```
In [1]: # Import libraries
        import os, cv2
        import time
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.utils import shuffle
        from sklearn.model_selection import train_test_split
        from keras.preprocessing import image
        from keras.utils import np utils
        from keras.models import Sequential
        from keras.layers import Input
        from keras.layers.core import Dense, Dropout, Activation, Flatten
        from keras.layers.convolutional import Convolution2D, MaxPooling2D
        from keras import callbacks
        from keras import backend as K
        K.set_image_data_format('channels_last')
        from sklearn.metrics import classification_report,confusion_matrix
        import itertools
        from keras.models import Model
        from tensorflow.keras.applications.resnet import ResNet50
```

Set path for application

```
In [2]: data_path = 'D:/Harold/MyDNN/DataSet/Chest_xray_seperate'
    data_dir_list = os.listdir(data_path)
    print(data_path)
```

D:/Harold/MyDNN/DataSet/Chest_xray_seperate

Set Image Size and Epocs

```
In [3]: img_rows=128
img_cols=128
num_channel=3
num_epoch=100
```

Define the number of classes

```
In [4]: num_classes = 2
   img_data_list=[]
```

```
In [5]: def preprocess_input(x):
            x[:, :, :, 0] = 103.939
            x[:, :, :, 1] = 116.779
            x[:, :, :, 2] = 123.68
            # 'RGB'->'BGR'
            x = x[:, :, :, ::-1]
            return x
        def data preparation():
            for dataset in data dir list:
                img list=os.listdir(data path+'/'+ dataset)
                print ('Loading the images of dataset-'+'{}\n'.format(dataset))
                for img in img list:
                    img path = data path + '/'+ dataset + '/'+ img
                    img = image.load_img(img_path, target_size=(224, 224))
                    x = image.img_to_array(img)
                    x = np.expand dims(x, axis=0)
                    x = preprocess input(x)
                      print('Input image shape:', x.shape)
                    img data list.append(x)
                print('Loading Complete')
              for dataset in data dir list:
                  img list=os.listdir(data path+'/'+ dataset)
                  print ('Loading the images of dataset-'+'{}\n'.format(dataset))
                  for img in img_list:
                      img path = data path + '/'+ dataset + '/'+ img
                      img = image.load_img(img_path, target_size=(224, 224))
                      x = image.img_to_array(img)
                      x = np.expand_dims(x, axis=0)
                      x = preprocess_input(x)
        #
                        print('Input image shape:', x.shape)
        #
                      img data list.append(x)
                  print('Loading Complete')
        def display loss accuracy(hist):
            train loss=hist.history['loss']
            val loss=hist.history['val loss']
            train acc=hist.history['accuracy']
            val acc=hist.history['val accuracy']
            xc=range(num_epoch)
            plt.figure(1, figsize=(7,5))
            plt.plot(xc, train loss)
            plt.plot(xc, val loss)
            plt.xlabel('num of Epochs')
            plt.ylabel('loss')
            plt.title('train loss vs val loss')
            plt.grid(True)
            plt.legend(['train','val'])
            #print plt.style.available # use bmh, classic,ggplot for big pictures
            plt.style.use(['classic'])
            plt.figure(2, figsize=(7,5))
            plt.plot(xc, train_acc)
            plt.plot(xc, val acc)
            plt.xlabel('num of Epochs')
            plt.ylabel('accuracy')
            plt.title('train_acc vs val_acc')
            plt.grid(True)
            plt.legend(['train','val'],loc=4)
            #print plt.style.available # use bmh, classic,ggplot for big pictures
            plt.style.use(['classic'])
```

```
def get featuremaps(model, layer idx, X batch):
    get activations = K.function([model.layers[0].input, K.learning phase()],[mode
1.layers[layer idx].output,])
    activations = get activations([X batch,0])
    return activations
def plot_featuremap_activations(activations):
    print (np.shape(activations))
    feature maps = activations[0][0]
    print (np.shape(feature maps))
   print (feature_maps.shape)
    fig=plt.figure(figsize=(16,16))
    plt.imshow(feature maps[:,:,filter num],cmap='gray')
    plt.savefig("featuremaps-layer-{}".format(layer_num) + "-filternum-{}".format(f
ilter num)+'.jpg')
    num of featuremaps=feature maps.shape[2]
    fig=plt.figure(figsize=(16,16))
    plt.title("featuremaps-layer-{}".format(layer num))
    subplot num=int(np.ceil(np.sqrt(num of featuremaps)))
    for i in range(int(num of featuremaps)):
        ax = fig.add subplot(subplot num, subplot num, i+1)
        \#ax.imshow(output\ image[0,:,:,i],interpolation='nearest')\ \#to\ see\ the\ firs
t filter
        ax.imshow(feature maps[:,:,i],cmap='gray')
        plt.xticks([])
        plt.yticks([])
        plt.tight layout()
    fig.savefig("featuremaps-layer-{}".format(layer num) + '.jpg')
# Plotting the confusion matrix
def plot confusion matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    plt.figure()
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
   plt.colorbar()
   tick_marks = np.arange(len(classes))
    plt.xticks(tick marks, classes, rotation=45)
    plt.yticks(tick marks, classes)
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')
    print(cm)
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
```

```
plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```

Data Preperation

```
In [6]: # Calling Data Preperation
        data preperation()
        Loading the images of dataset-NORMAL
        Loading Complete
        Loading the images of dataset-PNEUMONIA
        Loading Complete
In [7]: print (len(img_data_list))
        img_data = np.array(img_data_list)
        #img_data = img_data.astype('float32')
        print (img_data.shape)
        img data=np.rollaxis(img data,1,0)
        print (img data.shape)
        img_data=img_data[0]
        print (img data.shape)
        5856
        (5856, 1, 224, 224, 3)
        (1, 5856, 224, 224, 3)
        (5856, 224, 224, 3)
```

Assiging Labels

```
In [8]: num_of_samples = img_data.shape[0]
    labels = np.ones((num_of_samples,),dtype='int64')

    labels[0:1582]=0
    labels[1583:5856]=1

    names = ['normal','pneumonia']
```

Creating clasas labels to one-hot encoding

```
In [9]: # convert class labels to on-hot encoding
Y = np_utils.to_categorical(labels, num_classes)
```

Split Data set into training and validation set

```
In [10]: #Shuffle the dataset
    x,y = shuffle(img_data,Y, random_state=2)
    # Split the dataset
    X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=2)
```

Model Definition

Training the classifier alone

```
In [11]: image_input = Input(shape=(224, 224, 3))
    model = ResNet50(input_tensor=image_input, include_top=True, weights='imagenet')
    model.summary()
    last_layer = model.get_layer('avg_pool').output
    x= Flatten(name='flatten')(last_layer)
    out = Dense(num_classes, activation='softmax', name='output_layer')(x)
    custom_resnet_model = Model(inputs=image_input,outputs= out)
    custom_resnet_model.summary()
```

Model: "resnet50"

Layer (type)		Shape		Connected to
input_1 (InputLayer)		, 224, 224, 3)		
conv1_pad (ZeroPadding2D)	(None,	230, 230, 3)	0	input_1[0][0]
conv1_conv (Conv2D)	(None,	112, 112, 64)	9472	conv1_pad[0][0]
conv1_bn (BatchNormalization) [0][0]	(None,	112, 112, 64)	256	conv1_conv
conv1_relu (Activation)	(None,	112, 112, 64)	0	conv1_bn[0][0]
pool1_pad (ZeroPadding2D) [0][0]	(None,	114, 114, 64)	0	conv1_relu
pool1_pool (MaxPooling2D)	(None,	56, 56, 64)	0	pool1_pad[0][0]
conv2_block1_1_conv (Conv2D) [0][0]	(None,	56, 56, 64)	4160	pool1_pool
conv2_block1_1_bn (BatchNormali conv[0][0]	(None,	56, 56, 64)	256	conv2_block1_1_
conv2_block1_1_relu (Activation bn[0][0]	(None,	56, 56, 64)	0	conv2_block1_1_
conv2_block1_2_conv (Conv2D) relu[0][0]	(None,	56, 56, 64)	36928	conv2_block1_1_
conv2_block1_2_bn (BatchNormali conv[0][0]	(None,	56, 56, 64)	256	conv2_block1_2_
conv2_block1_2_relu (Activation bn[0][0]	(None,	56, 56, 64)	0	conv2_block1_2_
conv2_block1_0_conv (Conv2D) [0][0]	(None,	56, 56, 256)	16640	pool1_pool
conv2_block1_3_conv (Conv2D) relu[0][0]	(None,	56, 56, 256)	16640	conv2_block1_2_
conv2_block1_0_bn (BatchNormali conv[0][0]	(None,	56, 56, 256)	1024	conv2_block1_0_

conv2_block1_3_bn (BatchNormali conv[0][0]	(None,	56,	56,	256)	1024	conv2_block1_3_
conv2_block1_add (Add) bn[0][0]	(None,	56,	56,	256)	0	conv2_block1_0_
bn[0][0]						conv2_block1_3_
conv2_block1_out (Activation) d[0][0]	(None,	56,	56,	256)	0	conv2_block1_ad
conv2_block2_1_conv (Conv2D) t[0][0]	(None,	56,	56,	64)	16448	conv2_block1_ou
conv2_block2_1_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block2_1_
conv2_block2_1_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block2_1_
conv2_block2_2_conv (Conv2D) relu[0][0]	(None,	56,	56,	64)	36928	conv2_block2_1_
conv2_block2_2_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block2_2_
conv2_block2_2_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block2_2_
conv2_block2_3_conv (Conv2D) relu[0][0]	(None,	56,	56,	256)	16640	conv2_block2_2_
conv2_block2_3_bn (BatchNormali conv[0][0]	(None,	56,	56,	256)	1024	conv2_block2_3_
conv2_block2_add (Add) t[0][0]	(None,	56,	56,	256)	0	conv2_block1_ou
bn[0][0]						conv2_block2_3_
conv2_block2_out (Activation) d[0][0]	(None,	56,	56,	256)	0	conv2_block2_ad
conv2_block3_1_conv (Conv2D) t[0][0]	(None,	56,	56,	64)	16448	conv2_block2_ou
conv2_block3_1_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block3_1_

conv2_block3_1_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block3_1_
conv2_block3_2_conv (Conv2D) relu[0][0]	(None,	56,	56,	64)	36928	conv2_block3_1_
conv2_block3_2_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block3_2_
conv2_block3_2_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block3_2_
conv2_block3_3_conv (Conv2D) relu[0][0]	(None,	56,	56,	256)	16640	conv2_block3_2_
conv2_block3_3_bn (BatchNormali conv[0][0]	(None,	56,	56,	256)	1024	conv2_block3_3_
conv2_block3_add (Add) t[0][0]	(None,	56,	56,	256)	0	conv2_block2_ou
bn[0][0]						conv2_block3_3_
conv2_block3_out (Activation) d[0][0]	(None,	56,	56,	256)	0	conv2_block3_ad
conv3_block1_1_conv (Conv2D) t[0][0]	(None,	28,	28,	128)	32896	conv2_block3_ou
<pre>conv3_block1_1_bn (BatchNormali conv[0][0]</pre>	(None,	28,	28,	128)	512	conv3_block1_1_
conv3_block1_1_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block1_1_
conv3_block1_2_conv (Conv2D) relu[0][0]	(None,	28,	28,	128)	147584	conv3_block1_1_
<pre>conv3_block1_2_bn (BatchNormali conv[0][0]</pre>	(None,	28,	28,	128)	512	conv3_block1_2_
<pre>conv3_block1_2_relu (Activation bn[0][0]</pre>	(None,	28,	28,	128)	0	conv3_block1_2_
	(None,	28,	28,	512)	131584	conv2_block3_ou

conv3_block1_3_conv (Conv2D) relu[0][0]	(None,	28,	28,	512)	66048	conv3_block1_2_
conv3_block1_0_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block1_0_
conv3_block1_3_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block1_3_
conv3_block1_add (Add) bn[0][0]	(None,	28,	28,	512)	0	conv3_block1_0_
bn[0][0]						conv3_block1_3_
conv3_block1_out (Activation) d[0][0]	(None,	28,	28,	512)	0	conv3_block1_ad
conv3_block2_1_conv (Conv2D) t[0][0]	(None,	28,	28,	128)	65664	conv3_block1_ou
conv3_block2_1_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block2_1_
conv3_block2_1_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block2_1_
conv3_block2_2_conv (Conv2D) relu[0][0]	(None,	28,	28,	128)	147584	conv3_block2_1_
conv3_block2_2_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block2_2_
conv3_block2_2_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block2_2_
conv3_block2_3_conv (Conv2D) relu[0][0]	(None,	28,	28,	512)	66048	conv3_block2_2_
conv3_block2_3_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block2_3_
conv3_block2_add (Add) t[0][0]	(None,	28,	28,	512)	0	conv3_block1_ou
bn[0][0]						conv3_block2_3_
conv3_block2_out (Activation) d[0][0]	(None,	28,	28,	512)	0	conv3_block2_ad

<pre>conv3_block3_1_conv (Conv2D) t[0][0]</pre>	(None,	28,	28,	128)	65664	conv3_block2_ou
conv3_block3_1_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block3_1_
conv3_block3_1_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block3_1_
conv3_block3_2_conv (Conv2D) relu[0][0]	(None,	28,	28,	128)	147584	conv3_block3_1_
conv3_block3_2_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block3_2_
conv3_block3_2_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block3_2_
conv3_block3_3_conv (Conv2D) relu[0][0]	(None,	28,	28,	512)	66048	conv3_block3_2_
conv3_block3_3_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block3_3_
conv3_block3_add (Add) t[0][0]	(None,	28,	28,	512)	0	conv3_block2_ou
bn[0][0]						
conv3_block3_out (Activation) d[0][0]	(None,	28,	28,	512)	0	conv3_block3_ad
conv3_block4_1_conv (Conv2D) t[0][0]	(None,	28,	28,	128)	65664	conv3_block3_ou
conv3_block4_1_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block4_1_
conv3_block4_1_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block4_1_
conv3_block4_2_conv (Conv2D) relu[0][0]	(None,	28,	28,	128)	147584	conv3_block4_1_
conv3_block4_2_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block4_2_
conv3_block4_2_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block4_2_

conv3_block4_3_conv (Conv2D) relu[0][0]	(None,	28,	28,	512)	66048	conv3_block4_2_
conv3_block4_3_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block4_3_
conv3_block4_add (Add) t[0][0]	(None,	28,	28,	512)	0	conv3_block3_ou
bn[0][0]						
conv3_block4_out (Activation) d[0][0]	(None,	28,	28,	512)	0	conv3_block4_ad
conv4_block1_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	131328	conv3_block4_ou
conv4_block1_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block1_1_
conv4_block1_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block1_1_
conv4_block1_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block1_1_
conv4_block1_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block1_2_
conv4_block1_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block1_2_
conv4_block1_0_conv (Conv2D) t[0][0]	(None,	14,	14,	1024)	525312	conv3_block4_ou
conv4_block1_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block1_2_
conv4_block1_0_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block1_0_
conv4_block1_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block1_3_
conv4_block1_add (Add) bn[0][0]	(None,	14,	14,	1024)	0	conv4_block1_0_
bn[0][0]						00111 1 D10011 _ 0 _

conv4_block1_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block1_ad
conv4_block2_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block1_ou
conv4_block2_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block2_1_
conv4_block2_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block2_1_
conv4_block2_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block2_1_
conv4_block2_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block2_2_
conv4_block2_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block2_2_
conv4_block2_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block2_2_
conv4_block2_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block2_3_
conv4_block2_add (Add) t[0][0] bn[0][0]	(None,	14,	14,	1024)	0	conv4_block1_ou
conv4_block2_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block2_ad
conv4_block3_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block2_ou
conv4_block3_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block3_1_
conv4_block3_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block3_1_
conv4_block3_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block3_1_

<pre>conv4_block3_2_bn (BatchNormali conv[0][0]</pre>	(None,	14,	14,	256)	1024	conv4_block3_2_
conv4_block3_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block3_2_
conv4_block3_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block3_2_
conv4_block3_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block3_3_
conv4_block3_add (Add) t[0][0]	(None,	14,	14,	1024)	0	conv4_block2_ou
bn[0][0]						0011 1_010010_0_
conv4_block3_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block3_ad
conv4_block4_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block3_ou
conv4_block4_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block4_1_
conv4_block4_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block4_1_
conv4_block4_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block4_1_
conv4_block4_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block4_2_
conv4_block4_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block4_2_
conv4_block4_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block4_2_
conv4_block4_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block4_3_
conv4_block4_add (Add) t[0][0]	(None,	14,	14,	1024)	0	conv4_block3_ou
bn[0][0]						conv4_block4_3_

<pre>conv4_block4_out (Activation) d[0][0]</pre>	(None,	14,	14,	1024)	0	conv4_block4_ad
conv4_block5_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block4_ou
conv4_block5_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block5_1_
conv4_block5_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block5_1_
conv4_block5_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block5_1_
conv4_block5_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block5_2_
conv4_block5_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block5_2_
conv4_block5_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block5_2_
conv4_block5_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block5_3_
conv4_block5_add (Add) t[0][0]	(None,	14,	14,	1024)	0	conv4_block4_ou
bn[0][0]						conv4_block5_3_
conv4_block5_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block5_ad
conv4_block6_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block5_ou
conv4_block6_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block6_1_
conv4_block6_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block6_1_
conv4_block6_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block6_1_
conv4_block6_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block6_2_

conv4_block6_2_relu (Activation bn[0][0]	(None,	14, 14, 256)	0	conv4_block6_2_
conv4_block6_3_conv (Conv2D) relu[0][0]	(None,	14, 14, 1024)	263168	conv4_block6_2_
conv4_block6_3_bn (BatchNormali conv[0][0]	(None,	14, 14, 1024)	4096	conv4_block6_3_
conv4_block6_add (Add) t[0][0]	(None,	14, 14, 1024)	0	conv4_block5_ou
bn[0][0]				
conv4_block6_out (Activation) d[0][0]	(None,	14, 14, 1024)	0	conv4_block6_ad
conv5_block1_1_conv (Conv2D) t[0][0]	(None,	7, 7, 512)	524800	conv4_block6_ou
conv5_block1_1_bn (BatchNormali conv[0][0]	(None,	7, 7, 512)	2048	conv5_block1_1_
conv5_block1_1_relu (Activation bn[0][0]	(None,	7, 7, 512)	0	conv5_block1_1_
conv5_block1_2_conv (Conv2D) relu[0][0]	(None,	7, 7, 512)	2359808	conv5_block1_1_
conv5_block1_2_bn (BatchNormali conv[0][0]	(None,	7, 7, 512)	2048	conv5_block1_2_
conv5_block1_2_relu (Activation bn[0][0]	(None,	7, 7, 512)	0	conv5_block1_2_
conv5_block1_0_conv (Conv2D) t[0][0]	(None,	7, 7, 2048)	2099200	conv4_block6_ou
conv5_block1_3_conv (Conv2D) relu[0][0]	(None,	7, 7, 2048)	1050624	conv5_block1_2_
conv5_block1_0_bn (BatchNormali conv[0][0]	(None,	7, 7, 2048)	8192	conv5_block1_0_
conv5_block1_3_bn (BatchNormali conv[0][0]	(None,	7, 7, 2048)	8192	conv5_block1_3_

<pre>conv5_block1_add (Add) bn[0][0]</pre>	(None,	7,	7,	2048)	0	conv5_block1_0_
bn[0][0]						conv5_block1_3_
conv5_block1_out (Activation) d[0][0]	(None,	7,	7,	2048)	0	conv5_block1_ad
conv5_block2_1_conv (Conv2D) t[0][0]	(None,	7,	7,	512)	1049088	conv5_block1_ou
conv5_block2_1_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block2_1_
conv5_block2_1_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block2_1_
conv5_block2_2_conv (Conv2D) relu[0][0]	(None,	7,	7,	512)	2359808	conv5_block2_1_
conv5_block2_2_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block2_2_
conv5_block2_2_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block2_2_
conv5_block2_3_conv (Conv2D) relu[0][0]	(None,	7,	7,	2048)	1050624	conv5_block2_2_
conv5_block2_3_bn (BatchNormali conv[0][0]	(None,	7,	7,	2048)	8192	conv5_block2_3_
conv5_block2_add (Add) t[0][0]	(None,	7,	7,	2048)	0	conv5_block1_ou
bn[0][0]						conv5_block2_3_
conv5_block2_out (Activation) d[0][0]	(None,	7,	7,	2048)	0	conv5_block2_ad
conv5_block3_1_conv (Conv2D) t[0][0]	(None,	7,	7,	512)	1049088	conv5_block2_ou
conv5_block3_1_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block3_1_
conv5_block3_1_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block3_1_

conv5_block3_2_conv (Conv2D) relu[0][0]	(None,	7, 7,	512)	2359808	conv5_block3_1_
conv5_block3_2_bn (BatchNormali conv[0][0]	(None,	7, 7,	512)	2048	conv5_block3_2_
conv5_block3_2_relu (Activation bn[0][0]	(None,	7, 7,	512)	0	conv5_block3_2_
conv5_block3_3_conv (Conv2D) relu[0][0]	(None,	7, 7,	2048)	1050624	conv5_block3_2_
conv5_block3_3_bn (BatchNormali conv[0][0]	(None,	7, 7,	2048)	8192	conv5_block3_3_
conv5_block3_add (Add) t[0][0]	(None,	7, 7,	2048)	0	conv5_block2_ou
