Cifar10 Image Classification

May 1, 2020

0.1 Dataset Reading and Visulization

```
[1]: import matplotlib.pyplot as plt
     from keras.datasets import cifar10
     import numpy as np
     import time
     import cv2
     import pandas as pd
     from typing import Tuple, Callable
     import matplotlib.pyplot as plt
     import keras
     from keras.utils import to_categorical
     from keras import layers
     from keras import models
     from keras import regularizers
     from keras.applications.vgg16 import VGG16
     from keras.applications.resnet import ResNet50
     from keras.engine.training import Model
     import functools
     import os
     import numpy as np
```

Using TensorFlow backend.

```
[3]: (X_train, y_train), (X_test, y_test) = cifar10.load_data()
num_classes=len(np.unique(y_train))
y_train=y_train.reshape(-1)
y_test=y_test.reshape(-1)
Classes={0:'airplane',1:'automobile',2:'bird',3:'cat',4:'deer',5:'dog',6:
    →'frog',7:'horse',8:'ship',9:'truck'}
```

cifar-10 dataset consists of 50000 training images of digits and 10000 testing images. The dataset consists of 32323 rgb images.

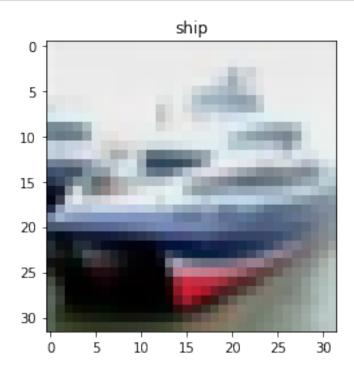
```
[4]: print('Training Dataset shape:',X_train.shape)
print('Training labels shape:',y_train.shape)
```

```
print('Testing Dataset shape:',X_test.shape)
print('Testing labels shape:',y_test.shape)

print('Unique Labels:',np.unique(y_train))

Training Dataset shape: (50000, 32, 32, 3)
Training labels shape: (50000,)
Testing Dataset shape: (10000, 32, 32, 3)
Testing labels shape: (10000,)
Unique Labels: [0 1 2 3 4 5 6 7 8 9]

[5]: # Visulizing Dataset one example.
plt.imshow(X_test[1])
plt.title(Classes[y_test[1]]);
```



Visualizing first 40 images from training dataset and their labels.

```
[6]: plt.figure(figsize=(14,80))
for i in range (0,40):
    plt.subplot(40,10,i+1)
    img1=X_train[i]
    plt.imshow(img1)
    plt.title(Classes[y_train[i]])
    plt.axis('off')
plt.show()
```



```
[7]: train_X=X_train
    test_X=X_test

    print('X_train shape:',train_X.shape)
    print('X_test shape:',test_X.shape)

X_train shape: (50000, 32, 32, 3)
X_test shape: (10000, 32, 32, 3)

[8]: train_y=to_categorical(y_train,num_classes)
    test_y=to_categorical(y_test,num_classes)

    print('y_train shape:',train_y.shape)
    print('y_test shape:',test_y.shape)

y_train shape: (50000, 10)
    y_test shape: (10000, 10)
```

0.2 Classification Method:

0.2.1 VGG:

```
[9]: def VGG_16(num_classes,img_size=(32,32,3)):
    initial_model: Model = VGG16(include_top=False,
    →weights=None,input_shape=img_size)

x = layers.Flatten()(initial_model.output)
x = layers.Dense(256, activation='relu')(x)
```

```
predictions = layers.Dense(num_classes, activation='softmax')(x)

model = Model(initial_model.input, predictions)
model.compile(loss='categorical_crossentropy', optimizer='adam',__

metrics=['acc'])
return model
```

```
[10]: VGG_model=VGG_16(num_classes,img_size=(32,32,3))
VGG_model.summary()
```

 $\label{lem:warning:tensorflow:from C:\Users\afaq.ahmad\.conda\envs\tf_gpu\lib\site-packages\keras\backend\tensorflow_backend.py:4070: The name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.$

Model: "model_1"

| Layer (type) | Output Shape | Param # |
|----------------------------|---------------------|---------|
| input_1 (InputLayer) | (None, 32, 32, 3) | 0 |
| block1_conv1 (Conv2D) | (None, 32, 32, 64) | 1792 |
| block1_conv2 (Conv2D) | (None, 32, 32, 64) | 36928 |
| block1_pool (MaxPooling2D) | (None, 16, 16, 64) | 0 |
| block2_conv1 (Conv2D) | (None, 16, 16, 128) | 73856 |
| block2_conv2 (Conv2D) | (None, 16, 16, 128) | 147584 |
| block2_pool (MaxPooling2D) | (None, 8, 8, 128) | 0 |
| block3_conv1 (Conv2D) | (None, 8, 8, 256) | 295168 |
| block3_conv2 (Conv2D) | (None, 8, 8, 256) | 590080 |
| block3_conv3 (Conv2D) | (None, 8, 8, 256) | 590080 |
| block3_pool (MaxPooling2D) | (None, 4, 4, 256) | 0 |
| block4_conv1 (Conv2D) | (None, 4, 4, 512) | 1180160 |
| block4_conv2 (Conv2D) | (None, 4, 4, 512) | 2359808 |
| block4_conv3 (Conv2D) | (None, 4, 4, 512) | 2359808 |
| block4_pool (MaxPooling2D) | (None, 2, 2, 512) | 0 |

```
block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808

block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808

block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808

block5_pool (MaxPooling2D) (None, 1, 1, 512) 0

flatten_1 (Flatten) (None, 512) 0

dense_1 (Dense) (None, 256) 131328

dense_2 (Dense) (None, 10) 2570
```

Total params: 14,848,586
Trainable params: 14,848,586
Non trainable params: 0

Non-trainable params: 0

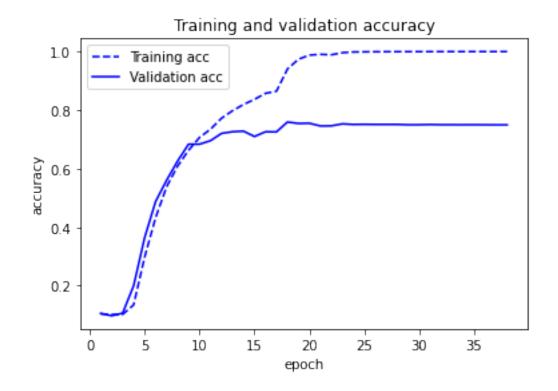
```
[13]: history_vgg = VGG_model.fit(train_X,train_y,batch_size=128,epochs = 200,callbacks=get_callbacks_list(),validation_split=0.1)
```

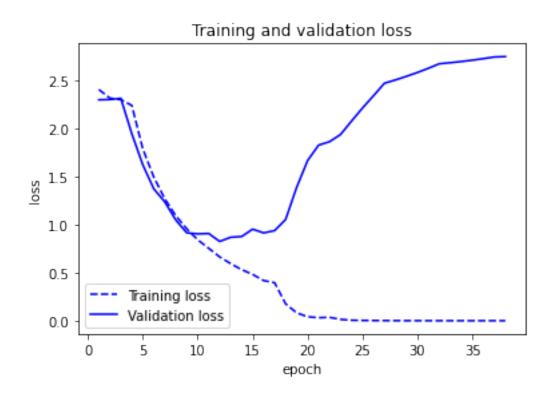
WARNING:tensorflow:From C:\Users\afaq.ahmad\.conda\envs\tf_gpu\lib\site-packages\keras\backend\tensorflow_backend.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

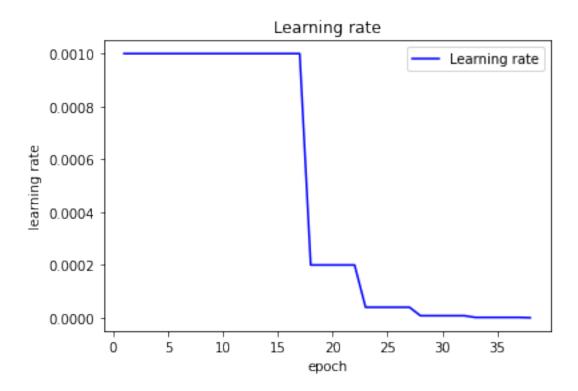
```
acc: 0.2976 - val_loss: 1.6247 - val_acc: 0.3642
Epoch 6/200
45000/45000 [============== ] - 54s 1ms/step - loss: 1.4971 -
acc: 0.4327 - val_loss: 1.3739 - val_acc: 0.4878
Epoch 7/200
45000/45000 [============== ] - 54s 1ms/step - loss: 1.2704 -
acc: 0.5380 - val_loss: 1.2387 - val_acc: 0.5602
Epoch 8/200
acc: 0.6087 - val_loss: 1.0503 - val_acc: 0.6258
Epoch 9/200
acc: 0.6625 - val_loss: 0.9165 - val_acc: 0.6836
Epoch 10/200
45000/45000 [============== ] - 57s 1ms/step - loss: 0.8435 -
acc: 0.7068 - val_loss: 0.9054 - val_acc: 0.6836
Epoch 11/200
acc: 0.7347 - val_loss: 0.9092 - val_acc: 0.6956
Epoch 12/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.6654 -
acc: 0.7721 - val_loss: 0.8264 - val_acc: 0.7204
Epoch 13/200
acc: 0.7978 - val_loss: 0.8701 - val_acc: 0.7262
Epoch 14/200
acc: 0.8191 - val_loss: 0.8775 - val_acc: 0.7280
45000/45000 [============== ] - 54s 1ms/step - loss: 0.4834 -
acc: 0.8367 - val_loss: 0.9546 - val_acc: 0.7098
Epoch 16/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.4192 -
acc: 0.8572 - val_loss: 0.9153 - val_acc: 0.7260
Epoch 17/200
45000/45000 [=============== ] - 54s 1ms/step - loss: 0.3967 -
acc: 0.8645 - val loss: 0.9393 - val acc: 0.7256
Epoch 18/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.1773 -
acc: 0.9403 - val_loss: 1.0546 - val_acc: 0.7592
Epoch 19/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.0833 -
acc: 0.9736 - val_loss: 1.3879 - val_acc: 0.7544
Epoch 20/200
acc: 0.9879 - val_loss: 1.6679 - val_acc: 0.7550
Epoch 21/200
```

```
acc: 0.9904 - val_loss: 1.8288 - val_acc: 0.7458
Epoch 22/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.0368 -
acc: 0.9889 - val_loss: 1.8648 - val_acc: 0.7462
Epoch 23/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.0151 -
acc: 0.9961 - val_loss: 1.9392 - val_acc: 0.7530
Epoch 24/200
acc: 0.9985 - val_loss: 2.0793 - val_acc: 0.7510
Epoch 25/200
acc: 0.9990 - val_loss: 2.2155 - val_acc: 0.7514
Epoch 26/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.0034 -
acc: 0.9993 - val_loss: 2.3429 - val_acc: 0.7510
Epoch 27/200
acc: 0.9995 - val_loss: 2.4738 - val_acc: 0.7510
Epoch 28/200
acc: 0.9996 - val_loss: 2.5077 - val_acc: 0.7510
Epoch 29/200
45000/45000 [=============== ] - 54s 1ms/step - loss: 0.0017 -
acc: 0.9996 - val_loss: 2.5452 - val_acc: 0.7498
Epoch 30/200
acc: 0.9997 - val_loss: 2.5853 - val_acc: 0.7500
45000/45000 [============== ] - 54s 1ms/step - loss: 0.0014 -
acc: 0.9998 - val_loss: 2.6291 - val_acc: 0.7506
Epoch 32/200
acc: 0.9998 - val_loss: 2.6763 - val_acc: 0.7500
Epoch 33/200
acc: 0.9998 - val loss: 2.6872 - val acc: 0.7500
Epoch 34/200
45000/45000 [=============== ] - 54s 1ms/step - loss: 0.0011 -
acc: 0.9998 - val_loss: 2.6996 - val_acc: 0.7498
Epoch 35/200
acc: 0.9998 - val_loss: 2.7133 - val_acc: 0.7500
Epoch 36/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.0011 -
acc: 0.9999 - val_loss: 2.7295 - val_acc: 0.7498
Epoch 37/200
45000/45000 [============== ] - 54s 1ms/step - loss: 0.0010 -
```

```
acc: 0.9999 - val_loss: 2.7469 - val_acc: 0.7496
     Epoch 38/200
     acc: 0.9999 - val_loss: 2.7509 - val_acc: 0.7496
[14]: def draw_training_info_plots(_history):
         """Draw loss graphs at the training and validation stage"""
         acc = _history.history['acc']
         val acc = history.history['val acc']
         loss = _history.history['loss']
         val_loss = _history.history['val_loss']
         epochs_plot = range(1, len(acc) + 1)
         plt.plot(epochs_plot, acc, 'b--', label='Training acc')
         plt.plot(epochs_plot, val_acc, 'b', label='Validation acc')
         plt.title('Training and validation accuracy')
         plt.xlabel('epoch')
         plt.ylabel('accuracy')
         plt.legend()
         plt.figure()
         plt.plot(epochs_plot, loss, 'b--', label='Training loss')
         plt.plot(epochs_plot, val_loss, 'b', label='Validation loss')
         plt.title('Training and validation loss')
         plt.xlabel('epoch')
         plt.ylabel('loss')
         plt.legend()
         plt.show()
         if 'lr' in _history.history:
             learning_rate = _history.history['lr']
             plt.plot(epochs_plot, learning_rate, 'b', label='Learning_rate')
             plt.title('Learning rate')
             plt.xlabel('epoch')
             plt.ylabel('learning rate')
             plt.legend()
             plt.show()
         return
     draw_training_info_plots(history_vgg)
```







```
[15]: print('Accuracy:',VGG_model.evaluate(test_X,test_y,verbose=0)[1])
```

