

Implementation Of the DenseNet Model and Testing it on Cifer 10 dataset

```

from google.colab import drive
drive.mount("/content/drive",force_remount=True)

Mounted at /content/drive

import os
os.chdir("/content/drive/My Drive")

# 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
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
import datetime

# this part will prevent tensorflow to allocate all the available GPU Memory
# backend
import tensorflow as tf
from tensorflow.keras.callbacks import LearningRateScheduler, TensorBoard, ReduceLROnPlateau, ModelCheckpoint

# Hyperparameters
batch_size = 128
num_classes = 10
epochs = 10
l = 40
num_filter = 12
compression = 0.75
dropout_rate = 0

# 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)


X_train = X_train.astype('float32')
X_test = X_test.astype('float32')

X_train /= 255
X_test /= 255

from sklearn.model_selection import train_test_split
X_train , X_cv , y_train , y_cv = train_test_split(X_train , y_train , test_size = 0.20 , str
print(X_train.shape , y_train.shape , X_cv.shape , y_cv.shape , X_test.shape , y_test.shape)

(40000, 32, 32, 3) (40000, 10) (10000, 32, 32, 3) (10000, 10) (10000, 32, 32, 3) (10000

```



```

# Lets see how images change when the augmentation affects are applied on them
# ImageDataGenerator horizontal and vertical shift
datagen = ImageDataGenerator(width_shift_range=0.1, height_shift_range=0.1 )

# iterator
aug_iter = datagen.flow(X_train[:1], batch_size=1)

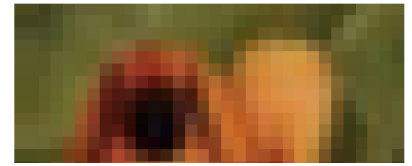
# generate samples and plot
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(25,25))

# generate batch of images
for i in range(3):

    # convert to unsigned integers
    image = next(aug_iter)[0].astype('uint8')

    # plot image
    ax[i].imshow(image)
    ax[i].axis('off')

```



```
# ImageDataGenerator zoom range
datagen = ImageDataGenerator(zoom_range=0.5)

# iterator
aug_iter = datagen.flow(X_train[:1], batch_size=1)

# generate samples and plot
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(25,25))

# generate batch of images
for i in range(3):

    # convert to unsigned integers
    image = next(aug_iter)[0].astype('uint8')

    # plot image
    ax[i].imshow(image)
    ax[i].axis('off')
```



```
# ImageDataGenerator brightness range
datagen = ImageDataGenerator(brightness_range=[0.4,1.5])

# iterator
aug_iter = datagen.flow(X_train[:1], batch_size=1)

# generate samples and plot
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(25,25))
```

```
# generate batch of images
for i in range(3):

    # convert to unsigned integers
    image = next(aug_iter)[0].astype('uint8')

    # plot image
    ax[i].imshow(image)
    ax[i].axis('off')
```



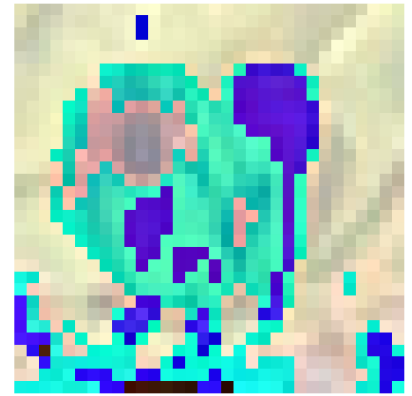
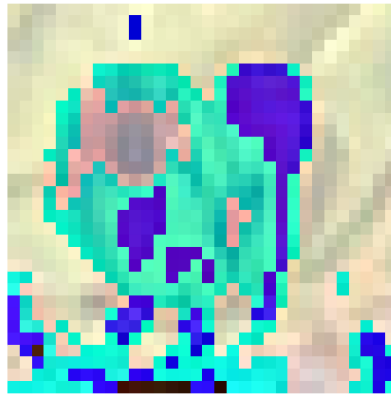
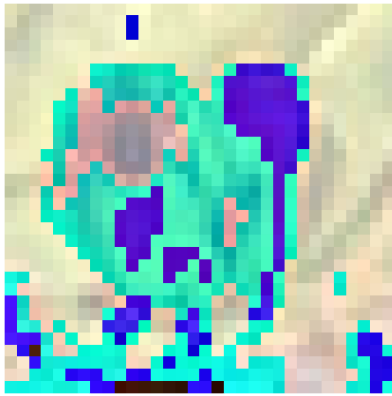
```
# ImageDataGenerator brightness range
datagen = ImageDataGenerator(featurewise_center=True )
datagen.fit(X_train)
# iterator
aug_iter = datagen.flow(X_train[:1], batch_size=1)

# generate samples and plot
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(25,25))

# generate batch of images
for i in range(3):

    # convert to unsigned integers
    image = next(aug_iter)[0].astype('uint8')

    # plot image
    ax[i].imshow(image)
    ax[i].axis('off')
```



```
# ImageDataGenerator brightness range
datagen = ImageDataGenerator(featurewise_std_normalization=True )
datagen.fit(X_train)
# iterator
aug_iter = datagen.flow(X_train[:1], batch_size=1)

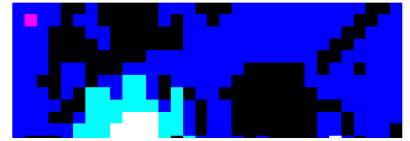
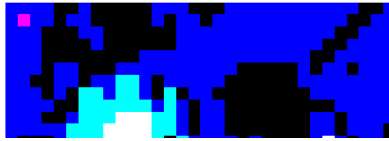
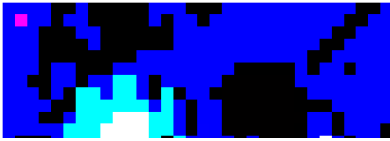
# generate samples and plot
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(25,25))

# generate batch of images
for i in range(3):

    # convert to unsigned integers
    image = next(aug_iter)[0].astype('uint8')

    # plot image
    ax[i].imshow(image)
    ax[i].axis('off')
```

```
/usr/local/lib/python3.7/dist-packages/keras_preprocessing/image/image_data_generator.p
warnings.warn('This ImageDataGenerator specifies '
```



```
# ImageDataGenerator brightness range
datagen = ImageDataGenerator(rescale = 0.5 )
datagen.fit(X_train)
# iterator
aug_iter = datagen.flow(X_train[:1], batch_size=1)

# generate samples and plot
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(25,25))

# generate batch of images
for i in range(3):

    # convert to unsigned integers
    image = next(aug_iter)[0].astype('uint8')

    # plot image
    ax[i].imshow(image)
    ax[i].axis('off')
```



```
# ImageDataGenerator brightness range
datagen = ImageDataGenerator(zca_whitening=True )
datagen.fit(X_train)
# iterator
aug_iter = datagen.flow(X_train[:1], batch_size=1)
```

```
# generate samples and plot
```

```
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(25,25))
```

```
# generate batch of images
```

```
for i in range(3):
```

```
    # convert to unsigned integers
```

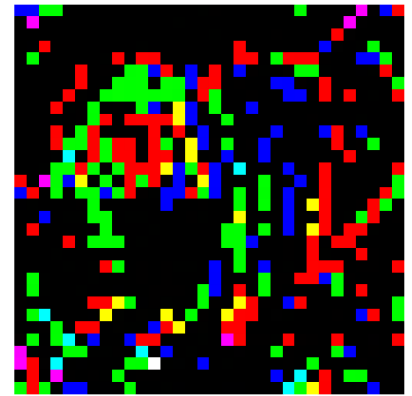
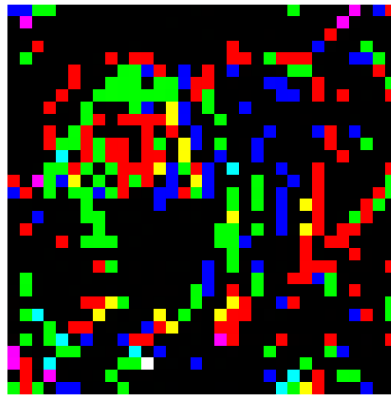
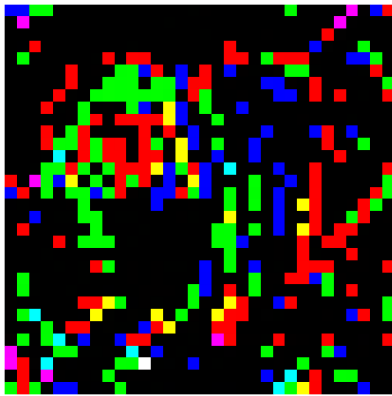
```
    image = next(aug_iter)[0].astype('uint8')
```

```
    # plot image
```

```
    ax[i].imshow(image)
```

```
    ax[i].axis('off')
```

```
/usr/local/lib/python3.7/dist-packages/keras_preprocessing/image/image_data_generator.p
warnings.warn('This ImageDataGenerator specifies '
```



```
# Dense Block
```

```
compression = 1
```

```
def denseblock(input, num_filter = 12, dropout_rate = 0):
```

```
    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')
        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), (1,1), use_bias=False ,padding='same')
    if dropout_rate>0:
        Conv2D_BottleNeck = layers.Dropout(dropout_rate)(Conv2D_BottleNeck)
    avg = layers.AveragePooling2D(pool_size=(2,2))(Conv2D_BottleNeck)
    return avg

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

num_filter = 17
dropout_rate = 0
l = 13
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])
model.summary()

```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	[(None, 32, 32, 3)]	0	
conv2d (Conv2D)	(None, 32, 32, 17)	459	input_1[0][0]

batch_normalization (BatchNormaliza	(None, 32, 32, 17)	68	conv2d[0][0]
activation (Activation)	(None, 32, 32, 17)	0	batch_normalization
conv2d_1 (Conv2D)	(None, 32, 32, 17)	2601	activation[0][0]
concatenate (Concatenate)	(None, 32, 32, 34)	0	conv2d[0][0] conv2d_1[0][0]
batch_normalization_1 (BatchNor	(None, 32, 32, 34)	136	concatenate[0][0]
activation_1 (Activation)	(None, 32, 32, 34)	0	batch_normalization
conv2d_2 (Conv2D)	(None, 32, 32, 17)	5202	activation_1[0][0]
concatenate_1 (Concatenate)	(None, 32, 32, 51)	0	concatenate[0][0] conv2d_2[0][0]
batch_normalization_2 (BatchNor	(None, 32, 32, 51)	204	concatenate_1[0][0]
activation_2 (Activation)	(None, 32, 32, 51)	0	batch_normalization
conv2d_3 (Conv2D)	(None, 32, 32, 17)	7803	activation_2[0][0]
concatenate_2 (Concatenate)	(None, 32, 32, 68)	0	concatenate_1[0][0] conv2d_3[0][0]
batch_normalization_3 (BatchNor	(None, 32, 32, 68)	272	concatenate_2[0][0]
activation_3 (Activation)	(None, 32, 32, 68)	0	batch_normalization
conv2d_4 (Conv2D)	(None, 32, 32, 17)	10404	activation_3[0][0]
concatenate_3 (Concatenate)	(None, 32, 32, 85)	0	concatenate_2[0][0] conv2d_4[0][0]
batch_normalization_4 (BatchNor	(None, 32, 32, 85)	340	concatenate_3[0][0]
activation_4 (Activation)	(None, 32, 32, 85)	0	batch_normalization
conv2d_5 (Conv2D)	(None, 32, 32, 17)	13005	activation_4[0][0]
concatenate_4 (Concatenate)	(None, 32, 32, 102)	0	concatenate_3[0][0] conv2d_5[0][0]
batch_normalization_5 (BatchNor	(None, 32, 32, 102)	408	concatenate_4[0][0]
activation_5 (Activation)	(None, 32, 32, 102)	0	batch_normalization
conv2d_6 (Conv2D)	(None, 32, 32, 17)	15606	activation_5[0][0]

```

datagen = ImageDataGenerator(
    rotation_range=25,
    horizontal_flip=True,
    width_shift_range=0.2,
    height_shift_range=0.2
)

```

```

    height_shift_range=0.2,
    zoom_range=0.2,
    shear_range=0.2,
    brightness_range = [0.4 ,1.5],
    featurewise_std_normalization = True,
)
datagen.fit(X_train)

/usr/local/lib/python3.7/dist-packages/keras_preprocessing/image/image_data_generator.p
warnings.warn('This ImageDataGenerator specifies '

train_iter = datagen.flow(X_train, y_train, batch_size=128)
cv_iter = datagen.flow(X_cv, y_cv, batch_size=128)
#test_iter = datagen.flow(X_test, y_test, batch_size=128)

def scheduler(epoch , lr):
    if epoch > 1 and epoch % 15 == 0:
        return lr*0.50
    else :
        return lr
lr_plateau = tf.keras.callbacks.ReduceLROnPlateau(monitor = "val_loss",mode = 'min',factor =
filepath="/content/drive/MyDrive/DenseNet_Model/weights-{epoch:02d}-{val_accuracy:.4f}.hdf5"
checkpoint_callback = ModelCheckpoint(filepath=filepath, monitor='val_accuracy', verbose=1)

earlystop = tf.keras.callbacks.EarlyStopping(
    monitor="val_loss",
    patience=15,
    verbose=1,
    mode="min",
    baseline=None,
    restore_best_weights=True,
)

# determine Loss function and Optimizer
model.compile(loss='categorical_crossentropy',
              optimizer=Adam(0.01),
              metrics=['accuracy'])

model.fit(train_iter, steps_per_epoch=len(train_iter), epochs = 100, validation_data=cv_iter, ca

```

Epoch 1/100

Epoch 00001: LearningRateScheduler reducing learning rate to 0.009999999776482582.
 352/352 [=====] - 99s 256ms/step - loss: 2.3721 - accuracy:

Epoch 00001: saving model to /content/drive/MyDrive/DenseNet_Model/weights-01-0.2380

Epoch 2/100

Epoch 00002: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 85s 242ms/step - loss: 1.7562 - accuracy:

Epoch 00002: saving model to /content/drive/MyDrive/DenseNet_Model/weights-02-0.3162
Epoch 3/100

Epoch 00003: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 85s 242ms/step - loss: 1.5283 - accuracy:

Epoch 00003: saving model to /content/drive/MyDrive/DenseNet_Model/weights-03-0.4250
Epoch 4/100

Epoch 00004: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 85s 242ms/step - loss: 1.3378 - accuracy:

Epoch 00004: saving model to /content/drive/MyDrive/DenseNet_Model/weights-04-0.5190
Epoch 5/100

Epoch 00005: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 85s 242ms/step - loss: 1.1826 - accuracy:

Epoch 00005: saving model to /content/drive/MyDrive/DenseNet_Model/weights-05-0.5566
Epoch 6/100

Epoch 00006: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 86s 243ms/step - loss: 1.0684 - accuracy:

Epoch 00006: saving model to /content/drive/MyDrive/DenseNet_Model/weights-06-0.5986
Epoch 7/100

Epoch 00007: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 85s 242ms/step - loss: 0.9958 - accuracy:

Epoch 00007: saving model to /content/drive/MyDrive/DenseNet_Model/weights-07-0.5878
Epoch 8/100

Epoch 00008: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 85s 242ms/step - loss: 0.9176 - accuracy:

Epoch 00008: saving model to /content/drive/MyDrive/DenseNet_Model/weights-08-0.6386
Epoch 9/100

Epoch 00009: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 85s 242ms/step - loss: 0.8387 - accuracy:

Epoch 00009: saving model to /content/drive/MyDrive/DenseNet_Model/weights-09-0.6418
Epoch 10/100

Epoch 00010: LearningRateScheduler reducing learning rate to 0.009999999776482582.
352/352 [=====] - 85s 242ms/step - loss: 0.7976 - accuracy:

model.load_weights('/content/drive/MyDrive/DenseNet_Model/weights-78-0.8906.hdf5')

```
model.compile(loss='categorical_crossentropy',
              optimizer=Adam(0.001),
              metrics=['accuracy'])

model.fit(train_iter, steps_per_epoch=len(train_iter), epochs = 100, validation_data=cv_iter, ca
```

Epoch 1/100

Epoch 00001: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 79s 251ms/step - loss: 0.2723 - accuracy:
Epoch 2/100

Epoch 00002: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 79s 252ms/step - loss: 0.2622 - accuracy:
Epoch 3/100

Epoch 00003: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 79s 254ms/step - loss: 0.2512 - accuracy:
Epoch 4/100

Epoch 00004: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 255ms/step - loss: 0.2512 - accuracy:
Epoch 5/100

Epoch 00005: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 255ms/step - loss: 0.2500 - accuracy:
Epoch 6/100

Epoch 00006: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 256ms/step - loss: 0.2396 - accuracy:
Epoch 7/100

Epoch 00007: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 256ms/step - loss: 0.2444 - accuracy:
Epoch 8/100

Epoch 00008: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 257ms/step - loss: 0.2420 - accuracy:
Epoch 9/100

Epoch 00009: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 256ms/step - loss: 0.2426 - accuracy:
Epoch 10/100

Epoch 00010: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 256ms/step - loss: 0.2400 - accuracy:
Epoch 11/100

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 256ms/step - loss: 0.2402 - accuracy:
Epoch 12/100

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 256ms/step - loss: 0.2315 - accuracy:

Epoch 13/100

Epoch 00013: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 257ms/step - loss: 0.2338 - accuracy:
Epoch 14/100

Epoch 00014: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
313/313 [=====] - 80s 256ms/step - loss: 0.2297 - accuracy:
Epoch 15/100

```
test_iter = datagen.flow(X_test, y_test, batch_size=128)
```

```
score = model.evaluate(test_iter, steps=len(test_iter), verbose=0)  
print('Test accuracy:', score[1])
```

Test accuracy: 0.9028000235557556

The model ran for $82+36 = 118$ epochs