

In [1]:

```
# import keras
# from keras.datasets import cifar10
# from keras.models import Model, Sequential
# from keras.layers import Dense, Dropout, Flatten, Input, AveragePooling2D, merge, Activation
# from keras.layers import Conv2D, MaxPooling2D, BatchNormalization
# from keras.layers import Concatenate
# from keras.optimizers import Adam
from tensorflow.keras import models, layers
from tensorflow.keras.models import Model
from tensorflow.keras.layers import BatchNormalization, Activation, Flatten
from tensorflow.keras.optimizers import Adam, Nadam

import numpy as np
from tqdm import tqdm
from matplotlib import pyplot
from prettytable import PrettyTable
from numpy import expand_dims
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ModelCheckpoint, LearningRateScheduler, CSVLogger, Callback, ReduceLROnPlateau

import matplotlib.pyplot as plt

from keras import models
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.

We recommend you [upgrade \(https://www.tensorflow.org/guide/migrate\)](https://www.tensorflow.org/guide/migrate) now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: [more info \(https://colab.research.google.com/notebooks/tensorflow_version.ipynb\)](https://colab.research.google.com/notebooks/tensorflow_version.ipynb).

Using TensorFlow backend.

In [13]:

```
from google.colab import drive
drive.mount('gdrive', force_remount=True)
```

Mounted at gdrive

In [0]:

```
# this part will prevent tensorflow to allocate all the available GPU Memory
# backend
import tensorflow as tf
# from tensorflow import keras

# from keras import backend as k

# Don't pre-allocate memory; allocate as-needed
# import tensorflow as tf
# tf.config.gpu.set_per_process_memory_fraction(0.75)
# tf.config.gpu.set_per_process_memory_growth(True)
# config = tf.ConfigProto()
# config.gpu_options.allow_growth = True

# Create a session with the above options specified.
# k.tensorflow_backend.set_session(tf.Session(config=config))
```

In [0]:

```
final_tab = PrettyTable(['Augmentation', 'l', 'num_filters', 'compression', 'Optimizer', 'Test Accuracy'])
```

In [0]:

```
# Hyperparameters
batch_size = 128
num_classes = 10
epochs = 100
l = 9
num_filter = 24
compression = 1.041
dropout_rate = 0.2
```

In [6]:

```
# Load CIFAR10 Data
(X_train, y_train), (X_test, y_test) = tf.keras.datasets.cifar10.load_data()
img_height, img_width, channel = X_train.shape[1], X_train.shape[2], X_train.shape[3]

# convert to one hot encoding
y_train = tf.keras.utils.to_categorical(y_train, num_classes)
y_test = tf.keras.utils.to_categorical(y_test, num_classes)
```

Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>
 170500096/170498071 [=====] - 6s 0us/step

In [7]:

```
print('Train Shape:', X_train.shape)
print('Test Shape:', X_test.shape)
```

Train Shape: (50000, 32, 32, 3)
 Test Shape: (10000, 32, 32, 3)

In [0]:

```
# 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
e ,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
    print('input',input.shape)
    BatchNorm = layers.BatchNormalization()(input)
    print('Batch',BatchNorm.shape)
    relu = layers.Activation('relu')(BatchNorm)
    print('relu',relu.shape)
    AvgPooling = layers.AveragePooling2D(pool_size=(2,2))(relu)
    # print('pooling',AvgPooling.shape)
    # flat = layers.Flatten()(AvgPooling)
    # print('flat',flat.shape)
    # # tf.reshape(flat,(4,246))
    # # print(flat.reshape(7,4,4,246,1))
    # output = layers.Conv1D(num_filter, kernel_size=1)(tf.reshape(flat,(1,4,246)))

    conv_layer = layers.Conv2D(10, (1,1), use_bias=False ,padding='same')(AvgPooling)
    last = layers.GlobalMaxPooling2D()(conv_layer)
    output = layers.Activation('softmax')(last)

    return output
```

In [0]:

```
num_filter = 12
dropout_rate = 0.2
l = 12
```

In [9]:

```
input = layers.Input(shape=(img_height, img_width, channel,))
First_Conv2D = layers.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)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow_core/python/ops/resource_variable_ops.py:1630: calling BaseResourceVariable.__init__ (from tensorflow.python.ops.resource_variable_ops) with constraint is deprecated and will be removed in a future version.

Instructions for updating:

If using Keras pass *_constraint arguments to layers.

input (?, 4, 4, 240)

Batch (?, 4, 4, 240)

relu (?, 4, 4, 240)

In [0]:

```
#https://arxiv.org/pdf/1608.06993.pdf
from IPython.display import IFrame, YouTubeVideo
YouTubeVideo(id='-W6y8xnd--U', width=600)
```

In [10]:

```
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) [0][0]	(None, 32, 32, 24)	648	input_1
batch_normalization (BatchNormaliza [0]	(None, 32, 32, 24)	96	conv2d[0]
activation (Activation) malization[0][0]	(None, 32, 32, 24)	0	batch_nor
conv2d_1 (Conv2D) n[0][0]	(None, 32, 32, 24)	5184	activatio
dropout (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_1
concatenate (Concatenate) [0]	(None, 32, 32, 48)	0	conv2d[0] dropout
batch_normalization_1 (BatchNor te[0][0]	(None, 32, 32, 48)	192	concatena
activation_1 (Activation) malization_1[0][0]	(None, 32, 32, 48)	0	batch_nor
conv2d_2 (Conv2D) n_1[0][0]	(None, 32, 32, 24)	10368	activatio
dropout_1 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_2
concatenate_1 (Concatenate) te[0][0]	(None, 32, 32, 72)	0	concatena dropout_1
batch_normalization_2 (BatchNor te_1[0][0]	(None, 32, 32, 72)	288	concatena

activation_2 (Activation) malization_2[0][0]	(None, 32, 32, 72)	0	batch_nor
conv2d_3 (Conv2D) n_2[0][0]	(None, 32, 32, 24)	15552	activatio
dropout_2 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_3
concatenate_2 (Concatenate) te_1[0][0]	(None, 32, 32, 96)	0	concatena dropout_2
batch_normalization_3 (BatchNor te_2[0][0]	(None, 32, 32, 96)	384	concatena
activation_3 (Activation) malization_3[0][0]	(None, 32, 32, 96)	0	batch_nor
conv2d_4 (Conv2D) n_3[0][0]	(None, 32, 32, 24)	20736	activatio
dropout_3 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_4
concatenate_3 (Concatenate) te_2[0][0]	(None, 32, 32, 120)	0	concatena dropout_3
batch_normalization_4 (BatchNor te_3[0][0]	(None, 32, 32, 120)	480	concatena
activation_4 (Activation) malization_4[0][0]	(None, 32, 32, 120)	0	batch_nor
conv2d_5 (Conv2D) n_4[0][0]	(None, 32, 32, 24)	25920	activatio
dropout_4 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_5
concatenate_4 (Concatenate) te_3[0][0]	(None, 32, 32, 144)	0	concatena dropout_4

batch_normalization_5 (BatchNormalizati on_4[0][0])	(None, 32, 32, 144)	576	concatena te_4[0][0]
activation_5 (Activation) malization_5[0][0]	(None, 32, 32, 144)	0	batch_nor malization_5[0][0]
conv2d_6 (Conv2D) n_5[0][0]	(None, 32, 32, 24)	31104	activatio n_5[0][0]
dropout_5 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_6 [0][0]
concatenate_5 (Concatenate) te_4[0][0]	(None, 32, 32, 168)	0	concatena te_4[0][0]
batch_normalization_6 (BatchNormalizati on_5[0][0])	(None, 32, 32, 168)	672	concatena te_5[0][0]
activation_6 (Activation) malization_6[0][0]	(None, 32, 32, 168)	0	batch_nor malization_6[0][0]
conv2d_7 (Conv2D) n_6[0][0]	(None, 32, 32, 24)	36288	activatio n_6[0][0]
dropout_6 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_7 [0][0]
concatenate_6 (Concatenate) te_5[0][0]	(None, 32, 32, 192)	0	concatena te_5[0][0]
batch_normalization_7 (BatchNormalizati on_6[0][0])	(None, 32, 32, 192)	768	concatena te_6[0][0]
activation_7 (Activation) malization_7[0][0]	(None, 32, 32, 192)	0	batch_nor malization_7[0][0]
conv2d_8 (Conv2D) n_7[0][0]	(None, 32, 32, 24)	41472	activatio n_7[0][0]
dropout_7 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_8 [0][0]

concatenate_7 (Concatenate) te_6[0][0]	(None, 32, 32, 216)	0	concatena dropout_7
batch_normalization_8 (BatchNor te_7[0][0]	(None, 32, 32, 216)	864	concatena
activation_8 (Activation) malization_8[0][0]	(None, 32, 32, 216)	0	batch_nor
conv2d_9 (Conv2D) n_8[0][0]	(None, 32, 32, 24)	46656	activatio
dropout_8 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_9
concatenate_8 (Concatenate) te_7[0][0]	(None, 32, 32, 240)	0	concatena dropout_8
batch_normalization_9 (BatchNor te_8[0][0]	(None, 32, 32, 240)	960	concatena
activation_9 (Activation) malization_9[0][0]	(None, 32, 32, 240)	0	batch_nor
conv2d_10 (Conv2D) n_9[0][0]	(None, 32, 32, 24)	5760	activatio
dropout_9 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_10
average_pooling2d (AveragePooli [0][0]	(None, 16, 16, 24)	0	dropout_9
batch_normalization_10 (BatchNo ooling2d[0][0]	(None, 16, 16, 24)	96	average_p ooling2d
activation_10 (Activation) malization_10[0][0]	(None, 16, 16, 24)	0	batch_nor
conv2d_11 (Conv2D) n_10[0][0]	(None, 16, 16, 24)	5184	activatio

dropout_10 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_11
concatenate_9 (Concatenate) ooling2d[0][0]	(None, 16, 16, 48)	0	average_p dropout_1
batch_normalization_11 (BatchNo te_9[0][0])	(None, 16, 16, 48)	192	concatena
activation_11 (Activation) malization_11[0][0]	(None, 16, 16, 48)	0	batch_nor
conv2d_12 (Conv2D) n_11[0][0]	(None, 16, 16, 24)	10368	activatio
dropout_11 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_12
concatenate_10 (Concatenate) te_9[0][0]	(None, 16, 16, 72)	0	concatena dropout_1
batch_normalization_12 (BatchNo te_10[0][0])	(None, 16, 16, 72)	288	concatena
activation_12 (Activation) malization_12[0][0]	(None, 16, 16, 72)	0	batch_nor
conv2d_13 (Conv2D) n_12[0][0]	(None, 16, 16, 24)	15552	activatio
dropout_12 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_13
concatenate_11 (Concatenate) te_10[0][0]	(None, 16, 16, 96)	0	concatena dropout_1
batch_normalization_13 (BatchNo te_11[0][0])	(None, 16, 16, 96)	384	concatena
activation_13 (Activation) malization_13[0][0]	(None, 16, 16, 96)	0	batch_nor

conv2d_14 (Conv2D) n_13[0][0]	(None, 16, 16, 24)	20736	activation_13[0][0]
dropout_13 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_14
concatenate_12 (Concatenate) te_11[0][0]	(None, 16, 16, 120)	0	concatenate_11[0][0]
3[0][0]			dropout_1
batch_normalization_14 (Batch Normalization) te_12[0][0]	(None, 16, 16, 120)	480	concatenate_12[0][0]
activation_14 (Activation) malization_14[0][0]	(None, 16, 16, 120)	0	batch_normalization_14[0][0]
conv2d_15 (Conv2D) n_14[0][0]	(None, 16, 16, 24)	25920	activation_14[0][0]
dropout_14 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_15
concatenate_13 (Concatenate) te_12[0][0]	(None, 16, 16, 144)	0	concatenate_12[0][0]
4[0][0]			dropout_1
batch_normalization_15 (Batch Normalization) te_13[0][0]	(None, 16, 16, 144)	576	concatenate_13[0][0]
activation_15 (Activation) malization_15[0][0]	(None, 16, 16, 144)	0	batch_normalization_15[0][0]
conv2d_16 (Conv2D) n_15[0][0]	(None, 16, 16, 24)	31104	activation_15[0][0]
dropout_15 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_16
concatenate_14 (Concatenate) te_13[0][0]	(None, 16, 16, 168)	0	concatenate_13[0][0]
5[0][0]			dropout_1
batch_normalization_16 (Batch Normalization) te_14[0][0]	(None, 16, 16, 168)	672	concatenate_14[0][0]

activation_16 (Activation) malization_16[0][0]	(None, 16, 16, 168)	0	batch_nor
conv2d_17 (Conv2D) n_16[0][0]	(None, 16, 16, 24)	36288	activatio
dropout_16 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_17
concatenate_15 (Concatenate) te_14[0][0]	(None, 16, 16, 192)	0	concatena
6[0][0]			dropout_1
batch_normalization_17 (BatchNo te_15[0][0]	(None, 16, 16, 192)	768	concatena
activation_17 (Activation) malization_17[0][0]	(None, 16, 16, 192)	0	batch_nor
conv2d_18 (Conv2D) n_17[0][0]	(None, 16, 16, 24)	41472	activatio
dropout_17 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_18
concatenate_16 (Concatenate) te_15[0][0]	(None, 16, 16, 216)	0	concatena
7[0][0]			dropout_1
batch_normalization_18 (BatchNo te_16[0][0]	(None, 16, 16, 216)	864	concatena
activation_18 (Activation) malization_18[0][0]	(None, 16, 16, 216)	0	batch_nor
conv2d_19 (Conv2D) n_18[0][0]	(None, 16, 16, 24)	46656	activatio
dropout_18 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_19
concatenate_17 (Concatenate) te_16[0][0]	(None, 16, 16, 240)	0	concatena
			dropout_1

8[0][0]

batch_normalization_19 (BatchNo	(None, 16, 16, 240)	960	concatena
te_17[0][0]			
activation_19 (Activation)	(None, 16, 16, 240)	0	batch_nor
malization_19[0][0]			
conv2d_20 (Conv2D)	(None, 16, 16, 24)	5760	activatio
n_19[0][0]			
dropout_19 (Dropout)	(None, 16, 16, 24)	0	conv2d_20
[0][0]			
average_pooling2d_1 (AveragePoo	(None, 8, 8, 24)	0	dropout_1
9[0][0]			
batch_normalization_20 (BatchNo	(None, 8, 8, 24)	96	average_p
ooling2d_1[0][0]			
activation_20 (Activation)	(None, 8, 8, 24)	0	batch_nor
malization_20[0][0]			
conv2d_21 (Conv2D)	(None, 8, 8, 24)	5184	activatio
n_20[0][0]			
dropout_20 (Dropout)	(None, 8, 8, 24)	0	conv2d_21
[0][0]			
concatenate_18 (Concatenate)	(None, 8, 8, 48)	0	average_p
ooling2d_1[0][0]			dropout_2
0[0][0]			
batch_normalization_21 (BatchNo	(None, 8, 8, 48)	192	concatena
te_18[0][0]			
activation_21 (Activation)	(None, 8, 8, 48)	0	batch_nor
malization_21[0][0]			
conv2d_22 (Conv2D)	(None, 8, 8, 24)	10368	activatio
n_21[0][0]			
dropout_21 (Dropout)	(None, 8, 8, 24)	0	conv2d_22
[0][0]			

concatenate_19 (Concatenate) te_18[0][0]	(None, 8, 8, 72)	0	concatena dropout_2
1[0][0]			
batch_normalization_22 (BatchNo te_19[0][0]	(None, 8, 8, 72)	288	concatena
activation_22 (Activation) malization_22[0][0]	(None, 8, 8, 72)	0	batch_nor
conv2d_23 (Conv2D) n_22[0][0]	(None, 8, 8, 24)	15552	activatio
dropout_22 (Dropout) [0][0]	(None, 8, 8, 24)	0	conv2d_23
concatenate_20 (Concatenate) te_19[0][0]	(None, 8, 8, 96)	0	concatena dropout_2
2[0][0]			
batch_normalization_23 (BatchNo te_20[0][0]	(None, 8, 8, 96)	384	concatena
activation_23 (Activation) malization_23[0][0]	(None, 8, 8, 96)	0	batch_nor
conv2d_24 (Conv2D) n_23[0][0]	(None, 8, 8, 24)	20736	activatio
dropout_23 (Dropout) [0][0]	(None, 8, 8, 24)	0	conv2d_24
concatenate_21 (Concatenate) te_20[0][0]	(None, 8, 8, 120)	0	concatena dropout_2
3[0][0]			
batch_normalization_24 (BatchNo te_21[0][0]	(None, 8, 8, 120)	480	concatena
activation_24 (Activation) malization_24[0][0]	(None, 8, 8, 120)	0	batch_nor
conv2d_25 (Conv2D) n_24[0][0]	(None, 8, 8, 24)	25920	activatio

dropout_24 (Dropout) [0][0]	(None, 8, 8, 24)	0	conv2d_25
concatenate_22 (Concatenate) te_21[0][0]	(None, 8, 8, 144)	0	concatena dropout_2
batch_normalization_25 (BatchNo te_22[0][0]	(None, 8, 8, 144)	576	concatena
activation_25 (Activation) malization_25[0][0]	(None, 8, 8, 144)	0	batch_nor
conv2d_26 (Conv2D) n_25[0][0]	(None, 8, 8, 24)	31104	activatio
dropout_25 (Dropout) [0][0]	(None, 8, 8, 24)	0	conv2d_26
concatenate_23 (Concatenate) te_22[0][0]	(None, 8, 8, 168)	0	concatena dropout_2
batch_normalization_26 (BatchNo te_23[0][0]	(None, 8, 8, 168)	672	concatena
activation_26 (Activation) malization_26[0][0]	(None, 8, 8, 168)	0	batch_nor
conv2d_27 (Conv2D) n_26[0][0]	(None, 8, 8, 24)	36288	activatio
dropout_26 (Dropout) [0][0]	(None, 8, 8, 24)	0	conv2d_27
concatenate_24 (Concatenate) te_23[0][0]	(None, 8, 8, 192)	0	concatena dropout_2
batch_normalization_27 (BatchNo te_24[0][0]	(None, 8, 8, 192)	768	concatena
activation_27 (Activation) malization_27[0][0]	(None, 8, 8, 192)	0	batch_nor

conv2d_28 (Conv2D) n_27[0][0]	(None, 8, 8, 24)	41472	activation_27[0][0]
dropout_27 (Dropout) [0][0]	(None, 8, 8, 24)	0	conv2d_28
concatenate_25 (Concatenate) te_24[0][0]	(None, 8, 8, 216)	0	concatenate_24[0][0]
batch_normalization_28 (Batch Normalization) te_25[0][0]	(None, 8, 8, 216)	864	concatenate_25[0][0]
activation_28 (Activation) malization_28[0][0]	(None, 8, 8, 216)	0	batch_normalization_28[0][0]
conv2d_29 (Conv2D) n_28[0][0]	(None, 8, 8, 24)	46656	activation_28[0][0]
dropout_28 (Dropout) [0][0]	(None, 8, 8, 24)	0	conv2d_29
concatenate_26 (Concatenate) te_25[0][0]	(None, 8, 8, 240)	0	concatenate_25[0][0]
batch_normalization_29 (Batch Normalization) te_26[0][0]	(None, 8, 8, 240)	960	concatenate_26[0][0]
activation_29 (Activation) malization_29[0][0]	(None, 8, 8, 240)	0	batch_normalization_29[0][0]
conv2d_30 (Conv2D) n_29[0][0]	(None, 8, 8, 24)	5760	activation_29[0][0]
dropout_29 (Dropout) [0][0]	(None, 8, 8, 24)	0	conv2d_30
average_pooling2d_2 (Average Pooling) 9[0][0]	(None, 4, 4, 24)	0	dropout_29
batch_normalization_30 (Batch Normalization) ooling2d_2[0][0]	(None, 4, 4, 24)	96	average_pooling2d_2[0][0]

activation_30 (Activation) malization_30[0][0]	(None, 4, 4, 24)	0	batch_nor
conv2d_31 (Conv2D) n_30[0][0]	(None, 4, 4, 24)	5184	activatio
dropout_30 (Dropout) [0][0]	(None, 4, 4, 24)	0	conv2d_31
concatenate_27 (Concatenate) ooling2d_2[0][0]	(None, 4, 4, 48)	0	average_p
0[0][0]			dropout_3
batch_normalization_31 (BatchNo te_27[0][0]	(None, 4, 4, 48)	192	concatena
activation_31 (Activation) malization_31[0][0]	(None, 4, 4, 48)	0	batch_nor
conv2d_32 (Conv2D) n_31[0][0]	(None, 4, 4, 24)	10368	activatio
dropout_31 (Dropout) [0][0]	(None, 4, 4, 24)	0	conv2d_32
concatenate_28 (Concatenate) te_27[0][0]	(None, 4, 4, 72)	0	concatena
1[0][0]			dropout_3
batch_normalization_32 (BatchNo te_28[0][0]	(None, 4, 4, 72)	288	concatena
activation_32 (Activation) malization_32[0][0]	(None, 4, 4, 72)	0	batch_nor
conv2d_33 (Conv2D) n_32[0][0]	(None, 4, 4, 24)	15552	activatio
dropout_32 (Dropout) [0][0]	(None, 4, 4, 24)	0	conv2d_33
concatenate_29 (Concatenate) te_28[0][0]	(None, 4, 4, 96)	0	concatena
2[0][0]			dropout_3

batch_normalization_33 (Batch Normalization)	(None, 4, 4, 96)	384	concatenate_29[0][0]
activation_33 (Activation)	(None, 4, 4, 96)	0	batch_normalization_33[0][0]
conv2d_34 (Conv2D)	(None, 4, 4, 24)	20736	activation_33[0][0]
dropout_33 (Dropout)	(None, 4, 4, 24)	0	conv2d_34[0][0]
concatenate_30 (Concatenate)	(None, 4, 4, 120)	0	concatenate_29[0][0] dropout_33[0][0]
batch_normalization_34 (Batch Normalization)	(None, 4, 4, 120)	480	concatenate_30[0][0]
activation_34 (Activation)	(None, 4, 4, 120)	0	batch_normalization_34[0][0]
conv2d_35 (Conv2D)	(None, 4, 4, 24)	25920	activation_34[0][0]
dropout_34 (Dropout)	(None, 4, 4, 24)	0	conv2d_35[0][0]
concatenate_31 (Concatenate)	(None, 4, 4, 144)	0	concatenate_30[0][0] dropout_34[0][0]
batch_normalization_35 (Batch Normalization)	(None, 4, 4, 144)	576	concatenate_31[0][0]
activation_35 (Activation)	(None, 4, 4, 144)	0	batch_normalization_35[0][0]
conv2d_36 (Conv2D)	(None, 4, 4, 24)	31104	activation_35[0][0]
dropout_35 (Dropout)	(None, 4, 4, 24)	0	conv2d_36[0][0]

concatenate_32 (Concatenate) te_31[0][0]	(None, 4, 4, 168)	0	concatena dropout_3 5[0][0]
batch_normalization_36 (BatchNo te_32[0][0]	(None, 4, 4, 168)	672	concatena
activation_36 (Activation) malization_36[0][0]	(None, 4, 4, 168)	0	batch_nor
conv2d_37 (Conv2D) n_36[0][0]	(None, 4, 4, 24)	36288	activatio
dropout_36 (Dropout) [0][0]	(None, 4, 4, 24)	0	conv2d_37
concatenate_33 (Concatenate) te_32[0][0]	(None, 4, 4, 192)	0	concatena dropout_3 6[0][0]
batch_normalization_37 (BatchNo te_33[0][0]	(None, 4, 4, 192)	768	concatena
activation_37 (Activation) malization_37[0][0]	(None, 4, 4, 192)	0	batch_nor
conv2d_38 (Conv2D) n_37[0][0]	(None, 4, 4, 24)	41472	activatio
dropout_37 (Dropout) [0][0]	(None, 4, 4, 24)	0	conv2d_38
concatenate_34 (Concatenate) te_33[0][0]	(None, 4, 4, 216)	0	concatena dropout_3 7[0][0]
batch_normalization_38 (BatchNo te_34[0][0]	(None, 4, 4, 216)	864	concatena
activation_38 (Activation) malization_38[0][0]	(None, 4, 4, 216)	0	batch_nor
conv2d_39 (Conv2D) n_38[0][0]	(None, 4, 4, 24)	46656	activatio

dropout_38 (Dropout) [0][0]	(None, 4, 4, 24)	0	conv2d_39
concatenate_35 (Concatenate) te_34[0][0]	(None, 4, 4, 240)	0	concatena
8[0][0]			dropout_3
batch_normalization_39 (BatchNo te_35[0][0])	(None, 4, 4, 240)	960	concatena
activation_39 (Activation) malization_39[0][0]	(None, 4, 4, 240)	0	batch_nor
average_pooling2d_3 (AveragePoo n_39[0][0])	(None, 2, 2, 240)	0	activatio
conv2d_40 (Conv2D) ooling2d_3[0][0]	(None, 2, 2, 10)	2400	average_p
global_max_pooling2d (GlobalMax [0][0])	(None, 10)	0	conv2d_40
activation_40 (Activation) x_pooling2d[0][0]	(None, 10)	0	global_ma
=====			
Total params: 974,568			
Trainable params: 964,008			
Non-trainable params: 10,560			

In [0]:

