Handwritten Recognition via Convolutional Neural Network

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2 Introduction

In this project, we implement two methods to recognize MNIST dataset.

One is to code the VGG-16 from scratch and train it with the MNIST from the very beginning, another method is to train MNISR with existing VGG-16 weight drawn from Imagenet dataset. Specifically, we will discuss the prediction capability after freezing all convolutional layers or freezing all fully connected layers. This will help us to learn the power of different layers in convolutional neural network. Before doing the experiment, we hypothesize that fully connected layer is vital crucial. Without it, the whole nerual network will perform extremely worse. Conversely, convolional layer doesn't play an important layer for MNIST dataset, since it is a binery image dataset, not the colorful one.

3 Model

3.1 Data Processing

The whole MNIST is splitted as the following three parts.

The training set has 48000 28X28 images;
the validation set has 12000 28X28 images;
the testing set has 10000 28X28 images.

Then, given that the VGG-16 doesn't accept image which size is smaller than 32X32, the current images have to be enlarged. The method here is adding paddings. And the final size is 34X34, which fits for VGG-16 model.

3.2 Train VGG-16 with MNIST from Scratch

This part starts from stacking layers. With the help of Sequence() from keras, we build the network up. And we set the batch size as 16, epoch as 500, optimizer as adam, loss as categorical cross entropy loss.

Callbacks funciton is used here to reduce the learning rate automatically and stop the training when validation loss doesn't change for 10 epochs, this function saves us lots of time and is very convenient.

3.3 Predict MNIST by Trained Imagenet Weight in VGG-16

A very powerful function, VGG16() from keras.applications helps to construct the neural network here. And we set the batch size as 16, epoch as 100, optimizer as adam, loss as categorical cross entropy loss.

Callbacks funciton is also used here to reduce the learning rate automatically and stop the training when validation loss doesn't change for 8 epochs, this function saves us lots of time and is very convenient.

3.4 Freeze All The Convolutional Layers Retrain VGG-16 Network On MNIST

A very powerful function, VGG16() from keras.applications helps to construct the neural network here. And we set the batch size as 16, epoch as 100, optimizer as adam, loss as categorical cross entropy loss. Additionally, the convolutional layers are frozen by code: layer.trainable = False.

Callbacks funciton is also used here to reduce the learning rate automatically and stop the training when validation loss doesn't change for 8 epochs, this function saves us lots of time and is very convenient.

3.5 Freeze All The Fully Connected Layers Retrain VGG-16 Network On MNIST

A very powerful function, VGG16() from keras.applications helps to construct the neural network here. And we set the batch size as 16, epoch as 100, optimizer as adam, loss as categorical cross entropy loss. Additionally, the fully connected layers are frozen by code: layer.trainable = False.

Callbacks funciton is also used here to reduce the learning rate automatically and stop the training when validation loss doesn't change for 8 epochs, this function saves us lots of time and is very convenient.

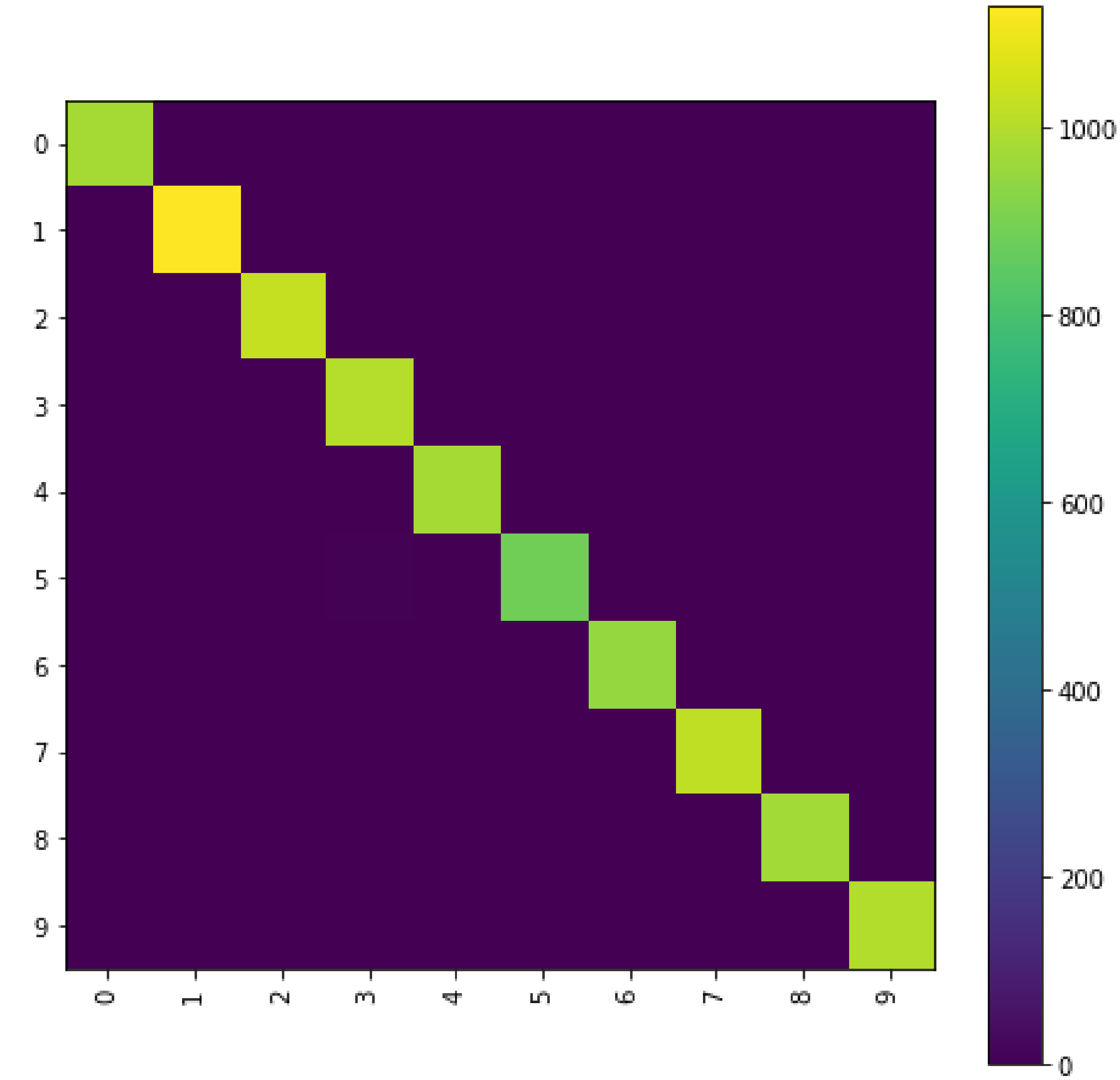
4 Train VGG-16 with MNIST from Scratch

The training stops at epoach 11 with the training loss of 4.9966e-04, the training accuracy of 0.9999, the validation loss of 0.0688 and the validation accuracy of 0.9934, when the learning rate is 7.999999979801942e-07.

Next, we use this weight to predict testing set, the prediction loss is 0.0492 and the prediction accuracy is 0.9953.

```
In [111]: print('Got %d / %d correct' % (num_correct, num_test))
          print('Accuracy = %f' % (np.mean(y_test == y_pred)))
          print(confusion_matrix(y_test, y_pred))
          print(classification_report(y_test, y_pred,
                                      target_names=list(label_dict.values()),digits=3))
          plt.figure(figsize=(8,8))
          cnf_matrix = confusion_matrix(y_test, y_pred)
          classes = list(label_dict.values())
          plt.imshow(cnf_matrix, interpolation='nearest')
          plt.colorbar()
          tick_marks = np.arange(len(classes))
          _ = plt.xticks(tick_marks, classes, rotation=90)
          _ = plt.yticks(tick_marks, classes)
```

```
Got 9953 / 10000 correct
Accuracy = 0.995300
[[ 977    0    0    0    0    0    2    1    0    0]
 [   0 1130    1    2    0    0    0    1    1    0]
 [   0    0 1029    1    0    0    0    2    0    0]
 [   0    0    0 1006    0    3    0    0    1    0]
 [   0    0    0    0  977    0    1    0    0    4]
 [   0    0    0    5    0  886    1    0    0    0]
 [   4    2    0    0    0    0  952    0    0    0]
 [   0    2    1    0    0    0    0 1024    0    1]
 [   0    0    0    1    0    0    0    0  972    1]
 [   0    0    0    0    4    1    0    2    2 1000]]
              precision    recall  f1-score   support

           0      0.996     0.997     0.996       980
           1      0.996     0.996     0.996      1135
           2      0.998     0.997     0.998      1032
           3      0.991     0.996     0.994      1010
           4      0.996     0.995     0.995       982
           5      0.996     0.993     0.994       892
           6      0.996     0.994     0.995       958
           7      0.994     0.996     0.995      1028
           8      0.996     0.998     0.997       974
           9      0.994     0.991     0.993      1009

    accuracy                          0.995     10000
   macro avg      0.995     0.995     0.995     10000
weighted avg      0.995     0.995     0.995     10000
```