Accuracy: 0.7437999844551086

Classification Score and Confusion Metric

```
[16]: predictions = VGG_model.predict(test_X)

from sklearn.metrics import classification_report
  print("EVALUATION ON TESTING DATA")
  print(classification_report(y_test, np.argmax(predictions,axis=1)))
```

EVALUATION ON TESTING DATA

| | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| | | | | |
| 0 | 0.76 | 0.79 | 0.77 | 1000 |
| 1 | 0.88 | 0.88 | 0.88 | 1000 |
| 2 | 0.64 | 0.63 | 0.63 | 1000 |
| 3 | 0.52 | 0.59 | 0.55 | 1000 |
| 4 | 0.72 | 0.66 | 0.69 | 1000 |
| 5 | 0.63 | 0.67 | 0.65 | 1000 |
| 6 | 0.82 | 0.80 | 0.81 | 1000 |
| 7 | 0.79 | 0.77 | 0.78 | 1000 |
| 8 | 0.86 | 0.83 | 0.85 | 1000 |
| 9 | 0.86 | 0.82 | 0.84 | 1000 |

```
accuracy 0.74 10000 macro avg 0.75 0.74 0.75 10000 weighted avg 0.75 0.74 0.75 10000
```

Confusion matrix

```
[27]:
                   airplane
                              automobile
                                           bird
                                                              dog
                                                                   frog horse
                                                                                  ship \
                                                  cat
                                                        deer
      airplane
                         790
                                                   26
                                                          16
                                                                 3
                                                                       5
                                                                                     50
                                       13
                                              59
                                                                              17
                                                                 2
      automobile
                                      880
                                                                       6
                                                                               2
                                                                                     29
                          10
                                               1
                                                   10
                                                           1
      bird
                                                   78
                                                                              20
                          67
                                        1
                                             627
                                                          81
                                                                64
                                                                      46
                                                                                     11
      cat
                          23
                                        6
                                              72
                                                  591
                                                          52 167
                                                                      43
                                                                              30
                                                                                     10
      deer
                          18
                                        1
                                              82
                                                   70
                                                         658
                                                                45
                                                                      53
                                                                              67
                                                                                      5
                           6
                                        2
                                                  182
                                                                              42
      dog
                                              44
                                                          33 673
                                                                      10
                                                                                      3
      frog
                           3
                                        3
                                              62
                                                   71
                                                          30
                                                               24
                                                                     795
                                                                               5
                                                                                      3
      horse
                          15
                                        1
                                              23
                                                   52
                                                          43
                                                                75
                                                                       4
                                                                             772
                                                                                      2
                          73
                                                                 5
                                                                               6
      ship
                                       28
                                              14
                                                   21
                                                           1
                                                                                   832
      truck
                          41
                                       65
                                               3
                                                   30
                                                           3
                                                                 6
                                                                       2
                                                                              13
                                                                                    17
```

```
truck
airplane
                 21
automobile
                 59
bird
                  5
                  6
cat
deer
                  1
                  5
dog
frog
                  4
horse
                 13
ship
                 14
truck
                820
```

```
[28]: VGG_model.save('VGG_model_cifar10.h5')
```

0.2.2 Resnet:

```
[29]: def Resnet_50(num_classes,img_size=(32,32,3)):
    initial_model: Model = ResNet50(include_top=False,
    →weights=None,input_shape=img_size)
```

```
x = layers.Flatten()(initial_model.output)
  x = layers.Dense(256, activation='relu')(x)
  predictions = layers.Dense(num_classes, activation='softmax')(x)
  model = Model(initial_model.input, predictions)
  model.compile(loss='categorical_crossentropy', optimizer='adam',__
→metrics=['acc'])
  return model
```

[33]: Resnet_model=Resnet_50(num_classes,img_size=(32,32,3)) Resnet_model.summary()

| Model: "model_3" | | | |
|---|--------------------|---------|-----------------|
| Layer (type) | Output Shape | Param # | Connected to |
| input_3 (InputLayer) | (None, 32, 32, 3) | 0 | |
| conv1_pad (ZeroPadding2D) | (None, 38, 38, 3) | 0 | input_3[0][0] |
| conv1_conv (Conv2D) | (None, 16, 16, 64) | 9472 | conv1_pad[0][0] |
| conv1_conv[0][0] | (None, 16, 16, 64) | 256 | |
| conv1_relu (Activation) | (None, 16, 16, 64) | 0 | conv1_bn[0][0] |
| pool1_pad (ZeroPadding2D) conv1_relu[0][0] | (None, 18, 18, 64) | 0 | |
| pool1_pool (MaxPooling2D) | (None, 8, 8, 64) | 0 | pool1_pad[0][0] |
| conv2_block1_1_conv (Conv2D) pool1_pool[0][0] | (None, 8, 8, 64) | 4160 | |
| conv2_block1_1_conv[0][0] | (None, 8, 8, 64) | 256 | |

| conv2_block1_1_relu (Activation conv2_block1_1_bn[0][0] | (None, 8, 8, 64) | 0 |
|--|-------------------|-------|
| conv2_block1_2_conv (Conv2D) conv2_block1_1_relu[0][0] | (None, 8, 8, 64) | 36928 |
| conv2_block1_2_bn (BatchNormali conv2_block1_2_conv[0][0] | (None, 8, 8, 64) | 256 |
| conv2_block1_2_relu (Activation conv2_block1_2_bn[0][0] | (None, 8, 8, 64) | 0 |
| conv2_block1_0_conv (Conv2D) pool1_pool[0][0] | (None, 8, 8, 256) | 16640 |
| conv2_block1_3_conv (Conv2D) conv2_block1_2_relu[0][0] | (None, 8, 8, 256) | 16640 |
| conv2_block1_0_bn (BatchNormali conv2_block1_0_conv[0][0] | (None, 8, 8, 256) | 1024 |
| conv2_block1_3_bn (BatchNormali conv2_block1_3_conv[0][0] | | 1024 |
| conv2_block1_add (Add) conv2_block1_0_bn[0][0] conv2_block1_3_bn[0][0] | (None, 8, 8, 256) | 0 |
| conv2_block1_out (Activation) conv2_block1_add[0][0] | (None, 8, 8, 256) | 0 |
| conv2_block2_1_conv (Conv2D) conv2_block1_out[0][0] | (None, 8, 8, 64) | 16448 |
| conv2_block2_1_bn (BatchNormali | (None, 8, 8, 64) | 256 |