bn[0][0]					conv5_block3_3_
conv5_block3_out (Activation) d[0][0]	(None,	7, 7,	2048)	0	conv5_block3_ad
avg_pool (GlobalAveragePooling2 t[0][0]	(None,	2048)		0	conv5_block3_ou
predictions (Dense)	(None,	1000)		2049000	avg_pool[0][0]
Total params: 25,636,712 Trainable params: 25,583,592 Non-trainable params: 53,120					
Model: "functional_1"					
Layer (type)	Output	Shape	:=======	Param #	Connected to
input_1 (InputLayer)	[(None	, 224,	224, 3)	0	
conv1_pad (ZeroPadding2D)	(None,	230,	230, 3)	0	input_1[0][0]
conv1_conv (Conv2D)	(None,	112,	112, 64)	9472	conv1_pad[0][0]
conv1_bn (BatchNormalization) [0][0]	(None,	112,	112, 64)	256	conv1_conv
conv1_relu (Activation)	(None,	112,	112, 64)	0	conv1_bn[0][0]

<pre>pool1_pad (ZeroPadding2D) [0][0]</pre>	(None,	114,	, 11	4, 64)	0	conv1_relu
pool1_pool (MaxPooling2D)	(None,	56,	56,	64)	0	pool1_pad[0][0]
conv2_block1_1_conv (Conv2D) [0][0]	(None,	56,	56,	64)	4160	pool1_pool
conv2_block1_1_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block1_1_
conv2_block1_1_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block1_1_
conv2_block1_2_conv (Conv2D) relu[0][0]	(None,	56,	56,	64)	36928	conv2_block1_1_
conv2_block1_2_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block1_2_
conv2_block1_2_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block1_2_
conv2_block1_0_conv (Conv2D) [0][0]	(None,	56,	56,	256)	16640	pool1_pool
conv2_block1_3_conv (Conv2D) relu[0][0]	(None,	56,	56,	256)	16640	conv2_block1_2_
conv2_block1_0_bn (BatchNormali conv[0][0]	(None,	56,	56,	256)	1024	conv2_block1_0_
conv2_block1_3_bn (BatchNormali conv[0][0]	(None,	56,	56,	256)	1024	conv2_block1_3_
conv2_block1_add (Add) bn[0][0]	(None,	56,	56,	256)	0	conv2_block1_0_
bn[0][0]						conv2_block1_3_
conv2_block1_out (Activation) d[0][0]	(None,	56,	56,	256)	0	conv2_block1_ad
conv2_block2_1_conv (Conv2D) t[0][0]	(None,	56,	56,	64)	16448	conv2_block1_ou
conv2_block2_1_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block2_1_

<pre>conv2_block2_1_relu (Activation bn[0][0]</pre>	(None,	56,	56,	64)	0	conv2_block2_1_
conv2_block2_2_conv (Conv2D) relu[0][0]	(None,	56,	56,	64)	36928	conv2_block2_1_
conv2_block2_2_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block2_2_
conv2_block2_2_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block2_2_
conv2_block2_3_conv (Conv2D) relu[0][0]	(None,	56,	56,	256)	16640	conv2_block2_2_
conv2_block2_3_bn (BatchNormali conv[0][0]	(None,	56,	56,	256)	1024	conv2_block2_3_
conv2_block2_add (Add) t[0][0]	(None,	56,	56,	256)	0	conv2_block1_ou
bn[0][0]						
conv2_block2_out (Activation) d[0][0]	(None,	56,	56,	256)	0	conv2_block2_ad
conv2_block3_1_conv (Conv2D) t[0][0]	(None,	56,	56,	64)	16448	conv2_block2_ou
conv2_block3_1_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block3_1_
conv2_block3_1_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block3_1_
conv2_block3_2_conv (Conv2D) relu[0][0]	(None,	56,	56,	64)	36928	conv2_block3_1_
conv2_block3_2_bn (BatchNormali conv[0][0]	(None,	56,	56,	64)	256	conv2_block3_2_
conv2_block3_2_relu (Activation bn[0][0]	(None,	56,	56,	64)	0	conv2_block3_2_
conv2_block3_3_conv (Conv2D) relu[0][0]	(None,	56,	56,	256)	16640	conv2_block3_2_
conv2_block3_3_bn (BatchNormali	(None,	56,	56,	256)	1024	conv2_block3_3_

conv[0][0]						
conv2_block3_add (Add) t[0][0]	(None,	56,	56,	256)	0	conv2_block2_ou
bn[0][0]						conv2_block3_3_
conv2_block3_out (Activation) d[0][0]	(None,	56,	56,	256)	0	conv2_block3_ad
conv3_block1_1_conv (Conv2D) t[0][0]	(None,	28,	28,	128)	32896	conv2_block3_ou
conv3_block1_1_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block1_1_
conv3_block1_1_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block1_1_
conv3_block1_2_conv (Conv2D) relu[0][0]	(None,	28,	28,	128)	147584	conv3_block1_1_
conv3_block1_2_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block1_2_
conv3_block1_2_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block1_2_
conv3_block1_0_conv (Conv2D) t[0][0]	(None,	28,	28,	512)	131584	conv2_block3_ou
conv3_block1_3_conv (Conv2D) relu[0][0]	(None,	28,	28,	512)	66048	conv3_block1_2_
conv3_block1_0_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block1_0_
conv3_block1_3_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block1_3_
conv3_block1_add (Add) bn[0][0]	(None,	28,	28,	512)	0	conv3_block1_0_
bn[0][0]						conv3_block1_3_
conv3_block1_out (Activation) d[0][0]	(None,	28,	28,	512)	0	conv3_block1_ad
conv3_block2_1_conv (Conv2D)	(None,	28,	28,	128)	65664	conv3_block1_ou

-	ΓΛ] [Γ	\cap	٦
L	L۷	١,	L	0	J

conv3_block2_1_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block2_1_
conv3_block2_1_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block2_1_
conv3_block2_2_conv (Conv2D) relu[0][0]	(None,	28,	28,	128)	147584	conv3_block2_1_
conv3_block2_2_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block2_2_
conv3_block2_2_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block2_2_
conv3_block2_3_conv (Conv2D) relu[0][0]	(None,	28,	28,	512)	66048	conv3_block2_2_
conv3_block2_3_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block2_3_
conv3_block2_add (Add) t[0][0] bn[0][0]	(None,	28,	28,	512)	0	conv3_block1_ou
conv3_block2_out (Activation) d[0][0]	(None,	28,	28,	512)	0	conv3_block2_ad
conv3_block3_1_conv (Conv2D) t[0][0]	(None,	28,	28,	128)	65664	conv3_block2_ou
conv3_block3_1_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block3_1_
conv3_block3_1_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block3_1_
conv3_block3_2_conv (Conv2D) relu[0][0]	(None,	28,	28,	128)	147584	conv3_block3_1_
conv3_block3_2_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block3_2_
conv3_block3_2_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block3_2_

conv3_block3_3_conv (Conv2D) relu[0][0]	(None,	28,	28,	512)	66048	conv3_block3_2_
conv3_block3_3_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block3_3_
conv3_block3_add (Add) t[0][0]	(None,	28,	28,	512)	0	conv3_block2_ou
bn[0][0]						001110_5100115_5_
conv3_block3_out (Activation) d[0][0]	(None,	28,	28,	512)	0	conv3_block3_ad
conv3_block4_1_conv (Conv2D) t[0][0]	(None,	28,	28,	128)	65664	conv3_block3_ou
conv3_block4_1_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block4_1_
conv3_block4_1_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block4_1_
conv3_block4_2_conv (Conv2D) relu[0][0]	(None,	28,	28,	128)	147584	conv3_block4_1_
conv3_block4_2_bn (BatchNormali conv[0][0]	(None,	28,	28,	128)	512	conv3_block4_2_
conv3_block4_2_relu (Activation bn[0][0]	(None,	28,	28,	128)	0	conv3_block4_2_
conv3_block4_3_conv (Conv2D) relu[0][0]	(None,	28,	28,	512)	66048	conv3_block4_2_
conv3_block4_3_bn (BatchNormali conv[0][0]	(None,	28,	28,	512)	2048	conv3_block4_3_
conv3_block4_add (Add) t[0][0]	(None,	28,	28,	512)	0	conv3_block3_ou
bn[0][0]						conv3_block4_3_
conv3_block4_out (Activation) d[0][0]	(None,	28,	28,	512)	0	conv3_block4_ad
conv4_block1_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	131328	conv3_block4_ou

<pre>conv4_block1_1_bn (BatchNormali conv[0][0]</pre>	(None,	14,	14,	256)	1024	conv4_block1_1_
conv4_block1_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block1_1_
conv4_block1_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block1_1_
conv4_block1_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block1_2_
conv4_block1_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block1_2_
conv4_block1_0_conv (Conv2D) t[0][0]	(None,	14,	14,	1024)	525312	conv3_block4_ou
conv4_block1_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block1_2_
conv4_block1_0_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block1_0_
conv4_block1_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block1_3_
conv4_block1_add (Add) bn[0][0] bn[0][0]	(None,	14,	14,	1024)	0	conv4_block1_0_ conv4_block1_3_
conv4_block1_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block1_ad
conv4_block2_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block1_ou
conv4_block2_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block2_1_
conv4_block2_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block2_1_
conv4_block2_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block2_1_
conv4_block2_2_bn (BatchNormali	(None,	14,	14,	256)	1024	conv4_block2_2_

conv[0][0]						
conv4_block2_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block2_2_
conv4_block2_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block2_2_
conv4_block2_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block2_3_
conv4_block2_add (Add) t[0][0]	(None,	14,	14,	1024)	0	conv4_block1_ou
bn[0][0]						
conv4_block2_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block2_ad
conv4_block3_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block2_ou
conv4_block3_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block3_1_
conv4_block3_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block3_1_
conv4_block3_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block3_1_
conv4_block3_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block3_2_
conv4_block3_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block3_2_
conv4_block3_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block3_2_
<pre>conv4_block3_3_bn (BatchNormali conv[0][0]</pre>	(None,	14,	14,	1024)	4096	conv4_block3_3_
conv4_block3_add (Add) t[0][0]	(None,	14,	14,	1024)	0	conv4_block2_ou
bn[0][0]						conv4_block3_3_
conv4_block3_out (Activation)	(None,	14,	14,	1024)	0	conv4_block3_ad

٦١	ГΛ	١٦	ГΛ	ר ר
u	0	ч.	[(IJ

conv4_block4_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block3_ou
conv4_block4_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block4_1_
conv4_block4_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block4_1_
conv4_block4_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block4_1_
conv4_block4_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block4_2_
conv4_block4_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block4_2_
conv4_block4_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block4_2_
conv4_block4_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block4_3_
conv4_block4_add (Add) t[0][0] bn[0][0]	(None,	14,	14,	1024)	0	conv4_block3_ou
conv4_block4_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block4_ad
conv4_block5_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block4_ou
conv4_block5_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block5_1_
conv4_block5_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block5_1_
conv4_block5_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block5_1_
conv4_block5_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block5_2_

conv4_block5_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block5_2_
conv4_block5_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block5_2_
conv4_block5_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block5_3_
conv4_block5_add (Add) t[0][0] bn[0][0]	(None,	14,	14,	1024)	0	conv4_block4_ou
conv4_block5_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block5_ad
conv4_block6_1_conv (Conv2D) t[0][0]	(None,	14,	14,	256)	262400	conv4_block5_ou
conv4_block6_1_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block6_1_
conv4_block6_1_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block6_1_
conv4_block6_2_conv (Conv2D) relu[0][0]	(None,	14,	14,	256)	590080	conv4_block6_1_
conv4_block6_2_bn (BatchNormali conv[0][0]	(None,	14,	14,	256)	1024	conv4_block6_2_
conv4_block6_2_relu (Activation bn[0][0]	(None,	14,	14,	256)	0	conv4_block6_2_
conv4_block6_3_conv (Conv2D) relu[0][0]	(None,	14,	14,	1024)	263168	conv4_block6_2_
conv4_block6_3_bn (BatchNormali conv[0][0]	(None,	14,	14,	1024)	4096	conv4_block6_3_
conv4_block6_add (Add) t[0][0] bn[0][0]	(None,	14,	14,	1024)	0	conv4_block5_ou
conv4_block6_out (Activation) d[0][0]	(None,	14,	14,	1024)	0	conv4_block6_ad

conv5_block1_1_conv (Conv2D) t[0][0]	(None,	7,	7,	512)	524800	conv4_block6_ou
conv5_block1_1_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block1_1_
conv5_block1_1_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block1_1_
conv5_block1_2_conv (Conv2D) relu[0][0]	(None,	7,	7,	512)	2359808	conv5_block1_1_
conv5_block1_2_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block1_2_
conv5_block1_2_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block1_2_
conv5_block1_0_conv (Conv2D) t[0][0]	(None,	7,	7,	2048)	2099200	conv4_block6_ou
conv5_block1_3_conv (Conv2D) relu[0][0]	(None,	7,	7,	2048)	1050624	conv5_block1_2_
conv5_block1_0_bn (BatchNormali conv[0][0]	(None,	7,	7,	2048)	8192	conv5_block1_0_
conv5_block1_3_bn (BatchNormali conv[0][0]	(None,	7,	7,	2048)	8192	conv5_block1_3_
conv5_block1_add (Add) bn[0][0] bn[0][0]	(None,	7,	7,	2048)	0	conv5_block1_0_ conv5_block1_3_
conv5_block1_out (Activation) d[0][0]	(None,	7,	7,	2048)	0	conv5_block1_ad
conv5_block2_1_conv (Conv2D) t[0][0]	(None,	7,	7,	512)	1049088	conv5_block1_ou
conv5_block2_1_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block2_1_
conv5_block2_1_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block2_1_
conv5_block2_2_conv (Conv2D)	(None,	7,	7,	512)	2359808	conv5_block2_1_

relu[0][0]						
conv5_block2_2_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block2_2_
conv5_block2_2_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block2_2_
conv5_block2_3_conv (Conv2D) relu[0][0]	(None,	7,	7,	2048)	1050624	conv5_block2_2_
conv5_block2_3_bn (BatchNormali conv[0][0]	(None,	7,	7,	2048)	8192	conv5_block2_3_
conv5_block2_add (Add) t[0][0] bn[0][0]	(None,	7,	7,	2048)	0	conv5_block1_ou
conv5_block2_out (Activation) d[0][0]	(None,	7,	7,	2048)	0	conv5_block2_ad
conv5_block3_1_conv (Conv2D) t[0][0]	(None,	7,	7,	512)	1049088	conv5_block2_ou
conv5_block3_1_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block3_1_
conv5_block3_1_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block3_1_
conv5_block3_2_conv (Conv2D) relu[0][0]	(None,	7,	7,	512)	2359808	conv5_block3_1_
conv5_block3_2_bn (BatchNormali conv[0][0]	(None,	7,	7,	512)	2048	conv5_block3_2_
conv5_block3_2_relu (Activation bn[0][0]	(None,	7,	7,	512)	0	conv5_block3_2_
conv5_block3_3_conv (Conv2D) relu[0][0]	(None,	7,	7,	2048)	1050624	conv5_block3_2_
conv5_block3_3_bn (BatchNormali conv[0][0]	(None,	7,	7,	2048)	8192	conv5_block3_3_
conv5_block3_add (Add) t[0][0]	(None,	7,	7,	2048)	0	conv5_block2_ou

```
bn[0][0]
         conv5_block3_out (Activation) (None, 7, 7, 2048) 0
                                                                          conv5_block3_ad
         d[0][0]
         avg_pool (GlobalAveragePooling2 (None, 2048)
                                                              0
                                                                          conv5_block3_ou
         t[0][0]
         flatten (Flatten)
                                         (None, 2048)
                                                              0
                                                                          avg_pool[0][0]
In [12]: for layer in custom_resnet_model.layers[:-1]:
             layer.trainable = False
         custom_resnet_model.layers[-1].trainable
Out[12]: True
In [13]: custom_resnet_model.compile(loss='categorical_crossentropy',optimizer='adam',metric
         s=['accuracy'])
```

```
In [14]: t=time.time()
hist = custom_resnet_model.fit(X_train, y_train, batch_size=32, epochs=num_epoch, v
erbose=1, validation_data=(X_test, y_test))
print('Training time: %s' % (t - time.time()))
(loss, accuracy) = custom_resnet_model.evaluate(X_test, y_test, batch_size=10, verb
ose=1)
print("[INFO] loss={:.4f}, accuracy: {:.4f}%".format(loss,accuracy * 100))
```

```
Epoch 1/100
cy: 0.9142 - val loss: 0.1091 - val accuracy: 0.9616
Epoch 2/100
147/147 [============ ] - 10s 65ms/step - loss: 0.1197 - accura
cy: 0.9554 - val loss: 0.0955 - val accuracy: 0.9676
Epoch 3/100
cy: 0.9661 - val_loss: 0.1064 - val_accuracy: 0.9582
Epoch 4/100
cy: 0.9654 - val_loss: 0.0828 - val_accuracy: 0.9718
Epoch 5/100
cy: 0.9686 - val loss: 0.0833 - val accuracy: 0.9753
Epoch 6/100
cy: 0.9733 - val loss: 0.0775 - val accuracy: 0.9761
Epoch 7/100
cy: 0.9757 - val loss: 0.0867 - val accuracy: 0.9744
Epoch 8/100
cy: 0.9765 - val loss: 0.0931 - val accuracy: 0.9701
Epoch 9/100
cy: 0.9782 - val loss: 0.0788 - val accuracy: 0.9727
Epoch 10/100
cy: 0.9793 - val_loss: 0.0762 - val_accuracy: 0.9770
Epoch 11/100
cy: 0.9827 - val loss: 0.0738 - val accuracy: 0.9753
Epoch 12/100
cy: 0.9821 - val loss: 0.0948 - val_accuracy: 0.9710
Epoch 13/100
cy: 0.9819 - val_loss: 0.0755 - val_accuracy: 0.9753
Epoch 14/100
cy: 0.9836 - val loss: 0.0798 - val_accuracy: 0.9770
Epoch 15/100
cy: 0.9842 - val_loss: 0.0955 - val_accuracy: 0.9625
Epoch 16/100
cy: 0.9861 - val loss: 0.0794 - val accuracy: 0.9744
Epoch 17/100
cy: 0.9878 - val_loss: 0.0813 - val_accuracy: 0.9744
Epoch 18/100
cy: 0.9855 - val_loss: 0.0734 - val_accuracy: 0.9787
Epoch 19/100
cy: 0.9872 - val loss: 0.0721 - val_accuracy: 0.9787
Epoch 20/100
cy: 0.9883 - val loss: 0.0855 - val accuracy: 0.9684
Epoch 21/100
cy: 0.9908 - val_loss: 0.0864 - val_accuracy: 0.9735
```

```
Epoch 22/100
cy: 0.9898 - val loss: 0.0735 - val accuracy: 0.9778
Epoch 23/100
cy: 0.9887 - val loss: 0.0731 - val accuracy: 0.9761
Epoch 24/100
cy: 0.9921 - val loss: 0.0750 - val accuracy: 0.9770
Epoch 25/100
cy: 0.9912 - val_loss: 0.0749 - val_accuracy: 0.9787
Epoch 26/100
cy: 0.9923 - val_loss: 0.0863 - val_accuracy: 0.9727
Epoch 27/100
cy: 0.9927 - val_loss: 0.0818 - val_accuracy: 0.9727
Epoch 28/100
147/147 [============] - 10s 66ms/step - loss: 0.0250 - accura
cy: 0.9940 - val loss: 0.0814 - val accuracy: 0.9735
Epoch 29/100
cy: 0.9936 - val loss: 0.0795 - val accuracy: 0.9753
Epoch 30/100
cy: 0.9936 - val loss: 0.0763 - val accuracy: 0.9778
Epoch 31/100
cy: 0.9925 - val loss: 0.0915 - val accuracy: 0.9727
Epoch 32/100
cy: 0.9951 - val_loss: 0.0808 - val_accuracy: 0.9735
Epoch 33/100
cy: 0.9951 - val_loss: 0.0782 - val_accuracy: 0.9761
Epoch 34/100
cy: 0.9964 - val loss: 0.0955 - val accuracy: 0.9693
cy: 0.9959 - val_loss: 0.0821 - val_accuracy: 0.9753
Epoch 36/100
cy: 0.9966 - val_loss: 0.0887 - val_accuracy: 0.9735
Epoch 37/100
cy: 0.9964 - val loss: 0.0857 - val accuracy: 0.9761
Epoch 38/100
cy: 0.9968 - val loss: 0.0872 - val accuracy: 0.9735
Epoch 39/100
cy: 0.9981 - val loss: 0.0834 - val accuracy: 0.9753
Epoch 40/100
cy: 0.9944 - val loss: 0.0843 - val accuracy: 0.9761
Epoch 41/100
cy: 0.9962 - val_loss: 0.0986 - val_accuracy: 0.9735
cy: 0.9972 - val loss: 0.0936 - val accuracy: 0.9735
Epoch 43/100
```

```
cy: 0.9962 - val loss: 0.0853 - val accuracy: 0.9761
Epoch 44/100
cy: 0.9983 - val loss: 0.1224 - val accuracy: 0.9684
cy: 0.9957 - val loss: 0.1033 - val accuracy: 0.9710
Epoch 46/100
cy: 0.9987 - val_loss: 0.0952 - val_accuracy: 0.9727
Epoch 47/100
cy: 0.9983 - val loss: 0.0926 - val accuracy: 0.9744
Epoch 48/100
cy: 0.9981 - val loss: 0.0909 - val accuracy: 0.9753
Epoch 49/100
cy: 0.9983 - val loss: 0.0916 - val accuracy: 0.9744
Epoch 50/100
cy: 0.9991 - val loss: 0.0862 - val accuracy: 0.9778
Epoch 51/100
cy: 0.9989 - val loss: 0.0902 - val accuracy: 0.9753
Epoch 52/100
147/147 [=============] - 10s 66ms/step - loss: 0.0094 - accura
cy: 0.9994 - val loss: 0.0990 - val accuracy: 0.9753
Epoch 53/100
cy: 0.9996 - val loss: 0.1023 - val accuracy: 0.9718
Epoch 54/100
cy: 0.9991 - val_loss: 0.0929 - val_accuracy: 0.9761
Epoch 55/100
cy: 0.9991 - val loss: 0.0948 - val accuracy: 0.9727
Epoch 56/100
cy: 0.9991 - val loss: 0.1009 - val accuracy: 0.9710
Epoch 57/100
cy: 0.9996 - val_loss: 0.0982 - val_accuracy: 0.9727
Epoch 58/100
cy: 0.9996 - val_loss: 0.0913 - val_accuracy: 0.9770
Epoch 59/100
cy: 0.9985 - val loss: 0.1036 - val accuracy: 0.9744
Epoch 60/100
cy: 0.9998 - val loss: 0.1002 - val accuracy: 0.9735
Epoch 61/100
cy: 0.9998 - val loss: 0.0951 - val accuracy: 0.9770
147/147 [============= ] - 10s 66ms/step - loss: 0.0062 - accura
cy: 1.0000 - val loss: 0.1036 - val accuracy: 0.9701
Epoch 63/100
cy: 0.9998 - val loss: 0.1074 - val accuracy: 0.9727
Epoch 64/100
```

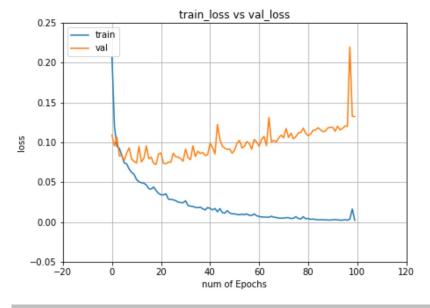
```
cy: 0.9998 - val loss: 0.0957 - val accuracy: 0.9770
Epoch 65/100
cy: 0.9998 - val loss: 0.1313 - val accuracy: 0.9659
Epoch 66/100
cy: 0.9998 - val loss: 0.1006 - val accuracy: 0.9761
Epoch 67/100
cy: 0.9998 - val loss: 0.1022 - val accuracy: 0.9753
Epoch 68/100
cy: 1.0000 - val loss: 0.1004 - val accuracy: 0.9753
Epoch 69/100
cy: 1.0000 - val_loss: 0.1055 - val_accuracy: 0.9710
Epoch 70/100
cy: 1.0000 - val_loss: 0.1090 - val_accuracy: 0.9718
Epoch 71/100
cy: 1.0000 - val loss: 0.1058 - val accuracy: 0.9744
147/147 [============] - 10s 66ms/step - loss: 0.0054 - accura
cy: 1.0000 - val loss: 0.1174 - val accuracy: 0.9710
Epoch 73/100
cy: 0.9998 - val loss: 0.1061 - val accuracy: 0.9761
Epoch 74/100
cy: 1.0000 - val loss: 0.1115 - val accuracy: 0.9718
Epoch 75/100
cy: 1.0000 - val loss: 0.1042 - val accuracy: 0.9753
Epoch 76/100
cy: 0.9994 - val_loss: 0.1071 - val_accuracy: 0.9744
Epoch 77/100
cy: 1.0000 - val loss: 0.1119 - val accuracy: 0.9718
Epoch 78/100
cy: 1.0000 - val loss: 0.1121 - val accuracy: 0.9735
Epoch 79/100
cy: 0.9989 - val_loss: 0.1177 - val_accuracy: 0.9735
Epoch 80/100
cy: 0.9998 - val loss: 0.1113 - val accuracy: 0.9761
Epoch 81/100
cy: 1.0000 - val loss: 0.1083 - val_accuracy: 0.9770
Epoch 82/100
cy: 1.0000 - val loss: 0.1102 - val accuracy: 0.9761
Epoch 83/100
cy: 1.0000 - val loss: 0.1150 - val accuracy: 0.9744
Epoch 84/100
cy: 1.0000 - val loss: 0.1154 - val accuracy: 0.9753
Epoch 85/100
cy: 1.0000 - val loss: 0.1183 - val accuracy: 0.9735
```

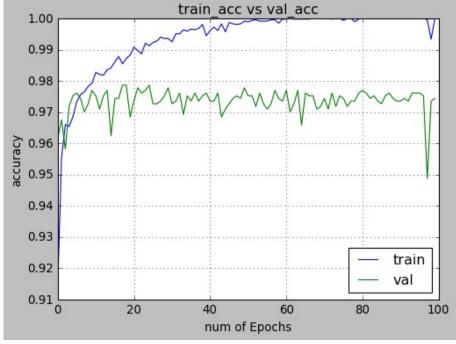
Epoch 86/100

```
cy: 1.0000 - val loss: 0.1158 - val accuracy: 0.9727
    Epoch 87/100
    cy: 1.0000 - val loss: 0.1133 - val accuracy: 0.9753
    Epoch 88/100
    cy: 1.0000 - val loss: 0.1141 - val accuracy: 0.9761
    Epoch 89/100
    cy: 1.0000 - val_loss: 0.1178 - val_accuracy: 0.9744
    Epoch 90/100
    cy: 1.0000 - val loss: 0.1189 - val accuracy: 0.9735
    Epoch 91/100
    cy: 1.0000 - val_loss: 0.1188 - val_accuracy: 0.9735
    Epoch 92/100
    147/147 [============] - 10s 65ms/step - loss: 0.0029 - accura
    cy: 1.0000 - val loss: 0.1139 - val accuracy: 0.9744
    Epoch 93/100
    cy: 1.0000 - val loss: 0.1202 - val accuracy: 0.9735
    Epoch 94/100
    cy: 1.0000 - val loss: 0.1155 - val accuracy: 0.9761
    Epoch 95/100
    cy: 1.0000 - val loss: 0.1174 - val accuracy: 0.9761
    Epoch 96/100
    cy: 1.0000 - val loss: 0.1203 - val accuracy: 0.9761
    Epoch 97/100
    cy: 1.0000 - val_loss: 0.1201 - val_accuracy: 0.9753
    Epoch 98/100
    cy: 0.9996 - val loss: 0.2196 - val accuracy: 0.9488
    cy: 0.9934 - val loss: 0.1327 - val accuracy: 0.9735
    Epoch 100/100
    cy: 1.0000 - val loss: 0.1323 - val_accuracy: 0.9744
    Training time: -975.6852314472198
    In [15]: (loss, accuracy) = custom resnet model.evaluate(X test, y test, batch size=10, verb
    ose=1)
    print("[INFO] loss={:.4f}, accuracy: {:.4f}%".format(loss,accuracy * 100))
    118/118 [============= ] - 3s 23ms/step - loss: 0.1323 - accurac
    [INFO] loss=0.1323, accuracy: 97.4403%
```

visualizing losses and accuracy







Evaluating the model

```
In [17]: score = custom_resnet_model.evaluate(X_test, y_test, verbose=0)
    print('Test Loss:', score[0])
    print('Test accuracy:', score[1])

    test_image = X_test[0:1]
    print (test_image.shape)

    print(model.predict(test_image))
    print(model.predict_classes(test_image))
    print(y_test[0:1])
```

```
Test Loss: 0.13225294649600983
Test accuracy: 0.9744027256965637
(1, 224, 224, 3)
[[4.82067890e-07 2.68882036e-06 2.46438071e-06 1.46347942e-04
  1.14383847e-05 4.81724349e-08 2.50176436e-06 1.93318300e-07
  1.12078631e-07 1.33230387e-07 1.55274762e-07 4.57866662e-07
  8.66559446e-07 2.24399500e-07 6.64423965e-08 1.10845995e-07
  1.35442542e-06 5.03833007e-07 1.79790817e-07 6.47744287e-07
  3.05023384e-08 9.56223190e-08 1.10445868e-07 1.10137853e-06
  7.54676677e-08 4.63201928e-07 2.87497016e-07 7.07335062e-08
  5.35643494e-07 1.51549584e-05 2.59477027e-08 2.91564879e-06
  7.73133081e-07 4.95935637e-07 1.98538643e-07 2.52716568e-08
  1.83687155e-06 7.88459204e-07 3.27636599e-07 1.85687998e-06
  1.74747020e-05 5.42289399e-07 8.17253891e-08 6.31402060e-08
  3.37520163e-07 1.02205229e-06 7.63697062e-06 5.59314408e-08
  7.33921922e-07 4.65218932e-07 4.84302063e-06 6.55129497e-08
  2.73576143e-06 3.79595463e-06 7.06228604e-07 5.70710426e-06
  9.65091203e-07 2.63103260e-07 4.50051573e-07 6.29083502e-07
  2.09377595e-06 1.72502826e-06 1.25136467e-06 6.38593519e-07
  7.39525774e-07 3.34286518e-08 9.70000769e-07 1.03747618e-06
  3.67367988e-07 1.14979400e-06 3.29745234e-07 2.08577912e-05
  1.47276842e-05 4.14989336e-06 7.56582722e-06 6.36893992e-06
  8.98751387e-06 9.69357734e-06 2.66852585e-05 2.10938379e-05
  9.31147923e-08 4.12824157e-08 4.71741544e-08 1.20277676e-07
  2.82732515e-07 7.39384305e-08 4.42064376e-08 4.16540644e-07
  7.95168603e-07 5.63529099e-08 8.61598224e-08 3.73003417e-07
  3.13063069e-08 1.43328606e-07 2.56055932e-06 1.59463571e-08
  2.61807202e-07 2.08426371e-07 2.79966450e-09 2.37027564e-07
  8.26529174e-07 9.52778294e-07 8.84871895e-07 6.70584797e-08
  4.19899031e-08 3.42380346e-08 7.15500903e-08 1.04467529e-06
  1.84370560e-06 1.10508445e-07 1.32549957e-07 1.20732386e-06
  4.30385662e-05 2.32143202e-06 1.15385831e-06 2.89288717e-08
  7.44268647e-08 1.84088658e-05 1.56171754e-05 3.71134149e-07
  2.79030104e-07 1.25042470e-06 1.56302053e-06 1.15310036e-06
  2.40664394e-06 1.65841428e-07 4.56227317e-05 2.70883021e-07
  7.59855823e-09 1.88321238e-07 1.26450095e-06 6.97321809e-08
  8.32176397e-07 2.10207972e-07 2.25861598e-07 9.37061273e-08
  1.62370782e-07 8.13763492e-08 4.42455530e-07 9.24499304e-08
  5.98086899e-06 3.80057621e-08 3.88246093e-08 8.12120277e-07
  1.10410170e-07 3.98443092e-07 2.99336165e-07 5.37295023e-07
  1.38613882e-06 2.95345467e-06 7.86266270e-08 2.17395083e-07
  7.75959563e-08 1.36170161e-06 7.63363289e-07 3.60099807e-06
  1.50860660e-06 4.62941415e-07 4.47918381e-07 1.67911749e-05
  5.81790516e-07 6.88692182e-07 1.80056261e-07 5.41830104e-06
  1.66806376e-06 1.10999708e-05 2.09217092e-06 5.40804081e-07
  2.85339570e-06 7.10956510e-06 7.90489878e-07 5.44291697e-06
  2.60349816e-06 4.81833240e-06 5.70534951e-07 5.57362114e-07
  1.02933473e-06 1.04458866e-06 4.40884469e-05 1.90422298e-07
  1.48606148e-07 4.46824458e-07 1.89701916e-06 3.72328145e-07
  2.70331907e-06 1.42775207e-06 2.15032173e-06 1.50941526e-06
  4.57386960e-07 2.96538616e-07 9.06139022e-08 1.39788681e-05
  1.63965376e-06 2.08460364e-07 8.88446650e-08 1.14750846e-05
  6.00025544e-07 1.29099749e-06 1.63062253e-07 1.93221626e-06
  3.26226086e-07 2.26011565e-07 1.00890395e-06 3.64552739e-06
  2.38593344e-07 3.57042865e-07 1.42592728e-06 1.51925451e-06
  1.76033518e-06 1.65332074e-06 1.73654357e-07 6.30601699e-06
  1.29027364e-06 2.55493205e-06 1.25809265e-07 6.50791947e-07
  2.88133009e-07 3.74395086e-07 1.28145970e-07 7.58302292e-07
  2.54769958e-07 5.29478257e-07 9.42013060e-07 1.10448559e-06
  1.35511527e-06 2.74070345e-07 4.58742932e-07 1.18524120e-07
  1.96650092e-07 8.79864217e-07 6.76232673e-07 1.05864603e-06
  7.84085387e-07 1.61685605e-07 1.75777370e-06 3.27096785e-07
  2.50208632e-06 2.27774103e-06 1.32969490e-06 2.00462722e-07
```

```
1.95692806e-07 3.73978310e-07 1.26169480e-05 9.73640454e-07
7.51481721e-09 3.16245831e-07 1.91538516e-06 1.11579197e-07
5.43942451e-06 3.55741150e-07 2.83933048e-07 5.07502136e-06
2.17246588e-06 2.19098570e-06 3.57639419e-06 2.53928022e-07
2.06906194e-07 3.27570973e-07 1.17160323e-06 3.96143605e-07
7.07220309e-08 2.98140570e-08 1.48195642e-08 5.41426914e-07
3.64813886e-08 8.76403021e-07 1.02535796e-06 6.06517460e-07
3.88640473e-07 7.15487602e-07 6.84218890e-07 4.20073462e-07
2.81511035e-07 4.72189640e-07 4.67730388e-08 1.60121218e-07
9.27563732e-08 2.03835686e-08 8.10001666e-09 6.71593412e-08
3.04826777e-08 2.13095677e-06 5.48989783e-06 3.82242615e-06
4.02625938e-06 2.03273908e-06 5.60944713e-08 3.95658226e-08
1.71023977e-08 2.75019083e-08 3.71704267e-08 3.75872098e-08
3.24326976e-07 1.62003513e-08 2.47091805e-08 5.32830882e-08
5.27075144e-07 6.81948364e-08 2.12066894e-07 4.73816954e-06
3.06480871e-07 4.37967174e-06 3.83125638e-07 2.59487564e-07
2.16806015e-07 1.23415191e-07 7.58255283e-07 5.34728883e-07
7.38245376e-07 1.07934525e-07 8.58397584e-07 6.98828399e-06
3.47092168e-06 1.10831215e-05 1.25559709e-05 2.39583405e-05
1.33940068e-06 1.43173759e-06 4.31827516e-07 5.54513917e-07
1.33714991e-07 2.53679673e-07 5.93662328e-08 6.51950813e-08
7.06708306e-07 8.72265176e-08 1.03443178e-07 4.26473889e-05
2.43622111e-07 4.32115826e-07 7.37000335e-07 5.41148424e-08
2.39720293e-07 1.38767909e-05 2.39044539e-07 1.00757500e-08
5.52106911e-08 2.85622832e-07 1.39397207e-06 8.98978954e-07
2.47298317e-06 2.48008291e-06 1.03912527e-07 9.20034751e-08
1.58720539e-07 2.18869877e-06 1.01007416e-07 9.33262001e-08
4.16232069e-07 2.41899780e-08 7.14705735e-08 8.87272677e-07
1.79500682e-06 2.23839402e-06 3.55981769e-07 2.05079019e-07
7.03610851e-07 5.05889552e-08 1.70242330e-07 3.62089213e-06
1.10505658e-08 1.03553134e-07 6.95341598e-08 7.76962622e-07
1.41140958e-07 2.01013586e-06 1.21628759e-07 1.97350872e-07
8.37480698e-08 1.60278351e-08 2.88566788e-08 1.44770496e-07
3.86343402e-07 2.70098553e-07 5.88721143e-08 1.20218971e-07
1.64466272e-07 1.54137524e-07 2.27946529e-07 6.77903458e-08
2.53453805e-07 5.70535192e-08 7.12599970e-08 7.95363135e-08
8.29713365e-09 8.91881768e-07 1.03283935e-06 2.96836102e-08
6.41702442e-08 8.35964215e-07 4.04590082e-06 5.43997976e-06
3.47285507e-08 7.03444130e-06 1.76835019e-05 4.78230675e-07
2.89848629e-07 6.81267096e-08 1.10332494e-05 7.61832460e-04
9.27375368e-06 2.28788940e-05 9.84669805e-06 4.32519073e-07
9.30536407e-06 8.10772235e-07 1.49337247e-05 1.51340806e-04
4.47854944e-08 5.67501527e-04 1.10032076e-07 2.25565200e-05
6.77242133e-05 6.33004038e-06 4.39342193e-06 8.99438674e-05
7.28008381e-05 2.19390568e-05 1.23546979e-05 1.25297393e-05
4.20370634e-06 3.13102093e-04 3.20764656e-07 5.62300329e-06
1.37011142e-04 1.94485983e-06 4.81351935e-06 9.91487832e-05
1.63843524e-05 8.57108080e-06 1.35260478e-07 1.85790210e-04
4.36487335e-06 2.35706648e-05 3.92094895e-04 1.27935903e-02
2.70703390e-06 1.01705751e-04 4.49157596e-05 6.13191901e-07
1.15572448e-05 1.44345540e-04 2.29499601e-05 1.85781857e-06
2.22390395e-06 9.81719568e-05 9.97880561e-05 7.91112107e-05
3.96518726e-06 3.96266415e-07 8.61680601e-04 6.50838228e-06
2.06842174e-06 7.68140399e-06 1.07899541e-05 2.91467586e-06
2.84931957e-06 1.47860090e-04 4.30169575e-06 1.07488831e-05
4.59787589e-05 5.46703232e-05 7.03009573e-06 1.99430560e-05
3.42860039e-06 4.22399671e-06 6.29881397e-05 5.03593292e-05
1.70047624e-05 2.34267577e-06 6.42493023e-06 1.19209335e-06
2.15346809e-04 3.78162440e-06 8.40231860e-06 5.85121888e-05
1.26830651e-06 3.94399819e-07 9.75983203e-05 3.36703924e-05
1.23899110e-04 3.43893862e-06 2.21809387e-06 2.35215539e-05
1.90323753e-05 1.14208233e-05 3.64518337e-06 2.74725782e-04
1.66802511e-05 4.90731800e-05 2.14859301e-05 8.27478743e-07
6.38046004e-06 6.69588553e-06 4.86439931e-05 2.94567570e-07
```

```
1.45346610e-06 2.36542764e-05 5.61834313e-05 5.70035423e-04
7.14134103e-06 5.04184165e-04 9.28850553e-04 2.66718762e-05
1.97937461e-05 2.34957828e-04 1.12313012e-06 1.54577606e-06
1.91156039e-04 2.92513650e-05 3.64735342e-06 8.05021045e-06
5.52102756e-06 2.36397736e-05 1.86461883e-04 8.69344076e-05
7.38855801e-04 1.13097872e-06 3.45201647e-06 2.67267733e-05
5.17669905e-05 3.94152949e-06 9.94110039e-08 1.02107367e-03
3.70649213e-05 7.88004545e-05 2.20635525e-06 1.11422360e-05
1.52004883e-04 2.07467747e-05 2.19970061e-05 1.89681759e-05
2.91477704e-07 2.03410423e-06 1.43415236e-04 4.07606819e-07
3.71343731e-07 1.21202063e-07 1.54469137e-06 5.18416382e-05
2.46199988e-07 1.38334117e-05 2.72481393e-05 1.73800756e-04
1.29404398e-07 1.32949333e-06 5.21159427e-06 4.13591010e-08
7.22797097e-07 5.77609389e-05 2.60100387e-06 2.77295186e-07
8.79857544e-05 2.48557399e-06 3.33061253e-05 1.84840428e-06
2.06588447e-06 9.42903935e-05 1.27391613e-05 3.86221131e-04
2.89812959e-07 9.07293781e-07 9.14044576e-05 1.18784788e-04
1.44671003e-05 3.06865513e-05 2.65360472e-06 2.47145545e-06
7.08662847e-05 4.67554706e-08 7.63243952e-05 4.61026211e-05
4.03199054e-04 2.75975566e-07 6.68384700e-06 3.74048363e-06
2.48065794e-06 7.88056695e-06 3.06886015e-03 1.04375024e-04
4.88235783e-05 3.22222841e-05 2.76110386e-05 3.63568074e-06
1.40114649e-08 3.91990943e-05 3.56440665e-07 2.30869646e-05
7.97552639e-05 1.15201226e-03 1.25383340e-05 3.24318215e-04
2.47357548e-06 6.83440303e-05 6.86029762e-06 4.83607437e-06
1.21831170e-06 4.36718392e-06 5.05537037e-06 3.59021215e-05
1.23418329e-04 4.54013381e-04 1.95090820e-06 1.79916094e-06
3.72640061e-04 2.53085134e-04 8.23253049e-06 1.11542977e-06
1.29810622e-04 6.05422611e-06 5.47393465e-05 3.38295195e-07
1.88352317e-07 1.01384667e-05 7.33205843e-06 4.75033376e-05
9.63159891e-06 5.74934878e-04 1.54930181e-04 4.78529284e-04
5.10371116e-04 1.49897926e-06 6.17007436e-06 1.60871841e-05
4.19408798e-06 2.20982770e-06 2.88490191e-05 2.74454069e-05
8.71936663e-06 3.60013473e-05 2.32321071e-03 2.51333404e-04
2.51822348e-04 4.09818222e-06 1.71445140e-06 9.45266763e-08
5.68463793e-06 1.36511799e-05 2.69595825e-04 1.61458447e-03
2.42772586e-07 1.55881673e-04 6.31328949e-05 4.16917392e-05
5.45173316e-06 7.44753208e-07 7.79232232e-06 5.39383000e-05
4.50248399e-06 3.55712473e-06 1.38671661e-04 2.44844637e-06
4.92295039e-05 1.22241481e-05 3.03424658e-05 1.46714054e-04
1.15310540e-05 3.78642610e-04 1.30925957e-06 3.95897177e-06
1.03032858e-06 2.12843702e-07 1.84312103e-05 1.35504897e-05
3.08177623e-05 9.31254078e-07 2.19377671e-06 1.40750149e-06
2.77103413e-06 1.50421634e-03 5.47954687e-06 7.84884105e-06
1.34442689e-05 1.27914784e-04 2.03610898e-06 2.55877762e-06
7.29639680e-07 4.32577008e-06 8.44035894e-05 1.19183301e-06
1.02465716e-03 6.94555201e-05 1.54967870e-06 5.26904332e-05
2.13380144e-06 3.60782650e-07 6.98907070e-06 5.14113344e-04
1.20219784e-05 3.05959074e-05 1.08575435e-07 1.02883430e-04
8.84334731e-04 3.34499382e-05 3.18635784e-06 7.57592898e-06
6.32017545e-05 6.54682008e-05 3.43472857e-05 1.74541310e-05
1.87886071e-05 8.99571205e-06 8.88989052e-06 3.25882465e-05
4.18749369e-06 3.24225698e-06 3.95771849e-06 5.82839266e-06
2.83199537e-04 1.09739551e-04 1.02437571e-06 2.33481678e-05
6.11256382e-07 3.62084575e-05 2.69073917e-06 6.38804295e-07
1.68975330e-05 7.29936858e-07 4.69654879e-05 9.58434839e-07
1.16623396e-05 3.18129332e-06 2.63417624e-05 1.61167279e-07
2.44845182e-07 1.47840212e-04 3.11488293e-06 1.70200997e-06
1.69117455e-04 1.04137844e-05 9.06369337e-07 7.02995094e-05
6.30474779e-06 3.74916417e-05 8.15141789e-07 1.95482149e-04
1.63665663e-05 9.46354266e-05 1.25333008e-05 1.66010122e-05
1.99244059e-05 2.11239931e-05 1.94751701e-05 2.05911729e-05
3.29209695e-04 3.14238532e-05 3.62695204e-07 3.52477255e-05
9.37491313e-06 1.92738080e-05 4.31706831e-05 2.57115266e-06
```

```
1.95169850e-05 8.58446956e-03 1.87854255e-06 1.59508318e-06
2.46171567e-05 2.86161753e-06 1.01712494e-05 3.48290519e-06
2.47714834e-05 2.18087720e-04 2.13829549e-06 5.23960916e-05
1.30321478e-05 4.40097683e-05 3.76050639e-06 3.32131895e-05
7.28104169e-07 9.54941061e-06 1.03316641e-04 2.34550794e-06
2.92102450e-05 4.44840378e-04 2.78215832e-03 3.26271955e-04
8.13547449e-05 9.37511345e-07 1.28339278e-04 3.95520556e-06
5.72408362e-06 4.45332120e-07 6.10011957e-05 9.87950716e-06
6.84851830e-06 6.87362626e-04 2.87053790e-05 1.62784681e-06
1.16443750e-03 1.19960787e-04 6.68877601e-06 7.05155526e-06
7.51127482e-06 4.41425545e-05 8.68385494e-01 4.11766086e-06
7.50159688e-06 4.51385858e-04 1.72617217e-06 3.76659416e-04
1.03966563e-07 6.19818229e-06 3.53539377e-07 2.29919351e-05
1.92507523e-05 9.72411362e-06 3.90483037e-04 3.46978004e-06
3.11856165e-05 2.66272559e-06 1.59578831e-05 2.38444496e-04
1.12737598e-05 9.12053565e-06 5.20690662e-07 1.06905558e-04
8.12665277e-08 8.96848462e-07 4.85853207e-06 1.47953815e-05
1.02085451e-07 1.24309815e-06 7.21049048e-07 1.65302597e-04
1.28473184e-05 1.82003646e-07 1.76036301e-05 3.73523676e-06
1.19854949e-05 6.30159866e-06 6.03208225e-03 6.73122471e-04
3.23600170e-06 6.13015072e-06 6.28529466e-04 4.05782004e-07
3.67343338e-04 2.02310417e-04 1.44595761e-04 2.47344688e-05
1.92117986e-05 2.67578725e-04 5.09061269e-04 1.11675604e-06
3.60307458e-05 5.94534067e-05 6.04638262e-05 9.43270777e-07
1.87736043e-06 1.16022029e-05 9.44192434e-05 2.90690459e-05
1.21500841e-06 1.10533176e-06 5.06489945e-04 3.64165658e-06
4.67211663e-07 5.10106838e-06 5.83519519e-04 3.80706479e-05
1.76308986e-05 5.20052490e-05 4.91349647e-06 8.12508097e-06
3.82704748e-08 2.07618473e-06 1.39368840e-05 5.41324471e-06
8.11370192e-05 8.19496287e-04 8.66509424e-08 5.77576611e-06
2.67183350e-05 3.54495683e-06 1.76372367e-07 7.78879257e-06
6.08678255e-03 1.53235869e-05 4.25836661e-05 1.81716296e-05
3.10815585e-06 1.14924820e-04 1.62769153e-04 5.68528594e-05
7.11927249e-04 4.77184221e-05 1.43913121e-06 3.70840717e-04
5.84533154e-06 1.34695501e-05 1.47781648e-07 4.95524375e-07
3.60853737e-04 3.74378851e-06 2.02726806e-03 8.60695764e-06
9.59523313e-04 1.05018029e-03 2.76033854e-04 1.06034509e-03
1.02264516e-04 5.07008451e-07 1.24075723e-05 4.30560576e-05
4.01811376e-05 3.60652879e-02 9.52280534e-05 1.05566389e-04
6.14607241e-04 4.45982351e-07 9.85839288e-05 1.09745661e-05
4.13857578e-07 1.45892869e-07 9.47745502e-06 1.27931187e-07
1.88063609e-06 7.31243233e-07 1.09413508e-04 5.59842147e-06
1.08451268e-05 2.47595250e-04 3.22890701e-05 5.87084855e-07
5.33968034e-07 1.60047946e-07 4.48863204e-08 6.79547218e-09
4.62726888e-07 4.34527137e-05 4.75226880e-05 2.52664768e-06
9.74151772e-06 3.40019170e-07 5.78103791e-05 4.44442804e-07
6.88957289e-06 8.11696373e-06 1.18416517e-06 7.13754634e-05
9.49173284e-07 2.48400141e-07 2.54554798e-05 9.35261924e-05
1.13045726e-05 2.96297640e-06 2.50614960e-07 6.59583566e-06
2.65514132e-06 5.55613678e-06 1.38014566e-05 4.61311402e-06
1.00772695e-06 3.14598365e-05 2.84581678e-03 1.14023233e-05
1.62482070e-06 4.54612916e-07 3.88075478e-06 6.19703883e-07
1.11640183e-07 1.78760547e-05 9.90545141e-06 7.91555806e-07
1.24757719e-07 3.79951121e-06 9.05809065e-06 4.07820153e-06
1.76368158e-05 6.19397781e-07 4.93730397e-07 3.93128685e-05
5.72621911e-06 2.75433791e-08 1.81638745e-06 3.58180927e-07
2.10690857e-07 2.07777812e-05 1.16643912e-06 3.86570804e-07
1.94599423e-07 4.16157627e-06 4.51370783e-04 7.39174948e-06
1.35012567e-06 7.68352857e-06 1.72485688e-08 1.03070211e-04
8.34732958e-08 9.23699091e-08 1.82024227e-08 2.52095500e-08
1.99341756e-07 4.80747442e-09 1.07438849e-08 4.42679458e-08
```

```
AttributeError Traceback (most recent call last)
<ipython-input-17-83421ec204f5> in <module>
7
8 print(model.predict(test_image))
----> 9 print(model.predict_classes(test_image))
```

Testing a new image

```
In [18]: test_image_path = 'D:/Harold/MyDNN/DataSet/Chest_xray_seperate/PNEUMONIA/person11_b
         acteria_45.jpeg'
         test_image = image.load_img(test_image_path, target_size=(224, 224))
         x = image.img_to_array(test_image)
         x = np.expand_dims(x, axis=0)
         x = preprocess_input(x)
         print (x.shape)
         # if num channel==1:
              if (K.image data format() == 'channels first'):
                  test image= np.expand dims(test image, axis=0)
                  test image= np.expand dims(test image, axis=0)
                  print (test image.shape)
              else:
                   test image= np.expand dims(test image, axis=3)
                   test image= np.expand dims(test image, axis=0)
                  print (test_image.shape)
         # else:
             if (K.image data format() == 'channels first'):
                   test image=np.rollaxis(test image,2,0)
                  test_image= np.expand_dims(test_image, axis=0)
                  print (test image.shape)
              else:
                  test image= np.expand dims(test image, axis=0)
                   print (test image.shape)
         # Predicting the test image
         print((custom resnet model.predict(x)))
         # print(custom_resnet_model.predict_classes(x))
         (1, 224, 224, 3)
         [[7.928144e-08 9.999999e-01]]
```

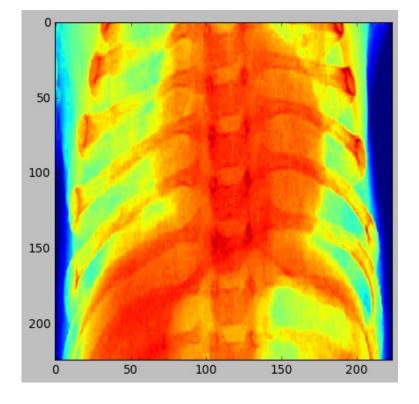
Visualizing the intermediate layer

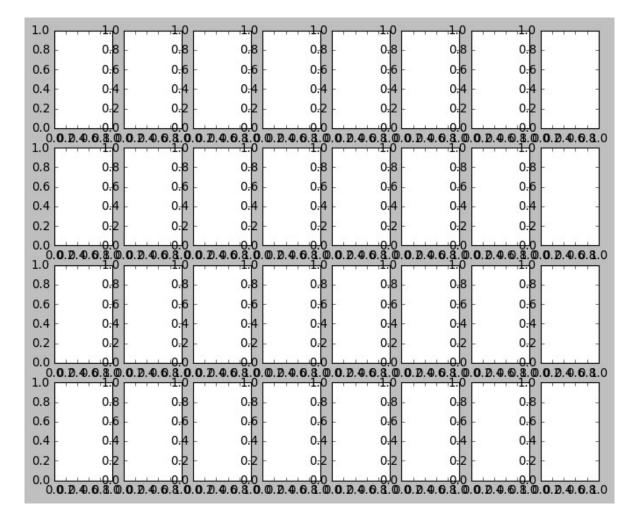
```
In [19]: from keras.models import Model
         layer outputs = [layer.output for layer in model.layers]
         activation_model = Model(inputs=custom_resnet_model.input, outputs=layer_outputs)
         activations = custom_resnet_model.predict(X_train[10].reshape(1,224,224,3))
         print(activations.shape)
         def display activation (activations, col size, row size, act index):
             activation = activations[0, act index]
             activation index=1
             fig, ax = plt.subplots(row size, col size, figsize=(row size*2.5,col size*1))
             for row in range(0, row size):
                 for col in range(0,col size):
                     ax[row][col].imshow(activation[0, :, :, activation index], cmap='gray')
                     activation_index += 1
         plt.imshow(test_image)
         plt.imshow(X_train[10][:,:,0]);
         display_activation(activations, 8, 4, 1)
```

```
(1, 2)
```

```
IndexError
                                          Traceback (most recent call last)
<ipython-input-19-32e8200fb41b> in <module>
     14 plt.imshow(test_image)
     15 plt.imshow(X_train[10][:,:,0]);
---> 16 display activation (activations, 8, 4, 1)
<ipython-input-19-32e8200fb41b> in display activation(activations, col size, row
_size, act_index)
    10
          for row in range(0, row size):
     11
              for col in range(0,col_size):
---> 12
                    ax[row][col].imshow(activation[0, :, :, activation_index], c
map='gray')
     13
                    activation index += 1
     14 plt.imshow(test_image)
```

IndexError: invalid index to scalar variable.



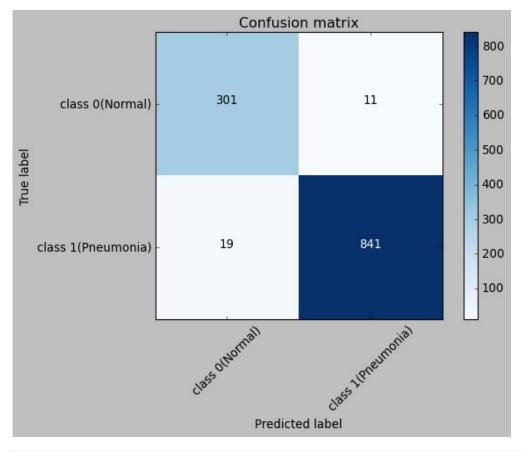


Confusion matrix

```
In [21]: Y_pred = custom_resnet_model.predict(X_test)
        print(Y pred)
        y_pred = np.argmax(Y_pred, axis=1)
        print(y_pred)
         #y_pred = model.predict_classes(X_test)
         #print(y pred)
         target names = ['class 0(Normal)', 'class 1(Pneumonia)']
        print(classification report(np.argmax(y test,axis=1), y pred,target names=target na
        print(confusion matrix(np.argmax(y test,axis=1), y pred))
         [[9.9328565e-07 9.9999905e-01]
         [1.0000000e+00 6.4503549e-16]
         [1.3406505e-04 9.9986589e-01]
         [1.9769919e-10 1.0000000e+00]
         [7.7234494e-09 1.0000000e+00]
         [9.9999988e-01 9.0127173e-08]]
         [1 0 1 ... 1 1 0]
                           precision recall f1-score support
           class 0(Normal) 0.94 0.96 0.95
                                                              312
                               0.99
                                        0.98
                                                  0.98
        class 1(Pneumonia)
                                                             860
                                                   0.97
                                                            1172
                  accuracy
                                                  1172
0.97
              macro avg 0.96 0.97 weighted avg 0.97 0.97
                                         0.97
         [[301 11]
          [ 19 841]]
```

Compute confusion matrix

Confusion matrix, without normalization [[301 11] [19 841]]



In []: