

1 Diagnosing Pneumonia using AI: A Convolution Neural Network Model from Chest X-Ray Images

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This report contains a detailed explanation of the extraction, exploration, data preparation and generation of deep learning models for the diagnosis of pneumonia from chest x-ray images.

1.1 I. Overview and Goals

Pneumonia is an inflammatory condition of the lung usually caused by infection with viruses or bacteria. Typically symptoms include some combination of productive or dry cough, chest pain, fever, and trouble breathing. Severity is variable, but in severe cases or cases that go undiagnosed pneumonia can cause death. In fact, each year, pneumonia affects about 450 million people globally (7% of the population) and results in about 4 million deaths. However, cases, if the disease is diagnosed and treated in its early stages, pneumonia is largely treatable. Therefore, it is critical to develop better tools that can streamline and improve the diagnosis of pneumonia. The ultimate goal of this project is to build an artificial intelligence model that can be used in clinical settings to diagnose pneumonia and thus improve the efficiency of the healthcare system.

To be able to better understand this problem and how to solve it, I have divided this analysis into three questions:

- 1) Can we distinguish healthy versus pneumonia patients solely by chest x-ray imaging?
- 2) Can we accurately predict the diagnosis of pneumonia from chest x-ray images?
- 3) What x-ray features contribute the most for the incorrect diagnosis of a patient?

1.2 II. Data Understanding and Preparation

The dataset used in this analysis/model is available on Kaggle (<https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia>) and contains a total number of 5863 chest x-ray images from either healthy (normal) or patients diagnosed with pneumonia (pneumonia). The dataset is comprised of three sub datasets:

- Training dataset
- Test dataset
- Validation dataset

In []:

1

```
In [1]: 1 # Import libraries
        2
        3 import os, sys, glob
        4 import numpy as np
        5 np.random.seed(123)
        6 import pandas as pd
        7 import seaborn as sns
        8 import matplotlib.pyplot as plt
        9 %matplotlib inline
```

```
In [2]: 1 pip install lime
```

Collecting lime

Downloading <https://files.pythonhosted.org/packages/f5/86/91a13127d83d793ecb50eb75e716f76e6eda809b6803c5a4ff462339789e/lime-0.2.0.1.tar.gz> (<http://files.pythonhosted.org/packages/f5/86/91a13127d83d793ecb50eb75e716f76e6eda809b6803c5a4ff462339789e/lime-0.2.0.1.tar.gz>) (275kB)

|██| 276kB 4.2MB/s eta 0:00:01

Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (from lime) (3.2.2)

Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from lime) (1.19.5)

Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from lime) (1.4.1)

Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from lime) (4.41.1)

Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.7/dist-packages (from lime) (0.22.2.post1)

Requirement already satisfied: scikit-image>=0.12 in /usr/local/lib/python3.7/dist-packages (from lime) (0.16.2)

Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib->lime) (0.10.0)

Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->lime) (2.4.7)

Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->lime) (2.8.1)

Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->lime) (1.3.1)

Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.18->lime) (1.0.1)

Requirement already satisfied: networkx>=2.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image>=0.12->lime) (2.5.1)

Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image>=0.12->lime) (2.4.1)

Requirement already satisfied: pillow>=4.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image>=0.12->lime) (7.1.2)

Requirement already satisfied: PyWavelets>=0.4.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image>=0.12->lime) (1.1.1)

Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from cycler>=0.10->matplotlib->lime) (1.15.0)

Requirement already satisfied: decorator<5,>=4.3 in /usr/local/lib/python3.7/dist-packages (from networkx>=2.0->scikit-image>=0.12->lime) (4.4.2)

Building wheels for collected packages: lime

Building wheel for lime (setup.py) ... done

Created wheel for lime: filename=lime-0.2.0.1-cp37-none-any.whl size=283858 sha256=12d36db144f4ffc567fe2229c59cd52487e6318ae92be4584600f2cbbbd6d9bc

Stored in directory: /root/.cache/pip/wheels/4c/4f/a5/0bc765457bd41378bf3ce8d17d7495369d6e7ca3b712c60c89

Successfully built lime

Installing collected packages: lime

Successfully installed lime-0.2.0.1

```

In [3]: 1 import tensorflow as tf
        2 from sklearn import metrics
        3 from keras import models
        4 from keras.preprocessing import image
        5 from keras.optimizers import Adam, SGD, RMSprop, Adadelta, Adagrad
        6
        7 from tensorflow.keras.preprocessing.image import ImageDataGenerator
        8 from tensorflow.keras.preprocessing.image import array_to_img, img_to_a
        9
       10 from tensorflow.keras.models import Sequential
       11 from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dens
       12 from tensorflow.keras import callbacks, models, layers, optimizers, reg
       13
       14 from sklearn.metrics import confusion_matrix, classification_report
       15 from sklearn.utils.class_weight import compute_class_weight
       16
       17 import lime
       18 from lime import lime_image
       19 from lime import lime_base
       20
       21 from lime.wrappers.scikit_image import SegmentationAlgorithm
       22 from skimage.segmentation import mark_boundaries
       23 lime_image.LimeImageExplainer
       24

```

```
Out[3]: lime.lime_image.LimeImageExplainer
```

```
In [4]: 1 os.listdir()
```

```
Out[4]: ['.config', 'sample_data']
```

```
In [5]: 1 # Data Upload
```

```

In [6]: 1 # Mount Google Drive
        2 from google.colab import drive
        3 drive.mount('/content/drive',force_remount=True)

```

Mounted at /content/drive

```
In [7]: 1 ls /content/drive/MyDrive/
```

```

archive.zip          machinelearning/
businessModel.docx   'Misplaced Priorities.docx'
cnn_b2_model.hd5/    'Nadir Sarigul Business Writing Final Project.g
doc'
cnn_model12.hd5/     'Nadir Sarigul_resume_2015.gdoc'
cnn_model.hd5/       'N&S.mp4'
'Colab Notebooks' /  pneumonia_detection_CNN/
'Copy of graduation.mp4' Resume.gdoc
deneme.ipynb

```

- [link to the dataset zip file](https://drive.google.com/file/d/1sskLnYWH5iByO3jFEIS2Hiq_gy5tJa3w/view?usp=sharing)
(https://drive.google.com/file/d/1sskLnYWH5iByO3jFEIS2Hiq_gy5tJa3w/view?usp=sharing)

- copy the zip file above to on google drive
- change the zip_path to match your on google drive

```
In [17]: 1 file = "archive.zip"
          2
          3 zip_path = "/content/drive/MyDrive/" + file
          4 zip_path
```

```
Out[17]: '/content/drive/MyDrive/archive.zip'
```

```
In [18]: 1 !cp "{zip_path}" .
          2
          3 !unzip -q "{file}"
          4 !rm "{file}"
```

```
In [19]: 1 ls
```

```
chest_xray/  drive/  sample_data/
```

```
In [20]: 1 # Assign the data to the base folder
          2 BASE_FOLDER = "chest_xray/"
          3 os.makedirs(BASE_FOLDER, exist_ok=True)
          4 os.listdir(BASE_FOLDER)
```

```
Out[20]: ['chest_xray', 'val', 'test', 'train', '__MACOSX']
```

```
In [21]: 1 ## Specify the training folder and test folder
          2 train_folder = BASE_FOLDER + "train/"
          3 test_folder = BASE_FOLDER + "test/"
          4 print(os.listdir(train_folder))
```

```
['NORMAL', 'PNEUMONIA']
```

1.3 III. Data Exploration

Here we explore how many images are in each dataset and what class do they belong to

```
In [22]: 1
2  for i in [train_folder, test_folder]:
3
4      print(":::::::::: ", i[11:-1], " ::::::::::::::")
5      pneumonia = len(os.listdir(os.path.join(i, "PNEUMONIA")))
6      normal = len(os.listdir(os.path.join(i, "NORMAL")))
7      print(f" Pneumonia = {pneumonia}")
8      print(f" Normal = {normal}")
9
10
```

```
:::::::::: train ::::::::::::::
Pneumonia = 3875
Normal = 1341
:::::::::: test ::::::::::::::
Pneumonia = 390
Normal = 234
```

```
In [23]: 1  from glob import glob
2  n_images = glob(train_folder + '/NORMAL/*.jpeg')
3  p_images = glob(train_folder + '/PNEUMONIA/*.jpeg')
4  print(f"Class Imbalance: There are normal {len(n_images)} and {len(p_im
```

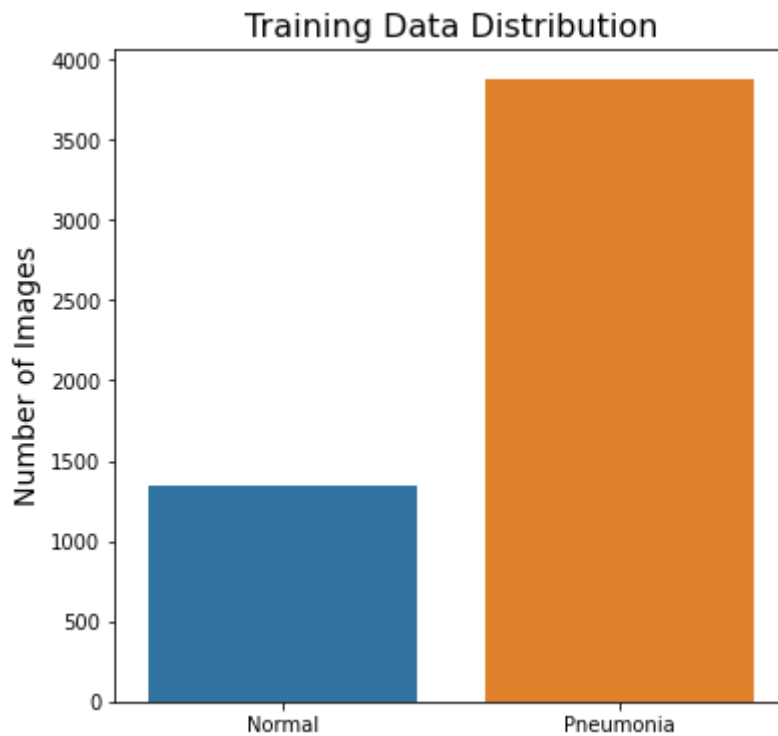
```
Class Imbalance: There are normal 1341 and 3875 Pneumonia
```

Here is a count of the number of chest x-ray images ascribed to each diagnosis included in the training dataset

```
In [24]: 1 # plot the training data distrubibution
2 plt.figure(figsize = (6,6))
3 sns.barplot(["Normal", "Pneumonia"], [len(n_images), len(p_images)])
4 plt.ylabel('Number of Images', fontsize = 14)
5 plt.title("Training Data Distribution", fontsize = 16);
```