```
# determine Loss function and Optimizer

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

In [0]:

```
model.fit(X_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(X_test, y_test))
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 112s 2ms/sample - loss: 1.7266 - acc: 0.3533 - val_loss: 1.5696 - val_acc: 0.4313

Epoch 2/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.3710 - acc: 0.4956 - val_loss: 1.6232 - val_acc: 0.4712

Epoch 3/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.2011 - acc: 0.5626 - val_loss: 1.2632 - val_acc: 0.5566

Epoch 4/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.0969 - acc: 0.6025 - val_loss: 1.2591 - val_acc: 0.5634

Epoch 5/10

50000/50000 [=====] - 95s 2ms/sample - loss: 1.0390 - acc: 0.6257 - val_loss: 1.2728 - val_acc: 0.5842

Epoch 6/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.9857 - acc: 0.6452 - val_loss: 1.4487 - val_acc: 0.5634

Epoch 7/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.9501 - acc: 0.6597 - val_loss: 1.9306 - val_acc: 0.4998

Epoch 8/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.9204 - acc: 0.6683 - val_loss: 1.0015 - val_acc: 0.6638

Epoch 9/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.8858 - acc: 0.6805 - val_loss: 1.3980 - val_acc: 0.5892

Epoch 10/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.8614 - acc: 0.6891 - val_loss: 1.3597 - val_acc: 0.5937

Out[0]:

<tensorflow.python.keras.callbacks.History at 0x7f368f86a518>

In [0]:

```
# Test the model
score = model.evaluate(X_test, y_test, verbose=1)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

10000/10000 [=====] - 8s 848us/sample - loss: 1.3597 - acc: 0.5937

Test loss: 1.3597363298416139

Test accuracy: 0.5937

In [0]:

```
# Save the trained weights in to .h5 format
model.save_weights("DNST_model.h5")
print("Saved model to disk")
```

In [0]:

```
# ['Augmentation', 'l', 'num_filters', 'compression', 'Optimizer', 'Test Accuracy']

final_tab.add_row([None, 1, num_filter, compression, 'Adam', 0.59])
```

In [0]:

```
print(final_tab)
```

```
+-----+-----+-----+-----+-----+-----+
--+
| Augmentation | 1 | num_filters | compression | Optimizer | Test Accurac
y |
+-----+-----+-----+-----+-----+-----+
--+
|      None      | 12 |      12      |      0.5      |      Adam      |      0.59
|
+-----+-----+-----+-----+-----+-----+
--+
```

DenseNet Function

In [0]:

```
def dense_net(xtrain,xtest, optim = Adam(),k_size=(3,3), b_size = batch_size, epoch = e
pochs):
    print('b_size:{} epochs:{}'.format(b_size,epoch))
    input = layers.Input(shape=(img_height, img_width, channel,))
    First_Conv2D = layers.Conv2D(num_filter, (3,3), use_bias=False ,padding='sam
e')(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)

    model = Model(inputs=[input], outputs=[output])

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

    model.fit(xtrain, y_train,
              batch_size=batch_size,
              epochs=epochs,
              verbose=1,
              validation_data=(xtest, y_test))

    score = model.evaluate(xtest, y_test, verbose=1)
    print('Test loss:', score[0])
    print('Test accuracy:', score[1])

    return model
```

Image Augmentation Techniques

Some of the augmentation techniques are as follows

1. Vertical Shift Augmentation
2. Horizontal Shift Augmentation
3. Vertical Flip Augmentation
4. Horizontal Flip Augmentation

Vertical and Horizontal Shift Augmentation:

A shift to an image means moving all pixels of the image in one direction, vertically, horizontally while keeping the image dimensions the same.

In [0]:

```
# Reff https://machinelearningmastery.com/how-to-configure-image-data-augmentation-when-training-deep-learning-neural-networks/

def vertical_horizontal_shift(arr_imgs):

    # convert to numpy array
    d = arr_imgs.copy()

    for i in tqdm(range(d.shape[0]), position=0):
        data = d[i]
        # expand dimension to one sample
        samples = expand_dims(data, 0)
        # create image data augmentation generator
        datagen = ImageDataGenerator(width_shift_range=[-15,15], height_shift_range=[
-15,15])
        # prepare iterator
        it = datagen.flow(samples, batch_size=1)
        # generate samples and plot
        # define subplot
        # pyplot.subplot(330 + 1 + i)
        # generate batch of images
        for j in range(9):
            batch = it.next()
            if j == 0:

                # convert to unsigned integers for viewing
                image = batch[0].astype('uint8')
                d[i] = image
                # plot raw pixel data
                break

    return d
```

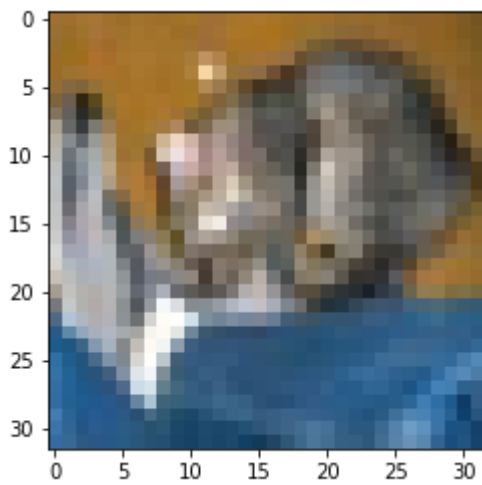
Original Image

In [0]:

```
pyplot.imshow(X_test[0])
```

Out[0]:

<matplotlib.image.AxesImage at 0x7fecfc932240>



After Vertical and Horizontal Shift

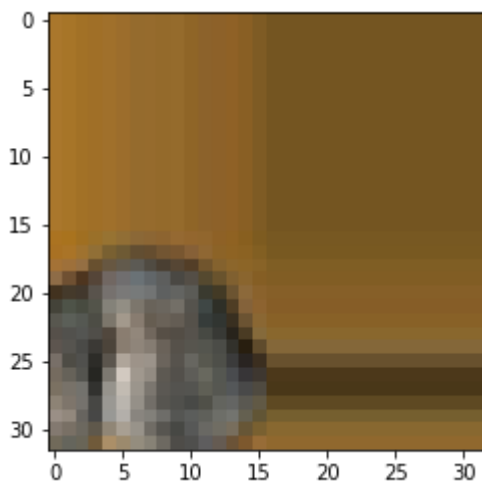
In [0]:

```
pyplot.imshow(vertical_horizontal_shift(X_test)[0])
```

100%|██████████| 10000/10000 [00:58<00:00, 169.87it/s]

Out[0]:

<matplotlib.image.AxesImage at 0x7fe0a7a5a278>



Applying vertical and horizontal shift on vertical and horizontal shift

In [0]:

```
v_h_shift_train = vertical_horizontal_shift(X_train)
v_h_shift_test  = vertical_horizontal_shift(X_test)
```

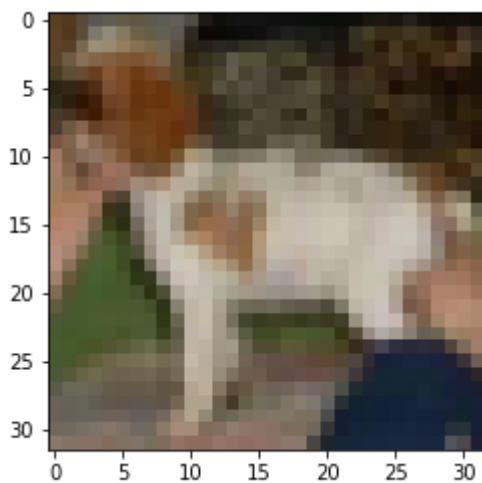
```
100%|██████████| 50000/50000 [00:42<00:00, 1170.97it/s]
100%|██████████| 10000/10000 [00:08<00:00, 1207.90it/s]
```

In [0]:

```
pyplot.imshow(X_test[12])
```

Out[0]:

<matplotlib.image.AxesImage at 0x7fe0a43b8550>

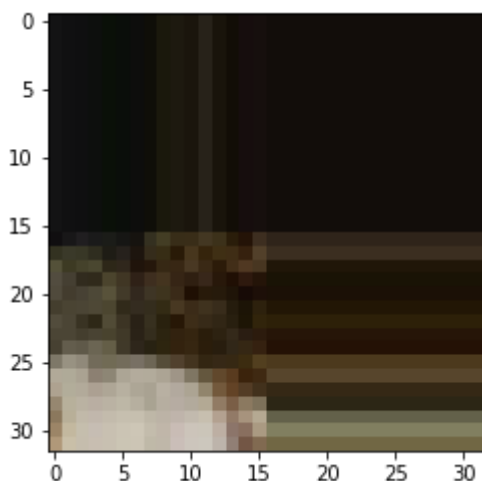


In [0]:

```
pyplot.imshow(v_h_shift_test[12])
```

Out[0]:

<matplotlib.image.AxesImage at 0x7fe0a33e3438>



DenseNet with Adam Optimizer on Vertical Horizontal Shift Data

In [0]:

```
v_h_shift_model = dense_net(v_h_shift_train, v_h_shift_test)
```

b_size:64 epochs:10

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 191s 4ms/sample - loss: 2.0

386 - acc: 0.2355 - val_loss: 1.9912 - val_acc: 0.2963

Epoch 2/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.8

141 - acc: 0.3226 - val_loss: 1.7621 - val_acc: 0.3535

Epoch 3/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.6

705 - acc: 0.3824 - val_loss: 1.9284 - val_acc: 0.3487

Epoch 4/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.5

842 - acc: 0.4157 - val_loss: 1.6201 - val_acc: 0.4319

Epoch 5/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.5

244 - acc: 0.4409 - val_loss: 1.7455 - val_acc: 0.4045

Epoch 6/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.4

734 - acc: 0.4619 - val_loss: 1.5040 - val_acc: 0.4666

Epoch 7/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.4

372 - acc: 0.4787 - val_loss: 1.6663 - val_acc: 0.4400

Epoch 8/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.4

007 - acc: 0.4926 - val_loss: 1.6158 - val_acc: 0.4545

Epoch 9/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.3

735 - acc: 0.5033 - val_loss: 1.4835 - val_acc: 0.4785

Epoch 10/10

50000/50000 [=====] - 174s 3ms/sample - loss: 1.3

441 - acc: 0.5166 - val_loss: 1.5579 - val_acc: 0.4632

10000/10000 [=====] - 11s 1ms/sample - loss: 1.55

79 - acc: 0.4632

Test loss: 1.5579216079711915

Test accuracy: 0.4632

In [0]:

```
final_tab.add_row(['Vertical_Horizontal_Shift',1, num_filter, compression,'Adam',0.42])
```