5 Predict MNIST by Trained Imagenet Weight in VGG-16

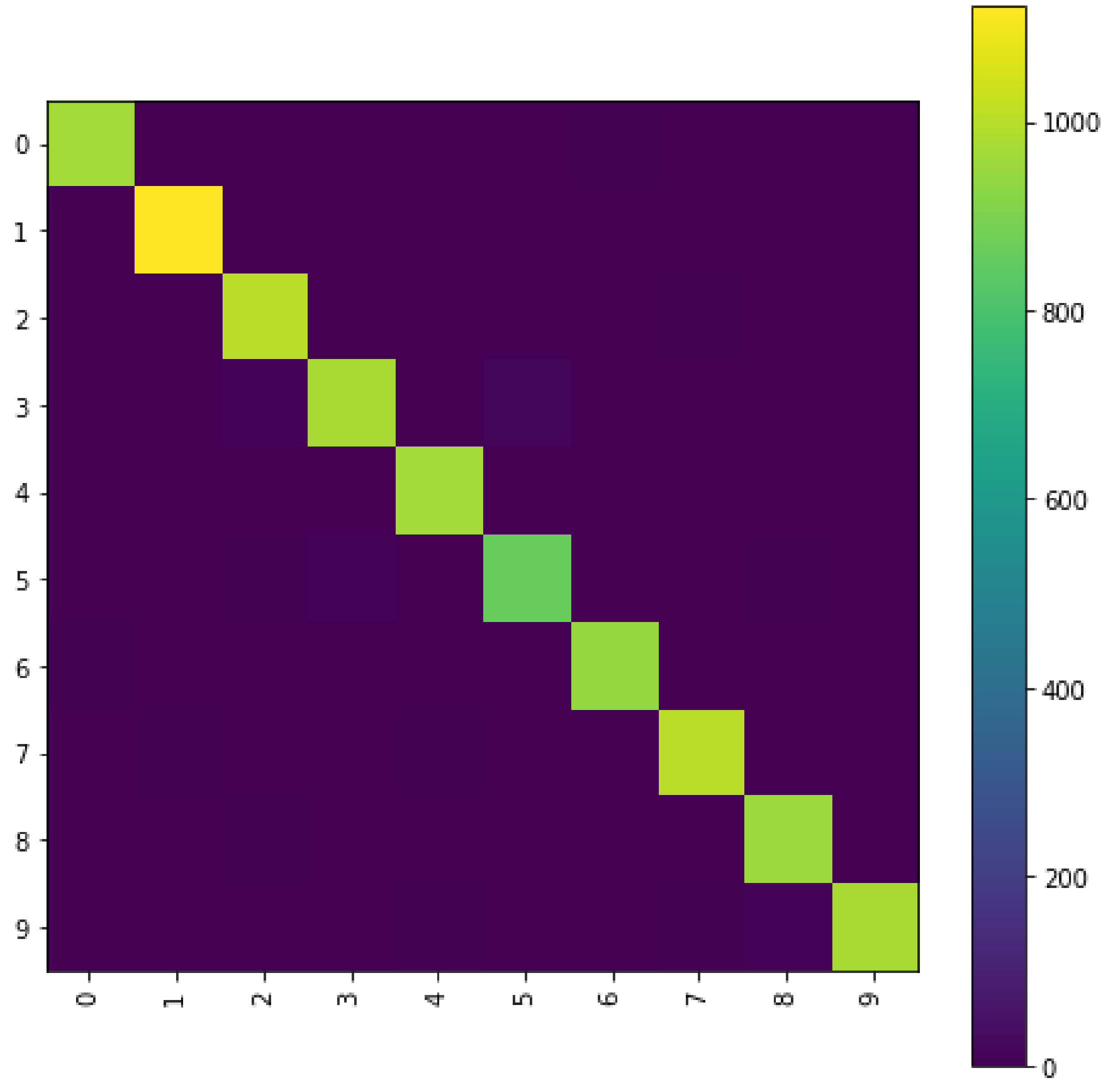
The training stops at epoach 37 with the training loss of 0.0303, the training accuracy of 0.9920, the validation loss of 0.0724 and the validation accuracy of 0.9778, when the learning rate is 6.400000529538374e-08.

Next, we use this weight to predict testing set, the prediction loss is 0.0672 and the prediction accuracy is 0.9788.

```
In [0]: print('Got %d / %d correct' % (num_correct, num_test))
        print('Accuracy = %f' % (np.mean(y_test == y_pred)))
        print(confusion_matrix(y_test, y_pred))
        print(classification_report(y_test, y_pred,
                                    target_names=list(label_dict.values()),digits=3))
```

```python
plt.figure(figsize=(8,8))
cnf_matrix = confusion_matrix(y_test, y_pred)
classes = list(label_dict.values())
plt.imshow(cnf_matrix, interpolation='nearest')
plt.colorbar()
tick_marks = np.arange(len(classes))
_ = plt.xticks(tick_marks, classes, rotation=90)
_ = plt.yticks(tick_marks, classes)
```

```
Got 9788 / 10000 correct
Accuracy = 0.978800
[[ 969    0    1    0    0    4    5    1    0    0]
 [    0 1123    0    0    3    0    4    4    1    0]
 [    1    1 1008    4    2    4    4    5    2    1]
 [    0    0   10  977    0   16    0    3    2    2]
 [    0    1    1    0  967    1    2    3    4    3]
 [    2    0    7    9    1  864    0    2    6    1]
 [    7    0    4    0    0    2  944    0    1    0]
 [    0    5    4    2    8    0    0 1004    1    4]
 [    0    0    6    2    3    4    1    1  956    1]
 [    3    0    3    2    7    2    0    5   11  976]]
              precision    recall  f1-score   support

           0      0.987     0.989     0.988       980
           1      0.994     0.989     0.992      1135
           2      0.966     0.977     0.971      1032
           3      0.981     0.967     0.974      1010
           4      0.976     0.985     0.980       982
           5      0.963     0.969     0.966       892
           6      0.983     0.985     0.984       958
           7      0.977     0.977     0.977      1028
           8      0.972     0.982     0.977       974
           9      0.988     0.967     0.977      1009

    accuracy                          0.979     10000
   macro avg      0.979     0.979     0.979     10000
weighted avg      0.979     0.979     0.979     10000
```



6 Freeze All The Convolutional Layers Retrain VGG-16 Network On MNIST

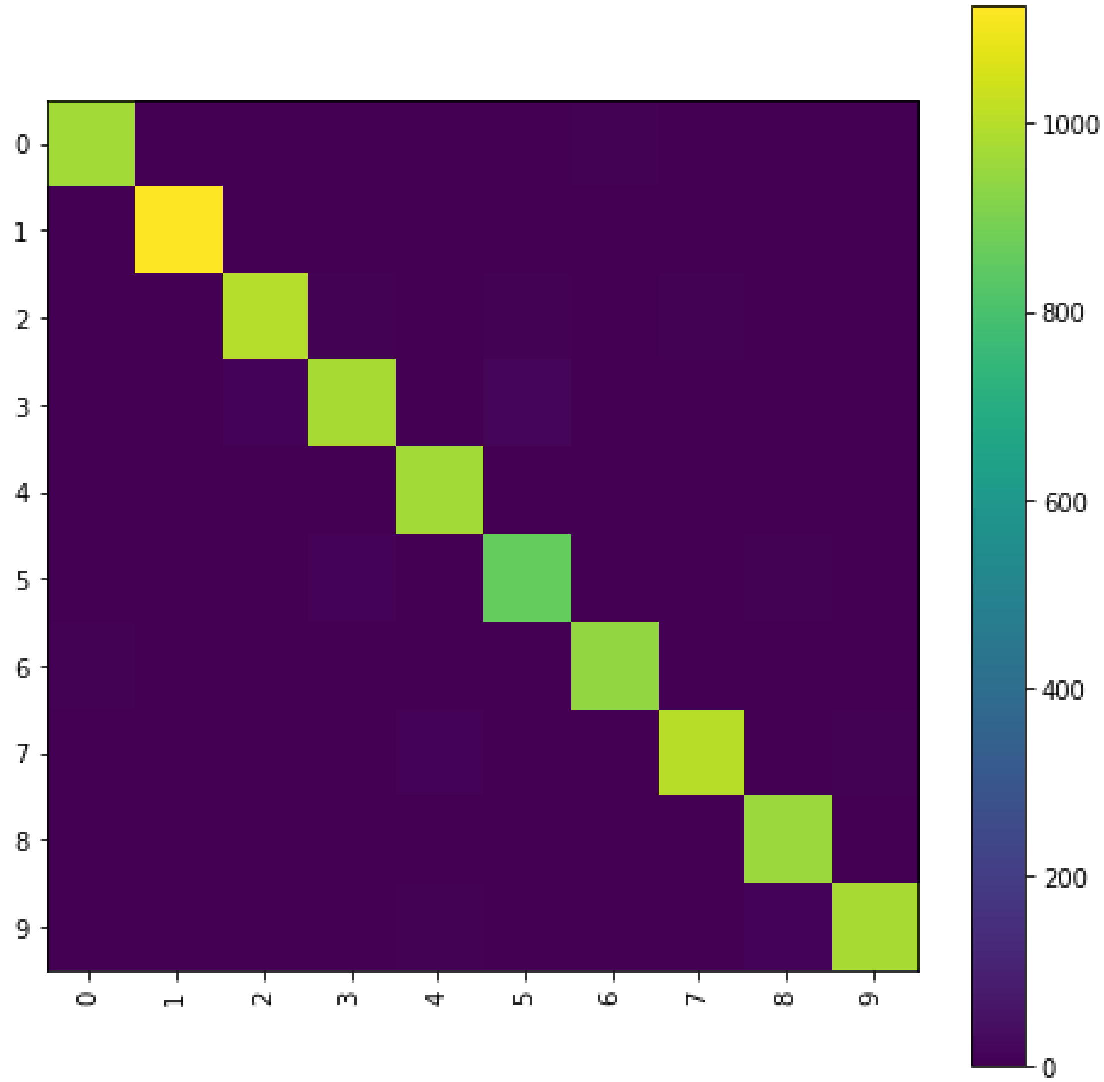
The training stops at epoach 22 with the training loss of 0.0272, the training accuracy of 0.9924, the validation loss of 0.0723 and the validation accuracy of 0.9788, when the learning rate is 6.400000529538374e-08.