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

FutureWarning



Before diving into building a complex model capable of accurately predicting pneumonia, it is important to understand how pneumonia is diagnosed. The most frequently used method to diagnose pneumonia is a chest x-ray. Here is how the chest x-ray images of healthy lungs looks like:

```

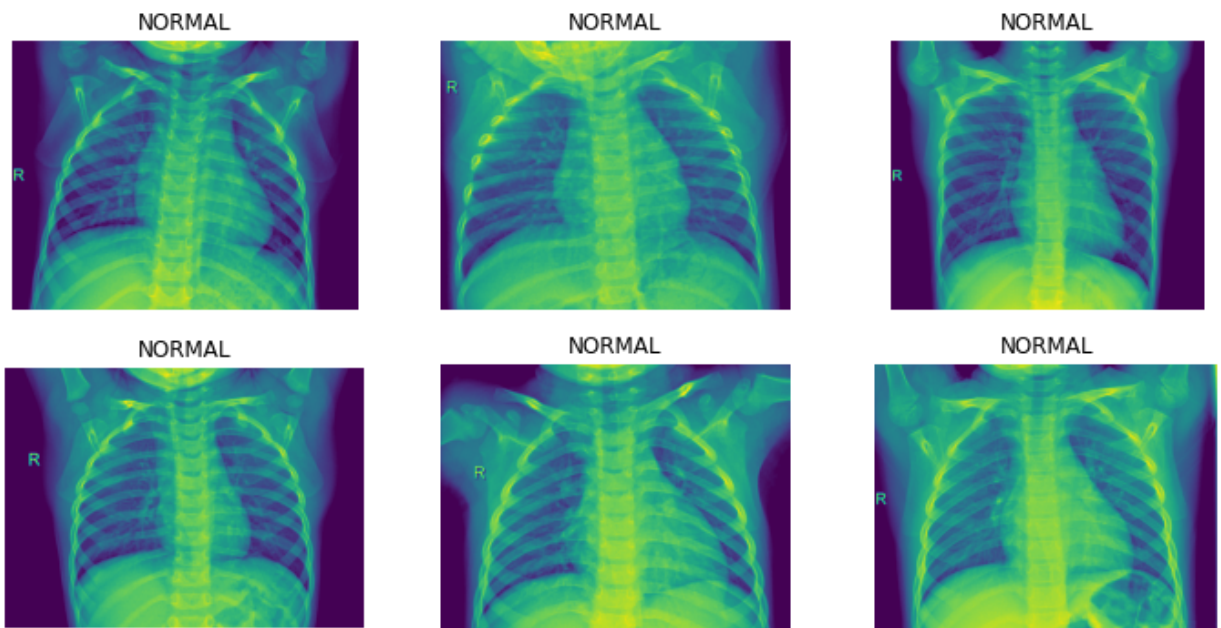
In [25]: 1 import matplotlib.image as mpimg
          2 def plot_images(path, labeled=False, max_images=6):
          3     amount = 0
          4     fig = plt.figure(figsize=(12, 6))
          5
          6     for file in os.listdir(path):
          7         if file.endswith('.jpeg'):
          8             if amount == max_images:
          9                 break
          10
          11         img = mpimg.imread(os.path.join(path, file))
          12         plt.subplot(231+amount)
          13         if labeled:
          14             plt.title(file.split('_')[1])
          15         plt.title(path[18:])
          16         plt.axis("off")
          17         imgplot = plt.imshow(img)
          18
          19         amount += 1

```

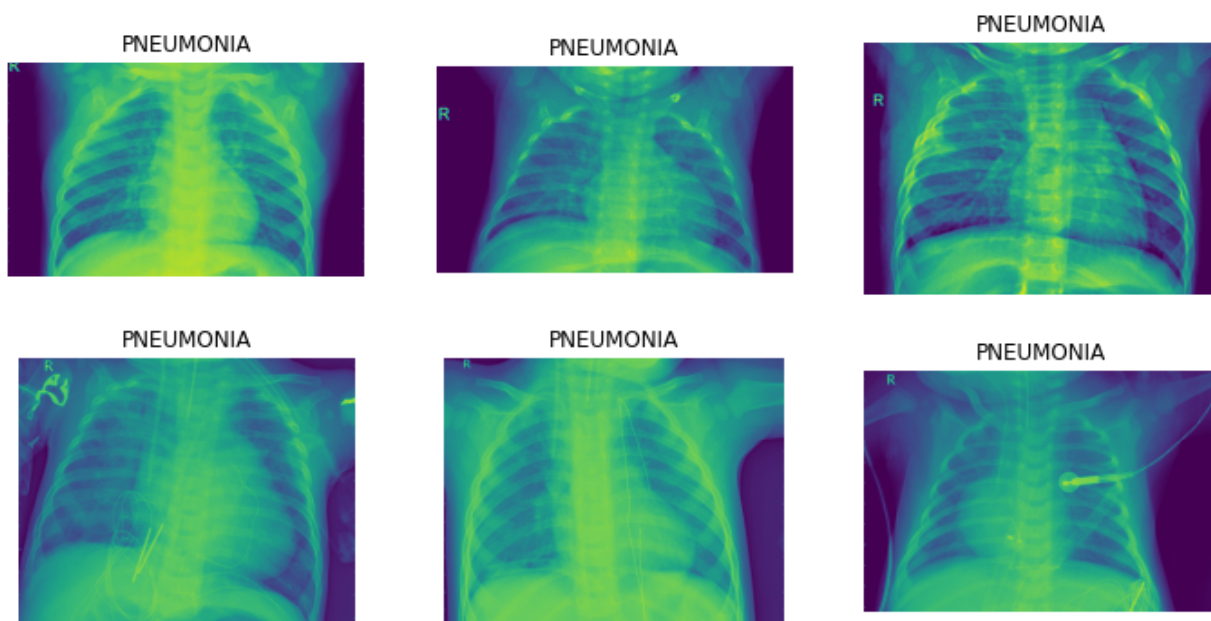
```

In [26]: 1 plot_images(train_folder + '/NORMAL')

```




```
In [27]: 1 plot_images(train_folder + '/PNEUMONIA', labeled= True)
```



When interpreting the x-ray, doctors look for white spots in the lungs (called infiltrates) that identify the infection. Looking at the x-ray images in our datasets we can see that chest x-rays of pneumonia patients show the presence of white spots and the general architecture of the lung is different than of healthy people. Thus, analysis of x-ray images are one of the most reliable ways to effectively diagnose pneumonia.

1.4 IV. Data Preparation for Modeling

Because the data provided as the validation dataset only contained 16 images, I decided to randomly split the test dataset into data to validate my models (20% of the data corresponding to 124 x-ray images) and data to test my models (80% of the data corresponding to 500 x-ray images).

To get the x-ray images ready for modeling, I have use the ImageDataGenerator class to load the data and prepare the data for modeling. This is very useful when handling large datasets as it allows for the images to be progressively loaded in batches from file, retrieving just enough data for what is needed immediately.

The constructor for the ImageDataGenerator contains many arguments to specify how to manipulate the image data after it is loaded, including pixel scaling and data augmentation. Thus, also allowing to not configure the specific details about each image as it is loaded but also expand the training dataset with new, plausible examples. Using this class I scaled the array of pixels in the original images of all my datasets to pixel values between 0 and 1, which a range preferred for neural networks modeling. I also used data augmentation methods including rotation, width and height shifts and zoom to create variations of the training set images that are likely to be seen by the model.

In addition, I also using the "flow_from_directory" method I also normalized the size of all the images to 64x64. I kept the batch size at 32 (the default size used) and used a binary classification as the datasets only contains two classes (pneumonia or normal).

```
In [28]: 1 #Image Dataset Settings
2 VAL_SPLIT = 0.2
3 IMG_SIZE = (64,64)
4 BATCH_SIZE = 32
5
6 # Create ImageDataGenerator for training data
7 train_datagen = ImageDataGenerator(rescale = 1./255,
8                                     rotation_range = 10,           # randomly
9                                     width_shift_range = 0.2,        #randomly
10                                    height_shift_range = 0.2,        #randomly
11                                    zoom_range = 0.1                #randomly
12                                    )
13
14 # Create ImageDataGenerator for validation and test data
15 test_val_datagen = ImageDataGenerator(rescale = 1./255,
16                                       validation_split=VAL_SPLIT,
17                                       )
```

```

In [29]: 1 #Use generators flow_from_directory train_set
2 train_set = train_datagen.flow_from_directory(train_folder,
3                                             target_size=IMG_SIZE,
4                                             batch_size=BATCH_SIZE,
5                                             classes = ["NORMAL",
6                                             class_mode='binary',
7                                             shuffle=False
8
9                                             )
10
11
12 # Makng a Test Set and validation set from the same folder.
13 test_set = test_val_datagen.flow_from_directory(test_folder,
14                                             target_size=IMG_SI
15                                             subset='training',
16                                             batch_size=BATCH_S
17                                             classes = ["NORMAL
18                                             class_mode='binary
19                                             shuffle=False
20                                             )
21
22 val_set = test_val_datagen.flow_from_directory(test_folder,target_size=
23                                             subset='validation',
24                                             batch_size=BATCH_SI
25                                             classes = ["NORMAL"
26                                             class_mode='binary'
27                                             shuffle=False
28                                             )

```

Found 5216 images belonging to 2 classes.

Found 500 images belonging to 2 classes.

Found 124 images belonging to 2 classes.

```

In [30]: 1 train_size = len(train_set.fileNames)
2 val_size = len(val_set.fileNames)
3 test_size = len(test_set.fileNames)
4 train_size, val_size, test_size

```

Out[30]: (5216, 124, 500)

1.4.0.1 Baseline Model

```

In [31]: 1
2 #initialising the CNN
3 model = models.Sequential()
4
5 #Add a convolution layer with 32 kernels of 3X3 shape padding of same a
6 model.add(Conv2D(32, (3, 3),padding="same", activation='relu',input_sha
7 # Add Max Pooling layer
8 model.add(MaxPooling2D((2, 2)))
9
10 #Add a convolution layer with 64 kernels of 3X3 shape padding of same a
11 model.add(Conv2D(64, (3, 3), padding="same", activation='relu'))
12 model.add(MaxPooling2D(3, 3))
13
14 model.add(Conv2D(64, (3, 3), padding="same", activation='relu'))
15 model.add(MaxPooling2D((2, 2)))
16
17
18 #Flatting the layer before fully connected layers
19 model.add(Flatten())
20
21 #Add a fully connected layer with 256 neurons
22
23 model.add(Dense(256, activation='relu'))
24 model.add(Dense(1, activation='sigmoid'))
25 model.compile(loss='binary_crossentropy',
26               optimizer='RMSprop',
27               metrics=['acc'])
28 model.summary()

```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_1 (Conv2D)	(None, 32, 32, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 10, 10, 64)	0
conv2d_2 (Conv2D)	(None, 10, 10, 64)	36928
max_pooling2d_2 (MaxPooling2	(None, 5, 5, 64)	0
flatten (Flatten)	(None, 1600)	0
dense (Dense)	(None, 256)	409856
dense_1 (Dense)	(None, 1)	257
=====		
Total params: 466,433		
Trainable params: 466,433		
Non-trainable params: 0		

```
In [32]: 1 history = model.fit_generator(train_set,
2                                     epochs= 10,
3                                     steps_per_epoch = train_size//BATCH_SIZE,
4                                     validation_steps = val_size//BATCH_SIZE,
5                                     validation_data= val_set)
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1940: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.
```

```
warnings.warn("`Model.fit_generator` is deprecated and "
```

```
Epoch 1/10
```

```
163/163 [=====] - 67s 315ms/step - loss: 0.7817
- acc: 0.7245 - val_loss: 1.6613 - val_acc: 0.5208
```

```
Epoch 2/10
```

```
163/163 [=====] - 51s 311ms/step - loss: 0.6410
- acc: 0.7498 - val_loss: 0.8157 - val_acc: 0.4792
```

```
Epoch 3/10
```

```
163/163 [=====] - 51s 312ms/step - loss: 0.5673
- acc: 0.7412 - val_loss: 0.6259 - val_acc: 0.5625
```

```
Epoch 4/10
```

```
163/163 [=====] - 51s 308ms/step - loss: 0.4642
- acc: 0.7933 - val_loss: 0.9125 - val_acc: 0.5521
```

```
Epoch 5/10
```

```
163/163 [=====] - 51s 312ms/step - loss: 0.4336
- acc: 0.8035 - val_loss: 1.2642 - val_acc: 0.5521
```

```
Epoch 6/10
```

```
163/163 [=====] - 51s 310ms/step - loss: 0.3946
- acc: 0.8372 - val_loss: 0.4541 - val_acc: 0.7604
```

```
Epoch 7/10
```

```
163/163 [=====] - 51s 310ms/step - loss: 0.3397
- acc: 0.8549 - val_loss: 0.2298 - val_acc: 0.9062
```

```
Epoch 8/10
```

```
163/163 [=====] - 51s 316ms/step - loss: 0.3858
- acc: 0.8485 - val_loss: 0.5388 - val_acc: 0.6979
```

```
Epoch 9/10
```

```
163/163 [=====] - 52s 314ms/step - loss: 0.3287
- acc: 0.8763 - val_loss: 0.2550 - val_acc: 0.9062
```

```
Epoch 10/10
```

```
163/163 [=====] - 51s 313ms/step - loss: 0.2981
- acc: 0.8844 - val_loss: 0.2496 - val_acc: 0.8854
```