DenseNet with Nadam Optimizer on Vertical Horizontal Shift Data

In [0]:

```
v_h_shift_model_nadam = dense_net(v_h_shift_train, v_h_shift_test, optim=Nadam())
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 105s 2ms/sample - loss: 2.1

528 - acc: 0.1884 - val_loss: 2.3496 - val_acc: 0.1900

Epoch 2/10

50000/50000 [=====] - 95s 2ms/sample - loss: 2.01

43 - acc: 0.2405 - val_loss: 2.0252 - val_acc: 0.2460

Epoch 3/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.88

41 - acc: 0.2924 - val_loss: 2.0804 - val_acc: 0.2567

Epoch 4/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.79

20 - acc: 0.3263 - val_loss: 1.9178 - val_acc: 0.3146

Epoch 5/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.72

42 - acc: 0.3547 - val_loss: 1.7486 - val_acc: 0.3612

Epoch 6/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.67

26 - acc: 0.3753 - val_loss: 1.7488 - val_acc: 0.3691

Epoch 7/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.62

98 - acc: 0.3925 - val_loss: 1.7267 - val_acc: 0.3831

Epoch 8/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.59

24 - acc: 0.4099 - val_loss: 1.7654 - val_acc: 0.3777

Epoch 9/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.56

21 - acc: 0.4232 - val_loss: 1.6809 - val_acc: 0.4004

Epoch 10/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.53

30 - acc: 0.4333 - val_loss: 1.5949 - val_acc: 0.4122

10000/10000 [=====] - 8s 757us/sample - loss: 1.5

949 - acc: 0.4122

Test loss: 1.5949444211959838

Test accuracy: 0.4122

In [0]:

```
final_tab.add_row(['Vertical_Horizantal_Shift',1, num_filter, compression, 'Nadam',0.41
])
```

Horizontal and Vertical Flip Augmentation

An image flip means reversing the rows or columns of pixels in the case of a vertical or horizontal flip respectively.

In [0]:

```
# Reff https://machinelearningmastery.com/how-to-configure-image-data-augmentation-when-training-deep-learning-neural-networks/
```

```
def vertical_horizontal_flip(arr_imgs):

    # convert to numpy array
    d = arr_imgs.copy()

    for i in tqdm(range(d.shape[0])):
        data = d[i]
        # expand dimension to one sample
        samples = expand_dims(data, 0)
        # create image data augmentation generator
        datagen = ImageDataGenerator(vertical_flip=True, horizontal_flip=True)
        # prepare iterator
        it = datagen.flow(samples, batch_size=1)
        # generate samples and plot
        # define subplot
        # pyplot.subplot(330 + 1 + i)
        # generate batch of images
        for j in range(9):
            batch = it.next()
            if j == 2:
                # convert to unsigned integers for viewing
                image = batch[0].astype('uint8')
                d[i] = image
                break
        # plot raw pixel data
    return d
```

In [0]:

DenseNet with Optimizer on Vertical Horizontal Flip Data

In [0]:

```
v_h_flip_xtrain = vertical_horizontal_flip(X_train)
v_h_flip_xtest = vertical_horizontal_flip(X_test)
```

```
100%|██████████| 50000/50000 [00:25<00:00, 1929.50it/s]
100%|██████████| 10000/10000 [00:05<00:00, 1898.82it/s]
```

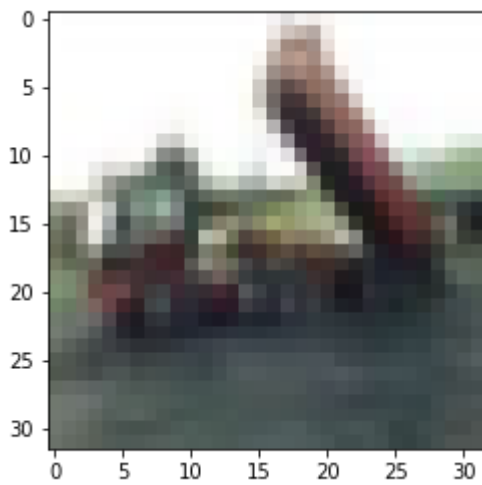
Before Flipping

In [0]:

```
pyplot.imshow(X_train[2])
```

Out[0]:

<matplotlib.image.AxesImage at 0x7fe0530cf400>



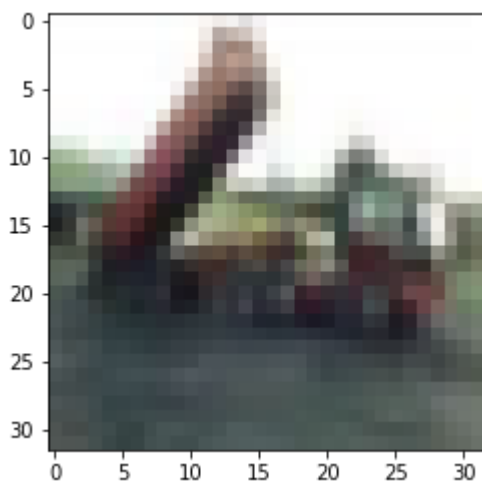
After Flipping

In [0]:

```
pyplot.imshow(v_h_flip_xtrain[2])
```

Out[0]:

<matplotlib.image.AxesImage at 0x7fe053061550>



In [0]:

```
v_h_flip_model = dense_net(v_h_flip_xtrain, v_h_flip_xtest)
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 107s 2ms/sample - loss: 1.7

911 - acc: 0.3097 - val_loss: 1.6606 - val_acc: 0.3809

Epoch 2/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.52

31 - acc: 0.4242 - val_loss: 1.6694 - val_acc: 0.4135

Epoch 3/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.38

28 - acc: 0.4865 - val_loss: 1.4306 - val_acc: 0.4768

Epoch 4/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.27

82 - acc: 0.5326 - val_loss: 1.4148 - val_acc: 0.5241

Epoch 5/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.19

89 - acc: 0.5606 - val_loss: 1.3927 - val_acc: 0.5238

Epoch 6/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.14

67 - acc: 0.5804 - val_loss: 1.4058 - val_acc: 0.5260

Epoch 7/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.10

55 - acc: 0.5982 - val_loss: 1.7325 - val_acc: 0.4948

Epoch 8/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.06

89 - acc: 0.6086 - val_loss: 1.3379 - val_acc: 0.5305

Epoch 9/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.04

25 - acc: 0.6206 - val_loss: 1.4536 - val_acc: 0.5383

Epoch 10/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.02

03 - acc: 0.6314 - val_loss: 1.3940 - val_acc: 0.5526

10000/10000 [=====] - 8s 824us/sample - loss: 1.3

940 - acc: 0.5526

Test loss: 1.3939515771865845

Test accuracy: 0.5526

In [0]:

```
final_tab.add_row(['Vertical_Horizantal_Flip',1, num_filter, compression,'Adam',0.55])
```

DenseNet with Nadam Optimizer on Vertical Horizantal Flip Data

In [0]:

```
v_h_flip_model_nadam = dense_net(v_h_flip_xtrain, v_h_flip_xtest, optim = Nadam())
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 108s 2ms/sample - loss: 1.8

078 - acc: 0.3088 - val_loss: 1.7010 - val_acc: 0.3601

Epoch 2/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.52

87 - acc: 0.4237 - val_loss: 1.4924 - val_acc: 0.4579

Epoch 3/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.41

01 - acc: 0.4767 - val_loss: 1.5825 - val_acc: 0.4363

Epoch 4/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.33

54 - acc: 0.5046 - val_loss: 1.4079 - val_acc: 0.4948

Epoch 5/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.27

51 - acc: 0.5342 - val_loss: 1.5963 - val_acc: 0.4315

Epoch 6/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.22

14 - acc: 0.5540 - val_loss: 1.3639 - val_acc: 0.5135

Epoch 7/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.17

18 - acc: 0.5729 - val_loss: 1.3339 - val_acc: 0.5423

Epoch 8/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.13

02 - acc: 0.5892 - val_loss: 1.2992 - val_acc: 0.5498

Epoch 9/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.10

01 - acc: 0.6005 - val_loss: 1.2659 - val_acc: 0.5631

Epoch 10/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.07

06 - acc: 0.6119 - val_loss: 1.1701 - val_acc: 0.5946

10000/10000 [=====] - 8s 823us/sample - loss: 1.1

701 - acc: 0.5946

Test loss: 1.1700947647094726

Test accuracy: 0.5946

In [0]:

```
final_tab.add_row(['Vertical_Horizantal_Flip',1, num_filter, compression,'Nadam',0.59])
```

Brightness Augmentation

The brightness of the image can be augmented by either randomly darkening images, brightening images, or both.

In [0]:

```
def brightness(arr_imgs):

    # convert to numpy array
    d = arr_imgs.copy()

    for i in tqdm(range(d.shape[0])):
        data = d[i]
        # expand dimension to one sample
        samples = expand_dims(data, 0)
        # create image data augmentation generator
        datagen = ImageDataGenerator(brightness_range=[0.5,0.6])
        # prepare iterator
        it = datagen.flow(samples, batch_size=1)
        # generate samples and plot
        # define subplot
        # pyplot.subplot(330 + 1 + i)
        # generate batch of images
        for j in range(9):
            batch = it.next()
            if j == 8:
                # convert to unsigned integers for viewing
                image = batch[0].astype('uint8')
                d[i] = image
                break
            # plot raw pixel data
    return d
```

In [0]:

```
bright_xtrain = brightness(X_train)
bright_xtest = brightness(X_test)
```

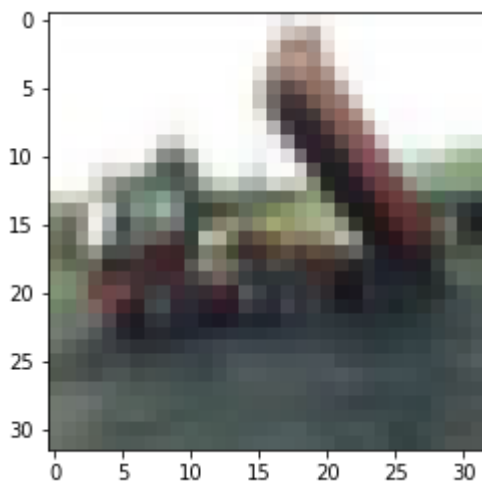
```
100%|██████████| 50000/50000 [02:29<00:00, 333.62it/s]
100%|██████████| 10000/10000 [00:30<00:00, 328.29it/s]
```

In [0]:

```
pyplot.imshow(X_train[2])
```

Out[0]:

```
<matplotlib.image.AxesImage at 0x7fe04e823518>
```

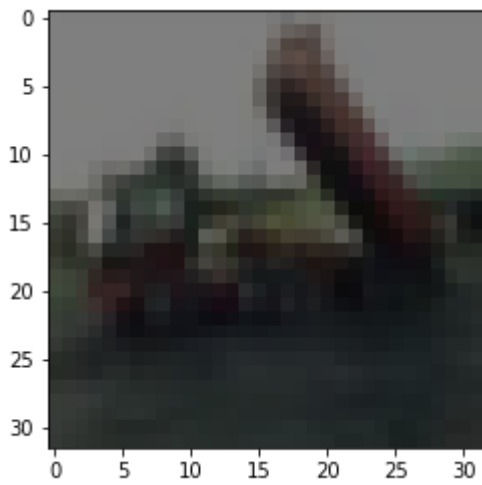


In [0]:

```
pyplot.imshow(bright_xtrain[2])
```

Out[0]:

<matplotlib.image.AxesImage at 0x7fe04dbf18d0>



DenseNet with Adam Optimizer on Brightness Augmentation Data

In [0]:

```
bright_model = dense_net(bright_xtrain, bright_xtest)
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 110s 2ms/sample - loss: 1.7

495 - acc: 0.3368 - val_loss: 2.0044 - val_acc: 0.3110

Epoch 2/10

50000/50000 [=====] - 97s 2ms/sample - loss: 1.39

59 - acc: 0.4854 - val_loss: 1.5577 - val_acc: 0.4708

Epoch 3/10

50000/50000 [=====] - 97s 2ms/sample - loss: 1.20

84 - acc: 0.5608 - val_loss: 1.2202 - val_acc: 0.5645

Epoch 4/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.09

93 - acc: 0.6017 - val_loss: 1.3322 - val_acc: 0.5412

Epoch 5/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.02

83 - acc: 0.6269 - val_loss: 1.1301 - val_acc: 0.6099

Epoch 6/10

50000/50000 [=====] - 97s 2ms/sample - loss: 0.98

44 - acc: 0.6458 - val_loss: 1.2942 - val_acc: 0.5640

Epoch 7/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.94

09 - acc: 0.6628 - val_loss: 1.1198 - val_acc: 0.6105

Epoch 8/10

50000/50000 [=====] - 97s 2ms/sample - loss: 0.90

53 - acc: 0.6769 - val_loss: 1.5355 - val_acc: 0.5591

Epoch 9/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.88

34 - acc: 0.6845 - val_loss: 1.2051 - val_acc: 0.6246

Epoch 10/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.85

41 - acc: 0.6950 - val_loss: 0.9743 - val_acc: 0.6735

10000/10000 [=====] - 8s 782us/sample - loss: 0.9

743 - acc: 0.6735

Test loss: 0.9742989232063294

Test accuracy: 0.6735

In [0]:

```
final_tab.add_row(['Brightness',1, num_filter, compression,'Adam',0.67])
```

DenseNet with Nadam Optimizer on Brightness Augmentation Data

In [0]:

```
bright_model_nadam = dense_net(bright_xtrain, bright_xtest, optim=Nadam())
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 112s 2ms/sample - loss: 1.7

422 - acc: 0.3393 - val_loss: 1.6212 - val_acc: 0.4032

Epoch 2/10

50000/50000 [=====] - 97s 2ms/sample - loss: 1.39

62 - acc: 0.4847 - val_loss: 1.5139 - val_acc: 0.4873

Epoch 3/10

50000/50000 [=====] - 97s 2ms/sample - loss: 1.21

54 - acc: 0.5559 - val_loss: 1.1808 - val_acc: 0.5713

Epoch 4/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.11

44 - acc: 0.5982 - val_loss: 1.2420 - val_acc: 0.5821

Epoch 5/10

50000/50000 [=====] - 96s 2ms/sample - loss: 1.04

50 - acc: 0.6246 - val_loss: 1.0905 - val_acc: 0.6186

Epoch 6/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.98

83 - acc: 0.6453 - val_loss: 1.2437 - val_acc: 0.5991

Epoch 7/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.94

78 - acc: 0.6600 - val_loss: 1.3254 - val_acc: 0.5601

Epoch 8/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.90

93 - acc: 0.6746 - val_loss: 1.1406 - val_acc: 0.6206

Epoch 9/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.88

46 - acc: 0.6830 - val_loss: 0.9157 - val_acc: 0.6844

Epoch 10/10

50000/50000 [=====] - 96s 2ms/sample - loss: 0.85

84 - acc: 0.6917 - val_loss: 0.9772 - val_acc: 0.6706

10000/10000 [=====] - 9s 924us/sample - loss: 0.9

772 - acc: 0.6706

Test loss: 0.9772336851119995

Test accuracy: 0.6706

In [0]:

```
final_tab.add_row(['Brightness',1, num_filter, compression,'Nadam',0.67])
```

Feature Standardization

In [0]:

```
def standard(arr_imgs):

    # convert to numpy array
    d = arr_imgs.copy()

    for i in tqdm(range(d.shape[0])):
        data = d[i]
        # expand dimension to one sample
        samples = expand_dims(data, 0)
        # create image data augmentation generator
        datagen = ImageDataGenerator(featurewise_center=True, featurewise_std_normali
zation=True)
        # prepare iterator
        it = datagen.flow(samples, batch_size=1)
        # generate samples and plot
        # define subplot
        # pyplot.subplot(330 + 1 + i)
        # generate batch of images
        for j in range(9):
            batch = it.next()
            if j == 5:
                # convert to unsigned integers for viewing
                image = batch[0].astype('uint8')
                d[i] = image
                break
            # plot raw pixel data

    return d
```

In [0]:

```
# stand_xtrain = standard(X_train)
stand_xtest = standard(X_test)
```

```
0%|          | 0/10000 [00:00<?, ?it/s]/usr/local/lib/python3.6/dist-pac
kages/keras_preprocessing/image/image_data_generator.py:716: UserWarning:
This ImageDataGenerator specifies `featurewise_center`, but it hasn't been
fit on any training data. Fit it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_dat
a_generator.py:724: UserWarning: This ImageDataGenerator specifies `featur
ewise_std_normalization`, but it hasn't been fit on any training data. Fit
it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
100%|██████████| 10000/10000 [00:08<00:00, 1211.73it/s]
```

DenseNet with Adam Optimizer on Standardized Data

In [0]:

```
stand_model = dense_net(stand_xtrain, stand_xtest)
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 116s 2ms/sample - loss: 1.7

418 - acc: 0.3469 - val_loss: 1.5594 - val_acc: 0.4418

Epoch 2/10

50000/50000 [=====] - 98s 2ms/sample - loss: 1.37

99 - acc: 0.4947 - val_loss: 1.6403 - val_acc: 0.4437

Epoch 3/10

50000/50000 [=====] - 98s 2ms/sample - loss: 1.21

29 - acc: 0.5580 - val_loss: 1.1566 - val_acc: 0.5843

Epoch 4/10

50000/50000 [=====] - 97s 2ms/sample - loss: 1.11

02 - acc: 0.6008 - val_loss: 1.2747 - val_acc: 0.5612

Epoch 5/10

50000/50000 [=====] - 97s 2ms/sample - loss: 1.04

14 - acc: 0.6250 - val_loss: 1.2837 - val_acc: 0.5759

Epoch 6/10

50000/50000 [=====] - 97s 2ms/sample - loss: 0.99

09 - acc: 0.6446 - val_loss: 1.2212 - val_acc: 0.5953

Epoch 7/10

50000/50000 [=====] - 98s 2ms/sample - loss: 0.94

81 - acc: 0.6585 - val_loss: 1.1835 - val_acc: 0.6058

Epoch 8/10

50000/50000 [=====] - 98s 2ms/sample - loss: 0.90

93 - acc: 0.6741 - val_loss: 1.0955 - val_acc: 0.6406

Epoch 9/10

50000/50000 [=====] - 98s 2ms/sample - loss: 0.88

40 - acc: 0.6811 - val_loss: 0.8493 - val_acc: 0.6984

Epoch 10/10

50000/50000 [=====] - 97s 2ms/sample - loss: 0.86

02 - acc: 0.6903 - val_loss: 1.0805 - val_acc: 0.6348

10000/10000 [=====] - 11s 1ms/sample - loss: 1.08

05 - acc: 0.6348

Test loss: 1.0804764985084534

Test accuracy: 0.6348

In [0]:

```
final_tab.add_row(['Standardized',1, num_filter, compression,'Adam',0.63])
```

