In [1]:

```
import os
import glob
import h5py
import shutil
import imgaug as aug
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.image as mimg
import imgaug.augmenters as iaa
from os import listdir, makedirs, getcwd, remove
from os.path import isfile, join, abspath, exists, isdir, expanduser
from PIL import Image
from pathlib import Path
from skimage.io import imread
from skimage.transform import resize
from keras.models import Sequential, Model
from keras.applications.vgg16 import VGG16, preprocess_input
from keras.preprocessing.image import ImageDataGenerator,load_img, img_to_array
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Dense, Dropout, Input, Flatten, SeparableConv2D
from keras.layers import GlobalMaxPooling2D
from keras.layers.normalization import BatchNormalization
from keras.layers.merge import Concatenate
from keras.models import Model
from keras.optimizers import Adam, SGD, RMSprop
from keras.callbacks import ModelCheckpoint, Callback, EarlyStopping
from keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from mlxtend.plotting import plot_confusion_matrix
from sklearn.metrics import confusion_matrix
import cv2
import tensorflow as tf
from keras import backend as K
color = sns.color_palette()
%matplotlib inline
```

```
Using TensorFlow backend.
```

In [2]:

```
import tensorflow as tf

# Set the seed for hash based operations in python
os.environ['PYTHONHASHSEED'] = '0'

# Set the numpy seed
np.random.seed(111)

# Disable multi-threading in tensorflow ops
session_conf = tf.compat.v1.ConfigProto(intra_op_parallelism_threads=1, inter_op_parallelism_threads=1)

# Set the random seed in tensorflow at graph level
tf.random.set_seed(111)



# Make the augmentation sequence deterministic
aug.seed(111)
```

In [3]:

```
# Define path to the data directory
data_dir = Path('chest_xray')

# Path to train directory (Fancy pathlib...no more os.path!!)
train_dir = data_dir / 'train'

# Path to test directory
test_dir = data_dir / 'test'
```

In [4]:

```
# Get the path to the normal and pneumonia sub-directories
normal_cases_dir = train_dir / 'NORMAL'
pneumonia_cases_dir = train_dir / 'PNEUMONIA'

# Get the list of all the images
normal_cases = normal_cases_dir.glob('*.*g')
#normal_cases.extend('*.png')
#normal_cases.extend('*.jpg')
pneumonia_cases = pneumonia_cases_dir.glob('*.*g')
#pneumonia_cases = pneumonia_cases_dir.glob('*.jpg')
#pneumonia_cases = pneumonia_cases_dir.glob('*.png')

print(normal_cases)
# An empty list. We will insert the data into this list in (img_path, label) format
train_data = []

# Go through all the normal cases. The label for these cases will be 0
for img in normal_cases:
    train_data.append((img,0))

# Go through all the pneumonia cases. The label for these cases will be 1
for img in pneumonia_cases:
    train_data.append((img, 1))

# Get a pandas dataframe from the data we have in our list
train_data = pd.DataFrame(train_data, columns=['image', 'label'],index=None)

# Shuffle the data
train_data = train_data.sample(frac=1.).reset_index(drop=True)
# How the dataframe looks like?
train_data.head()
```

```
<generator object Path.glob at 0x7fd1e8b9fad0>
```

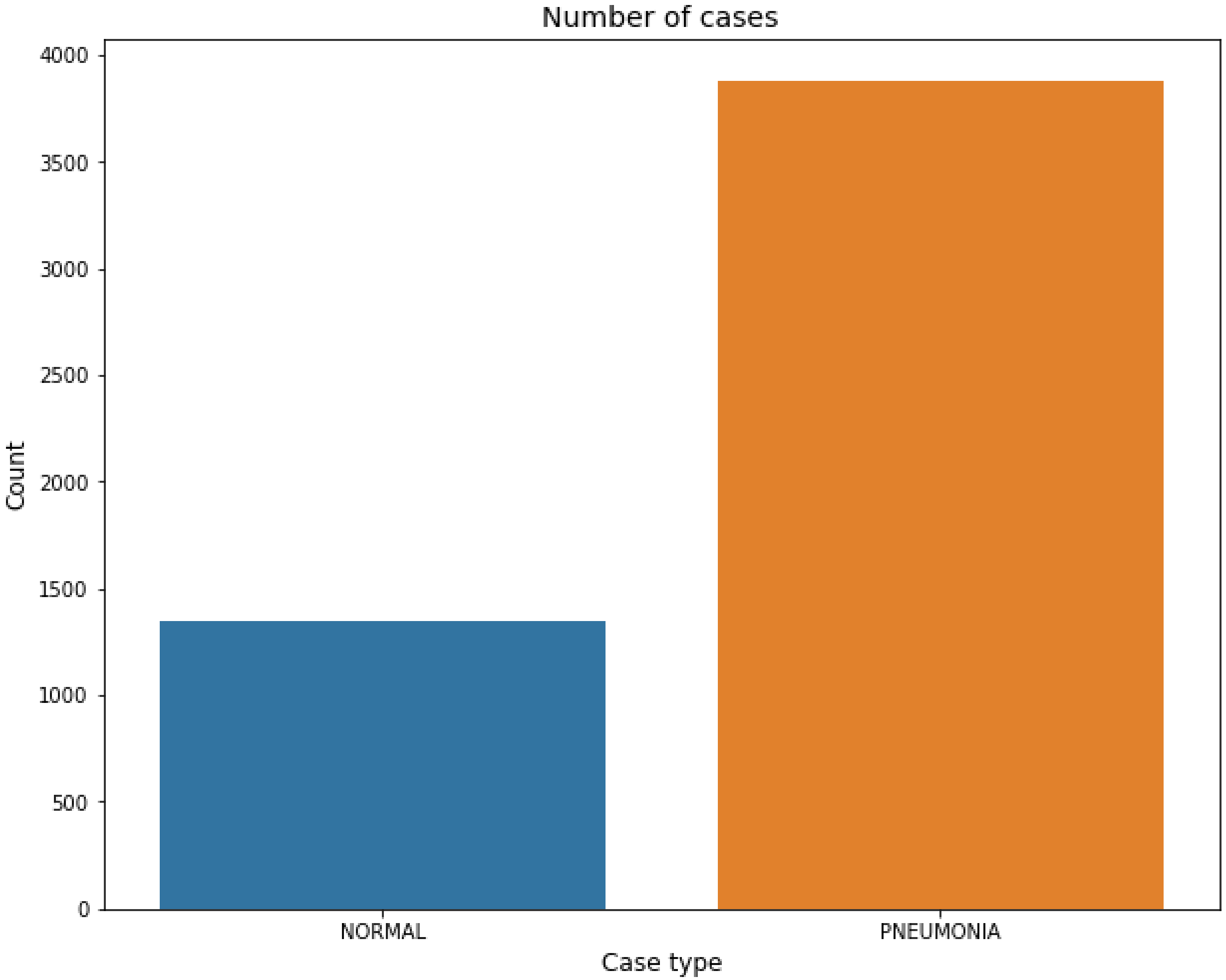
Out[4]:

	image	label
0	chest_xray/train/PNEUMONIA/BACTERIA-3134196-00...	1
1	chest_xray/train/PNEUMONIA/BACTERIA-1083680-00...	1
2	chest_xray/train/PNEUMONIA/BACTERIA-1950119-00...	1
3	chest_xray/train/PNEUMONIA/VIRUS-8028911-0002....	1
4	chest_xray/train/PNEUMONIA/VIRUS-5331068-0002....	1

In [5]:

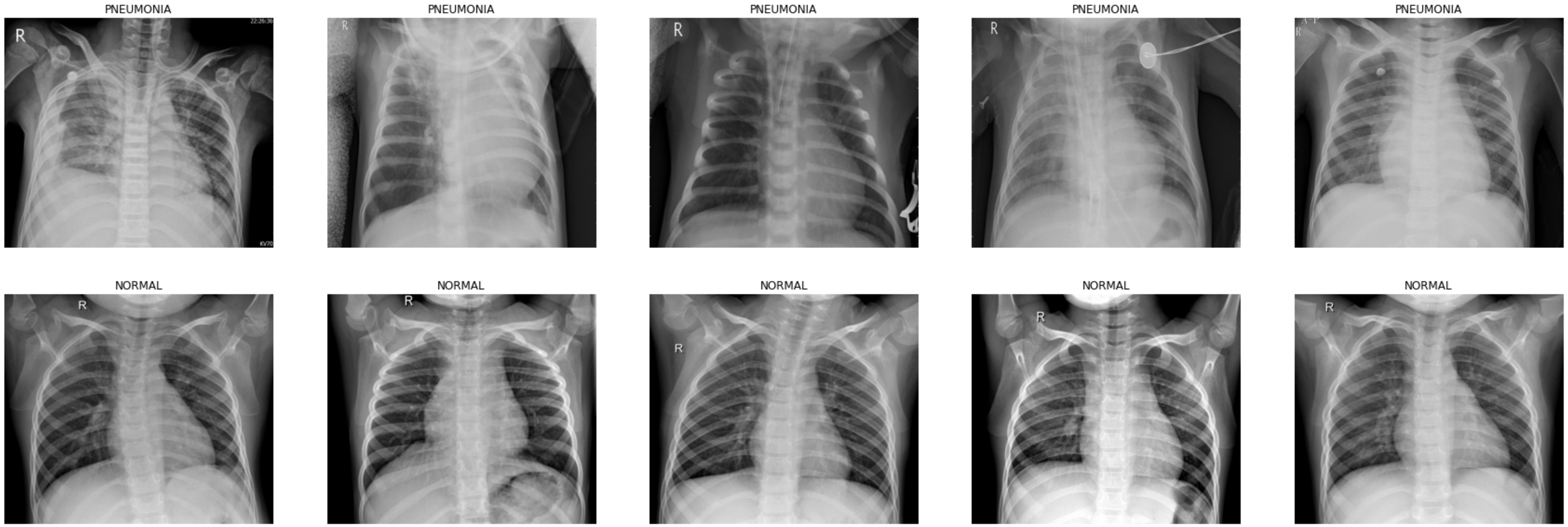
```
# Get the counts for each class
cases_count = train_data['label'].value_counts()
print(cases_count)

# Plot the results
plt.figure(figsize=(10,8))
sns.barplot(x=cases_count.index, y= cases_count.values)
plt.title('Number of cases', fontsize=14)
plt.xlabel('Case type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(range(len(cases_count.index)), ['NORMAL', 'PNEUMONIA'])
plt.show()
```

```
1    3883
0    1349
Name: label, dtype: int64
```


Number of cases
Count
4000
3500
3000
2500
2000
1500
1000
500
0
NORMAL
PNEUMONIA
Case type

In [6]:

```
pneumonia_samples = (train_data[train_data['label']==1]['image'].iloc[:5]).tolist()
normal_samples = (train_data[train_data['label']==0]['image'].iloc[:5]).tolist()

# Concat the data in a single list and del the above two list
samples = pneumonia_samples + normal_samples
del pneumonia_samples, normal_samples

# Plot the data
f, ax = plt.subplots(2,5, figsize=(30,10))
for i in range(10):
    img = imread(samples[i])
    ax[i//5, i%5].imshow(img, cmap='gray')
    if i<5:
        ax[i//5, i%5].set_title("PNEUMONIA")
    else:
        ax[i//5, i%5].set_title("NORMAL")
    ax[i//5, i%5].axis('off')
    ax[i//5, i%5].set_aspect('auto')
plt.show()
```



In [ ]:

In [7]:

```
# Get the path to the sub-directories
normal_cases_dir = test_dir / 'NORMAL'
pneumonia_cases_dir = test_dir / 'PNEUMONIA'

# Get the list of all the images
normal_cases = normal_cases_dir.glob('*.*g')
pneumonia_cases = pneumonia_cases_dir.glob('*.*g')

# List that are going to contain validation images data and the corresponding labels
valid_data = []
valid_labels = []


# Some images are in grayscale while majority of them contains 3 channels. So, if the image is grayscale, we will convert into a image with 3 channels.
# We will normalize the pixel values and resizing all the images to 224x224

# Normal cases
for img in normal_cases:
    img = cv2.imread(str(img))
    img = cv2.resize(img, (224,224))
    if img.shape[2] ==1:
        img = np.dstack([img, img, img])
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = img.astype(np.float32)/255.
    label = to_categorical(0, num_classes=2)
    valid_data.append(img)
    valid_labels.append(label)

# Pneumonia cases
for img in pneumonia_cases:
    img = cv2.imread(str(img))
    img = cv2.resize(img, (224,224))
    if img.shape[2] ==1:
        img = np.dstack([img, img, img])
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = img.astype(np.float32)/255.
    label = to_categorical(1, num_classes=2)
    valid_data.append(img)
    valid_labels.append(label)

# Convert the list into numpy arrays
valid_data = np.array(valid_data)
valid_labels = np.array(valid_labels)

print("Total number of validation examples: ", valid_data.shape)
print("Total number of labels:", valid_labels.shape)
```

```
Total number of validation examples:  (624, 224, 224, 3)
Total number of labels: (624, 2)
```

In [8]:

```
# Augmentation sequence
seq = iaa.OneOf([
    iaa.Fliplr(), # horizontal flips
    iaa.Affine(rotate=40), # roatation
    iaa.Multiply((1.2, 1.5))]) #random brightness
```

In [9]:

```
def data_gen(data, batch_size):
    # Get total number of samples in the data
    n = len(data)
    steps = n//batch_size

    # Define two numpy arrays for containing batch data and labels
    batch_data = np.zeros((batch_size, 224, 224, 3), dtype=np.float32)
    batch_labels = np.zeros((batch_size,2), dtype=np.float32)

    # Get a numpy array of all the indices of the input data
    indices = np.arange(n)

    # Initialize a counter
    i =0
    while True:
        np.random.shuffle(indices)
        # Get the next batch
        count = 0
        next_batch = indices[(i*batch_size):(i+1)*batch_size]
        for j, idx in enumerate(next_batch):
            img_name = data.iloc[idx]['image']
            label = data.iloc[idx]['label']

            # one hot encoding
            encoded_label = to_categorical(label, num_classes=2)
            # read the image and resize
            img = cv2.imread(str(img_name))
            img = cv2.resize(img, (224,224))

            # check if it's grayscale
            if img.shape[2]==1:
                img = np.dstack([img, img, img])

            # cv2 reads in BGR mode by default
            orig_img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
            # normalize the image pixels
            orig_img = img.astype(np.float32)/255.

            batch_data[count] = orig_img
            batch_labels[count] = encoded_label

            # generating more samples of the undersampled class
            if label==0 and count < batch_size-2:
                aug_img1 = seq.augment_image(img)
                aug_img2 = seq.augment_image(img)
                aug_img1 = cv2.cvtColor(aug_img1, cv2.COLOR_BGR2RGB)
                aug_img2 = cv2.cvtColor(aug_img2, cv2.COLOR_BGR2RGB)
                aug_img1 = aug_img1.astype(np.float32)/255.
                aug_img2 = aug_img2.astype(np.float32)/255.

                batch_data[count+1] = aug_img1
                batch_labels[count+1] = encoded_label
                batch_data[count+2] = aug_img2
                batch_labels[count+2] = encoded_label
                count +=2

            else:
                count+=1

            if count==batch_size-1:
                break

        i+=1
        yield batch_data, batch_labels

        if i>=steps:
            i=0
```

In [10]:

```
def build_model():
    input_img = Input(shape=(224,224,3), name='ImageInput')
    x = Conv2D(64, (3,3), activation='relu', padding='same', name='Conv1_1')(input_img)
    x = Conv2D(64, (3,3), activation='relu', padding='same', name='Conv1_2')(x)
    x = MaxPooling2D((2,2), name='pool1')(x)

    x = SeparableConv2D(128, (3,3), activation='relu', padding='same', name='Conv2_1')(x)
    x = SeparableConv2D(128, (3,3), activation='relu', padding='same', name='Conv2_2')(x)
    x = MaxPooling2D((2,2), name='pool2')(x)

    x = SeparableConv2D(256, (3,3), activation='relu', padding='same', name='Conv3_1')(x)
    x = BatchNormalization(name='bn1')(x)
    x = SeparableConv2D(256, (3,3), activation='relu', padding='same', name='Conv3_2')(x)
    x = BatchNormalization(name='bn2')(x)
    x = SeparableConv2D(256, (3,3), activation='relu', padding='same', name='Conv3_3')(x)
    x = MaxPooling2D((2,2), name='pool3')(x)

    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv4_1')(x)
    x = BatchNormalization(name='bn3')(x)
    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv4_2')(x)
    x = BatchNormalization(name='bn4')(x)
    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv4_3')(x)
    x = MaxPooling2D((2,2), name='pool4')(x)

    x = Flatten(name='flatten')(x)
    x = Dense(1024, activation='relu', name='fc1')(x)
    x = Dropout(0.5, name='dropout1')(x)
    x = Dense(512, activation='relu', name='fc2')(x)
    x = Dropout(0.4, name='dropout2')(x)
    x = Dense(2, activation='softmax', name='fc3')(x)

    model = Model(inputs=input_img, outputs=x)
    return model
```

In [11]:

```python
def build_modelSOTA():
    input_img = Input(shape=(224,224,3), name='ImageInput')
    x = Conv2D(64, (3,3), activation='relu', padding='same', name='Conv1_1')(input_img)
    x = Conv2D(64, (3,3), activation='relu', padding='same', name='Conv1_2')(x)
    x = MaxPooling2D((2,2), name='pool1')(x)

    x = SeparableConv2D(128, (3,3), activation='relu', padding='same', name='Conv2_1')(x)
    x = SeparableConv2D(128, (3,3), activation='relu', padding='same', name='Conv2_2')(x)
    x = MaxPooling2D((2,2), name='pool2')(x)

    x = SeparableConv2D(256, (3,3), activation='relu', padding='same', name='Conv3_1')(x)
    x = SeparableConv2D(256, (3,3), activation='relu', padding='same', name='Conv3_2')(x)
    x = SeparableConv2D(256, (3,3), activation='relu', padding='same', name='Conv3_3')(x)
    x = MaxPooling2D((2,2), name='pool3')(x)

    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv4_1')(x)
    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv4_2')(x)
    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv4_3')(x)
    x = MaxPooling2D((2,2), name='pool4')(x)

    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv5_1')(x)
    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv5_2')(x)
    x = SeparableConv2D(512, (3,3), activation='relu', padding='same', name='Conv5_3')(x)
    x = MaxPooling2D((2,2), name='pool5')(x)

    x = Flatten(name='flatten')(x)
    x = Dense(512, activation='relu', name='fc1')(x)
    x = BatchNormalization(name='bn1')(x)
    x = Dense(512, activation='relu', name='fc2')(x)
    x = BatchNormalization(name='bn2')(x)
    x = Dropout(0.5, name='dropout1')(x)
    x = Dense(2, activation='softmax', name='fc3')(x)

    model = Model(inputs=input_img, outputs=x)
    return model
```

In [12]:

```
model =  build_model()
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
ImageInput (InputLayer)      (None, 224, 224, 3)       0         
_________________________________________________________________
Conv1_1 (Conv2D)             (None, 224, 224, 64)      1792      
_________________________________________________________________
Conv1_2 (Conv2D)             (None, 224, 224, 64)      36928     
_________________________________________________________________
pool1 (MaxPooling2D)         (None, 112, 112, 64)      0         
_________________________________________________________________
Conv2_1 (SeparableConv2D)    (None, 112, 112, 128)     8896      
_________________________________________________________________
Conv2_2 (SeparableConv2D)    (None, 112, 112, 128)     17664     
_________________________________________________________________
pool2 (MaxPooling2D)         (None, 56, 56, 128)       0         
_________________________________________________________________
Conv3_1 (SeparableConv2D)    (None, 56, 56, 256)       34176     
_________________________________________________________________
bn1 (BatchNormalization)     (None, 56, 56, 256)       1024      
_________________________________________________________________
Conv3_2 (SeparableConv2D)    (None, 56, 56, 256)       68096     
_________________________________________________________________
bn2 (BatchNormalization)     (None, 56, 56, 256)       1024      
_________________________________________________________________
Conv3_3 (SeparableConv2D)    (None, 56, 56, 256)       68096     
_________________________________________________________________
pool3 (MaxPooling2D)         (None, 28, 28, 256)       0         
_________________________________________________________________
Conv4_1 (SeparableConv2D)    (None, 28, 28, 512)       133888    
_________________________________________________________________
bn3 (BatchNormalization)     (None, 28, 28, 512)       2048      
_________________________________________________________________
Conv4_2 (SeparableConv2D)    (None, 28, 28, 512)       267264    
_________________________________________________________________
bn4 (BatchNormalization)     (None, 28, 28, 512)       2048      
_________________________________________________________________
Conv4_3 (SeparableConv2D)    (None, 28, 28, 512)       267264    
_________________________________________________________________
pool4 (MaxPooling2D)         (None, 14, 14, 512)       0         
```

```
_________________________________________________________________
flatten (Flatten)            (None, 100352)            0
_________________________________________________________________
fc1 (Dense)                  (None, 1024)              102761472
_________________________________________________________________
dropout1 (Dropout)           (None, 1024)              0
_________________________________________________________________
fc2 (Dense)                  (None, 512)               524800
_________________________________________________________________
dropout2 (Dropout)           (None, 512)               0
_________________________________________________________________
fc3 (Dense)                  (None, 2)                 1026
=================================================================
Total params: 104,197,506
Trainable params: 104,194,434
Non-trainable params: 3,072
_________________________________________________________________
```

In [13]:

```
model.layers
print(len(model.layers))
```

```
25
```

In [14]:

```
# Open the VGG16 weight file
f = h5py.File('vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5', 'r')

# Select the layers for which you want to set weight.

w,b = f['block1_conv1']['block1_conv1_W_1:0'], f['block1_conv1']['block1_conv1_b_1:0']
model.layers[1].set_weights = [w,b]

w,b = f['block1_conv2']['block1_conv2_W_1:0'], f['block1_conv2']['block1_conv2_b_1:0']
model.layers[2].set_weights = [w,b]

w,b = f['block2_conv1']['block2_conv1_W_1:0'], f['block2_conv1']['block2_conv1_b_1:0']
model.layers[4].set_weights = [w,b]

w,b = f['block2_conv2']['block2_conv2_W_1:0'], f['block2_conv2']['block2_conv2_b_1:0']
model.layers[5].set_weights = [w,b]

f.close()
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
ImageInput (InputLayer)      (None, 224, 224, 3)       0         
_________________________________________________________________
Conv1_1 (Conv2D)             (None, 224, 224, 64)      1792      
_________________________________________________________________
Conv1_2 (Conv2D)             (None, 224, 224, 64)      36928     
_________________________________________________________________
pool1 (MaxPooling2D)         (None, 112, 112, 64)      0         
_________________________________________________________________
Conv2_1 (SeparableConv2D)    (None, 112, 112, 128)     8896      
_________________________________________________________________
Conv2_2 (SeparableConv2D)    (None, 112, 112, 128)     17664     
_________________________________________________________________
pool2 (MaxPooling2D)         (None, 56, 56, 128)       0         
_________________________________________________________________
Conv3_1 (SeparableConv2D)    (None, 56, 56, 256)       34176     
_________________________________________________________________
bn1 (BatchNormalization)     (None, 56, 56, 256)       1024      
_________________________________________________________________
Conv3_2 (SeparableConv2D)    (None, 56, 56, 256)       68096     
_________________________________________________________________
bn2 (BatchNormalization)     (None, 56, 56, 256)       1024      
_________________________________________________________________
Conv3_3 (SeparableConv2D)    (None, 56, 56, 256)       68096     
_________________________________________________________________
pool3 (MaxPooling2D)         (None, 28, 28, 256)       0         
_________________________________________________________________
Conv4_1 (SeparableConv2D)    (None, 28, 28, 512)       133888    
_________________________________________________________________
bn3 (BatchNormalization)     (None, 28, 28, 512)       2048      
_________________________________________________________________
Conv4_2 (SeparableConv2D)    (None, 28, 28, 512)       267264    
_________________________________________________________________
bn4 (BatchNormalization)     (None, 28, 28, 512)       2048      
_________________________________________________________________
Conv4_3 (SeparableConv2D)    (None, 28, 28, 512)       267264    
_________________________________________________________________
pool4 (MaxPooling2D)         (None, 14, 14, 512)       0         
```

```
_________________________________________________________________
flatten (Flatten)            (None, 100352)            0
_________________________________________________________________
fc1 (Dense)                  (None, 1024)              102761472
_________________________________________________________________
dropout1 (Dropout)           (None, 1024)              0
_________________________________________________________________
fc2 (Dense)                  (None, 512)               524800
_________________________________________________________________
dropout2 (Dropout)           (None, 512)               0
_________________________________________________________________
fc3 (Dense)                  (None, 2)                 1026
=================================================================
Total params: 104,197,506
Trainable params: 104,194,434
Non-trainable params: 3,072
_________________________________________________________________
```

In [15]:

```
opt = RMSprop(lr=0.0001, decay=1e-6)
#opt = RMSprop(lr=1e-4, decay=0.9) # SOTA
#opt = Adam(lr=0.0001, decay=1e-5)
#opt = Adam(lr=0.0001, decay=1e-5)
es = EarlyStopping(patience=15)
chkpt = ModelCheckpoint(filepath='best_modelvgg.hdf5', save_best_only=True, save_weights_only=True)
model.compile(loss='binary_crossentropy', metrics=['accuracy'],optimizer=opt)
```

In [16]:

```
batch_size = 16
nb_epochs = 50

# Get a train data generator
train_data_gen = data_gen(data=train_data, batch_size=batch_size)

# Define the number of training steps
nb_train_steps = train_data.shape[0]//batch_size

print("Number of training and validation steps: {} and {}".format(nb_train_steps, len(valid_data)))
```

```
Number of training and validation steps: 327 and 624
```

In [17]:

```
# # Fit the model
history = model.fit_generator(train_data_gen, epochs=nb_epochs, steps_per_epoch=nb_train_steps,
                              validation_data=(valid_data, valid_labels), callbacks=[chkpt],
                              class_weight={0:1.0, 1:0.4})
```

```
Epoch 1/50
327/327 [==============================] - 110s 337ms/step - loss: 0.1887 - accuracy: 0.8182 - val_loss: 0.6856 - val
_accuracy: 0.6250
Epoch 2/50
327/327 [==============================] - 106s 324ms/step - loss: 0.0667 - accuracy: 0.9599 - val_loss: 1.4365 - val
_accuracy: 0.6250
Epoch 3/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0631 - accuracy: 0.9627 - val_loss: 0.9952 - val
_accuracy: 0.7308
Epoch 4/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0455 - accuracy: 0.9734 - val_loss: 0.4632 - val
_accuracy: 0.8285
Epoch 5/50
327/327 [==============================] - 105s 323ms/step - loss: 0.0432 - accuracy: 0.9731 - val_loss: 0.6883 - val
_accuracy: 0.8157
Epoch 6/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0313 - accuracy: 0.9809 - val_loss: 0.4797 - val
_accuracy: 0.8910
Epoch 7/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0364 - accuracy: 0.9771 - val_loss: 0.8449 - val
_accuracy: 0.8269
Epoch 8/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0257 - accuracy: 0.9838 - val_loss: 0.8207 - val
_accuracy: 0.8413
Epoch 9/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0303 - accuracy: 0.9811 - val_loss: 0.7090 - val
_accuracy: 0.8381
Epoch 10/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0256 - accuracy: 0.9838 - val_loss: 0.8196 - val
_accuracy: 0.8718
Epoch 11/50
327/327 [==============================] - 105s 323ms/step - loss: 0.0266 - accuracy: 0.9843 - val_loss: 0.6280 - val
_accuracy: 0.8542
Epoch 12/50
327/327 [==============================] - 105s 323ms/step - loss: 0.0272 - accuracy: 0.9868 - val_loss: 1.6273 - val
_accuracy: 0.7468
Epoch 13/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0216 - accuracy: 0.9881 - val_loss: 0.5969 - val
_accuracy: 0.8814
Epoch 14/50
327/327 [==============================] - 105s 323ms/step - loss: 0.0184 - accuracy: 0.9912 - val_loss: 0.8957 - val
```

```
_accuracy: 0.8702
Epoch 15/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0205 - accuracy: 0.9897 - val_loss: 1.9860 - val
_accuracy: 0.7708
Epoch 16/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0192 - accuracy: 0.9891 - val_loss: 0.5540 - val
_accuracy: 0.9022
Epoch 17/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0166 - accuracy: 0.9906 - val_loss: 1.3020 - val
_accuracy: 0.7917
Epoch 18/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0132 - accuracy: 0.9927 - val_loss: 0.9660 - val
_accuracy: 0.8782
Epoch 19/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0126 - accuracy: 0.9935 - val_loss: 0.9907 - val
_accuracy: 0.8462
Epoch 20/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0159 - accuracy: 0.9914 - val_loss: 1.0310 - val
_accuracy: 0.8029
Epoch 21/50
327/327 [==============================] - 105s 323ms/step - loss: 0.0155 - accuracy: 0.9935 - val_loss: 0.6984 - val
_accuracy: 0.8750
Epoch 22/50
327/327 [==============================] - 106s 324ms/step - loss: 0.0136 - accuracy: 0.9933 - val_loss: 1.1119 - val
_accuracy: 0.8702
Epoch 23/50
327/327 [==============================] - 106s 323ms/step - loss: 0.0128 - accuracy: 0.9935 - val_loss: 0.9616 - val
_accuracy: 0.8622
Epoch 24/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0088 - accuracy: 0.9952 - val_loss: 1.8931 - val
_accuracy: 0.8109
Epoch 25/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0113 - accuracy: 0.9952 - val_loss: 1.4487 - val
_accuracy: 0.8526
Epoch 26/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0154 - accuracy: 0.9950 - val_loss: 0.6043 - val
_accuracy: 0.9231
Epoch 27/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0123 - accuracy: 0.9935 - val_loss: 1.2802 - val
_accuracy: 0.8381
Epoch 28/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0111 - accuracy: 0.9952 - val_loss: 1.5201 - val
```

```
_accuracy: 0.8349
Epoch 29/50
327/327 [==============================] - 105s 321ms/step - loss: 0.0062 - accuracy: 0.9966 - val_loss: 2.4692 - val
_accuracy: 0.7901
Epoch 30/50
327/327 [==============================] - 105s 321ms/step - loss: 0.0122 - accuracy: 0.9958 - val_loss: 1.1980 - val
_accuracy: 0.8798
Epoch 31/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0089 - accuracy: 0.9952 - val_loss: 0.9941 - val
_accuracy: 0.8798
Epoch 32/50
327/327 [==============================] - 105s 321ms/step - loss: 0.0069 - accuracy: 0.9979 - val_loss: 1.9426 - val
_accuracy: 0.8141
Epoch 33/50
327/327 [==============================] - 105s 321ms/step - loss: 0.0078 - accuracy: 0.9966 - val_loss: 1.5633 - val
_accuracy: 0.8205
Epoch 34/50
327/327 [==============================] - 105s 321ms/step - loss: 0.0059 - accuracy: 0.9971 - val_loss: 1.4823 - val
_accuracy: 0.8494
Epoch 35/50
327/327 [==============================] - 105s 322ms/step - loss: 0.0086 - accuracy: 0.9962 - val_loss: 2.0664 - val
_accuracy: 0.7772
Epoch 36/50
327/327 [==============================] - 105s 321ms/step - loss: 0.0064 - accuracy: 0.9977 - val_loss: 2.5154 - val
_accuracy: 0.7740
Epoch 37/50
327/327 [==============================] - 104s 319ms/step - loss: 0.0045 - accuracy: 0.9983 - val_loss: 1.6524 - val
_accuracy: 0.8574
Epoch 38/50
327/327 [==============================] - 104s 317ms/step - loss: 0.0025 - accuracy: 0.9985 - val_loss: 2.4753 - val
_accuracy: 0.7917
Epoch 39/50
327/327 [==============================] - 104s 319ms/step - loss: 0.0057 - accuracy: 0.9969 - val_loss: 1.7175 - val
_accuracy: 0.8381
Epoch 40/50
327/327 [==============================] - 104s 319ms/step - loss: 0.0036 - accuracy: 0.9981 - val_loss: 2.4091 - val
_accuracy: 0.7933
Epoch 41/50
327/327 [==============================] - 104s 319ms/step - loss: 0.0034 - accuracy: 0.9990 - val_loss: 1.1618 - val
_accuracy: 0.9054
Epoch 42/50
327/327 [==============================] - 104s 317ms/step - loss: 0.0066 - accuracy: 0.9985 - val_loss: 2.3331 - val
```

```
_accuracy: 0.8077
Epoch 43/50
327/327 [==============================] - 104s 317ms/step - loss: 0.0019 - accuracy: 0.9992 - val_loss: 2.1067 - val
_accuracy: 0.8237
Epoch 44/50
327/327 [==============================] - 103s 316ms/step - loss: 9.4232e-04 - accuracy: 0.9996 - val_loss: 2.2957 -
val_accuracy: 0.8173
Epoch 45/50
327/327 [==============================] - 103s 316ms/step - loss: 0.0024 - accuracy: 0.9987 - val_loss: 2.3746 - val
_accuracy: 0.7997
Epoch 46/50
327/327 [==============================] - 103s 316ms/step - loss: 0.0038 - accuracy: 0.9987 - val_loss: 2.5611 - val
_accuracy: 0.7949
Epoch 47/50
327/327 [==============================] - 104s 317ms/step - loss: 0.0025 - accuracy: 0.9990 - val_loss: 1.8953 - val
_accuracy: 0.8510
Epoch 48/50
327/327 [==============================] - 103s 315ms/step - loss: 7.8524e-04 - accuracy: 0.9998 - val_loss: 2.7886 -
val_accuracy: 0.7901
Epoch 49/50
327/327 [==============================] - 103s 316ms/step - loss: 0.0018 - accuracy: 0.9990 - val_loss: 1.9421 - val
_accuracy: 0.8413
Epoch 50/50
327/327 [==============================] - 103s 316ms/step - loss: 0.0034 - accuracy: 0.9985 - val_loss: 2.1013 - val
_accuracy: 0.8317
```

In [18]:

```
#print(history.history)
```

In [19]:

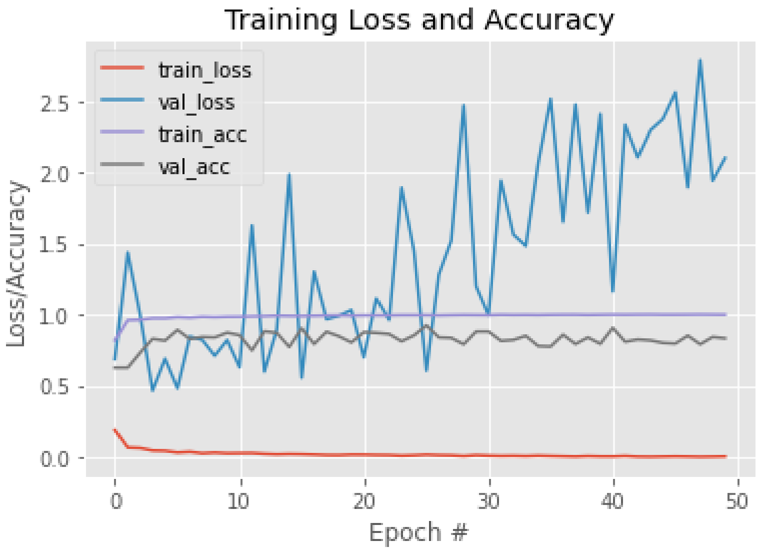
```
#print(history)
```

In [20]:

```
def showGraph(Histroy, epochs):
    # plot the training loss and accuracy
    plt.style.use("ggplot")
    plt.figure()
    plt.plot(np.arange(0, epochs), Histroy.history["loss"], label="train_loss")
    plt.plot(np.arange(0, epochs), Histroy.history["val_loss"], label="val_loss")
    plt.plot(np.arange(0, epochs), Histroy.history["accuracy"], label="train_acc")
    plt.plot(np.arange(0, epochs), Histroy.history["val_accuracy"], label="val_acc")
    plt.title("Training Loss and Accuracy")
    plt.xlabel("Epoch #")
    plt.ylabel("Loss/Accuracy")
    plt.legend()
    plt.show()
```

In [21]:

```
showGraph(history, nb_epochs)
```



In [22]:

```
# # Visualize training history
# from keras.models import Sequential
# from keras.layers import Dense
# import matplotlib.pyplot as plt
# import numpy


# # summarize history for accuracy

# plt.plot(history.history['val_accuracy'])
# plt.plot(history.history['accuracy'])
# plt.title('model accuracy')
# plt.ylabel('accuracy')
# plt.xlabel('epoch')
# plt.legend(['train', 'test'], loc='upper left')
# plt.show()
# # summarize history for loss
# plt.plot(history.history['loss'])
# plt.plot(history.history['val_loss'])
# plt.title('model loss')
# plt.ylabel('loss')
# plt.xlabel('epoch')
# plt.legend(['train', 'test'], loc='upper left')
# plt.show()


# # summarize history for loss
# plt.plot(history.history['loss'])
# plt.plot(history.history['val_loss'])
# plt.plot(history.history['val_accuracy'])
# plt.plot(history.history['accuracy'])
# plt.legend(['loss', 'val_loss','val_accuracy','accuracy' ], loc='upper left')
# plt.show()
```

In [23]:

```
# Load the model weights
model.load_weights("best_modelvgg.hdf5")
```

In [24]:

```
# Preparing test data
normal_cases_dir = test_dir / 'NORMAL'
pneumonia_cases_dir = test_dir / 'PNEUMONIA'

normal_cases = normal_cases_dir.glob('*.*g')
pneumonia_cases = pneumonia_cases_dir.glob('*.*g')

test_data = []
test_labels = []

for img in normal_cases:
    img = cv2.imread(str(img))
    img = cv2.resize(img, (224,224))
    if img.shape[2] ==1:
        img = np.dstack([img, img, img])
    else:
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = img.astype(np.float32)/255.
    label = to_categorical(0, num_classes=2)
    test_data.append(img)
    test_labels.append(label)

for img in pneumonia_cases:
    img = cv2.imread(str(img))
    img = cv2.resize(img, (224,224))
    if img.shape[2] ==1:
        img = np.dstack([img, img, img])
    else:
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = img.astype(np.float32)/255.
    label = to_categorical(1, num_classes=2)
    test_data.append(img)
    test_labels.append(label)


test_data = np.array(test_data)
test_labels = np.array(test_labels)
```

```
print("Total number of test examples: ", test_data.shape)
print("Total number of labels: ", test_labels.shape)
```

```
Total number of test examples:  (624, 224, 224, 3)
Total number of labels: (624, 2)
```

In [25]:

```
# Evaluation on test dataset
test_loss, test_score = model.evaluate(test_data, test_labels, batch_size=16)
print("Loss on test set: ", test_loss)
print("Accuracy on test set: ", test_score)
```

```
624/624 [==============================] - 2s 4ms/step
Loss on test set:  0.46320982254707277
Accuracy on test set:  0.8285256624221802
```

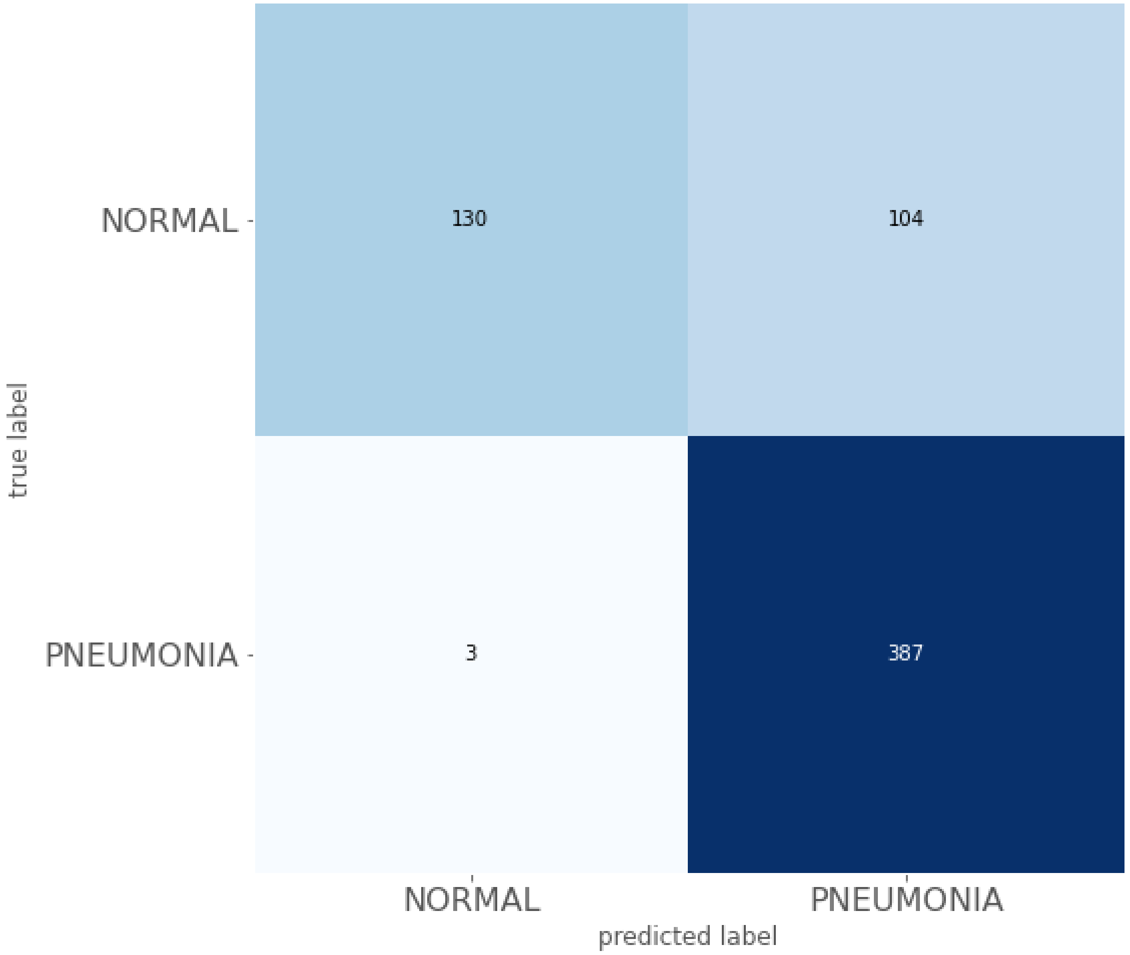
In [26]:

```
# Get the predictions on test set
preds = model.predict(test_data, batch_size=16)
preds = np.squeeze((preds > 0.5).astype('int'))
orig = test_labels.astype('int')
#print(preds)
#print(orig)

# Get predictions
preds = model.predict(test_data, batch_size=16)
preds = np.argmax(preds, axis=-1)

# Original labels
orig = np.argmax(test_labels, axis=-1)

#print(orig)
#print(preds)
```

In [27]:

```
# Get the confusion matrix
cm  = confusion_matrix(orig, preds)
plt.figure()
plot_confusion_matrix
plot_confusion_matrix(cm,figsize=(12,8), hide_ticks=True, cmap=plt.cm.Blues)
plt.xticks(range(2), ['NORMAL', 'PNEUMONIA'], fontsize=16)
plt.yticks(range(2), ['NORMAL', 'PNEUMONIA'], fontsize=16)
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```


NORMAL
PNEUMONIA
true label
130
104
3
387
NORMAL
PNEUMONIA
predicted label

In [28]:

```
# Calculate Precision and Recall
tn, fp, fn, tp = cm.ravel()

precision = tp/(tp+fp)
recall = tp/(tp+fn)


print("Recall of the model is {:.2f}".format(recall))
print("Precision of the model is {:.2f}".format(precision))
```

```
Recall of the model is 0.99
Precision of the model is 0.79
```

In [29]:

```
model.save("SOTA_V_SOTA_STRUCTURE.h5")
```

Fine tuning

In [30]:

```
def showGraph(Histroy, epochs):
    # plot the training loss and accuracy
    plt.style.use("ggplot")
    plt.figure()
    plt.plot(np.arange(0, epochs), Histroy.history["loss"], label="train_loss")
    plt.plot(np.arange(0, epochs), Histroy.history["val_loss"], label="val_loss")
    plt.plot(np.arange(0, epochs), Histroy.history["accuracy"], label="train_acc")
    plt.plot(np.arange(0, epochs), Histroy.history["val_accuracy"], label="val_acc")
    plt.title("Training Loss and Accuracy")
    plt.xlabel("Epoch #")
    plt.ylabel("Loss/Accuracy")
    plt.legend()
    plt.show()
```

## Step 1 & 2: # Freezing all the layers & added a new fully connected layer

In [82]:

```
model = build_model()
# Open the VGG16 weight file
f = h5py.File('vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5', 'r')

# Select the layers for which you want to set weight.

w,b = f['block1_conv1']['block1_conv1_W_1:0'], f['block1_conv1']['block1_conv1_b_1:0']
model.layers[1].set_weights = [w,b]

w,b = f['block1_conv2']['block1_conv2_W_1:0'], f['block1_conv2']['block1_conv2_b_1:0']
model.layers[2].set_weights = [w,b]

w,b = f['block2_conv1']['block2_conv1_W_1:0'], f['block2_conv1']['block2_conv1_b_1:0']
model.layers[4].set_weights = [w,b]

w,b = f['block2_conv2']['block2_conv2_W_1:0'], f['block2_conv2']['block2_conv2_b_1:0']
model.layers[5].set_weights = [w,b]

f.close()
model.summary()
model.trainable = False
```

```
Model: "model_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
ImageInput (InputLayer)      (None, 224, 224, 3)       0         
_________________________________________________________________
Conv1_1 (Conv2D)             (None, 224, 224, 64)      1792      
_________________________________________________________________
Conv1_2 (Conv2D)             (None, 224, 224, 64)      36928     
_________________________________________________________________
pool1 (MaxPooling2D)         (None, 112, 112, 64)      0         
_________________________________________________________________
Conv2_1 (SeparableConv2D)    (None, 112, 112, 128)     8896      
_________________________________________________________________
Conv2_2 (SeparableConv2D)    (None, 112, 112, 128)     17664     
_________________________________________________________________
pool2 (MaxPooling2D)         (None, 56, 56, 128)       0         
_________________________________________________________________
Conv3_1 (SeparableConv2D)    (None, 56, 56, 256)       34176     
_________________________________________________________________
Conv3_2 (SeparableConv2D)    (None, 56, 56, 256)       68096     
_________________________________________________________________
Conv3_3 (SeparableConv2D)    (None, 56, 56, 256)       68096     
_________________________________________________________________
pool3 (MaxPooling2D)         (None, 28, 28, 256)       0         
_________________________________________________________________
Conv4_1 (SeparableConv2D)    (None, 28, 28, 512)       133888    
_________________________________________________________________
Conv4_2 (SeparableConv2D)    (None, 28, 28, 512)       267264    
_________________________________________________________________
Conv4_3 (SeparableConv2D)    (None, 28, 28, 512)       267264    
_________________________________________________________________
pool4 (MaxPooling2D)         (None, 14, 14, 512)       0         
_________________________________________________________________
Conv5_1 (SeparableConv2D)    (None, 14, 14, 512)       267264    
_________________________________________________________________
Conv5_2 (SeparableConv2D)    (None, 14, 14, 512)       267264    
_________________________________________________________________
Conv5_3 (SeparableConv2D)    (None, 14, 14, 512)       267264    
_________________________________________________________________
pool5 (MaxPooling2D)         (None, 7, 7, 512)         0         
```

```
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0         
_________________________________________________________________
fc1 (Dense)                  (None, 512)               12845568  
_________________________________________________________________
bn1 (BatchNormalization)     (None, 512)               2048      
_________________________________________________________________
fc2 (Dense)                  (None, 512)               262656    
_________________________________________________________________
bn2 (BatchNormalization)     (None, 512)               2048      
_________________________________________________________________
dropout2 (Dropout)           (None, 512)               0         
_________________________________________________________________
fc3 (Dense)                  (None, 2)                 1026      
=================================================================
Total params: 14,819,202
Trainable params: 14,817,154
Non-trainable params: 2,048
_________________________________________________________________
```

Step 3: Train the weights on the new FC layer.

In [30]:

```
opt = RMSprop(lr=1e-3, decay=0.9)
#opt = Adam(lr=0.0001, decay=1e-5)
es = EarlyStopping(patience=10)
#chkpt = ModelCheckpoint(filepath='best_modelvgg.hdf5', save_best_only=True, save_weights_only=True)
model.compile(loss='categorical_crossentropy', metrics=['accuracy'],optimizer=opt)

batch_size = 16
nb_epochs = 3

# Get a train data generator
train_data_gen = data_gen(data=train_data, batch_size=batch_size)

# Define the number of training steps
nb_train_steps = train_data.shape[0]//batch_size

print("Number of training and validation steps: {} and {}".format(nb_train_steps, len(valid_data)))


# # Fit the model
checkpoint = tf.keras.callbacks.ModelCheckpoint("PreFineTunebestVGG_StateOfTheArtData.h5", monitor="val_loss", mode="min", save_be
st_only=True, verbose=1)
history = model.fit_generator(train_data_gen, epochs=nb_epochs, steps_per_epoch=nb_train_steps,
                              validation_data=(valid_data, valid_labels),
                              callbacks=[es, checkpoint],
                              class_weight={0:1.0, 1:0.4})
```

```
Number of training and validation steps: 8 and 170
Epoch 1/3
8/8 [==============================] - 33s 4s/step - loss: 0.5742 - accuracy: 0.7422 - val_loss: 0.6949 - val_accurac
y: 0.4647

Epoch 00001: val_loss improved from inf to 0.69494, saving model to PreFineTunebestVGG_StateOfTheArtData.h5
Epoch 2/3
8/8 [==============================] - 34s 4s/step - loss: 0.5654 - accuracy: 0.7266 - val_loss: 0.6951 - val_accurac
y: 0.4647

Epoch 00002: val_loss did not improve from 0.69494
Epoch 3/3
8/8 [==============================] - 33s 4s/step - loss: 0.5289 - accuracy: 0.6328 - val_loss: 0.6952 - val_accurac
y: 0.4647

Epoch 00003: val_loss did not improve from 0.69494
```

Step 4: Unfreeze the trainable weights on some of the convolutional layers in the base network.

In [33]:

```
model.trainable = True
set_trainable = False
for layer in model.layers:
    if layer.name in ['block5_conv1']:
            set_trainable = True
    if set_trainable:
        layer.trainable = True
    else:
        layer.trainable = False
```

In [48]:

```
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
ImageInput (InputLayer)      (None, 224, 224, 3)       0         
_________________________________________________________________
Conv1_1 (Conv2D)             (None, 224, 224, 64)      1792      
_________________________________________________________________
Conv1_2 (Conv2D)             (None, 224, 224, 64)      36928     
_________________________________________________________________
pool1 (MaxPooling2D)         (None, 112, 112, 64)      0         
_________________________________________________________________
Conv2_1 (SeparableConv2D)    (None, 112, 112, 128)     8896      
_________________________________________________________________
Conv2_2 (SeparableConv2D)    (None, 112, 112, 128)     17664     
_________________________________________________________________
pool2 (MaxPooling2D)         (None, 56, 56, 128)       0         
_________________________________________________________________
Conv3_1 (SeparableConv2D)    (None, 56, 56, 256)       34176     
_________________________________________________________________
Conv3_2 (SeparableConv2D)    (None, 56, 56, 256)       68096     
_________________________________________________________________
Conv3_3 (SeparableConv2D)    (None, 56, 56, 256)       68096     
_________________________________________________________________
pool3 (MaxPooling2D)         (None, 28, 28, 256)       0         
_________________________________________________________________
Conv4_1 (SeparableConv2D)    (None, 28, 28, 512)       133888    
_________________________________________________________________
Conv4_2 (SeparableConv2D)    (None, 28, 28, 512)       267264    
_________________________________________________________________
Conv4_3 (SeparableConv2D)    (None, 28, 28, 512)       267264    
_________________________________________________________________
pool4 (MaxPooling2D)         (None, 14, 14, 512)       0         
_________________________________________________________________
Conv5_1 (SeparableConv2D)    (None, 14, 14, 512)       267264    
_________________________________________________________________
Conv5_2 (SeparableConv2D)    (None, 14, 14, 512)       267264    
_________________________________________________________________
Conv5_3 (SeparableConv2D)    (None, 14, 14, 512)       267264    
_________________________________________________________________
pool5 (MaxPooling2D)         (None, 7, 7, 512)         0         
```

```
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
fc1 (Dense)                  (None, 512)               12845568
_________________________________________________________________
bn1 (BatchNormalization)     (None, 512)               2048
_________________________________________________________________
fc2 (Dense)                  (None, 512)               262656
_________________________________________________________________
bn2 (BatchNormalization)     (None, 512)               2048
_________________________________________________________________
dropout2 (Dropout)           (None, 512)               0
_________________________________________________________________
fc3 (Dense)                  (None, 2)                 1026
=================================================================
Total params: 29,636,356
Trainable params: 14,817,154
Non-trainable params: 14,819,202
_________________________________________________________________

C:\Users\StudyEasy\anaconda3\lib\site-packages\keras\engine\training.py:297: UserWarning: Discrepancy between trainab
le weights and collected trainable weights, did you set `model.trainable` without calling `model.compile` after ?
  'Discrepancy between trainable weights and collected trainable'
```

In [63]:

```
# baseModel = VGG16(weights="imagenet", include_top=False,
# input_tensor=Input(shape=(224, 224, 3)))


# headModel = baseModel.output
# headModel = Flatten(name="flatten")(headModel)
# headModel = Dense(512, activation="relu")(headModel)
# headModel = Dropout(0.5)(headModel)
# headModel = Dense(2, activation="softmax")(headModel)


# model = Model(inputs=baseModel.input, outputs=headModel)
```

In [64]:

```
opt = RMSprop(lr=1e-4, decay=0.9)
#opt = Adam(lr=0.0001, decay=1e-5)
es = EarlyStopping(patience=10)
#chkpt = ModelCheckpoint(filepath='best_modelvgg.hdf5', save_best_only=True, save_weights_only=True)
model.compile(loss='categorical_crossentropy', metrics=['accuracy'],optimizer=opt)

batch_size = 16
nb_epochs = 3

# Get a train data generator
train_data_gen = data_gen(data=train_data, batch_size=batch_size)

# Define the number of training steps
nb_train_steps = train_data.shape[0]//batch_size

print("Number of training and validation steps: {} and {}".format(nb_train_steps, len(valid_data)))


# # Fit the model
checkpoint = tf.keras.callbacks.ModelCheckpoint("PreFineTunebestVGG_StateOfTheArtData.h5", monitor="val_loss", mode="min", save_be
st_only=True, verbose=1)
history = model.fit_generator(train_data_gen, epochs=nb_epochs, steps_per_epoch=nb_train_steps,
                              validation_data=(valid_data, valid_labels),
                              callbacks=[es, checkpoint],
                              class_weight={0:1.0, 1:0.4})
```

```
Number of training and validation steps: 8 and 170
Epoch 1/3
8/8 [==============================] - 80s 10s/step - loss: 0.5284 - accuracy: 0.6250 - val_loss: 0.8946 - val_accura
cy: 0.4647

Epoch 00001: val_loss improved from inf to 0.89462, saving model to PreFineTunebestVGG_StateOfTheArtData.h5
Epoch 2/3
8/8 [==============================] - 83s 10s/step - loss: 0.3401 - accuracy: 0.6641 - val_loss: 0.9224 - val_accura
cy: 0.4647

Epoch 00002: val_loss did not improve from 0.89462
Epoch 3/3
8/8 [==============================] - 86s 11s/step - loss: 0.3114 - accuracy: 0.7031 - val_loss: 1.0490 - val_accura
cy: 0.4647

Epoch 00003: val_loss did not improve from 0.89462
```

In [ ]:

In [ ]:

In [ ]:

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In [ ]:
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