

# sota\_neural\_network\_architectures\_erick

December 16, 2018

## 1 Homework- 26.11.2018:

### 1.1 State of the Art Neural Network Architectures

The purpose of this homework is to implement and evaluate the sota architectures presented in the lecture. However, you are encouraged to try your own layer module ideas. Feel free to consult the [Keras source code](#):

1. Based on the CNN modules presented in the lecture e.g. VGG16, Inception, ResNet, Xception, DenseNet, come up with your own CNN module and write a small text discussing your idea and motivations behind the module.
2. Evaluate all your module using the Keras CIFAR10 dataset splits (The model with best test accuracy will present their solution to the class).

### 1.2 Original ResNet implementation for CIFAR10 dataset

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In [0]: """Trains a ResNet on the CIFAR10 dataset.  
ResNet v1  
[a] Deep Residual Learning for Image Recognition  
https://arxiv.org/pdf/1512.03385.pdf  
ResNet v2  
[b] Identity Mappings in Deep Residual Networks  
https://arxiv.org/pdf/1603.05027.pdf  
"""  
  
from __future__ import print_function  
import keras  
from keras.layers import Dense, Conv2D, BatchNormalization, Activation  
from keras.layers import AveragePooling2D, Input, Flatten  
from keras.optimizers import Adam  
from keras.callbacks import ModelCheckpoint, LearningRateScheduler  
from keras.callbacks import ReduceLROnPlateau  
from keras.preprocessing.image import ImageDataGenerator  
from keras.regularizers import l2  
from keras import backend as K  
from keras.models import Model  
from keras.datasets import cifar10
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import numpy as np
import os

# Training parameters
batch_size = 128 # orig paper trained all networks with batch_size=128
epochs = 50
data_augmentation = True
num_classes = 10

# Subtracting pixel mean improves accuracy
subtract_pixel_mean = True

n = 3

# Model version
# Orig paper: version = 1 (ResNet v1), Improved ResNet: version = 2 (ResNet v2)
version = 2

# Computed depth from supplied model parameter n
if version == 1:
    depth = n * 6 + 2
elif version == 2:
    depth = n * 9 + 2

# Model name, depth and version
model_type = 'ResNet%dv%d' % (depth, version)

# Load the CIFAR10 data.
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Input image dimensions.
input_shape = x_train.shape[1:]

# Normalize data.
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# If subtract pixel mean is enabled
if subtract_pixel_mean:
    x_train_mean = np.mean(x_train, axis=0)
    x_train -= x_train_mean
    x_test -= x_train_mean

print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
print('y_train shape:', y_train.shape)

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# Convert class vectors to binary class matrices.
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

def lr_schedule(epoch):
    """Learning Rate Schedule
    Learning rate is scheduled to be reduced after 80, 120, 160, 180 epochs.
    Called automatically every epoch as part of callbacks during training.
    # Arguments
        epoch (int): The number of epochs
    # Returns
        lr (float32): learning rate
    """
    lr = 1e-3
    if epoch > 180:
        lr *= 0.5e-3
    elif epoch > 160:
        lr *= 1e-3
    elif epoch > 120:
        lr *= 1e-2
    elif epoch > 80:
        lr *= 1e-1
    print('Learning rate: ', lr)
    return lr

def resnet_layer(inputs,
                  num_filters=16,
                  kernel_size=3,
                  strides=1,
                  activation='relu',
                  batch_normalization=True,
                  conv_first=True):
    """2D Convolution-Batch Normalization-Activation stack builder
    # Arguments
        inputs (tensor): input tensor from input image or previous layer
        num_filters (int): Conv2D number of filters
        kernel_size (int): Conv2D square kernel dimensions
        strides (int): Conv2D square stride dimensions
        activation (string): activation name
        batch_normalization (bool): whether to include batch normalization
        conv_first (bool): conv-bn-activation (True) or
            bn-activation-conv (False)
    # Returns
        x (tensor): tensor as input to the next layer
    """
    conv = Conv2D(num_filters,

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        kernel_size=kernel_size,
        strides=strides,
        padding='same',
        kernel_initializer='he_normal',
        kernel_regularizer=l2(1e-4))

x = inputs
if conv_first:
    x = conv(x)
    if batch_normalization:
        x = BatchNormalization()(x)
    if activation is not None:
        x = Activation(activation)(x)
else:
    if batch_normalization:
        x = BatchNormalization()(x)
    if activation is not None:
        x = Activation(activation)(x)
    x = conv(x)
return x

def resnet_v1(input_shape, depth, num_classes=10):
    """ResNet Version 1 Model builder [a]
    Stacks of 2 x (3 x 3) Conv2D-BN-ReLU
    Last ReLU is after the shortcut connection.
    At the beginning of each stage, the feature map size is halved (downsampled)
    by a convolutional layer with strides=2, while the number of filters is
    doubled. Within each stage, the layers have the same number filters and the
    same number of filters.
    Features maps sizes:
    stage 0: 32x32, 16
    stage 1: 16x16, 32
    stage 2: 8x8, 64
    The Number of parameters is approx the same as Table 6 of [a]:
    ResNet20 0.27M
    ResNet32 0.46M
    ResNet44 0.66M
    ResNet56 0.85M
    ResNet110 1.7M
    # Arguments
        input_shape (tensor): shape of input image tensor
        depth (int): number of core convolutional layers
        num_classes (int): number of classes (CIFAR10 has 10)
    # Returns
        model (Model): Keras model instance
    """
    if (depth - 2) % 6 != 0:

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        raise ValueError('depth should be 6n+2 (eg 20, 32, 44 in [a])')
    # Start model definition.
    num_filters = 16
    num_res_blocks = int((depth - 2) / 6)

    inputs = Input(shape=input_shape)
    x = resnet_layer(inputs=inputs)
    # Instantiate the stack of residual units
    for stack in range(3):
        for res_block in range(num_res_blocks):
            strides = 1
            if stack > 0 and res_block == 0: # first layer but not first stack
                strides = 2 # downsample
            y = resnet_layer(inputs=x,
                             num_filters=num_filters,
                             strides=strides)
            y = resnet_layer(inputs=y,
                             num_filters=num_filters,
                             activation=None)
            if stack > 0 and res_block == 0: # first layer but not first stack
                # linear projection residual shortcut connection to match
                # changed dims
                x = resnet_layer(inputs=x,
                                 num_filters=num_filters,
                                 kernel_size=1,
                                 strides=strides,
                                 activation=None,
                                 batch_normalization=False)
            x = keras.layers.add([x, y])
            x = Activation('relu')(x)
        num_filters *= 2

    # Add classifier on top.
    # v1 does not use BN after last shortcut connection-ReLU
    x = AveragePooling2D(pool_size=8)(x)
    y = Flatten()(x)
    outputs = Dense(num_classes,
                    activation='softmax',
                    kernel_initializer='he_normal')(y)

    # Instantiate model.
    model = Model(inputs=inputs, outputs=outputs)
    return model

def resnet_v2(input_shape, depth, num_classes=10):
    """ResNet Version 2 Model builder [b]
    Stacks of (1 x 1)-(3 x 3)-(1 x 1) BN-ReLU-Conv2D or also known as

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bottleneck layer
First shortcut connection per layer is 1 x 1 Conv2D.
Second and onwards shortcut connection is identity.
At the beginning of each stage, the feature map size is halved (downsampled)
by a convolutional layer with strides=2, while the number of filter maps is
doubled. Within each stage, the layers have the same number filters and the
same filter map sizes.
Features maps sizes:
conv1 : 32x32, 16
stage 0: 32x32, 64
stage 1: 16x16, 128
stage 2: 8x8, 256
# Arguments
    input_shape (tensor): shape of input image tensor
    depth (int): number of core convolutional layers
    num_classes (int): number of classes (CIFAR10 has 10)
# Returns
    model (Model): Keras model instance
"""
if (depth - 2) % 9 != 0:
    raise ValueError('depth should be 9n+2 (eg 56 or 110 in [b])')
# Start model definition.
num_filters_in = 16
num_res_blocks = int((depth - 2) / 9)

inputs = Input(shape=input_shape)
# v2 performs Conv2D with BN-ReLU on input before splitting into 2 paths
x = resnet_layer(inputs=inputs,
                  num_filters=num_filters_in,
                  conv_first=True)

# Instantiate the stack of residual units
for stage in range(3):
    for res_block in range(num_res_blocks):
        activation = 'relu'
        batch_normalization = True
        strides = 1
        if stage == 0:
            num_filters_out = num_filters_in * 4
            if res_block == 0: # first layer and first stage
                activation = None
                batch_normalization = False
        else:
            num_filters_out = num_filters_in * 2
            if res_block == 0: # first layer but not first stage
                strides = 2 # downsample

        # bottleneck residual unit

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        y = resnet_layer(inputs=x,
                          num_filters=num_filters_in,
                          kernel_size=1,
                          strides=strides,
                          activation=activation,
                          batch_normalization=batch_normalization,
                          conv_first=False)
        y = resnet_layer(inputs=y,
                          num_filters=num_filters_in,
                          conv_first=False)
        y = resnet_layer(inputs=y,
                          num_filters=num_filters_out,
                          kernel_size=1,
                          conv_first=False)
    if res_block == 0:
        # linear projection residual shortcut connection to match
        # changed dims
        x = resnet_layer(inputs=x,
                          num_filters=num_filters_out,
                          kernel_size=1,
                          strides=strides,
                          activation=None,
                          batch_normalization=False)
        x = keras.layers.add([x, y])

    num_filters_in = num_filters_out

    # Add classifier on top.
    # v2 has BN-ReLU before Pooling
    x = BatchNormalization()(x)
    x = Activation('relu')(x)
    x = AveragePooling2D(pool_size=8)(x)
    y = Flatten()(x)
    outputs = Dense(num_classes,
                    activation='softmax',
                    kernel_initializer='he_normal')(y)

    # Instantiate model.
    model = Model(inputs=inputs, outputs=outputs)
    return model

if version == 2:
    model = resnet_v2(input_shape=input_shape, depth=depth)
else:
    model = resnet_v1(input_shape=input_shape, depth=depth)

model.compile(loss='categorical_crossentropy',

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        optimizer=Adam(lr=lr_schedule(0)),
        metrics=['accuracy'])
model.summary()
print(model_type)

# Prepare model saving directory.
save_dir = os.path.join(os.getcwd(), 'saved_models')
model_name = 'cifar10_%s_model.{epoch:03d}.h5' % model_type
if not os.path.isdir(save_dir):
    os.makedirs(save_dir)
filepath = os.path.join(save_dir, model_name)

# Prepare callbacks for model saving and for learning rate adjustment.
checkpoint = ModelCheckpoint(filepath=filepath,
                             monitor='val_acc',
                             verbose=1,
                             save_best_only=True)

lr_scheduler = LearningRateScheduler(lr_schedule)

lr_reducer = ReduceLROnPlateau(factor=np.sqrt(0.1),
                               cooldown=0,
                               patience=5,
                               min_lr=0.5e-6)

callbacks = [checkpoint, lr_reducer, lr_scheduler]

# Run training, with or without data augmentation.
if not data_augmentation:
    print('Not using data augmentation.')
    model.fit(x_train, y_train,
              batch_size=batch_size,
              epochs=epochs,
              validation_data=(x_test, y_test),
              shuffle=True,
              callbacks=callbacks)
else:
    print('Using real-time data augmentation.')
    # This will do preprocessing and realtime data augmentation:
    datagen = ImageDataGenerator(
        # set input mean to 0 over the dataset
        featurewise_center=False,
        # set each sample mean to 0
        samplewise_center=False,
        # divide inputs by std of dataset
        featurewise_std_normalization=False,
        # divide each input by its std
        samplewise_std_normalization=False,

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```

# apply ZCA whitening
zca_whitening=False,
# epsilon for ZCA whitening
zca_epsilon=1e-06,
# randomly rotate images in the range (deg 0 to 180)
rotation_range=0,
# randomly shift images horizontally
width_shift_range=0.1,
# randomly shift images vertically
height_shift_range=0.1,
# set range for random shear
shear_range=0.,
# set range for random zoom
zoom_range=0.,
# set range for random channel shifts
channel_shift_range=0.,
# set mode for filling points outside the input boundaries
fill_mode='nearest',
# value used for fill_mode = "constant"
cval=0.,
# randomly flip images
horizontal_flip=True,
# randomly flip images
vertical_flip=False,
# set rescaling factor (applied before any other transformation)
rescale=None,
# set function that will be applied on each input
preprocessing_function=None,
# image data format, either "channels_first" or "channels_last"
data_format=None,
# fraction of images reserved for validation (strictly between 0 and 1)
validation_split=0.0)

# Compute quantities required for featurewise normalization
# (std, mean, and principal components if ZCA whitening is applied).
datagen.fit(x_train)

# Fit the model on the batches generated by datagen.flow().
model.fit_generator(datagen.flow(x_train, y_train, batch_size=batch_size),
                    validation_data=(x_test, y_test),
                    epochs=epochs, verbose=1, workers=4, steps_per_epoch=1000,
                    callbacks=callbacks)

# Score trained model.
scores = model.evaluate(x_test, y_test, verbose=1)
print('Test loss:', scores[0])
print('Test accuracy:', scores[1])

```

x\_train shape: (50000, 32, 32, 3)  
50000 train samples  
10000 test samples  
y\_train shape: (50000, 1)  
Learning rate: 0.001

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	(None, 32, 32, 3)	0	
conv2d_32 (Conv2D)	(None, 32, 32, 16)	448	input_2[0][0]
batch_normalization_29 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_32[0][0]
activation_29 (Activation)	(None, 32, 32, 16)	0	batch_normalization_29[0][0]
conv2d_33 (Conv2D)	(None, 32, 32, 16)	272	activation_29[0][0]
batch_normalization_30 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_33[0][0]
activation_30 (Activation)	(None, 32, 32, 16)	0	batch_normalization_30[0][0]
conv2d_34 (Conv2D)	(None, 32, 32, 16)	2320	activation_30[0][0]
batch_normalization_31 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_34[0][0]
activation_31 (Activation)	(None, 32, 32, 16)	0	batch_normalization_31[0][0]
conv2d_36 (Conv2D)	(None, 32, 32, 64)	1088	activation_29[0][0]
conv2d_35 (Conv2D)	(None, 32, 32, 64)	1088	activation_31[0][0]
add_10 (Add)	(None, 32, 32, 64)	0	conv2d_36[0][0] conv2d_35[0][0]
batch_normalization_32 (Batch Normalization)	(None, 32, 32, 64)	256	add_10[0][0]
activation_32 (Activation)	(None, 32, 32, 64)	0	batch_normalization_32[0][0]
conv2d_37 (Conv2D)	(None, 32, 32, 16)	1040	activation_32[0][0]
batch_normalization_33 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_37[0][0]
activation_33 (Activation)	(None, 32, 32, 16)	0	batch_normalization_33[0][0]
conv2d_38 (Conv2D)	(None, 32, 32, 16)	2320	activation_33[0][0]
batch_normalization_34 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_38[0][0]

activation_34 (Activation)	(None, 32, 32, 16)	0	batch_normalization_34[0][0]
conv2d_39 (Conv2D)	(None, 32, 32, 64)	1088	activation_34[0][0]
add_11 (Add)	(None, 32, 32, 64)	0	add_10[0][0] conv2d_39[0][0]
batch_normalization_35 (BatchNo	(None, 32, 32, 64)	256	add_11[0][0]
activation_35 (Activation)	(None, 32, 32, 64)	0	batch_normalization_35[0][0]
conv2d_40 (Conv2D)	(None, 32, 32, 16)	1040	activation_35[0][0]
batch_normalization_36 (BatchNo	(None, 32, 32, 16)	64	conv2d_40[0][0]
activation_36 (Activation)	(None, 32, 32, 16)	0	batch_normalization_36[0][0]
conv2d_41 (Conv2D)	(None, 32, 32, 16)	2320	activation_36[0][0]
batch_normalization_37 (BatchNo	(None, 32, 32, 16)	64	conv2d_41[0][0]
activation_37 (Activation)	(None, 32, 32, 16)	0	batch_normalization_37[0][0]
conv2d_42 (Conv2D)	(None, 32, 32, 64)	1088	activation_37[0][0]
add_12 (Add)	(None, 32, 32, 64)	0	add_11[0][0] conv2d_42[0][0]
batch_normalization_38 (BatchNo	(None, 32, 32, 64)	256	add_12[0][0]
activation_38 (Activation)	(None, 32, 32, 64)	0	batch_normalization_38[0][0]
conv2d_43 (Conv2D)	(None, 16, 16, 64)	4160	activation_38[0][0]
batch_normalization_39 (BatchNo	(None, 16, 16, 64)	256	conv2d_43[0][0]
activation_39 (Activation)	(None, 16, 16, 64)	0	batch_normalization_39[0][0]
conv2d_44 (Conv2D)	(None, 16, 16, 64)	36928	activation_39[0][0]
batch_normalization_40 (BatchNo	(None, 16, 16, 64)	256	conv2d_44[0][0]
activation_40 (Activation)	(None, 16, 16, 64)	0	batch_normalization_40[0][0]
conv2d_46 (Conv2D)	(None, 16, 16, 128)	8320	add_12[0][0]
conv2d_45 (Conv2D)	(None, 16, 16, 128)	8320	activation_40[0][0]

add_13 (Add)	(None, 16, 16, 128)	0	conv2d_46[0][0] conv2d_45[0][0]
batch_normalization_41 (BatchNo	(None, 16, 16, 128)	512	add_13[0][0]
activation_41 (Activation)	(None, 16, 16, 128)	0	batch_normalization_41[0][0]
conv2d_47 (Conv2D)	(None, 16, 16, 64)	8256	activation_41[0][0]
batch_normalization_42 (BatchNo	(None, 16, 16, 64)	256	conv2d_47[0][0]
activation_42 (Activation)	(None, 16, 16, 64)	0	batch_normalization_42[0][0]
conv2d_48 (Conv2D)	(None, 16, 16, 64)	36928	activation_42[0][0]
batch_normalization_43 (BatchNo	(None, 16, 16, 64)	256	conv2d_48[0][0]
activation_43 (Activation)	(None, 16, 16, 64)	0	batch_normalization_43[0][0]
conv2d_49 (Conv2D)	(None, 16, 16, 128)	8320	activation_43[0][0]
add_14 (Add)	(None, 16, 16, 128)	0	add_13[0][0] conv2d_49[0][0]
batch_normalization_44 (BatchNo	(None, 16, 16, 128)	512	add_14[0][0]
activation_44 (Activation)	(None, 16, 16, 128)	0	batch_normalization_44[0][0]
conv2d_50 (Conv2D)	(None, 16, 16, 64)	8256	activation_44[0][0]
batch_normalization_45 (BatchNo	(None, 16, 16, 64)	256	conv2d_50[0][0]
activation_45 (Activation)	(None, 16, 16, 64)	0	batch_normalization_45[0][0]
conv2d_51 (Conv2D)	(None, 16, 16, 64)	36928	activation_45[0][0]
batch_normalization_46 (BatchNo	(None, 16, 16, 64)	256	conv2d_51[0][0]
activation_46 (Activation)	(None, 16, 16, 64)	0	batch_normalization_46[0][0]
conv2d_52 (Conv2D)	(None, 16, 16, 128)	8320	activation_46[0][0]
add_15 (Add)	(None, 16, 16, 128)	0	add_14[0][0] conv2d_52[0][0]
batch_normalization_47 (BatchNo	(None, 16, 16, 128)	512	add_15[0][0]

activation_47 (Activation)	(None, 16, 16, 128)	0	batch_normalization_47[0][0]
conv2d_53 (Conv2D)	(None, 8, 8, 128)	16512	activation_47[0][0]
batch_normalization_48 (BatchNo	(None, 8, 8, 128)	512	conv2d_53[0][0]
activation_48 (Activation)	(None, 8, 8, 128)	0	batch_normalization_48[0][0]
conv2d_54 (Conv2D)	(None, 8, 8, 128)	147584	activation_48[0][0]
batch_normalization_49 (BatchNo	(None, 8, 8, 128)	512	conv2d_54[0][0]
activation_49 (Activation)	(None, 8, 8, 128)	0	batch_normalization_49[0][0]
conv2d_56 (Conv2D)	(None, 8, 8, 256)	33024	add_15[0][0]
conv2d_55 (Conv2D)	(None, 8, 8, 256)	33024	activation_49[0][0]
add_16 (Add)	(None, 8, 8, 256)	0	conv2d_56[0][0] conv2d_55[0][0]
batch_normalization_50 (BatchNo	(None, 8, 8, 256)	1024	add_16[0][0]
activation_50 (Activation)	(None, 8, 8, 256)	0	batch_normalization_50[0][0]
conv2d_57 (Conv2D)	(None, 8, 8, 128)	32896	activation_50[0][0]
batch_normalization_51 (BatchNo	(None, 8, 8, 128)	512	conv2d_57[0][0]
activation_51 (Activation)	(None, 8, 8, 128)	0	batch_normalization_51[0][0]
conv2d_58 (Conv2D)	(None, 8, 8, 128)	147584	activation_51[0][0]
batch_normalization_52 (BatchNo	(None, 8, 8, 128)	512	conv2d_58[0][0]
activation_52 (Activation)	(None, 8, 8, 128)	0	batch_normalization_52[0][0]
conv2d_59 (Conv2D)	(None, 8, 8, 256)	33024	activation_52[0][0]
add_17 (Add)	(None, 8, 8, 256)	0	add_16[0][0] conv2d_59[0][0]
batch_normalization_53 (BatchNo	(None, 8, 8, 256)	1024	add_17[0][0]
activation_53 (Activation)	(None, 8, 8, 256)	0	batch_normalization_53[0][0]
conv2d_60 (Conv2D)	(None, 8, 8, 128)	32896	activation_53[0][0]

batch_normalization_54 (BatchNo	(None, 8, 8, 128)	512	conv2d_60[0][0]
activation_54 (Activation)	(None, 8, 8, 128)	0	batch_normalization_54[0][0]
conv2d_61 (Conv2D)	(None, 8, 8, 128)	147584	activation_54[0][0]
batch_normalization_55 (BatchNo	(None, 8, 8, 128)	512	conv2d_61[0][0]
activation_55 (Activation)	(None, 8, 8, 128)	0	batch_normalization_55[0][0]
conv2d_62 (Conv2D)	(None, 8, 8, 256)	33024	activation_55[0][0]
add_18 (Add)	(None, 8, 8, 256)	0	add_17[0][0] conv2d_62[0][0]
batch_normalization_56 (BatchNo	(None, 8, 8, 256)	1024	add_18[0][0]
activation_56 (Activation)	(None, 8, 8, 256)	0	batch_normalization_56[0][0]
average_pooling2d_2 (AveragePoo	(None, 1, 1, 256)	0	activation_56[0][0]
flatten_2 (Flatten)	(None, 256)	0	average_pooling2d_2[0][0]
dense_2 (Dense)	(None, 10)	2570	flatten_2[0][0]

Total params: 849,002  
 Trainable params: 843,786  
 Non-trainable params: 5,216

ResNet29v2

Using real-time data augmentation.

Epoch 1/50

Learning rate: 0.001

1000/1000 [=====] - 216s 216ms/step - loss: 1.6375 - acc: 0.5708 - val\_

Epoch 00001: val\_acc improved from -inf to 0.66120, saving model to /content/saved\_models/cifar1

Epoch 2/50

Learning rate: 0.001

1000/1000 [=====] - 204s 204ms/step - loss: 1.1090 - acc: 0.7302 - val\_

Epoch 00002: val\_acc did not improve from 0.66120

Epoch 3/50

Learning rate: 0.001

1000/1000 [=====] - 204s 204ms/step - loss: 0.9232 - acc: 0.7851 - val\_

Epoch 00003: val\_acc improved from 0.66120 to 0.66380, saving model to /content/saved\_models/cif

Epoch 4/50

Learning rate: 0.001

1000/1000 [=====] - 204s 204ms/step - loss: 0.8154 - acc: 0.8156 - val\_

Epoch 00004: val\_acc improved from 0.66380 to 0.76920, saving model to /content/saved\_models/cif

Epoch 5/50

Learning rate: 0.001

1000/1000 [=====] - 204s 204ms/step - loss: 0.7485 - acc: 0.8344 - val\_

Epoch 00005: val\_acc did not improve from 0.76920

Epoch 6/50

Learning rate: 0.001

1000/1000 [=====] - 205s 205ms/step - loss: 0.6888 - acc: 0.8506 - val\_

Epoch 00006: val\_acc did not improve from 0.76920

Epoch 7/50

Learning rate: 0.001

1000/1000 [=====] - 206s 206ms/step - loss: 0.6496 - acc: 0.8625 - val\_

Epoch 00007: val\_acc did not improve from 0.76920

Epoch 8/50

Learning rate: 0.001

1000/1000 [=====] - 206s 206ms/step - loss: 0.6164 - acc: 0.8708 - val\_

Epoch 00008: val\_acc did not improve from 0.76920

Epoch 9/50

Learning rate: 0.001

1000/1000 [=====] - 205s 205ms/step - loss: 0.5948 - acc: 0.8769 - val\_

Epoch 00009: val\_acc improved from 0.76920 to 0.79250, saving model to /content/saved\_models/cif

Epoch 10/50

Learning rate: 0.001

1000/1000 [=====] - 205s 205ms/step - loss: 0.5724 - acc: 0.8840 - val\_

Epoch 00010: val\_acc did not improve from 0.79250

Epoch 11/50

Learning rate: 0.001

1000/1000 [=====] - 210s 210ms/step - loss: 0.5561 - acc: 0.8890 - val\_

Epoch 00011: val\_acc improved from 0.79250 to 0.83710, saving model to /content/saved\_models/cif

Epoch 12/50

Learning rate: 0.001

1000/1000 [=====] - 206s 206ms/step - loss: 0.5356 - acc: 0.8952 - val\_

Epoch 00012: val\_acc did not improve from 0.83710

Epoch 13/50

Learning rate: 0.001

1000/1000 [=====] - 205s 205ms/step - loss: 0.5194 - acc: 0.8995 - val\_

Epoch 00013: val\_acc did not improve from 0.83710

Epoch 14/50  
Learning rate: 0.001  
1000/1000 [=====] - 205s 205ms/step - loss: 0.5119 - acc: 0.9011 - val\_

Epoch 00014: val\_acc improved from 0.83710 to 0.84890, saving model to /content/saved\_models/cif  
Epoch 15/50  
Learning rate: 0.001  
1000/1000 [=====] - 205s 205ms/step - loss: 0.4971 - acc: 0.9064 - val\_

Epoch 00015: val\_acc did not improve from 0.84890  
Epoch 16/50  
Learning rate: 0.001  
1000/1000 [=====] - 205s 205ms/step - loss: 0.4897 - acc: 0.9079 - val\_

Epoch 00016: val\_acc did not improve from 0.84890  
Epoch 17/50  
Learning rate: 0.001  
1000/1000 [=====] - 205s 205ms/step - loss: 0.4774 - acc: 0.9123 - val\_

Epoch 00017: val\_acc did not improve from 0.84890  
Epoch 18/50  
Learning rate: 0.001  
1000/1000 [=====] - 206s 206ms/step - loss: 0.4705 - acc: 0.9148 - val\_

Epoch 00018: val\_acc improved from 0.84890 to 0.85160, saving model to /content/saved\_models/cif  
Epoch 19/50  
Learning rate: 0.001  
1000/1000 [=====] - 205s 205ms/step - loss: 0.4638 - acc: 0.9159 - val\_

Epoch 00019: val\_acc improved from 0.85160 to 0.86300, saving model to /content/saved\_models/cif  
Epoch 20/50  
Learning rate: 0.001  
1000/1000 [=====] - 205s 205ms/step - loss: 0.4584 - acc: 0.9175 - val\_

Epoch 00020: val\_acc did not improve from 0.86300  
Epoch 21/50  
Learning rate: 0.001  
1000/1000 [=====] - 206s 206ms/step - loss: 0.4517 - acc: 0.9200 - val\_

Epoch 00021: val\_acc did not improve from 0.86300  
Epoch 22/50  
Learning rate: 0.001  
1000/1000 [=====] - 205s 205ms/step - loss: 0.4475 - acc: 0.9207 - val\_

Epoch 00022: val\_acc did not improve from 0.86300  
Epoch 23/50  
Learning rate: 0.001  
1000/1000 [=====] - 205s 205ms/step - loss: 0.4413 - acc: 0.9231 - val\_



Epoch 00023: val\_acc did not improve from 0.86300

Epoch 24/50

Learning rate: 0.001

1000/1000 [=====] - 206s 206ms/step - loss: 0.4354 - acc: 0.9239 - val\_

Epoch 00024: val\_acc did not improve from 0.86300

Epoch 25/50

Learning rate: 0.001

1000/1000 [=====] - 206s 206ms/step - loss: 0.4333 - acc: 0.9252 - val\_

Epoch 00025: val\_acc did not improve from 0.86300

Epoch 26/50

Learning rate: 0.001

1000/1000 [=====] - 206s 206ms/step - loss: 0.4228 - acc: 0.9288 - val\_

Epoch 00026: val\_acc did not improve from 0.86300

Epoch 27/50

Learning rate: 0.001

145/1000 [==>...] - ETA: 2:52 - loss: 0.4307 - acc: 0.9241

-----

KeyboardInterrupt

Traceback (most recent call last)

```
<ipython-input-16-2fc70d9ece25> in <module>()
411             validation_data=(x_test, y_test),
412             epochs=epochs, verbose=1, workers=4, steps_per_epoch=1000,
--> 413             callbacks=callbacks)
414
415 # Score trained model.

/usr/local/lib/python3.6/dist-packages/keras/legacy/interfaces.py in wrapper(*args, **kw
89         warnings.warn('Update your ``' + object_name + '` call to the ' +
90             'Keras 2 API: ' + signature, stacklevel=2)
---> 91         return func(*args, **kwargs)
92         wrapper._original_function = func
93         return wrapper

/usr/local/lib/python3.6/dist-packages/keras/engine/training.py in fit_generator(self, g
1416         use_multiprocessing=use_multiprocessing,
1417         shuffle=shuffle,
-> 1418         initial_epoch=initial_epoch)
1419
1420     @interfaces.legacy_generator_methods_support
```

```

/usr/local/lib/python3.6/dist-packages/keras/engine/training_generator.py in fit_generat
215         outs = model.train_on_batch(x, y,
216                                     sample_weight=sample_weight,
--> 217                                     class_weight=class_weight)
218
219         outs = to_list(outs)

/usr/local/lib/python3.6/dist-packages/keras/engine/training.py in train_on_batch(self,
1215         ins = x + y + sample_weights
1216         self._make_train_function()
-> 1217         outputs = self.train_function(ins)
1218         return unpack_singleton(outputs)
1219

/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py in __call__(s
2713         return self._legacy_call(inputs)
2714
-> 2715         return self._call(inputs)
2716     else:
2717         if py_any(is_tensor(x) for x in inputs):

/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py in _call(self
2673         fetched = self._callable_fn(*array_vals, run_metadata=self.run_metadata)
2674     else:
-> 2675         fetched = self._callable_fn(*array_vals)
2676         return fetched[:len(self.outputs)]
2677

/usr/local/lib/python3.6/dist-packages/tensorflow/python/client/session.py in __call__(s
1437         ret = tf_session.TF_SessionRunCallable(
1438             self._session._session, self._handle, args, status,
-> 1439             run_metadata_ptr)
1440         if run_metadata:
1441             proto_data = tf_session.TF_GetBuffer(run_metadata_ptr)

```

KeyboardInterrupt:

### 1.2.1 Results:

The original implementation of ResNetV2 for CIFAR obtained **0.863** for the validation accuracy at the 19 epoch out of the 27 epochs it was executed. We decided to stop the training/validation of the model at that number, because we were not appreciating any improvement in the accuracy.

## 1.3 Customized ResNetv2 implementation for CIFAR

```
In [0]: import time
import matplotlib.pyplot as plt
import numpy as np
from keras.models import Sequential
from keras.layers import Dropout
from keras.layers import AveragePooling2D, Input, Flatten
from keras.constraints import maxnorm
from keras.optimizers import SGD
from keras.optimizers import Adam
from keras.callbacks import ModelCheckpoint, LearningRateScheduler
from keras.callbacks import ReduceLROnPlateau
from keras.regularizers import l2
from keras.preprocessing.image import ImageDataGenerator
from keras.layers.convolutional import MaxPooling2D
from keras.layers import Dense, Conv2D, BatchNormalization, Activation
from keras.utils import np_utils
# from keras_sequential_ascii import sequential_model_to_ascii_printout
from keras import backend as K
# if K.backend()=='tensorflow':
#     K.set_image_dim_ordering("th")
# Import Tensorflow with multiprocessing
import tensorflow as tf
import multiprocessing as mp

# Loading the CIFAR-10 datasets
from keras.datasets import cifar10

import seaborn as sn
import pandas as pd

from sklearn.metrics import classification_report, confusion_matrix

# Training parameters
batch_size = 128 # orig paper trained all networks with batch_size=128
epochs = 100
data_augmentation = True
num_classes = 10
n = 3
depth = n * 9 + 2
```

```

(x_train, y_train), (x_test, y_test) = cifar10.load_data()

#----- Preprocessing -----
# Input image dimensions.
input_shape = x_train.shape[1:]

# Normalize data.
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# Subtract mean
x_train_mean = np.mean(x_train, axis=0)
x_train -= x_train_mean
x_test -= x_train_mean

print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
print('y_train shape:', y_train.shape)

# Convert class vectors to binary class matrices.
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

# ----- Callbacks functions -----
def lr_schedule(epoch):
    """Learning Rate Schedule
    Learning rate is scheduled to be reduced after 80, 120, 160, 180 epochs.
    Called automatically every epoch as part of callbacks during training.
    # Arguments
        epoch (int): The number of epochs
    # Returns
        lr (float32): learning rate
    """
    lr = 1e-3
    if epoch > 180:
        lr *= 0.5e-3
    elif epoch > 160:
        lr *= 1e-3
    elif epoch > 120:
        lr *= 1e-2
    elif epoch > 80:
        lr *= 1e-1
    print('Learning rate: ', lr)
    return lr

# # Prepare callbacks for model saving and for learning rate adjustment.
# checkpoint = ModelCheckpoint(filepath=filepath,

```

```

#                                     monitor='val_acc',
#                                     verbose=1,
#                                     save_best_only=True)

lr_scheduler = LearningRateScheduler(lr_schedule)

lr_reducer = ReduceLROnPlateau(factor=np.sqrt(0.1),
                                cooldown=0,
                                patience=5,
                                min_lr=0.5e-6)

callbacks = [lr_reducer, lr_scheduler]

# Create the model
def resnet_layer(inputs,
                 num_filters=16,
                 kernel_size=3,
                 strides=1,
                 activation='relu',
                 batch_normalization=True,
                 conv_first=True):
    """2D Convolution-Batch Normalization-Activation stack builder
    # Arguments
        inputs (tensor): input tensor from input image or previous layer
        num_filters (int): Conv2D number of filters
        kernel_size (int): Conv2D square kernel dimensions
        strides (int): Conv2D square stride dimensions
        activation (string): activation name
        batch_normalization (bool): whether to include batch normalization
        conv_first (bool): conv-bn-activation (True) or
            bn-activation-conv (False)
    # Returns
        x (tensor): tensor as input to the next layer
    """
    conv = Conv2D(num_filters,
                  kernel_size=kernel_size,
                  strides=strides,
                  padding='same',
                  kernel_initializer='he_normal',
                  kernel_regularizer=l2(1e-4))

    x = inputs
    if conv_first:
        x = conv(x)
        if batch_normalization:
            x = BatchNormalization()(x)
        if activation is not None:
            x = Activation(activation)(x)

```

```

    else:
        if batch_normalization:
            x = BatchNormalization()(x)
        if activation is not None:
            x = Activation(activation)(x)
        x = conv(x)
    return x

num_filters_in = 16
num_res_blocks = int((depth - 2) / 9)

inputs = Input(shape=input_shape)

x = resnet_layer(inputs=inputs,
                 num_filters=num_filters_in,
                 conv_first=True)

for stage in range(3):
    for res_block in range(num_res_blocks):
        activation = 'relu'
        batch_normalization = True
        strides = 1
        if stage == 0:
            num_filters_out = num_filters_in * 4
            if res_block == 0: # first layer and first stage
                activation = None
                batch_normalization = False
        else:
            num_filters_out = num_filters_in * 2
            if res_block == 0: # first layer but not first stage
                strides = 2 # downsample

        # bottleneck residual unit
        y = resnet_layer(inputs=x,
                        num_filters=num_filters_in,
                        kernel_size=1,
                        strides=strides,
                        activation=activation,
                        batch_normalization=batch_normalization,
                        conv_first=False)
        y = Dropout(0.2)(y)

        y = resnet_layer(inputs=y,
                        num_filters=num_filters_in,
                        conv_first=False)
        y = Dropout(0.2)(y)

```

```

y = resnet_layer(inputs=y,
                  num_filters=num_filters_out,
                  kernel_size=1,
                  conv_first=False)
y = Dropout(0.2)(y)

if res_block == 0:
    # linear projection residual shortcut connection to match
    # changed dims
    x = resnet_layer(inputs=x,
                      num_filters=num_filters_out,
                      kernel_size=1,
                      strides=strides,
                      activation=None,
                      batch_normalization=False)

    x = keras.layers.add([x, y])

    num_filters_in = num_filters_out
    # Customizing last layers of the ResNet Model
    # Add classifier on top
    x = BatchNormalization()(x)
    x = Activation('relu')(x)
    # x = AveragePooling2D(pool_size=8)(x)
    x = MaxPooling2D(pool_size=8)(x)
    y = Flatten()(x)
    y = Dense(1024, activation='relu', kernel_constraint=maxnorm(3))(y)
    y = Dropout(0.2)(y)
    y = Dense(512, activation='relu', kernel_constraint=maxnorm(3))(y)
    y = Dropout(0.2)(y)

outputs = Dense(num_classes,
                 activation='softmax',
                 kernel_initializer='he_normal')(y)

model = Model(inputs=inputs, outputs=outputs)

model.compile(loss='categorical_crossentropy',
              optimizer=Adam(lr=lr_schedule(0)),
              metrics=['accuracy'])
model.summary()

# Run training, with or without data augmentation.
if not data_augmentation:
    print('Not using data augmentation.')
    model.fit(x_train, y_train,
              batch_size=batch_size,
              epochs=epochs,

```

```

        validation_data=(x_test, y_test),
        shuffle=True,
        callbacks=callbacks)

else:
    print('Using real-time data augmentation.')
    # This will do preprocessing and realtime data augmentation:
    datagen = ImageDataGenerator(
        # set input mean to 0 over the dataset
        featurewise_center=False,
        # set each sample mean to 0
        samplewise_center=False,
        # divide inputs by std of dataset
        featurewise_std_normalization=False,
        # divide each input by its std
        samplewise_std_normalization=False,
        # apply ZCA whitening
        zca_whitening=False,
        # epsilon for ZCA whitening
        zca_epsilon=1e-06,
        # randomly rotate images in the range (deg 0 to 180)
        rotation_range=0,
        # randomly shift images horizontally
        width_shift_range=0.1,
        # randomly shift images vertically
        height_shift_range=0.1,
        # set range for random shear
        shear_range=0.,
        # set range for random zoom
        zoom_range=0.,
        # set range for random channel shifts
        channel_shift_range=0.,
        # set mode for filling points outside the input boundaries
        fill_mode='nearest',
        # value used for fill_mode = "constant"
        cval=0.,
        # randomly flip images
        horizontal_flip=True,
        # randomly flip images
        vertical_flip=False,
        # set rescaling factor (applied before any other transformation)
        rescale=None,
        # set function that will be applied on each input
        preprocessing_function=None,
        # image data format, either "channels_first" or "channels_last"
        data_format=None,
        # fraction of images reserved for validation (strictly between 0 and 1)
        validation_split=0.0)

```



```

# Compute quantities required for featurewise normalization
# (std, mean, and principal components if ZCA whitening is applied).
datagen.fit(x_train)

# Fit the model on the batches generated by datagen.flow().
model.fit_generator(datagen.flow(x_train, y_train, batch_size=batch_size),
                    validation_data=(x_test, y_test),
                    epochs=epochs, verbose=1, workers=4, steps_per_epoch=1000,
                    callbacks=callbacks)

# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

```

```

x_train shape: (50000, 3, 32, 32)
50000 train samples
10000 test samples
y_train shape: (50000, 1)
Learning rate: 0.001

```

Layer (type)	Output Shape	Param #	Connected to
input_7 (InputLayer)	(None, 3, 32, 32)	0	
conv2d_177 (Conv2D)	(None, 16, 32, 32)	448	input_7[0][0]
batch_normalization_151 (Batch Normalization)	(None, 16, 32, 32)	128	conv2d_177[0][0]
activation_151 (Activation)	(None, 16, 32, 32)	0	batch_normalization_151[0][0]
conv2d_178 (Conv2D)	(None, 16, 32, 32)	272	activation_151[0][0]
dropout_9 (Dropout)	(None, 16, 32, 32)	0	conv2d_178[0][0]
batch_normalization_152 (Batch Normalization)	(None, 16, 32, 32)	128	dropout_9[0][0]
activation_152 (Activation)	(None, 16, 32, 32)	0	batch_normalization_152[0][0]
conv2d_179 (Conv2D)	(None, 16, 32, 32)	2320	activation_152[0][0]
dropout_10 (Dropout)	(None, 16, 32, 32)	0	conv2d_179[0][0]
batch_normalization_153 (Batch Normalization)	(None, 16, 32, 32)	128	dropout_10[0][0]
activation_153 (Activation)	(None, 16, 32, 32)	0	batch_normalization_153[0][0]
conv2d_180 (Conv2D)	(None, 64, 32, 32)	1088	activation_153[0][0]

conv2d_181 (Conv2D)	(None, 64, 32, 32)	1088	activation_151[0][0]
dropout_11 (Dropout)	(None, 64, 32, 32)	0	conv2d_180[0][0]
add_49 (Add)	(None, 64, 32, 32)	0	conv2d_181[0][0] dropout_11[0][0]
batch_normalization_154 (BatchN	(None, 64, 32, 32)	128	add_49[0][0]
activation_154 (Activation)	(None, 64, 32, 32)	0	batch_normalization_154[0][0]
conv2d_182 (Conv2D)	(None, 16, 32, 32)	1040	activation_154[0][0]
dropout_12 (Dropout)	(None, 16, 32, 32)	0	conv2d_182[0][0]
batch_normalization_155 (BatchN	(None, 16, 32, 32)	128	dropout_12[0][0]
activation_155 (Activation)	(None, 16, 32, 32)	0	batch_normalization_155[0][0]
conv2d_183 (Conv2D)	(None, 16, 32, 32)	2320	activation_155[0][0]
dropout_13 (Dropout)	(None, 16, 32, 32)	0	conv2d_183[0][0]
batch_normalization_156 (BatchN	(None, 16, 32, 32)	128	dropout_13[0][0]
activation_156 (Activation)	(None, 16, 32, 32)	0	batch_normalization_156[0][0]
conv2d_184 (Conv2D)	(None, 64, 32, 32)	1088	activation_156[0][0]
dropout_14 (Dropout)	(None, 64, 32, 32)	0	conv2d_184[0][0]
add_50 (Add)	(None, 64, 32, 32)	0	add_49[0][0] dropout_14[0][0]
batch_normalization_157 (BatchN	(None, 64, 32, 32)	128	add_50[0][0]
activation_157 (Activation)	(None, 64, 32, 32)	0	batch_normalization_157[0][0]
conv2d_185 (Conv2D)	(None, 16, 32, 32)	1040	activation_157[0][0]
dropout_15 (Dropout)	(None, 16, 32, 32)	0	conv2d_185[0][0]
batch_normalization_158 (BatchN	(None, 16, 32, 32)	128	dropout_15[0][0]
activation_158 (Activation)	(None, 16, 32, 32)	0	batch_normalization_158[0][0]
conv2d_186 (Conv2D)	(None, 16, 32, 32)	2320	activation_158[0][0]

dropout_16 (Dropout)	(None, 16, 32, 32)	0	conv2d_186[0][0]
batch_normalization_159 (BatchN	(None, 16, 32, 32)	128	dropout_16[0][0]
activation_159 (Activation)	(None, 16, 32, 32)	0	batch_normalization_159[0][0]
conv2d_187 (Conv2D)	(None, 64, 32, 32)	1088	activation_159[0][0]
dropout_17 (Dropout)	(None, 64, 32, 32)	0	conv2d_187[0][0]
add_51 (Add)	(None, 64, 32, 32)	0	add_50[0][0] dropout_17[0][0]
batch_normalization_160 (BatchN	(None, 64, 32, 32)	128	add_51[0][0]
activation_160 (Activation)	(None, 64, 32, 32)	0	batch_normalization_160[0][0]
conv2d_188 (Conv2D)	(None, 64, 16, 16)	4160	activation_160[0][0]
dropout_18 (Dropout)	(None, 64, 16, 16)	0	conv2d_188[0][0]
batch_normalization_161 (BatchN	(None, 64, 16, 16)	64	dropout_18[0][0]
activation_161 (Activation)	(None, 64, 16, 16)	0	batch_normalization_161[0][0]
conv2d_189 (Conv2D)	(None, 64, 16, 16)	36928	activation_161[0][0]
dropout_19 (Dropout)	(None, 64, 16, 16)	0	conv2d_189[0][0]
batch_normalization_162 (BatchN	(None, 64, 16, 16)	64	dropout_19[0][0]
activation_162 (Activation)	(None, 64, 16, 16)	0	batch_normalization_162[0][0]
conv2d_190 (Conv2D)	(None, 128, 16, 16)	8320	activation_162[0][0]
conv2d_191 (Conv2D)	(None, 128, 16, 16)	8320	add_51[0][0]
dropout_20 (Dropout)	(None, 128, 16, 16)	0	conv2d_190[0][0]
add_52 (Add)	(None, 128, 16, 16)	0	conv2d_191[0][0] dropout_20[0][0]
batch_normalization_163 (BatchN	(None, 128, 16, 16)	64	add_52[0][0]
activation_163 (Activation)	(None, 128, 16, 16)	0	batch_normalization_163[0][0]
conv2d_192 (Conv2D)	(None, 64, 16, 16)	8256	activation_163[0][0]

dropout_21 (Dropout)	(None, 64, 16, 16)	0	conv2d_192[0][0]
batch_normalization_164 (BatchN	(None, 64, 16, 16)	64	dropout_21[0][0]
activation_164 (Activation)	(None, 64, 16, 16)	0	batch_normalization_164[0][0]
conv2d_193 (Conv2D)	(None, 64, 16, 16)	36928	activation_164[0][0]
dropout_22 (Dropout)	(None, 64, 16, 16)	0	conv2d_193[0][0]
batch_normalization_165 (BatchN	(None, 64, 16, 16)	64	dropout_22[0][0]
activation_165 (Activation)	(None, 64, 16, 16)	0	batch_normalization_165[0][0]
conv2d_194 (Conv2D)	(None, 128, 16, 16)	8320	activation_165[0][0]
dropout_23 (Dropout)	(None, 128, 16, 16)	0	conv2d_194[0][0]
add_53 (Add)	(None, 128, 16, 16)	0	add_52[0][0] dropout_23[0][0]
batch_normalization_166 (BatchN	(None, 128, 16, 16)	64	add_53[0][0]
activation_166 (Activation)	(None, 128, 16, 16)	0	batch_normalization_166[0][0]
conv2d_195 (Conv2D)	(None, 64, 16, 16)	8256	activation_166[0][0]
dropout_24 (Dropout)	(None, 64, 16, 16)	0	conv2d_195[0][0]
batch_normalization_167 (BatchN	(None, 64, 16, 16)	64	dropout_24[0][0]
activation_167 (Activation)	(None, 64, 16, 16)	0	batch_normalization_167[0][0]
conv2d_196 (Conv2D)	(None, 64, 16, 16)	36928	activation_167[0][0]
dropout_25 (Dropout)	(None, 64, 16, 16)	0	conv2d_196[0][0]
batch_normalization_168 (BatchN	(None, 64, 16, 16)	64	dropout_25[0][0]
activation_168 (Activation)	(None, 64, 16, 16)	0	batch_normalization_168[0][0]
conv2d_197 (Conv2D)	(None, 128, 16, 16)	8320	activation_168[0][0]
dropout_26 (Dropout)	(None, 128, 16, 16)	0	conv2d_197[0][0]
add_54 (Add)	(None, 128, 16, 16)	0	add_53[0][0] dropout_26[0][0]

batch_normalization_169 (BatchN	(None, 128, 16, 16)	64	add_54[0][0]
activation_169 (Activation)	(None, 128, 16, 16)	0	batch_normalization_169[0][0]
conv2d_198 (Conv2D)	(None, 128, 8, 8)	16512	activation_169[0][0]
dropout_27 (Dropout)	(None, 128, 8, 8)	0	conv2d_198[0][0]
batch_normalization_170 (BatchN	(None, 128, 8, 8)	32	dropout_27[0][0]
activation_170 (Activation)	(None, 128, 8, 8)	0	batch_normalization_170[0][0]
conv2d_199 (Conv2D)	(None, 128, 8, 8)	147584	activation_170[0][0]
dropout_28 (Dropout)	(None, 128, 8, 8)	0	conv2d_199[0][0]
batch_normalization_171 (BatchN	(None, 128, 8, 8)	32	dropout_28[0][0]
activation_171 (Activation)	(None, 128, 8, 8)	0	batch_normalization_171[0][0]
conv2d_200 (Conv2D)	(None, 256, 8, 8)	33024	activation_171[0][0]
conv2d_201 (Conv2D)	(None, 256, 8, 8)	33024	add_54[0][0]
dropout_29 (Dropout)	(None, 256, 8, 8)	0	conv2d_200[0][0]
add_55 (Add)	(None, 256, 8, 8)	0	conv2d_201[0][0] dropout_29[0][0]
batch_normalization_172 (BatchN	(None, 256, 8, 8)	32	add_55[0][0]
activation_172 (Activation)	(None, 256, 8, 8)	0	batch_normalization_172[0][0]
conv2d_202 (Conv2D)	(None, 128, 8, 8)	32896	activation_172[0][0]
dropout_30 (Dropout)	(None, 128, 8, 8)	0	conv2d_202[0][0]
batch_normalization_173 (BatchN	(None, 128, 8, 8)	32	dropout_30[0][0]
activation_173 (Activation)	(None, 128, 8, 8)	0	batch_normalization_173[0][0]
conv2d_203 (Conv2D)	(None, 128, 8, 8)	147584	activation_173[0][0]
dropout_31 (Dropout)	(None, 128, 8, 8)	0	conv2d_203[0][0]
batch_normalization_174 (BatchN	(None, 128, 8, 8)	32	dropout_31[0][0]
activation_174 (Activation)	(None, 128, 8, 8)	0	batch_normalization_174[0][0]

conv2d_204 (Conv2D)	(None, 256, 8, 8)	33024	activation_174[0][0]
dropout_32 (Dropout)	(None, 256, 8, 8)	0	conv2d_204[0][0]
add_56 (Add)	(None, 256, 8, 8)	0	add_55[0][0] dropout_32[0][0]
batch_normalization_175 (BatchN	(None, 256, 8, 8)	32	add_56[0][0]
activation_175 (Activation)	(None, 256, 8, 8)	0	batch_normalization_175[0][0]
conv2d_205 (Conv2D)	(None, 128, 8, 8)	32896	activation_175[0][0]
dropout_33 (Dropout)	(None, 128, 8, 8)	0	conv2d_205[0][0]
batch_normalization_176 (BatchN	(None, 128, 8, 8)	32	dropout_33[0][0]
activation_176 (Activation)	(None, 128, 8, 8)	0	batch_normalization_176[0][0]
conv2d_206 (Conv2D)	(None, 128, 8, 8)	147584	activation_176[0][0]
dropout_34 (Dropout)	(None, 128, 8, 8)	0	conv2d_206[0][0]
batch_normalization_177 (BatchN	(None, 128, 8, 8)	32	dropout_34[0][0]
activation_177 (Activation)	(None, 128, 8, 8)	0	batch_normalization_177[0][0]
conv2d_207 (Conv2D)	(None, 256, 8, 8)	33024	activation_177[0][0]
dropout_35 (Dropout)	(None, 256, 8, 8)	0	conv2d_207[0][0]
add_57 (Add)	(None, 256, 8, 8)	0	add_56[0][0] dropout_35[0][0]
batch_normalization_178 (BatchN	(None, 256, 8, 8)	32	add_57[0][0]
activation_178 (Activation)	(None, 256, 8, 8)	0	batch_normalization_178[0][0]
max_pooling2d_5 (MaxPooling2D)	(None, 256, 1, 1)	0	activation_178[0][0]
flatten_8 (Flatten)	(None, 256)	0	max_pooling2d_5[0][0]
dense_8 (Dense)	(None, 1024)	263168	flatten_8[0][0]
dropout_36 (Dropout)	(None, 1024)	0	dense_8[0][0]
dense_9 (Dense)	(None, 512)	524800	dropout_36[0][0]

```

-----
dropout_37 (Dropout)                (None, 512)                0                dense_9[0][0]
-----
dense_10 (Dense)                    (None, 10)                  5130             dropout_37[0][0]
=====
Total params: 1,631,242
Trainable params: 1,630,170
Non-trainable params: 1,072
-----
Using real-time data augmentation.
Epoch 1/100
Learning rate: 0.001
1000/1000 [=====] - 336s 336ms/step - loss: 2.1289 - acc: 0.3178 - val_
Epoch 2/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 1.5934 - acc: 0.4890 - val_
Epoch 3/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 1.3653 - acc: 0.5788 - val_
Epoch 4/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 1.2336 - acc: 0.6293 - val_
Epoch 5/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 1.1421 - acc: 0.6629 - val_
Epoch 6/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 1.0715 - acc: 0.6902 - val_
Epoch 7/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 1.0253 - acc: 0.7090 - val_
Epoch 8/100
Learning rate: 0.001
1000/1000 [=====] - 317s 317ms/step - loss: 0.9716 - acc: 0.7282 - val_
Epoch 9/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 0.9310 - acc: 0.7435 - val_
Epoch 10/100
Learning rate: 0.001
1000/1000 [=====] - 317s 317ms/step - loss: 0.8991 - acc: 0.7570 - val_
Epoch 11/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 0.8690 - acc: 0.7673 - val_
Epoch 12/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 0.8423 - acc: 0.7779 - val_
Epoch 13/100
Learning rate: 0.001

```

1000/1000 [=====] - 316s 316ms/step - loss: 0.8247 - acc: 0.7843 - val\_  
 Epoch 14/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.8071 - acc: 0.7907 - val\_  
 Epoch 15/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7902 - acc: 0.7966 - val\_  
 Epoch 16/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7768 - acc: 0.8015 - val\_  
 Epoch 17/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7651 - acc: 0.8066 - val\_  
 Epoch 18/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7568 - acc: 0.8089 - val\_  
 Epoch 19/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7447 - acc: 0.8137 - val\_  
 Epoch 20/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7363 - acc: 0.8176 - val\_  
 Epoch 21/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7275 - acc: 0.8205 - val\_  
 Epoch 22/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7205 - acc: 0.8228 - val\_  
 Epoch 23/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7162 - acc: 0.8244 - val\_  
 Epoch 24/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 316s 316ms/step - loss: 0.7111 - acc: 0.8263 - val\_  
 Epoch 25/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 315s 315ms/step - loss: 0.7067 - acc: 0.8276 - val\_  
 Epoch 26/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 314s 314ms/step - loss: 0.6935 - acc: 0.8329 - val\_  
 Epoch 27/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 315s 315ms/step - loss: 0.6893 - acc: 0.8335 - val\_  
 Epoch 28/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 315s 315ms/step - loss: 0.6863 - acc: 0.8355 - val\_  
 Epoch 29/100  
 Learning rate: 0.001



```

1000/1000 [=====] - 317s 317ms/step - loss: 0.6802 - acc: 0.8359 - val_
Epoch 30/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 0.6757 - acc: 0.8386 - val_
Epoch 31/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 0.6772 - acc: 0.8380 - val_
Epoch 32/100
Learning rate: 0.001
1000/1000 [=====] - 316s 316ms/step - loss: 0.6656 - acc: 0.8407 - val_
Epoch 33/100
Learning rate: 0.001
690/1000 [=====>...] - ETA: 1:35 - loss: 0.6633 - acc: 0.8456

```

```

-----
KeyboardInterrupt                                Traceback (most recent call last)

```

```

<ipython-input-23-34e4b60880fa> in <module>()
    302             validation_data=(x_test, y_test),
    303             epochs=epochs, verbose=1, workers=4, steps_per_epoch=1000,
--> 304             callbacks=callbacks)
    305
    306 # Final evaluation of the model

/usr/local/lib/python3.6/dist-packages/keras/legacy/interfaces.py in wrapper(*args, **kwargs)
    89         warnings.warn('Update your `' + object_name + '` call to the `' +
    90             'Keras 2 API: ' + signature, stacklevel=2)
---> 91         return func(*args, **kwargs)
    92     wrapper._original_function = func
    93     return wrapper

/usr/local/lib/python3.6/dist-packages/keras/engine/training.py in fit_generator(self, generator,
1416         use_multiprocessing=use_multiprocessing,
1417         shuffle=shuffle,
-> 1418         initial_epoch=initial_epoch)
1419
1420     @interfaces.legacy_generator_methods_support

/usr/local/lib/python3.6/dist-packages/keras/engine/training_generator.py in fit_generator
215         outs = model.train_on_batch(x, y,
216             sample_weight=sample_weight,
--> 217             class_weight=class_weight)
218

```

```

219             outs = to_list(outs)

/usr/local/lib/python3.6/dist-packages/keras/engine/training.py in train_on_batch(self,
1215         ins = x + y + sample_weights
1216         self._make_train_function()
-> 1217         outputs = self.train_function(ins)
1218         return unpack_singleton(outputs)
1219

/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py in __call__(self,
2713         return self._legacy_call(inputs)
2714
-> 2715         return self._call(inputs)
2716     else:
2717         if py_any(is_tensor(x) for x in inputs):