DenseNet with Nadam Optimizer on Standardized Data

In [0]:

```
stand_model_nadam = dense_net(stand_xtrain,stand_xtest, optim = Nadam())
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 117s 2ms/sample - loss: 1.7

193 - acc: 0.3541 - val_loss: 2.2187 - val_acc: 0.3326

Epoch 2/10

50000/50000 [=====] - 98s 2ms/sample - loss: 1.36

88 - acc: 0.4973 - val_loss: 1.5857 - val_acc: 0.4589

Epoch 3/10

50000/50000 [=====] - 98s 2ms/sample - loss: 1.22

11 - acc: 0.5536 - val_loss: 1.5198 - val_acc: 0.5076

Epoch 4/10

50000/50000 [=====] - 98s 2ms/sample - loss: 1.11

58 - acc: 0.5921 - val_loss: 1.4742 - val_acc: 0.5246

Epoch 5/10

50000/50000 [=====] - 98s 2ms/sample - loss: 1.03

99 - acc: 0.6241 - val_loss: 1.0491 - val_acc: 0.6400

Epoch 6/10

50000/50000 [=====] - 98s 2ms/sample - loss: 0.99

17 - acc: 0.6427 - val_loss: 1.0171 - val_acc: 0.6433

Epoch 7/10

50000/50000 [=====] - 98s 2ms/sample - loss: 0.94

90 - acc: 0.6574 - val_loss: 1.4362 - val_acc: 0.5504

Epoch 8/10

50000/50000 [=====] - 98s 2ms/sample - loss: 0.91

09 - acc: 0.6737 - val_loss: 1.0236 - val_acc: 0.6586

Epoch 9/10

50000/50000 [=====] - 98s 2ms/sample - loss: 0.87

78 - acc: 0.6854 - val_loss: 1.4910 - val_acc: 0.5662

Epoch 10/10

50000/50000 [=====] - 98s 2ms/sample - loss: 0.85

48 - acc: 0.6942 - val_loss: 0.9976 - val_acc: 0.6743

10000/10000 [=====] - 10s 1ms/sample - loss: 0.99

76 - acc: 0.6743

Test loss: 0.9975716045379639

Test accuracy: 0.6743

In [0]:

```
final_tab.add_row(['Standardized',1, num_filter, compression,'Nadam',0.63])
```

Now lets try with changing some of the parameters

In [0]:

```
l = 8
num_filter = 38
compression = 1
```

DenseNet with Adam Optimizer on Vertical Horizontal Shift

In [0]:

```
v_h_shift_model2 = dense_net(v_h_shift_train,v_h_shift_test)
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 295s 6ms/sample - loss: 1.9

932 - acc: 0.2628 - val_loss: 2.8806 - val_acc: 0.2111

Epoch 2/10

50000/50000 [=====] - 269s 5ms/sample - loss: 1.6

862 - acc: 0.3815 - val_loss: 1.8009 - val_acc: 0.3622

Epoch 3/10

50000/50000 [=====] - 269s 5ms/sample - loss: 1.5

389 - acc: 0.4382 - val_loss: 1.7920 - val_acc: 0.4283

Epoch 4/10

50000/50000 [=====] - 269s 5ms/sample - loss: 1.4

265 - acc: 0.4839 - val_loss: 1.6365 - val_acc: 0.4426

Epoch 5/10

50000/50000 [=====] - 269s 5ms/sample - loss: 1.3

483 - acc: 0.5146 - val_loss: 1.5748 - val_acc: 0.4719

Epoch 6/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.2

871 - acc: 0.5360 - val_loss: 1.4691 - val_acc: 0.4993

Epoch 7/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.2

317 - acc: 0.5591 - val_loss: 1.5214 - val_acc: 0.4985

Epoch 8/10

50000/50000 [=====] - 271s 5ms/sample - loss: 1.1

819 - acc: 0.5803 - val_loss: 1.5452 - val_acc: 0.5099

Epoch 9/10

50000/50000 [=====] - 271s 5ms/sample - loss: 1.1

379 - acc: 0.5932 - val_loss: 1.6148 - val_acc: 0.4963

Epoch 10/10

50000/50000 [=====] - 271s 5ms/sample - loss: 1.1

026 - acc: 0.6052 - val_loss: 1.5244 - val_acc: 0.5223

10000/10000 [=====] - 20s 2ms/sample - loss: 1.52

44 - acc: 0.5223

Test loss: 1.5243553981781006

Test accuracy: 0.5223

In [0]:

```
final_tab.add_row(['Vertical_Horizantal_shift',1, num_filter, compression,'Adam',0.52])
```

DenseNet with Nadam Optimizer on Vertical Horizantal Shift

In [0]:

```
v_h_shift_model2_nadam = dense_net(v_h_shift_train,v_h_shift_test,optim=Nadam())
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 288s 6ms/sample - loss: 1.9

957 - acc: 0.2672 - val_loss: 2.0370 - val_acc: 0.2677

Epoch 2/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.6

974 - acc: 0.3788 - val_loss: 5.1156 - val_acc: 0.1736

Epoch 3/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.5

542 - acc: 0.4349 - val_loss: 1.7738 - val_acc: 0.3912

Epoch 4/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.4

505 - acc: 0.4729 - val_loss: 2.0385 - val_acc: 0.3929

Epoch 5/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.3

684 - acc: 0.5075 - val_loss: 1.6887 - val_acc: 0.4409

Epoch 6/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.3

042 - acc: 0.5300 - val_loss: 1.4545 - val_acc: 0.5053

Epoch 7/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.2

509 - acc: 0.5508 - val_loss: 1.8779 - val_acc: 0.4289

Epoch 8/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.2

035 - acc: 0.5672 - val_loss: 1.8281 - val_acc: 0.4424

Epoch 9/10

50000/50000 [=====] - 270s 5ms/sample - loss: 1.1

597 - acc: 0.5850 - val_loss: 3.2673 - val_acc: 0.3621

Epoch 10/10

50000/50000 [=====] - 271s 5ms/sample - loss: 1.1

192 - acc: 0.6013 - val_loss: 1.4267 - val_acc: 0.5364

10000/10000 [=====] - 19s 2ms/sample - loss: 1.42

67 - acc: 0.5364

Test loss: 1.426656289100647

Test accuracy: 0.5364

In [0]:

```
final_tab.add_row(['Vertical_Horizantal_shift',1, num_filter, compression,'Nadam',0.53])
```

DenseNet with Adam Optimizer on Vertical Horizantal Flip

In [0]:

```
v_h_flip_model2 = dense_net(v_h_flip_xtrain,v_h_flip_xtest)
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 292s 6ms/sample - loss: 1.5

497 - acc: 0.4271 - val_loss: 2.2234 - val_acc: 0.3542

Epoch 2/10

50000/50000 [=====] - 271s 5ms/sample - loss: 1.1

109 - acc: 0.6005 - val_loss: 1.9077 - val_acc: 0.4839

Epoch 3/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.9

230 - acc: 0.6673 - val_loss: 1.4761 - val_acc: 0.5829

Epoch 4/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.8

136 - acc: 0.7084 - val_loss: 1.4341 - val_acc: 0.5631

Epoch 5/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.7

315 - acc: 0.7382 - val_loss: 1.2017 - val_acc: 0.6418

Epoch 6/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.6

601 - acc: 0.7642 - val_loss: 1.3863 - val_acc: 0.6156

Epoch 7/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.6

100 - acc: 0.7844 - val_loss: 0.9802 - val_acc: 0.7015

Epoch 8/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.5

659 - acc: 0.7992 - val_loss: 1.0941 - val_acc: 0.6696

Epoch 9/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.5

260 - acc: 0.8134 - val_loss: 0.8848 - val_acc: 0.7286

Epoch 10/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.4

873 - acc: 0.8256 - val_loss: 1.0112 - val_acc: 0.7244

10000/10000 [=====] - 20s 2ms/sample - loss: 1.01

12 - acc: 0.7244

Test loss: 1.0111705540180207

Test accuracy: 0.7244

In [0]:

```
final_tab.add_row(['Vertical_Horizantal_flip',1, num_filter, compression,'Adam',0.72])
```

DenseNet with Nadam Optimizer on Vertical Horizantal Flip

In [0]:

```
v_h_flip_model2_nadam = dense_net(v_h_flip_xtrain,v_h_flip_xtest,optim=Nadam())
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 293s 6ms/sample - loss: 1.5

328 - acc: 0.4368 - val_loss: 1.8540 - val_acc: 0.3984

Epoch 2/10

50000/50000 [=====] - 272s 5ms/sample - loss: 1.0

911 - acc: 0.6057 - val_loss: 1.1753 - val_acc: 0.6160

Epoch 3/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.9

227 - acc: 0.6685 - val_loss: 1.1697 - val_acc: 0.6228

Epoch 4/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.8

073 - acc: 0.7112 - val_loss: 2.4143 - val_acc: 0.4619

Epoch 5/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.7

319 - acc: 0.7377 - val_loss: 1.4257 - val_acc: 0.6086

Epoch 6/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.6

665 - acc: 0.7597 - val_loss: 1.1833 - val_acc: 0.6594

Epoch 7/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.6

127 - acc: 0.7821 - val_loss: 1.2028 - val_acc: 0.6588

Epoch 8/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.5

698 - acc: 0.7967 - val_loss: 0.8314 - val_acc: 0.7259

Epoch 9/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.5

264 - acc: 0.8124 - val_loss: 0.8623 - val_acc: 0.7422

Epoch 10/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.4

910 - acc: 0.8264 - val_loss: 1.1797 - val_acc: 0.6763

10000/10000 [=====] - 18s 2ms/sample - loss: 1.17

97 - acc: 0.6763

Test loss: 1.1797264897346496

Test accuracy: 0.6763

In [0]:

```
final_tab.add_row(['Vertical_Horizontaflip',1, num_filter, compression,'Nadam',0.67])
```

DenseNet with Adam Optimizer on Brightness

In [0]:

```
bright_model2 = dense_net(bright_xtrain, bright_xtest)
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 262s 5ms/sample - loss: 1.3

957 - acc: 0.4889 - val_loss: 2.1067 - val_acc: 0.4403

Epoch 2/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.8

968 - acc: 0.6821 - val_loss: 1.0364 - val_acc: 0.6581

Epoch 3/10

50000/50000 [=====] - 246s 5ms/sample - loss: 0.7

104 - acc: 0.7495 - val_loss: 0.9763 - val_acc: 0.6957

Epoch 4/10

50000/50000 [=====] - 246s 5ms/sample - loss: 0.6

112 - acc: 0.7871 - val_loss: 1.1059 - val_acc: 0.6766

Epoch 5/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.5

337 - acc: 0.8115 - val_loss: 1.3122 - val_acc: 0.6740

Epoch 6/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.4

847 - acc: 0.8298 - val_loss: 1.0951 - val_acc: 0.7134

Epoch 7/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.4

338 - acc: 0.8492 - val_loss: 0.7656 - val_acc: 0.7695

Epoch 8/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.3

972 - acc: 0.8608 - val_loss: 0.9332 - val_acc: 0.7533

Epoch 9/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.3

658 - acc: 0.8720 - val_loss: 0.8406 - val_acc: 0.7652

Epoch 10/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.3

417 - acc: 0.8804 - val_loss: 0.7648 - val_acc: 0.7923

10000/10000 [=====] - 15s 2ms/sample - loss: 0.76

48 - acc: 0.7923

Test loss: 0.7648081164598465

Test accuracy: 0.7923

In [0]:

```
final_tab.add_row(['Brightness',1, num_filter, compression,'Adam',0.79])
```

DenseNet with Nadam Optimizer on Brightness

In [0]:

```
bright_model2_nadam = dense_net(bright_xtrain, bright_xtest, optim=Nadam())
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 252s 5ms/sample - loss: 1.3

535 - acc: 0.5083 - val_loss: 2.6686 - val_acc: 0.3786

Epoch 2/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.8

746 - acc: 0.6905 - val_loss: 1.4745 - val_acc: 0.5859

Epoch 3/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.7

027 - acc: 0.7521 - val_loss: 1.2347 - val_acc: 0.6524

Epoch 4/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.6

028 - acc: 0.7891 - val_loss: 0.9355 - val_acc: 0.7102

Epoch 5/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.5

348 - acc: 0.8140 - val_loss: 0.7049 - val_acc: 0.7758

Epoch 6/10

50000/50000 [=====] - 246s 5ms/sample - loss: 0.4

797 - acc: 0.8329 - val_loss: 0.8034 - val_acc: 0.7683

Epoch 7/10

50000/50000 [=====] - 246s 5ms/sample - loss: 0.4

343 - acc: 0.8484 - val_loss: 1.1576 - val_acc: 0.6972

Epoch 8/10

50000/50000 [=====] - 246s 5ms/sample - loss: 0.4

059 - acc: 0.8565 - val_loss: 0.6769 - val_acc: 0.8014

Epoch 9/10

50000/50000 [=====] - 246s 5ms/sample - loss: 0.3

660 - acc: 0.8709 - val_loss: 0.9298 - val_acc: 0.7320

Epoch 10/10

50000/50000 [=====] - 247s 5ms/sample - loss: 0.3

360 - acc: 0.8828 - val_loss: 1.2232 - val_acc: 0.7018

10000/10000 [=====] - 15s 1ms/sample - loss: 1.22

32 - acc: 0.7018

Test loss: 1.2232139734268188

Test accuracy: 0.7018

In [0]:

```
final_tab.add_row(['Brightness',1, num_filter, compression,'Nadam',0.70])
```

DenseNet with Adam Optimizer on Standardized Data

In [0]:

```
stand_model2 = dense_net(stand_xtrain,stand_xtest)
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 290s 6ms/sample - loss: 1.3

630 - acc: 0.5059 - val_loss: 1.8054 - val_acc: 0.4663

Epoch 2/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.8

947 - acc: 0.6818 - val_loss: 2.0782 - val_acc: 0.5325

Epoch 3/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.7

168 - acc: 0.7482 - val_loss: 1.2432 - val_acc: 0.6331

Epoch 4/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.6

117 - acc: 0.7844 - val_loss: 1.6101 - val_acc: 0.6382

Epoch 5/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.5

369 - acc: 0.8114 - val_loss: 1.1828 - val_acc: 0.6678

Epoch 6/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.4

824 - acc: 0.8326 - val_loss: 0.9018 - val_acc: 0.7418

Epoch 7/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.4

367 - acc: 0.8485 - val_loss: 1.2826 - val_acc: 0.6894

Epoch 8/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.3

977 - acc: 0.8611 - val_loss: 0.7730 - val_acc: 0.7711

Epoch 9/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.3

629 - acc: 0.8738 - val_loss: 1.0036 - val_acc: 0.7356

Epoch 10/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.3

349 - acc: 0.8831 - val_loss: 0.8019 - val_acc: 0.7713

10000/10000 [=====] - 19s 2ms/sample - loss: 0.80

19 - acc: 0.7713

Test loss: 0.8018832360267639

Test accuracy: 0.7713

In [0]:

```
final_tab.add_row(['Standardized',1, num_filter, compression,'Adam',0.77])
```

DenseNet with Nadam Optimizer on Standardized Data

In [0]:

```
stand_model2_nadam = dense_net(stand_xtrain,stand_xtest, optim = Nadam())
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/10

50000/50000 [=====] - 291s 6ms/sample - loss: 1.3

426 - acc: 0.5116 - val_loss: 1.8898 - val_acc: 0.4669

Epoch 2/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.8

734 - acc: 0.6906 - val_loss: 2.5935 - val_acc: 0.4521

Epoch 3/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.7

015 - acc: 0.7531 - val_loss: 1.2029 - val_acc: 0.6608

Epoch 4/10

50000/50000 [=====] - 273s 5ms/sample - loss: 0.5

990 - acc: 0.7908 - val_loss: 1.4715 - val_acc: 0.6416

Epoch 5/10

50000/50000 [=====] - 273s 5ms/sample - loss: 0.5

287 - acc: 0.8131 - val_loss: 0.6723 - val_acc: 0.7890

Epoch 6/10

50000/50000 [=====] - 273s 5ms/sample - loss: 0.4

771 - acc: 0.8332 - val_loss: 2.1752 - val_acc: 0.5709

Epoch 7/10

50000/50000 [=====] - 272s 5ms/sample - loss: 0.4

321 - acc: 0.8491 - val_loss: 0.9137 - val_acc: 0.7556

Epoch 8/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.3

960 - acc: 0.8619 - val_loss: 0.5650 - val_acc: 0.8256

Epoch 9/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.3

607 - acc: 0.8754 - val_loss: 0.7361 - val_acc: 0.7944

Epoch 10/10

50000/50000 [=====] - 271s 5ms/sample - loss: 0.3

387 - acc: 0.8808 - val_loss: 0.6667 - val_acc: 0.8088

10000/10000 [=====] - 20s 2ms/sample - loss: 0.66

67 - acc: 0.8088

Test loss: 0.6666583400726318

Test accuracy: 0.8088

In [0]:

```
final_tab.add_row(['Standardized',1, num_filter, compression,'Nadam',0.80])
```

In [0]:

```
print(final_tab)
```

```

+-----+-----+-----+-----+-----+
+-----+
|      Augmentation      | 1 | num_filters | compression | Optimizer |
Test Accuracy |
+-----+-----+-----+-----+-----+
+-----+
|      None              | 12 |      12     |      0.5     |      Adam   |
0.59 |
| Vertical_Horizontal_Shift | 12 |      12     |      0.5     |      Adam   |
0.41 |
| Vertical_Horizontal_Shift | 12 |      12     |      0.5     |      Nadam   |
0.409 |
| Vertical_Horizontal_Flip  | 12 |      12     |      0.5     |      Adam   |
0.604 |
| Vertical_Horizontal_Flip  | 12 |      12     |      0.5     |      Nadam   |
0.61 |
|      Brightness          | 12 |      12     |      0.5     |      Adam   |
0.66 |
|      Brightness          | 12 |      12     |      0.5     |      Nadam   |
0.67 |
|      Standardized        | 12 |      12     |      0.5     |      Adam   |
0.63 |
|      Standardized        | 12 |      12     |      0.5     |      Nadam   |
0.63 |
| Vertical_Horizontal_shift | 8  |      38     |      1       |      Adam   |
0.52 |
| Vertical_Horizontal_shift | 8  |      38     |      1       |      Nadam   |
0.53 |
| Vertical_Horizontal_flip  | 8  |      38     |      1       |      Adam   |
0.72 |
| Vertical_Horizontal_flip  | 8  |      38     |      1       |      Nadam   |
0.67 |
|      Brightness          | 8  |      38     |      1       |      Adam   |
0.79 |
|      Brightness          | 8  |      38     |      1       |      Nadam   |
0.7 |
|      Standardized        | 8  |      38     |      1       |      Adam   |
0.77 |
|      Standardized        | 8  |      38     |      1       |      Nadam   |
0.8 |
+-----+-----+-----+-----+-----+
+-----+

```

Observations:

If we observe the test accuracy when $l=8$, $no_filters=38$, $compression=1$ is higher so we shall use these changed parameters

We shall add the image augmentation which influenced the test accuracy lot i.e brightness, standardization, flipping

In [0]:

In [11]:

%%time

```

datagen = ImageDataGenerator(

    brightness_range=[0.5,1.9],
    featurewise_center=True, featurewise_std_normalization=True,
    width_shift_range = 0.125,
    horizontal_flip=True,vertical_flip=True,rotation_range=15,
    fill_mode='nearest'
)

```

CPU times: user 178 µs, sys: 35 µs, total: 213 µs

Wall time: 218 µs

In [0]:

```

for X_batch, y_batch in datagen.flow(X_train[:9], y_train[:9], batch_size=9):
    for i in range(0, 9):
        plt.subplot(330 + 1 + i)

        plt.imshow(X_batch[i].astype('uint8'), cmap=plt.get_cmap('prism'))
    plt.show()
    break

```

/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.

warnings.warn('This ImageDataGenerator specifies '

/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:724: UserWarning: This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.

warnings.warn('This ImageDataGenerator specifies '



In [0]:

1

In [0]:

```

def dense_net2(xtrain,xtest, optim = Adam(),k_size=(3,3), b_size = batch_size, epoch =
epochs):
    print('b_size:{} epochs:{}'.format(b_size,epoch))
    input = layers.Input(shape=(img_height, img_width, channel,))
    First_Conv2D = layers.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)

    model = Model(inputs=[input], outputs=[output])

    reduce_lr = ReduceLROnPlateau(monitor = 'val_loss', factor = 0.1, patience =
5, min_lr = 0.000001)

    # early_stop = EarlyStopping(monitor = "val_loss", patience = 10)

    def decay_fn(epoch, lr):
        if epoch < 50:
            return 0.001
        elif epoch >= 50 and epoch < 75:
            return 0.0001
        else:
            return 0.00001

    lr_scheduler = LearningRateScheduler(decay_fn)

    csv_logger = CSVLogger('training.log')

    checkpoint = ModelCheckpoint('gdrive/My Drive/cnnoncifar/models/model-{epoch:
03d}-{acc:03f}-{val_acc:03f}.h5',
                                verbose=1, monitor='val_acc', save_best_only=True
, mode='auto')

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

    # model.fit(xtrain, y_train,
    #           batch_size=batch_size,
    #           epochs=epochs,
    #           verbose=1,
    #           validation_data=(xtest, y_test))

```

```
print(model.summary())
model.fit_generator(
    datagen.flow(xtrain, y_train, batch_size=b_size),
    steps_per_epoch=(len(xtrain)/batch_size)*5,
    epochs=epoch,
    verbose = 1,
    validation_data=(xtest, y_test),callbacks=[checkpoint])

score = model.evaluate(xtest, y_test, verbose=1)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

return model
```

In [0]:

```
# L = 8
# num_filter = 27
compression = 1.041
#
#

# no of layers in dense block
l = 9
# growth rate k
num_filter = 24
```

In [0]:

```
model = dense_net2(X_train,X_test,epoch=150)
```

```

b_size:128 epochs:150
input (?, 4, 4, 240)
Batch (?, 4, 4, 240)
relu (?, 4, 4, 240)
Model: "model_2"

```

Layer (type) to	Output Shape	Param #	Connected
=====			
input_3 (InputLayer)	[(None, 32, 32, 3)]	0	
conv2d_82 (Conv2D) [0][0]	(None, 32, 32, 24)	648	input_3
batch_normalization_80 (BatchNo [0][0]	(None, 32, 32, 24)	96	conv2d_82
activation_82 (Activation) malization_80[0][0]	(None, 32, 32, 24)	0	batch_nor
conv2d_83 (Conv2D) n_82[0][0]	(None, 32, 32, 24)	5184	activatio
dropout_78 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_83
concatenate_72 (Concatenate) [0][0]	(None, 32, 32, 48)	0	conv2d_82 dropout_7
8[0][0]			
batch_normalization_81 (BatchNo te_72[0][0]	(None, 32, 32, 48)	192	concatena
activation_83 (Activation) malization_81[0][0]	(None, 32, 32, 48)	0	batch_nor
conv2d_84 (Conv2D) n_83[0][0]	(None, 32, 32, 24)	10368	activatio
dropout_79 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_84
concatenate_73 (Concatenate) te_72[0][0]	(None, 32, 32, 72)	0	concatena dropout_7
9[0][0]			

batch_normalization_82 (BatchNo	(None, 32, 32, 72)	288	concatena
te_73[0][0]			
activation_84 (Activation)	(None, 32, 32, 72)	0	batch_nor
malization_82[0][0]			
conv2d_85 (Conv2D)	(None, 32, 32, 24)	15552	activatio
n_84[0][0]			
dropout_80 (Dropout)	(None, 32, 32, 24)	0	conv2d_85
[0][0]			
concatenate_74 (Concatenate)	(None, 32, 32, 96)	0	concatena
te_73[0][0]			
0[0][0]			dropout_8
batch_normalization_83 (BatchNo	(None, 32, 32, 96)	384	concatena
te_74[0][0]			
activation_85 (Activation)	(None, 32, 32, 96)	0	batch_nor
malization_83[0][0]			
conv2d_86 (Conv2D)	(None, 32, 32, 24)	20736	activatio
n_85[0][0]			
dropout_81 (Dropout)	(None, 32, 32, 24)	0	conv2d_86
[0][0]			
concatenate_75 (Concatenate)	(None, 32, 32, 120)	0	concatena
te_74[0][0]			
1[0][0]			dropout_8
batch_normalization_84 (BatchNo	(None, 32, 32, 120)	480	concatena
te_75[0][0]			
activation_86 (Activation)	(None, 32, 32, 120)	0	batch_nor
malization_84[0][0]			
conv2d_87 (Conv2D)	(None, 32, 32, 24)	25920	activatio
n_86[0][0]			
dropout_82 (Dropout)	(None, 32, 32, 24)	0	conv2d_87
[0][0]			

concatenate_76 (Concatenate) te_75[0][0]	(None, 32, 32, 144)	0	concatena dropout_8
2[0][0]			
batch_normalization_85 (BatchNo te_76[0][0])	(None, 32, 32, 144)	576	concatena
activation_87 (Activation) malization_85[0][0])	(None, 32, 32, 144)	0	batch_nor
conv2d_88 (Conv2D) n_87[0][0])	(None, 32, 32, 24)	31104	activatio
dropout_83 (Dropout) [0][0])	(None, 32, 32, 24)	0	conv2d_88
concatenate_77 (Concatenate) te_76[0][0]	(None, 32, 32, 168)	0	concatena dropout_8
3[0][0]			
batch_normalization_86 (BatchNo te_77[0][0])	(None, 32, 32, 168)	672	concatena
activation_88 (Activation) malization_86[0][0])	(None, 32, 32, 168)	0	batch_nor
conv2d_89 (Conv2D) n_88[0][0])	(None, 32, 32, 24)	36288	activatio
dropout_84 (Dropout) [0][0])	(None, 32, 32, 24)	0	conv2d_89
concatenate_78 (Concatenate) te_77[0][0]	(None, 32, 32, 192)	0	concatena dropout_8
4[0][0]			
batch_normalization_87 (BatchNo te_78[0][0])	(None, 32, 32, 192)	768	concatena
activation_89 (Activation) malization_87[0][0])	(None, 32, 32, 192)	0	batch_nor
conv2d_90 (Conv2D) n_89[0][0])	(None, 32, 32, 24)	41472	activatio

dropout_85 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_90
concatenate_79 (Concatenate) te_78[0][0]	(None, 32, 32, 216)	0	concatena dropout_8
5[0][0]			
batch_normalization_88 (BatchNo te_79[0][0])	(None, 32, 32, 216)	864	concatena
activation_90 (Activation) malization_88[0][0]	(None, 32, 32, 216)	0	batch_nor
conv2d_91 (Conv2D) n_90[0][0]	(None, 32, 32, 24)	46656	activatio
dropout_86 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_91
concatenate_80 (Concatenate) te_79[0][0]	(None, 32, 32, 240)	0	concatena dropout_8
6[0][0]			
batch_normalization_89 (BatchNo te_80[0][0])	(None, 32, 32, 240)	960	concatena
activation_91 (Activation) malization_89[0][0]	(None, 32, 32, 240)	0	batch_nor
conv2d_92 (Conv2D) n_91[0][0]	(None, 32, 32, 24)	5760	activatio
dropout_87 (Dropout) [0][0]	(None, 32, 32, 24)	0	conv2d_92
average_pooling2d_8 (AveragePoo 7[0][0])	(None, 16, 16, 24)	0	dropout_8
batch_normalization_90 (BatchNo ooling2d_8[0][0])	(None, 16, 16, 24)	96	average_p
activation_92 (Activation) malization_90[0][0]	(None, 16, 16, 24)	0	batch_nor

conv2d_93 (Conv2D) n_92[0][0]	(None, 16, 16, 24)	5184	activation_92[0][0]
dropout_88 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_93
concatenate_81 (Concatenate) ooling2d_8[0][0]	(None, 16, 16, 48)	0	average_pooling2d_8[0][0]
batch_normalization_91 (Batch Normalization) te_81[0][0]	(None, 16, 16, 48)	192	concatenate_81[0][0]
activation_93 (Activation) malization_91[0][0]	(None, 16, 16, 48)	0	batch_normalization_91[0][0]
conv2d_94 (Conv2D) n_93[0][0]	(None, 16, 16, 24)	10368	activation_93[0][0]
dropout_89 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_94
concatenate_82 (Concatenate) te_81[0][0]	(None, 16, 16, 72)	0	concatenate_81[0][0]
batch_normalization_92 (Batch Normalization) te_82[0][0]	(None, 16, 16, 72)	288	concatenate_82[0][0]
activation_94 (Activation) malization_92[0][0]	(None, 16, 16, 72)	0	batch_normalization_92[0][0]
conv2d_95 (Conv2D) n_94[0][0]	(None, 16, 16, 24)	15552	activation_94[0][0]
dropout_90 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_95
concatenate_83 (Concatenate) te_82[0][0]	(None, 16, 16, 96)	0	concatenate_82[0][0]
batch_normalization_93 (Batch Normalization) te_83[0][0]	(None, 16, 16, 96)	384	concatenate_83[0][0]

activation_95 (Activation) malization_93[0][0]	(None, 16, 16, 96)	0	batch_nor
conv2d_96 (Conv2D) n_95[0][0]	(None, 16, 16, 24)	20736	activatio
dropout_91 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_96
concatenate_84 (Concatenate) te_83[0][0]	(None, 16, 16, 120)	0	concatena
1[0][0]			dropout_9
batch_normalization_94 (BatchNo te_84[0][0]	(None, 16, 16, 120)	480	concatena
activation_96 (Activation) malization_94[0][0]	(None, 16, 16, 120)	0	batch_nor
conv2d_97 (Conv2D) n_96[0][0]	(None, 16, 16, 24)	25920	activatio
dropout_92 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_97
concatenate_85 (Concatenate) te_84[0][0]	(None, 16, 16, 144)	0	concatena
2[0][0]			dropout_9
batch_normalization_95 (BatchNo te_85[0][0]	(None, 16, 16, 144)	576	concatena
activation_97 (Activation) malization_95[0][0]	(None, 16, 16, 144)	0	batch_nor
conv2d_98 (Conv2D) n_97[0][0]	(None, 16, 16, 24)	31104	activatio
dropout_93 (Dropout) [0][0]	(None, 16, 16, 24)	0	conv2d_98
concatenate_86 (Concatenate) te_85[0][0]	(None, 16, 16, 168)	0	concatena
3[0][0]			dropout_9

batch_normalization_96 (BatchNo	(None, 16, 16, 168)	672	concatena
te_86[0][0]			
activation_98 (Activation)	(None, 16, 16, 168)	0	batch_nor
malization_96[0][0]			
conv2d_99 (Conv2D)	(None, 16, 16, 24)	36288	activatio
n_98[0][0]			
dropout_94 (Dropout)	(None, 16, 16, 24)	0	conv2d_99
[0][0]			
concatenate_87 (Concatenate)	(None, 16, 16, 192)	0	concatena
te_86[0][0]			
			dropout_9
4[0][0]			
batch_normalization_97 (BatchNo	(None, 16, 16, 192)	768	concatena
te_87[0][0]			
activation_99 (Activation)	(None, 16, 16, 192)	0	batch_nor
malization_97[0][0]			
conv2d_100 (Conv2D)	(None, 16, 16, 24)	41472	activatio
n_99[0][0]			
dropout_95 (Dropout)	(None, 16, 16, 24)	0	conv2d_10
0[0][0]			
concatenate_88 (Concatenate)	(None, 16, 16, 216)	0	concatena
te_87[0][0]			
			dropout_9
5[0][0]			
batch_normalization_98 (BatchNo	(None, 16, 16, 216)	864	concatena
te_88[0][0]			
activation_100 (Activation)	(None, 16, 16, 216)	0	batch_nor
malization_98[0][0]			
conv2d_101 (Conv2D)	(None, 16, 16, 24)	46656	activatio
n_100[0][0]			
dropout_96 (Dropout)	(None, 16, 16, 24)	0	conv2d_10
1[0][0]			

concatenate_89 (Concatenate) te_88[0][0]	(None, 16, 16, 240)	0	concatena dropout_9 6[0][0]
batch_normalization_99 (BatchNo te_89[0][0]	(None, 16, 16, 240)	960	concatena
activation_101 (Activation) malization_99[0][0]	(None, 16, 16, 240)	0	batch_nor
conv2d_102 (Conv2D) n_101[0][0]	(None, 16, 16, 24)	5760	activatio
dropout_97 (Dropout) 2[0][0]	(None, 16, 16, 24)	0	conv2d_10
average_pooling2d_9 (AveragePoo 7[0][0]	(None, 8, 8, 24)	0	dropout_9
batch_normalization_100 (BatchN ooling2d_9[0][0]	(None, 8, 8, 24)	96	average_p
activation_102 (Activation) malization_100[0][0]	(None, 8, 8, 24)	0	batch_nor
conv2d_103 (Conv2D) n_102[0][0]	(None, 8, 8, 24)	5184	activatio
dropout_98 (Dropout) 3[0][0]	(None, 8, 8, 24)	0	conv2d_10
concatenate_90 (Concatenate) ooling2d_9[0][0]	(None, 8, 8, 48)	0	average_p dropout_9 8[0][0]
batch_normalization_101 (BatchN te_90[0][0]	(None, 8, 8, 48)	192	concatena
activation_103 (Activation) malization_101[0][0]	(None, 8, 8, 48)	0	batch_nor
conv2d_104 (Conv2D) n_103[0][0]	(None, 8, 8, 24)	10368	activatio

dropout_99 (Dropout) 4[0][0]	(None, 8, 8, 24)	0	conv2d_10
concatenate_91 (Concatenate) te_90[0][0]	(None, 8, 8, 72)	0	concatena dropout_9
batch_normalization_102 (BatchN te_91[0][0]	(None, 8, 8, 72)	288	concatena
activation_104 (Activation) malization_102[0][0]	(None, 8, 8, 72)	0	batch_nor
conv2d_105 (Conv2D) n_104[0][0]	(None, 8, 8, 24)	15552	activatio
dropout_100 (Dropout) 5[0][0]	(None, 8, 8, 24)	0	conv2d_10
concatenate_92 (Concatenate) te_91[0][0]	(None, 8, 8, 96)	0	concatena dropout_1
batch_normalization_103 (BatchN te_92[0][0]	(None, 8, 8, 96)	384	concatena
activation_105 (Activation) malization_103[0][0]	(None, 8, 8, 96)	0	batch_nor
conv2d_106 (Conv2D) n_105[0][0]	(None, 8, 8, 24)	20736	activatio
dropout_101 (Dropout) 6[0][0]	(None, 8, 8, 24)	0	conv2d_10
concatenate_93 (Concatenate) te_92[0][0]	(None, 8, 8, 120)	0	concatena dropout_1
batch_normalization_104 (BatchN te_93[0][0]	(None, 8, 8, 120)	480	concatena
activation_106 (Activation) malization_104[0][0]	(None, 8, 8, 120)	0	batch_nor

conv2d_107 (Conv2D) n_106[0][0]	(None, 8, 8, 24)	25920	activation_106[0][0]
dropout_102 (Dropout) 7[0][0]	(None, 8, 8, 24)	0	conv2d_107[0][0]
concatenate_94 (Concatenate) te_93[0][0]	(None, 8, 8, 144)	0	concatenate_93[0][0]
02[0][0]			dropout_102[0][0]
batch_normalization_105 (Batch Normalization) te_94[0][0]	(None, 8, 8, 144)	576	concatenate_94[0][0]
activation_107 (Activation) malization_105[0][0]	(None, 8, 8, 144)	0	batch_normalization_105[0][0]
conv2d_108 (Conv2D) n_107[0][0]	(None, 8, 8, 24)	31104	activation_107[0][0]
dropout_103 (Dropout) 8[0][0]	(None, 8, 8, 24)	0	conv2d_108[0][0]
concatenate_95 (Concatenate) te_94[0][0]	(None, 8, 8, 168)	0	concatenate_94[0][0]
03[0][0]			dropout_103[0][0]
batch_normalization_106 (Batch Normalization) te_95[0][0]	(None, 8, 8, 168)	672	concatenate_95[0][0]
activation_108 (Activation) malization_106[0][0]	(None, 8, 8, 168)	0	batch_normalization_106[0][0]
conv2d_109 (Conv2D) n_108[0][0]	(None, 8, 8, 24)	36288	activation_108[0][0]
dropout_104 (Dropout) 9[0][0]	(None, 8, 8, 24)	0	conv2d_109[0][0]
concatenate_96 (Concatenate) te_95[0][0]	(None, 8, 8, 192)	0	concatenate_95[0][0]
04[0][0]			dropout_104[0][0]
batch_normalization_107 (Batch Normalization) te_96[0][0]	(None, 8, 8, 192)	768	concatenate_96[0][0]

activation_109 (Activation) malization_107[0][0]	(None, 8, 8, 192)	0	batch_nor
conv2d_110 (Conv2D) n_109[0][0]	(None, 8, 8, 24)	41472	activatio
dropout_105 (Dropout) 0[0][0]	(None, 8, 8, 24)	0	conv2d_11
concatenate_97 (Concatenate) te_96[0][0]	(None, 8, 8, 216)	0	concatena
05[0][0]			dropout_1
batch_normalization_108 (BatchN te_97[0][0]	(None, 8, 8, 216)	864	concatena
activation_110 (Activation) malization_108[0][0]	(None, 8, 8, 216)	0	batch_nor
conv2d_111 (Conv2D) n_110[0][0]	(None, 8, 8, 24)	46656	activatio
dropout_106 (Dropout) 1[0][0]	(None, 8, 8, 24)	0	conv2d_11
concatenate_98 (Concatenate) te_97[0][0]	(None, 8, 8, 240)	0	concatena
06[0][0]			dropout_1
batch_normalization_109 (BatchN te_98[0][0]	(None, 8, 8, 240)	960	concatena
activation_111 (Activation) malization_109[0][0]	(None, 8, 8, 240)	0	batch_nor
conv2d_112 (Conv2D) n_111[0][0]	(None, 8, 8, 24)	5760	activatio
dropout_107 (Dropout) 2[0][0]	(None, 8, 8, 24)	0	conv2d_11
average_pooling2d_10 (AveragePo 07[0][0]	(None, 4, 4, 24)	0	dropout_1

batch_normalization_110 (Batch Normalization)	(None, 4, 4, 24)	96	average_pooling2d_10[0][0]
activation_112 (Activation)	(None, 4, 4, 24)	0	batch_normalization_110[0][0]
conv2d_113 (Conv2D)	(None, 4, 4, 24)	5184	activation_112[0][0]
dropout_108 (Dropout)	(None, 4, 4, 24)	0	conv2d_113[0][0]
concatenate_99 (Concatenate)	(None, 4, 4, 48)	0	average_pooling2d_10[0][0]
batch_normalization_111 (Batch Normalization)	(None, 4, 4, 48)	192	dropout_108[0][0]
activation_113 (Activation)	(None, 4, 4, 48)	0	concatenate_99[0][0]
conv2d_114 (Conv2D)	(None, 4, 4, 24)	10368	batch_normalization_111[0][0]
dropout_109 (Dropout)	(None, 4, 4, 24)	0	activation_113[0][0]
concatenate_100 (Concatenate)	(None, 4, 4, 72)	0	conv2d_114[0][0]
batch_normalization_112 (Batch Normalization)	(None, 4, 4, 72)	288	dropout_109[0][0]
activation_114 (Activation)	(None, 4, 4, 72)	0	concatenate_100[0][0]
conv2d_115 (Conv2D)	(None, 4, 4, 24)	15552	batch_normalization_112[0][0]
dropout_110 (Dropout)	(None, 4, 4, 24)	0	activation_114[0][0]

concatenate_101 (Concatenate) te_100[0][0]	(None, 4, 4, 96)	0	concatena dropout_1
10[0][0]			
batch_normalization_113 (BatchN te_101[0][0]	(None, 4, 4, 96)	384	concatena
activation_115 (Activation) malization_113[0][0]	(None, 4, 4, 96)	0	batch_nor
conv2d_116 (Conv2D) n_115[0][0]	(None, 4, 4, 24)	20736	activatio
dropout_111 (Dropout) 6[0][0]	(None, 4, 4, 24)	0	conv2d_11
concatenate_102 (Concatenate) te_101[0][0]	(None, 4, 4, 120)	0	concatena dropout_1
11[0][0]			
batch_normalization_114 (BatchN te_102[0][0]	(None, 4, 4, 120)	480	concatena
activation_116 (Activation) malization_114[0][0]	(None, 4, 4, 120)	0	batch_nor
conv2d_117 (Conv2D) n_116[0][0]	(None, 4, 4, 24)	25920	activatio
dropout_112 (Dropout) 7[0][0]	(None, 4, 4, 24)	0	conv2d_11
concatenate_103 (Concatenate) te_102[0][0]	(None, 4, 4, 144)	0	concatena dropout_1
12[0][0]			
batch_normalization_115 (BatchN te_103[0][0]	(None, 4, 4, 144)	576	concatena
activation_117 (Activation) malization_115[0][0]	(None, 4, 4, 144)	0	batch_nor
conv2d_118 (Conv2D) n_117[0][0]	(None, 4, 4, 24)	31104	activatio

dropout_113 (Dropout) 8[0][0]	(None, 4, 4, 24)	0	conv2d_11
concatenate_104 (Concatenate) te_103[0][0] 13[0][0]	(None, 4, 4, 168)	0	concatena dropout_1
batch_normalization_116 (BatchN te_104[0][0])	(None, 4, 4, 168)	672	concatena
activation_118 (Activation) malization_116[0][0]	(None, 4, 4, 168)	0	batch_nor
conv2d_119 (Conv2D) n_118[0][0]	(None, 4, 4, 24)	36288	activatio
dropout_114 (Dropout) 9[0][0]	(None, 4, 4, 24)	0	conv2d_11
concatenate_105 (Concatenate) te_104[0][0] 14[0][0]	(None, 4, 4, 192)	0	concatena dropout_1
batch_normalization_117 (BatchN te_105[0][0])	(None, 4, 4, 192)	768	concatena
activation_119 (Activation) malization_117[0][0]	(None, 4, 4, 192)	0	batch_nor
conv2d_120 (Conv2D) n_119[0][0]	(None, 4, 4, 24)	41472	activatio
dropout_115 (Dropout) 0[0][0]	(None, 4, 4, 24)	0	conv2d_12
concatenate_106 (Concatenate) te_105[0][0] 15[0][0]	(None, 4, 4, 216)	0	concatena dropout_1
batch_normalization_118 (BatchN te_106[0][0])	(None, 4, 4, 216)	864	concatena
activation_120 (Activation) malization_118[0][0]	(None, 4, 4, 216)	0	batch_nor

conv2d_121 (Conv2D) n_120[0][0]	(None, 4, 4, 24)	46656	activation_120[0][0]
dropout_116 (Dropout) 1[0][0]	(None, 4, 4, 24)	0	conv2d_121[0][0]
concatenate_107 (Concatenate) te_106[0][0]	(None, 4, 4, 240)	0	concatenate_106[0][0]
batch_normalization_119 (Batch Normalization) te_107[0][0]	(None, 4, 4, 240)	960	concatenate_107[0][0]
activation_121 (Activation) malization_119[0][0]	(None, 4, 4, 240)	0	batch_normalization_119[0][0]
average_pooling2d_11 (Average Pooling) n_121[0][0]	(None, 2, 2, 240)	0	activation_121[0][0]
conv2d_122 (Conv2D) ooling2d_11[0][0]	(None, 2, 2, 10)	2400	average_pooling2d_11[0][0]
global_max_pooling2d_2 (Global Max Pooling) 2[0][0]	(None, 10)	0	conv2d_122[0][0]
activation_122 (Activation) x_pooling2d_2[0][0]	(None, 10)	0	global_max_pooling2d_2[0][0]
=====			
Total params: 974,568			
Trainable params: 964,008			
Non-trainable params: 10,560			

None

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:724: UserWarning: This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies ')
```

Epoch 1/150

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
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```
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```
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```
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```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:724: UserWarning: This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:724: UserWarning: This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

1953/1953 [=====>.] - ETA: 0s - loss: 1.3263 - acc:
0.5146Epoch 1/150
10000/1953 [=====]
=====]
=====] - 11s 1ms/sample - loss: 2.4117 - acc: 0.4869

Epoch 00001: val_acc improved from -inf to 0.48690, saving model to gdrive/My Drive/cnnoncifار/models/model-001-0.514679-0.486900.h5

1954/1953 [=====] - 948s 485ms/step - loss: 1.3261 - acc: 0.5147 - val_loss: 2.1875 - val_acc: 0.4869

Epoch 2/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.9238 - acc:
0.6700Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 873us/sample - loss: 1.3751 - acc: 0.6039

Epoch 00002: val_acc improved from 0.48690 to 0.60390, saving model to gdrive/My Drive/cnnoncifار/models/model-002-0.670043-0.603900.h5

1954/1953 [=====] - 897s 459ms/step - loss: 0.9237 - acc: 0.6700 - val_loss: 1.4341 - val_acc: 0.6039

Epoch 3/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.7871 - acc:
0.7215Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 867us/sample - loss: 0.6290 - acc: 0.7389

Epoch 00003: val_acc improved from 0.60390 to 0.73890, saving model to gdrive/My Drive/cnnoncifار/models/model-003-0.721513-0.738900.h5

1954/1953 [=====] - 896s 459ms/step - loss: 0.7871 - acc: 0.7215 - val_loss: 0.8146 - val_acc: 0.7389

Epoch 4/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.7034 - acc:
0.7523Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 867us/sample - loss: 0.7341 - acc: 0.6968

Epoch 00004: val_acc did not improve from 0.73890

1954/1953 [=====] - 896s 459ms/step - loss: 0.7034 - acc: 0.7523 - val_loss: 0.9627 - val_acc: 0.6968

Epoch 5/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.6418 - acc:
0.7744Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 868us/sample - loss: 0.8542 - acc: 0.7726

Epoch 00005: val_acc improved from 0.73890 to 0.77260, saving model to gdrive/My Drive/cnnoncifار/models/model-005-0.774404-0.772600.h5

1954/1953 [=====] - 895s 458ms/step - loss: 0.6418 - acc: 0.7744 - val_loss: 0.7399 - val_acc: 0.7726

Epoch 6/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.5994 - acc:
0.7902Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 866us/sample - loss: 0.5927 - acc: 0.7792

Epoch 00006: val_acc improved from 0.77260 to 0.77920, saving model to gdrive/My Drive/cnnoncifار/models/model-006-0.790200-0.779200.h5

```
ive/My Drive/cnnoncifar/models/model-006-0.790261-0.779200.h5
1954/1953 [=====] - 896s 459ms/step - loss: 0.599
3 - acc: 0.7903 - val_loss: 0.6867 - val_acc: 0.7792
Epoch 7/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.5637 - acc:
0.8025Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 867us/sample - loss: 0.6857 - acc: 0.7771

Epoch 00007: val_acc did not improve from 0.77920
1954/1953 [=====] - 896s 458ms/step - loss: 0.563
8 - acc: 0.8025 - val_loss: 0.7391 - val_acc: 0.7771
Epoch 8/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.5349 - acc:
0.8121Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 870us/sample - loss: 0.5309 - acc: 0.8246

Epoch 00008: val_acc improved from 0.77920 to 0.82460, saving model to gdr
ive/My Drive/cnnoncifar/models/model-008-0.812116-0.824600.h5
1954/1953 [=====] - 898s 460ms/step - loss: 0.534
9 - acc: 0.8121 - val_loss: 0.5517 - val_acc: 0.8246
Epoch 9/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.5086 - acc:
0.8211Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 871us/sample - loss: 0.7793 - acc: 0.7970

Epoch 00009: val_acc did not improve from 0.82460
1954/1953 [=====] - 896s 459ms/step - loss: 0.508
6 - acc: 0.8211 - val_loss: 0.6852 - val_acc: 0.7970
Epoch 10/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.4893 - acc:
0.8287Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 869us/sample - loss: 0.7258 - acc: 0.7877

Epoch 00010: val_acc did not improve from 0.82460
1954/1953 [=====] - 897s 459ms/step - loss: 0.489
3 - acc: 0.8287 - val_loss: 0.7360 - val_acc: 0.7877
Epoch 11/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.4712 - acc:
0.8345Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 869us/sample - loss: 0.7942 - acc: 0.8304

Epoch 00011: val_acc improved from 0.82460 to 0.83040, saving model to gdr
ive/My Drive/cnnoncifar/models/model-011-0.834511-0.830400.h5
1954/1953 [=====] - 897s 459ms/step - loss: 0.471
2 - acc: 0.8345 - val_loss: 0.5485 - val_acc: 0.8304
Epoch 12/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.4553 - acc:
0.8402Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 871us/sample - loss: 0.4233 - acc: 0.8440
```

Epoch 00012: val_acc improved from 0.83040 to 0.84400, saving model to gdrive/My Drive/cnnoncifار/models/model-012-0.840162-0.844000.h5

1954/1953 [=====] - 898s 460ms/step - loss: 0.4553 - acc: 0.8402 - val_loss: 0.4925 - val_acc: 0.8440

Epoch 13/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.4421 - acc: 0.8453Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 870us/sample - loss: 0.5550 - acc: 0.8282

Epoch 00013: val_acc did not improve from 0.84400

1954/1953 [=====] - 897s 459ms/step - loss: 0.4421 - acc: 0.8453 - val_loss: 0.5625 - val_acc: 0.8282

Epoch 14/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.4289 - acc: 0.8501Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 875us/sample - loss: 0.5656 - acc: 0.8378

Epoch 00014: val_acc did not improve from 0.84400

1954/1953 [=====] - 894s 457ms/step - loss: 0.4289 - acc: 0.8500 - val_loss: 0.5419 - val_acc: 0.8378

Epoch 15/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.4160 - acc: 0.8542Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 873us/sample - loss: 0.3844 - acc: 0.8407

Epoch 00015: val_acc did not improve from 0.84400

1954/1953 [=====] - 896s 458ms/step - loss: 0.4161 - acc: 0.8542 - val_loss: 0.5108 - val_acc: 0.8407

Epoch 16/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.4061 - acc: 0.8585Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 870us/sample - loss: 0.4045 - acc: 0.8563

Epoch 00016: val_acc improved from 0.84400 to 0.85630, saving model to gdrive/My Drive/cnnoncifار/models/model-016-0.858456-0.856300.h5

1954/1953 [=====] - 897s 459ms/step - loss: 0.4061 - acc: 0.8585 - val_loss: 0.4657 - val_acc: 0.8563

Epoch 17/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.3976 - acc: 0.8610Epoch 1/150

10000/1953 [=====]
=====]
=====] - 9s 868us/sample - loss: 0.4291 - acc: 0.8581

Epoch 00017: val_acc improved from 0.85630 to 0.85810, saving model to gdrive/My Drive/cnnoncifار/models/model-017-0.861049-0.858100.h5

1954/1953 [=====] - 896s 459ms/step - loss: 0.3975 - acc: 0.8610 - val_loss: 0.4625 - val_acc: 0.8581

Epoch 18/150

1953/1953 [=====>.] - ETA: 0s - loss: 0.3877 - acc: 0.8636Epoch 1/150

10000/1953 [=====]

```
=====
=====] - 9s 864us/sample - loss: 0.5011 - acc: 0.8249

Epoch 00018: val_acc did not improve from 0.85810
1954/1953 [=====] - 895s 458ms/step - loss: 0.387
7 - acc: 0.8636 - val_loss: 0.5859 - val_acc: 0.8249
Epoch 19/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.3804 - acc:
0.8669Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 871us/sample - loss: 0.5224 - acc: 0.8575

Epoch 00019: val_acc did not improve from 0.85810
1954/1953 [=====] - 893s 457ms/step - loss: 0.380
5 - acc: 0.8669 - val_loss: 0.4739 - val_acc: 0.8575
Epoch 20/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.3712 - acc:
0.8694Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 864us/sample - loss: 0.5189 - acc: 0.8610

Epoch 00020: val_acc improved from 0.85810 to 0.86100, saving model to gdr
ive/My Drive/cnnoncifar/models/model-020-0.869445-0.861000.h5
1954/1953 [=====] - 896s 458ms/step - loss: 0.371
2 - acc: 0.8694 - val_loss: 0.4580 - val_acc: 0.8610
Epoch 21/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.3651 - acc:
0.8718Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 869us/sample - loss: 0.5567 - acc: 0.8217

Epoch 00021: val_acc did not improve from 0.86100
1954/1953 [=====] - 896s 458ms/step - loss: 0.365
0 - acc: 0.8718 - val_loss: 0.6434 - val_acc: 0.8217
Epoch 22/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.3581 - acc:
0.8743Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 869us/sample - loss: 0.3746 - acc: 0.8685

Epoch 00022: val_acc improved from 0.86100 to 0.86850, saving model to gdr
ive/My Drive/cnnoncifar/models/model-022-0.874284-0.868500.h5
1954/1953 [=====] - 900s 461ms/step - loss: 0.358
1 - acc: 0.8743 - val_loss: 0.4142 - val_acc: 0.8685
Epoch 23/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.3504 - acc:
0.8769Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 868us/sample - loss: 0.5342 - acc: 0.8205

Epoch 00023: val_acc did not improve from 0.86850
1954/1953 [=====] - 897s 459ms/step - loss: 0.350
4 - acc: 0.8769 - val_loss: 0.5972 - val_acc: 0.8205
Epoch 24/150
1953/1953 [=====>.] - ETA: 0s - loss: 0.3437 - acc:
0.8796Epoch 1/150
```



```
10000/1953 [=====]
=====
=====] - 9s 872us/sample - loss: 0.3367 - acc: 0.8749
```

