

CNN on CIFR Assignment:

1. Please visit this link to access the state-of-art DenseNet code for reference - DenseNet - cifar10 notebook link
2. You need to create a copy of this and "retrain" this model to achieve 90+ test accuracy.
3. You cannot use DropOut layers.
4. You MUST use Image Augmentation Techniques.
5. You cannot use an already trained model as a beginning points, you have to initilize as your own
6. You cannot run the program for more than 300 Epochs, and it should be clear from your log, that you have only used 300 Epochs
7. You cannot use test images for training the model.
8. You cannot change the general architecture of DenseNet (which means you must use Dense Block, Transition and Output blocks as mentioned in the code)
9. You are free to change Convolution types (e.g. from 3x3 normal convolution to Depthwise Separable, etc)
10. You cannot have more than 1 Million parameters in total
11. You are free to move the code from Keras to Tensorflow, Pytorch, MXNET etc.
12. You can use any optimization algorithm you need.
13. You can checkpoint your model and retrain the model from that checkpoint so that no need of training the model from first if you lost at any epoch while training. You can directly load that model and Train from that epoch.

```
In [1]: # Importing required Libraries
import warnings
warnings.filterwarnings('ignore')
import tensorflow as tf
from tensorflow.keras import models, layers
from tensorflow.keras.models import Model
from keras.models import load_model
from tensorflow.keras.optimizers import Adam
import keras
from keras.preprocessing.image import ImageDataGenerator
from keras.layers import Dense, Dropout, Flatten, Input, AveragePooling2D, merge, Activation
from keras.layers import Conv2D, MaxPooling2D, BatchNormalization, DepthwiseConv2D
from keras.layers import Concatenate
```

```
In [2]: # This code snippet is copied from DenseNet - cifar10.ipynb, provided by Applied AI
# Hyperparameters
batch_size = 128
num_classes = 10
epochs = 100
l = 10
num_filter = 42
compression = 0.5
dropout_rate = 0
```

```
In [3]: # This code snippet is copied from DenseNet - cifar10.ipynb, provided by Applied AI
# Load dataset
(X_train, y_train), (X_test, y_test) = keras.datasets.cifar10.load_data()
img_height, img_width, channel = X_train.shape[1], X_train.shape[2], X_train.shape[3]
# one hot encode target values
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>
170500096/170498071 [=====] - 2s 0us/step

```
In [4]: X_train.shape
```

```
Out[4]: (50000, 32, 32, 3)
```

```
In [5]: X_test.shape
```

```
Out[5]: (10000, 32, 32, 3)
```

```
In [6]: y_train.shape
```

```
Out[6]: (50000, 10)
```

```
In [7]: y_test.shape
```

```
Out[7]: (10000, 10)
```

Ref - <https://machinelearningmastery.com/how-to-develop-a-cnn-from-scratch-for-cifar-10-photo-classification/>
[\(https://machinelearningmastery.com/how-to-develop-a-cnn-from-scratch-for-cifar-10-photo-classification/\)](https://machinelearningmastery.com/how-to-develop-a-cnn-from-scratch-for-cifar-10-photo-classification/)

```
In [8]: # scale pixels
def prep_pixels(train, test):
    # convert from integers to floats
    train_norm = train.astype('float32')
    test_norm = test.astype('float32')
    # normalize to range 0-1
    train_norm = train_norm / 255.0
    test_norm = test_norm / 255.0
    # return normalized images
    return train_norm, test_norm
```

```
In [9]: X_train,X_test=prep_pixels(X_train,X_test)
```

```
In [10]: # This code snippet is copied from DenseNet - cifar10.ipynb, provided by Applied AI
# Dense Block
def denseblock(input, num_filter = 12, dropout_rate = 0.2):
    global compression
    temp = input
    for _ in range(1):
        BatchNorm = layers.BatchNormalization()(temp)
        relu = layers.Activation('relu')(BatchNorm)
        Conv2D_3_3 = layers.Conv2D(int(num_filter*compression), (3,3), use_bias=False, padding='same')(relu)
        if dropout_rate>0:
            Conv2D_3_3 = layers.Dropout(dropout_rate)(Conv2D_3_3)
        concat = layers.Concatenate(axis=-1)([temp,Conv2D_3_3])

        temp = concat

    return temp

## transition Block
def transition(input, num_filter = 12, dropout_rate = 0.2):
    global compression
    BatchNorm = layers.BatchNormalization()(input)
    relu = layers.Activation('relu')(BatchNorm)
    Conv2D_BottleNeck = layers.Conv2D(int(num_filter*compression), (1,1), use_bias=False, padding='same')(relu)
    if dropout_rate>0:
        Conv2D_BottleNeck = layers.Dropout(dropout_rate)(Conv2D_BottleNeck)
    avg = layers.AveragePooling2D(pool_size=(2,2))(Conv2D_BottleNeck)
    return avg

#output Layer
def output_layer(input):
    global compression
    BatchNorm = layers.BatchNormalization()(input)
    relu = layers.Activation('relu')(BatchNorm)
    AvgPooling = layers.AveragePooling2D(pool_size=(2,2))(relu)
    flat = layers.Flatten()(AvgPooling)
    output = layers.Dense(num_classes, activation='softmax')(flat)
    return output
```

```
In [11]: # This code snippet is copied from DenseNet - cifar10.ipynb, provided by Applied AI
input = layers.Input(shape=(img_height, img_width, channel,))
First_Conv2D = Conv2D(num_filter, (3,3), use_bias=False ,padding='same')(input
)

First_Block = denseblock(First_Conv2D, num_filter, dropout_rate)
First_Transition = transition(First_Block, num_filter, dropout_rate)

Second_Block = denseblock(First_Transition, num_filter, dropout_rate)
Second_Transition = transition(Second_Block, num_filter, dropout_rate)

Third_Block = denseblock(Second_Transition, num_filter, dropout_rate)
Third_Transition = transition(Third_Block, num_filter, dropout_rate)

Last_Block = denseblock(Third_Transition, num_filter, dropout_rate)
output = output_layer(Last_Block)
```

```
In [12]: model = Model(inputs=[input], outputs=[output])  
         model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	[(None, 32, 32, 3)]	0	

conv2d (Conv2D)	(None, 32, 32, 42)	1134	input_1[0]

batch_normalization (BatchNorma	(None, 32, 32, 42)	168	conv2d[0][0]

activation (Activation)	(None, 32, 32, 42)	0	batch_normal
ization[0][0]			

conv2d_1 (Conv2D)	(None, 32, 32, 21)	7938	activation
[0][0]			

concatenate (Concatenate)	(None, 32, 32, 63)	0	conv2d[0][0]

batch_normalization_1 (BatchNor	(None, 32, 32, 63)	252	concatenate
[0][0]			

activation_1 (Activation)	(None, 32, 32, 63)	0	batch_normal
ization_1[0][0]			

conv2d_2 (Conv2D)	(None, 32, 32, 21)	11907	activation_1
[0][0]			

concatenate_1 (Concatenate)	(None, 32, 32, 84)	0	concatenate

batch_normalization_2 (BatchNor	(None, 32, 32, 84)	336	concatenate_
1[0][0]			

activation_2 (Activation)	(None, 32, 32, 84)	0	batch_normal
ization_2[0][0]			

conv2d_3 (Conv2D)	(None, 32, 32, 21)	15876	activation_2
[0][0]			

concatenate_2 (Concatenate) 1[0][0]	(None, 32, 32, 105)	0	concatenate_1[0]
batch_normalization_3 (BatchNormal 2[0][0])	(None, 32, 32, 105)	420	conv2d_3[0]
activation_3 (Activation) ization_3[0][0]	(None, 32, 32, 105)	0	batch_normalization_3[0][0]
conv2d_4 (Conv2D) [0][0]	(None, 32, 32, 21)	19845	activation_3[0]
concatenate_3 (Concatenate) 2[0][0]	(None, 32, 32, 126)	0	conv2d_4[0]
batch_normalization_4 (BatchNormal 3[0][0])	(None, 32, 32, 126)	504	concatenate_2[0]
activation_4 (Activation) ization_4[0][0]	(None, 32, 32, 126)	0	batch_normalization_4[0][0]
conv2d_5 (Conv2D) [0][0]	(None, 32, 32, 21)	23814	activation_3[0]
concatenate_4 (Concatenate) 3[0][0]	(None, 32, 32, 147)	0	conv2d_5[0]
batch_normalization_5 (BatchNormal 4[0][0])	(None, 32, 32, 147)	588	concatenate_3[0]
activation_5 (Activation) ization_5[0][0]	(None, 32, 32, 147)	0	batch_normalization_5[0][0]
conv2d_6 (Conv2D) [0][0]	(None, 32, 32, 21)	27783	activation_4[0]
concatenate_5 (Concatenate)	(None, 32, 32, 168)	0	concatenate_4[0]

4[0][0]			conv2d_6[0]
[0]			
<hr/>			
batch_normalization_6 (BatchNor	(None, 32, 32, 168)	672	concatenate_5[0][0]
<hr/>			
activation_6 (Activation)	(None, 32, 32, 168)	0	batch_normalization_6[0][0]
<hr/>			
conv2d_7 (Conv2D)	(None, 32, 32, 21)	31752	activation_6[0][0]
<hr/>			
concatenate_6 (Concatenate)	(None, 32, 32, 189)	0	concatenate_5[0][0]
<hr/>			
batch_normalization_7 (BatchNor	(None, 32, 32, 189)	756	concatenate_6[0][0]
<hr/>			
activation_7 (Activation)	(None, 32, 32, 189)	0	batch_normalization_7[0][0]
<hr/>			
conv2d_8 (Conv2D)	(None, 32, 32, 21)	35721	activation_7[0][0]
<hr/>			
concatenate_7 (Concatenate)	(None, 32, 32, 210)	0	concatenate_6[0][0]
<hr/>			
batch_normalization_8 (BatchNor	(None, 32, 32, 210)	840	concatenate_7[0][0]
<hr/>			
activation_8 (Activation)	(None, 32, 32, 210)	0	batch_normalization_8[0][0]
<hr/>			
conv2d_9 (Conv2D)	(None, 32, 32, 21)	39690	activation_8[0][0]
<hr/>			
concatenate_8 (Concatenate)	(None, 32, 32, 231)	0	concatenate_7[0][0]
<hr/>			
			conv2d_9[0]
[0]			

batch_normalization_9 (BatchNormalizer)	(None, 32, 32, 231)	924	concatenate_8[0][0]
activation_9 (Activation)	(None, 32, 32, 231)	0	batch_normalization_9[0][0]
conv2d_10 (Conv2D)	(None, 32, 32, 21)	43659	activation_9[0][0]
concatenate_9 (Concatenate)	(None, 32, 32, 252)	0	concatenate_8[0][0] conv2d_10[0]
batch_normalization_10 (BatchNormalizer)	(None, 32, 32, 252)	1008	concatenate_9[0][0]
activation_10 (Activation)	(None, 32, 32, 252)	0	batch_normalization_10[0][0]
conv2d_11 (Conv2D)	(None, 32, 32, 21)	5292	activation_10[0][0]
average_pooling2d (AveragePooling2D)	(None, 16, 16, 21)	0	conv2d_11[0]
batch_normalization_11 (BatchNormalizer)	(None, 16, 16, 21)	84	average_pooling2d[0][0]
activation_11 (Activation)	(None, 16, 16, 21)	0	batch_normalization_11[0][0]
conv2d_12 (Conv2D)	(None, 16, 16, 21)	3969	activation_11[0][0]
concatenate_10 (Concatenate)	(None, 16, 16, 42)	0	average_pooling2d[0][0] conv2d_12[0]
batch_normalization_12 (BatchNormalizer)	(None, 16, 16, 42)	168	concatenate_10[0][0]

activation_12 (Activation) ization_12[0][0]	(None, 16, 16, 42)	0	batch_normal
conv2d_13 (Conv2D) 2[0][0]	(None, 16, 16, 21)	7938	activation_1
concatenate_11 (Concatenate) 10[0][0] [0]	(None, 16, 16, 63)	0	concatenate_ conv2d_13[0]
batch_normalization_13 (BatchNo 11[0][0]	(None, 16, 16, 63)	252	concatenate_
activation_13 (Activation) ization_13[0][0]	(None, 16, 16, 63)	0	batch_normal
conv2d_14 (Conv2D) 3[0][0]	(None, 16, 16, 21)	11907	activation_1
concatenate_12 (Concatenate) 11[0][0] [0]	(None, 16, 16, 84)	0	concatenate_ conv2d_14[0]
batch_normalization_14 (BatchNo 12[0][0]	(None, 16, 16, 84)	336	concatenate_
activation_14 (Activation) ization_14[0][0]	(None, 16, 16, 84)	0	batch_normal
conv2d_15 (Conv2D) 4[0][0]	(None, 16, 16, 21)	15876	activation_1
concatenate_13 (Concatenate) 12[0][0] [0]	(None, 16, 16, 105)	0	concatenate_ conv2d_15[0]
batch_normalization_15 (BatchNo 13[0][0]	(None, 16, 16, 105)	420	concatenate_
activation_15 (Activation) ization_15[0][0]	(None, 16, 16, 105)	0	batch_normal

conv2d_16 (Conv2D) 5[0][0]	(None, 16, 16, 21)	19845	activation_15[0][0]
concatenate_14 (Concatenate) 13[0][0]	(None, 16, 16, 126)	0	concatenate_13[0][0] conv2d_16[0]
batch_normalization_16 (BatchNo 14[0][0])	(None, 16, 16, 126)	504	concatenate_14[0][0]
activation_16 (Activation) 16[0][0]	(None, 16, 16, 126)	0	batch_normalization_16[0][0]
conv2d_17 (Conv2D) 6[0][0]	(None, 16, 16, 21)	23814	activation_16[0][0]
concatenate_15 (Concatenate) 14[0][0]	(None, 16, 16, 147)	0	concatenate_14[0][0] conv2d_17[0]
batch_normalization_17 (BatchNo 15[0][0])	(None, 16, 16, 147)	588	concatenate_15[0][0]
activation_17 (Activation) 17[0][0]	(None, 16, 16, 147)	0	batch_normalization_17[0][0]
conv2d_18 (Conv2D) 7[0][0]	(None, 16, 16, 21)	27783	activation_17[0][0]
concatenate_16 (Concatenate) 15[0][0]	(None, 16, 16, 168)	0	concatenate_15[0][0] conv2d_18[0]
batch_normalization_18 (BatchNo 16[0][0])	(None, 16, 16, 168)	672	concatenate_16[0][0]
activation_18 (Activation) 18[0][0]	(None, 16, 16, 168)	0	batch_normalization_18[0][0]
conv2d_19 (Conv2D)	(None, 16, 16, 21)	31752	activation_1

8[0][0]

concatenate_17 (Concatenate) 16[0][0] [0]	(None, 16, 16, 189)	0	concatenate_ conv2d_19[0]
batch_normalization_19 (BatchNo 17[0][0]	(None, 16, 16, 189)	756	concatenate_ 17[0][0]
activation_19 (Activation) ization_19[0][0]	(None, 16, 16, 189)	0	batch_normal ization_19[0][0]
conv2d_20 (Conv2D) 9[0][0]	(None, 16, 16, 21)	35721	activation_1 9[0][0]
concatenate_18 (Concatenate) 17[0][0] [0]	(None, 16, 16, 210)	0	concatenate_ conv2d_20[0]
batch_normalization_20 (BatchNo 18[0][0]	(None, 16, 16, 210)	840	concatenate_ 18[0][0]
activation_20 (Activation) ization_20[0][0]	(None, 16, 16, 210)	0	batch_normal ization_20[0][0]
conv2d_21 (Conv2D) 0[0][0]	(None, 16, 16, 21)	39690	activation_2 0[0][0]
concatenate_19 (Concatenate) 18[0][0] [0]	(None, 16, 16, 231)	0	concatenate_ conv2d_21[0]
batch_normalization_21 (BatchNo 19[0][0]	(None, 16, 16, 231)	924	concatenate_ 19[0][0]
activation_21 (Activation) ization_21[0][0]	(None, 16, 16, 231)	0	batch_normal ization_21[0][0]
conv2d_22 (Conv2D) 1[0][0]	(None, 16, 16, 21)	4851	activation_2 1[0][0]

average_pooling2d_1 (AveragePool)	(None, 8, 8, 21)	0	conv2d_22[0][0]
batch_normalization_22 (BatchNormalization)	(None, 8, 8, 21)	84	average_pooling2d_1[0][0]
activation_22 (Activation)	(None, 8, 8, 21)	0	batch_normalization_22[0][0]
conv2d_23 (Conv2D)	(None, 8, 8, 21)	3969	activation_22[0][0]
concatenate_20 (Concatenate)	(None, 8, 8, 42)	0	average_pooling2d_1[0][0] conv2d_23[0][0]
batch_normalization_23 (BatchNormalization)	(None, 8, 8, 42)	168	concatenate_20[0][0]
activation_23 (Activation)	(None, 8, 8, 42)	0	batch_normalization_23[0][0]
conv2d_24 (Conv2D)	(None, 8, 8, 21)	7938	activation_23[0][0]
concatenate_21 (Concatenate)	(None, 8, 8, 63)	0	concatenate_20[0][0] conv2d_24[0][0]
batch_normalization_24 (BatchNormalization)	(None, 8, 8, 63)	252	concatenate_21[0][0]
activation_24 (Activation)	(None, 8, 8, 63)	0	batch_normalization_24[0][0]
conv2d_25 (Conv2D)	(None, 8, 8, 21)	11907	activation_24[0][0]
concatenate_22 (Concatenate)	(None, 8, 8, 84)	0	concatenate_21[0][0] conv2d_25[0][0]

batch_normalization_25 (BatchNo	(None, 8, 8, 84)	336	concatenate_22[0][0]
activation_25 (Activation)	(None, 8, 8, 84)	0	batch_normalization_25[0][0]
conv2d_26 (Conv2D)	(None, 8, 8, 21)	15876	activation_25[0][0]
concatenate_23 (Concatenate)	(None, 8, 8, 105)	0	concatenate_22[0][0]
			conv2d_26[0][0]
batch_normalization_26 (BatchNo	(None, 8, 8, 105)	420	concatenate_23[0][0]
activation_26 (Activation)	(None, 8, 8, 105)	0	batch_normalization_26[0][0]
conv2d_27 (Conv2D)	(None, 8, 8, 21)	19845	activation_26[0][0]
concatenate_24 (Concatenate)	(None, 8, 8, 126)	0	concatenate_23[0][0]
			conv2d_27[0][0]
batch_normalization_27 (BatchNo	(None, 8, 8, 126)	504	concatenate_24[0][0]
activation_27 (Activation)	(None, 8, 8, 126)	0	batch_normalization_27[0][0]
conv2d_28 (Conv2D)	(None, 8, 8, 21)	23814	activation_27[0][0]
concatenate_25 (Concatenate)	(None, 8, 8, 147)	0	concatenate_24[0][0]
			conv2d_28[0][0]
batch_normalization_28 (BatchNo	(None, 8, 8, 147)	588	concatenate_25[0][0]

activation_28 (Activation) ization_28[0][0]	(None, 8, 8, 147)	0	batch_normal
conv2d_29 (Conv2D) 8[0][0]	(None, 8, 8, 21)	27783	activation_2
concatenate_26 (Concatenate) 25[0][0] [0]	(None, 8, 8, 168)	0	concatenate_ conv2d_29[0]
batch_normalization_29 (BatchNo 26[0][0]	(None, 8, 8, 168)	672	concatenate_
activation_29 (Activation) ization_29[0][0]	(None, 8, 8, 168)	0	batch_normal
conv2d_30 (Conv2D) 9[0][0]	(None, 8, 8, 21)	31752	activation_2
concatenate_27 (Concatenate) 26[0][0] [0]	(None, 8, 8, 189)	0	concatenate_ conv2d_30[0]
batch_normalization_30 (BatchNo 27[0][0]	(None, 8, 8, 189)	756	concatenate_
activation_30 (Activation) ization_30[0][0]	(None, 8, 8, 189)	0	batch_normal
conv2d_31 (Conv2D) 0[0][0]	(None, 8, 8, 21)	35721	activation_3
concatenate_28 (Concatenate) 27[0][0] [0]	(None, 8, 8, 210)	0	concatenate_ conv2d_31[0]
batch_normalization_31 (BatchNo 28[0][0]	(None, 8, 8, 210)	840	concatenate_
activation_31 (Activation)	(None, 8, 8, 210)	0	batch_normal

ization_31[0][0]

conv2d_32 (Conv2D) 1[0][0]	(None, 8, 8, 21)	39690	activation_31[0][0]
concatenate_29 (Concatenate) 28[0][0]	(None, 8, 8, 231)	0	concatenate_28[0][0]
batch_normalization_32 (BatchNo 29[0][0]	(None, 8, 8, 231)	924	concatenate_29[0][0]
activation_32 (Activation) ization_32[0][0]	(None, 8, 8, 231)	0	batch_normalization_32[0][0]
conv2d_33 (Conv2D) 2[0][0]	(None, 8, 8, 21)	4851	activation_32[0][0]
average_pooling2d_2 (AveragePoo [0]	(None, 4, 4, 21)	0	conv2d_33[0][0]
batch_normalization_33 (BatchNo ing2d_2[0][0]	(None, 4, 4, 21)	84	average_pooling2d_2[0][0]
activation_33 (Activation) ization_33[0][0]	(None, 4, 4, 21)	0	batch_normalization_33[0][0]
conv2d_34 (Conv2D) 3[0][0]	(None, 4, 4, 21)	3969	activation_33[0][0]
concatenate_30 (Concatenate) ing2d_2[0][0]	(None, 4, 4, 42)	0	average_pooling2d_2[0][0]
batch_normalization_34 (BatchNo 30[0][0]	(None, 4, 4, 42)	168	concatenate_30[0][0]
activation_34 (Activation) ization_34[0][0]	(None, 4, 4, 42)	0	batch_normalization_34[0][0]
conv2d_35 (Conv2D) 4[0][0]	(None, 4, 4, 21)	7938	activation_34[0][0]

concatenate_31 (Concatenate) 30[0][0]	(None, 4, 4, 63)	0	concatenate_ conv2d_35[0]
[0]			
batch_normalization_35 (BatchNo 31[0][0]	(None, 4, 4, 63)	252	concatenate_
activation_35 (Activation) ization_35[0][0]	(None, 4, 4, 63)	0	batch_normal
conv2d_36 (Conv2D) 5[0][0]	(None, 4, 4, 21)	11907	activation_3
concatenate_32 (Concatenate) 31[0][0]	(None, 4, 4, 84)	0	concatenate_
[0]			conv2d_36[0]
batch_normalization_36 (BatchNo 32[0][0]	(None, 4, 4, 84)	336	concatenate_
activation_36 (Activation) ization_36[0][0]	(None, 4, 4, 84)	0	batch_normal
conv2d_37 (Conv2D) 6[0][0]	(None, 4, 4, 21)	15876	activation_3
concatenate_33 (Concatenate) 32[0][0]	(None, 4, 4, 105)	0	concatenate_
[0]			conv2d_37[0]
batch_normalization_37 (BatchNo 33[0][0]	(None, 4, 4, 105)	420	concatenate_
activation_37 (Activation) ization_37[0][0]	(None, 4, 4, 105)	0	batch_normal
conv2d_38 (Conv2D) 7[0][0]	(None, 4, 4, 21)	19845	activation_3
concatenate_34 (Concatenate)	(None, 4, 4, 126)	0	concatenate_

33[0][0]			conv2d_38[0]
[0]			
batch_normalization_38 (BatchNo	(None, 4, 4, 126)	504	concatenate_34[0][0]
34[0][0]			
activation_38 (Activation)	(None, 4, 4, 126)	0	batch_normalization_38[0][0]
ization_38[0][0]			
conv2d_39 (Conv2D)	(None, 4, 4, 21)	23814	activation_38[0][0]
8[0][0]			
concatenate_35 (Concatenate)	(None, 4, 4, 147)	0	concatenate_34[0][0]
34[0][0]			conv2d_39[0]
[0]			
batch_normalization_39 (BatchNo	(None, 4, 4, 147)	588	concatenate_35[0][0]
35[0][0]			
activation_39 (Activation)	(None, 4, 4, 147)	0	batch_normalization_39[0][0]
ization_39[0][0]			
conv2d_40 (Conv2D)	(None, 4, 4, 21)	27783	activation_39[0][0]
9[0][0]			
concatenate_36 (Concatenate)	(None, 4, 4, 168)	0	concatenate_35[0][0]
35[0][0]			conv2d_40[0]
[0]			
batch_normalization_40 (BatchNo	(None, 4, 4, 168)	672	concatenate_36[0][0]
36[0][0]			
activation_40 (Activation)	(None, 4, 4, 168)	0	batch_normalization_40[0][0]
ization_40[0][0]			
conv2d_41 (Conv2D)	(None, 4, 4, 21)	31752	activation_40[0][0]
0[0][0]			
concatenate_37 (Concatenate)	(None, 4, 4, 189)	0	concatenate_36[0][0]
36[0][0]			conv2d_41[0]
[0]			

batch_normalization_41 (BatchNo	(None, 4, 4, 189)	756	concatenate_37[0][0]
activation_41 (Activation)	(None, 4, 4, 189)	0	batch_normalization_41[0][0]
conv2d_42 (Conv2D)	(None, 4, 4, 21)	35721	activation_41[0][0]
concatenate_38 (Concatenate)	(None, 4, 4, 210)	0	concatenate_37[0][0]
			conv2d_42[0][0]
batch_normalization_42 (BatchNo	(None, 4, 4, 210)	840	concatenate_38[0][0]
activation_42 (Activation)	(None, 4, 4, 210)	0	batch_normalization_42[0][0]
conv2d_43 (Conv2D)	(None, 4, 4, 21)	39690	activation_42[0][0]
concatenate_39 (Concatenate)	(None, 4, 4, 231)	0	concatenate_38[0][0]
			conv2d_43[0][0]
batch_normalization_43 (BatchNo	(None, 4, 4, 231)	924	concatenate_39[0][0]
activation_43 (Activation)	(None, 4, 4, 231)	0	batch_normalization_43[0][0]
average_pooling2d_3 (AveragePoo	(None, 2, 2, 231)	0	activation_43[0][0]
flatten (Flatten)	(None, 924)	0	average_pooling2d_3[0][0]
dense (Dense)	(None, 10)	9250	flatten[0][0]

=====

```
=====
Total params: 961,348
Trainable params: 949,798
Non-trainable params: 11,550
```

```
In [13]: model.compile(loss='categorical_crossentropy',
                      optimizer=Adam(),
                      metrics=['accuracy'])
```

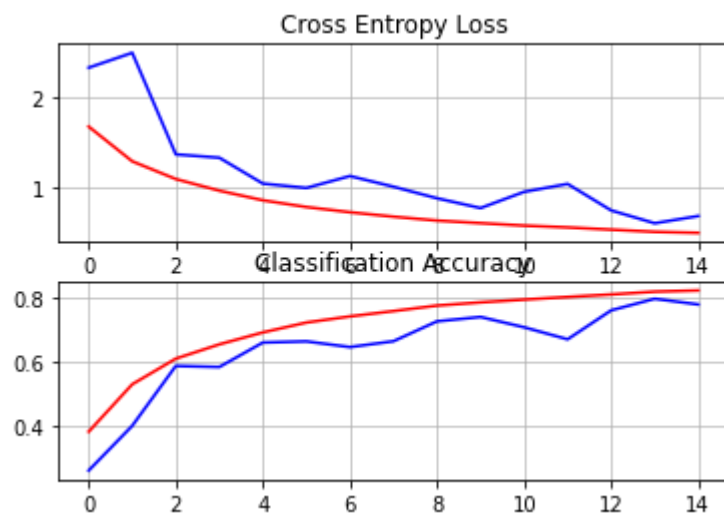
Ref - <https://machinelearningmastery.com/how-to-develop-a-cnn-from-scratch-for-cifar-10-photo-classification/>
(<https://machinelearningmastery.com/how-to-develop-a-cnn-from-scratch-for-cifar-10-photo-classification/>)

```
In [14]: # plot diagnostic learning curves
from matplotlib import pyplot
%matplotlib inline
def summarize_diagnostics(history):
    # plot loss
    pyplot.subplot(211)
    pyplot.title('Cross Entropy Loss')
    pyplot.plot(history.history['loss'], color='red', label='train')
    pyplot.plot(history.history['val_loss'], color='blue', label='test')
    pyplot.grid(alpha=0.8)
    # plot accuracy
    pyplot.subplot(212)
    pyplot.title('Classification Accuracy')
    pyplot.plot(history.history['accuracy'], color='red', label='train')
    pyplot.plot(history.history['val_accuracy'], color='blue', label='test')
    pyplot.grid(alpha=0.8)
    pyplot.show()
    pyplot.close()
```

```
In [15]: """https://machinelearningmastery.com/how-to-develop-a-cnn-from-scratch-for-ci  
far-10-photo-classification/"""  
def run_test_harness(trainX, testX, trainY, testY, a, b, training_model, name  
):  
    datagen = ImageDataGenerator(rotation_range=20, width_shift_range=0.25, height_shift_range=0.25,  
                                horizontal_flip=True, fill_mode='nearest', zoom_range=0.10)  
    final_train = datagen.flow(trainX, trainY, batch_size=a)  
    history = training_model.fit_generator(final_train, epochs=b, validation_data=(testX, testY), verbose=1)  
    _, acc = training_model.evaluate(testX, testY, verbose=1)  
    print('> %.3f' % (acc * 100.0))  
    summarize_diagnostics(history)  
    x = "/content/After-"+name+"-epochs.h5"  
    training_model.save(x)
```

```
In [16]: run_test_harness(X_train, X_test, y_train, y_test, 128, 15, model, '15')
```

Epoch 1/15
391/391 [=====] - 99s 223ms/step - loss: 1.8718 - accuracy: 0.3165 - val_loss: 2.3281 - val_accuracy: 0.2624
Epoch 2/15
391/391 [=====] - 86s 220ms/step - loss: 1.3563 - accuracy: 0.5072 - val_loss: 2.4923 - val_accuracy: 0.4021
Epoch 3/15
391/391 [=====] - 86s 220ms/step - loss: 1.1392 - accuracy: 0.5975 - val_loss: 1.3717 - val_accuracy: 0.5891
Epoch 4/15
391/391 [=====] - 86s 220ms/step - loss: 0.9903 - accuracy: 0.6483 - val_loss: 1.3349 - val_accuracy: 0.5858
Epoch 5/15
391/391 [=====] - 86s 220ms/step - loss: 0.8899 - accuracy: 0.6854 - val_loss: 1.0495 - val_accuracy: 0.6622
Epoch 6/15
391/391 [=====] - 86s 221ms/step - loss: 0.7948 - accuracy: 0.7237 - val_loss: 1.0013 - val_accuracy: 0.6658
Epoch 7/15
391/391 [=====] - 86s 220ms/step - loss: 0.7375 - accuracy: 0.7422 - val_loss: 1.1326 - val_accuracy: 0.6480
Epoch 8/15
391/391 [=====] - 86s 220ms/step - loss: 0.6880 - accuracy: 0.7593 - val_loss: 1.0150 - val_accuracy: 0.6663
Epoch 9/15
391/391 [=====] - 86s 220ms/step - loss: 0.6454 - accuracy: 0.7776 - val_loss: 0.8874 - val_accuracy: 0.7285
Epoch 10/15
391/391 [=====] - 86s 220ms/step - loss: 0.6214 - accuracy: 0.7846 - val_loss: 0.7794 - val_accuracy: 0.7421
Epoch 11/15
391/391 [=====] - 86s 220ms/step - loss: 0.5852 - accuracy: 0.7976 - val_loss: 0.9584 - val_accuracy: 0.7099
Epoch 12/15
391/391 [=====] - 86s 220ms/step - loss: 0.5658 - accuracy: 0.8045 - val_loss: 1.0457 - val_accuracy: 0.6723
Epoch 13/15
391/391 [=====] - 86s 220ms/step - loss: 0.5440 - accuracy: 0.8110 - val_loss: 0.7536 - val_accuracy: 0.7628
Epoch 14/15
391/391 [=====] - 86s 220ms/step - loss: 0.5211 - accuracy: 0.8196 - val_loss: 0.6117 - val_accuracy: 0.7990
Epoch 15/15
391/391 [=====] - 86s 220ms/step - loss: 0.4991 - accuracy: 0.8284 - val_loss: 0.6914 - val_accuracy: 0.7812
313/313 [=====] - 4s 14ms/step - loss: 0.6914 - accuracy: 0.7812
> 78.120

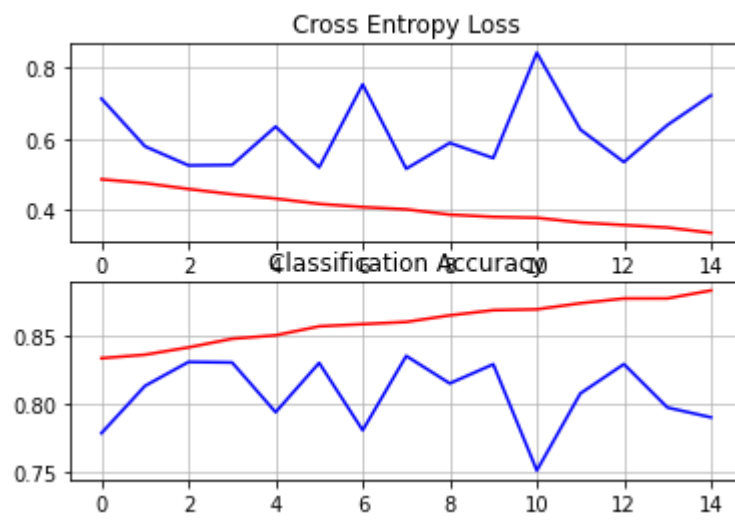


```
In [17]: epoch_15 = keras.models.load_model('/content/After-15-epochs.h5')
```



```
In [18]: run_test_harness(X_train, X_test, y_train, y_test, 128, 15, epoch_15, '30')
```

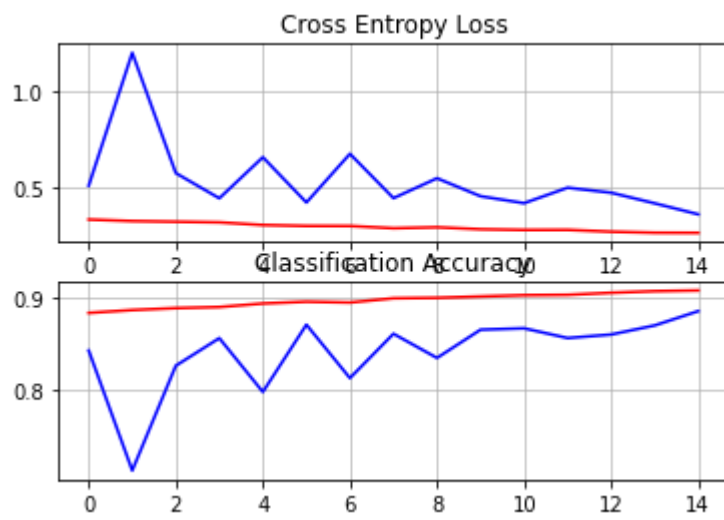
Epoch 1/15
391/391 [=====] - 89s 221ms/step - loss: 0.4859 - accuracy: 0.8330 - val_loss: 0.7124 - val_accuracy: 0.7783
Epoch 2/15
391/391 [=====] - 86s 220ms/step - loss: 0.4750 - accuracy: 0.8356 - val_loss: 0.5785 - val_accuracy: 0.8128
Epoch 3/15
391/391 [=====] - 86s 220ms/step - loss: 0.4586 - accuracy: 0.8409 - val_loss: 0.5249 - val_accuracy: 0.8303
Epoch 4/15
391/391 [=====] - 86s 219ms/step - loss: 0.4438 - accuracy: 0.8472 - val_loss: 0.5262 - val_accuracy: 0.8299
Epoch 5/15
391/391 [=====] - 86s 220ms/step - loss: 0.4317 - accuracy: 0.8498 - val_loss: 0.6340 - val_accuracy: 0.7936
Epoch 6/15
391/391 [=====] - 86s 220ms/step - loss: 0.4168 - accuracy: 0.8563 - val_loss: 0.5195 - val_accuracy: 0.8296
Epoch 7/15
391/391 [=====] - 86s 219ms/step - loss: 0.4079 - accuracy: 0.8579 - val_loss: 0.7526 - val_accuracy: 0.7804
Epoch 8/15
391/391 [=====] - 86s 219ms/step - loss: 0.4015 - accuracy: 0.8595 - val_loss: 0.5155 - val_accuracy: 0.8347
Epoch 9/15
391/391 [=====] - 86s 219ms/step - loss: 0.3866 - accuracy: 0.8643 - val_loss: 0.5882 - val_accuracy: 0.8146
Epoch 10/15
391/391 [=====] - 86s 219ms/step - loss: 0.3803 - accuracy: 0.8681 - val_loss: 0.5455 - val_accuracy: 0.8286
Epoch 11/15
391/391 [=====] - 86s 219ms/step - loss: 0.3777 - accuracy: 0.8687 - val_loss: 0.8414 - val_accuracy: 0.7510
Epoch 12/15
391/391 [=====] - 86s 219ms/step - loss: 0.3644 - accuracy: 0.8732 - val_loss: 0.6257 - val_accuracy: 0.8073
Epoch 13/15
391/391 [=====] - 86s 219ms/step - loss: 0.3573 - accuracy: 0.8767 - val_loss: 0.5345 - val_accuracy: 0.8287
Epoch 14/15
391/391 [=====] - 86s 219ms/step - loss: 0.3503 - accuracy: 0.8767 - val_loss: 0.6385 - val_accuracy: 0.7970
Epoch 15/15
391/391 [=====] - 86s 219ms/step - loss: 0.3354 - accuracy: 0.8825 - val_loss: 0.7218 - val_accuracy: 0.7898
313/313 [=====] - 4s 14ms/step - loss: 0.7218 - accuracy: 0.7898
> 78.980



```
In [19]: epoch_30 = keras.models.load_model('/content/After-30-epochs.h5')
```

```
In [20]: run_test_harness(X_train, X_test, y_train, y_test, 128, 15, epoch_30, '45')
```

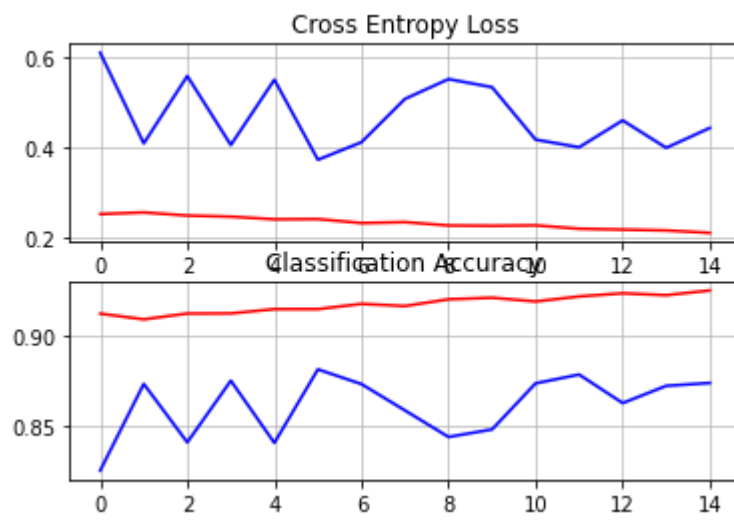
Epoch 1/15
391/391 [=====] - 88s 220ms/step - loss: 0.3341 - accuracy: 0.8832 - val_loss: 0.5107 - val_accuracy: 0.8427
Epoch 2/15
391/391 [=====] - 86s 219ms/step - loss: 0.3260 - accuracy: 0.8863 - val_loss: 1.2036 - val_accuracy: 0.7135
Epoch 3/15
391/391 [=====] - 86s 219ms/step - loss: 0.3226 - accuracy: 0.8883 - val_loss: 0.5764 - val_accuracy: 0.8263
Epoch 4/15
391/391 [=====] - 86s 219ms/step - loss: 0.3193 - accuracy: 0.8895 - val_loss: 0.4449 - val_accuracy: 0.8560
Epoch 5/15
391/391 [=====] - 86s 219ms/step - loss: 0.3054 - accuracy: 0.8933 - val_loss: 0.6589 - val_accuracy: 0.7981
Epoch 6/15
391/391 [=====] - 86s 219ms/step - loss: 0.3007 - accuracy: 0.8953 - val_loss: 0.4230 - val_accuracy: 0.8705
Epoch 7/15
391/391 [=====] - 86s 219ms/step - loss: 0.3003 - accuracy: 0.8944 - val_loss: 0.6766 - val_accuracy: 0.8130
Epoch 8/15
391/391 [=====] - 86s 219ms/step - loss: 0.2886 - accuracy: 0.8989 - val_loss: 0.4456 - val_accuracy: 0.8607
Epoch 9/15
391/391 [=====] - 86s 219ms/step - loss: 0.2936 - accuracy: 0.8994 - val_loss: 0.5493 - val_accuracy: 0.8347
Epoch 10/15
391/391 [=====] - 86s 219ms/step - loss: 0.2834 - accuracy: 0.9009 - val_loss: 0.4556 - val_accuracy: 0.8651
Epoch 11/15
391/391 [=====] - 86s 219ms/step - loss: 0.2797 - accuracy: 0.9023 - val_loss: 0.4193 - val_accuracy: 0.8666
Epoch 12/15
391/391 [=====] - 85s 219ms/step - loss: 0.2801 - accuracy: 0.9026 - val_loss: 0.5001 - val_accuracy: 0.8561
Epoch 13/15
391/391 [=====] - 86s 219ms/step - loss: 0.2705 - accuracy: 0.9049 - val_loss: 0.4739 - val_accuracy: 0.8599
Epoch 14/15
391/391 [=====] - 86s 219ms/step - loss: 0.2652 - accuracy: 0.9066 - val_loss: 0.4186 - val_accuracy: 0.8697
Epoch 15/15
391/391 [=====] - 86s 219ms/step - loss: 0.2646 - accuracy: 0.9074 - val_loss: 0.3613 - val_accuracy: 0.8851
313/313 [=====] - 4s 14ms/step - loss: 0.3613 - accuracy: 0.8851
> 88.510



```
In [21]: epoch_45 = keras.models.load_model('/content/After-45-epochs.h5')
```

```
In [22]: run_test_harness(X_train, X_test, y_train, y_test, 128, 15, epoch_45, '60')
```

Epoch 1/15
391/391 [=====] - 88s 221ms/step - loss: 0.2536 - accuracy: 0.9124 - val_loss: 0.6109 - val_accuracy: 0.8249
Epoch 2/15
391/391 [=====] - 85s 218ms/step - loss: 0.2572 - accuracy: 0.9092 - val_loss: 0.4101 - val_accuracy: 0.8732
Epoch 3/15
391/391 [=====] - 86s 219ms/step - loss: 0.2503 - accuracy: 0.9124 - val_loss: 0.5596 - val_accuracy: 0.8406
Epoch 4/15
391/391 [=====] - 86s 219ms/step - loss: 0.2479 - accuracy: 0.9125 - val_loss: 0.4066 - val_accuracy: 0.8750
Epoch 5/15
391/391 [=====] - 86s 219ms/step - loss: 0.2420 - accuracy: 0.9149 - val_loss: 0.5514 - val_accuracy: 0.8403
Epoch 6/15
391/391 [=====] - 86s 219ms/step - loss: 0.2425 - accuracy: 0.9149 - val_loss: 0.3740 - val_accuracy: 0.8813
Epoch 7/15
391/391 [=====] - 86s 219ms/step - loss: 0.2337 - accuracy: 0.9178 - val_loss: 0.4128 - val_accuracy: 0.8731
Epoch 8/15
391/391 [=====] - 86s 219ms/step - loss: 0.2357 - accuracy: 0.9166 - val_loss: 0.5088 - val_accuracy: 0.8584
Epoch 9/15
391/391 [=====] - 86s 219ms/step - loss: 0.2283 - accuracy: 0.9204 - val_loss: 0.5527 - val_accuracy: 0.8436
Epoch 10/15
391/391 [=====] - 85s 219ms/step - loss: 0.2276 - accuracy: 0.9212 - val_loss: 0.5348 - val_accuracy: 0.8478
Epoch 11/15
391/391 [=====] - 85s 219ms/step - loss: 0.2286 - accuracy: 0.9192 - val_loss: 0.4186 - val_accuracy: 0.8735
Epoch 12/15
391/391 [=====] - 86s 219ms/step - loss: 0.2211 - accuracy: 0.9220 - val_loss: 0.4016 - val_accuracy: 0.8784
Epoch 13/15
391/391 [=====] - 86s 219ms/step - loss: 0.2192 - accuracy: 0.9237 - val_loss: 0.4612 - val_accuracy: 0.8625
Epoch 14/15
391/391 [=====] - 86s 219ms/step - loss: 0.2172 - accuracy: 0.9227 - val_loss: 0.4004 - val_accuracy: 0.8721
Epoch 15/15
391/391 [=====] - 86s 219ms/step - loss: 0.2119 - accuracy: 0.9253 - val_loss: 0.4443 - val_accuracy: 0.8737
313/313 [=====] - 4s 14ms/step - loss: 0.4443 - accuracy: 0.8737
> 87.370



```
In [23]: epoch_60 = keras.models.load_model('/content/After-60-epochs.h5')
```

```
In [24]: run_test_harness(X_train, X_test, y_train, y_test, 128, 25, epoch_60, '85')
```

Epoch 1/25
391/391 [=====] - 88s 221ms/step - loss: 0.2104 - accuracy: 0.9269 - val_loss: 0.5128 - val_accuracy: 0.8569

Epoch 2/25
391/391 [=====] - 86s 219ms/step - loss: 0.2106 - accuracy: 0.9263 - val_loss: 0.5307 - val_accuracy: 0.8477

Epoch 3/25
391/391 [=====] - 86s 219ms/step - loss: 0.2033 - accuracy: 0.9289 - val_loss: 0.3807 - val_accuracy: 0.8858

Epoch 4/25
391/391 [=====] - 86s 219ms/step - loss: 0.1998 - accuracy: 0.9303 - val_loss: 0.4812 - val_accuracy: 0.8640

Epoch 5/25
391/391 [=====] - 86s 219ms/step - loss: 0.1991 - accuracy: 0.9309 - val_loss: 0.5667 - val_accuracy: 0.8540

Epoch 6/25
391/391 [=====] - 86s 219ms/step - loss: 0.1983 - accuracy: 0.9292 - val_loss: 0.6214 - val_accuracy: 0.8334

Epoch 7/25
391/391 [=====] - 85s 218ms/step - loss: 0.1987 - accuracy: 0.9301 - val_loss: 0.4594 - val_accuracy: 0.8721

Epoch 8/25
391/391 [=====] - 85s 218ms/step - loss: 0.1934 - accuracy: 0.9323 - val_loss: 0.5048 - val_accuracy: 0.8595

Epoch 9/25
391/391 [=====] - 86s 219ms/step - loss: 0.1909 - accuracy: 0.9328 - val_loss: 0.4637 - val_accuracy: 0.8690

Epoch 10/25
391/391 [=====] - 86s 220ms/step - loss: 0.1892 - accuracy: 0.9333 - val_loss: 0.4240 - val_accuracy: 0.8752

Epoch 11/25
391/391 [=====] - 86s 219ms/step - loss: 0.1864 - accuracy: 0.9342 - val_loss: 0.3630 - val_accuracy: 0.8962

Epoch 12/25
391/391 [=====] - 85s 218ms/step - loss: 0.1826 - accuracy: 0.9362 - val_loss: 0.4530 - val_accuracy: 0.8743

Epoch 13/25
391/391 [=====] - 85s 218ms/step - loss: 0.1877 - accuracy: 0.9341 - val_loss: 0.5083 - val_accuracy: 0.8609

Epoch 14/25
391/391 [=====] - 85s 218ms/step - loss: 0.1852 - accuracy: 0.9348 - val_loss: 0.4679 - val_accuracy: 0.8695

Epoch 15/25
391/391 [=====] - 86s 219ms/step - loss: 0.1791 - accuracy: 0.9369 - val_loss: 0.5080 - val_accuracy: 0.8600

Epoch 16/25
391/391 [=====] - 85s 218ms/step - loss: 0.1755 - accuracy: 0.9378 - val_loss: 0.4117 - val_accuracy: 0.8882

Epoch 17/25
391/391 [=====] - 85s 218ms/step - loss: 0.1744 - accuracy: 0.9390 - val_loss: 0.4647 - val_accuracy: 0.8763

Epoch 18/25
391/391 [=====] - 86s 219ms/step - loss: 0.1742 - accuracy: 0.9386 - val_loss: 0.4480 - val_accuracy: 0.8748

Epoch 19/25
391/391 [=====] - 85s 218ms/step - loss: 0.1693 - accuracy: 0.9403 - val_loss: 0.4951 - val_accuracy: 0.8684

Epoch 20/25
 391/391 [=====] - 85s 218ms/step - loss: 0.1724 - accuracy: 0.9392 - val_loss: 0.4249 - val_accuracy: 0.8855
 Epoch 21/25
 391/391 [=====] - 85s 218ms/step - loss: 0.1712 - accuracy: 0.9400 - val_loss: 0.3938 - val_accuracy: 0.8874
 Epoch 22/25
 391/391 [=====] - 85s 219ms/step - loss: 0.1682 - accuracy: 0.9406 - val_loss: 0.4833 - val_accuracy: 0.8712
 Epoch 23/25
 391/391 [=====] - 86s 219ms/step - loss: 0.1630 - accuracy: 0.9432 - val_loss: 0.3543 - val_accuracy: 0.8959
 Epoch 24/25
 391/391 [=====] - 86s 219ms/step - loss: 0.1613 - accuracy: 0.9430 - val_loss: 0.3400 - val_accuracy: 0.9028
 Epoch 25/25
 391/391 [=====] - 86s 219ms/step - loss: 0.1592 - accuracy: 0.9443 - val_loss: 0.5562 - val_accuracy: 0.8569
 313/313 [=====] - 4s 14ms/step - loss: 0.5562 - accuracy: 0.8569
 > 85.690



```
In [25]: epoch_85 = keras.models.load_model('/content/After-85-epochs.h5')
```

```
In [26]: run_test_harness(X_train, X_test, y_train, y_test, 128, 25, epoch_85, '110')
```

Epoch 1/25
391/391 [=====] - 88s 220ms/step - loss: 0.1655 - accuracy: 0.9420 - val_loss: 0.4425 - val_accuracy: 0.8796

Epoch 2/25
391/391 [=====] - 85s 219ms/step - loss: 0.1538 - accuracy: 0.9465 - val_loss: 0.4212 - val_accuracy: 0.8880

Epoch 3/25
391/391 [=====] - 86s 219ms/step - loss: 0.1623 - accuracy: 0.9424 - val_loss: 0.3997 - val_accuracy: 0.8855

Epoch 4/25
391/391 [=====] - 86s 219ms/step - loss: 0.1588 - accuracy: 0.9432 - val_loss: 0.3618 - val_accuracy: 0.9002

Epoch 5/25
391/391 [=====] - 85s 218ms/step - loss: 0.1550 - accuracy: 0.9456 - val_loss: 0.3659 - val_accuracy: 0.8988

Epoch 6/25
391/391 [=====] - 85s 218ms/step - loss: 0.1530 - accuracy: 0.9459 - val_loss: 0.4817 - val_accuracy: 0.8730

Epoch 7/25
391/391 [=====] - 86s 219ms/step - loss: 0.1536 - accuracy: 0.9458 - val_loss: 0.4132 - val_accuracy: 0.8866

Epoch 8/25
391/391 [=====] - 86s 219ms/step - loss: 0.1480 - accuracy: 0.9483 - val_loss: 0.3581 - val_accuracy: 0.9006

Epoch 9/25
391/391 [=====] - 85s 218ms/step - loss: 0.1509 - accuracy: 0.9461 - val_loss: 0.4224 - val_accuracy: 0.8929

Epoch 10/25
391/391 [=====] - 86s 219ms/step - loss: 0.1489 - accuracy: 0.9467 - val_loss: 0.3720 - val_accuracy: 0.8971

Epoch 11/25
391/391 [=====] - 85s 218ms/step - loss: 0.1478 - accuracy: 0.9485 - val_loss: 0.4642 - val_accuracy: 0.8801

Epoch 12/25
391/391 [=====] - 85s 218ms/step - loss: 0.1441 - accuracy: 0.9490 - val_loss: 0.3451 - val_accuracy: 0.9038

Epoch 13/25
391/391 [=====] - 85s 218ms/step - loss: 0.1457 - accuracy: 0.9485 - val_loss: 0.4098 - val_accuracy: 0.8886

Epoch 14/25
391/391 [=====] - 85s 218ms/step - loss: 0.1435 - accuracy: 0.9496 - val_loss: 0.3638 - val_accuracy: 0.8981

Epoch 15/25
391/391 [=====] - 85s 218ms/step - loss: 0.1406 - accuracy: 0.9493 - val_loss: 0.3581 - val_accuracy: 0.9045

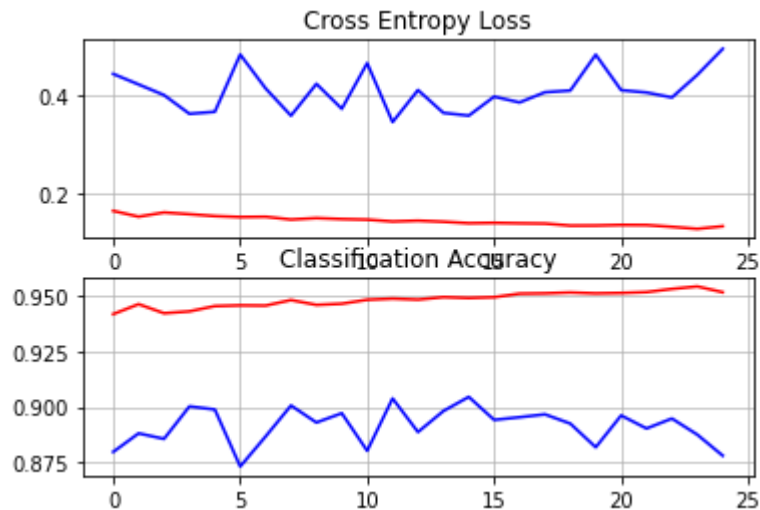
Epoch 16/25
391/391 [=====] - 85s 218ms/step - loss: 0.1413 - accuracy: 0.9496 - val_loss: 0.3966 - val_accuracy: 0.8941

Epoch 17/25
391/391 [=====] - 85s 218ms/step - loss: 0.1404 - accuracy: 0.9512 - val_loss: 0.3848 - val_accuracy: 0.8953

Epoch 18/25
391/391 [=====] - 85s 218ms/step - loss: 0.1398 - accuracy: 0.9514 - val_loss: 0.4054 - val_accuracy: 0.8966

Epoch 19/25
391/391 [=====] - 86s 219ms/step - loss: 0.1357 - accuracy: 0.9517 - val_loss: 0.4089 - val_accuracy: 0.8924

Epoch 20/25
 391/391 [=====] - 86s 219ms/step - loss: 0.1359 - accuracy: 0.9513 - val_loss: 0.4814 - val_accuracy: 0.8817
 Epoch 21/25
 391/391 [=====] - 85s 218ms/step - loss: 0.1370 - accuracy: 0.9515 - val_loss: 0.4096 - val_accuracy: 0.8961
 Epoch 22/25
 391/391 [=====] - 85s 218ms/step - loss: 0.1368 - accuracy: 0.9519 - val_loss: 0.4049 - val_accuracy: 0.8902
 Epoch 23/25
 391/391 [=====] - 86s 219ms/step - loss: 0.1332 - accuracy: 0.9534 - val_loss: 0.3949 - val_accuracy: 0.8947
 Epoch 24/25
 391/391 [=====] - 86s 219ms/step - loss: 0.1291 - accuracy: 0.9545 - val_loss: 0.4407 - val_accuracy: 0.8874
 Epoch 25/25
 391/391 [=====] - 86s 219ms/step - loss: 0.1344 - accuracy: 0.9519 - val_loss: 0.4933 - val_accuracy: 0.8779
 313/313 [=====] - 4s 14ms/step - loss: 0.4933 - accuracy: 0.8779
 > 87.790



```
In [27]: epoch_110 = keras.models.load_model('/content/After-110-epochs.h5')
```

```
In [28]: run_test_harness(X_train, X_test, y_train, y_test, 128, 25, epoch_110, '135')
```


Epoch 1/30
391/391 [=====] - 88s 221ms/step - loss: 0.1305 - accuracy: 0.9530 - val_loss: 0.4095 - val_accuracy: 0.8969

Epoch 2/30
391/391 [=====] - 86s 219ms/step - loss: 0.1273 - accuracy: 0.9546 - val_loss: 0.3737 - val_accuracy: 0.8963

Epoch 3/30
391/391 [=====] - 85s 218ms/step - loss: 0.1308 - accuracy: 0.9533 - val_loss: 0.3288 - val_accuracy: 0.9093

Epoch 4/30
391/391 [=====] - 85s 218ms/step - loss: 0.1292 - accuracy: 0.9546 - val_loss: 0.6810 - val_accuracy: 0.8413

Epoch 5/30
391/391 [=====] - 85s 218ms/step - loss: 0.1255 - accuracy: 0.9557 - val_loss: 0.4017 - val_accuracy: 0.8944

Epoch 6/30
391/391 [=====] - 85s 218ms/step - loss: 0.1278 - accuracy: 0.9549 - val_loss: 0.5129 - val_accuracy: 0.8726

Epoch 7/30
391/391 [=====] - 85s 218ms/step - loss: 0.1256 - accuracy: 0.9559 - val_loss: 0.4347 - val_accuracy: 0.8875

Epoch 8/30
391/391 [=====] - 85s 218ms/step - loss: 0.1261 - accuracy: 0.9558 - val_loss: 0.3499 - val_accuracy: 0.9058

Epoch 9/30
391/391 [=====] - 85s 218ms/step - loss: 0.1234 - accuracy: 0.9566 - val_loss: 0.3555 - val_accuracy: 0.9088

Epoch 10/30
391/391 [=====] - 85s 218ms/step - loss: 0.1213 - accuracy: 0.9574 - val_loss: 0.4878 - val_accuracy: 0.8779

Epoch 11/30
391/391 [=====] - 86s 219ms/step - loss: 0.1200 - accuracy: 0.9580 - val_loss: 0.4686 - val_accuracy: 0.8811

Epoch 12/30
391/391 [=====] - 86s 219ms/step - loss: 0.1246 - accuracy: 0.9554 - val_loss: 0.4614 - val_accuracy: 0.8853

Epoch 13/30
391/391 [=====] - 86s 219ms/step - loss: 0.1177 - accuracy: 0.9595 - val_loss: 0.3916 - val_accuracy: 0.8979

Epoch 14/30
391/391 [=====] - 86s 219ms/step - loss: 0.1239 - accuracy: 0.9556 - val_loss: 0.3440 - val_accuracy: 0.9082

Epoch 15/30
391/391 [=====] - 85s 218ms/step - loss: 0.1157 - accuracy: 0.9582 - val_loss: 0.3862 - val_accuracy: 0.8982

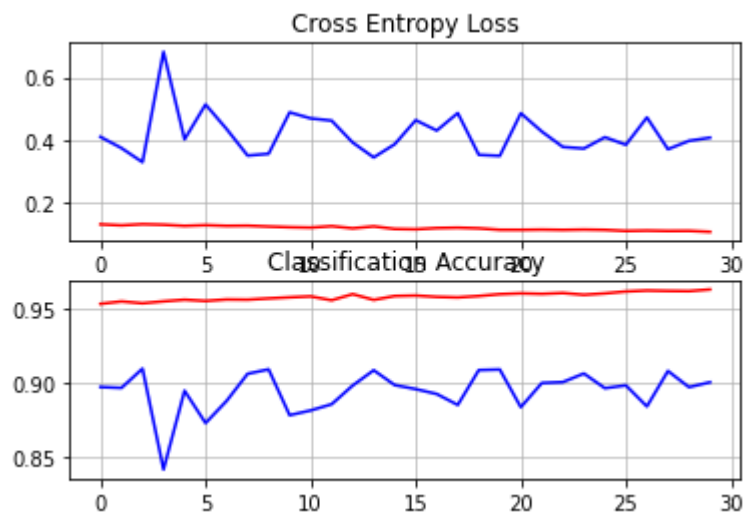
Epoch 16/30
391/391 [=====] - 85s 218ms/step - loss: 0.1147 - accuracy: 0.9585 - val_loss: 0.4629 - val_accuracy: 0.8955

Epoch 17/30
391/391 [=====] - 85s 218ms/step - loss: 0.1185 - accuracy: 0.9577 - val_loss: 0.4298 - val_accuracy: 0.8922

Epoch 18/30
391/391 [=====] - 86s 219ms/step - loss: 0.1197 - accuracy: 0.9573 - val_loss: 0.4855 - val_accuracy: 0.8848

Epoch 19/30
391/391 [=====] - 86s 219ms/step - loss: 0.1177 - accuracy: 0.9582 - val_loss: 0.3522 - val_accuracy: 0.9083

Epoch 20/30
 391/391 [=====] - 86s 219ms/step - loss: 0.1129 - accuracy: 0.9595 - val_loss: 0.3490 - val_accuracy: 0.9087
 Epoch 21/30
 391/391 [=====] - 86s 219ms/step - loss: 0.1128 - accuracy: 0.9600 - val_loss: 0.4849 - val_accuracy: 0.8833
 Epoch 22/30
 391/391 [=====] - 86s 219ms/step - loss: 0.1136 - accuracy: 0.9597 - val_loss: 0.4265 - val_accuracy: 0.8996
 Epoch 23/30
 391/391 [=====] - 85s 218ms/step - loss: 0.1126 - accuracy: 0.9603 - val_loss: 0.3774 - val_accuracy: 0.9002
 Epoch 24/30
 391/391 [=====] - 85s 218ms/step - loss: 0.1137 - accuracy: 0.9591 - val_loss: 0.3723 - val_accuracy: 0.9060
 Epoch 25/30
 391/391 [=====] - 85s 218ms/step - loss: 0.1126 - accuracy: 0.9600 - val_loss: 0.4083 - val_accuracy: 0.8961
 Epoch 26/30
 391/391 [=====] - 86s 219ms/step - loss: 0.1094 - accuracy: 0.9613 - val_loss: 0.3844 - val_accuracy: 0.8980
 Epoch 27/30
 391/391 [=====] - 86s 219ms/step - loss: 0.1105 - accuracy: 0.9619 - val_loss: 0.4716 - val_accuracy: 0.8838
 Epoch 28/30
 391/391 [=====] - 86s 219ms/step - loss: 0.1093 - accuracy: 0.9617 - val_loss: 0.3701 - val_accuracy: 0.9077
 Epoch 29/30
 391/391 [=====] - 86s 219ms/step - loss: 0.1096 - accuracy: 0.9615 - val_loss: 0.3969 - val_accuracy: 0.8968
 Epoch 30/30
 391/391 [=====] - 85s 219ms/step - loss: 0.1064 - accuracy: 0.9627 - val_loss: 0.4069 - val_accuracy: 0.9001
 313/313 [=====] - 4s 14ms/step - loss: 0.4069 - accuracy: 0.9001
 > 90.010



In 125th epoch val_accuracy is 90.87% & after running the model another 10 epoch to 135th epoch no improvement is seen. Thus the maximum val_accuracy I got is 90.87