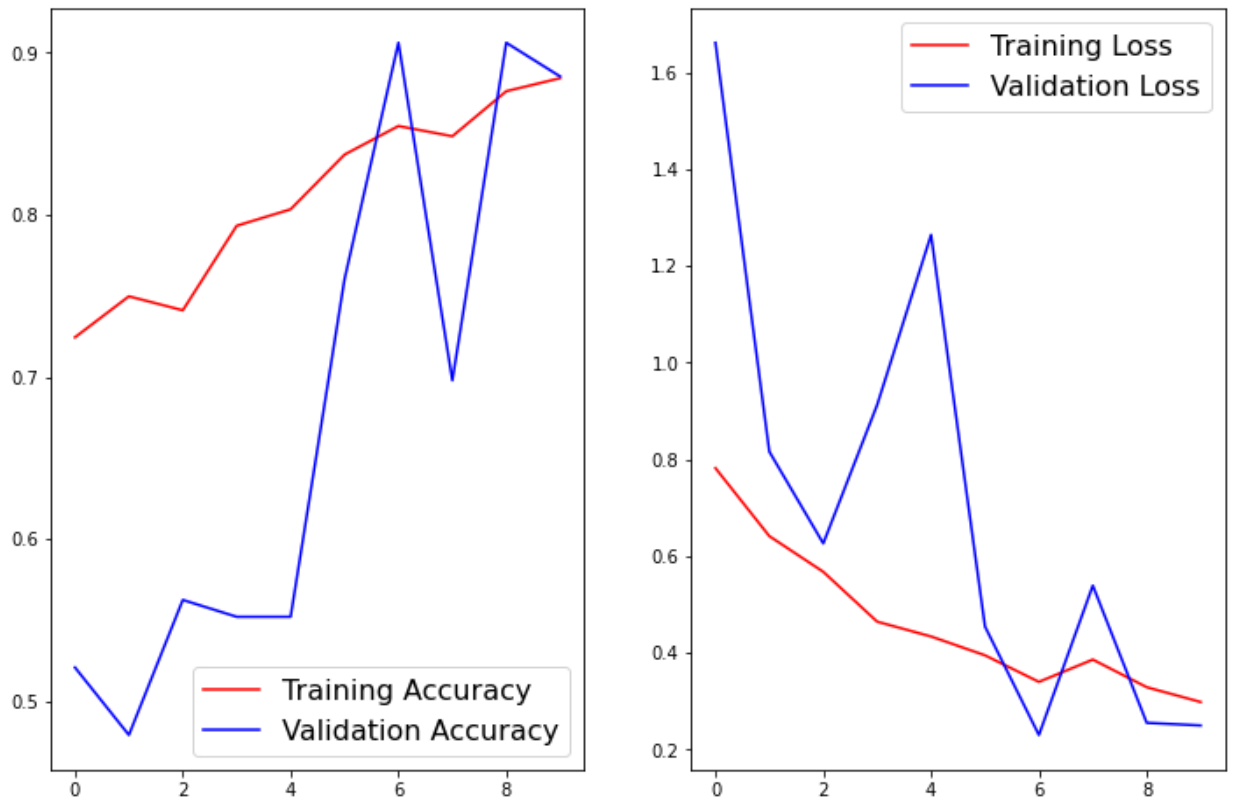
```
In [33]: 1 # Model evaluation
```

```

In [34]: 1 def model_evaluate(model, history):
2
3     train_loss = history.history["loss"]
4     validation_loss = history.history["val_loss"]
5
6     # train loss and validation loss
7     train_accuracy = history.history["acc"]
8     validation_accuracy = history.history["val_acc"]
9
10    # line plot of train and validation loss
11    fig , ax = plt.subplots(1,2, figsize=(12,8))
12    #plt.figure(figsize=(10,8))
13
14    ax[0].plot(train_accuracy, label= "Training Accuracy", color= "red")
15    ax[0].plot(validation_accuracy, label= "Validation Accuracy", color=
16    ax[0].legend(fontsize = 16)
17
18    # line plot of train and validation loss
19
20    ax[1].plot(train_loss, label= "Training Loss", color= "red")
21    ax[1].plot(validation_loss, label= "Validation Loss", color= "blue")
22    ax[1].legend(fontsize = 16)
23    plt.show()
24
25    print('***'*20)
26    print('Classification Report')
27    print('***'*20)
28
29    predictions = model.predict_generator(generator=test_set,
30                                         steps = test_size/BATCH_SIZE
31                                         )
32
33
34    #y_hat = np.where(predictions > 0.5, 1, 0)
35    y_hat = (predictions > 0.5).astype(int)
36    y_true = test_set.classes
37
38    print(metrics.classification_report(y_true,y_hat, target_names=list(t
39
40    cm = confusion_matrix(y_true, y_hat, normalize="true")
41
42    f,ax = plt.subplots(figsize=(8, 8))
43    sns.heatmap(cm, annot=True, linewidths=0.01,cmap="Greens",linecolor="
44    plt.xlabel("Predicted Label")
45    plt.ylabel("True Label")
46    plt.title("Confusion Matrix")
47    ax.xaxis.set_ticklabels(['NORMAL', 'PNEUMONIA'])
48    ax.yaxis.set_ticklabels(['NORMAL', 'PNEUMONIA'])
49    plt.show()

```

```
In [35]: 1 model_evaluate(model, history)
```

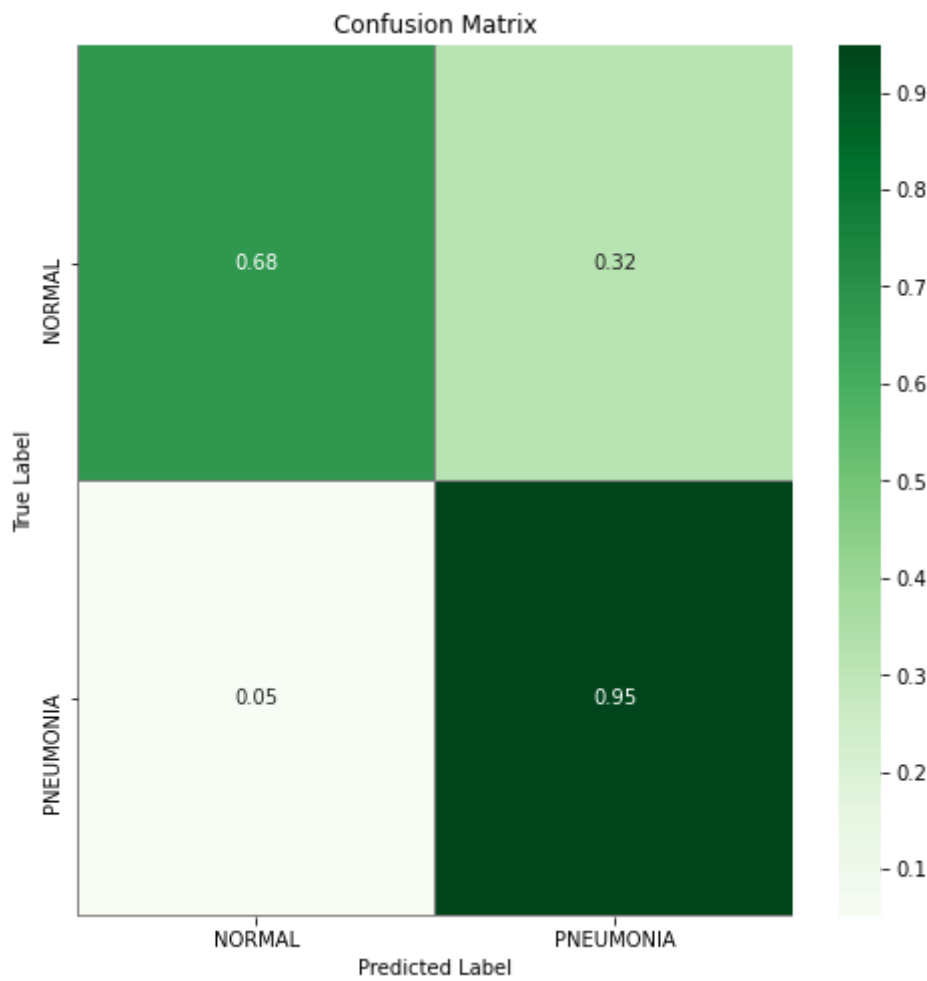


```
*****
Classification Report
*****
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:2001: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
```

```
warnings.warn("`Model.predict_generator` is deprecated and "
```

	precision	recall	f1-score	support
NORMAL	0.89	0.68	0.77	188
PNEUMONIA	0.83	0.95	0.89	312
accuracy			0.85	500
macro avg	0.86	0.81	0.83	500
weighted avg	0.85	0.85	0.84	500



Looking at this model, we can see that the accuracy is 85%, which is pretty good to start with, and has the ability to predict 95% of pneumonia cases. However, its ability to predict healthy x-rays is limited, resulting in a high false positive rate (32%).

1.4.1 Model 1

In order to see if I could improve the baseline model, I added an additional convolution layer and fine-tuned the kernels within the different convolution layers. I also added an additional pooling layers and added 3 additional dense fully connected layers.


```

In [36]: 1 #initialising the CNN
2 model_1 = models.Sequential()
3
4 #Add a convolution layer with 32 kernels of 3X3 shape padding of same a
5 model_1.add(Conv2D(32, (3,3 ),padding="same", activation='relu',
6                   input_shape=(64, 64, 3)))
7 model_1.add(layers.MaxPooling2D((2, 2)))
8 model_1.add(Conv2D(64, (3, 3), padding="same", activation='relu'))
9 # Add Max Pooling layer
10 model_1.add(MaxPooling2D((2, 2)))
11
12
13 #Add a convolution layer with 128 kernels of 3X3 shape padding of same
14 model_1.add(Conv2D(128, (3, 3), padding="same", activation='relu'))
15 model_1.add(MaxPooling2D(2, 2))
16
17 model_1.add(Conv2D(128, (3, 3), padding="same", activation='relu'))
18 model_1.add(MaxPooling2D((2, 2)))
19
20
21
22 model_1.add(Flatten())
23 #Add a fully connected layers
24 model_1.add(Dense(64, activation='relu'))
25 model_1.add(Dense(128, activation='relu'))
26 model_1.add(Dense(256, activation='relu'))
27 model_1.add(Dense(512, activation='relu'))
28
29 model_1.add(Dense(1, activation='sigmoid'))
30
31 model_1.compile(loss='binary_crossentropy',
32                optimizer='RMSprop',
33                metrics=['acc'])
34
35 model_1.summary()

```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
=====		
conv2d_3 (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d_3 (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_4 (Conv2D)	(None, 32, 32, 64)	18496
max_pooling2d_4 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_5 (Conv2D)	(None, 16, 16, 128)	73856
max_pooling2d_5 (MaxPooling2D)	(None, 8, 8, 128)	0
conv2d_6 (Conv2D)	(None, 8, 8, 128)	147584
max_pooling2d_6 (MaxPooling2D)	(None, 4, 4, 128)	0

flatten_1 (Flatten)	(None, 2048)	0
dense_2 (Dense)	(None, 64)	131136
dense_3 (Dense)	(None, 128)	8320
dense_4 (Dense)	(None, 256)	33024
dense_5 (Dense)	(None, 512)	131584
dense_6 (Dense)	(None, 1)	513
=====		
Total params: 545,409		
Trainable params: 545,409		
Non-trainable params: 0		

```
In [37]: 1 history = model_1.fit_generator(train_set,
2                                     epochs= 10,
3                                     steps_per_epoch = train_size//BATCH_SIZE,
4                                     validation_steps = val_size//BATCH_SIZE,
5                                     validation_data= val_set)
```

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1940: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.

warnings.warn("`Model.fit_generator` is deprecated and "

Epoch 1/10

163/163 [=====] - 52s 312ms/step - loss: 0.6908
- acc: 0.7318 - val_loss: 10.3727 - val_acc: 0.5208

Epoch 2/10

163/163 [=====] - 50s 307ms/step - loss: 0.8125
- acc: 0.7343 - val_loss: 0.7635 - val_acc: 0.5208

Epoch 3/10

163/163 [=====] - 50s 309ms/step - loss: 0.6032
- acc: 0.7393 - val_loss: 1.3786 - val_acc: 0.5000

Epoch 4/10

163/163 [=====] - 51s 316ms/step - loss: 0.4984
- acc: 0.7799 - val_loss: 2.3887 - val_acc: 0.5417

Epoch 5/10

163/163 [=====] - 50s 306ms/step - loss: 0.4862
- acc: 0.7947 - val_loss: 0.5892 - val_acc: 0.6458

Epoch 6/10

163/163 [=====] - 50s 308ms/step - loss: 0.4290
- acc: 0.8334 - val_loss: 0.3713 - val_acc: 0.8021

Epoch 7/10

163/163 [=====] - 50s 307ms/step - loss: 0.4410
- acc: 0.8558 - val_loss: 0.6032 - val_acc: 0.6146

Epoch 8/10

163/163 [=====] - 50s 304ms/step - loss: 0.4063
- acc: 0.8518 - val_loss: 0.1936 - val_acc: 0.9583

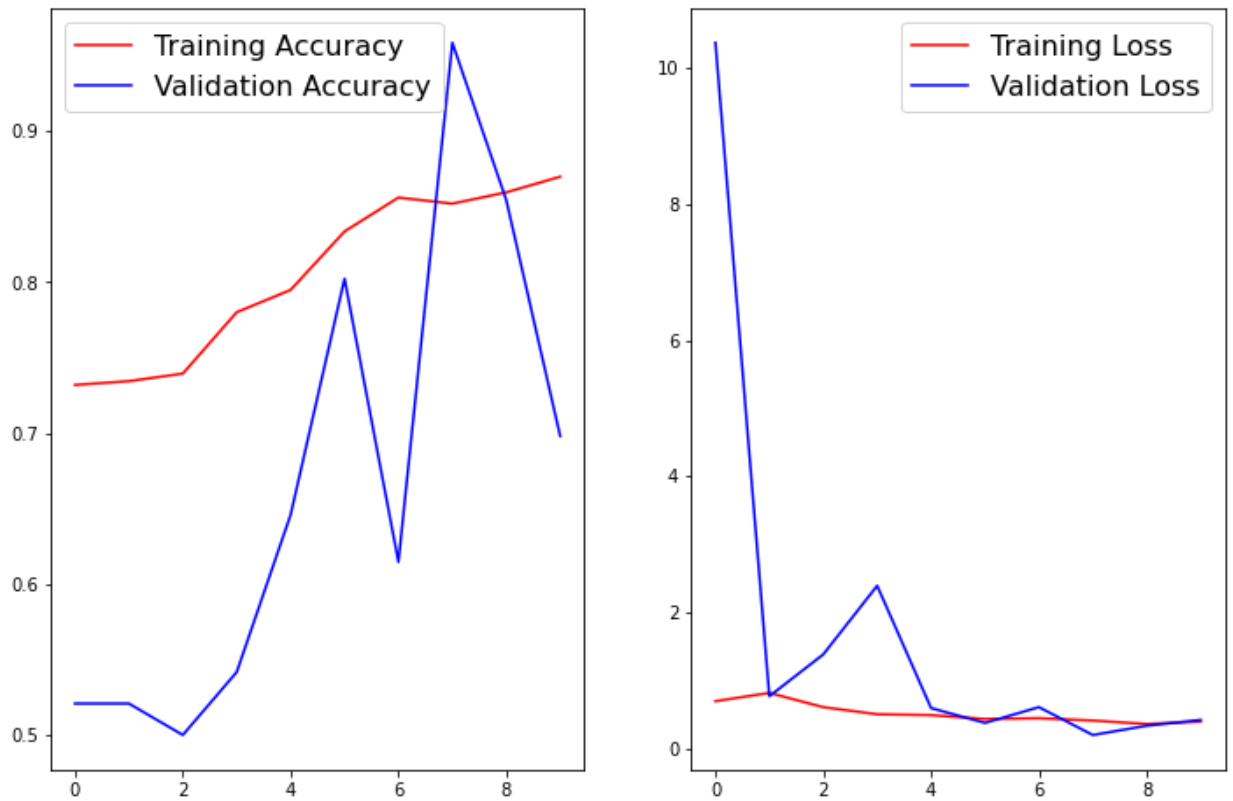
Epoch 9/10

163/163 [=====] - 51s 311ms/step - loss: 0.3554
- acc: 0.8593 - val_loss: 0.3295 - val_acc: 0.8542

Epoch 10/10

163/163 [=====] - 50s 308ms/step - loss: 0.3897
- acc: 0.8696 - val_loss: 0.4155 - val_acc: 0.6979

```
In [38]: 1 model_evaluate(model_1, history)
```



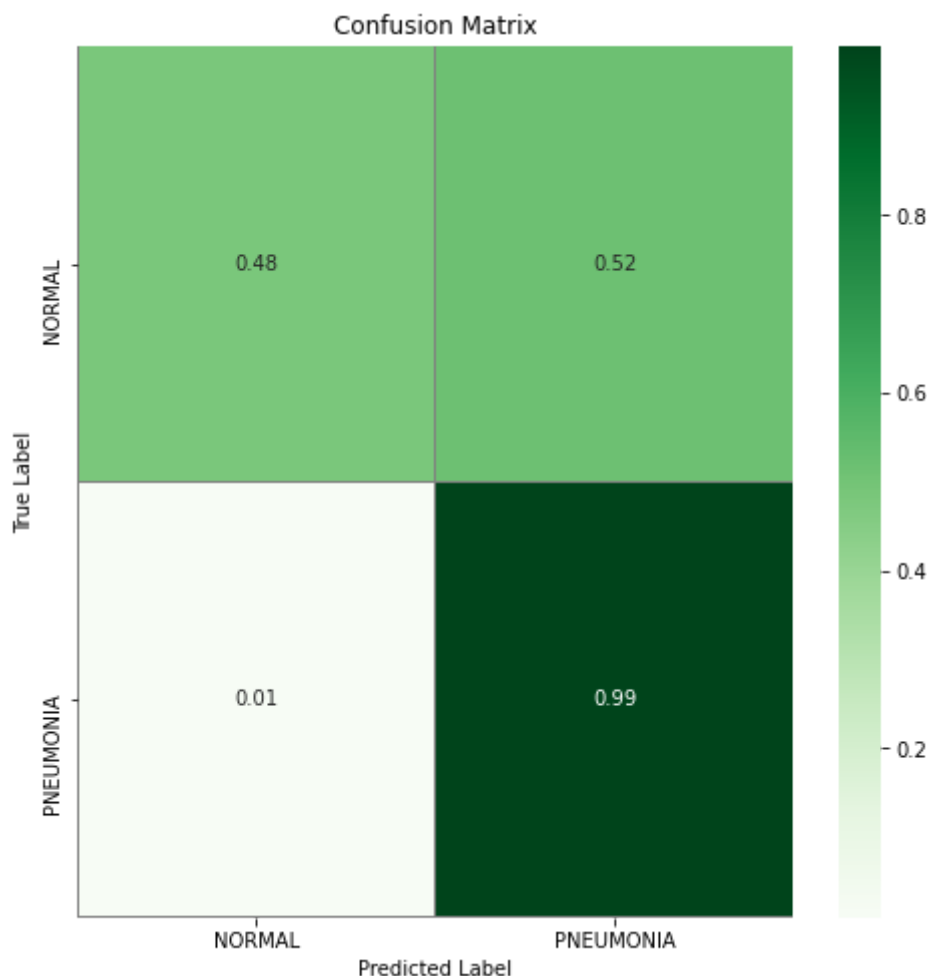
```
*****
Classification Report
*****
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:2001: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
```

```
warnings.warn("`Model.predict_generator` is deprecated and "
```

	precision	recall	f1-score	support
NORMAL	0.97	0.48	0.65	188
PNEUMONIA	0.76	0.99	0.86	312
accuracy			0.80	500

macro avg	0.86	0.74	0.75	500
weighted avg	0.84	0.80	0.78	500



Looking at the results of Model 1 we can see that the CNN architecture that I developed here actually had the opposite effect, as the model became less accurate (from 85% in the baseline model to 80% in this model). The ability to correctly predict pneumonia increased to 99%, however this model has an even harder time recalling normal x-rays with a false positive rate of 52%.

1.4.2 Model 2

Because the changes I made in Model 1 did not improve the ability to accurately predict the x-ray images, I decided to change a little bit the architecture of the CNN network. This time, I decided to introduced two dropout layers. Dropout is a technique where randomly selected neurons are ignored during training. The effect is that the network becomes less sensitive to the specific weights of neurons. This in turn results in a network that is capable of better generalization. I added one dropout layer after the convolution and pooling layers just before flattening the layers into a one dimensional array of features. In addition, I increased the number of dense fully connected layers to 5, and added another dropout layer between the second and the third dense fully connected layers.

```

In [39]: 1 #initialising the CNN
2 model_2 = models.Sequential()
3
4 #Add a convolution layer with 32 kernels of 3X3 shape padding of same a
5 model_2.add(Conv2D(32, (3,3 ),padding="same", activation='relu',
6                  input_shape=(64, 64, 3)))
7 model_2.add(layers.MaxPooling2D((2, 2)))
8 model_2.add(Conv2D(64, (3, 3), padding="same", activation='relu'))
9 # Add Max Pooling layer
10 model_2.add(MaxPooling2D((2, 2)))
11
12
13 #Add a convolution layer with 128 kernels of 3X3 shape padding of same
14 model_2.add(Conv2D(128, (3, 3), padding="same", activation='relu'))
15 model_2.add(MaxPooling2D(2, 2))
16
17 model_2.add(Conv2D(128, (3, 3), padding="same", activation='relu'))
18 model_2.add(MaxPooling2D((2, 2)))
19
20
21 #model_2.add(Dropout(0.2))
22 #Flattting the layer before fully connected layers
23 model_2.add(Flatten())
24 #Add a fully connected layers
25 #model_2.add(Dense(64, activation='relu'))
26 model_2.add(Dense(128, activation='relu'))
27 model_2.add(Dropout(0.1))
28 model_2.add(Dense(256, activation='relu'))
29 model_2.add(Dense(512, activation='relu'))
30 model_2.add(Dense(1, activation='sigmoid'))
31 model_2.compile(loss='binary_crossentropy',
32                optimizer='RMSprop',
33                metrics=['acc'])
34
35 model_2.summary()

```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_7 (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d_7 (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_8 (Conv2D)	(None, 32, 32, 64)	18496
max_pooling2d_8 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_9 (Conv2D)	(None, 16, 16, 128)	73856
max_pooling2d_9 (MaxPooling2D)	(None, 8, 8, 128)	0
conv2d_10 (Conv2D)	(None, 8, 8, 128)	147584
max_pooling2d_10 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten_2 (Flatten)	(None, 2048)	0

dense_7 (Dense)	(None, 128)	262272
dropout (Dropout)	(None, 128)	0
dense_8 (Dense)	(None, 256)	33024
dense_9 (Dense)	(None, 512)	131584
dense_10 (Dense)	(None, 1)	513
=====		
Total params: 668,225		
Trainable params: 668,225		
Non-trainable params: 0		


```
In [40]: 1 history = model_2.fit_generator(train_set,
2                                     epochs= 10,
3                                     steps_per_epoch = train_size//BATCH_SIZE,
4                                     validation_steps = val_size//BATCH_SIZE,
5                                     validation_data= val_set)
```

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1940: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.

warnings.warn("`Model.fit_generator` is deprecated and "

Epoch 1/10

163/163 [=====] - 52s 317ms/step - loss: 0.7535
- acc: 0.7375 - val_loss: 2.8385 - val_acc: 0.5208

Epoch 2/10

163/163 [=====] - 50s 308ms/step - loss: 0.6796
- acc: 0.7416 - val_loss: 7.4437 - val_acc: 0.5208

Epoch 3/10

163/163 [=====] - 51s 314ms/step - loss: 0.6529
- acc: 0.7490 - val_loss: 0.8210 - val_acc: 0.5208

Epoch 4/10

163/163 [=====] - 51s 313ms/step - loss: 0.5328
- acc: 0.7510 - val_loss: 0.6166 - val_acc: 0.5938

Epoch 5/10

163/163 [=====] - 51s 313ms/step - loss: 0.4698
- acc: 0.7972 - val_loss: 0.5138 - val_acc: 0.6667

Epoch 6/10

163/163 [=====] - 52s 316ms/step - loss: 0.4335
- acc: 0.8223 - val_loss: 0.7815 - val_acc: 0.6042

Epoch 7/10

163/163 [=====] - 51s 316ms/step - loss: 0.3972
- acc: 0.8499 - val_loss: 0.4163 - val_acc: 0.7812

Epoch 8/10

163/163 [=====] - 52s 318ms/step - loss: 0.3754
- acc: 0.8669 - val_loss: 4.4370 - val_acc: 0.5208

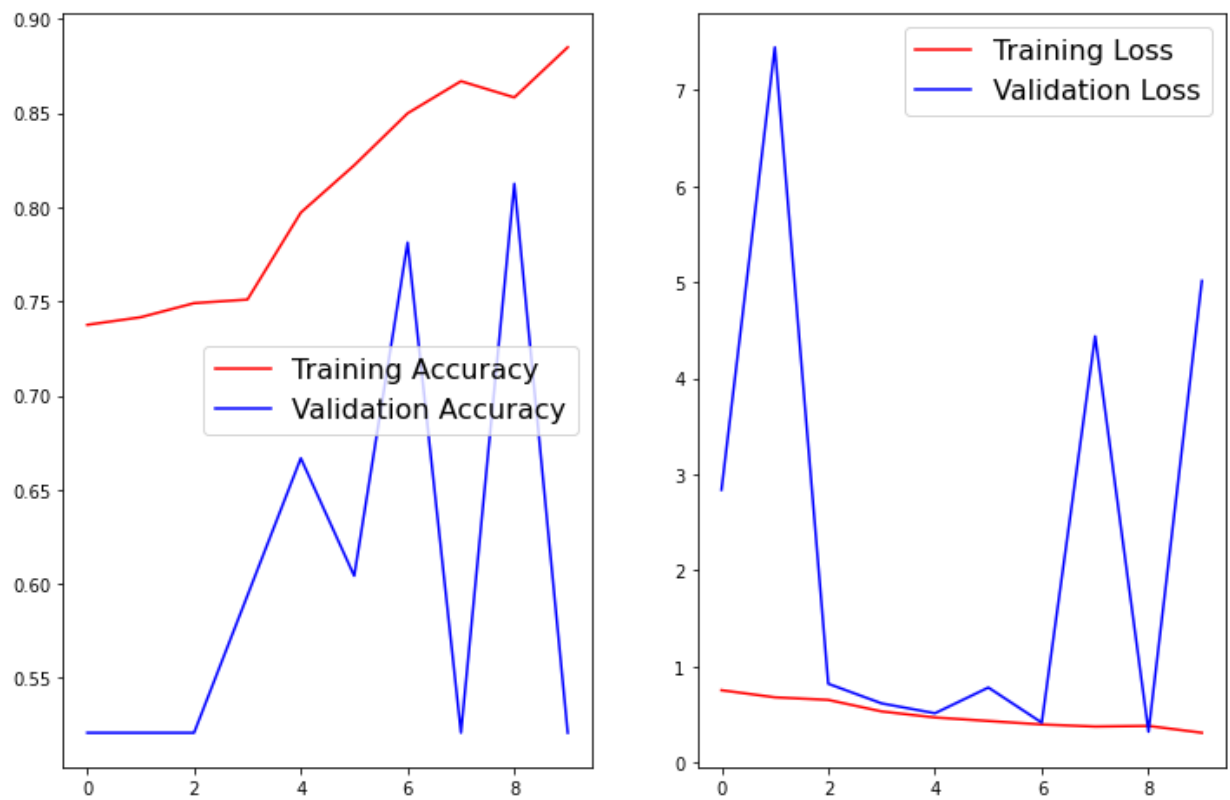
Epoch 9/10

163/163 [=====] - 52s 322ms/step - loss: 0.3820
- acc: 0.8583 - val_loss: 0.3210 - val_acc: 0.8125

Epoch 10/10

163/163 [=====] - 51s 314ms/step - loss: 0.3108
- acc: 0.8850 - val_loss: 5.0133 - val_acc: 0.5208

```
In [41]: 1 model_evaluate(model_2, history)
```



```
*****
```

Classification Report

```
*****
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:2001: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
```

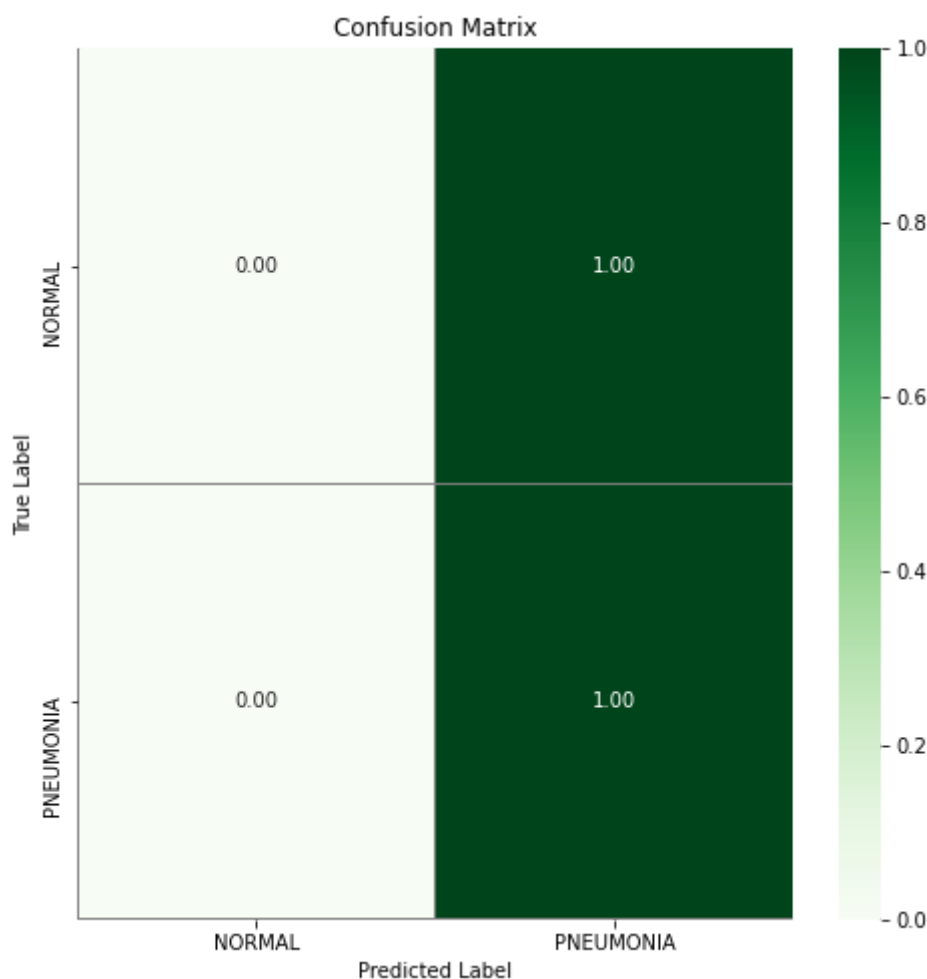
```
warnings.warn("`Model.predict_generator` is deprecated and "
```

	precision	recall	f1-score	support
NORMAL	0.00	0.00	0.00	188
PNEUMONIA	0.62	1.00	0.77	312
accuracy			0.62	500

macro avg	0.31	0.50	0.38	500
weighted avg	0.39	0.62	0.48	500

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```



Looking at the results it looks like model 2's accuracy is much reduced (62%) with 100% false positive rate, suggesting that the additions I made to the CNN architecture were actually detrimental to the performance of the model.

1.4.3 Balancing data and early stop callback implementation

Looking at the confusion matrices for all the models developed so far, it is clear that all three CNN models have trouble distinguishing the healthy (normal) x-rays from pneumonia x-rays, thus causing a very high false positive rate. As seen above, the training data that these models are using is greatly imbalanced having about 3 times more pneumonia x-rays than normal x-rays. Imbalances in the number of images in each class will invariably affect how the model performs as it bias the model towards the more abundant class. Because of this, I reasoned that if the classes are more balanced, the models will perform better. To balance the data, I first calculated weight of each class of x-ray images by dividing the number of x-rays images in each class by the total number of images. This show how much one class is represented versus the other. Then I assigned the weight of the pneumonia class to the value of weight that I calculated the normal class to have and vice-versa to equally penalize under or over-represented classes in the training set.

In addition, a problem with training neural networks is in the choice of the number of training epochs to use. Too many epochs can lead to overfitting of the training dataset, whereas too few may result in an underfit model. In the previous models I had chosen to use 10 epochs, which was a rather arbitrary choice, based on previous experiences. But since the models that I have created thus far could use some improvement, I decided to use an automated method, called early stopping, that allows you to specify an arbitrary large number of training epochs and stop training once the model performance stops improving on a hold out validation dataset.

Using these alterations, I went back and used the same CNN architecture as before and tested if balancing the data and adding the early stopping callback would be sufficient to improve the models.

```
In [42]: 1 pneumonia = len(os.listdir(os.path.join(train_folder, "PNEUMONIA")))
          2 normal = len(os.listdir(os.path.join(train_folder, "NORMAL")))
          3 pneumonia, normal
          4
```

Out[42]: (3875, 1341)

```
In [43]: 1 class_1 = pneumonia / (normal + pneumonia)
          2 class_2 = normal / (normal + pneumonia)
          3
          4 class_weight = {0: class_1, 1: class_2}
          5 print(f"Weight for class 0: {class_1:.2f}")
          6 print(f"Weight for class 1: {class_2:.2f}")
          7
          8 https://stackoverflow.com/questions/53860734/adding-class-weights-for-imbalanced-data
```

Weight for class 0: 0.74

Weight for class 1: 0.26

```
In [44]: 1 # Set up early stopping and learning rate reduction
2 from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping,
3 early_stop = EarlyStopping(monitor='val_loss', patience=3)
4 lr_redux = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3)
5 callbacks = [early_stop, lr_redux]
```

1.4.3.1 Baseline Model with balanced data

```

In [45]: 1 #initialising the CNN
2 Balance_model = models.Sequential()
3
4 #Add a convolution layer with 32 kernels of 3X3 shape padding of same a
5 Balance_model.add(Conv2D(32, (3, 3),padding="same", activation='relu',
6
7             input_shape=(64, 64, 3)
8             ))
9 # Add Max Pooling layer
10 Balance_model.add(MaxPooling2D((2, 2)))
11
12 #Add a convolution layer with 64 kernels of 3X3 shape padding of same a
13 Balance_model.add(Conv2D(64, (3, 3), padding="same", activation='relu')
14 Balance_model.add(MaxPooling2D(3, 3))
15
16 Balance_model.add(Conv2D(64, (3, 3), padding="same", activation='relu'
17 Balance_model.add(MaxPooling2D((2, 2)))
18
19
20 #Flatting the layer before fully connected layers
21 Balance_model.add(Flatten())
22
23 #Add a fully connected layer with 512 neurons
24
25 Balance_model.add(Dense(124, activation='relu'))
26 Balance_model.add(Dense(1, activation='sigmoid'))
27 Balance_model.compile(loss='binary_crossentropy',
28             optimizer='RMSprop',
29             metrics=['acc'])
30
31 Balance_model.summary()

```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
=====		
conv2d_11 (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d_11 (MaxPooling)	(None, 32, 32, 32)	0
conv2d_12 (Conv2D)	(None, 32, 32, 64)	18496
max_pooling2d_12 (MaxPooling)	(None, 10, 10, 64)	0
conv2d_13 (Conv2D)	(None, 10, 10, 64)	36928
max_pooling2d_13 (MaxPooling)	(None, 5, 5, 64)	0
flatten_3 (Flatten)	(None, 1600)	0
dense_11 (Dense)	(None, 124)	198524
dense_12 (Dense)	(None, 1)	125
=====		
Total params: 254,969		
Trainable params: 254,969		

Non-trainable params: 0

```
In [46]: 1 history = Balance_model.fit_generator(train_set,
2         epochs= 20,
3         steps_per_epoch = train_size//BATCH_SIZE,
4         validation_steps = val_size//BATCH_SIZE,
5         validation_data= val_set,
6         class_weight=class_weight,
7         callbacks=callbacks
8         )
```

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1940: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.

warnings.warn(`Model.fit_generator` is deprecated and '

WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/python/ops/array_ops.py:5049: calling gather (from tensorflow.python.ops.array_ops) with validate_indices is deprecated and will be removed in a future version.

Instructions for updating:

The `validate_indices` argument has no effect. Indices are always validated on CPU and never validated on GPU.

Epoch 1/20

163/163 [=====] - 52s 314ms/step - loss: 0.2925
- acc: 0.6300 - val_loss: 0.7149 - val_acc: 0.4896

Epoch 2/20

163/163 [=====] - 51s 314ms/step - loss: 0.2954
- acc: 0.6812 - val_loss: 0.6841 - val_acc: 0.5000

Epoch 3/20

163/163 [=====] - 51s 312ms/step - loss: 0.2465
- acc: 0.7034 - val_loss: 0.5409 - val_acc: 0.6875

Epoch 4/20

163/163 [=====] - 51s 312ms/step - loss: 0.2192
- acc: 0.7391 - val_loss: 0.6152 - val_acc: 0.5833

Epoch 5/20

163/163 [=====] - 51s 313ms/step - loss: 0.1864
- acc: 0.7868 - val_loss: 0.5427 - val_acc: 0.6771

Epoch 6/20

163/163 [=====] - 52s 318ms/step - loss: 0.1961
- acc: 0.7887 - val_loss: 0.3707 - val_acc: 0.8438

Epoch 7/20

163/163 [=====] - 52s 317ms/step - loss: 0.1691
- acc: 0.8215 - val_loss: 0.3511 - val_acc: 0.8021

Epoch 8/20

163/163 [=====] - 51s 314ms/step - loss: 0.1576
- acc: 0.8443 - val_loss: 0.4150 - val_acc: 0.8333

Epoch 9/20

163/163 [=====] - 52s 318ms/step - loss: 0.1667
- acc: 0.8397 - val_loss: 0.3679 - val_acc: 0.8125

Epoch 10/20

163/163 [=====] - 51s 315ms/step - loss: 0.1499
- acc: 0.8489 - val_loss: 0.3321 - val_acc: 0.8333

Epoch 11/20

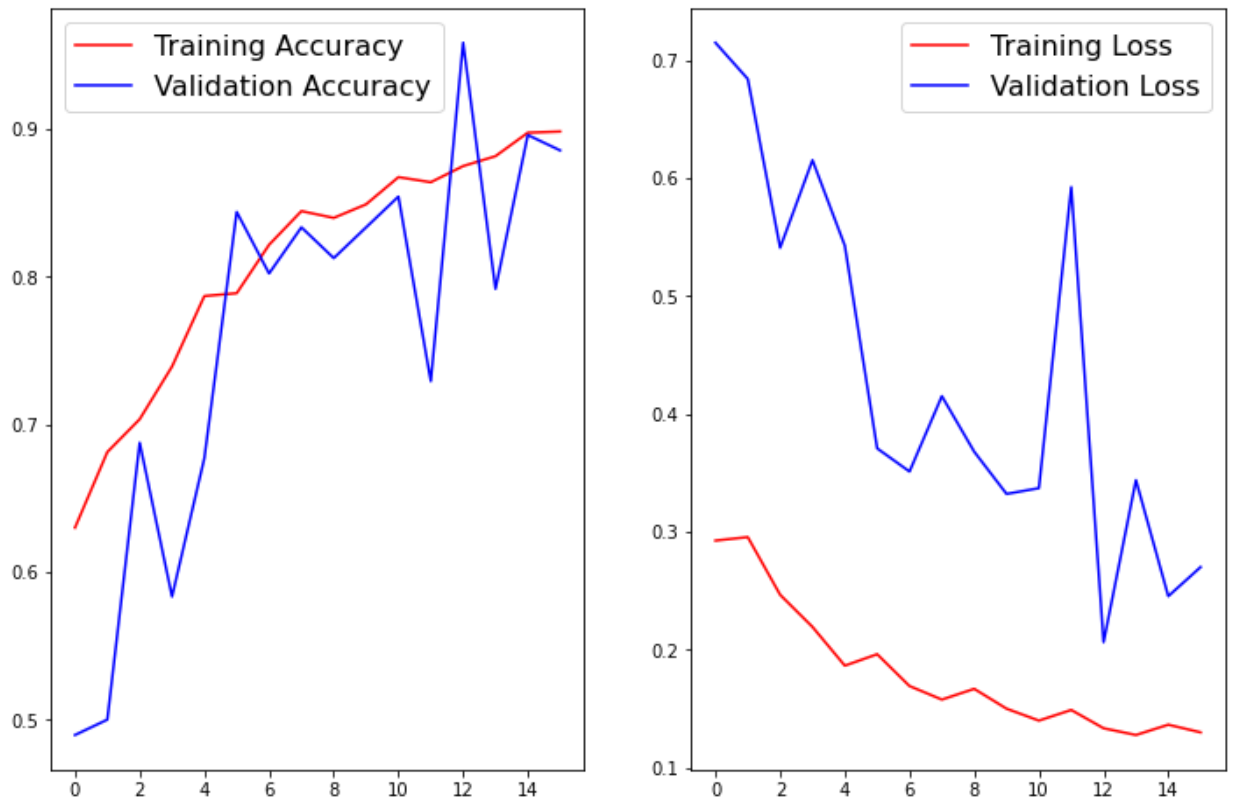
163/163 [=====] - 51s 313ms/step - loss: 0.1397
- acc: 0.8673 - val_loss: 0.3370 - val_acc: 0.8542

Epoch 12/20

163/163 [=====] - 51s 314ms/step - loss: 0.1488


```
- acc: 0.8639 - val_loss: 0.5924 - val_acc: 0.7292
Epoch 13/20
163/163 [=====] - 51s 315ms/step - loss: 0.1333
- acc: 0.8748 - val_loss: 0.2063 - val_acc: 0.9583
Epoch 14/20
163/163 [=====] - 51s 316ms/step - loss: 0.1275
- acc: 0.8815 - val_loss: 0.3438 - val_acc: 0.7917
Epoch 15/20
163/163 [=====] - 51s 316ms/step - loss: 0.1363
- acc: 0.8974 - val_loss: 0.2453 - val_acc: 0.8958
Epoch 16/20
163/163 [=====] - 52s 316ms/step - loss: 0.1298
- acc: 0.8982 - val_loss: 0.2700 - val_acc: 0.8854
```

```
In [47]: 1 model_evaluate(Balance_model, history)
```

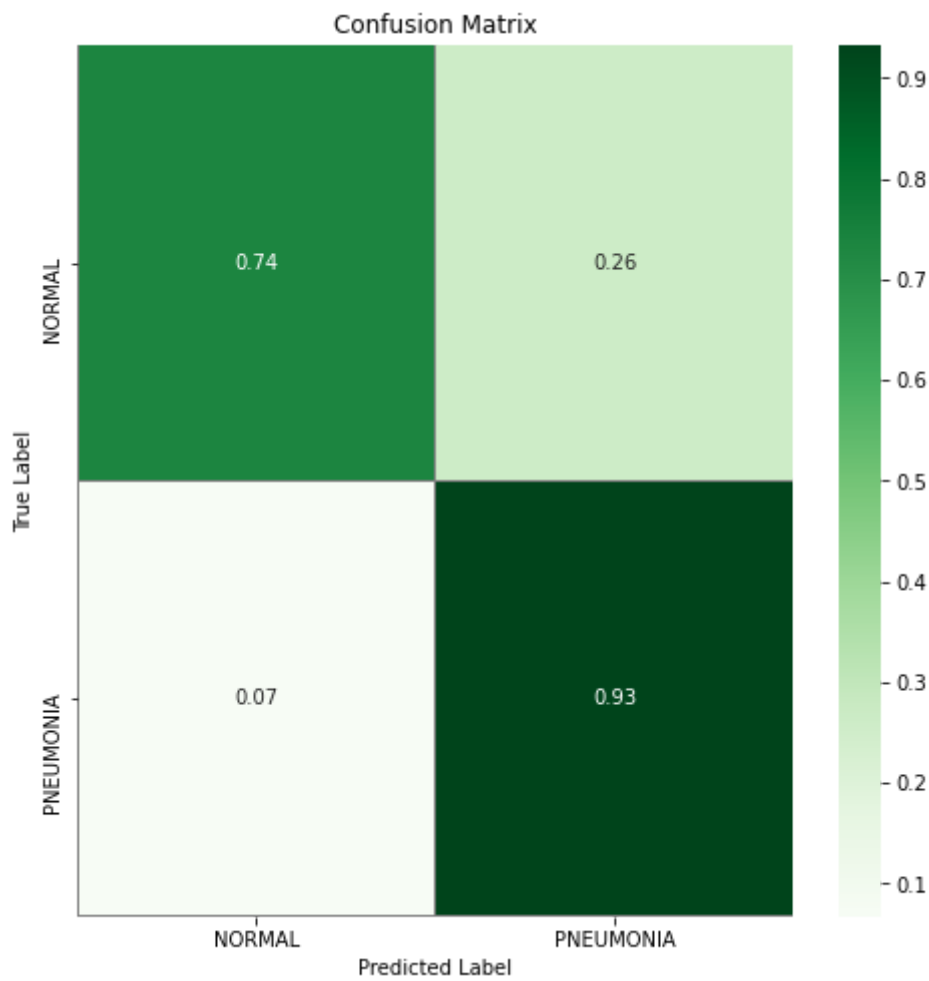


Classification Report

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:2001: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
```

```
warnings.warn("`Model.predict_generator` is deprecated and "
```

	precision	recall	f1-score	support
NORMAL	0.87	0.74	0.80	188
PNEUMONIA	0.86	0.93	0.89	312
accuracy			0.86	500
macro avg	0.86	0.84	0.85	500
weighted avg	0.86	0.86	0.86	500



Balancing the data and implementing the early stop call back definitely improved the baseline model. It's accuracy is only mildly increased (86% from 85%), but the false positive rate is reduced to 26%, suggesting that the imbalance in the original data as in fact introducing bias in the model.

1.4.3.2 Model 1 with balanced data

```

In [48]: 1 #initialising the CNN
2 Balance_model_1 = models.Sequential()
3
4 #Add a convolution layer with 32 kernels of 3X3 shape padding of same a
5 Balance_model_1.add(Conv2D(32, (3,3),padding="same", activation='relu'
6                        input_shape=(64, 64, 3)))
7 Balance_model_1.add(layers.MaxPooling2D((2, 2)))
8 Balance_model_1.add(Conv2D(64, (3, 3), padding="same", activation='relu'
9 # Add Max Pooling layer
10 Balance_model_1.add(MaxPooling2D((2, 2)))
11
12
13 #Add a convolution layer with 128 kernels of 3X3 shape padding of same
14 Balance_model_1.add(Conv2D(128, (3, 3), padding="same", activation='relu'
15 Balance_model_1.add(MaxPooling2D(2, 2))
16
17 Balance_model_1.add(Conv2D(128, (3, 3), padding="same", activation='relu'
18 Balance_model_1.add(MaxPooling2D((2, 2)))
19
20
21
22 #Flatting the layer before fully connected layers
23 Balance_model_1.add(Flatten())
24 #Balance_model_1.add(Dense(64, activation='relu'))
25 Balance_model_1.add(Dense(128, activation='relu'))
26 Balance_model_1.add(Dense(256, activation='relu'))
27 Balance_model_1.add(Dense(512, activation='relu'))
28
29 Balance_model_1.add(Dense(1, activation='sigmoid'))
30
31 Balance_model_1.compile(loss='binary_crossentropy',
32                        optimizer='RMSprop',
33                        metrics=['acc'])
34
35 Balance_model_1.summary()

```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv2d_14 (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d_14 (MaxPooling)	(None, 32, 32, 32)	0
conv2d_15 (Conv2D)	(None, 32, 32, 64)	18496
max_pooling2d_15 (MaxPooling)	(None, 16, 16, 64)	0
conv2d_16 (Conv2D)	(None, 16, 16, 128)	73856
max_pooling2d_16 (MaxPooling)	(None, 8, 8, 128)	0
conv2d_17 (Conv2D)	(None, 8, 8, 128)	147584
max_pooling2d_17 (MaxPooling)	(None, 4, 4, 128)	0

flatten_4 (Flatten)	(None, 2048)	0
dense_13 (Dense)	(None, 128)	262272
dense_14 (Dense)	(None, 256)	33024
dense_15 (Dense)	(None, 512)	131584
dense_16 (Dense)	(None, 1)	513
=====		
Total params: 668,225		
Trainable params: 668,225		
Non-trainable params: 0		
=====		

In [49]:

```

1
2 history = Balance_model_1.fit_generator(train_set,
3                                         epochs= 20,
4                                         steps_per_epoch = train_size//BATCH_SIZE,
5                                         validation_steps = val_size//BATCH_SIZE,
6                                         validation_data= val_set,
7                                         class_weight=class_weight,
8                                         callbacks=callbacks
9                                         )

```

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1940: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.

warnings.warn("`Model.fit_generator` is deprecated and "

Epoch 1/20

163/163 [=====] - 53s 318ms/step - loss: 0.6178
- acc: 0.5159 - val_loss: 0.6956 - val_acc: 0.5208

Epoch 2/20

163/163 [=====] - 51s 315ms/step - loss: 0.3128
- acc: 0.6609 - val_loss: 0.7087 - val_acc: 0.5208

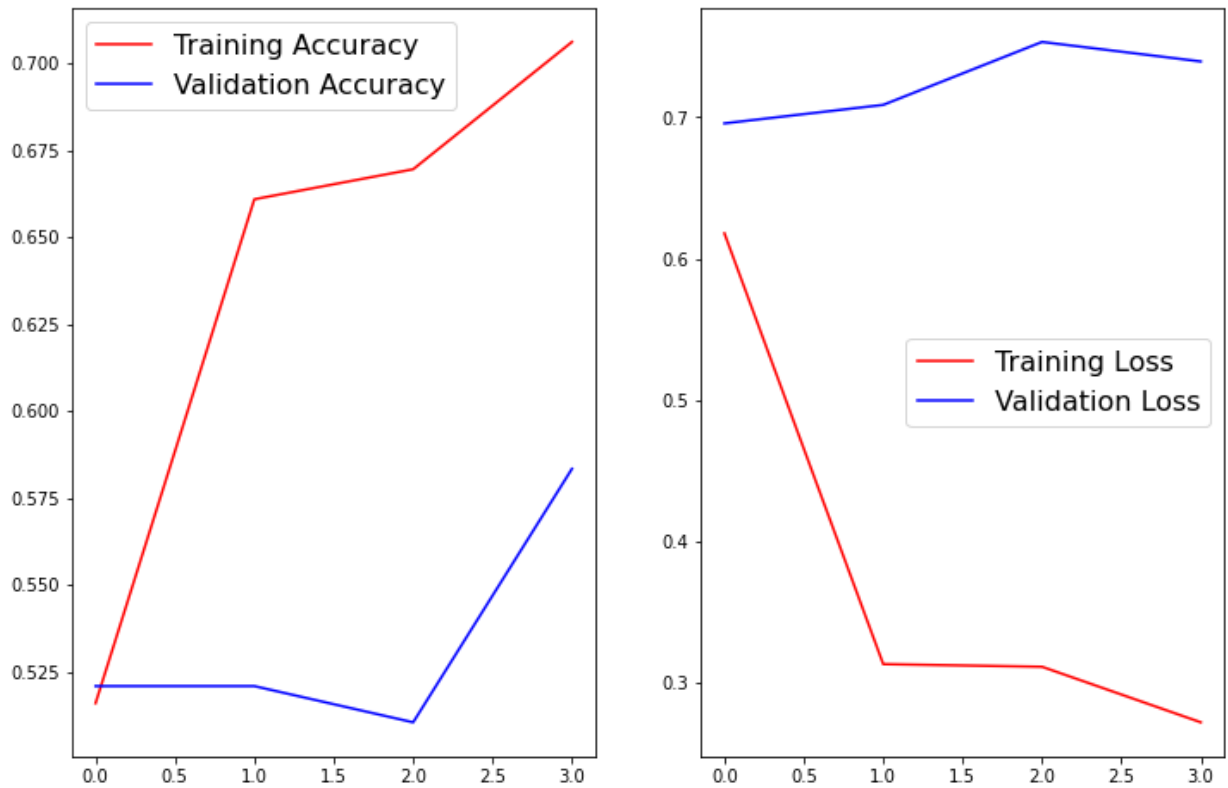
Epoch 3/20

163/163 [=====] - 52s 317ms/step - loss: 0.3110
- acc: 0.6695 - val_loss: 0.7533 - val_acc: 0.5104

Epoch 4/20

163/163 [=====] - 51s 315ms/step - loss: 0.2717
- acc: 0.7061 - val_loss: 0.7395 - val_acc: 0.5833

```
In [50]: 1 model_evaluate(Balance_model_1, history)
        2
```



```
*****
Classification Report
*****
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:2001: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
```

```
warnings.warn("`Model.predict_generator` is deprecated and "
```

	precision	recall	f1-score	support
NORMAL	0.75	0.70	0.73	188
PNEUMONIA	0.83	0.86	0.84	312
accuracy			0.80	500
macro avg	0.79	0.78	0.79	500

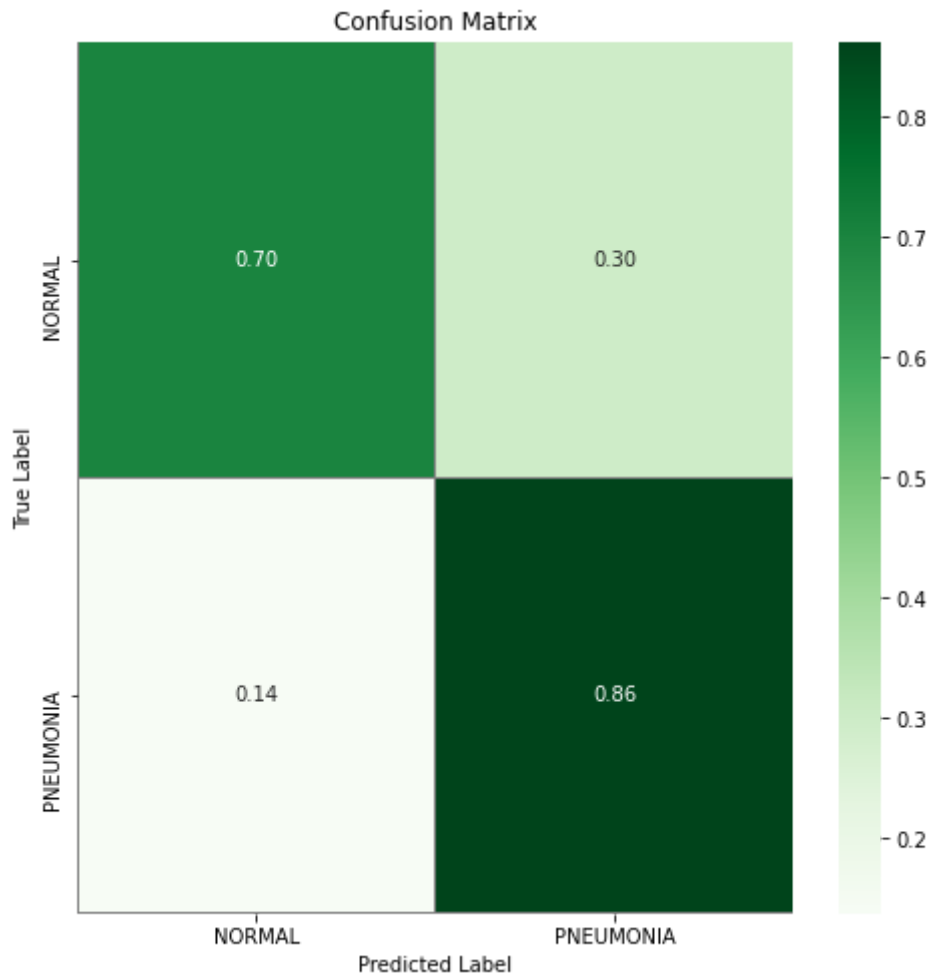
weighted avg

0.80

0.80

0.80

500



Much like what happened with the Baseline Model, Model 1's accuracy was also not greatly affected by these alterations. However, its ability to correctly predict normal x-rays is much higher (from 48% with the original data to 70% with the balanced data). Unfortunately, the increase in correct detection of normal x-rays came at the cost of reducing the amount of correct pneumonia recalls (from 99% with the original data to 86%).

1.4.3.3 Model 2 with balanced data