Epoch 00024: val_acc improved from 0.86850 to 0.87490, saving model to gdrive/My Drive/cnnoncifار/models/model-024-0.879570-0.874900.h5

```
1954/1953 [=====] - 897s 459ms/step - loss: 0.3437 - acc: 0.8796 - val_loss: 0.4168 - val_acc: 0.8749
```

Epoch 25/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.3399 - acc: 0.8805Epoch 1/150
```

```
10000/1953 [=====]
=====
=====] - 9s 873us/sample - loss: 0.3277 - acc: 0.8692
```

Epoch 00025: val_acc did not improve from 0.87490

```
1954/1953 [=====] - 899s 460ms/step - loss: 0.3399 - acc: 0.8805 - val_loss: 0.4483 - val_acc: 0.8692
```

Epoch 26/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.3328 - acc: 0.8827Epoch 1/150
```

```
10000/1953 [=====]
=====
=====] - 9s 868us/sample - loss: 0.4074 - acc: 0.8695
```

Epoch 00026: val_acc did not improve from 0.87490

```
1954/1953 [=====] - 896s 459ms/step - loss: 0.3329 - acc: 0.8827 - val_loss: 0.4386 - val_acc: 0.8695
```

Epoch 27/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.3300 - acc: 0.8841Epoch 1/150
```

```
10000/1953 [=====]
=====
=====] - 9s 866us/sample - loss: 0.2969 - acc: 0.8739
```

Epoch 00027: val_acc did not improve from 0.87490

```
1954/1953 [=====] - 895s 458ms/step - loss: 0.3300 - acc: 0.8841 - val_loss: 0.4191 - val_acc: 0.8739
```

Epoch 28/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.3246 - acc: 0.8863Epoch 1/150
```

```
10000/1953 [=====]
=====
=====] - 9s 870us/sample - loss: 0.3948 - acc: 0.8735
```

Epoch 00028: val_acc did not improve from 0.87490

```
1954/1953 [=====] - 896s 458ms/step - loss: 0.3246 - acc: 0.8863 - val_loss: 0.4408 - val_acc: 0.8735
```

Epoch 29/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.3203 - acc: 0.8871Epoch 1/150
```

```
10000/1953 [=====]
=====
=====] - 9s 866us/sample - loss: 0.4339 - acc: 0.8747
```

Epoch 00029: val_acc did not improve from 0.87490

```
1954/1953 [=====] - 896s 458ms/step - loss: 0.3203 - acc: 0.8871 - val_loss: 0.4207 - val_acc: 0.8747
```

Epoch 30/150

```
1693/1953 [=====>....] - ETA: 1:58 - loss: 0.3151 - acc: 0.8887Buffered data was truncated after reaching the output size limit.
```

At epoch 33 the accuracy was 87% but because of time restrictions by google colab fitting the model is stoped any how since model is already saved at 33rd epoch we shall continue to fit from that epoch

In [0]:

```

# reduce_lr = ReduceLROnPlateau(monitor = 'val_loss', factor = 0.1, patience = 5, min_lr = 0.000001)

# early_stop = EarlyStopping(monitor = "val_loss", patience = 10)

def decay_fn(epoch, lr):
    if epoch < 50:
        return 0.001
    elif epoch >= 50 and epoch < 75:
        return 0.0001
    else:
        return 0.00001

lr_scheduler = LearningRateScheduler(decay_fn)

csv_logger = CSVLogger('training.log')

checkpoint = ModelCheckpoint('gdrive/My Drive/cnnoncifار/models/model-{epoch:03d}-{acc:03f}-{val_acc:03f}.h5',
                             verbose=1, monitor='val_acc', save_best_only=True,
                             mode='auto')

model.load_weights('gdrive/My Drive/cnnoncifار/models/model-033-0.893153-0.879100.h5')

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

# model.fit(xtrain, y_train,
#           batch_size=batch_size,
#           epochs=epochs,
#           verbose=1,
#           validation_data=(xtest, y_test))
print(model.summary())
model.fit_generator(
    datagen.flow(X_train, y_train, batch_size=batch_size),
    steps_per_epoch=(len(X_train)/batch_size)*5,

    epochs=150, verbose = 1, initial_epoch = 32,
    validation_data=(X_test, y_test),
    callbacks=[checkpoint])

```

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2364 - acc:
0.9161Epoch 1/150
10000/1953 [=====
=====
=====] - 8s 848us/sample - loss: 0.3856 - acc: 0.8887

Epoch 00061: val_acc did not improve from 0.90130
1954/1953 [=====] - 886s 454ms/step - loss: 0.236
3 - acc: 0.9161 - val_loss: 0.4000 - val_acc: 0.8887
Epoch 62/150
1699/1953 [=====>....] - ETA: 1:53 - loss: 0.2356 - ac
c: 0.9166Buffered data was truncated after reaching the output size limit.
```

At epoch 60 the accuracy was 90% but because of time restrictions by google colab fitting the model is stoped any how since model is already saved at 60rd epoch we shall continue to fit from that epoch

In [0]:

```

# reduce_lr = ReduceLRonPlateau(monitor = 'val_loss', factor = 0.1, patience = 5, min_lr = 0.000001)

# early_stop = EarlyStopping(monitor = "val_loss", patience = 10)

def decay_fn(epoch, lr):
    if epoch < 50:
        return 0.001
    elif epoch >= 50 and epoch < 75:
        return 0.0001
    else:
        return 0.00001

lr_scheduler = LearningRateScheduler(decay_fn)

csv_logger = CSVLogger('training.log')

checkpoint = ModelCheckpoint('gdrive/My Drive/cnnoncifار/models/model-{epoch:03d}-{acc:03f}-{val_acc:03f}.h5',
                             verbose=1, monitor='val_acc', save_best_only=True,
                             mode='auto')

model.load_weights('gdrive/My Drive/cnnoncifار/models/model-060-0.915397-0.901300.h5')

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

# model.fit(xtrain, y_train,
#           batch_size=batch_size,
#           epochs=epochs,
#           verbose=1,
#           validation_data=(xtest, y_test))
print(model.summary())
model.fit_generator(
    datagen.flow(X_train, y_train, batch_size=batch_size),
    steps_per_epoch=(len(X_train)/batch_size)*5,

    epochs=150, verbose = 1, initial_epoch = 61,
    validation_data=(X_test, y_test),
    callbacks=[checkpoint])

```

Model: "model_1"

Layer (type) connected to	Output Shape	Param #	Connected to
=====			
input_2 (InputLayer)	[(None, 32, 32, 3)]	0	
conv2d_165 (Conv2D)	(None, 32, 32, 24)	648	input_2[0][0]
batch_normalization_164 (Batch Normalization)	(None, 32, 32, 24)	96	conv2d_165[0][0]
activation_165 (Activation)	(None, 32, 32, 24)	0	batch_normalization_164[0][0]
conv2d_166 (Conv2D)	(None, 32, 32, 24)	5184	activation_165[0][0]
dropout_163 (Dropout)	(None, 32, 32, 24)	0	conv2d_166[0][0]
concatenate_160 (Concatenate)	(None, 32, 32, 48)	0	conv2d_166[0][0] dropout_163[0][0]
batch_normalization_165 (Batch Normalization)	(None, 32, 32, 48)	192	concatenate_160[0][0]
activation_166 (Activation)	(None, 32, 32, 48)	0	batch_normalization_165[0][0]
conv2d_167 (Conv2D)	(None, 32, 32, 24)	10368	activation_166[0][0]
dropout_164 (Dropout)	(None, 32, 32, 24)	0	conv2d_167[0][0]
concatenate_161 (Concatenate)	(None, 32, 32, 72)	0	conv2d_167[0][0] dropout_164[0][0]
batch_normalization_166 (Batch Normalization)	(None, 32, 32, 72)	288	concatenate_161[0][0]

activation_167 (Activation) normalization_166[0][0]	(None, 32, 32, 72)	0	batch_
conv2d_168 (Conv2D) tion_167[0][0]	(None, 32, 32, 24)	15552	activa
dropout_165 (Dropout) _168[0][0]	(None, 32, 32, 24)	0	conv2d
concatenate_162 (Concatenate) enate_161[0][0]	(None, 32, 32, 96)	0	concat
t_165[0][0]			dropou
batch_normalization_167 (BatchN enate_162[0][0]	(None, 32, 32, 96)	384	concat
activation_168 (Activation) normalization_167[0][0]	(None, 32, 32, 96)	0	batch_
conv2d_169 (Conv2D) tion_168[0][0]	(None, 32, 32, 24)	20736	activa
dropout_166 (Dropout) _169[0][0]	(None, 32, 32, 24)	0	conv2d
concatenate_163 (Concatenate) enate_162[0][0]	(None, 32, 32, 120)	0	concat
t_166[0][0]			dropou
batch_normalization_168 (BatchN enate_163[0][0]	(None, 32, 32, 120)	480	concat
activation_169 (Activation) normalization_168[0][0]	(None, 32, 32, 120)	0	batch_
conv2d_170 (Conv2D) tion_169[0][0]	(None, 32, 32, 24)	25920	activa
dropout_167 (Dropout) _170[0][0]	(None, 32, 32, 24)	0	conv2d
concatenate_164 (Concatenate) enate_163[0][0]	(None, 32, 32, 144)	0	concat
t_167[0][0]			dropou

batch_normalization_169 (Batch Normalization)	(None, 32, 32, 144)	576	concatenate_164[0][0]
activation_170 (Activation)	(None, 32, 32, 144)	0	batch_normalization_169[0][0]
conv2d_171 (Conv2D)	(None, 32, 32, 24)	31104	activation_170[0][0]
dropout_168 (Dropout)	(None, 32, 32, 24)	0	conv2d_171[0][0]
concatenate_165 (Concatenate)	(None, 32, 32, 168)	0	concatenate_164[0][0]
activation_169 (Activation)	(None, 32, 32, 168)	0	dropout_168[0][0]
batch_normalization_170 (Batch Normalization)	(None, 32, 32, 168)	672	concatenate_165[0][0]
activation_171 (Activation)	(None, 32, 32, 168)	0	batch_normalization_170[0][0]
conv2d_172 (Conv2D)	(None, 32, 32, 24)	36288	activation_171[0][0]
dropout_169 (Dropout)	(None, 32, 32, 24)	0	conv2d_172[0][0]
concatenate_166 (Concatenate)	(None, 32, 32, 192)	0	concatenate_165[0][0]
activation_170 (Activation)	(None, 32, 32, 192)	0	dropout_169[0][0]
batch_normalization_171 (Batch Normalization)	(None, 32, 32, 192)	768	concatenate_166[0][0]
activation_172 (Activation)	(None, 32, 32, 192)	0	batch_normalization_171[0][0]
conv2d_173 (Conv2D)	(None, 32, 32, 24)	41472	activation_172[0][0]
dropout_170 (Dropout)	(None, 32, 32, 24)	0	conv2d_173[0][0]

concatenate_167 (Concatenate) enate_166[0][0]	(None, 32, 32, 216)	0	concat
t_170[0][0]			dropou
batch_normalization_172 (BatchN enate_167[0][0]	(None, 32, 32, 216)	864	concat
activation_173 (Activation) normalization_172[0][0]	(None, 32, 32, 216)	0	batch_
conv2d_174 (Conv2D) tion_173[0][0]	(None, 32, 32, 24)	46656	activa
dropout_171 (Dropout) _174[0][0]	(None, 32, 32, 24)	0	conv2d
concatenate_168 (Concatenate) enate_167[0][0]	(None, 32, 32, 240)	0	concat
t_171[0][0]			dropou
batch_normalization_173 (BatchN enate_168[0][0]	(None, 32, 32, 240)	960	concat
activation_174 (Activation) normalization_173[0][0]	(None, 32, 32, 240)	0	batch_
conv2d_175 (Conv2D) tion_174[0][0]	(None, 32, 32, 24)	5760	activa
dropout_172 (Dropout) _175[0][0]	(None, 32, 32, 24)	0	conv2d
average_pooling2d_4 (AveragePoo t_172[0][0]	(None, 16, 16, 24)	0	dropou
batch_normalization_174 (BatchN e_pooling2d_4[0][0]	(None, 16, 16, 24)	96	averag
activation_175 (Activation) normalization_174[0][0]	(None, 16, 16, 24)	0	batch_
conv2d_176 (Conv2D) tion_175[0][0]	(None, 16, 16, 24)	5184	activa

dropout_173 (Dropout) _176[0][0]	(None, 16, 16, 24)	0	conv2d
concatenate_169 (Concatenate) e_pooling2d_4[0][0] t_173[0][0]	(None, 16, 16, 48)	0	average pooling2d_4 dropout_173
batch_normalization_175 (Batch Normalization) enate_169[0][0]	(None, 16, 16, 48)	192	concatenate_169
activation_176 (Activation) normalization_175[0][0]	(None, 16, 16, 48)	0	batch_normalization_175
conv2d_177 (Conv2D) tion_176[0][0]	(None, 16, 16, 24)	10368	activation_176
dropout_174 (Dropout) _177[0][0]	(None, 16, 16, 24)	0	conv2d_177
concatenate_170 (Concatenate) enate_169[0][0] t_174[0][0]	(None, 16, 16, 72)	0	concatenate_169 dropout_174
batch_normalization_176 (Batch Normalization) enate_170[0][0]	(None, 16, 16, 72)	288	concatenate_170
activation_177 (Activation) normalization_176[0][0]	(None, 16, 16, 72)	0	batch_normalization_176
conv2d_178 (Conv2D) tion_177[0][0]	(None, 16, 16, 24)	15552	activation_177
dropout_175 (Dropout) _178[0][0]	(None, 16, 16, 24)	0	conv2d_178
concatenate_171 (Concatenate) enate_170[0][0] t_175[0][0]	(None, 16, 16, 96)	0	concatenate_170 dropout_175
batch_normalization_177 (Batch Normalization) enate_171[0][0]	(None, 16, 16, 96)	384	concatenate_171
activation_178 (Activation) normalization_177[0][0]	(None, 16, 16, 96)	0	batch_normalization_177

conv2d_179 (Conv2D) t_178[0][0]	(None, 16, 16, 24)	20736	activation_178[0][0]
dropout_176 (Dropout) _179[0][0]	(None, 16, 16, 24)	0	conv2d_179[0][0]
concatenate_172 (Concatenate) enate_171[0][0]	(None, 16, 16, 120)	0	concatenate_176[0][0]
batch_normalization_178 (Batch Normalization) enate_172[0][0]	(None, 16, 16, 120)	480	concatenate_177[0][0]
activation_179 (Activation) normalization_178[0][0]	(None, 16, 16, 120)	0	batch_normalization_179[0][0]
conv2d_180 (Conv2D) t_179[0][0]	(None, 16, 16, 24)	25920	activation_179[0][0]
dropout_177 (Dropout) _180[0][0]	(None, 16, 16, 24)	0	conv2d_180[0][0]
concatenate_173 (Concatenate) enate_172[0][0]	(None, 16, 16, 144)	0	concatenate_177[0][0]
batch_normalization_179 (Batch Normalization) enate_173[0][0]	(None, 16, 16, 144)	576	concatenate_178[0][0]
activation_180 (Activation) normalization_179[0][0]	(None, 16, 16, 144)	0	batch_normalization_180[0][0]
conv2d_181 (Conv2D) t_180[0][0]	(None, 16, 16, 24)	31104	activation_180[0][0]
dropout_178 (Dropout) _181[0][0]	(None, 16, 16, 24)	0	conv2d_181[0][0]
concatenate_174 (Concatenate) enate_173[0][0]	(None, 16, 16, 168)	0	concatenate_178[0][0]
batch_normalization_180 (Batch Normalization) enate_174[0][0]	(None, 16, 16, 168)	672	concatenate_179[0][0]

activation_181 (Activation) normalization_180[0][0]	(None, 16, 16, 168)	0	batch_
conv2d_182 (Conv2D) tion_181[0][0]	(None, 16, 16, 24)	36288	activa
dropout_179 (Dropout) _182[0][0]	(None, 16, 16, 24)	0	conv2d
concatenate_175 (Concatenate) enate_174[0][0]	(None, 16, 16, 192)	0	concat
t_179[0][0]			dropou
batch_normalization_181 (BatchN enate_175[0][0]	(None, 16, 16, 192)	768	concat
activation_182 (Activation) normalization_181[0][0]	(None, 16, 16, 192)	0	batch_
conv2d_183 (Conv2D) tion_182[0][0]	(None, 16, 16, 24)	41472	activa
dropout_180 (Dropout) _183[0][0]	(None, 16, 16, 24)	0	conv2d
concatenate_176 (Concatenate) enate_175[0][0]	(None, 16, 16, 216)	0	concat
t_180[0][0]			dropou
batch_normalization_182 (BatchN enate_176[0][0]	(None, 16, 16, 216)	864	concat
activation_183 (Activation) normalization_182[0][0]	(None, 16, 16, 216)	0	batch_
conv2d_184 (Conv2D) tion_183[0][0]	(None, 16, 16, 24)	46656	activa
dropout_181 (Dropout) _184[0][0]	(None, 16, 16, 24)	0	conv2d
concatenate_177 (Concatenate) enate_176[0][0]	(None, 16, 16, 240)	0	concat
			dropou

t_181[0][0]

batch_normalization_183 (BatchN	(None, 16, 16, 240)	960	concat
---------------------------------	---------------------	-----	--------

enate_177[0][0]			
-----------------	--	--	--

activation_184 (Activation)	(None, 16, 16, 240)	0	batch_
-----------------------------	---------------------	---	--------

normalization_183[0][0]			
-------------------------	--	--	--

conv2d_185 (Conv2D)	(None, 16, 16, 24)	5760	activa
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tion_184[0][0]			
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dropout_182 (Dropout)	(None, 16, 16, 24)	0	conv2d
-----------------------	--------------------	---	--------

_185[0][0]			
------------	--	--	--

average_pooling2d_5 (AveragePoo	(None, 8, 8, 24)	0	dropou
---------------------------------	------------------	---	--------

t_182[0][0]			
-------------	--	--	--

batch_normalization_184 (BatchN	(None, 8, 8, 24)	96	averag
---------------------------------	------------------	----	--------

e_pooling2d_5[0][0]			
---------------------	--	--	--

activation_185 (Activation)	(None, 8, 8, 24)	0	batch_
-----------------------------	------------------	---	--------

normalization_184[0][0]			
-------------------------	--	--	--

conv2d_186 (Conv2D)	(None, 8, 8, 24)	5184	activa
---------------------	------------------	------	--------

tion_185[0][0]			
----------------	--	--	--

dropout_183 (Dropout)	(None, 8, 8, 24)	0	conv2d
-----------------------	------------------	---	--------

_186[0][0]			
------------	--	--	--

concatenate_178 (Concatenate)	(None, 8, 8, 48)	0	averag
-------------------------------	------------------	---	--------

e_pooling2d_5[0][0]			
---------------------	--	--	--

t_183[0][0]			dropou
-------------	--	--	--------

batch_normalization_185 (BatchN	(None, 8, 8, 48)	192	concat
---------------------------------	------------------	-----	--------

enate_178[0][0]			
-----------------	--	--	--

activation_186 (Activation)	(None, 8, 8, 48)	0	batch_
-----------------------------	------------------	---	--------

normalization_185[0][0]			
-------------------------	--	--	--

conv2d_187 (Conv2D)	(None, 8, 8, 24)	10368	activa
---------------------	------------------	-------	--------

tion_186[0][0]			
----------------	--	--	--

dropout_184 (Dropout)	(None, 8, 8, 24)	0	conv2d
-----------------------	------------------	---	--------

_187[0][0]			
------------	--	--	--

concatenate_179 (Concatenate)	(None, 8, 8, 72)	0	concat
enate_178[0][0]			dropou
t_184[0][0]			
batch_normalization_186 (BatchN	(None, 8, 8, 72)	288	concat
enate_179[0][0]			
activation_187 (Activation)	(None, 8, 8, 72)	0	batch_
normalization_186[0][0]			
conv2d_188 (Conv2D)	(None, 8, 8, 24)	15552	activa
tion_187[0][0]			
dropout_185 (Dropout)	(None, 8, 8, 24)	0	conv2d
_188[0][0]			
concatenate_180 (Concatenate)	(None, 8, 8, 96)	0	concat
enate_179[0][0]			dropou
t_185[0][0]			
batch_normalization_187 (BatchN	(None, 8, 8, 96)	384	concat
enate_180[0][0]			
activation_188 (Activation)	(None, 8, 8, 96)	0	batch_
normalization_187[0][0]			
conv2d_189 (Conv2D)	(None, 8, 8, 24)	20736	activa
tion_188[0][0]			
dropout_186 (Dropout)	(None, 8, 8, 24)	0	conv2d
_189[0][0]			
concatenate_181 (Concatenate)	(None, 8, 8, 120)	0	concat
enate_180[0][0]			dropou
t_186[0][0]			
batch_normalization_188 (BatchN	(None, 8, 8, 120)	480	concat
enate_181[0][0]			
activation_189 (Activation)	(None, 8, 8, 120)	0	batch_
normalization_188[0][0]			
conv2d_190 (Conv2D)	(None, 8, 8, 24)	25920	activa
tion_189[0][0]			

dropout_187 (Dropout) _190[0][0]	(None, 8, 8, 24)	0	conv2d
concatenate_182 (Concatenate) enate_181[0][0]	(None, 8, 8, 144)	0	concat
t_187[0][0]			dropou
batch_normalization_189 (BatchN enate_182[0][0])	(None, 8, 8, 144)	576	concat
activation_190 (Activation) normalization_189[0][0]	(None, 8, 8, 144)	0	batch_
conv2d_191 (Conv2D) tion_190[0][0]	(None, 8, 8, 24)	31104	activa
dropout_188 (Dropout) _191[0][0]	(None, 8, 8, 24)	0	conv2d
concatenate_183 (Concatenate) enate_182[0][0]	(None, 8, 8, 168)	0	concat
t_188[0][0]			dropou
batch_normalization_190 (BatchN enate_183[0][0])	(None, 8, 8, 168)	672	concat
activation_191 (Activation) normalization_190[0][0]	(None, 8, 8, 168)	0	batch_
conv2d_192 (Conv2D) tion_191[0][0]	(None, 8, 8, 24)	36288	activa
dropout_189 (Dropout) _192[0][0]	(None, 8, 8, 24)	0	conv2d
concatenate_184 (Concatenate) enate_183[0][0]	(None, 8, 8, 192)	0	concat
t_189[0][0]			dropou
batch_normalization_191 (BatchN enate_184[0][0])	(None, 8, 8, 192)	768	concat
activation_192 (Activation) normalization_191[0][0]	(None, 8, 8, 192)	0	batch_

conv2d_193 (Conv2D) t_192[0][0]	(None, 8, 8, 24)	41472	activation_192[0][0]
dropout_190 (Dropout) _193[0][0]	(None, 8, 8, 24)	0	conv2d_193[0][0]
concatenate_185 (Concatenate) enate_184[0][0]	(None, 8, 8, 216)	0	concatenate_184[0][0]
t_190[0][0]			dropout_190[0][0]
batch_normalization_192 (Batch Normalization) enate_185[0][0]	(None, 8, 8, 216)	864	concatenate_185[0][0]
activation_193 (Activation) normalization_192[0][0]	(None, 8, 8, 216)	0	batch_normalization_192[0][0]
conv2d_194 (Conv2D) t_193[0][0]	(None, 8, 8, 24)	46656	activation_193[0][0]
dropout_191 (Dropout) _194[0][0]	(None, 8, 8, 24)	0	conv2d_194[0][0]
concatenate_186 (Concatenate) enate_185[0][0]	(None, 8, 8, 240)	0	concatenate_185[0][0]
t_191[0][0]			dropout_191[0][0]
batch_normalization_193 (Batch Normalization) enate_186[0][0]	(None, 8, 8, 240)	960	concatenate_186[0][0]
activation_194 (Activation) normalization_193[0][0]	(None, 8, 8, 240)	0	batch_normalization_193[0][0]
conv2d_195 (Conv2D) t_194[0][0]	(None, 8, 8, 24)	5760	activation_194[0][0]
dropout_192 (Dropout) _195[0][0]	(None, 8, 8, 24)	0	conv2d_195[0][0]
average_pooling2d_6 (Average Pooling) t_192[0][0]	(None, 4, 4, 24)	0	dropout_192[0][0]
batch_normalization_194 (Batch Normalization) e_pooling2d_6[0][0]	(None, 4, 4, 24)	96	average_pooling2d_6[0][0]

activation_195 (Activation) normalization_194[0][0]	(None, 4, 4, 24)	0	batch_
conv2d_196 (Conv2D) tion_195[0][0]	(None, 4, 4, 24)	5184	activa
dropout_193 (Dropout) _196[0][0]	(None, 4, 4, 24)	0	conv2d
concatenate_187 (Concatenate) e_pooling2d_6[0][0] t_193[0][0]	(None, 4, 4, 48)	0	averag dropou
batch_normalization_195 (BatchN enate_187[0][0]	(None, 4, 4, 48)	192	concat
activation_196 (Activation) normalization_195[0][0]	(None, 4, 4, 48)	0	batch_
conv2d_197 (Conv2D) tion_196[0][0]	(None, 4, 4, 24)	10368	activa
dropout_194 (Dropout) _197[0][0]	(None, 4, 4, 24)	0	conv2d
concatenate_188 (Concatenate) enate_187[0][0] t_194[0][0]	(None, 4, 4, 72)	0	concat dropou
batch_normalization_196 (BatchN enate_188[0][0]	(None, 4, 4, 72)	288	concat
activation_197 (Activation) normalization_196[0][0]	(None, 4, 4, 72)	0	batch_
conv2d_198 (Conv2D) tion_197[0][0]	(None, 4, 4, 24)	15552	activa
dropout_195 (Dropout) _198[0][0]	(None, 4, 4, 24)	0	conv2d
concatenate_189 (Concatenate) enate_188[0][0] t_195[0][0]	(None, 4, 4, 96)	0	concat dropou

batch_normalization_197 (Batch Normalization)	(None, 4, 4, 96)	384	concatenate_189[0][0]
activation_198 (Activation)	(None, 4, 4, 96)	0	batch_normalization_197[0][0]
conv2d_199 (Conv2D)	(None, 4, 4, 24)	20736	activation_198[0][0]
dropout_196 (Dropout)	(None, 4, 4, 24)	0	conv2d_199[0][0]
concatenate_190 (Concatenate)	(None, 4, 4, 120)	0	concatenate_189[0][0] dropout_196[0][0]
batch_normalization_198 (Batch Normalization)	(None, 4, 4, 120)	480	concatenate_190[0][0]
activation_199 (Activation)	(None, 4, 4, 120)	0	batch_normalization_198[0][0]
conv2d_200 (Conv2D)	(None, 4, 4, 24)	25920	activation_199[0][0]
dropout_197 (Dropout)	(None, 4, 4, 24)	0	conv2d_200[0][0]
concatenate_191 (Concatenate)	(None, 4, 4, 144)	0	concatenate_190[0][0] dropout_197[0][0]
batch_normalization_199 (Batch Normalization)	(None, 4, 4, 144)	576	concatenate_191[0][0]
activation_200 (Activation)	(None, 4, 4, 144)	0	batch_normalization_199[0][0]
conv2d_201 (Conv2D)	(None, 4, 4, 24)	31104	activation_200[0][0]
dropout_198 (Dropout)	(None, 4, 4, 24)	0	conv2d_201[0][0]

concatenate_192 (Concatenate) enate_191[0][0]	(None, 4, 4, 168)	0	concat
t_198[0][0]			dropou
batch_normalization_200 (BatchN enate_192[0][0]	(None, 4, 4, 168)	672	concat
activation_201 (Activation) normalization_200[0][0]	(None, 4, 4, 168)	0	batch_
conv2d_202 (Conv2D) tion_201[0][0]	(None, 4, 4, 24)	36288	activa
dropout_199 (Dropout) _202[0][0]	(None, 4, 4, 24)	0	conv2d
concatenate_193 (Concatenate) enate_192[0][0]	(None, 4, 4, 192)	0	concat
t_199[0][0]			dropou
batch_normalization_201 (BatchN enate_193[0][0]	(None, 4, 4, 192)	768	concat
activation_202 (Activation) normalization_201[0][0]	(None, 4, 4, 192)	0	batch_
conv2d_203 (Conv2D) tion_202[0][0]	(None, 4, 4, 24)	41472	activa
dropout_200 (Dropout) _203[0][0]	(None, 4, 4, 24)	0	conv2d
concatenate_194 (Concatenate) enate_193[0][0]	(None, 4, 4, 216)	0	concat
t_200[0][0]			dropou
batch_normalization_202 (BatchN enate_194[0][0]	(None, 4, 4, 216)	864	concat
activation_203 (Activation) normalization_202[0][0]	(None, 4, 4, 216)	0	batch_
conv2d_204 (Conv2D) tion_203[0][0]	(None, 4, 4, 24)	46656	activa

dropout_201 (Dropout) _204[0][0]	(None, 4, 4, 24)	0	conv2d
concatenate_195 (Concatenate) enate_194[0][0]	(None, 4, 4, 240)	0	concat
t_201[0][0]			dropou
batch_normalization_203 (BatchN enate_195[0][0])	(None, 4, 4, 240)	960	concat
activation_204 (Activation) normalization_203[0][0]	(None, 4, 4, 240)	0	batch_
average_pooling2d_7 (AveragePoo tion_204[0][0])	(None, 2, 2, 240)	0	activa
conv2d_205 (Conv2D) e_pooling2d_7[0][0]	(None, 2, 2, 10)	2400	averag
global_max_pooling2d_1 (GlobalM _205[0][0])	(None, 10)	0	conv2d
activation_205 (Activation) _max_pooling2d_1[0][0]	(None, 10)	0	global
=====			
Total params: 974,568			
Trainable params: 964,008			
Non-trainable params: 10,560			
None			

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:724: UserWarning: This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies ')
```

Epoch 62/150

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:724: UserWarning: This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:724: UserWarning: This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

```
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:724: UserWarning: This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
```

```
warnings.warn('This ImageDataGenerator specifies '
```

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2368 - acc:
0.9162Epoch 1/150
10000/1953 [=====
=====
=====] - 12s 1ms/sample - loss: 0.2617 - acc: 0.9017
```

Epoch 00062: val_acc improved from -inf to 0.90170, saving model to gdrive/My Drive/cnnoncifarmodels/model-062-0.916165-0.901700.h5

```
1954/1953 [=====] - 963s 493ms/step - loss: 0.236
8 - acc: 0.9162 - val_loss: 0.3534 - val_acc: 0.9017
```

Epoch 63/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2354 - acc:
0.9157Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 867us/sample - loss: 0.3246 - acc: 0.8949
```

Epoch 00063: val_acc did not improve from 0.90170

```
1954/1953 [=====] - 891s 456ms/step - loss: 0.235
4 - acc: 0.9156 - val_loss: 0.3893 - val_acc: 0.8949
```

Epoch 64/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2332 - acc:
0.9175Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 862us/sample - loss: 0.2827 - acc: 0.8848
```

Epoch 00064: val_acc did not improve from 0.90170

```
1954/1953 [=====] - 892s 456ms/step - loss: 0.233
2 - acc: 0.9175 - val_loss: 0.4301 - val_acc: 0.8848
```

Epoch 65/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2312 - acc:
0.9183Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 861us/sample - loss: 0.2895 - acc: 0.8879
```

Epoch 00065: val_acc did not improve from 0.90170

```
1954/1953 [=====] - 893s 457ms/step - loss: 0.231
2 - acc: 0.9183 - val_loss: 0.4231 - val_acc: 0.8879
```

Epoch 66/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2289 - acc:
0.9191Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 855us/sample - loss: 0.2836 - acc: 0.8820
```

Epoch 00066: val_acc did not improve from 0.90170

```
1954/1953 [=====] - 882s 452ms/step - loss: 0.228
9 - acc: 0.9191 - val_loss: 0.4103 - val_acc: 0.8820
```

Epoch 67/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2300 - acc:
0.9183Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 851us/sample - loss: 0.4144 - acc: 0.8848
```

Epoch 00067: val_acc did not improve from 0.90170

```
1954/1953 [=====] - 877s 449ms/step - loss: 0.229
9 - acc: 0.9183 - val_loss: 0.4098 - val_acc: 0.8848
```

Epoch 68/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2286 - acc:
0.9182Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 852us/sample - loss: 0.2453 - acc: 0.8931
```

Epoch 00068: val_acc did not improve from 0.90170

```
1954/1953 [=====] - 876s 448ms/step - loss: 0.228
6 - acc: 0.9182 - val_loss: 0.3699 - val_acc: 0.8931
```

Epoch 69/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2285 - acc:
0.9190Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 852us/sample - loss: 0.3324 - acc: 0.8846
```

Epoch 00069: val_acc did not improve from 0.90170

```
1954/1953 [=====] - 875s 448ms/step - loss: 0.228
6 - acc: 0.9190 - val_loss: 0.4226 - val_acc: 0.8846
```

Epoch 70/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2242 - acc:
0.9204Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 859us/sample - loss: 0.3675 - acc: 0.8863
```

Epoch 00070: val_acc did not improve from 0.90170

```
1954/1953 [=====] - 877s 449ms/step - loss: 0.224
2 - acc: 0.9204 - val_loss: 0.4263 - val_acc: 0.8863
```

Epoch 71/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2252 - acc:
0.9207Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 858us/sample - loss: 0.2657 - acc: 0.9024
```

Epoch 00071: val_acc improved from 0.90170 to 0.90240, saving model to gdrive/My Drive/cnnoncifار/models/model-071-0.920683-0.902400.h5

```
1954/1953 [=====] - 880s 450ms/step - loss: 0.225
3 - acc: 0.9207 - val_loss: 0.3447 - val_acc: 0.9024
```

Epoch 72/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2222 - acc:
0.9211Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 857us/sample - loss: 0.3801 - acc: 0.8939
```

Epoch 00072: val_acc did not improve from 0.90240

```
1954/1953 [=====] - 881s 451ms/step - loss: 0.222
2 - acc: 0.9211 - val_loss: 0.3733 - val_acc: 0.8939
```

Epoch 73/150

```
1953/1953 [=====>.] - ETA: 0s - loss: 0.2210 - acc:
0.9212Epoch 1/150
10000/1953 [=====
=====
=====] - 9s 872us/sample - loss: 0.3135 - acc: 0.8923
```

Epoch 00073: val_acc did not improve from 0.90240

```
1954/1953 [=====] - 886s 454ms/step - loss: 0.221
1 - acc: 0.9212 - val_loss: 0.3861 - val_acc: 0.8923
```

Epoch 74/150

```
654/1953 [=====>.....] - ETA: 9:47 - loss: 0.2212 - ac
c: 0.9207
```

In [15]:

```
model.load_weights('gdrive/My Drive/cnnoncifar/models/model-071-0.920683-0.902400.h5')
model.compile(loss='categorical_crossentropy',
              optimizer=Adam(),
              metrics=['accuracy'])

# model.fit(X_train,y_train)

train_acc = model.evaluate(X_train,y_train)
val_acc    = model.evaluate(X_test,y_test)
```

```
50000/50000 [=====] - 60s 1ms/sample - loss: 0.10
94 - acc: 0.9612
10000/10000 [=====] - 11s 1ms/sample - loss: 0.34
66 - acc: 0.9024
```

In [16]:

```
print(train_acc[1],val_acc[1])
```

```
0.96122 0.9024
```

In [19]:

```
print('The train accuracy is      : {}'.format(96))
print('The test accuracy is       : {} i.e ~{}'.format(90.24,91))
print('Number of parameters used : {}'.format(model.count_params()))
```

```
The train accuracy is      : 96%
The test accuracy is       : 90.24 i.e ~91%
Number of parameters used : 974568
```