MNIST_Kaggle

February 9, 2020

1 Soupir Kaggle MNIST Notebook

1.1 Importing

Since my GPU is AMD (RX 480 8 GB; OC'd to 1400MHz clock and VRAM to 2150 MHz), I used PlaidML for Keras in order to use it, rather than trying to get it to run on CPU. Previous testing had shown about a 7x improvement with GPU over CPU times.

[1]:
```
import plaidml.keras
plaidml.keras.install_backend()
```

[2]:
```
import tensorflow as tf
#from tensorflow import set_random_seed
#set_random_seed(333)

import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras.layers.normalization import BatchNormalization
from keras import backend as K
from keras.models import Model
from keras.preprocessing.image import ImageDataGenerator

from sklearn.model_selection import train_test_split

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
%matplotlib inline

import time
```

1.2 Importing Data

[3]:
```
test = pd.read_csv("test.csv")
train = pd.read_csv("train.csv")
```

View the shape of the train and test data frames and the head of the data. Give some idea of the data that is being worked with.

[4]:
```
print(train.shape)
train.head()
```

```
(42000, 785)
```

[4]:
```
   label  pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  \
0      1       0       0       0       0       0       0       0       0
1      0       0       0       0       0       0       0       0       0
2      1       0       0       0       0       0       0       0       0
3      4       0       0       0       0       0       0       0       0
4      0       0       0       0       0       0       0       0       0

   pixel8  ...  pixel774  pixel775  pixel776  pixel777  pixel778  pixel779  \
0       0  ...         0         0         0         0         0         0
1       0  ...         0         0         0         0         0         0
2       0  ...         0         0         0         0         0         0
3       0  ...         0         0         0         0         0         0
4       0  ...         0         0         0         0         0         0

   pixel780  pixel781  pixel782  pixel783
0         0         0         0         0
1         0         0         0         0
2         0         0         0         0
3         0         0         0         0
4         0         0         0         0

[5 rows x 785 columns]
```

[5]:
```
print(test.shape)
test.head()
```

```
(28000, 784)
```

[5]:
```
   pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  pixel8  \
0       0       0       0       0       0       0       0       0       0
1       0       0       0       0       0       0       0       0       0
2       0       0       0       0       0       0       0       0       0
3       0       0       0       0       0       0       0       0       0
4       0       0       0       0       0       0       0       0       0

   pixel9  ...  pixel774  pixel775  pixel776  pixel777  pixel778  pixel779  \
```

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

   pixel780  pixel781  pixel782  pixel783
0         0         0         0         0
1         0         0         0         0
2         0         0         0         0
3         0         0         0         0
4         0         0         0         0

[5 rows x 784 columns]
```

Using the train data frame to create the training data as well as the response for training. Then the data frames are then viewed.

[6]:
```
X_train = (train.iloc[:,1:].values).astype('float32') # all pixel values
y_train = train.iloc[:,0].values.astype('int32') # only labels i.e targets␣
 ↪digits
X_test = test.values.astype('float32')
```

[7]:
```
X_train
```

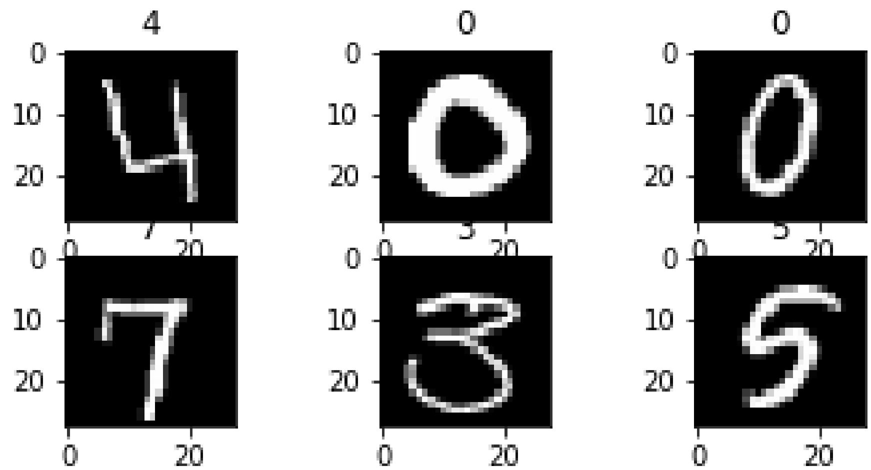
[7]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]], dtype=float32)
```

[8]:
```
y_train
```

[8]:
```
array([1, 0, 1, ..., 7, 6, 9])
```

Read somewhere that Keras doesn't automatically detect the dimensions of the images that are being worked with so it has to be reshaped for it to pick it up. Then viewing 6 of the images.

[9]:
```
#Convert train datset to (num_images, img_rows, img_cols) format
X_train = X_train.reshape(X_train.shape[0], 28, 28)

for i in range(3, 9):
    plt.subplot(330 + (i+1))
    plt.imshow(X_train[i], cmap=plt.get_cmap('gray'))
    plt.title(y_train[i]);
```



[10]:
```
#expand 1 more dimention as 1 for colour channel gray
X_train = X_train.reshape(X_train.shape[0], 28, 28,1)
X_train.shape
```

[10]:
```
(42000, 28, 28, 1)
```

[11]:
```
X_test = X_test.reshape(X_test.shape[0], 28, 28,1)
X_test.shape
```

[11]:
```
(28000, 28, 28, 1)
```

Setting some variables to be used later for training the CNN. Also, the data off of Kaggle is pixel values, from 0 to 255. Dividing these values by 255 will standardize them between 0 and 1. I have generally done something similar to this when working with data that is continuous without a set max like this is, but it seems to be fairly common practice to keep it between 0 and 1 to prevent bias in predictors that are way higher than others and are mostly unrelated (such as using different experimental results; not using images)

[12]:
```
batch_size = 128
num_classes = 10
epochs = 20
```

[13]:
```
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255
X_test /= 255
print('X_train shape:', X_train.shape)
print(X_train.shape[0], 'train samples')
print(X_test.shape[0], 'test samples')
```

```
X_train shape: (42000, 28, 28, 1)
42000 train samples
28000 test samples
```

Convert response variable to categorical rather than numerical (an image of 1.1 doesn't make sense).

[14]:
```
# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
```

[15]:
```
num_classes = y_train.shape[1]
num_classes
```

[15]:
```
10
```

Need to set a random seed when splitting the data to keep it reproducible from run to run. The annotated training data is then split to a 90% training set and a 10% validation set for keras.

[16]:
```
np.random.seed(333)
```

[17]:
```
X = X_train
y = y_train
X_train, X_val, y_train, y_val = train_test_split(X_train,
                                                  y_train,
                                                  test_size=0.10,
                                                  random_state=42)
```

[18]:
```
print(X_train.shape)
print(y_train.shape)
print("\n")
print(X_val.shape)
print(y_val.shape)
```

```
(37800, 28, 28, 1)
(37800, 10)



(4200, 28, 28, 1)
(4200, 10)
```

Time to build the model! Here several convolutional layers are created with a 3x3 scanning window. I mostly just guessed and after training a handful of tries, I settled on 2x 32 conv layers, 2x 65 conv layers, 1x 128 conv layer, then a dropout followed by a 256 dense layer and another, larger, dropout before a final dense layer with the same number of outputs as the number of classes that is being predicted (10). The model is then compiled and fit using the train test splits of the annotated training data.

[19]:
```
input_shape = (28, 28, 1)
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
model.add(Conv2D(32, (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(Conv2D(64, (3, 3), activation='relu'))
```

```
model.add(BatchNormalization())
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(BatchNormalization())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(Dense(num_classes, activation='softmax'))
```

```
INFO:plaidml:Opening device "opencl_amd_ellesmere.0"
```

[20]:
```
model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])
```

[21]:
```
start_time = time.time()
model.fit(X_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(X_val, y_val))
print("--- %s seconds ---" % (time.time() - start_time))
```

```
Train on 37800 samples, validate on 4200 samples
Epoch 1/20
37800/37800 [==============================] - 63s 2ms/step - loss: 0.1353 -
acc: 0.9601 - val_loss: 1.3904 - val_acc: 0.4562
Epoch 2/20
37800/37800 [==============================] - 28s 751us/step - loss: 0.0548 -
acc: 0.9838 - val_loss: 0.0854 - val_acc: 0.9724
Epoch 3/20
37800/37800 [==============================] - 28s 753us/step - loss: 0.0371 -
acc: 0.9889 - val_loss: 0.0555 - val_acc: 0.9824
Epoch 4/20
37800/37800 [==============================] - 28s 750us/step - loss: 0.0275 -
acc: 0.9920 - val_loss: 0.0450 - val_acc: 0.9869
Epoch 5/20
37800/37800 [==============================] - 28s 751us/step - loss: 0.0226 -
acc: 0.9934 - val_loss: 0.0296 - val_acc: 0.9905
Epoch 6/20
37800/37800 [==============================] - 28s 752us/step - loss: 0.0186 -
acc: 0.9947 - val_loss: 0.0305 - val_acc: 0.9900
Epoch 7/20
37800/37800 [==============================] - 28s 748us/step - loss: 0.0139 -
```

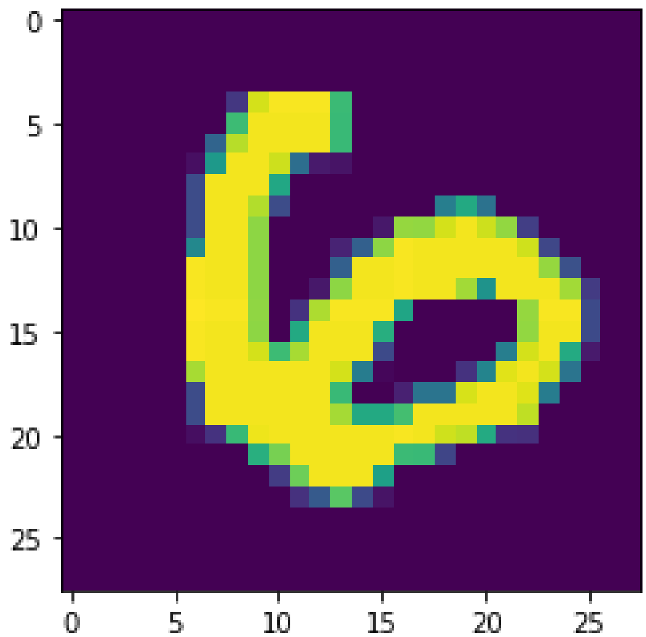
```
acc: 0.9959 - val_loss: 0.0309 - val_acc: 0.9893
Epoch 8/20
37800/37800 [==============================] - 28s 750us/step - loss: 0.0131 -
acc: 0.9960 - val_loss: 0.0212 - val_acc: 0.9924
Epoch 9/20
37800/37800 [==============================] - 28s 749us/step - loss: 0.0109 -
acc: 0.9965 - val_loss: 0.0265 - val_acc: 0.9910
Epoch 10/20
37800/37800 [==============================] - 28s 750us/step - loss: 0.0090 -
acc: 0.9974 - val_loss: 0.0177 - val_acc: 0.9936
Epoch 11/20
37800/37800 [==============================] - 29s 754us/step - loss: 0.0073 -
acc: 0.9979 - val_loss: 0.0196 - val_acc: 0.9933
Epoch 12/20
37800/37800 [==============================] - 28s 749us/step - loss: 0.0066 -
acc: 0.9980 - val_loss: 0.0210 - val_acc: 0.9924
Epoch 13/20
37800/37800 [==============================] - 28s 749us/step - loss: 0.0057 -
acc: 0.9981 - val_loss: 0.0227 - val_acc: 0.9933
Epoch 14/20
37800/37800 [==============================] - 28s 748us/step - loss: 0.0046 -
acc: 0.9987 - val_loss: 0.0218 - val_acc: 0.9936
Epoch 15/20
37800/37800 [==============================] - 28s 747us/step - loss: 0.0050 -
acc: 0.9985 - val_loss: 0.0200 - val_acc: 0.9938
Epoch 16/20
37800/37800 [==============================] - 28s 749us/step - loss: 0.0036 -
acc: 0.9990 - val_loss: 0.0162 - val_acc: 0.9952
Epoch 17/20
37800/37800 [==============================] - 28s 751us/step - loss: 0.0032 -
acc: 0.9990 - val_loss: 0.0199 - val_acc: 0.9931
Epoch 18/20
37800/37800 [==============================] - 29s 759us/step - loss: 0.0032 -
acc: 0.9991 - val_loss: 0.0240 - val_acc: 0.9924
Epoch 19/20
37800/37800 [==============================] - 28s 753us/step - loss: 0.0028 -
acc: 0.9993 - val_loss: 0.0306 - val_acc: 0.9912
Epoch 20/20
37800/37800 [==============================] - 28s 753us/step - loss: 0.0027 -
acc: 0.9993 - val_loss: 0.0229 - val_acc: 0.9919
--- 602.9864394664764 seconds ---
```

I've always been interested in how the different layers look like so I displayed each different step of the model to see how the conv layers were changing in what they were looking for.

[22]:
```
layer_outputs = [layer.output for layer in model.layers]
activation_model = Model(inputs=model.input, outputs=layer_outputs)
activations = activation_model.predict(X_train[10].reshape(1,28,28,1))
```

```
def display_activation(activations, col_size, row_size, act_index):
    activation = activations[act_index]
    activation_index=0
    fig, ax = plt.subplots(row_size, col_size, figsize=(row_size*2.5,col_size*1.
 ↪5))
    for row in range(0,row_size):
        for col in range(0,col_size):
            ax[row][col].imshow(activation[0, :, :, activation_index],␣
 ↪cmap='gray')
            activation_index += 1
```

[23]:
```
plt.imshow(X_train[10][:,:,0]);
```



[24]:
```
model.summary()
```

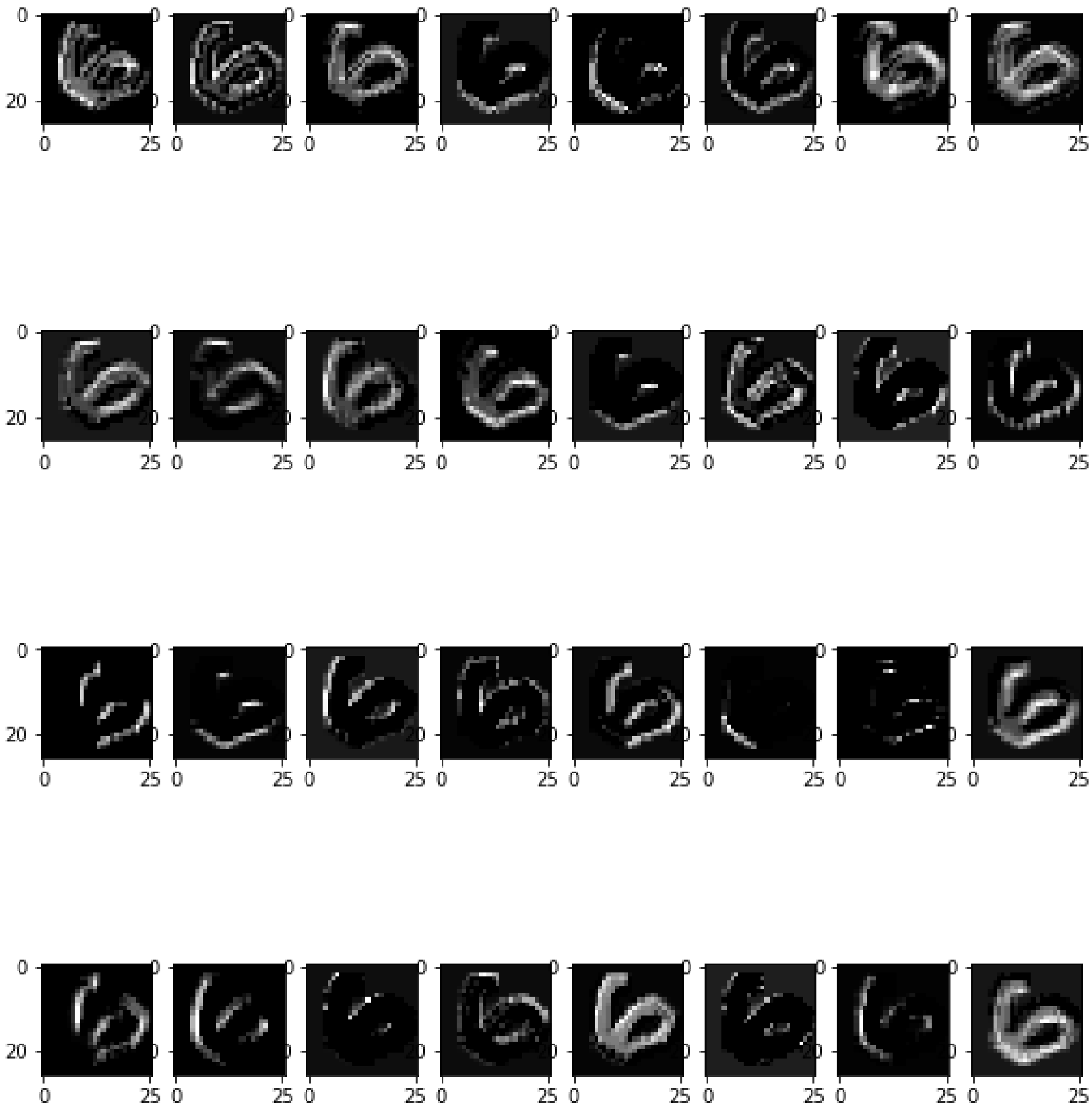
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320       
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 24, 24, 32)        9248      
_________________________________________________________________
batch_normalization_1 (Batch (None, 24, 24, 32)        128       
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 22, 22, 64)        18496     
```

```
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 20, 20, 64)        36928
_________________________________________________________________
batch_normalization_2 (Batch (None, 20, 20, 64)        256
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 18, 18, 128)       73856
_________________________________________________________________
batch_normalization_3 (Batch (None, 18, 18, 128)       512
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 9, 9, 128)         0
_________________________________________________________________
dropout_1 (Dropout)          (None, 9, 9, 128)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 10368)             0
_________________________________________________________________
batch_normalization_4 (Batch (None, 10368)             41472
_________________________________________________________________
dense_1 (Dense)              (None, 256)               2654464
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
batch_normalization_5 (Batch (None, 256)               1024
_________________________________________________________________
dense_2 (Dense)              (None, 10)                2570
=================================================================
Total params: 2,839,274
Trainable params: 2,817,578
Non-trainable params: 21,696
_________________________________________________________________
```

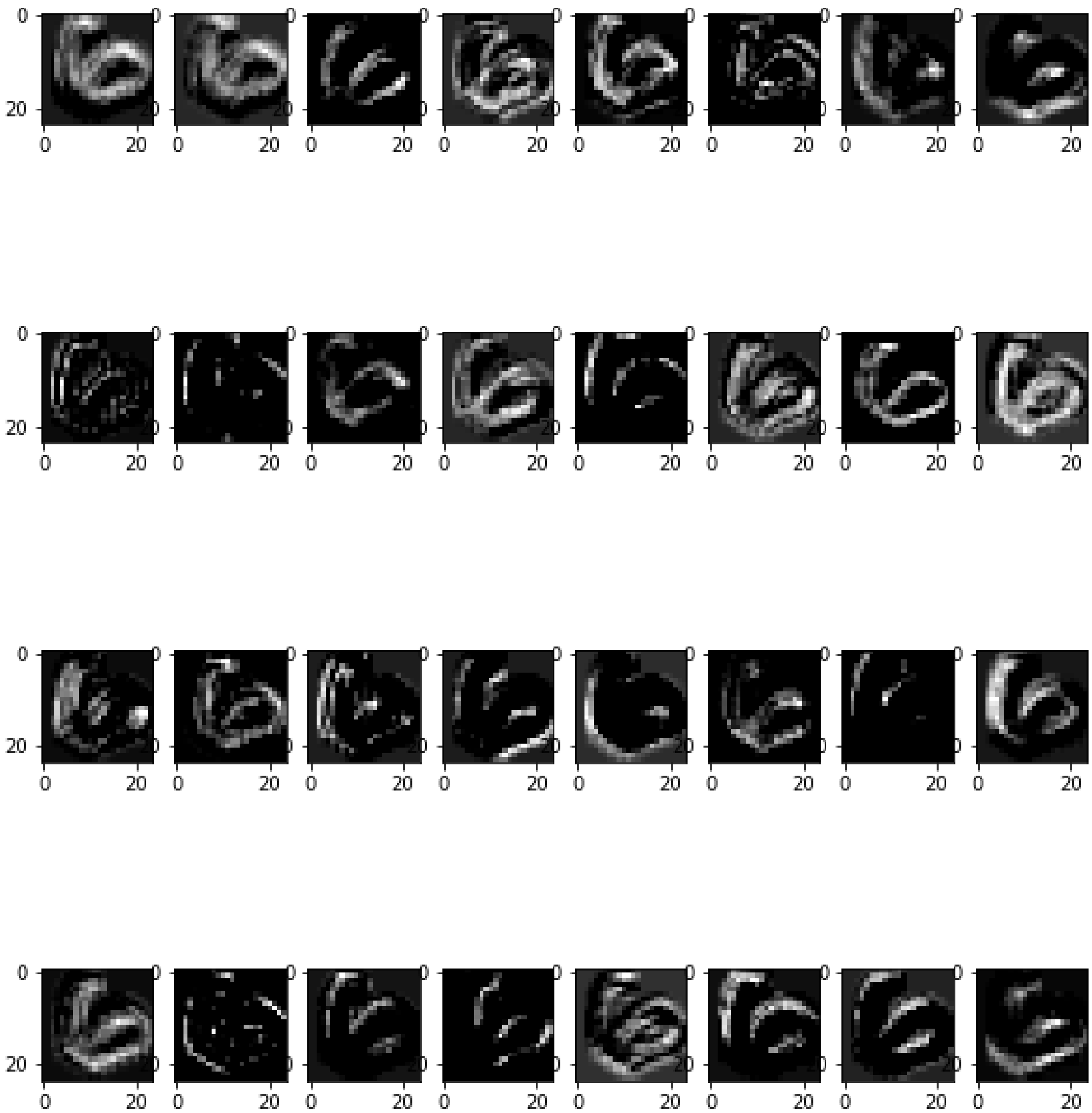
[25]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from keras.utils.vis_utils import plot_model
```

[26]:
```
plot_model(model, show_shapes=True, show_layer_names=True)
```

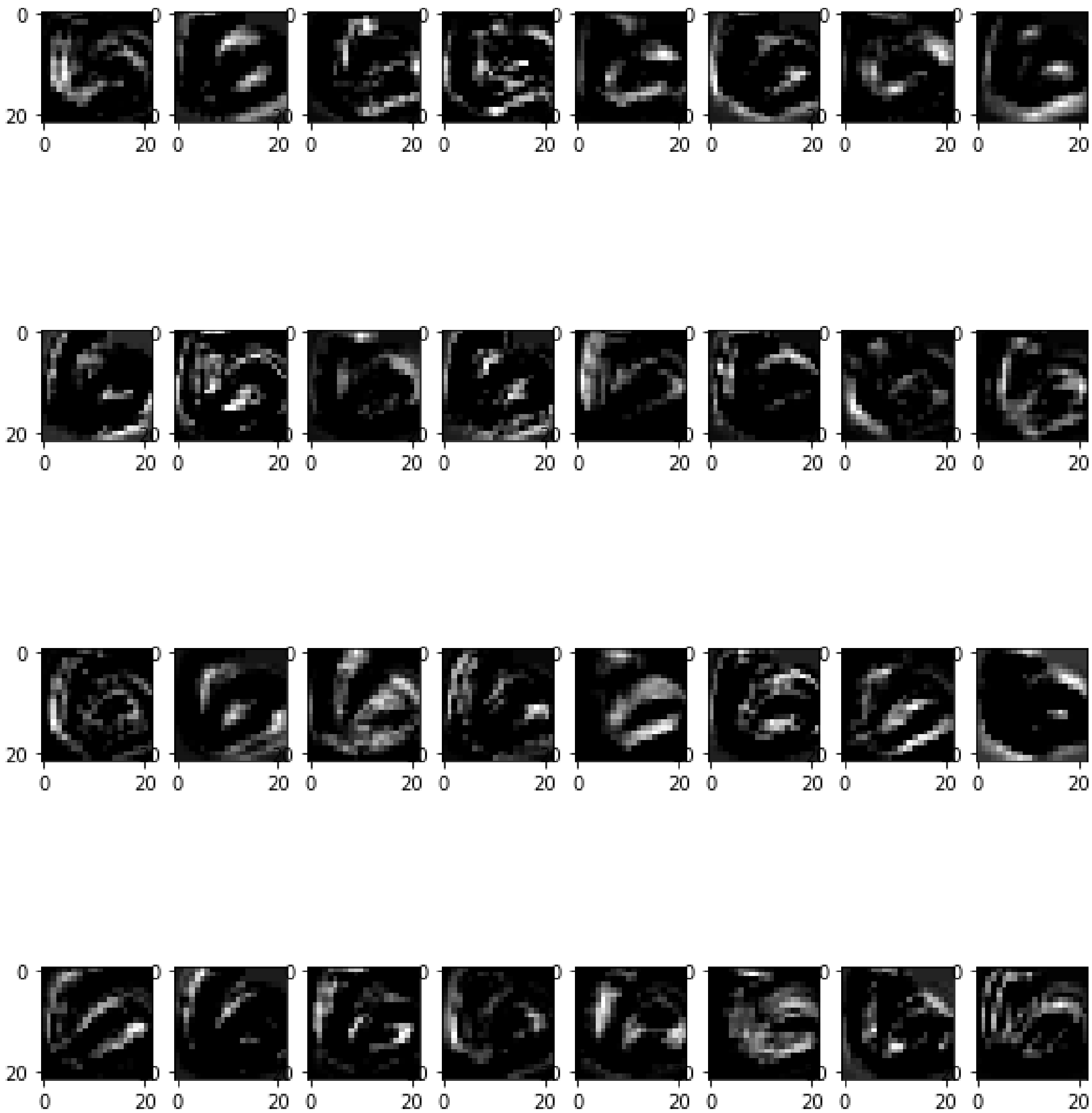
[27]:
```
display_activation(activations, 8, 4, 0)
```



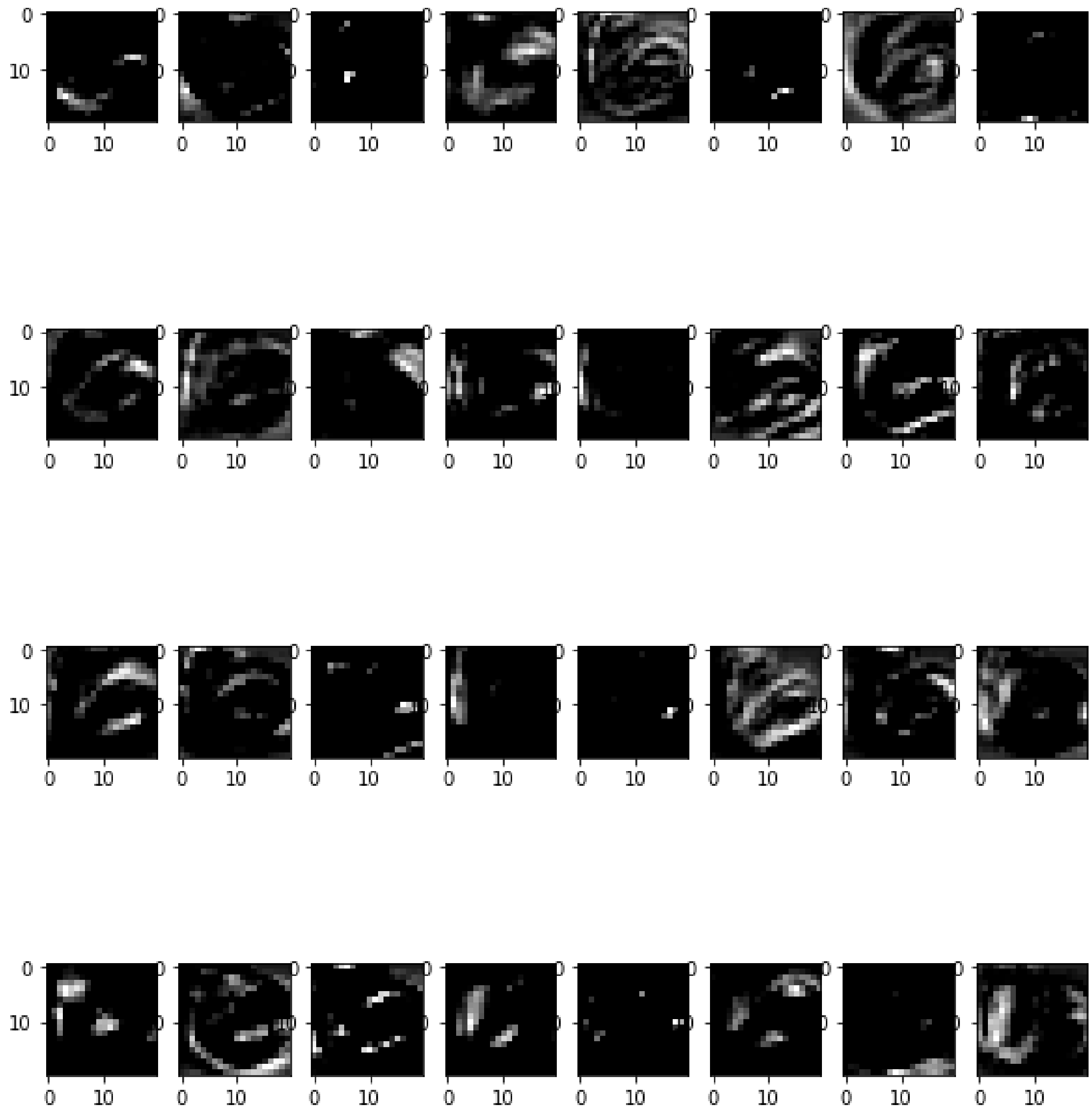
[28]:
```
display_activation(activations, 8, 4, 1)
```



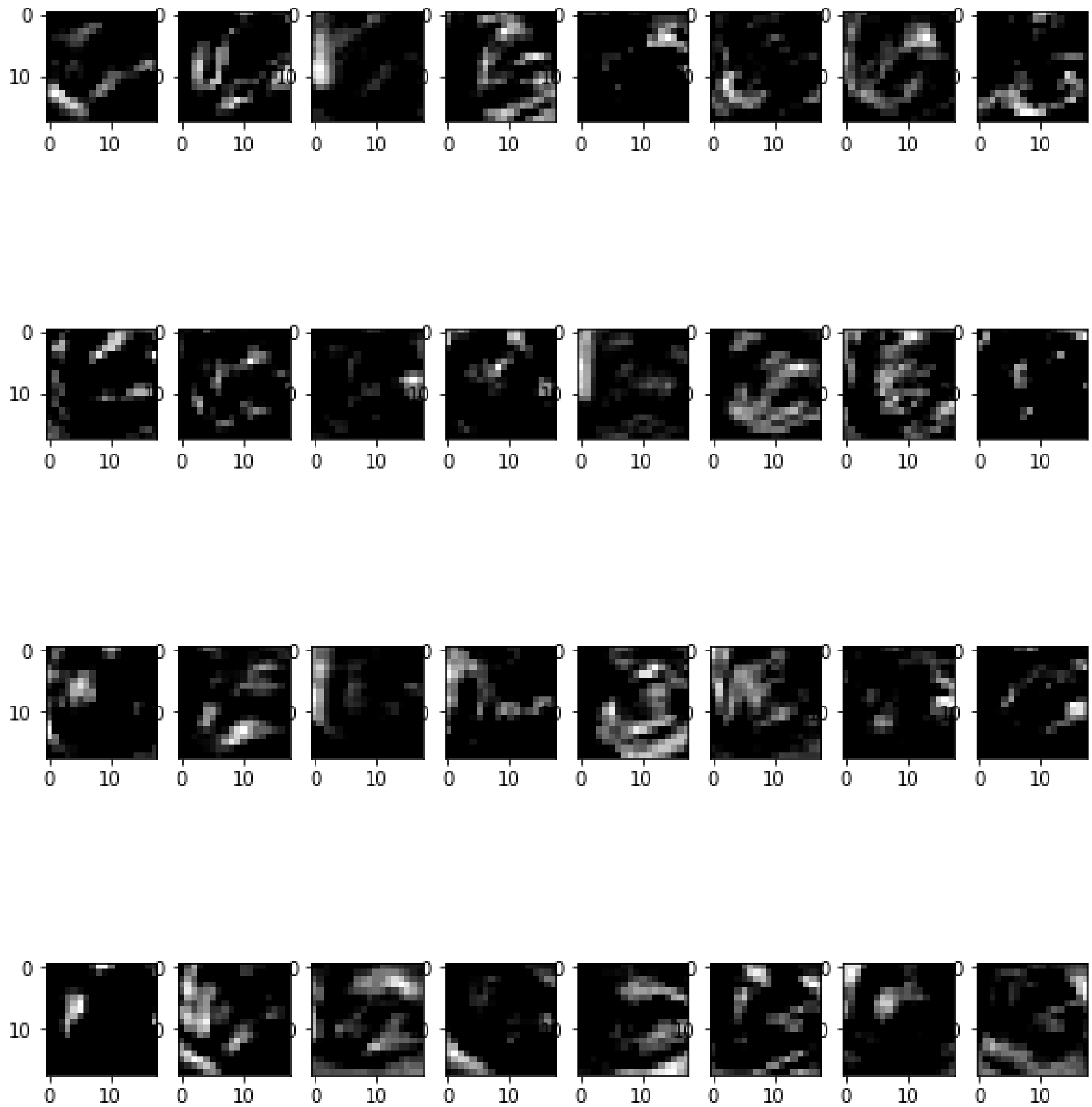
[29]:
```
display_activation(activations, 8, 4, 3)
```



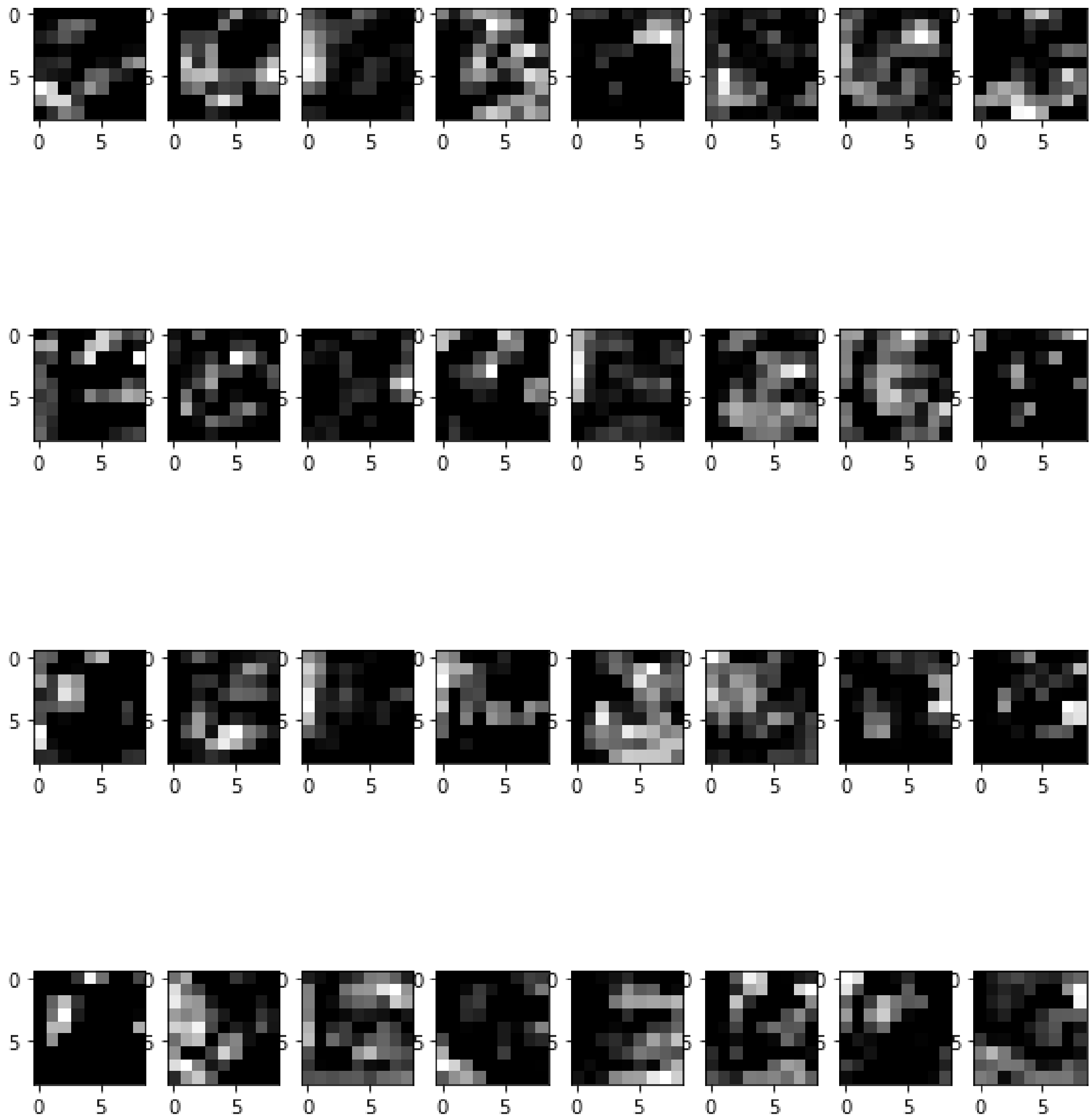
[30]:
```
display_activation(activations, 8, 4, 4)
```



[31]:
```
display_activation(activations, 8, 4, 6)
```



[32]:
```
display_activation(activations, 8, 4, 8)
```



Now that the model is trained and has been looked at, time to make predictions for submissions

[33]:
```
predictions = model.predict_classes(X_test, verbose=0)
print(predictions)
```

```
[2 0 9 ... 3 9 2]
```

[34]:
```
submission = pd.DataFrame({"ImageID":list(range(1,len(predictions)+1)),
                           "Label":predictions})
```

[35]:
```
#submission.to_csv("Soupir_results6.csv", index=False, header=True)
```

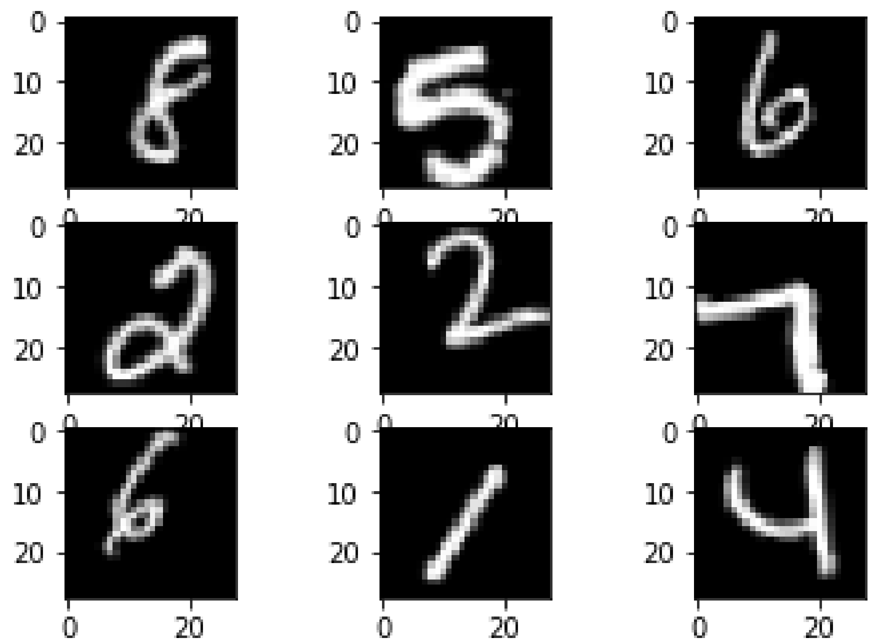
Saw online that some were recommending generating images with different wobbles and scaling to better train the model.

[36]:
```
datagen = ImageDataGenerator(
        featurewise_center=True,  # set input mean to 0 over the dataset
        samplewise_center=False,  # set each sample mean to 0
        featurewise_std_normalization=True,  # divide inputs by std of the␣
 ↪dataset
        samplewise_std_normalization=False,  # divide each input by its std
        zca_whitening=False,  # apply ZCA whitening
        rotation_range=10,  # randomly rotate images in the range (degrees, 0␣
 ↪to 180)
        zoom_range = 0.1, # Randomly zoom image
        width_shift_range=0.1,  # randomly shift images horizontally (fraction␣
 ↪of total width)
        height_shift_range=0.1,  # randomly shift images vertically (fraction␣
 ↪of total height)
        horizontal_flip=False,  # randomly flip images
        vertical_flip=False)  # randomly flip images

# X_train, X_val, y_train, y_val

datagen.fit(X_train)
```

There seemed to be a limit to the number of generated images that can be made (or at least I was not able to figure out how to overcome the limit which is something like 33,400 images), so here following what someone else had done I just created 64.

My final submission though was just using the same data as before but letting Keras perform the split as 80/20 train/test. The generator didn't seem practical with the low number of generated images.

[37]:
```
for X_batch, y_batch in datagen.flow(X_train, y_train, batch_size=64,␣
 ↪shuffle=False, seed=333):
    # create a grid of 3x3 images
    for i in range(0, 9):
        plt.subplot(330 + 1 + i)
        plt.imshow(X_batch[i].reshape(28, 28), cmap=plt.get_cmap('gray'))
    # show the plot
    plt.show()
    break
```



[38]:
```
len(X_batch)
```

[38]: 64

To save time, I only have this notebook running 10 epochs but the final submission that I made used 500 (DEFINITELY hit the ceiling on diminishing returns but YOLO). This final one received a score of **0.99542** when submitted on kaggle, which is better than the previous submissions which were around **0.99071** to **0.99328**.

[39]:
```
model.fit(X, y, batch_size = batch_size, validation_split=0.2, epochs=10,␣
 ↪verbose=1)
```

```
Train on 33600 samples, validate on 8400 samples
Epoch 1/10
33600/33600 [==============================] - 44s 1ms/step - loss: 0.0070 -
acc: 0.9977 - val_loss: 0.0042 - val_acc: 0.9988
Epoch 2/10
33600/33600 [==============================] - 26s 782us/step - loss: 0.0050 -
acc: 0.9982 - val_loss: 0.0040 - val_acc: 0.9993
Epoch 3/10
33600/33600 [==============================] - 26s 780us/step - loss: 0.0045 -
acc: 0.9987 - val_loss: 0.0034 - val_acc: 0.9993
Epoch 4/10
33600/33600 [==============================] - 26s 782us/step - loss: 0.0032 -
acc: 0.9990 - val_loss: 0.0033 - val_acc: 0.9992
Epoch 5/10
33600/33600 [==============================] - 26s 781us/step - loss: 0.0023 -
acc: 0.9995 - val_loss: 0.0024 - val_acc: 0.9993
```

```
Epoch 6/10
33600/33600 [==============================] - 26s 783us/step - loss: 0.0023 -
acc: 0.9992 - val_loss: 0.0033 - val_acc: 0.9989
Epoch 7/10
33600/33600 [==============================] - 26s 781us/step - loss: 0.0018 -
acc: 0.9996 - val_loss: 0.0018 - val_acc: 0.9995
Epoch 8/10
33600/33600 [==============================] - 26s 782us/step - loss: 0.0021 -
acc: 0.9995 - val_loss: 0.0022 - val_acc: 0.9993 - loss: 0.0021 - acc: 0.
Epoch 9/10
33600/33600 [==============================] - 26s 779us/step - loss: 0.0012 -
acc: 0.9996 - val_loss: 0.0028 - val_acc: 0.9990
Epoch 10/10
33600/33600 [==============================] - 26s 780us/step - loss: 0.0015 -
acc: 0.9996 - val_loss: 0.0033 - val_acc: 0.9990
```

[39]:
```
<keras.callbacks.History at 0x19d6ca834a8>
```

[40]:
```
predictions = model.predict_classes(X_test, verbose=0)
submission = pd.DataFrame({"ImageID":list(range(1,len(predictions)+1)),
                           "Label":predictions})
submission.to_csv("Soupir_results_github.csv", index=False, header=True)
```