| conv2_block2_1_conv[0][0] | | | | | |
|---|--------|----|----|------|-------|
| conv2_block2_1_relu (Activation conv2_block2_1_bn[0][0] | (None, | 8, | 8, | 64) | 0 |
| conv2_block2_2_conv (Conv2D) conv2_block2_1_relu[0][0] | (None, | 8, | 8, | 64) | 36928 |
| conv2_block2_2_bn (BatchNormali conv2_block2_2_conv[0][0] | | | | 64) | 256 |
| conv2_block2_2_relu (Activation conv2_block2_2_bn[0][0] | | | | 64) | 0 |
| conv2_block2_3_conv (Conv2D) conv2_block2_2_relu[0][0] | (None, | 8, | 8, | 256) | 16640 |
| conv2_block2_3_bn (BatchNormali conv2_block2_3_conv[0][0] | (None, | 8, | 8, | 256) | 1024 |
| conv2_block2_add (Add) conv2_block1_out[0][0] conv2_block2_3_bn[0][0] | (None, | 8, | 8, | 256) | 0 |
| conv2_block2_out (Activation) conv2_block2_add[0][0] | | | | | 0 |
| conv2_block3_1_conv (Conv2D) conv2_block2_out[0][0] | (None, | 8, | 8, | 64) | 16448 |
| conv2_block3_1_bn (BatchNormali conv2_block3_1_conv[0][0] | (None, | 8, | 8, | 64) | 256 |
| conv2_block3_1_relu (Activation conv2_block3_1_bn[0][0] | (None, | 8, | 8, | 64) | 0 |
| | | | | | |

| conv2_block3_2_conv (Conv2D) conv2_block3_1_relu[0][0] | (None, | 8, | 8, | 64) | 36928 |
|---|--------|----|----|------|-------|
| conv2_block3_2_bn (BatchNormali conv2_block3_2_conv[0][0] | (None, | 8, | 8, | 64) | 256 |
| conv2_block3_2_relu (Activation conv2_block3_2_bn[0][0] | (None, | 8, | 8, | 64) | 0 |
| conv2_block3_3_conv (Conv2D) conv2_block3_2_relu[0][0] | (None, | 8, | 8, | 256) | 16640 |
| conv2_block3_3_bn (BatchNormali conv2_block3_3_conv[0][0] | (None, | 8, | 8, | 256) | 1024 |
| conv2_block3_add (Add) conv2_block2_out[0][0] conv2_block3_3_bn[0][0] | (None, | 8, | 8, | 256) | 0 |
| conv2_block3_out (Activation) conv2_block3_add[0][0] | (None, | 8, | 8, | 256) | 0 |
| conv3_block1_1_conv (Conv2D) conv2_block3_out[0][0] | (None, | 4, | 4, | 128) | 32896 |
| conv3_block1_1_bn (BatchNormali conv3_block1_1_conv[0][0] | | | 4, | | 512 |
| conv3_block1_1_relu (Activation conv3_block1_1_bn[0][0] | (None, | 4, | | | 0 |
| conv3_block1_2_conv (Conv2D) conv3_block1_1_relu[0][0] | | | | 128) | |
| conv3_block1_2_bn (BatchNormali conv3_block1_2_conv[0][0] | (None, | 4, | 4, | 128) | 512 |

```
conv3_block1_2_relu (Activation (None, 4, 4, 128)
conv3_block1_2_bn[0][0]
conv3_block1_0_conv (Conv2D) (None, 4, 4, 512) 131584
conv2 block3 out[0][0]
_____
conv3_block1_3_conv (Conv2D) (None, 4, 4, 512) 66048
conv3_block1_2_relu[0][0]
conv3_block1_0_bn (BatchNormali (None, 4, 4, 512)
                                  2048
conv3_block1_0_conv[0][0]
conv3_block1_3_bn (BatchNormali (None, 4, 4, 512)
                                  2048
conv3_block1_3_conv[0][0]
______
conv3_block1_add (Add)
                    (None, 4, 4, 512)
conv3_block1_0_bn[0][0]
conv3_block1_3_bn[0][0]
_____
conv3_block1_out (Activation) (None, 4, 4, 512)
conv3_block1_add[0][0]
______
conv3_block2_1_conv (Conv2D) (None, 4, 4, 128) 65664
conv3_block1_out[0][0]
conv3_block2_1_bn (BatchNormali (None, 4, 4, 128)
conv3_block2_1_conv[0][0]
______
conv3_block2_1_relu (Activation (None, 4, 4, 128)
conv3_block2_1_bn[0][0]
______
conv3_block2_2_conv (Conv2D) (None, 4, 4, 128) 147584
conv3_block2_1_relu[0][0]
______
conv3_block2_2_bn (BatchNormali (None, 4, 4, 128)
                                  512
conv3_block2_2_conv[0][0]
```

| conv3_block2_2_relu (Activation conv3_block2_2_bn[0][0] | (None, 4, 4, 128) | 0 |
|---|-------------------|-------|
| conv3_block2_3_conv (Conv2D) conv3_block2_2_relu[0][0] | (None, 4, 4, 512) | 66048 |
| conv3_block2_3_bn (BatchNormali conv3_block2_3_conv[0][0] | (None, 4, 4, 512) | 2048 |
| conv3_block2_add (Add) conv3_block1_out[0][0] conv3_block2_3_bn[0][0] | (None, 4, 4, 512) | 0 |
| conv3_block2_out (Activation) conv3_block2_add[0][0] | (None, 4, 4, 512) | 0 |
| conv3_block3_1_conv (Conv2D) conv3_block2_out[0][0] | (None, 4, 4, 128) | 65664 |
| conv3_block3_1_bn (BatchNormali conv3_block3_1_conv[0][0] | (None, 4, 4, 128) | 512 |
| conv3_block3_1_relu (Activation conv3_block3_1_bn[0][0] | (None, 4, 4, 128) | 0 |
| conv3_block3_2_conv (Conv2D) conv3_block3_1_relu[0][0] | (None, 4, 4, 128) | |
| conv3_block3_2_bn (BatchNormali conv3_block3_2_conv[0][0] | (None, 4, 4, 128) | 512 |
| conv3_block3_2_relu (Activation conv3_block3_2_bn[0][0] | (None, 4, 4, 128) | 0 |
| conv3_block3_3_conv (Conv2D) | (None, 4, 4, 512) | |

| conv3_block3_2_relu[0][0] | | |
|---|-------------------|--------|
| conv3_block3_3_bn (BatchNormali conv3_block3_3_conv[0][0] | (None, 4, 4, 512) | 2048 |
| conv3_block3_add (Add) conv3_block2_out[0][0] conv3_block3_3_bn[0][0] | (None, 4, 4, 512) | 0 |
| | (None, 4, 4, 512) | 0 |
| conv3_block4_1_conv (Conv2D) conv3_block3_out[0][0] | (None, 4, 4, 128) | 65664 |
| conv3_block4_1_bn (BatchNormali conv3_block4_1_conv[0][0] | (None, 4, 4, 128) | 512 |
| conv3_block4_1_relu (Activation conv3_block4_1_bn[0][0] | (None, 4, 4, 128) | 0 |
| conv3_block4_2_conv (Conv2D) conv3_block4_1_relu[0][0] | (None, 4, 4, 128) | 147584 |
| conv3_block4_2_bn (BatchNormali conv3_block4_2_conv[0][0] | | 512 |
| conv3_block4_2_relu (Activation conv3_block4_2_bn[0][0] | (None, 4, 4, 128) | 0 |
| conv3_block4_3_conv (Conv2D) conv3_block4_2_relu[0][0] | (None, 4, 4, 512) | 66048 |
| conv3_block4_3_bn (BatchNormali conv3_block4_3_conv[0][0] | (None, 4, 4, 512) | 2048 |
| | | |

| conv3_block4_add (Add) conv3_block3_out[0][0] conv3_block4_3_bn[0][0] | (None, | 4, 4, | 512) | 0 |
|---|--------|-------|-------|--------|
| conv3_block4_out (Activation) conv3_block4_add[0][0] | | 4, 4, | 512) | 0 |
| conv4_block1_1_conv (Conv2D) conv3_block4_out[0][0] | (None, | 2, 2, | 256) | 131328 |
| conv4_block1_1_bn (BatchNormali conv4_block1_1_conv[0][0] | (None, | 2, 2, | 256) | 1024 |
| conv4_block1_1_relu (Activation conv4_block1_1_bn[0][0] | (None, | 2, 2, | 256) | 0 |
| conv4_block1_2_conv (Conv2D) conv4_block1_1_relu[0][0] | (None, | 2, 2, | 256) | 590080 |
| conv4_block1_2_bn (BatchNormali conv4_block1_2_conv[0][0] | (None, | 2, 2, | 256) | 1024 |
| conv4_block1_2_relu (Activation conv4_block1_2_bn[0][0] | (None, | 2, 2, | 256) | 0 |
| conv4_block1_0_conv (Conv2D) conv3_block4_out[0][0] | | | 1024) | 525312 |
| conv4_block1_3_conv (Conv2D) conv4_block1_2_relu[0][0] | (None, | 2, 2, | 1024) | 263168 |
| conv4_block1_0_conv[0][0] | (None, | 2, 2, | 1024) | 4096 |
| conv4_block1_3_bn (BatchNormali conv4_block1_3_conv[0][0] | (None, | 2, 2, | 1024) | 4096 |

| conv4_block1_add (Add) conv4_block1_0_bn[0][0] conv4_block1_3_bn[0][0] | (None, 2, 2, 1024) | 0 |
|--|--------------------|--------|
| conv4_block1_add[0][0] | (None, 2, 2, 1024) | 0 |
| conv4_block2_1_conv (Conv2D) conv4_block1_out[0][0] | (None, 2, 2, 256) | 262400 |
| conv4_block2_1_bn (BatchNormali conv4_block2_1_conv[0][0] | (None, 2, 2, 256) | 1024 |
| conv4_block2_1_relu (Activation conv4_block2_1_bn[0][0] | (None, 2, 2, 256) | 0 |
| conv4_block2_2_conv (Conv2D) conv4_block2_1_relu[0][0] | (None, 2, 2, 256) | 590080 |
| conv4_block2_2_conv[0][0] | (None, 2, 2, 256) | 1024 |
| conv4_block2_2_relu (Activation conv4_block2_2_bn[0][0] | (None, 2, 2, 256) | 0 |
| conv4_block2_3_conv (Conv2D) conv4_block2_2_relu[0][0] | (None, 2, 2, 1024) | 263168 |
| conv4_block2_3_bn (BatchNormali conv4_block2_3_conv[0][0] | | 4096 |
| conv4_block2_add (Add) conv4_block1_out[0][0] conv4_block2_3_bn[0][0] | (None, 2, 2, 1024) | 0 |
| conv4_block2_out (Activation) | | 0 |

| conv4_block2_add[0][0] | | | | | |
|---|--------|----|----|-------|--------|
| conv4_block3_1_conv (Conv2D) conv4_block2_out[0][0] | (None, | | | 256) | 262400 |
| conv4_block3_1_bn (BatchNormali conv4_block3_1_conv[0][0] | | | | 256) | 1024 |
| conv4_block3_1_relu (Activation conv4_block3_1_bn[0][0] | | | | | 0 |
| conv4_block3_2_conv (Conv2D) conv4_block3_1_relu[0][0] | (None, | 2, | 2, | 256) | 590080 |
| conv4_block3_2_bn (BatchNormali conv4_block3_2_conv[0][0] | (None, | 2, | 2, | 256) | 1024 |
| conv4_block3_2_relu (Activation conv4_block3_2_bn[0][0] | (None, | 2, | 2, | 256) | 0 |
| conv4_block3_3_conv (Conv2D) conv4_block3_2_relu[0][0] | | | | 1024) | 263168 |
| conv4_block3_3_bn (BatchNormali conv4_block3_3_conv[0][0] | (None, | 2, | 2, | 1024) | 4096 |
| conv4_block3_add (Add) conv4_block2_out[0][0] conv4_block3_3_bn[0][0] | (None, | 2, | 2, | 1024) | 0 |
| conv4_block3_out (Activation) conv4_block3_add[0][0] | | | | 1024) | 0 |
| conv4_block4_1_conv (Conv2D) conv4_block3_out[0][0] | (None, | 2, | 2, | 256) | 262400 |
| | | | | | |

```
conv4_block4_1_bn (BatchNormali (None, 2, 2, 256)
                              1024
conv4_block4_1_conv[0][0]
______
conv4_block4_1_relu (Activation (None, 2, 2, 256)
conv4_block4_1_bn[0][0]
______
conv4_block4_2_conv (Conv2D) (None, 2, 2, 256)
                              590080
conv4_block4_1_relu[0][0]
-----
conv4_block4_2_bn (BatchNormali (None, 2, 2, 256)
conv4_block4_2_conv[0][0]
______
conv4_block4_2_relu (Activation (None, 2, 2, 256)
conv4_block4_2_bn[0][0]
______
conv4_block4_3_conv (Conv2D) (None, 2, 2, 1024)
conv4_block4_2_relu[0][0]
_____
conv4_block4_3_bn (BatchNormali (None, 2, 2, 1024)
conv4_block4_3_conv[0][0]
conv4_block4_add (Add)
                  (None, 2, 2, 1024) 0
conv4_block3_out[0][0]
conv4_block4_3_bn[0][0]
_____
conv4_block4_out (Activation) (None, 2, 2, 1024) 0
conv4 block4 add[0][0]
______
conv4_block5_1_conv (Conv2D) (None, 2, 2, 256) 262400
conv4_block4_out[0][0]
______
conv4_block5_1_bn (BatchNormali (None, 2, 2, 256)
conv4_block5_1_conv[0][0]
conv4_block5_1_relu (Activation (None, 2, 2, 256) 0
conv4_block5_1_bn[0][0]
______
```

| conv4_block5_2_conv (Conv2D) conv4_block5_1_relu[0][0] | (None, 2, 2, 256) | 590080 |
|---|---------------------|--------|
| conv4_block5_2_bn (BatchNormali conv4_block5_2_conv[0][0] | (None, 2, 2, 256) | 1024 |
| conv4_block5_2_relu (Activation conv4_block5_2_bn[0][0] | (None, 2, 2, 256) | 0 |
| conv4_block5_3_conv (Conv2D) conv4_block5_2_relu[0][0] | (None, 2, 2, 1024) | 263168 |
| conv4_block5_3_conv[0][0] | (None, 2, 2, 1024) | 4096 |
| conv4_block5_add (Add) conv4_block4_out[0][0] conv4_block5_3_bn[0][0] | (None, 2, 2, 1024) | 0 |
| conv4_block5_out (Activation) conv4_block5_add[0][0] | (None, 2, 2, 1024) | 0 |
| conv4_block5_out[0][0] | (None, 2, 2, 256) | 262400 |
| conv4_block6_1_bn (BatchNormali conv4_block6_1_conv[0][0] | | 1024 |
| conv4_block6_1_relu (Activation conv4_block6_1_bn[0][0] | (None, 2, 2, 256) | 0 |
| conv4_block6_2_conv (Conv2D) conv4_block6_1_relu[0][0] | (None, 2, 2, 256) | |
| conv4_block6_2_conv[0][0] | . (None, 2, 2, 256) | 1024 |

| conv4_block6_2_relu (Activation conv4_block6_2_bn[0][0] | (None, 2, 2, 256) |) 0 |
|---|-------------------|-----------|
| conv4_block6_3_conv (Conv2D) conv4_block6_2_relu[0][0] | (None, 2, 2, 1024 | 4) 263168 |
| conv4_block6_3_bn (BatchNormali conv4_block6_3_conv[0][0] | (None, 2, 2, 1024 | 4) 4096 |
| conv4_block6_add (Add) conv4_block5_out[0][0] conv4_block6_3_bn[0][0] | (None, 2, 2, 1024 | 1) 0 |
| conv4_block6_out (Activation) conv4_block6_add[0][0] | (None, 2, 2, 1024 | 4) 0 |
| conv5_block1_1_conv (Conv2D) conv4_block6_out[0][0] | (None, 1, 1, 512) |) 524800 |
| conv5_block1_1_bn (BatchNormali conv5_block1_1_conv[0][0] | (None, 1, 1, 512) |) 2048 |
| conv5_block1_1_relu (Activation conv5_block1_1_bn[0][0] | (None, 1, 1, 512) |) 0 |
| conv5_block1_2_conv (Conv2D) conv5_block1_1_relu[0][0] | (None, 1, 1, 512) | |
| conv5_block1_2_bn (BatchNormali conv5_block1_2_conv[0][0] | (None, 1, 1, 512) | |
| conv5_block1_2_relu (Activation conv5_block1_2_bn[0][0] | (None, 1, 1, 512) | |
| conv5_block1_0_conv (Conv2D) | (None, 1, 1, 2048 | |

| conv4_block6_out[0][0] | | |
|--|--------------------|---------|
| conv5_block1_3_conv (Conv2D) conv5_block1_2_relu[0][0] | (None, 1, 1, 2048) | 1050624 |
| conv5_block1_0_bn (BatchNormali conv5_block1_0_conv[0][0] | (None, 1, 1, 2048) | 8192 |
| conv5_block1_3_bn (BatchNormali conv5_block1_3_conv[0][0] | | 8192 |
| conv5_block1_add (Add) conv5_block1_0_bn[0][0] conv5_block1_3_bn[0][0] | (None, 1, 1, 2048) | 0 |
| conv5_block1_out (Activation) conv5_block1_add[0][0] | (None, 1, 1, 2048) | 0 |
| conv5_block2_1_conv (Conv2D) conv5_block1_out[0][0] | (None, 1, 1, 512) | 1049088 |
| conv5_block2_1_bn (BatchNormali conv5_block2_1_conv[0][0] | (None, 1, 1, 512) | 2048 |
| conv5_block2_1_relu (Activation conv5_block2_1_bn[0][0] | | 0 |
| conv5_block2_1_relu[0][0] | (None, 1, 1, 512) | 2359808 |
| conv5_block2_2_bn (BatchNormali conv5_block2_2_conv[0][0] | (None, 1, 1, 512) | 2048 |
| conv5_block2_2_relu (Activation conv5_block2_2_bn[0][0] | (None, 1, 1, 512) | 0 |
| | | |

```
conv5_block2_3_conv (Conv2D) (None, 1, 1, 2048) 1050624
conv5_block2_2_relu[0][0]
conv5_block2_3_bn (BatchNormali (None, 1, 1, 2048)
conv5_block2_3_conv[0][0]
______
_____
conv5_block2_add (Add)
                     (None, 1, 1, 2048) 0
conv5_block1_out[0][0]
conv5_block2_3_bn[0][0]
conv5_block2_out (Activation) (None, 1, 1, 2048) 0
conv5_block2_add[0][0]
conv5_block3_1_conv (Conv2D) (None, 1, 1, 512) 1049088
conv5_block2_out[0][0]
______
conv5_block3_1_bn (BatchNormali (None, 1, 1, 512)
                                   2048
conv5_block3_1_conv[0][0]
______
conv5_block3_1_relu (Activation (None, 1, 1, 512) 0
conv5_block3_1_bn[0][0]
conv5_block3_2_conv (Conv2D) (None, 1, 1, 512)
                                   2359808
conv5_block3_1_relu[0][0]
______
conv5_block3_2_bn (BatchNormali (None, 1, 1, 512)
                                   2048
conv5 block3 2 conv[0][0]
_____
conv5_block3_2_relu (Activation (None, 1, 1, 512) 0
conv5_block3_2_bn[0][0]
______
conv5_block3_3_conv (Conv2D) (None, 1, 1, 2048)
                                  1050624
conv5_block3_2_relu[0][0]
conv5_block3_3_bn (BatchNormali (None, 1, 1, 2048) 8192
conv5_block3_3_conv[0][0]
```

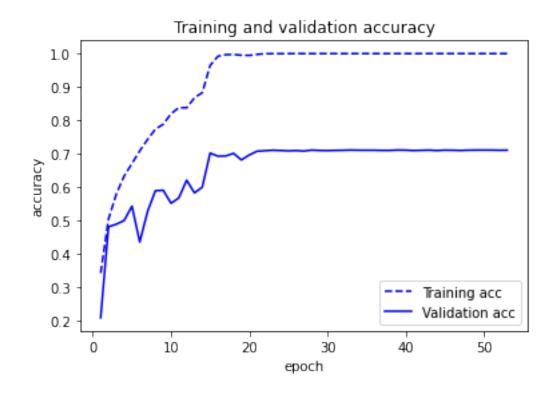
```
(None, 1, 1, 2048) 0
    conv5_block3_add (Add)
    conv5_block2_out[0][0]
    conv5_block3_3_bn[0][0]
    conv5 block3 out (Activation) (None, 1, 1, 2048) 0
    conv5_block3_add[0][0]
    ______
    flatten_3 (Flatten)
                           (None, 2048)
                                      0
    conv5_block3_out[0][0]
                                   ______
    dense_5 (Dense)
                            (None, 256) 524544 flatten_3[0][0]
    _____
    _____
                           (None, 10)
    dense_6 (Dense)
                                            2570 dense_5[0][0]
    ______
    _____
    Total params: 24,114,826
    Trainable params: 24,061,706
    Non-trainable params: 53,120
[34]: def get_callbacks_list():
       """Get callbacks for a model"""
       return [keras.callbacks.EarlyStopping(monitor='val_acc',patience=20),
          keras.callbacks.ReduceLROnPlateau(monitor='val_loss',factor=0.
     \rightarrow2,patience=5)]
[35]: history_resnet = Resnet_model.fit(train_X,train_y,batch_size=256,epochs =___
     →200,callbacks=get_callbacks_list(),validation_split=0.1)
    Train on 45000 samples, validate on 5000 samples
    Epoch 1/200
    45000/45000 [=============== ] - 62s 1ms/step - loss: 1.9366 -
    acc: 0.3421 - val_loss: 2.1362 - val_acc: 0.2084
    acc: 0.5038 - val_loss: 1.4493 - val_acc: 0.4808
    45000/45000 [============== ] - 53s 1ms/step - loss: 1.1794 -
    acc: 0.5789 - val_loss: 1.4986 - val_acc: 0.4886
    Epoch 4/200
    45000/45000 [============= ] - 53s 1ms/step - loss: 1.0378 -
    acc: 0.6325 - val_loss: 1.4795 - val_acc: 0.4996
```

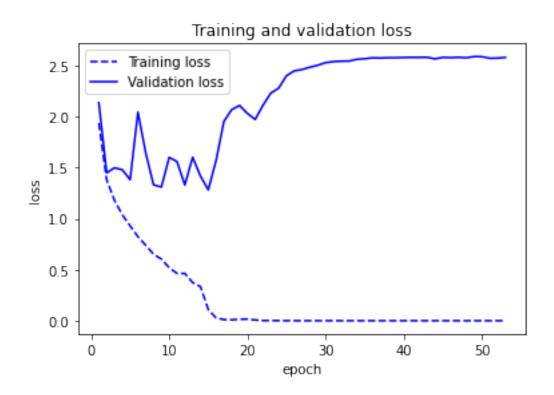
```
Epoch 5/200
45000/45000 [============== ] - 53s 1ms/step - loss: 0.9305 -
acc: 0.6705 - val_loss: 1.3818 - val_acc: 0.5426
Epoch 6/200
45000/45000 [============== ] - 52s 1ms/step - loss: 0.8244 -
acc: 0.7084 - val_loss: 2.0437 - val_acc: 0.4354
Epoch 7/200
acc: 0.7425 - val_loss: 1.6434 - val_acc: 0.5270
Epoch 8/200
acc: 0.7735 - val_loss: 1.3320 - val_acc: 0.5888
Epoch 9/200
45000/45000 [============== ] - 52s 1ms/step - loss: 0.6042 -
acc: 0.7881 - val_loss: 1.3096 - val_acc: 0.5904
Epoch 10/200
45000/45000 [============== ] - 52s 1ms/step - loss: 0.5203 -
acc: 0.8195 - val_loss: 1.6008 - val_acc: 0.5514
Epoch 11/200
45000/45000 [============== ] - 52s 1ms/step - loss: 0.4639 -
acc: 0.8380 - val_loss: 1.5592 - val_acc: 0.5674
Epoch 12/200
45000/45000 [============== ] - 53s 1ms/step - loss: 0.4640 -
acc: 0.8374 - val_loss: 1.3299 - val_acc: 0.6206
Epoch 13/200
acc: 0.8674 - val_loss: 1.6018 - val_acc: 0.5824
Epoch 14/200
45000/45000 [=============== ] - 53s 1ms/step - loss: 0.3349 -
acc: 0.8828 - val_loss: 1.4178 - val_acc: 0.5998
Epoch 15/200
45000/45000 [============== ] - 53s 1ms/step - loss: 0.1106 -
acc: 0.9642 - val_loss: 1.2826 - val_acc: 0.7016
Epoch 16/200
45000/45000 [============== ] - 53s 1ms/step - loss: 0.0281 -
acc: 0.9919 - val_loss: 1.5703 - val_acc: 0.6926
Epoch 17/200
acc: 0.9967 - val_loss: 1.9534 - val_acc: 0.6930
Epoch 18/200
45000/45000 [=============== ] - 53s 1ms/step - loss: 0.0098 -
acc: 0.9972 - val_loss: 2.0684 - val_acc: 0.7010
acc: 0.9950 - val_loss: 2.1089 - val_acc: 0.6812
Epoch 20/200
45000/45000 [=============== ] - 53s 1ms/step - loss: 0.0169 -
acc: 0.9944 - val_loss: 2.0313 - val_acc: 0.6960
```