/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py in _call(self,
2673         fetched = self._callable_fn(*array_vals, run_metadata=self.run_metadata)
2674     else:
-> 2675         fetched = self._callable_fn(*array_vals)
2676         return fetched[:len(self.outputs)]
2677

/usr/local/lib/python3.6/dist-packages/tensorflow/python/client/session.py in __call__(self,
1437         ret = tf_session.TF_SessionRunCallable(
1438             self._session._session, self._handle, args, status,
-> 1439             run_metadata_ptr)
1440         if run_metadata:
1441             proto_data = tf_session.TF_GetBuffer(run_metadata_ptr)

KeyboardInterrupt:

```

### 1.3.1 Results:

We decided to customize ResNetV2 by adding 2 fully-connected layers combined with a dropout layer. Unfortunately, this customization did not add any benefit to the original implementation. In fact, we found that the performance was worse than the original one. At the 19 epoch the custom model had a validation accuracy of **0.833** while the original one had **0.863** validation accuracy.

3. Evaluate your module using the FERPlus dataset (The model with the best test accuracy will present their solution to the class).

3.1 Download the [FER2013 dataset](#) (images\_path).

3.2 Download the [FERPlus labels](#) (labels\_path).

3.3 Use the following code snippet to load the dataset giving the appropriate paths to the csv files downloaded in 3.1 and 3.2:

## 1.4 FERPlus dataset collection

```
In [0]: class FERPlus(object):
        """Class for loading FER2013 [1] emotion classification dataset with
        the FERPlus labels [2]:
        [1] kaggle.com/c/challenges-in-representation-learning-facial-
            expression-recognition-challenge
        [2] github.com/Microsoft/FERPlu://github.com/Microsoft/FERPlus"""

        def __init__(self, images_path, labels_path, split='train', image_size=(48, 48),
                      dataset_name='FERPlus'):

            self.split = split
            self.image_size = image_size
            self.dataset_name = dataset_name
            self.images_path = images_path
            self.labels_path = labels_path
            self.class_names = ['neutral', 'happiness', 'surprise', 'sadness',
                                'anger', 'disgust', 'fear', 'contempt']
            self.num_classes = len(self.class_names)
            self.arg_to_name = dict(zip(range(self.num_classes), self.class_names))
            self.name_to_arg = dict(zip(self.class_names, range(self.num_classes)))
            self._split_to_filter = {
                'train': 'Training', 'val': 'PublicTest', 'test': 'PrivateTest'}

        def load_data(self):
            filter_name = self._split_to_filter[self.split]
            pixel_sequences = pd.read_csv(self.images_path)
            pixel_sequences = pixel_sequences[pixel_sequences.Usage == filter_name]
            pixel_sequences = pixel_sequences['pixels'].tolist()
            faces = []
            for pixel_sequence in pixel_sequences:
                face = [float(pixel) for pixel in pixel_sequence.split(' ')]
                face = np.asarray(face).reshape(48, 48)
                faces.append(cv2.resize(face, self.image_size))
            faces = np.asarray(faces)
            faces = np.expand_dims(faces, -1)

            emotions = pd.read_csv(self.labels_path)
            emotions = emotions[emotions.Usage == filter_name]
            emotions = emotions.iloc[:, 2:10].values
            N = np.sum(emotions, axis=1)
            mask = N != 0
            N, faces, emotions = N[mask], faces[mask], emotions[mask]
```

```

        emotions = emotions / np.expand_dims(N, 1)
    return faces, emotions

```

## 1.5 Customized ResNetv2 implementation for FERPlus dataset

```

In [0]: import time
import matplotlib.pyplot as plt
import numpy as np
from keras.models import Sequential
from keras.layers import Dropout
from keras.layers import AveragePooling2D, Input, Flatten
from keras.layers import Convolution2D
from keras.constraints import maxnorm
from keras.optimizers import SGD
from keras.optimizers import Adam
from keras.callbacks import ModelCheckpoint, LearningRateScheduler
from keras.callbacks import ReduceLROnPlateau
from keras.regularizers import l2
from keras.preprocessing.image import ImageDataGenerator
from keras.layers.convolutional import MaxPooling2D
from keras.layers import GlobalAveragePooling2D
from keras.layers import Dense, Conv2D, BatchNormalization, Activation
import keras.utils
import cv2
from keras.models import Model
from keras import backend as K
import tensorflow as tf
import multiprocessing as mp
import seaborn as sn
import pandas as pd
from sklearn.metrics import classification_report, confusion_matrix

# Training parameters
batch_size = 128 # orig paper trained all networks with batch_size=128
epochs = 100
data_augmentation = True

n = 3
depth = n * 9 + 2

FER_Data = FERPlus('drive/My Drive/Colab Notebooks/FERPlus_data/fer2013/fer2013.csv', \
                   'drive/My Drive/Colab Notebooks/FERPlus_data/FERPlus/fer2013new.csv', \
x_train, y_train = FER_Data.load_data()
FER_Data = FERPlus('drive/My Drive/Colab Notebooks/FERPlus_data/fer2013/fer2013.csv', \
                   'drive/My Drive/Colab Notebooks/FERPlus_data/FERPlus/fer2013new.csv', \
x_test, y_test = FER_Data.load_data()
print(x_train.shape)
print(x_test.shape)

```

```

print(FER_Data.num_classes)
num_classes = FER_Data.num_classes

#----- Preprocessing -----
# Input image dimensions.
input_shape = x_train.shape[1:]

# Normalize data.
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# Subtract mean
x_train_mean = np.mean(x_train, axis=0)
x_train -= x_train_mean
x_test -= x_train_mean

print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
print('y_train shape:', y_train.shape)

# ----- Callbacks functions -----
def lr_schedule(epoch):
    """Learning Rate Schedule
    Learning rate is scheduled to be reduced after 80, 120, 160, 180 epochs.
    Called automatically every epoch as part of callbacks during training.
    # Arguments
        epoch (int): The number of epochs
    # Returns
        lr (float32): learning rate
    """
    lr = 1e-3
    if epoch > 180:
        lr *= 0.5e-3
    elif epoch > 160:
        lr *= 1e-3
    elif epoch > 120:
        lr *= 1e-2
    elif epoch > 80:
        lr *= 1e-1
    print('Learning rate: ', lr)
    return lr

lr_scheduler = LearningRateScheduler(lr_schedule)

lr_reducer = ReduceLROnPlateau(factor=np.sqrt(0.1),
                               cooldown=0,
                               patience=5,

```

```

min_lr=0.5e-6)

callbacks = [lr_reducer, lr_scheduler]

# Create the model
def resnet_layer(inputs,
                 num_filters=16,
                 kernel_size=3,
                 strides=1,
                 activation='relu',
                 batch_normalization=True,
                 conv_first=True):
    """2D Convolution-Batch Normalization-Activation stack builder
    # Arguments
        inputs (tensor): input tensor from input image or previous layer
        num_filters (int): Conv2D number of filters
        kernel_size (int): Conv2D square kernel dimensions
        strides (int): Conv2D square stride dimensions
        activation (string): activation name
        batch_normalization (bool): whether to include batch normalization
        conv_first (bool): conv-bn-activation (True) or
            bn-activation-conv (False)
    # Returns
        x (tensor): tensor as input to the next layer
    """
    conv = Conv2D(num_filters,
                  kernel_size=kernel_size,
                  strides=strides,
                  padding='same',
                  kernel_initializer='he_normal',
                  kernel_regularizer=l2(1e-4))

    x = inputs
    if conv_first:
        x = conv(x)
        if batch_normalization:
            x = BatchNormalization()(x)
        if activation is not None:
            x = Activation(activation)(x)
    else:
        if batch_normalization:
            x = BatchNormalization()(x)
        if activation is not None:
            x = Activation(activation)(x)
        x = conv(x)
    return x

```

```

num_filters_in = 16
num_res_blocks = int((depth - 2) / 9)

inputs = Input(shape=input_shape)

x = resnet_layer(inputs=inputs,
                  num_filters=num_filters_in,
                  conv_first=True)

for stage in range(3):
    for res_block in range(num_res_blocks):
        activation = 'relu'
        batch_normalization = True
        strides = 1
        if stage == 0:
            num_filters_out = num_filters_in * 4
            if res_block == 0: # first layer and first stage
                activation = None
                batch_normalization = False
        else:
            num_filters_out = num_filters_in * 2
            if res_block == 0: # first layer but not first stage
                strides = 2 # downsample

        # bottleneck residual unit
        y = resnet_layer(inputs=x,
                          num_filters=num_filters_in,
                          kernel_size=1,
                          strides=strides,
                          activation=activation,
                          batch_normalization=batch_normalization,
                          conv_first=False)
        y = Dropout(0.2)(y)

        y = resnet_layer(inputs=y,
                          num_filters=num_filters_in,
                          conv_first=False)
        y = Dropout(0.2)(y)

        y = resnet_layer(inputs=y,
                          num_filters=num_filters_out,
                          kernel_size=1,
                          conv_first=False)
        y = Dropout(0.2)(y)

    if res_block == 0:
        # linear projection residual shortcut connection to match
        # changed dims

```

```

        x = resnet_layer(inputs=x,
                        num_filters=num_filters_out,
                        kernel_size=1,
                        strides=strides,
                        activation=None,
                        batch_normalization=False)

    x = keras.layers.add([x, y])

    num_filters_in = num_filters_out

# Add classifier on top
x = BatchNormalization()(x)
x = Activation('relu')(x)
# x = AveragePooling2D(pool_size=8)(x)
x = MaxPooling2D(pool_size=8)(x)
# y = Flatten()(x)
y = Dense(1024, activation='relu', kernel_constraint=maxnorm(3))(y)
y = Dropout(0.2)(y)
y = Dense(512, activation='relu', kernel_constraint=maxnorm(3))(y)
y = Dropout(0.2)(y)
y = Convolution2D(filters=256, kernel_size=(3, 3), padding='same')(y)
y = AveragePooling2D(pool_size=(2, 2), padding='same')(y)
y = Dropout(0.5)(y)
y = BatchNormalization()(y)
y = Convolution2D(filters=num_classes,
                  kernel_size=(3, 3),
                  padding='same')(y)
y = GlobalAveragePooling2D()(y)
outputs = Activation('softmax', name='predictions')(y)

# outputs = Dense(num_classes,
#                 activation='softmax',
#                 kernel_initializer='he_normal')(y)

model = Model(inputs=inputs, outputs=outputs)

model.compile(loss='categorical_crossentropy',
              optimizer=Adam(lr=lr_schedule(0)),
              metrics=['accuracy'])
model.summary()

# Run training, with or without data augmentation.
if not data_augmentation:
    print('Not using data augmentation.')
    model.fit(x_train, y_train,
              batch_size=batch_size,
              epochs=epochs,

```



```

        validation_data=(x_test, y_test),
        shuffle=True,
        callbacks=callbacks)

else:
    print('Using real-time data augmentation.')
    # This will do preprocessing and realtime data augmentation:
    datagen = ImageDataGenerator(
        # set input mean to 0 over the dataset
        featurewise_center=False,
        # set each sample mean to 0
        samplewise_center=False,
        # divide inputs by std of dataset
        featurewise_std_normalization=False,
        # divide each input by its std
        samplewise_std_normalization=False,
        # apply ZCA whitening
        zca_whitening=False,
        # epsilon for ZCA whitening
        zca_epsilon=1e-06,
        # randomly rotate images in the range (deg 0 to 180)
        rotation_range=0,
        # randomly shift images horizontally
        width_shift_range=0.1,
        # randomly shift images vertically
        height_shift_range=0.1,
        # set range for random shear
        shear_range=0.,
        # set range for random zoom
        zoom_range=0.,
        # set range for random channel shifts
        channel_shift_range=0.,
        # set mode for filling points outside the input boundaries
        fill_mode='nearest',
        # value used for fill_mode = "constant"
        cval=0.,
        # randomly flip images
        horizontal_flip=True,
        # randomly flip images
        vertical_flip=False,
        # set rescaling factor (applied before any other transformation)
        rescale=None,
        # set function that will be applied on each input
        preprocessing_function=None,
        # image data format, either "channels_first" or "channels_last"
        data_format=None,
        # fraction of images reserved for validation (strictly between 0 and 1)
        validation_split=0.0)

```

```

# Compute quantities required for featurewise normalization
# (std, mean, and principal components if ZCA whitening is applied).
datagen.fit(x_train)

# Fit the model on the batches generated by datagen.flow().
model.fit_generator(datagen.flow(x_train, y_train, batch_size=batch_size),
                    validation_data=(x_test, y_test),
                    epochs=epochs, verbose=1, workers=4, steps_per_epoch=1000,
                    callbacks=callbacks)

# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

```

```

(28559, 48, 48, 1)
(3573, 48, 48, 1)
8
x_train shape: (28559, 48, 48, 1)
28559 train samples
3573 test samples
y_train shape: (28559, 8)
Learning rate: 0.001

```

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	(None, 48, 48, 1)	0	
conv2d_34 (Conv2D)	(None, 48, 48, 16)	160	input_2[0][0]
batch_normalization_30 (Batch Normalization)	(None, 48, 48, 16)	64	conv2d_34[0][0]
activation_29 (Activation)	(None, 48, 48, 16)	0	batch_normalization_30[0][0]
conv2d_35 (Conv2D)	(None, 48, 48, 16)	272	activation_29[0][0]
dropout_31 (Dropout)	(None, 48, 48, 16)	0	conv2d_35[0][0]
batch_normalization_31 (Batch Normalization)	(None, 48, 48, 16)	64	dropout_31[0][0]
activation_30 (Activation)	(None, 48, 48, 16)	0	batch_normalization_31[0][0]
conv2d_36 (Conv2D)	(None, 48, 48, 16)	2320	activation_30[0][0]
dropout_32 (Dropout)	(None, 48, 48, 16)	0	conv2d_36[0][0]
batch_normalization_32 (Batch Normalization)	(None, 48, 48, 16)	64	dropout_32[0][0]
activation_31 (Activation)	(None, 48, 48, 16)	0	batch_normalization_32[0][0]

conv2d_37 (Conv2D)	(None, 48, 48, 64)	1088	activation_31[0][0]
conv2d_38 (Conv2D)	(None, 48, 48, 64)	1088	activation_29[0][0]
dropout_33 (Dropout)	(None, 48, 48, 64)	0	conv2d_37[0][0]
add_10 (Add)	(None, 48, 48, 64)	0	conv2d_38[0][0] dropout_33[0][0]
batch_normalization_33 (BatchNo	(None, 48, 48, 64)	256	add_10[0][0]
activation_32 (Activation)	(None, 48, 48, 64)	0	batch_normalization_33[0][0]
conv2d_39 (Conv2D)	(None, 48, 48, 16)	1040	activation_32[0][0]
dropout_34 (Dropout)	(None, 48, 48, 16)	0	conv2d_39[0][0]
batch_normalization_34 (BatchNo	(None, 48, 48, 16)	64	dropout_34[0][0]
activation_33 (Activation)	(None, 48, 48, 16)	0	batch_normalization_34[0][0]
conv2d_40 (Conv2D)	(None, 48, 48, 16)	2320	activation_33[0][0]
dropout_35 (Dropout)	(None, 48, 48, 16)	0	conv2d_40[0][0]
batch_normalization_35 (BatchNo	(None, 48, 48, 16)	64	dropout_35[0][0]
activation_34 (Activation)	(None, 48, 48, 16)	0	batch_normalization_35[0][0]
conv2d_41 (Conv2D)	(None, 48, 48, 64)	1088	activation_34[0][0]
dropout_36 (Dropout)	(None, 48, 48, 64)	0	conv2d_41[0][0]
add_11 (Add)	(None, 48, 48, 64)	0	add_10[0][0] dropout_36[0][0]
batch_normalization_36 (BatchNo	(None, 48, 48, 64)	256	add_11[0][0]
activation_35 (Activation)	(None, 48, 48, 64)	0	batch_normalization_36[0][0]
conv2d_42 (Conv2D)	(None, 48, 48, 16)	1040	activation_35[0][0]
dropout_37 (Dropout)	(None, 48, 48, 16)	0	conv2d_42[0][0]
batch_normalization_37 (BatchNo	(None, 48, 48, 16)	64	dropout_37[0][0]
activation_36 (Activation)	(None, 48, 48, 16)	0	batch_normalization_37[0][0]

conv2d_43 (Conv2D)	(None, 48, 48, 16)	2320	activation_36[0][0]
dropout_38 (Dropout)	(None, 48, 48, 16)	0	conv2d_43[0][0]
batch_normalization_38 (BatchNo	(None, 48, 48, 16)	64	dropout_38[0][0]
activation_37 (Activation)	(None, 48, 48, 16)	0	batch_normalization_38[0][0]
conv2d_44 (Conv2D)	(None, 48, 48, 64)	1088	activation_37[0][0]
dropout_39 (Dropout)	(None, 48, 48, 64)	0	conv2d_44[0][0]
add_12 (Add)	(None, 48, 48, 64)	0	add_11[0][0] dropout_39[0][0]
batch_normalization_39 (BatchNo	(None, 48, 48, 64)	256	add_12[0][0]
activation_38 (Activation)	(None, 48, 48, 64)	0	batch_normalization_39[0][0]
conv2d_45 (Conv2D)	(None, 24, 24, 64)	4160	activation_38[0][0]
dropout_40 (Dropout)	(None, 24, 24, 64)	0	conv2d_45[0][0]
batch_normalization_40 (BatchNo	(None, 24, 24, 64)	256	dropout_40[0][0]
activation_39 (Activation)	(None, 24, 24, 64)	0	batch_normalization_40[0][0]
conv2d_46 (Conv2D)	(None, 24, 24, 64)	36928	activation_39[0][0]
dropout_41 (Dropout)	(None, 24, 24, 64)	0	conv2d_46[0][0]
batch_normalization_41 (BatchNo	(None, 24, 24, 64)	256	dropout_41[0][0]
activation_40 (Activation)	(None, 24, 24, 64)	0	batch_normalization_41[0][0]
conv2d_47 (Conv2D)	(None, 24, 24, 128)	8320	activation_40[0][0]
conv2d_48 (Conv2D)	(None, 24, 24, 128)	8320	add_12[0][0]
dropout_42 (Dropout)	(None, 24, 24, 128)	0	conv2d_47[0][0]
add_13 (Add)	(None, 24, 24, 128)	0	conv2d_48[0][0] dropout_42[0][0]
batch_normalization_42 (BatchNo	(None, 24, 24, 128)	512	add_13[0][0]
activation_41 (Activation)	(None, 24, 24, 128)	0	batch_normalization_42[0][0]

conv2d_49 (Conv2D)	(None, 24, 24, 64)	8256	activation_41[0][0]
dropout_43 (Dropout)	(None, 24, 24, 64)	0	conv2d_49[0][0]
batch_normalization_43 (Batch Normalization)	(None, 24, 24, 64)	256	dropout_43[0][0]
activation_42 (Activation)	(None, 24, 24, 64)	0	batch_normalization_43[0][0]
conv2d_50 (Conv2D)	(None, 24, 24, 64)	36928	activation_42[0][0]
dropout_44 (Dropout)	(None, 24, 24, 64)	0	conv2d_50[0][0]
batch_normalization_44 (Batch Normalization)	(None, 24, 24, 64)	256	dropout_44[0][0]
activation_43 (Activation)	(None, 24, 24, 64)	0	batch_normalization_44[0][0]
conv2d_51 (Conv2D)	(None, 24, 24, 128)	8320	activation_43[0][0]
dropout_45 (Dropout)	(None, 24, 24, 128)	0	conv2d_51[0][0]
add_14 (Add)	(None, 24, 24, 128)	0	add_13[0][0] dropout_45[0][0]
batch_normalization_45 (Batch Normalization)	(None, 24, 24, 128)	512	add_14[0][0]
activation_44 (Activation)	(None, 24, 24, 128)	0	batch_normalization_45[0][0]
conv2d_52 (Conv2D)	(None, 24, 24, 64)	8256	activation_44[0][0]
dropout_46 (Dropout)	(None, 24, 24, 64)	0	conv2d_52[0][0]
batch_normalization_46 (Batch Normalization)	(None, 24, 24, 64)	256	dropout_46[0][0]
activation_45 (Activation)	(None, 24, 24, 64)	0	batch_normalization_46[0][0]
conv2d_53 (Conv2D)	(None, 24, 24, 64)	36928	activation_45[0][0]
dropout_47 (Dropout)	(None, 24, 24, 64)	0	conv2d_53[0][0]
batch_normalization_47 (Batch Normalization)	(None, 24, 24, 64)	256	dropout_47[0][0]
activation_46 (Activation)	(None, 24, 24, 64)	0	batch_normalization_47[0][0]
conv2d_54 (Conv2D)	(None, 24, 24, 128)	8320	activation_46[0][0]
dropout_48 (Dropout)	(None, 24, 24, 128)	0	conv2d_54[0][0]

add_15 (Add)	(None, 24, 24, 128)	0	add_14[0][0] dropout_48[0][0]
batch_normalization_48 (BatchNo	(None, 24, 24, 128)	512	add_15[0][0]
activation_47 (Activation)	(None, 24, 24, 128)	0	batch_normalization_48[0][0]
conv2d_55 (Conv2D)	(None, 12, 12, 128)	16512	activation_47[0][0]
dropout_49 (Dropout)	(None, 12, 12, 128)	0	conv2d_55[0][0]
batch_normalization_49 (BatchNo	(None, 12, 12, 128)	512	dropout_49[0][0]
activation_48 (Activation)	(None, 12, 12, 128)	0	batch_normalization_49[0][0]
conv2d_56 (Conv2D)	(None, 12, 12, 128)	147584	activation_48[0][0]
dropout_50 (Dropout)	(None, 12, 12, 128)	0	conv2d_56[0][0]
batch_normalization_50 (BatchNo	(None, 12, 12, 128)	512	dropout_50[0][0]
activation_49 (Activation)	(None, 12, 12, 128)	0	batch_normalization_50[0][0]
conv2d_57 (Conv2D)	(None, 12, 12, 256)	33024	activation_49[0][0]
conv2d_58 (Conv2D)	(None, 12, 12, 256)	33024	add_15[0][0]
dropout_51 (Dropout)	(None, 12, 12, 256)	0	conv2d_57[0][0]
add_16 (Add)	(None, 12, 12, 256)	0	conv2d_58[0][0] dropout_51[0][0]
batch_normalization_51 (BatchNo	(None, 12, 12, 256)	1024	add_16[0][0]
activation_50 (Activation)	(None, 12, 12, 256)	0	batch_normalization_51[0][0]
conv2d_59 (Conv2D)	(None, 12, 12, 128)	32896	activation_50[0][0]
dropout_52 (Dropout)	(None, 12, 12, 128)	0	conv2d_59[0][0]
batch_normalization_52 (BatchNo	(None, 12, 12, 128)	512	dropout_52[0][0]
activation_51 (Activation)	(None, 12, 12, 128)	0	batch_normalization_52[0][0]
conv2d_60 (Conv2D)	(None, 12, 12, 128)	147584	activation_51[0][0]
dropout_53 (Dropout)	(None, 12, 12, 128)	0	conv2d_60[0][0]

batch_normalization_53 (BatchNo	(None, 12, 12, 128)	512	dropout_53[0][0]
activation_52 (Activation)	(None, 12, 12, 128)	0	batch_normalization_53[0][0]
conv2d_61 (Conv2D)	(None, 12, 12, 256)	33024	activation_52[0][0]
dropout_54 (Dropout)	(None, 12, 12, 256)	0	conv2d_61[0][0]
add_17 (Add)	(None, 12, 12, 256)	0	add_16[0][0] dropout_54[0][0]
batch_normalization_54 (BatchNo	(None, 12, 12, 256)	1024	add_17[0][0]
activation_53 (Activation)	(None, 12, 12, 256)	0	batch_normalization_54[0][0]
conv2d_62 (Conv2D)	(None, 12, 12, 128)	32896	activation_53[0][0]
dropout_55 (Dropout)	(None, 12, 12, 128)	0	conv2d_62[0][0]
batch_normalization_55 (BatchNo	(None, 12, 12, 128)	512	dropout_55[0][0]
activation_54 (Activation)	(None, 12, 12, 128)	0	batch_normalization_55[0][0]
conv2d_63 (Conv2D)	(None, 12, 12, 128)	147584	activation_54[0][0]
dropout_56 (Dropout)	(None, 12, 12, 128)	0	conv2d_63[0][0]
batch_normalization_56 (BatchNo	(None, 12, 12, 128)	512	dropout_56[0][0]
activation_55 (Activation)	(None, 12, 12, 128)	0	batch_normalization_56[0][0]
conv2d_64 (Conv2D)	(None, 12, 12, 256)	33024	activation_55[0][0]
dropout_57 (Dropout)	(None, 12, 12, 256)	0	conv2d_64[0][0]
dense_3 (Dense)	(None, 12, 12, 1024)	263168	dropout_57[0][0]
dropout_58 (Dropout)	(None, 12, 12, 1024)	0	dense_3[0][0]
dense_4 (Dense)	(None, 12, 12, 512)	524800	dropout_58[0][0]
dropout_59 (Dropout)	(None, 12, 12, 512)	0	dense_4[0][0]
conv2d_65 (Conv2D)	(None, 12, 12, 256)	1179904	dropout_59[0][0]
average_pooling2d_2 (AveragePoo	(None, 6, 6, 256)	0	conv2d_65[0][0]
dropout_60 (Dropout)	(None, 6, 6, 256)	0	average_pooling2d_2[0][0]

```

-----
batch_normalization_58 (BatchNo (None, 6, 6, 256)    1024      dropout_60[0][0]
-----
conv2d_66 (Conv2D)                (None, 6, 6, 8)    18440     batch_normalization_58[0][0]
-----
global_average_pooling2d_2 (Glo (None, 8)        0         conv2d_66[0][0]
-----
predictions (Activation)          (None, 8)          0         global_average_pooling2d_2[0][0]
=====

```

```

Total params: 2,832,456
Trainable params: 2,827,240
Non-trainable params: 5,216

```

```

-----
Using real-time data augmentation.

```

```

Epoch 1/100
Learning rate: 0.001
1000/1000 [=====] - 611s 611ms/step - loss: 1.7608 - acc: 0.5300 - val_
Epoch 2/100
Learning rate: 0.001
1000/1000 [=====] - 589s 589ms/step - loss: 1.3438 - acc: 0.6810 - val_
Epoch 3/100
Learning rate: 0.001
1000/1000 [=====] - 590s 590ms/step - loss: 1.2275 - acc: 0.7197 - val_
Epoch 4/100
Learning rate: 0.001
1000/1000 [=====] - 592s 592ms/step - loss: 1.1718 - acc: 0.7379 - val_
Epoch 5/100
Learning rate: 0.001
1000/1000 [=====] - 588s 588ms/step - loss: 1.1333 - acc: 0.7525 - val_
Epoch 6/100
Learning rate: 0.001
1000/1000 [=====] - 592s 592ms/step - loss: 1.1130 - acc: 0.7596 - val_
Epoch 7/100
Learning rate: 0.001
1000/1000 [=====] - 591s 591ms/step - loss: 1.0920 - acc: 0.7663 - val_
Epoch 8/100
Learning rate: 0.001
1000/1000 [=====] - 589s 589ms/step - loss: 1.0797 - acc: 0.7706 - val_
Epoch 9/100
Learning rate: 0.001
1000/1000 [=====] - 592s 592ms/step - loss: 1.0689 - acc: 0.7753 - val_
Epoch 10/100
Learning rate: 0.001
1000/1000 [=====] - 590s 590ms/step - loss: 1.0608 - acc: 0.7792 - val_
Epoch 11/100
Learning rate: 0.001
1000/1000 [=====] - 589s 589ms/step - loss: 1.0532 - acc: 0.7817 - val_
Epoch 12/100

```



Learning rate: 0.001  
 1000/1000 [=====] - 592s 592ms/step - loss: 1.0514 - acc: 0.7818 - val\_  
 Epoch 13/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 587s 587ms/step - loss: 1.0457 - acc: 0.7844 - val\_  
 Epoch 14/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 594s 594ms/step - loss: 1.0402 - acc: 0.7888 - val\_  
 Epoch 15/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 593s 593ms/step - loss: 1.0362 - acc: 0.7889 - val\_  
 Epoch 16/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 593s 593ms/step - loss: 1.0344 - acc: 0.7906 - val\_  
 Epoch 17/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 593s 593ms/step - loss: 1.0296 - acc: 0.7926 - val\_  
 Epoch 18/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 593s 593ms/step - loss: 1.0276 - acc: 0.7929 - val\_  
 Epoch 19/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 591s 591ms/step - loss: 1.0237 - acc: 0.7955 - val\_  
 Epoch 20/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 593s 593ms/step - loss: 1.0238 - acc: 0.7960 - val\_  
 Epoch 21/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 592s 592ms/step - loss: 1.0193 - acc: 0.7967 - val\_  
 Epoch 22/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 593s 593ms/step - loss: 1.0200 - acc: 0.7969 - val\_  
 Epoch 23/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 591s 591ms/step - loss: 1.0173 - acc: 0.7984 - val\_  
 Epoch 24/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 593s 593ms/step - loss: 1.0148 - acc: 0.7996 - val\_  
 Epoch 25/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 592s 592ms/step - loss: 1.0129 - acc: 0.8000 - val\_  
 Epoch 26/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 592s 592ms/step - loss: 1.0136 - acc: 0.7983 - val\_  
 Epoch 27/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 589s 589ms/step - loss: 1.0105 - acc: 0.8000 - val\_  
 Epoch 28/100

Learning rate: 0.001  
 1000/1000 [=====] - 593s 593ms/step - loss: 1.0083 - acc: 0.8018 - val\_  
 Epoch 29/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 589s 589ms/step - loss: 1.0066 - acc: 0.8030 - val\_  
 Epoch 30/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 591s 591ms/step - loss: 1.0071 - acc: 0.8006 - val\_  
 Epoch 31/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 588s 588ms/step - loss: 1.0066 - acc: 0.8028 - val\_  
 Epoch 32/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 590s 590ms/step - loss: 1.0035 - acc: 0.8036 - val\_  
 Epoch 33/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 588s 588ms/step - loss: 1.0012 - acc: 0.8051 - val\_  
 Epoch 34/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 590s 590ms/step - loss: 0.9998 - acc: 0.8041 - val\_  
 Epoch 35/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 590s 590ms/step - loss: 0.9979 - acc: 0.8052 - val\_  
 Epoch 36/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 590s 590ms/step - loss: 0.9974 - acc: 0.8067 - val\_  
 Epoch 37/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 590s 590ms/step - loss: 0.9967 - acc: 0.8059 - val\_  
 Epoch 38/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 589s 589ms/step - loss: 0.9978 - acc: 0.8059 - val\_  
 Epoch 39/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 589s 589ms/step - loss: 0.9951 - acc: 0.8068 - val\_  
 Epoch 40/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9938 - acc: 0.8076 - val\_  
 Epoch 41/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9953 - acc: 0.8051 - val\_  
 Epoch 42/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9919 - acc: 0.8084 - val\_  
 Epoch 43/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9909 - acc: 0.8082 - val\_  
 Epoch 44/100

Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9900 - acc: 0.8090 - val\_  
 Epoch 45/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9896 - acc: 0.8088 - val\_  
 Epoch 46/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 585s 585ms/step - loss: 0.9906 - acc: 0.8088 - val\_  
 Epoch 47/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9886 - acc: 0.8080 - val\_  
 Epoch 48/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9864 - acc: 0.8105 - val\_  
 Epoch 49/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9875 - acc: 0.8103 - val\_  
 Epoch 50/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 585s 585ms/step - loss: 0.9827 - acc: 0.8108 - val\_  
 Epoch 51/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9837 - acc: 0.8108 - val\_  
 Epoch 52/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 585s 585ms/step - loss: 0.9837 - acc: 0.8093 - val\_  
 Epoch 53/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9824 - acc: 0.8121 - val\_  
 Epoch 54/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 585s 585ms/step - loss: 0.9812 - acc: 0.8108 - val\_  
 Epoch 55/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 585s 585ms/step - loss: 0.9824 - acc: 0.8109 - val\_  
 Epoch 56/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 587s 587ms/step - loss: 0.9796 - acc: 0.8133 - val\_  
 Epoch 57/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9798 - acc: 0.8113 - val\_  
 Epoch 58/100  
 Learning rate: 0.001  
 1000/1000 [=====] - 586s 586ms/step - loss: 0.9814 - acc: 0.8126 - val\_  
 Epoch 59/100  
 Learning rate: 0.001  
 665/1000 [=====>...] - ETA: 3:15 - loss: 0.9764 - acc: 0.8147

## 1.6 Results:

For the FERPlus dataset we wanted to explore a completely new and different architecture. Therefore, we added a sequence of the following layers: \* Fully-connected \* Dropout \* Fully-connected \* Dropout \* Convolution \* AveragePooling \* Dropout \* Batch normalization \* Convolution \* GlobalAveragePooling

The results obtained using this "frankenstein" architecture were better than what we were expecting. We obtained a validation accuracy of **0.803** at the 48 epoch.

We are not fully-aware of the effect of having convolutional layers after fully-connected layers had during the learning process. We were just trying something different that what it is normally done.

## 2 Conclusion

### 2.1 Models

- InceptionV3
- ResNetV1
- ResNetV2

### 2.2 Hyperparameters

- Dense layer size
- Dropout probability
- Number of fixed layers
- Learning rate
- decay schedule
- batch size
- epochs

### 2.3 Network architecture description:

We have used ResNetv2 as our base model. The number of convolutional and batch normalization layers and also the number of filters in each of the convolutional layers has been taken the resnet paper [1][5].

We have convolutional filter of size  $3 \times 3$  as described in the VGG paper [2]. Since stacking two  $3 \times 3$  convolutional gives the same receptive field as a single  $5 \times 5$  with lesser number of parameters to train.

We have also used Global average pooling layer instead of the fully connected layer as described in the "Network inside Network"[3] as it enforces correspondance between feature maps and categories and is less prone to overfitting and hence does not require aggressive dropout mechanism. For the global average pooling to work we need to have as many filters as the number of classes. Hence the final convolutional layer has 10 filters.

This worked well for FER dataset. For CIFAR, we got better results when using the fully connected layer rather than the global pooling. We have used three fully connected layer to avoid the computational bottleneck which would be the case if only layer were used. This has been followed from Inception v2 paper [4].

## 2.4 Reference:

- [1] He, Kaiming et al. "Deep Residual Learning for Image Recognition." 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016): 770-778.
- [2] Min Lin et al. "Network In Network", arxiv 2013
- [3] Simonyan et al. "Very Deep Convolutional Networks for Large-Scale Image Recognition ", International Conference on Learning Representations 2015
- [4] Rethinking the Inception Architecture for Computer Vision
- [5] ResNet implementation acquired from [https://github.com/keras-team/keras/blob/master/examples/cifar10\\_resnet.py](https://github.com/keras-team/keras/blob/master/examples/cifar10_resnet.py)