```
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
        # from tensorflow.keras.applications.inception_v3 import InceptionV3
        # from tensorflow.keras.applications.mobilenet import MobileNet
        # from tensorflow.keras.applications.vgg19 import VGG19
        from tensorflow.keras.applications.mobilenet v2 import MobileNetV2
        from tensorflow.keras.applications.inception v3 import decode predictions
```

#### 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 = MobileNetV2(input_tensor=image_input, include_top=True, weights='imagenet')
    model.summary()
    output_layer = model(image_input)

# last_layer = model.get_layer('avg_pool').output
    x= Flatten(name='flatten')(output_layer)
    out = Dense(num_classes, activation='softmax', name='output_layer')(x)
    custom_resnet_model = Model(inputs=image_input,outputs= out)
    custom_resnet_model.summary()
```

Layer (type)	Output	Shape	Param #	Connected to
input_1 (InputLayer)	[(None	, 224, 224, 3)	0	
Conv1_pad (ZeroPadding2D)	(None,	225, 225, 3)	0	input_1[0][0]
Conv1 (Conv2D)	(None,	112, 112, 32)	864	Conv1_pad[0][0]
bn_Conv1 (BatchNormalization)	(None,	112, 112, 32)	128	Conv1[0][0]
Conv1_relu (ReLU)	(None,	112, 112, 32)	0	bn_Conv1[0][0]
expanded_conv_depthwise (Depthw [0][0]	(None,	112, 112, 32)	288	Conv1_relu
expanded_conv_depthwise_BN (Bat epthwise[0][0]	(None,	112, 112, 32)	128	expanded_conv_d
expanded_conv_depthwise_relu (R epthwise_BN[0][0]	(None,	112, 112, 32)	0	expanded_conv_d
<pre>expanded_conv_project (Conv2D) epthwise_relu[0][0</pre>	(None,	112, 112, 16)	512	expanded_conv_d
<pre>expanded_conv_project_BN (Batch roject[0][0]</pre>	(None,	112, 112, 16)	64	expanded_conv_p
block_1_expand (Conv2D) roject_BN[0][0]	(None,	112, 112, 96)	1536	expanded_conv_p
block_1_expand_BN (BatchNormali [0][0]	(None,	112, 112, 96)	384	block_1_expand
block_1_expand_relu (ReLU) BN[0][0]	(None,	112, 112, 96)	0	block_1_expand_
block_1_pad (ZeroPadding2D) relu[0][0]	(None,	113, 113, 96)	0	block_1_expand_
block_1_depthwise (DepthwiseCon [0][0]	(None,	56, 56, 96)	864	block_1_pad

block_1_depthwise_BN (BatchNorm se[0][0]	(None,	56,	56,	96)	384	block_1_depthwi
block_1_depthwise_relu (ReLU) se_BN[0][0]	(None,	56,	56,	96)	0	block_1_depthwi
block_1_project (Conv2D) se_relu[0][0]	(None,	56,	56,	24)	2304	block_1_depthwi
block_1_project_BN (BatchNormal [0][0]	(None,	56,	56,	24)	96	block_1_project
block_2_expand (Conv2D) _BN[0][0]	(None,	56,	56,	144)	3456	block_1_project
block_2_expand_BN (BatchNormali [0][0]	(None,	56,	56,	144)	576	block_2_expand
block_2_expand_relu (ReLU) BN[0][0]	(None,	56,	56,	144)	0	block_2_expand_
block_2_depthwise (DepthwiseCon relu[0][0]	(None,	56,	56,	144)	1296	block_2_expand_
block_2_depthwise_BN (BatchNorm se[0][0]	(None,	56,	56,	144)	576	block_2_depthwi
block_2_depthwise_relu (ReLU) se_BN[0][0]	(None,	56,	56,	144)	0	block_2_depthwi
block_2_project (Conv2D) se_relu[0][0]	(None,	56,	56,	24)	3456	block_2_depthwi
block_2_project_BN (BatchNormal [0][0]	(None,	56,	56,	24)	96	block_2_project
block_2_add (Add) _BN[0][0]	(None,	56,	56,	24)	0	block_1_project block_2_project
_BN[0][0]						
block_3_expand (Conv2D) [0][0]	(None,	56,	56,	144)	3456	block_2_add
block_3_expand_BN (BatchNormali [0][0]	(None,	56,	56,	144)	576	block_3_expand
block_3_expand_relu (ReLU)	(None,	56,	56,	144)	0	block_3_expand_

BN	0	]	[	0	]

block_3_pad (ZeroPadding2D) relu[0][0]	(None,	57,	57,	144)	0	block_3_expand_
block_3_depthwise (DepthwiseCon	(None,	28,	28,	144)	1296	block_3_pad
block_3_depthwise_BN (BatchNorm se[0][0]	(None,	28,	28,	144)	576	block_3_depthwi
block_3_depthwise_relu (ReLU) se_BN[0][0]	(None,	28,	28,	144)	0	block_3_depthwi
block_3_project (Conv2D) se_relu[0][0]	(None,	28,	28,	32)	4608	block_3_depthwi
block_3_project_BN (BatchNormal [0][0]	(None,	28,	28,	32)	128	block_3_project
block_4_expand (Conv2D) _BN[0][0]	(None,	28,	28,	192)	6144	block_3_project
block_4_expand_BN (BatchNormali [0][0]	(None,	28,	28,	192)	768	block_4_expand
block_4_expand_relu (ReLU) BN[0][0]	(None,	28,	28,	192)	0	block_4_expand_
block_4_depthwise (DepthwiseCon relu[0][0]	(None,	28,	28,	192)	1728	block_4_expand_
block_4_depthwise_BN (BatchNorm se[0][0]	(None,	28,	28,	192)	768	block_4_depthwi
block_4_depthwise_relu (ReLU) se_BN[0][0]	(None,	28,	28,	192)	0	block_4_depthwi
block_4_project (Conv2D) se_relu[0][0]	(None,	28,	28,	32)	6144	block_4_depthwi
block_4_project_BN (BatchNormal	(None,	28,	28,	32)	128	block_4_project
block_4_add (Add) _BN[0][0]	(None,	28,	28,	32)	0	block_3_project block 4 project
_BN[0][0]						

block_5_expand (Conv2D) [0][0]	(None,	28,	28,	192)	6144	block_4_add
block_5_expand_BN (BatchNormali [0][0]	(None,	28,	28,	192)	768	block_5_expand
block_5_expand_relu (ReLU) BN[0][0]	(None,	28,	28,	192)	0	block_5_expand_
block_5_depthwise (DepthwiseCon relu[0][0]	(None,	28,	28,	192)	1728	block_5_expand_
block_5_depthwise_BN (BatchNorm se[0][0]	(None,	28,	28,	192)	768	block_5_depthwi
block_5_depthwise_relu (ReLU) se_BN[0][0]	(None,	28,	28,	192)	0	block_5_depthwi
block_5_project (Conv2D) se_relu[0][0]	(None,	28,	28,	32)	6144	block_5_depthwi
block_5_project_BN (BatchNormal [0][0]	(None,	28,	28,	32)	128	block_5_project
block_5_add (Add) [0][0] _BN[0][0]	(None,	28,	28,	32)	0	block_4_add block_5_project
[0][0]	(None,					
[0][0] _BN[0][0]	(None,	28,	28,	192)	6144	block_5_project
[0][0]  _BN[0][0]	(None,	28,	28,	192)	6144	block_5_project block_5_add
[0][0]  _BN[0][0]  block_6_expand (Conv2D)  [0][0]  block_6_expand_BN (BatchNormali  [0][0]  block_6_expand_relu (ReLU)	(None,	28,	28,	192) 192)	768	block_5_project  block_5_add  block_6_expand
[0][0]  _BN[0][0]  block_6_expand (Conv2D)  [0][0]  block_6_expand_BN (BatchNormali  [0][0]  block_6_expand_relu (ReLU)  BN[0][0]  block_6_pad (ZeroPadding2D)	(None, (None,	28,	28,	192) 192) 192)	6144 768 0	block_5_project  block_5_add  block_6_expand  block_6_expand_
[0][0]  _BN[0][0]  _block_6_expand (Conv2D)  [0][0]	(None, (None, (None,	28, 28, 29, 14,	28, 28, 29,	192) 192) 192) 192)	6144 768 0	block_5_project  block_5_add  block_6_expand  block_6_expand_  block_6_expand_

se_BN[0][0]						
block_6_project (Conv2D) se_relu[0][0]	(None,	14,	14,	64)	12288	block_6_depthwi
block_6_project_BN (BatchNormal [0][0]	(None,	14,	14,	64)	256	block_6_project
block_7_expand (Conv2D) _BN[0][0]	(None,	14,	14,	384)	24576	block_6_project
block_7_expand_BN (BatchNormali [0][0]	(None,	14,	14,	384)	1536	block_7_expand
block_7_expand_relu (ReLU) BN[0][0]	(None,	14,	14,	384)	0	block_7_expand_
block_7_depthwise (DepthwiseCon relu[0][0]	(None,	14,	14,	384)	3456	block_7_expand_
block_7_depthwise_BN (BatchNorm se[0][0]	(None,	14,	14,	384)	1536	block_7_depthwi
block_7_depthwise_relu (ReLU) se_BN[0][0]	(None,	14,	14,	384)	0	block_7_depthwi
block_7_project (Conv2D) se_relu[0][0]	(None,	14,	14,	64)	24576	block_7_depthwi
block_7_project_BN (BatchNormal [0][0]	(None,	14,	14,	64)	256	block_7_project
block_7_add (Add) _BN[0][0]	(None,	14,	14,	64)	0	block_6_project
_BN[0][0]						block_7_project
block_8_expand (Conv2D) [0][0]	(None,	14,	14,	384)	24576	block_7_add
block_8_expand_BN (BatchNormali [0][0]	(None,	14,	14,	384)	1536	block_8_expand
block_8_expand_relu (ReLU) BN[0][0]	(None,	14,	14,	384)	0	block_8_expand_
block_8_depthwise (DepthwiseCon relu[0][0]	(None,	14,	14,	384)	3456	block_8_expand_

block_8_depthwise_BN (BatchNorm se[0][0]	(None,	14,	14,	384)	1536	block_8_depthwi
block_8_depthwise_relu (ReLU) se_BN[0][0]	(None,	14,	14,	384)	0	block_8_depthwi
block_8_project (Conv2D) se_relu[0][0]	(None,	14,	14,	64)	24576	block_8_depthwi
block_8_project_BN (BatchNormal [0][0]	(None,	14,	14,	64)	256	block_8_project
block_8_add (Add) [0][0] _BN[0][0]	(None,	14,	14,	64)	0	block_7_add block_8_project
block_9_expand (Conv2D) [0][0]	(None,	14,	14,	384)	24576	block_8_add
block_9_expand_BN (BatchNormali [0][0]	(None,	14,	14,	384)	1536	block_9_expand
block_9_expand_relu (ReLU) BN[0][0]	(None,	14,	14,	384)	0	block_9_expand_
block_9_depthwise (DepthwiseCon relu[0][0]	(None,	14,	14,	384)	3456	block_9_expand_
block_9_depthwise_BN (BatchNorm se[0][0]	(None,	14,	14,	384)	1536	block_9_depthwi
block_9_depthwise_relu (ReLU) se_BN[0][0]	(None,	14,	14,	384)	0	block_9_depthwi
block_9_project (Conv2D) se_relu[0][0]	(None,	14,	14,	64)	24576	block_9_depthwi
block_9_project_BN (BatchNormal [0][0]	(None,	14,	14,	64)	256	block_9_project
block_9_add (Add) [0][0] BN[0][0]	(None,	14,	14,	64)	0	block_8_add block_9_project
block_10_expand (Conv2D) [0][0]	(None,	14,	14,	384)	24576	block_9_add

block_10_expand_BN (BatchNormal [0][0]	(None,	14,	14,	384)	1536	block_10_expand
block_10_expand_relu (ReLU) _BN[0][0]	(None,	14,	14,	384)	0	block_10_expand
block_10_depthwise (DepthwiseCo _relu[0][0]	(None,	14,	14,	384)	3456	block_10_expand
block_10_depthwise_BN (BatchNorise[0][0]	(None,	14,	14,	384)	1536	block_10_depthw
block_10_depthwise_relu (ReLU) ise_BN[0][0]	(None,	14,	14,	384)	0	block_10_depthw
block_10_project (Conv2D) ise_relu[0][0]	(None,	14,	14,	96)	36864	block_10_depthw
block_10_project_BN (BatchNorma t[0][0]	(None,	14,	14,	96)	384	block_10_projec
block_11_expand (Conv2D) t_BN[0][0]	(None,	14,	14,	576)	55296	block_10_projec
block_11_expand_BN (BatchNormal [0][0]	(None,	14,	14,	576)	2304	block_11_expand
block_11_expand_relu (ReLU) _BN[0][0]	(None,	14,	14,	576)	0	block_11_expand
block_11_depthwise (DepthwiseCo _relu[0][0]	(None,	14,	14,	576)	5184	block_11_expand
block_11_depthwise_BN (BatchNor ise[0][0]	(None,	14,	14,	576)	2304	block_11_depthw
block_11_depthwise_relu (ReLU) ise_BN[0][0]	(None,	14,	14,	576)	0	block_11_depthw
block_11_project (Conv2D) ise_relu[0][0]	(None,	14,	14,	96)	55296	block_11_depthw
block_11_project_BN (BatchNorma t[0][0]	(None,	14,	14,	96)	384	block_11_projec
block_11_add (Add) t_BN[0][0]	(None,	14,	14,	96)	0	block_10_projec

t	BN	[	0]	[ (	) ]

_						
block_12_expand (Conv2D) [0][0]	(None,	14, 14	1, 5	76)	55296	block_11_add
block_12_expand_BN (BatchNormal [0][0]	(None,	14, 14	1, 5	76)	2304	block_12_expand
block_12_expand_relu (ReLU) _BN[0][0]	(None,	14, 14	1, 5	76)	0	block_12_expand
block_12_depthwise (DepthwiseCo _relu[0][0]	(None,	14, 14	1, 5	76)	5184	block_12_expand
block_12_depthwise_BN (BatchNor ise[0][0]	(None,	14, 14	1, 5	76)	2304	block_12_depthw
block_12_depthwise_relu (ReLU) ise_BN[0][0]	(None,	14, 14	1, 5	76)	0	block_12_depthw
block_12_project (Conv2D) ise_relu[0][0]	(None,	14, 14	1, 9	6)	55296	block_12_depthw
block_12_project_BN (BatchNorma t[0][0]	(None,	14, 14	1, 9	6)	384	block_12_projec
block_12_add (Add) [0][0] t_BN[0][0]	(None,	14, 14	1, 9	6)	0	block_11_add block_12_projec
block_13_expand (Conv2D) [0][0]	(None,	14, 14	1, 5	76)	55296	block_12_add
block_13_expand_BN (BatchNormal [0][0]	(None,	14, 14	1, 5	76)	2304	block_13_expand
block_13_expand_relu (ReLU) _BN[0][0]	(None,	14, 14	1, 5	76)	0	block_13_expand
block_13_pad (ZeroPadding2D) _relu[0][0]	(None,	15, 15	5, 5	76)	0	block_13_expand
block_13_depthwise (DepthwiseCo [0][0]	(None,	7, 7,	576	)	5184	block_13_pad
block_13_depthwise_BN (BatchNor ise[0][0]	(None,	7, 7,	576	)	2304	block_13_depthw
<del></del>						

block_13_depthwise_relu (ReLU) ise_BN[0][0]	(None,	7,	7,	576)	0	block_13_depthw
block_13_project (Conv2D) ise_relu[0][0]	(None,	7,	7,	160)	92160	block_13_depthw
block_13_project_BN (BatchNorma t[0][0]	(None,	7,	7,	160)	640	block_13_projec
block_14_expand (Conv2D) t_BN[0][0]	(None,	7,	7,	960)	153600	block_13_projec
block_14_expand_BN (BatchNormal [0][0]	(None,	7,	7,	960)	3840	block_14_expand
block_14_expand_relu (ReLU) _BN[0][0]	(None,	7,	7,	960)	0	block_14_expand
block_14_depthwise (DepthwiseCo _relu[0][0]	(None,	7,	7,	960)	8640	block_14_expand
block_14_depthwise_BN (BatchNor ise[0][0]	(None,	7,	7,	960)	3840	block_14_depthw
block_14_depthwise_relu (ReLU) ise_BN[0][0]	(None,	7,	7,	960)	0	block_14_depthw
block_14_project (Conv2D) ise_relu[0][0]	(None,	7,	7,	160)	153600	block_14_depthw
block_14_project_BN (BatchNormat[0][0]	(None,	7,	7,	160)	640	block_14_projec
block_14_add (Add) t_BN[0][0] t_BN[0][0]	(None,	7,	7,	160)	0	block_13_projec
block_15_expand (Conv2D) [0][0]	(None,	7,	7,	960)	153600	block_14_add
block_15_expand_BN (BatchNormal [0][0]	(None,	7,	7,	960)	3840	block_15_expand
block_15_expand_relu (ReLU) _BN[0][0]	(None,	7,	7,	960)	0	block_15_expand
block_15_depthwise (DepthwiseCo	(None,	7,	7,	960)	8640	block_15_expand

_relu[0][0]						
block_15_depthwise_BN (BatchNorise[0][0]	(None,	7,	7,	960)	3840	block_15_depthw
block_15_depthwise_relu (ReLU) ise_BN[0][0]	(None,	7,	7,	960)	0	block_15_depthw
block_15_project (Conv2D) ise_relu[0][0]	(None,	7,	7,	160)	153600	block_15_depthw
block_15_project_BN (BatchNorma t[0][0]	(None,	7,	7,	160)	640	block_15_projec
block_15_add (Add) [0][0]  t_BN[0][0]	(None,	7,	7,	160)	0	block_14_add block_15_projec
block_16_expand (Conv2D) [0][0]	(None,	7,	7,	960)	153600	block_15_add
block_16_expand_BN (BatchNormal [0][0]	(None,	7,	7,	960)	3840	block_16_expand
block_16_expand_relu (ReLU) _BN[0][0]	(None,	7,	7,	960)	0	block_16_expand
block_16_depthwise (DepthwiseCo _relu[0][0]	(None,	7,	7,	960)	8640	block_16_expand
block_16_depthwise_BN (BatchNor ise[0][0]	(None,	7,	7,	960)	3840	block_16_depthw
block_16_depthwise_relu (ReLU) ise_BN[0][0]	(None,	7,	7,	960)	0	block_16_depthw
block_16_project (Conv2D) ise_relu[0][0]	(None,	7,	7,	320)	307200	block_16_depthw
block_16_project_BN (BatchNorma t[0][0]	(None,	7,	7,	320)	1280	block_16_projec
Conv_1 (Conv2D) t_BN[0][0]	(None,	7,	7,	1280)	409600	block_16_projec
Conv_1_bn (BatchNormalization)	(None,	7,	7,	1280)	5120	Conv_1[0][0]

```
(None, 7, 7, 1280) 0
out relu (ReLU)
                                               Conv 1 bn[0][0]
global average pooling2d (Globa (None, 1280)
                                      0
                                               out relu[0][0]
predictions (Dense)
                       (None, 1000)
                                      1281000
                                               global_average_
pooling2d[0][0]
_____
Total params: 3,538,984
Trainable params: 3,504,872
Non-trainable params: 34,112
Model: "functional_1"
Layer (type)
                    Output Shape
                                        Param #
input 1 (InputLayer)
                    [(None, 224, 224, 3)]
mobilenetv2 1.00 224 (Functi (None, 1000)
                                        3538984
flatten (Flatten)
                     (None, 1000)
                 (None, 2)
                                        2002
output layer (Dense)
______
  layer.trainable = False
custom_resnet_model.layers[-1].trainable
```

```
In [12]: for layer in custom resnet model.layers[:-1]:
```

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
y: 0.7252 - val loss: 0.6028 - val_accuracy: 0.7338
Epoch 2/100
147/147 [============= ] - 6s 41ms/step - loss: 0.5841 - accurac
y: 0.7289 - val loss: 0.5623 - val accuracy: 0.7338
Epoch 3/100
y: 0.7289 - val_loss: 0.5391 - val_accuracy: 0.7338
Epoch 4/100
y: 0.7293 - val_loss: 0.5222 - val_accuracy: 0.7338
Epoch 5/100
y: 0.7312 - val loss: 0.5073 - val accuracy: 0.7398
Epoch 6/100
y: 0.7340 - val loss: 0.4940 - val accuracy: 0.7406
Epoch 7/100
y: 0.7376 - val_loss: 0.4815 - val_accuracy: 0.7449
Epoch 8/100
y: 0.7427 - val loss: 0.4699 - val accuracy: 0.7517
Epoch 9/100
y: 0.7487 - val loss: 0.4591 - val_accuracy: 0.7568
Epoch 10/100
y: 0.7556 - val_loss: 0.4488 - val_accuracy: 0.7568
Epoch 11/100
y: 0.7626 - val loss: 0.4394 - val accuracy: 0.7619
Epoch 12/100
y: 0.7690 - val loss: 0.4305 - val accuracy: 0.7628
Epoch 13/100
y: 0.7763 - val_loss: 0.4221 - val_accuracy: 0.7713
Epoch 14/100
y: 0.7835 - val loss: 0.4143 - val accuracy: 0.7807
Epoch 15/100
y: 0.7912 - val_loss: 0.4069 - val_accuracy: 0.7850
Epoch 16/100
y: 0.7965 - val loss: 0.4000 - val accuracy: 0.7884
Epoch 17/100
y: 0.8019 - val_loss: 0.3934 - val_accuracy: 0.7986
Epoch 18/100
y: 0.8104 - val_loss: 0.3872 - val_accuracy: 0.8063
Epoch 19/100
y: 0.8164 - val loss: 0.3813 - val accuracy: 0.8217
Epoch 20/100
y: 0.8228 - val loss: 0.3758 - val accuracy: 0.8294
Epoch 21/100
y: 0.8256 - val_loss: 0.3705 - val_accuracy: 0.8345
```

```
Epoch 22/100
y: 0.8309 - val loss: 0.3656 - val accuracy: 0.8370
Epoch 23/100
y: 0.8373 - val loss: 0.3608 - val accuracy: 0.8413
Epoch 24/100
y: 0.8407 - val loss: 0.3563 - val accuracy: 0.8456
Epoch 25/100
y: 0.8448 - val_loss: 0.3520 - val_accuracy: 0.8473
Epoch 26/100
y: 0.8486 - val_loss: 0.3480 - val_accuracy: 0.8549
Epoch 27/100
y: 0.8499 - val_loss: 0.3441 - val_accuracy: 0.8592
Epoch 28/100
y: 0.8540 - val loss: 0.3403 - val accuracy: 0.8601
Epoch 29/100
y: 0.8559 - val loss: 0.3368 - val accuracy: 0.8626
Epoch 30/100
y: 0.8589 - val loss: 0.3334 - val accuracy: 0.8686
Epoch 31/100
y: 0.8610 - val loss: 0.3301 - val accuracy: 0.8712
Epoch 32/100
y: 0.8649 - val_loss: 0.3270 - val_accuracy: 0.8754
Epoch 33/100
y: 0.8678 - val loss: 0.3240 - val accuracy: 0.8763
Epoch 34/100
y: 0.8706 - val loss: 0.3211 - val accuracy: 0.8788
y: 0.8711 - val loss: 0.3183 - val accuracy: 0.8823
Epoch 36/100
y: 0.8723 - val_loss: 0.3157 - val_accuracy: 0.8848
Epoch 37/100
y: 0.8762 - val loss: 0.3131 - val accuracy: 0.8874
Epoch 38/100
y: 0.8772 - val loss: 0.3106 - val accuracy: 0.8865
Epoch 39/100
y: 0.8787 - val loss: 0.3083 - val accuracy: 0.8891
Epoch 40/100
y: 0.8796 - val loss: 0.3060 - val accuracy: 0.8916
Epoch 41/100
y: 0.8798 - val loss: 0.3038 - val accuracy: 0.8916
Epoch 42/100
y: 0.8813 - val loss: 0.3017 - val accuracy: 0.8925
Epoch 43/100
```

```
y: 0.8817 - val loss: 0.2996 - val accuracy: 0.8933
Epoch 44/100
y: 0.8826 - val loss: 0.2977 - val accuracy: 0.8933
147/147 [============== ] - 6s 41ms/step - loss: 0.3188 - accurac
y: 0.8830 - val loss: 0.2958 - val accuracy: 0.8951
Epoch 46/100
y: 0.8847 - val_loss: 0.2939 - val_accuracy: 0.8951
Epoch 47/100
y: 0.8854 - val loss: 0.2921 - val accuracy: 0.8942
Epoch 48/100
y: 0.8875 - val loss: 0.2903 - val accuracy: 0.8951
Epoch 49/100
y: 0.8871 - val loss: 0.2886 - val accuracy: 0.8959
Epoch 50/100
y: 0.8881 - val loss: 0.2870 - val accuracy: 0.8968
Epoch 51/100
y: 0.8890 - val loss: 0.2854 - val accuracy: 0.8976
Epoch 52/100
y: 0.8894 - val loss: 0.2838 - val accuracy: 0.8976
Epoch 53/100
y: 0.8898 - val loss: 0.2823 - val accuracy: 0.8976
Epoch 54/100
y: 0.8911 - val loss: 0.2809 - val_accuracy: 0.8985
Epoch 55/100
y: 0.8907 - val_loss: 0.2795 - val_accuracy: 0.8985
Epoch 56/100
y: 0.8915 - val_loss: 0.2781 - val_accuracy: 0.9019
Epoch 57/100
y: 0.8920 - val loss: 0.2768 - val accuracy: 0.9019
Epoch 58/100
y: 0.8922 - val_loss: 0.2755 - val_accuracy: 0.9019
Epoch 59/100
y: 0.8924 - val loss: 0.2742 - val accuracy: 0.9027
Epoch 60/100
y: 0.8930 - val loss: 0.2730 - val accuracy: 0.9036
Epoch 61/100
y: 0.8928 - val loss: 0.2718 - val accuracy: 0.9053
y: 0.8922 - val loss: 0.2706 - val accuracy: 0.9061
Epoch 63/100
y: 0.8943 - val loss: 0.2695 - val accuracy: 0.9070
Epoch 64/100
```

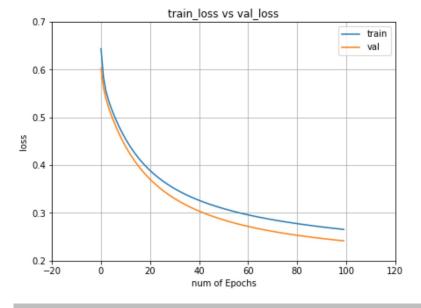
```
y: 0.8950 - val loss: 0.2684 - val accuracy: 0.9070
Epoch 65/100
y: 0.8950 - val_loss: 0.2673 - val_accuracy: 0.9078
Epoch 66/100
y: 0.8952 - val loss: 0.2663 - val accuracy: 0.9078
Epoch 67/100
y: 0.8960 - val loss: 0.2652 - val accuracy: 0.9087
Epoch 68/100
y: 0.8954 - val loss: 0.2642 - val accuracy: 0.9096
Epoch 69/100
y: 0.8975 - val loss: 0.2633 - val accuracy: 0.9096
Epoch 70/100
y: 0.8975 - val loss: 0.2623 - val accuracy: 0.9096
Epoch 71/100
y: 0.8986 - val loss: 0.2614 - val accuracy: 0.9113
y: 0.8986 - val loss: 0.2605 - val accuracy: 0.9104
Epoch 73/100
y: 0.8984 - val loss: 0.2596 - val accuracy: 0.9113
Epoch 74/100
y: 0.8984 - val loss: 0.2588 - val accuracy: 0.9113
Epoch 75/100
y: 0.8982 - val loss: 0.2579 - val accuracy: 0.9113
Epoch 76/100
y: 0.8990 - val_loss: 0.2571 - val_accuracy: 0.9113
Epoch 77/100
y: 0.8997 - val loss: 0.2563 - val accuracy: 0.9121
Epoch 78/100
y: 0.8999 - val_loss: 0.2555 - val_accuracy: 0.9104
Epoch 79/100
y: 0.9005 - val_loss: 0.2548 - val_accuracy: 0.9113
Epoch 80/100
y: 0.9005 - val loss: 0.2540 - val accuracy: 0.9113
Epoch 81/100
y: 0.9007 - val loss: 0.2533 - val_accuracy: 0.9113
Epoch 82/100
y: 0.9016 - val loss: 0.2525 - val accuracy: 0.9121
Epoch 83/100
y: 0.9018 - val loss: 0.2518 - val accuracy: 0.9130
Epoch 84/100
y: 0.9022 - val loss: 0.2512 - val accuracy: 0.9121
Epoch 85/100
y: 0.9014 - val_loss: 0.2505 - val_accuracy: 0.9130
```

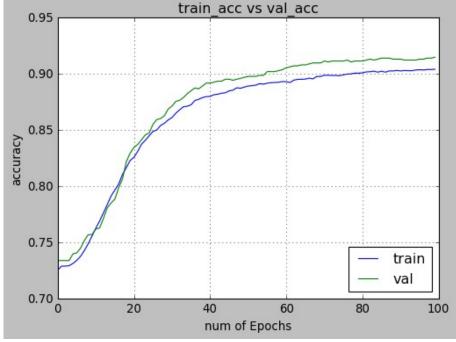
Epoch 86/100

```
y: 0.9022 - val loss: 0.2498 - val accuracy: 0.9138
    Epoch 87/100
    y: 0.9014 - val loss: 0.2492 - val accuracy: 0.9138
    Epoch 88/100
    147/147 [============== ] - 6s 41ms/step - loss: 0.2727 - accurac
    y: 0.9024 - val loss: 0.2485 - val accuracy: 0.9138
    y: 0.9024 - val_loss: 0.2479 - val_accuracy: 0.9130
    Epoch 90/100
    y: 0.9029 - val loss: 0.2473 - val accuracy: 0.9130
    Epoch 91/100
    y: 0.9024 - val_loss: 0.2466 - val_accuracy: 0.9130
    Epoch 92/100
    y: 0.9029 - val loss: 0.2460 - val accuracy: 0.9121
    Epoch 93/100
    y: 0.9026 - val loss: 0.2454 - val accuracy: 0.9121
    Epoch 94/100
    y: 0.9026 - val loss: 0.2449 - val accuracy: 0.9121
    Epoch 95/100
    y: 0.9033 - val loss: 0.2443 - val accuracy: 0.9121
    Epoch 96/100
    y: 0.9035 - val loss: 0.2437 - val accuracy: 0.9130
    Epoch 97/100
    y: 0.9033 - val_loss: 0.2432 - val_accuracy: 0.9130
    Epoch 98/100
    y: 0.9037 - val loss: 0.2426 - val accuracy: 0.9138
    y: 0.9037 - val loss: 0.2421 - val accuracy: 0.9138
    Epoch 100/100
    y: 0.9039 - val_loss: 0.2416 - val_accuracy: 0.9147
    Training time: -609.8109776973724
    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 [============= ] - 2s 15ms/step - loss: 0.2416 - accurac
    [INFO] loss=0.2416, accuracy: 91.4676%
```

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: 0.24162615835666656 Test accuracy: 0.914675772190094 (1, 224, 224, 3) [[8.33914601e-05 9.43122213e-05 6.17418555e-05 6.54168252e-05 1.13233073e-04 4.74682347e-05 5.82300017e-05 1.08953674e-04 2.47885200e-05 1.91886254e-04 7.08437146e-05 3.57683566e-05 2.95793929e-04 5.55347469e-05 2.16536369e-04 6.21841609e-05 3.03070352e-04 4.57870956e-05 1.19120559e-04 8.90225492e-05 1.66406928e-04 9.70872716e-05 1.62744705e-04 1.49278203e-04 7.53177155e-05 1.09933528e-04 2.17667766e-04 1.03260376e-04 1.68310271e-05 4.71250714e-05 2.25656520e-04 1.11117632e-04 1.19079450e-04 3.50336049e-05 7.37054288e-05 1.12858543e-04 1.31092936e-04 5.13734412e-05 1.09661698e-04 1.33358277e-04 1.32257570e-04 3.87834370e-05 6.33041956e-04 8.69823198e-05 1.75937254e-04 4.36656082e-05 3.17085214e-04 4.07961088e-05 3.52774805e-05 9.89007895e-05 3.13197001e-04 3.97188778e-05 3.01094784e-04 2.42384500e-04 3.31761781e-04 3.03487395e-05 3.10513788e-05 1.01327387e-04 8.12207290e-04 2.79306027e-04 7.95677552e-05 3.58391902e-04 2.18163841e-04 1.20014038e-05 3.81811369e-05 1.32926434e-04 2.31196143e-04 2.24524265e-05 9.85946317e-05 1.02861639e-04 1.61079763e-04 2.17821958e-04 3.50604132e-05 2.44382943e-04 6.57923752e-04 1.51681917e-04 2.78034480e-04 1.11821643e-03 1.29941225e-04 7.72509258e-04 3.47995025e-04 1.38023504e-04 6.40542203e-05 4.19817152e-054.27196617e-04 4.55504705e-05 4.25938524e-05 6.52940753e-06 2.40640133e-04 1.50604916e-04 5.46822557e-04 1.12956704e-03 1.23571826e-03 6.57338824e-05 9.26602224e-05 4.90679340e-05 2.16124783e-04 5.13464547e-05 7.67093807e-05 4.40209726e-04 1.56303606e-04 3.04156449e-04 3.77853285e-05 1.33213616e-05 7.79672555e-05 1.12029833e-04 4.41315169e-05 5.07919642e-04 2.39844224e-03 1.99436821e-04 1.03430102e-04 1.63807563e-05 4.74627122e-05 1.43858822e-04 3.36380654e-05 9.86379018e-05 3.65483051e-04 2.97627383e-04 3.29633949e-05 1.55277128e-04 1.97401114e-05 5.45085131e-05 7.30986221e-06 7.17431467e-05 1.04610435e-05 1.34972914e-04 8.48182535e-05 5.58899483e-04 8.61329172e-05 1.34347181e-03 4.01100580e-04 9.56244621e-05 5.89205556e-05 7.04675767e-05 1.13356138e-04 1.90605904e-04 5.86017450e-05 2.83766531e-05 2.41395646e-05 2.35308864e-04 1.98521317e-04 9.12860487e-05 2.52444355e-04 1.62257536e-04 6.40077284e-04 1.32496934e-04 2.10071681e-04 6.35759934e-05 1.41753102e-04 1.35031165e-04 5.41926653e-04 3.66952663e-05 3.07578885e-05 6.28180278e-04 2.15198015e-05 8.01470087e-05 8.16880274e-05 8.74915640e-05 4.15920149e-05 7.44503195e-05 8.24786548e-05 5.42770031e-05 5.48054668e-05 4.74896988e-05 9.28548325e-05 4.52796885e-05 1.77980764e-05 1.84390505e-04 1.98084726e-05 1.04686733e-04 1.61515454e-05 1.20808099e-05 1.41941000e-05 6.96301358e-05 2.30870028e-05 1.98415233e-04 1.17952135e-04 5.10479294e-05 1.49995074e-04 8.08492041e-05 3.51375347e-05 2.29028607e-04 8.90064184e-05 3.12090066e-041.59218849e-04 4.08091466e-04 2.47155094e-05 6.27728441e-055.85914713e-05 1.24783706e-04 8.47743824e-04 2.00780225e-04 1.14579025e-05 4.24381542e-05 2.20518123e-04 2.41503993e-04 3.80996120e-04 1.66334023e-04 4.57426009e-04 2.28657053e-04 8.80086518e-05 2.42261885e-04 1.38663643e-04 1.01071002e-03 5.62849418e-05 1.17982512e-04 8.66682560e-04 2.85082497e-04 5.68611940e-05 3.75254785e-05 3.42668318e-05 9.50891044e-05 5.70256343e-05 1.05972678e-04 3.37440358e-03 1.68348161e-05 1.13453483e-03 9.97516909e-05 2.97156566e-05 9.10738425e-04 8.94142868e-05 3.80023732e-04 1.13284055e-04 1.53732763e-05 6.09609342e-05 4.30636464e-05 7.16900686e-05 1.03029714e-04 1.17967102e-04 2.91551783e-04 2.07727862e-05 2.68855474e-05 3.98764096e-04 1.12831323e-04 5.65429684e-04 1.08823864e-04 2.27547629e-04 8.15887543e-05 1.31144631e-03 1.72377404e-04

```
3.01062464e-05 1.25550898e-04 7.60590920e-05 1.35162845e-04
3.01215259e-05 7.59201357e-04 1.18775715e-04 1.13286223e-04
9.98448813e-05 5.13336236e-05 5.72519348e-05 2.53097154e-04
1.25184335e-04 2.11916649e-05 1.37296462e-04 3.80941747e-05
6.89057060e-06 1.19045166e-04 2.11454069e-04 4.46508348e-05
4.96068569e-05 4.19014759e-05 2.39833011e-04 1.74566085e-05
3.02299904e-05 6.74980110e-05 3.35405115e-04 9.43383129e-05
5.71627970e-05 1.47618804e-04 2.56361207e-04 8.28940611e-05
1.76530288e-04 5.17332774e-05 1.28926558e-05 2.16640274e-05
5.26299800e-06 6.59979298e-04 1.14130096e-04 2.94375030e-04
4.49465224e-05 3.86519037e-04 4.72550419e-05 5.00234251e-04
1.12830836e-03 8.48204363e-05 5.19808455e-05 9.09078008e-05
1.57584349e-04 2.78345804e-04 2.19877635e-04 4.03005979e-05
2.55742081e-04 1.43388272e-04 4.44702513e-04 2.79434986e-04
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1.25893086e-04 1.04214778e-04 5.29835888e-05 8.40803841e-05
```

```
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)
                  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
         yhat = custom resnet model.predict(x)
         print(yhat)
         # print(custom resnet model.predict classes(x))
         label = decode_predictions(yhat)
         # retrieve the most likely result, e.g. highest probability
         label = label[0][0]
```

```
(1, 224, 224, 3)
[[0.04744451 0.95255554]]
.....
ValueError
                                      Traceback (most recent call last)
<ipython-input-18-505048f79341> in <module>
    30 print(yhat)
    31 # print(custom resnet model.predict classes(x))
---> 32 label = decode predictions (yhat)
    33 # retrieve the most likely result, e.g. highest probability
    34 label = label[0][0]
D:\Anaconda3\lib\site-packages\tensorflow\python\keras\applications\inception v
3.py in decode predictions(preds, top)
   412 @keras export ('keras.applications.inception v3.decode predictions')
   413 def decode predictions (preds, top=5):
--> 414 return imagenet_utils.decode_predictions(preds, top=top)
   415
   416
D:\Anaconda3\lib\site-packages\tensorflow\python\keras\applications\imagenet uti
ls.py in decode predictions(preds, top)
   149
                           'a batch of predictions '
   150
                           '(i.e. a 2D array of shape (samples, 1000)). '
--> 151
                           'Found array with shape: ' + str(preds.shape))
   if CLASS_INDEX is None:
   fpath = data_utils.get_file(
ValueError: `decode predictions` expects a batch of predictions (i.e. a 2D array
of shape (samples, 1000)). Found array with shape: (1, 2)
```

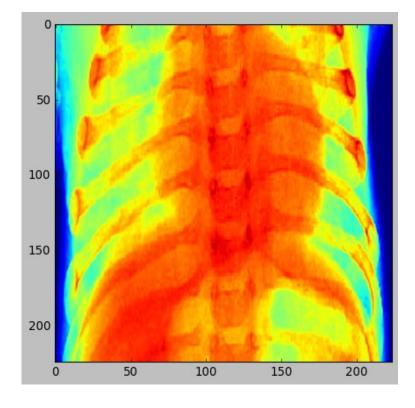
Visualizing the intermediate layer

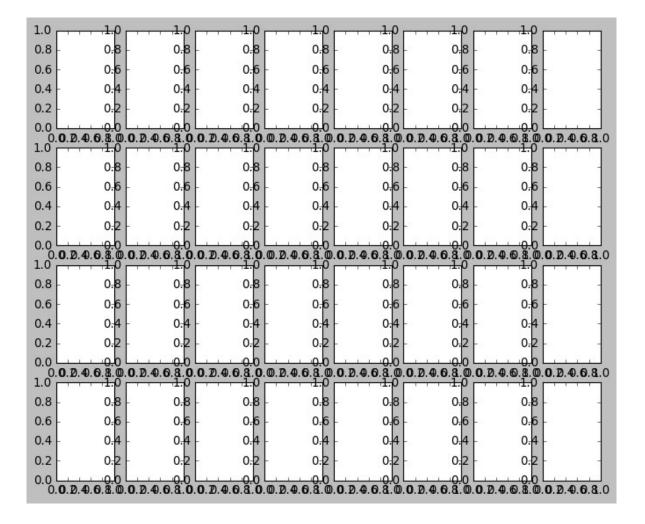
```
In [19]: | from keras.models import Model
         layer outputs = [layer.output for layer in model.layers]
         activation_model = Model(inputs=custom_resnet_model.input, outputs=layer_outputs)
         activations = custom_resnet_model.predict(X_train[10].reshape(1,224,224,3))
         print(activations.shape)
         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.



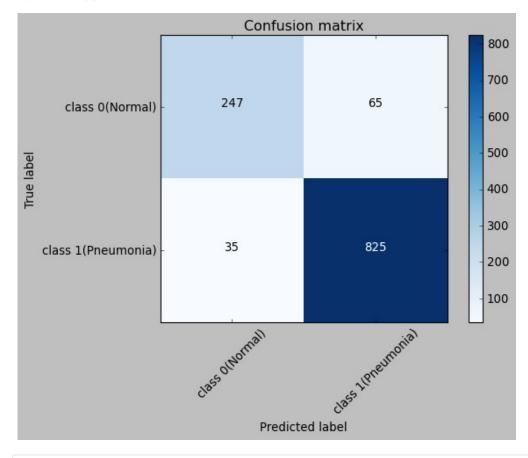


Confusion matrix

```
In [20]: 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))
         [[0.01631579 0.9836842 ]
          [0.83765393 0.16234608]
          [0.01476637 0.9852336 ]
          [0.015543 0.98445696]
          [0.10139033 0.89860964]
          [0.8255221 0.17447793]]
         [1 0 1 ... 1 1 0]
                             precision recall f1-score support
            class 0(Normal) 0.88 0.79 0.83 ass 1(Pneumonia) 0.93 0.96 0.94
                                                                 312
         class 1(Pneumonia)
                                                                 860
                                                  0.89 1172
0.91 1172
                   accuracy
               macro avg 0.90 0.88 weighted avg 0.91 0.91
         [[247 65]
          [ 35 825]]
```

Compute confusion matrix

Confusion matrix, without normalization [[247 65] [ 35 825]]



```
In []:
In []:
```