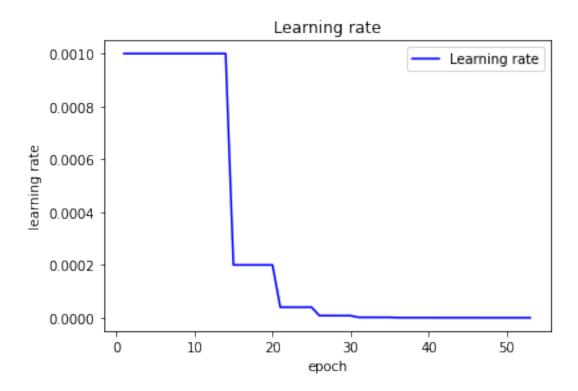
```
Epoch 21/200
45000/45000 [============== ] - 53s 1ms/step - loss: 0.0084 -
acc: 0.9975 - val_loss: 1.9724 - val_acc: 0.7072
Epoch 22/200
45000/45000 [============== ] - 53s 1ms/step - loss: 0.0027 -
acc: 0.9995 - val_loss: 2.1115 - val_acc: 0.7088
Epoch 23/200
acc: 0.9996 - val_loss: 2.2299 - val_acc: 0.7104
Epoch 24/200
acc: 0.9997 - val_loss: 2.2782 - val_acc: 0.7094
Epoch 25/200
45000/45000 [=============== ] - 52s 1ms/step - loss: 0.0014 -
acc: 0.9998 - val_loss: 2.3991 - val_acc: 0.7084
Epoch 26/200
45000/45000 [============== ] - 53s 1ms/step - loss: 0.0012 -
acc: 0.9998 - val_loss: 2.4482 - val_acc: 0.7092
Epoch 27/200
acc: 0.9999 - val_loss: 2.4611 - val_acc: 0.7078
Epoch 28/200
acc: 0.9998 - val_loss: 2.4836 - val_acc: 0.7108
Epoch 29/200
acc: 0.9999 - val_loss: 2.5028 - val_acc: 0.7096
Epoch 30/200
acc: 0.9999 - val_loss: 2.5280 - val_acc: 0.7092
Epoch 31/200
acc: 0.9998 - val_loss: 2.5388 - val_acc: 0.7098
Epoch 32/200
acc: 0.9998 - val_loss: 2.5427 - val_acc: 0.7102
Epoch 33/200
acc: 0.9998 - val_loss: 2.5437 - val_acc: 0.7110
Epoch 34/200
acc: 0.9999 - val_loss: 2.5610 - val_acc: 0.7104
45000/45000 [============== ] - 53s 1ms/step - loss: 7.4927e-04 -
acc: 0.9999 - val_loss: 2.5669 - val_acc: 0.7104
Epoch 36/200
acc: 0.9999 - val_loss: 2.5757 - val_acc: 0.7104
```

```
Epoch 37/200
acc: 0.9998 - val_loss: 2.5738 - val_acc: 0.7098
Epoch 38/200
acc: 0.9999 - val_loss: 2.5766 - val_acc: 0.7098
Epoch 39/200
acc: 0.9999 - val_loss: 2.5768 - val_acc: 0.7110
Epoch 40/200
acc: 0.9999 - val_loss: 2.5791 - val_acc: 0.7106
Epoch 41/200
acc: 0.9998 - val_loss: 2.5801 - val_acc: 0.7094
Epoch 42/200
acc: 0.9998 - val_loss: 2.5799 - val_acc: 0.7100
Epoch 43/200
acc: 0.9999 - val_loss: 2.5809 - val_acc: 0.7108
Epoch 44/200
acc: 0.9999 - val_loss: 2.5657 - val_acc: 0.7094
Epoch 45/200
acc: 0.9999 - val_loss: 2.5800 - val_acc: 0.7106
Epoch 46/200
acc: 0.9998 - val_loss: 2.5773 - val_acc: 0.7104
Epoch 47/200
acc: 0.9999 - val_loss: 2.5805 - val_acc: 0.7096
Epoch 48/200
acc: 0.9999 - val_loss: 2.5765 - val_acc: 0.7104
Epoch 49/200
acc: 0.9998 - val_loss: 2.5878 - val_acc: 0.7108
Epoch 50/200
acc: 0.9999 - val_loss: 2.5868 - val_acc: 0.7108
45000/45000 [============== ] - 53s 1ms/step - loss: 6.5927e-04 -
acc: 0.9999 - val_loss: 2.5712 - val_acc: 0.7108
Epoch 52/200
acc: 0.9999 - val_loss: 2.5727 - val_acc: 0.7102
```

```
Epoch 53/200
     acc: 0.9999 - val_loss: 2.5795 - val_acc: 0.7106
[36]: def draw_training_info_plots(_history):
         """Draw loss graphs at the training and validation stage"""
         acc = _history.history['acc']
         val_acc = _history.history['val_acc']
         loss = _history.history['loss']
         val_loss = _history.history['val_loss']
         epochs_plot = range(1, len(acc) + 1)
         plt.plot(epochs_plot, acc, 'b--', label='Training acc')
         plt.plot(epochs_plot, val_acc, 'b', label='Validation acc')
         plt.title('Training and validation accuracy')
         plt.xlabel('epoch')
         plt.ylabel('accuracy')
         plt.legend()
         plt.figure()
         plt.plot(epochs_plot, loss, 'b--', label='Training loss')
         plt.plot(epochs_plot, val_loss, 'b', label='Validation loss')
         plt.title('Training and validation loss')
         plt.xlabel('epoch')
         plt.ylabel('loss')
         plt.legend()
         plt.show()
         if 'lr' in _history.history:
             learning_rate = _history.history['lr']
             plt.plot(epochs_plot, learning_rate, 'b', label='Learning_rate')
             plt.title('Learning rate')
             plt.xlabel('epoch')
             plt.ylabel('learning rate')
             plt.legend()
             plt.show()
         return
     draw_training_info_plots(history_resnet)
```







```
[37]: print('Accuracy:',Resnet_model.evaluate(test_X,test_y,verbose=0)[1])
```

Accuracy: 0.70169997215271

Classification Score and Confusion Metric

```
[38]: predictions = Resnet_model.predict(test_X)

from sklearn.metrics import classification_report
print("EVALUATION ON TESTING DATA")
print(classification_report(y_test, np.argmax(predictions,axis=1)))
```

EVALUATION ON TESTING DATA

| | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| | | | | |
| 0 | 0.74 | 0.77 | 0.75 | 1000 |
| 1 | 0.79 | 0.82 | 0.81 | 1000 |
| 2 | 0.62 | 0.58 | 0.60 | 1000 |
| 3 | 0.50 | 0.52 | 0.51 | 1000 |
| 4 | 0.65 | 0.66 | 0.65 | 1000 |
| 5 | 0.61 | 0.60 | 0.60 | 1000 |
| 6 | 0.77 | 0.77 | 0.77 | 1000 |
| 7 | 0.74 | 0.75 | 0.74 | 1000 |
| 8 | 0.84 | 0.81 | 0.82 | 1000 |
| 9 | 0.77 | 0.75 | 0.76 | 1000 |

```
macro avg
                          0.70
                                    0.70
                                               0.70
                                                         10000
     weighted avg
                          0.70
                                    0.70
                                               0.70
                                                         10000
[39]: from sklearn.metrics import confusion_matrix
      import pandas as pd
      print ("Confusion matrix")
      pd.DataFrame(confusion_matrix(y_test,np.
       →argmax(predictions,axis=1)),columns=list(np.array(list(Classes.items()))[:
       →,1]),index=list(np.array(list(Classes.items()))[:,1]))
     Confusion matrix
[39]:
                             automobile
                                                                  frog
                                                                        horse
                                                                                ship \
                   airplane
                                          bird
                                                 cat
                                                      deer
                                                             dog
                                                                     6
      airplane
                        765
                                      22
                                             54
                                                  19
                                                        25
                                                              11
                                                                            11
                                                                                  52
                                                               9
                                                                     7
      automobile
                                     816
                                                         3
                                                                             3
                                                                                  31
                         17
                                             13
                                                  11
                         73
      bird
                                       9
                                                  78
                                                        92
                                                              56
                                                                    54
                                                                            35
                                                                                  11
                                            581
      cat
                         24
                                      13
                                             66
                                                 523
                                                        63
                                                             173
                                                                    63
                                                                            46
                                                                                  10
      deer
                         20
                                       5
                                             70
                                                  72
                                                       656
                                                              28
                                                                    51
                                                                            85
                                                                                   7
                         11
                                       7
                                                 197
                                                        45 597
                                                                    27
                                                                                   8
      dog
                                             48
                                                                            51
                                       7
      frog
                          7
                                             48
                                                  61
                                                        46
                                                              40
                                                                   767
                                                                            10
                                                                                   5
      horse
                         19
                                       4
                                             28
                                                  52
                                                        62
                                                              57
                                                                     8
                                                                           748
                                                                                   2
      ship
                         66
                                      35
                                                        12
                                                               7
                                                                     4
                                                                             3
                                             19
                                                  16
                                                                                 811
      truck
                         37
                                     109
                                             14
                                                  15
                                                         5
                                                               7
                                                                    11
                                                                            17
                                                                                  32
                   truck
      airplane
                      35
      automobile
                      90
      bird
                      11
                      19
      cat
      deer
                       6
      dog
                       9
                       9
      frog
      horse
                      20
                      27
      ship
      truck
                     753
[40]:
     Resnet_model.save('Resnet_model_cifar10.h5')
 []:
```

0.70

accuracy

[]: