loss: 0.0192 - accuracy: 0.9947 - val_loss: 0.0330 - val_accuracy: 0.9926

Epoch 6/30

37800/37800 [=====] - 322s 9ms/step - loss: 0.0178 - accuracy: 0.9951 - val_loss: 0.0327 - val_accuracy: 0.9929

Epoch 7/30

37800/37800 [=====] - 1389s 37ms/step - loss: 0.0183 - accuracy: 0.9947 - val_loss: 0.0323 - val_accuracy: 0.9933

Epoch 8/30

37800/37800 [=====] - 2006s 53ms/step - loss: 0.0186 - accuracy: 0.9948 - val_loss: 0.0320 - val_accuracy: 0.9933

Epoch 9/30

37800/37800 [=====] - 1214s 32ms/step - loss: 0.0162 - accuracy: 0.9960 - val_loss: 0.0321 - val_accuracy: 0.9938

Epoch 10/30

37800/37800 [=====] - 177s 5ms/step - loss: 0.0172 - accuracy: 0.9952 - val_loss: 0.0324 - val_accuracy: 0.9938

Epoch 11/30

37800/37800 [=====] - 174s 5ms/step - loss: 0.0166 - accuracy: 0.9957 - val_loss: 0.0329 - val_accuracy: 0.9940

Epoch 12/30

37800/37800 [=====] - 172s 5ms/step - loss: 0.0170 - accuracy: 0.9952 - val_loss: 0.0325 - val_accuracy: 0.9940

Epoch 13/30

37800/37800 [=====] - 568s 15ms/step - loss: 0.0169 - accuracy: 0.9953 - val_loss: 0.0319 - val_accuracy: 0.9943

Epoch 14/30

37800/37800 [=====] - 180s 5ms/step - loss: 0.0158 - accuracy: 0.9958 - val_loss: 0.0321 - val_accuracy: 0.9938

Epoch 15/30

37800/37800 [=====] - 179s 5ms/step - loss: 0.0156 - accuracy: 0.9959 - val_loss: 0.0321 - val_accuracy: 0.9938
Epoch 16/30
37800/37800 [=====] - 179s 5ms/step - loss: 0.0148 - accuracy: 0.9963 - val_loss: 0.0324 - val_accuracy: 0.9936
Epoch 17/30
37800/37800 [=====] - 181s 5ms/step - loss: 0.0163 - accuracy: 0.9953 - val_loss: 0.0328 - val_accuracy: 0.9938
Epoch 18/30
37800/37800 [=====] - 180s 5ms/step - loss: 0.0153 - accuracy: 0.9958 - val_loss: 0.0328 - val_accuracy: 0.9936
Epoch 19/30
37800/37800 [=====] - 184s 5ms/step - loss: 0.0159 - accuracy: 0.9958 - val_loss: 0.0331 - val_accuracy: 0.9938
Epoch 20/30
37800/37800 [=====] - 181s 5ms/step - loss: 0.0137 - accuracy: 0.9963 - val_loss: 0.0329 - val_accuracy: 0.9938
Epoch 21/30
37800/37800 [=====] - 180s 5ms/step - loss: 0.0153 - accuracy: 0.9959 - val_loss: 0.0325 - val_accuracy: 0.9936
Epoch 22/30
37800/37800 [=====] - 180s 5ms/step - loss: 0.0154 - accuracy: 0.9958 - val_loss: 0.0325 - val_accuracy: 0.9933
Epoch 23/30
37800/37800 [=====] - 182s 5ms/step - loss: 0.0151 - accuracy: 0.9957 - val_loss: 0.0324 - val_accuracy: 0.9936
Epoch 24/30
37800/37800 [=====] - 182s 5ms/step - loss: 0.0152 - accuracy: 0.9958 - val_loss: 0.0328 - val_accuracy: 0.9938
Epoch 25/30
37800/37800 [=====] - 183s 5ms/step - loss: 0.0134 - accuracy: 0.9966 - val_loss: 0.0323 - val_accuracy: 0.9940
Epoch 26/30
37800/37800 [=====] - 182s 5ms/step - loss: 0.0145 - accuracy: 0.9959 - val_loss: 0.0323 - val_accuracy: 0.9943
Epoch 27/30
37800/37800 [=====] - 187s 5ms/step - loss: 0.0130 - accuracy: 0.9965 - val_loss: 0.0326 - val_accuracy: 0.9938
Epoch 28/30
37800/37800 [=====] - 182s 5ms/step - loss: 0.0137 - accuracy: 0.9960 - val_loss: 0.0324 - val_accuracy: 0.9940
Epoch 29/30
37800/37800 [=====] - 183s 5ms/step - loss: 0.0139 - accuracy: 0.9961 - val_loss: 0.0329 - val_accuracy: 0.9936

Epoch 30/30
37800/37800 [=====] - 184s 5ms/step - loss: 0.
0151 - accuracy: 0.9958 - val_loss: 0.0326 - val_accuracy: 0.9933

Out[14]: <keras.callbacks.callbacks.History at 0x7f8bf7b7c350>

```
In [16]: y_pred = conv_model.predict(X_test) y_pred =  
np.argmax(y_pred,axis=1)  
my_submission = pd.DataFrame({'ImageId': list(range(1, len(y_pred)+1)),  
'Label': y_pred}) my_submission.to_csv('dig_submission.csv', index=False)
```

In []:

Works Cited:

sriram2397. "Digit-Recognizer-Kaggle/digit_recognizer.ipynb at Master · SRIRAM2397/Digit-Recognizer-Kaggle." GitHub. Accessed February 6, 2022. https://github.com/sriram2397/digit-recognizer-kaggle/blob/master/Digit_Recognizer.ipynb.