Next, we use this weight to predict testing set, the prediction loss is 0.0693 and the prediction accuracy is 0.9771.

```
In [0]: print('Got %d / %d correct' % (num_correct, num_test))
        print('Accuracy = %f' % (np.mean(y_test == y_pred)))
        print(confusion_matrix(y_test, y_pred))
```

```python
print(classification_report(y_test, y_pred,
                            target_names=list(label_dict.values()),digits=3))
plt.figure(figsize=(8,8))
cnf_matrix = confusion_matrix(y_test, y_pred)
classes = list(label_dict.values())
plt.imshow(cnf_matrix, interpolation='nearest')
plt.colorbar()
tick_marks = np.arange(len(classes))
_ = plt.xticks(tick_marks, classes, rotation=90)
_ = plt.yticks(tick_marks, classes)
```

```
Got 9771 / 10000 correct
Accuracy = 0.977100
[[ 967    0    1    0    0    3    5    1    2    1]
 [    0 1125    0    0    3    0    4    2    1    0]
 [    1    2 1000    8    2    6    3    6    3    1]
 [    0    0    9  976    0   18    0    4    2    1]
 [    0    1    0    0  968    1    3    2    3    4]
 [    2    0    4   13    1  861    3    2    5    1]
 [    7    1    2    0    1    3  941    0    2    1]
 [    0    3    4    3   10    0    0 1002    1    5]
 [    0    0    3    4    2    4    2    2  955    2]
 [    3    0    3    3    5    3    0    4   12  976]]
              precision    recall  f1-score   support

           0      0.987     0.987     0.987       980
           1      0.994     0.991     0.993      1135
           2      0.975     0.969     0.972      1032
           3      0.969     0.966     0.968      1010
           4      0.976     0.986     0.981       982
           5      0.958     0.965     0.961       892
           6      0.979     0.982     0.981       958
           7      0.978     0.975     0.976      1028
           8      0.969     0.980     0.974       974
           9      0.984     0.967     0.976      1009

    accuracy                          0.977     10000
   macro avg      0.977     0.977     0.977     10000
weighted avg      0.977     0.977     0.977     10000
```



7 Freeze All The Fully Connected Layers Retrain VGG-16 Network On MNIST

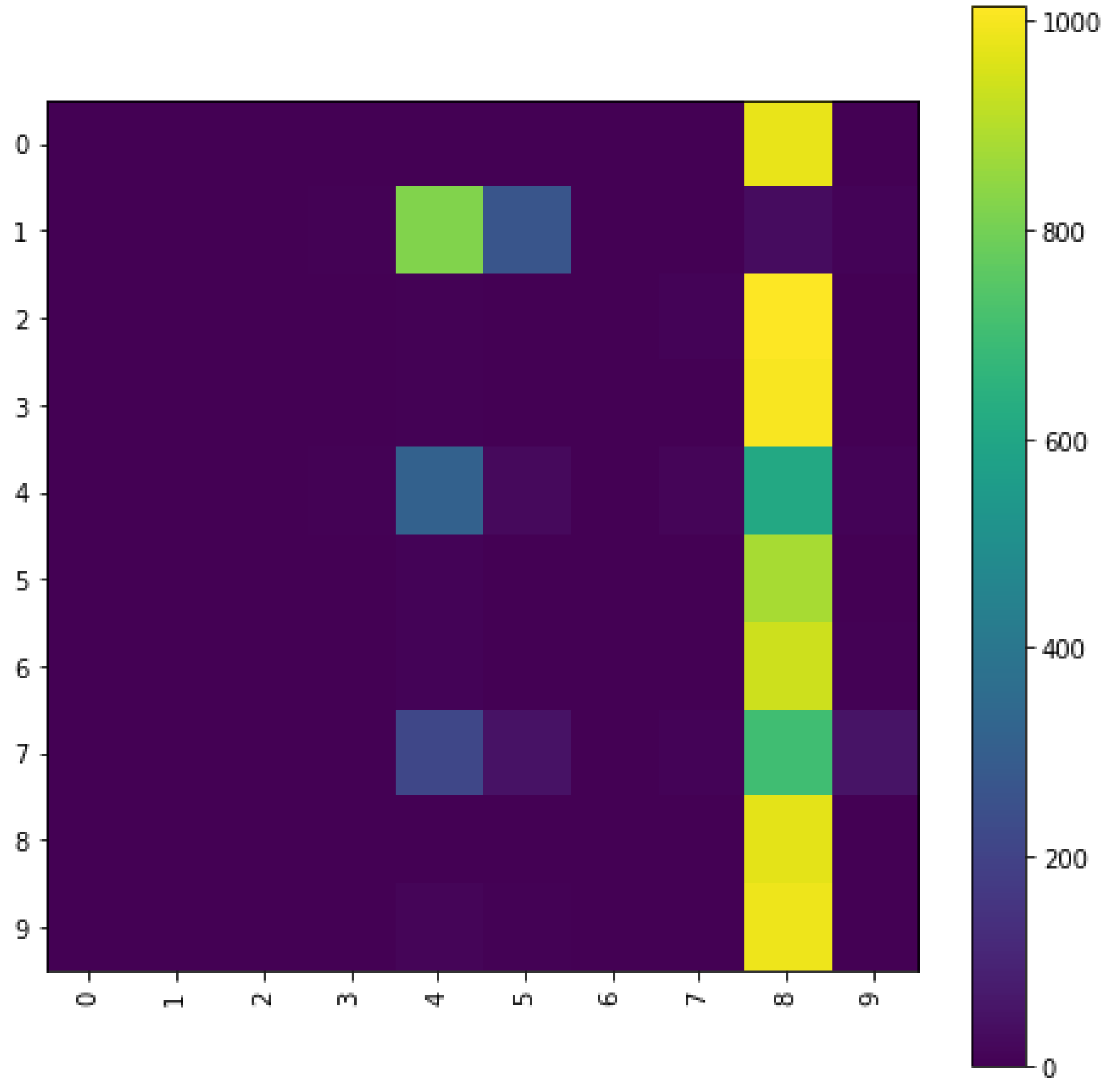
The training stops at epoach 9 with the training loss of 2.4916, the training accuracy of 0.1330, the validation loss of 2.5009 and the validation accuracy of 0.1352, when the learning rate is 8.000000525498762e-06.

Next, we use this weight to predict testing set, the prediction loss is 2.4918 and the prediction accuracy is 0.1296.

```
In [0]: print('Got %d / %d correct' % (num_correct, num_test))
        print('Accuracy = %f' % (np.mean(y_test == y_pred)))
        print(confusion_matrix(y_test, y_pred))
```

```python
print(classification_report(y_test, y_pred,
                            target_names=list(label_dict.values()),digits=3))
plt.figure(figsize=(8,8))
cnf_matrix = confusion_matrix(y_test, y_pred)
classes = list(label_dict.values())
plt.imshow(cnf_matrix, interpolation='nearest')
plt.colorbar()
tick_marks = np.arange(len(classes))
_ = plt.xticks(tick_marks, classes, rotation=90)
_ = plt.yticks(tick_marks, classes)
```

```
Got 1296 / 10000 correct
Accuracy = 0.129600
[[   0    0    0    0    0    0    0    0  980    0]
 [   0    0    0    4  821  266    0    2   34    8]
 [   0    0    0    0    5    0    0   10 1015    2]
 [   0    0    0    0    4    0    0    0 1005    1]
 [   0    0    0    5  315   27    0   12  612   11]
 [   0    0    0    0    8    0    0    2  881    1]
 [   0    0    0    0    8    1    0    3  939    7]
 [   0    0    0    0  217   48    0    8  702   53]
 [   0    0    0    0    2    0    0    0  972    0]
 [   0    0    0    0   15    5    0    0  988    1]]
              precision    recall  f1-score   support

           0      0.000     0.000     0.000       980
           1      0.000     0.000     0.000      1135
           2      0.000     0.000     0.000      1032
           3      0.000     0.000     0.000      1010
           4      0.226     0.321     0.265       982
           5      0.000     0.000     0.000       892
           6      0.000     0.000     0.000       958
           7      0.216     0.008     0.015      1028
           8      0.120     0.998     0.214       974
           9      0.012     0.001     0.002      1009

    accuracy                          0.130     10000
   macro avg      0.057     0.133     0.050     10000
weighted avg      0.057     0.130     0.049     10000


/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1437: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```



7.1 Discussion

Here is a detailed table for all 4 parts.

Methods	Scratch	Retrain	Freeze Conv	Freeze Fully Con
Train Acc	99.99%	99.20%	99.24%	13.30%
Train Loss	5eˆ-4	0.0303	0.0272	2.4916
Valid Acc	99.34%	97.78%	97.88%	13.52%
Valid Loss	0.0688	0.0724	0.0723	2.5009
Test Acc	99.53%	97.88%	97.71%	12.96%
Test Loss	0.0492	0.0672	0.0693	2.4918
Time Per Epoch	143s	5s	5.5s	3s
Learning Rate	8eˆ-7	6eˆ-8	6eˆ-8	8eˆ-6

As we can see, the total rank for training part is Scratch > Freeze Conv > Retrain > Freeze Fully Con. Scratch performs best on training part. VGG-16 freezing all convolutional layers performs bettern than Retrain it on MNIST. It is a little weird, but it is truth. Meanwhile, VGG-16 freezing all full connected layers performs worst.

The total rank for testing part is Scratch > Retrain > Freeze Conv > Freeze Fully Con.

In general, from this comparison, we recognize that full connected layer is so important for CNN, however, if we close convolutional layer, our result will not be influenced a lot. Perhaps, it is due to MNIST dataset as the binery image dataset, not the colorful one. Thus lossing convoluitonal layers doesn't affect a lot on CNN's performance. However, lossing fully connected layer means different, it will ruin your prediction, since we need softmax to do classification.

CNN is a powerful model, there is huge CNN families. We hope to dig more.

8 Appendix

8.1 Load Packages

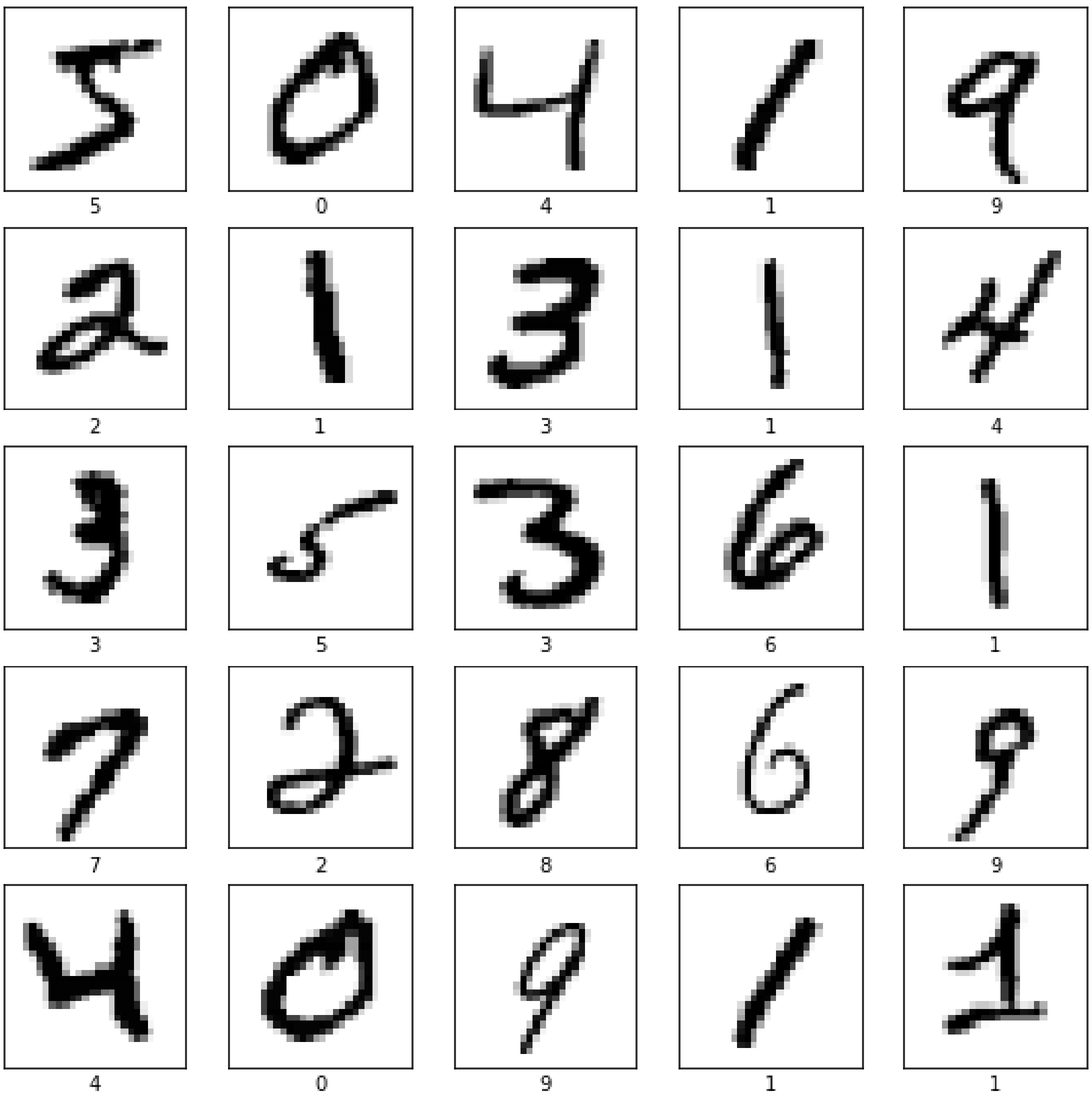
```
In [0]: # import dataset and seperate them as train set and test set
        # index x represents image, index y represents label

        import tensorflow as tf
        import keras
        from numpy.linalg import *
        from tensorflow import keras
        import matplotlib.pyplot as plt
        from keras.optimizers import Adam
        from keras.models import Sequential
        from keras.applications import VGG16
        from keras.utils import to_categorical
        from keras.layers.convolutional import *
        from keras import callbacks, layers, optimizers, models
        import os, cv2, random, sklearn, sklearn.metrics, numpy as np
        from sklearn.preprocessing import StandardScaler
        from keras.metrics import categorical_crossentropy
        from sklearn.model_selection import train_test_split
        from keras.layers.normalization import BatchNormalization
        from keras.layers import Input, Dense, Conv2D, MaxPooling2D, Activation, Dropout, Flat
        from sklearn.metrics import classification_report, confusion_matrix
        from keras.layers.convolutional import Convolution2D, MaxPooling2D, ZeroPadding2D
        from __future__ import absolute_import, division, print_function, unicode_literals
```

8.2 Load Dataset and Data Preparing

```
In [0]: # download MNIST dataset from keras
        (x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()
        y_train_labels = to_categorical(y_train)
        y_test_labels = to_categorical(y_test)
        # make sure the 10 classes
```

```python
label_dict = {0: '0', 1: '1', 2: '2', 3: '3', 4: '4',
              5: '5', 6: '6', 7: '7', 8: '8', 9: '9'}
```

In [86]:
```python
# Verify that the data is in the correct format.
plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(x_train[i], cmap=plt.cm.binary)
    plt.xlabel(label_dict[y_train[i]])
plt.show()
```



In [186]:
```
x_train = x_train.reshape(np.shape(x_train)[0], 28*28)
x_test = x_test.reshape(np.shape(x_test)[0], 28*28)
# Convert the images into 3 channels
X_train=np.dstack([x_train] * 3)
X_test=np.dstack([x_test] * 3)
print(np.shape(X_train))
print(np.shape(X_test))
# Reshape images as per the tensor format required by tensorflow
X_train = X_train.reshape(-1, 28,28,3)
X_test = X_test.reshape (-1,28,28,3)
print(np.shape(X_train))
print(np.shape(X_test))
# Resize the images 34*34 as required by VGG16
X_tr = np.pad(X_train, ((0,0),(3,3),(3,3),(0,0)), 'constant')
X_te = np.pad(X_test, ((0,0),(3,3),(3,3),(0,0)), 'constant')
X_tr = np.float32(X_tr)/255.
X_te = np.float32(X_te)/255.
print(np.shape(X_tr))
print(np.shape(X_te))
```

```
(60000, 784, 3)
(10000, 784, 3)
(60000, 28, 28, 3)
(10000, 28, 28, 3)
(60000, 34, 34, 3)
(10000, 34, 34, 3)
```

In [187]:
```
# Splitting train data as train and validation data
train_X,valid_X,train_label,valid_label = train_test_split(X_tr,
                                                           y_train_labels,
                                                           test_size=0.2,
                                                           random_state=13)
# Finally check the data size whether it is as per tensorflow and VGG16 requirement
train_X.shape,valid_X.shape,train_label.shape,valid_label.shape
```

Out[187]:
```
((48000, 34, 34, 3), (12000, 34, 34, 3), (48000, 10), (12000, 10))
```

In [0]:
```
# Define the parameters for instanitaing VGG16 model.
IMG_WIDTH = 34
IMG_HEIGHT = 34
IMG_DEPTH = 3
BATCH_SIZE = 16
```

8.3 Train VGG-16 with MNIST from Scratch

In [176]:
```
input_tensor = Input(shape=(IMG_WIDTH, IMG_HEIGHT, IMG_DEPTH))
#input_tensor = input_tensor
vg16_m = VGG16(weights=None,input_tensor = input_tensor)
```

```python
type(vg16_m)
model = Sequential()
for layer in vg16_m.layers[0:22]:
  model.add(layer)
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
block1_conv1 (Conv2D)        (None, 34, 34, 64)        1792      
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 34, 34, 64)        36928     
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 17, 17, 64)        0         
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 17, 17, 128)       73856     
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 17, 17, 128)       147584    
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 8, 8, 128)         0         
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 8, 8, 256)         295168    
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 8, 8, 256)         590080    
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 8, 8, 256)         590080    
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 4, 4, 256)         0         
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 4, 4, 512)         1180160   
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 4, 4, 512)         2359808   
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 4, 4, 512)         2359808   
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 2, 2, 512)         0         
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 2, 2, 512)         2359808   
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 2, 2, 512)         2359808   
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 2, 2, 512)         2359808   
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 1, 1, 512)         0         
_________________________________________________________________
flatten (Flatten)            (None, 512)               0         
_________________________________________________________________
fc1 (Dense)                  (None, 4096)              2101248   
```

```
_________________________________________________________________
fc2 (Dense)                  (None, 4096)              16781312
=================================================================
Total params: 33,597,248
Trainable params: 33,597,248
Non-trainable params: 0
_________________________________________________________________
```

```
In [140]: model.add(Dense(10, activation='softmax'))
          model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
block1_conv1 (Conv2D)        (None, 34, 34, 64)        1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 34, 34, 64)        36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 17, 17, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 17, 17, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 17, 17, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 8, 8, 128)         0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 8, 8, 256)         295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 4, 4, 256)         0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 4, 4, 512)         1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 2, 2, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 2, 2, 512)         2359808
```

```
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 1, 1, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 512)               0
_________________________________________________________________
fc1 (Dense)                  (None, 4096)              2101248
_________________________________________________________________
fc2 (Dense)                  (None, 4096)              16781312
_________________________________________________________________
dense_10 (Dense)             (None, 10)                40970
=================================================================
Total params: 33,638,218
Trainable params: 33,638,218
Non-trainable params: 0
_________________________________________________________________
```

```
In [0]: NB_EPOCHS = 100

        # Compile the model.
        model.compile(Adam(lr=0.0001),
                      loss='categorical_crossentropy',
                      metrics=['accuracy'])
```

```
In [105]: from keras import callbacks
          # Incorporating reduced learning and early stopping for callback
          reduce_learning = callbacks.ReduceLROnPlateau(
              monitor='val_loss',
              factor=0.2,
              patience=2,
              verbose=1,
              mode='auto',
              epsilon=0.0001,
              cooldown=2,
              min_lr=0)

          eary_stopping = callbacks.EarlyStopping(
              monitor='val_loss',
              min_delta=0.0003,
              patience=6,
              verbose=1,
              mode='auto')

          callbacks = [reduce_learning, eary_stopping]
```

```
/usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1065: UserWarning: `epsilon` argumen
  warnings.warn('`epsilon` argument is deprecated and '
```

```
In [106]: mt=model.fit(train_X, train_label,
                      batch_size=16, epochs=NB_EPOCHS,
                      verbose=2, callbacks=callbacks,
                      validation_data=(valid_X, valid_label)
                     )
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/100
 - 147s - loss: 0.0311 - acc: 0.9933 - val_loss: 0.0585 - val_acc: 0.9894
Epoch 2/100
 - 144s - loss: 0.0332 - acc: 0.9933 - val_loss: 0.0518 - val_acc: 0.9914
Epoch 3/100
 - 144s - loss: 0.0261 - acc: 0.9943 - val_loss: 0.0554 - val_acc: 0.9905
Epoch 4/100
 - 143s - loss: 0.0269 - acc: 0.9948 - val_loss: 0.0533 - val_acc: 0.9892

Epoch 00004: ReduceLROnPlateau reducing learning rate to 1.9999999494757503e-05.
Epoch 5/100
 - 143s - loss: 0.0080 - acc: 0.9984 - val_loss: 0.0374 - val_acc: 0.9930
Epoch 6/100
 - 143s - loss: 0.0030 - acc: 0.9992 - val_loss: 0.0491 - val_acc: 0.9936
Epoch 7/100
 - 143s - loss: 0.0039 - acc: 0.9994 - val_loss: 0.0528 - val_acc: 0.9937

Epoch 00007: ReduceLROnPlateau reducing learning rate to 3.999999898951501e-06.
Epoch 8/100
 - 143s - loss: 0.0015 - acc: 0.9997 - val_loss: 0.0550 - val_acc: 0.9934
Epoch 9/100
 - 143s - loss: 7.9653e-04 - acc: 0.9999 - val_loss: 0.0622 - val_acc: 0.9932
Epoch 10/100
 - 143s - loss: 6.3383e-04 - acc: 0.9999 - val_loss: 0.0677 - val_acc: 0.9933

Epoch 00010: ReduceLROnPlateau reducing learning rate to 7.999999979801942e-07.
Epoch 11/100
 - 143s - loss: 4.9966e-04 - acc: 0.9999 - val_loss: 0.0688 - val_acc: 0.9934
Epoch 00011: early stopping
```

```
In [110]: test_loss, test_acc = model.evaluate(X_te, y_test_labels)
          print('Test Accuracy:%4f, Test Loss:%4f.' %(test_acc,test_loss))
          # Make Prediction
          pred_result = model.predict(X_te)
          y_pred=[]
          for i in range(np.shape(y_test)[0]):
            num = np.where(pred_result[i]==max(pred_result[i]))
            y_pred.append(num[0][0])
          y_pred = np.transpose(y_pred)
          # calculate accuracy
```

```
num_test = len(y_test)
num_correct = np.sum(y_pred == y_test)
print('Got %d / %d correct' % (num_correct, num_test))
print('Accuracy = %f' % (np.mean(y_test == y_pred)))
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred,
                            target_names=list(label_dict.values()),digits=3))
```

```
10000/10000 [==============================] - 3s 310us/step
Test Accuracy:0.995300, Test Loss:0.049209.
Got 9953 / 10000 correct
Accuracy = 0.995300
[[ 977    0    0    0    0    0    2    1    0    0]
 [   0 1130    1    2    0    0    0    1    1    0]
 [   0    0 1029    1    0    0    0    2    0    0]
 [   0    0    0 1006    0    3    0    0    1    0]
 [   0    0    0    0  977    0    1    0    0    4]
 [   0    0    0    5    0  886    1    0    0    0]
 [   4    2    0    0    0    0  952    0    0    0]
 [   0    2    1    0    0    0    0 1024    0    1]
 [   0    0    0    1    0    0    0    0  972    1]
 [   0    0    0    0    4    1    0    2    2 1000]]
              precision    recall  f1-score   support

           0      0.996     0.997     0.996       980
           1      0.996     0.996     0.996      1135
           2      0.998     0.997     0.998      1032
           3      0.991     0.996     0.994      1010
           4      0.996     0.995     0.995       982
           5      0.996     0.993     0.994       892
           6      0.996     0.994     0.995       958
           7      0.994     0.996     0.995      1028
           8      0.996     0.998     0.997       974
           9      0.994     0.991     0.993      1009

    accuracy                          0.995     10000
   macro avg      0.995     0.995     0.995     10000
weighted avg      0.995     0.995     0.995     10000
```

8.4 Predict MNIST by Trained Imagenet Weight in VGG-16

In [195]:
```
#  Create base model of VGG16
from keras.layers import Input
input_tensor = Input(shape=(IMG_HEIGHT, IMG_WIDTH, IMG_DEPTH))
conv_base = VGG16(weights='imagenet',include_top=False,
```

```
                              input_tensor = input_tensor)

          type(conv_base)
```

```
Out[195]: '\n#conv_base.summary()\nmodel = Sequential()\nfor layer in conv_base.layers:\n
```

```
In [0]:  # Extracting features
         train_features = conv_base.predict(np.array(train_X), batch_size=BATCH_SIZE, verbose=1)
         test_features = conv_base.predict(np.array(X_te), batch_size=BATCH_SIZE, verbose=1)
         val_features = conv_base.predict(np.array(valid_X), batch_size=BATCH_SIZE, verbose=1)
```

```
48000/48000 [==============================] - 18s 381us/step
10000/10000 [==============================] - 4s 381us/step
12000/12000 [==============================] - 5s 383us/step
```

```
In [0]: np.savez("train_features", train_features, train_label)
        np.savez("test_features", test_features, y_test_labels)
        np.savez("val_features", val_features, valid_label)
```

```
In [0]: # Current shape of features
        print(train_features.shape, "\n",  test_features.shape, "\n", val_features.shape)
```

```
(48000, 1, 1, 512)
 (10000, 1, 1, 512)
 (12000, 1, 1, 512)
```

```
In [0]: # Flatten extracted features
        train_features_flat = np.reshape(train_features, (48000, 1*1*512))
        test_features_flat = np.reshape(test_features, (10000, 1*1*512))
        val_features_flat = np.reshape(val_features, (12000, 1*1*512))
```

```
In [0]: from keras import models
        from keras.models import Model
        from keras import layers
        from keras import optimizers
        from keras import callbacks
        from keras.layers.advanced_activations import LeakyReLU
        model_c = models.Sequential()
        model_c.add(layers.Dense(512, activation='relu', input_dim=(1*1*512)))
        model_c.add(layers.LeakyReLU(alpha=0.1))
        model_c.add(layers.Dense(10, activation='softmax'))
```

```
In [0]: NB_TRAIN_SAMPLES = train_features_flat.shape[0]
        NB_VALIDATION_SAMPLES = val_features_flat.shape[0]
        NB_EPOCHS = 100

        # Compile the model.
        model_c.compile(optimizer='adam',
                      loss='categorical_crossentropy',
                      metrics=['accuracy'])
```

In [0]:
```
# Incorporating reduced learning and early stopping for callback
reduce_learning = callbacks.ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.2,
    patience=2,
    verbose=1,
    mode='auto',
    epsilon=0.0001,
    cooldown=2,
    min_lr=0)

eary_stopping = callbacks.EarlyStopping(
    monitor='val_loss',
    min_delta=0.0003,
    patience=8,
    verbose=1,
    mode='auto')

callbacks = [reduce_learning, eary_stopping]
```

```
/usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1065: UserWarning: `epsilon` argumen
  warnings.warn('`epsilon` argument is deprecated and '
```

In [0]:
```
# Train the the model
mt=model_c.fit(
    train_features_flat,
    train_label,
    epochs=NB_EPOCHS,
    validation_data=(val_features_flat, valid_label),
    callbacks=callbacks
)
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/100
48000/48000 [==============================] - 5s 112us/step - loss: 0.3400 - acc: 0.8962 - va
Epoch 2/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.1631 - acc: 0.9472 - val
Epoch 3/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.1389 - acc: 0.9547 - val
Epoch 4/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.1198 - acc: 0.9608 - val
Epoch 5/100
48000/48000 [==============================] - 5s 95us/step - loss: 0.1087 - acc: 0.9643 - val
Epoch 6/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.1028 - acc: 0.9663 - val
Epoch 7/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0941 - acc: 0.9685 - val
```

```
Epoch 8/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0897 - acc: 0.9692 - val_
Epoch 9/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0842 - acc: 0.9719 - val_

Epoch 00009: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
Epoch 10/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0556 - acc: 0.9821 - val_
Epoch 11/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0524 - acc: 0.9832 - val_
Epoch 12/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.0505 - acc: 0.9837 - val_
Epoch 13/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0493 - acc: 0.9841 - val_
Epoch 14/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0478 - acc: 0.9847 - val_
Epoch 15/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.0457 - acc: 0.9854 - val_
Epoch 16/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0447 - acc: 0.9860 - val_
Epoch 17/100
48000/48000 [==============================] - 5s 107us/step - loss: 0.0432 - acc: 0.9863 - va
Epoch 18/100
48000/48000 [==============================] - 5s 106us/step - loss: 0.0425 - acc: 0.9867 - va
Epoch 19/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.0410 - acc: 0.9866 - val_
Epoch 20/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0403 - acc: 0.9875 - val_
Epoch 21/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.0385 - acc: 0.9880 - val_

Epoch 00021: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
Epoch 22/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0333 - acc: 0.9901 - val_
Epoch 23/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.0326 - acc: 0.9907 - val_
Epoch 24/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.0322 - acc: 0.9908 - val_

Epoch 00024: ReduceLROnPlateau reducing learning rate to 8.000000525498762e-06.
Epoch 25/100
48000/48000 [==============================] - 5s 95us/step - loss: 0.0310 - acc: 0.9915 - val_
Epoch 26/100
48000/48000 [==============================] - 5s 95us/step - loss: 0.0309 - acc: 0.9915 - val_
Epoch 27/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.0308 - acc: 0.9916 - val_
Epoch 28/100
48000/48000 [==============================] - 5s 95us/step - loss: 0.0307 - acc: 0.9915 - val_
```

```
Epoch 29/100
48000/48000 [==============================] - 5s 96us/step - loss: 0.0307 - acc: 0.9918 - val_

Epoch 00029: ReduceLROnPlateau reducing learning rate to 1.6000001778593287e-06.
Epoch 30/100
48000/48000 [==============================] - 5s 101us/step - loss: 0.0304 - acc: 0.9918 - val
Epoch 31/100
48000/48000 [==============================] - 5s 113us/step - loss: 0.0304 - acc: 0.9918 - val
Epoch 32/100
48000/48000 [==============================] - 5s 106us/step - loss: 0.0304 - acc: 0.9919 - val

Epoch 00032: ReduceLROnPlateau reducing learning rate to 3.200000264769187e-07.
Epoch 33/100
48000/48000 [==============================] - 5s 100us/step - loss: 0.0303 - acc: 0.9919 - val
Epoch 34/100
48000/48000 [==============================] - 5s 108us/step - loss: 0.0303 - acc: 0.9919 - val
Epoch 35/100
48000/48000 [==============================] - 5s 105us/step - loss: 0.0303 - acc: 0.9920 - val

Epoch 00035: ReduceLROnPlateau reducing learning rate to 6.400000529538374e-08.
Epoch 36/100
48000/48000 [==============================] - 5s 97us/step - loss: 0.0303 - acc: 0.9920 - val_
Epoch 37/100
48000/48000 [==============================] - 5s 98us/step - loss: 0.0303 - acc: 0.9920 - val_
Epoch 00037: early stopping
```

In [0]:
```python
# Evaluate accuracy
test_loss, test_acc = model_c.evaluate(test_features_flat, y_test_labels)
print('Test Accuracy:%4f, Test Loss:%4f.' %(test_acc,test_loss))
```

```
10000/10000 [==============================] - 0s 36us/step
Test Accuracy:0.978800, Test Loss:0.067221.
```

In [0]:
```python
# Make Prediction
pred_result = model_c.predict(test_features_flat)
y_pred=[]
for i in range(np.shape(y_test)[0]):
    num = np.where(pred_result[i]==max(pred_result[i]))
    y_pred.append(num[0][0])
y_pred = np.transpose(y_pred)
```

In [0]:
```python
# calculate accuracy
num_test = len(y_test)
num_correct = np.sum(y_pred == y_test)
print('Got %d / %d correct' % (num_correct, num_test))
print('Accuracy = %f' % (np.mean(y_test == y_pred)))
from sklearn.metrics import classification_report, confusion_matrix
```

```
        print(confusion_matrix(y_test, y_pred))
        print(classification_report(y_test, y_pred,
                                    target_names=list(label_dict.values()),digits=3))
```

```
Got 9788 / 10000 correct
Accuracy = 0.978800
[[ 969    0    1    0    0    4    5    1    0    0]
 [    0 1123    0    0    3    0    4    4    1    0]
 [    1    1 1008    4    2    4    4    5    2    1]
 [    0    0   10  977    0   16    0    3    2    2]
 [    0    1    1    0  967    1    2    3    4    3]
 [    2    0    7    9    1  864    0    2    6    1]
 [    7    0    4    0    0    2  944    0    1    0]
 [    0    5    4    2    8    0    0 1004    1    4]
 [    0    0    6    2    3    4    1    1  956    1]
 [    3    0    3    2    7    2    0    5   11  976]]
              precision    recall  f1-score   support

           0      0.987     0.989     0.988       980
           1      0.994     0.989     0.992      1135
           2      0.966     0.977     0.971      1032
           3      0.981     0.967     0.974      1010
           4      0.976     0.985     0.980       982
           5      0.963     0.969     0.966       892
           6      0.983     0.985     0.984       958
           7      0.977     0.977     0.977      1028
           8      0.972     0.982     0.977       974
           9      0.988     0.967     0.977      1009

    accuracy                          0.979     10000
   macro avg      0.979     0.979     0.979     10000
weighted avg      0.979     0.979     0.979     10000
```

8.5 Freeze All The Convolutional Layers Retrain VGG-16 Network On MNIST

```
In [0]: #  Create base model of VGG16
        from keras.applications import VGG16;
        from keras.layers import Input
        input_tensor = Input(shape=(IMG_HEIGHT, IMG_WIDTH, IMG_DEPTH))
        freeze = VGG16(weights='imagenet',include_top=False,
                          input_tensor = input_tensor)
        freeze.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
```

```
input_4 (InputLayer)         (None, 34, 34, 3)         0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 34, 34, 64)        1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 34, 34, 64)        36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 17, 17, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 17, 17, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 17, 17, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 8, 8, 128)         0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 8, 8, 256)         295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 4, 4, 256)         0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 4, 4, 512)         1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 2, 2, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 1, 1, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

In [0]:
```
# Freeze the layers which you don't want to train. Here I am freezing the first 5 laye
for layer in freeze.layers:
    layer.trainable = False
```

Out[0]:
```
'\n    for layer in freeze.layers[3:4]:\n    layer.trainable = False\nfor layer in free
```

```
In [0]: # Extracting features
        train_features = freeze.predict(np.array(train_X), batch_size=BATCH_SIZE, verbose=1)
        test_features = freeze.predict(np.array(X_te), batch_size=BATCH_SIZE, verbose=1)
        val_features = freeze.predict(np.array(valid_X), batch_size=BATCH_SIZE, verbose=1)
```

```
48000/48000 [==============================] - 18s 383us/step
10000/10000 [==============================] - 4s 383us/step
12000/12000 [==============================] - 5s 383us/step
```

```
In [0]: np.savez("train_features", train_features, train_label)
        np.savez("test_features", test_features, y_test_labels)
        np.savez("val_features", val_features, valid_label)
```

```
In [0]: # Current shape of features
        print(train_features.shape, "\n",  test_features.shape, "\n", val_features.shape)
```

```
(48000, 1, 1, 512)
 (10000, 1, 1, 512)
 (12000, 1, 1, 512)
```

```
In [0]: # Flatten extracted features
        train_features_flat = np.reshape(train_features, (48000, 1*1*512))
        test_features_flat = np.reshape(test_features, (10000, 1*1*512))
        val_features_flat = np.reshape(val_features, (12000, 1*1*512))
```

```
In [0]: from keras import models
        from keras.models import Model
        from keras import layers
        from keras import optimizers
        from keras import callbacks
        from keras.layers.advanced_activations import LeakyReLU
        frz_con = models.Sequential()
        frz_con.add(layers.Dense(512, activation='relu', input_dim=(1*1*512)))
        frz_con.add(layers.LeakyReLU(alpha=0.1))
        frz_con.add(layers.Dense(512, activation='relu', input_dim=(1*1*512)))
        frz_con.add(layers.Dense(10, activation='softmax'))
```

```
In [0]: NB_TRAIN_SAMPLES = train_features_flat.shape[0]
        NB_VALIDATION_SAMPLES = val_features_flat.shape[0]
        NB_EPOCHS = 100

        # Compile the model.
        frz_con.compile(optimizer='adam',
                      loss='categorical_crossentropy',
                      metrics=['accuracy'])
```

```
In [0]: # Incorporating reduced learning and early stopping for callback
        reduce_learning = callbacks.ReduceLROnPlateau(
```

```
            monitor='val_loss',
            factor=0.2,
            patience=2,
            verbose=1,
            mode='auto',
            epsilon=0.0001,
            cooldown=2,
            min_lr=0)

        eary_stopping = callbacks.EarlyStopping(
            monitor='val_loss',
            min_delta=0,
            patience=8,
            verbose=1,
            mode='auto')

        callbacks = [reduce_learning, eary_stopping]
```

```
/usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1065: UserWarning: `epsilon` argumen
  warnings.warn('`epsilon` argument is deprecated and '
```

In [0]:
```
# Train the the model
mt=frz_con.fit(
    train_features_flat,
    train_label,
    epochs=NB_EPOCHS,
    validation_data=(val_features_flat, valid_label),
    callbacks=callbacks
)
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/100
48000/48000 [==============================] - 6s 121us/step - loss: 0.3069 - acc: 0.8986 - va
Epoch 2/100
48000/48000 [==============================] - 5s 112us/step - loss: 0.1606 - acc: 0.9480 - va
Epoch 3/100
48000/48000 [==============================] - 6s 119us/step - loss: 0.1342 - acc: 0.9561 - va
Epoch 4/100
48000/48000 [==============================] - 6s 121us/step - loss: 0.1205 - acc: 0.9593 - va
Epoch 5/100
48000/48000 [==============================] - 5s 110us/step - loss: 0.1077 - acc: 0.9648 - va
Epoch 6/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0987 - acc: 0.9674 - va

Epoch 00006: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
Epoch 7/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0571 - acc: 0.9815 - va
```

```
Epoch 8/100
48000/48000 [==============================] - 5s 112us/step - loss: 0.0503 - acc: 0.9838 - val
Epoch 9/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0476 - acc: 0.9844 - val
Epoch 10/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0447 - acc: 0.9853 - val
Epoch 11/100
48000/48000 [==============================] - 5s 110us/step - loss: 0.0409 - acc: 0.9861 - val
Epoch 12/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0387 - acc: 0.9874 - val

Epoch 00012: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
Epoch 13/100
48000/48000 [==============================] - 5s 110us/step - loss: 0.0288 - acc: 0.9914 - val
Epoch 14/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0271 - acc: 0.9917 - val
Epoch 15/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0264 - acc: 0.9920 - val

Epoch 00015: ReduceLROnPlateau reducing learning rate to 8.000000525498762e-06.
Epoch 16/100
48000/48000 [==============================] - 5s 112us/step - loss: 0.0243 - acc: 0.9933 - val
Epoch 17/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0239 - acc: 0.9933 - val
Epoch 18/100
48000/48000 [==============================] - 6s 120us/step - loss: 0.0237 - acc: 0.9936 - val
Epoch 19/100
48000/48000 [==============================] - 6s 120us/step - loss: 0.0236 - acc: 0.9934 - val

Epoch 00019: ReduceLROnPlateau reducing learning rate to 1.6000001778593287e-06.
Epoch 20/100
48000/48000 [==============================] - 5s 110us/step - loss: 0.0231 - acc: 0.9936 - val
Epoch 21/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0230 - acc: 0.9936 - val
Epoch 22/100
48000/48000 [==============================] - 5s 111us/step - loss: 0.0230 - acc: 0.9937 - val

Epoch 00022: ReduceLROnPlateau reducing learning rate to 3.200000264769187e-07.
Epoch 23/100
48000/48000 [==============================] - 5s 112us/step - loss: 0.0229 - acc: 0.9938 - val
Epoch 24/100
48000/48000 [==============================] - 5s 110us/step - loss: 0.0229 - acc: 0.9938 - val
Epoch 25/100
48000/48000 [==============================] - 5s 110us/step - loss: 0.0228 - acc: 0.9938 - val

Epoch 00025: ReduceLROnPlateau reducing learning rate to 6.400000529538374e-08.
Epoch 00025: early stopping
```

```
In [0]: # Evaluate accuracy
        test_loss, test_acc = frz_con.evaluate(test_features_flat, y_test_labels)
        print('Test Accuracy:%4f, Test Loss:%4f.' %(test_acc,test_loss))
```

```
10000/10000 [==============================] - 0s 40us/step
Test Accuracy:0.977100, Test Loss:0.069289.
```

```
In [0]: # Make Prediction
        pred_result = frz_con.predict(test_features_flat)
        y_pred=[]
        for i in range(np.shape(y_test)[0]):
          num = np.where(pred_result[i]==max(pred_result[i]))
          y_pred.append(num[0][0])
        y_pred = np.transpose(y_pred)
```

```
In [0]: # calculate accuracy
        num_test = len(y_test)
        num_correct = np.sum(y_pred == y_test)
        print('Got %d / %d correct' % (num_correct, num_test))
        print('Accuracy = %f' % (np.mean(y_test == y_pred)))
        from sklearn.metrics import classification_report, confusion_matrix
        print(confusion_matrix(y_test, y_pred))
        print(classification_report(y_test, y_pred,
                                    target_names=list(label_dict.values()),digits=3))
```

```
Got 9771 / 10000 correct
Accuracy = 0.977100
[[ 967    0    1    0    0    3    5    1    2    1]
 [   0 1125    0    0    3    0    4    2    1    0]
 [   1    2 1000    8    2    6    3    6    3    1]
 [   0    0    9  976    0   18    0    4    2    1]
 [   0    1    0    0  968    1    3    2    3    4]
 [   2    0    4   13    1  861    3    2    5    1]
 [   7    1    2    0    1    3  941    0    2    1]
 [   0    3    4    3   10    0    0 1002    1    5]
 [   0    0    3    4    2    4    2    2  955    2]
 [   3    0    3    3    5    3    0    4   12  976]]
              precision    recall  f1-score   support

           0      0.987     0.987     0.987       980
           1      0.994     0.991     0.993      1135
           2      0.975     0.969     0.972      1032
           3      0.969     0.966     0.968      1010
           4      0.976     0.986     0.981       982
           5      0.958     0.965     0.961       892
           6      0.979     0.982     0.981       958
           7      0.978     0.975     0.976      1028
           8      0.969     0.980     0.974       974
```

```
           9      0.984     0.967     0.976      1009

    accuracy                          0.977     10000
   macro avg      0.977     0.977     0.977     10000
weighted avg      0.977     0.977     0.977     10000
```

8.6 Freeze All The Full Connected Layers Retrain VGG-16 Network On MNIST

```
In [0]: #  Create base model of VGG16
        from keras.applications import VGG16;
        from keras.layers import Input
        input_tensor = Input(shape=(IMG_HEIGHT, IMG_WIDTH, IMG_DEPTH))
        freeze = VGG16(weights='imagenet',include_top=False,
                          input_tensor = input_tensor)
        freeze.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_9 (InputLayer)         (None, 34, 34, 3)         0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 34, 34, 64)        1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 34, 34, 64)        36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 17, 17, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 17, 17, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 17, 17, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 8, 8, 128)         0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 8, 8, 256)         295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 4, 4, 256)         0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 4, 4, 512)         1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 4, 4, 512)         2359808
```

```
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 2, 2, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 1, 1, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

```
In [0]: # Extracting features
        train_features = freeze.predict(np.array(train_X), batch_size=BATCH_SIZE, verbose=1)
        test_features = freeze.predict(np.array(X_te), batch_size=BATCH_SIZE, verbose=1)
        val_features = freeze.predict(np.array(valid_X), batch_size=BATCH_SIZE, verbose=1)
```

```
48000/48000 [==============================] - 19s 401us/step
10000/10000 [==============================] - 4s 400us/step
12000/12000 [==============================] - 5s 403us/step
```

```
In [0]: np.savez("train_features", train_features, train_label)
        np.savez("test_features", test_features, y_test_labels)
        np.savez("val_features", val_features, valid_label)
```

```
In [0]: # Current shape of features
        print(train_features.shape, "\n",  test_features.shape, "\n", val_features.shape)
```

```
(48000, 1, 1, 512)
 (10000, 1, 1, 512)
 (12000, 1, 1, 512)
```

```
In [0]: # Flatten extracted features
        train_features_flat = np.reshape(train_features, (48000, 1*1*512))
        test_features_flat = np.reshape(test_features, (10000, 1*1*512))
        val_features_flat = np.reshape(val_features, (12000, 1*1*512))
```

```
In [0]: from keras import models
        from keras.models import Model
        from keras import layers
        from keras import optimizers
        from keras import callbacks
```

```
from keras.layers.advanced_activations import LeakyReLU
frz_fcn = models.Sequential()
frz_fcn.add(layers.Dense(512, activation='relu', input_dim=(1*1*512)))
frz_con.add(layers.Dense(512, activation='relu', input_dim=(1*1*512)))
frz_fcn.add(layers.Dense(10, activation='softmax'))
```

In [0]:
```
# Freeze the layers which you don't want to train. Here I am freezing the first 5 laye
for layer in frz_fcn.layers[0:2]:
    layer.trainable = False
```

In [0]:
```
NB_TRAIN_SAMPLES = train_features_flat.shape[0]
NB_VALIDATION_SAMPLES = val_features_flat.shape[0]
NB_EPOCHS = 100

# Compile the model.

frz_fcn.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

In [0]:
```
# Incorporating reduced learning and early stopping for callback
reduce_learning = callbacks.ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.2,
    patience=2,
    verbose=1,
    mode='auto',
    epsilon=0.0001,
    cooldown=2,
    min_lr=0)

eary_stopping = callbacks.EarlyStopping(
    monitor='val_loss',
    min_delta=0,
    patience=8,
    verbose=1,
    mode='auto')

callbacks = [reduce_learning, eary_stopping]
```

```
/usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1065: UserWarning: `epsilon` argumen
  warnings.warn('`epsilon` argument is deprecated and '
```

In [0]:
```
# Train the the model
mt=frz_fcn.fit(
    train_features_flat,
    train_label,
    epochs=NB_EPOCHS,
```

```
            validation_data=(val_features_flat, valid_label),
            callbacks=callbacks
        )
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/100
48000/48000 [==============================] - 4s 73us/step - loss: 2.4916 - acc: 0.1330 - val_
Epoch 2/100
48000/48000 [==============================] - 3s 55us/step - loss: 2.4916 - acc: 0.1330 - val_
Epoch 3/100
48000/48000 [==============================] - 3s 55us/step - loss: 2.4916 - acc: 0.1330 - val_

Epoch 00003: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
Epoch 4/100
48000/48000 [==============================] - 3s 61us/step - loss: 2.4916 - acc: 0.1330 - val_
Epoch 5/100
48000/48000 [==============================] - 3s 64us/step - loss: 2.4916 - acc: 0.1330 - val_
Epoch 6/100
48000/48000 [==============================] - 3s 54us/step - loss: 2.4916 - acc: 0.1330 - val_

Epoch 00006: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
Epoch 7/100
48000/48000 [==============================] - 3s 54us/step - loss: 2.4916 - acc: 0.1330 - val_
Epoch 8/100
48000/48000 [==============================] - 3s 55us/step - loss: 2.4916 - acc: 0.1330 - val_
Epoch 9/100
48000/48000 [==============================] - 3s 54us/step - loss: 2.4916 - acc: 0.1330 - val_

Epoch 00009: ReduceLROnPlateau reducing learning rate to 8.000000525498762e-06.
Epoch 00009: early stopping
```

```
In [0]: # Evaluate accuracy
        test_loss, test_acc = frz_fcn.evaluate(test_features_flat, y_test_labels)
        print('Test Accuracy:%4f, Test Loss:%4f.' %(test_acc,test_loss))
```

```
10000/10000 [==============================] - 0s 43us/step
Test Accuracy:0.129600, Test Loss:2.491812.
```

```
In [0]: # Make Prediction
        pred_result = frz_fcn.predict(test_features_flat)
        y_pred=[]
        for i in range(np.shape(y_test)[0]):
          num = np.where(pred_result[i]==max(pred_result[i]))
          y_pred.append(num[0][0])
        y_pred = np.transpose(y_pred)
```

```
In [0]: # calculate accuracy
        num_test = len(y_test)
```

```python
num_correct = np.sum(y_pred == y_test)
print('Got %d / %d correct' % (num_correct, num_test))
print('Accuracy = %f' % (np.mean(y_test == y_pred)))
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred,
                            target_names=list(label_dict.values()),digits=3))
```

```
Got 1296 / 10000 correct
Accuracy = 0.129600
[[   0    0    0    0    0    0    0    0  980    0]
 [   0    0    0    4  821  266    0    2   34    8]
 [   0    0    0    0    5    0    0   10 1015    2]
 [   0    0    0    0    4    0    0    0 1005    1]
 [   0    0    0    5  315   27    0   12  612   11]
 [   0    0    0    0    8    0    0    2  881    1]
 [   0    0    0    0    8    1    0    3  939    7]
 [   0    0    0    0  217   48    0    8  702   53]
 [   0    0    0    0    2    0    0    0  972    0]
 [   0    0    0    0   15    5    0    0  988    1]]
              precision    recall  f1-score   support

           0      0.000     0.000     0.000       980
           1      0.000     0.000     0.000      1135
           2      0.000     0.000     0.000      1032
           3      0.000     0.000     0.000      1010
           4      0.226     0.321     0.265       982
           5      0.000     0.000     0.000       892
           6      0.000     0.000     0.000       958
           7      0.216     0.008     0.015      1028
           8      0.120     0.998     0.214       974
           9      0.012     0.001     0.002      1009

    accuracy                          0.130     10000
   macro avg      0.057     0.133     0.050     10000
weighted avg      0.057     0.130     0.049     10000


/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1437: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```