```

In [51]: 1 #initialising the CNN
2 Balance_model_2 = models.Sequential()
3
4 #Add a convolution layer with 32 kernels of 3X3 shape padding of same a
5 Balance_model_2.add(Conv2D(32, (3, 3), padding="same", activation='relu'
6                        input_shape=(64, 64, 3)))
7 Balance_model_2.add(layers.MaxPooling2D((2, 2)))
8 Balance_model_2.add(Conv2D(64, (3, 3), padding="same", activation='relu'
9 # Add Max Pooling layer
10 Balance_model_2.add(MaxPooling2D((2, 2)))
11
12
13 #Add a convolution layer with 128 kernels of 3X3 shape padding of same
14 Balance_model_2.add(Conv2D(128, (3, 3), padding="same", activation='relu'
15 Balance_model_2.add(MaxPooling2D(2, 2))
16
17 Balance_model_2.add(Conv2D(128, (3, 3), padding="same", activation='relu'
18 Balance_model_2.add(MaxPooling2D((2, 2)))
19
20
21 Balance_model_2.add(Dropout(0.2))
22 #Flattening the layer before fully connected layers
23 Balance_model_2.add(Flatten())
24 #Add a fully connected layers
25 #Balance_model_2.add(Dense(64, activation='relu'))
26 Balance_model_2.add(Dense(128, activation='relu'))
27 Balance_model_2.add(Dropout(0.2))
28 Balance_model_2.add(Dense(128, activation='relu'))
29 Balance_model_2.add(Dense(512, activation='relu'))
30 Balance_model_2.add(Dense(1, activation='sigmoid'))
31
32 Balance_model_2.compile(loss='binary_crossentropy',
33                        optimizer='RMSprop',
34                        metrics=['acc'])
35
36 Balance_model_2.summary()

```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_18 (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d_18 (MaxPooling)	(None, 32, 32, 32)	0
conv2d_19 (Conv2D)	(None, 32, 32, 64)	18496
max_pooling2d_19 (MaxPooling)	(None, 16, 16, 64)	0
conv2d_20 (Conv2D)	(None, 16, 16, 128)	73856
max_pooling2d_20 (MaxPooling)	(None, 8, 8, 128)	0
conv2d_21 (Conv2D)	(None, 8, 8, 128)	147584
max_pooling2d_21 (MaxPooling)	(None, 4, 4, 128)	0

dropout_1 (Dropout)	(None, 4, 4, 128)	0
flatten_5 (Flatten)	(None, 2048)	0
dense_17 (Dense)	(None, 128)	262272
dropout_2 (Dropout)	(None, 128)	0
dense_18 (Dense)	(None, 128)	16512
dense_19 (Dense)	(None, 512)	66048
dense_20 (Dense)	(None, 1)	513
=====		
Total params: 586,177		
Trainable params: 586,177		
Non-trainable params: 0		

```
In [66]: 1 history = Balance_model_2.fit_generator(train_set,
2         epochs= 20,
3         steps_per_epoch = train_size//BATCH_SIZE,
4         validation_steps = val_size//BATCH_SIZE,
5         validation_data= val_set,
6         class_weight=class_weight,
7         callbacks=callbacks
8         )
```

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1940: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.

warnings.warn('`Model.fit_generator` is deprecated and '

Epoch 1/20

163/163 [=====] - 51s 316ms/step - loss: 0.2222
- acc: 0.6660 - val_loss: 0.7169 - val_acc: 0.5625

Epoch 2/20

163/163 [=====] - 51s 312ms/step - loss: 0.2234
- acc: 0.7383 - val_loss: 0.5116 - val_acc: 0.8333

Epoch 3/20

163/163 [=====] - 51s 310ms/step - loss: 0.2050
- acc: 0.7270 - val_loss: 0.5093 - val_acc: 0.8125

Epoch 4/20

163/163 [=====] - 51s 315ms/step - loss: 0.1964
- acc: 0.7736 - val_loss: 1.6616 - val_acc: 0.4792

Epoch 5/20

163/163 [=====] - 51s 310ms/step - loss: 0.1891
- acc: 0.7619 - val_loss: 0.5984 - val_acc: 0.5833

Epoch 6/20

163/163 [=====] - 51s 315ms/step - loss: 0.1791
- acc: 0.7985 - val_loss: 0.4388 - val_acc: 0.7812

Epoch 7/20

163/163 [=====] - 51s 310ms/step - loss: 0.1616
- acc: 0.7972 - val_loss: 0.4418 - val_acc: 0.7292

Epoch 8/20

163/163 [=====] - 51s 311ms/step - loss: 0.1669
- acc: 0.8188 - val_loss: 0.3970 - val_acc: 0.7812

Epoch 9/20

163/163 [=====] - 51s 316ms/step - loss: 0.1522
- acc: 0.8507 - val_loss: 0.3291 - val_acc: 0.9062

Epoch 10/20

163/163 [=====] - 51s 312ms/step - loss: 0.1406
- acc: 0.8531 - val_loss: 0.2783 - val_acc: 0.8958

Epoch 11/20

163/163 [=====] - 51s 314ms/step - loss: 0.1412
- acc: 0.8702 - val_loss: 0.4592 - val_acc: 0.6562

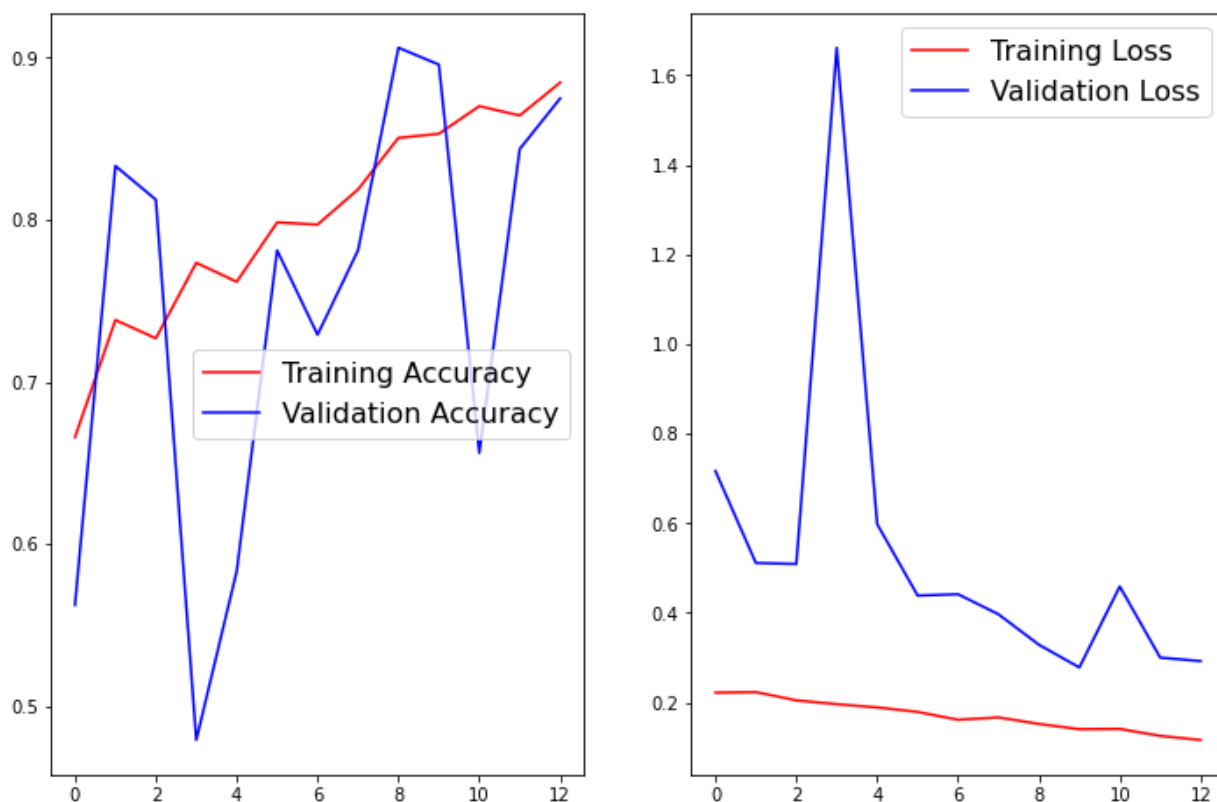
Epoch 12/20

163/163 [=====] - 51s 311ms/step - loss: 0.1256
- acc: 0.8645 - val_loss: 0.3003 - val_acc: 0.8438

Epoch 13/20

163/163 [=====] - 51s 313ms/step - loss: 0.1164
- acc: 0.8848 - val_loss: 0.2926 - val_acc: 0.8750

```
In [67]: 1 model_evaluate(Balance_model_2, history)
```

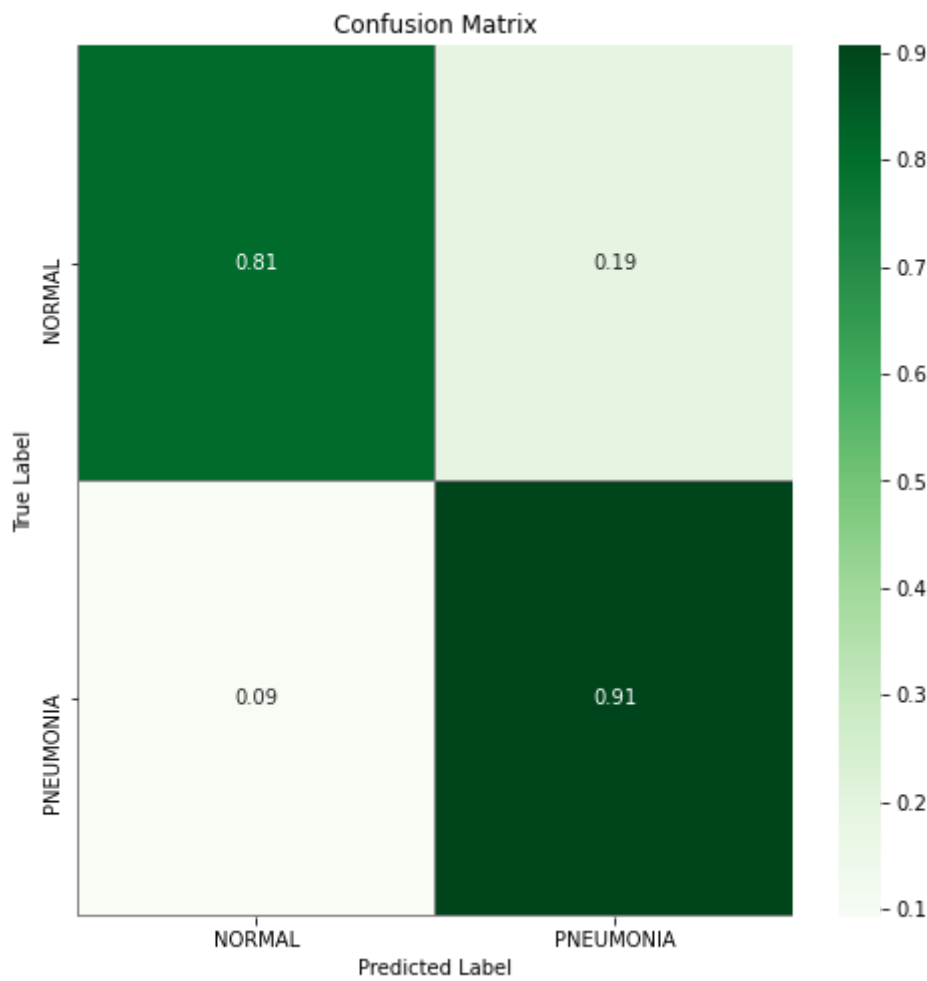


```
*****
Classification Report
*****
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:2001: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
```

```
warnings.warn("`Model.predict_generator` is deprecated and "
```

	precision	recall	f1-score	support
NORMAL	0.84	0.81	0.82	188
PNEUMONIA	0.89	0.91	0.90	312
accuracy			0.87	500
macro avg	0.86	0.86	0.86	500
weighted avg	0.87	0.87	0.87	500



In []:

1

Model 2, which with the original data had a really poor performance, with the balanced data and early stop callback performs much better. In fact, model 2's accuracy using these settings is the highest of all CNN architectures that I have constructed here (87%) and it has the best performance at recalling correctly normal x-rays while still maintaining a high recall performance for pneumonia x-rays (91%).

1.4.3.4 VGG16 model with balanced data

In addition to the models that I have constructed above, I also implemented the VGG16 architecture to see if it would result in a model with higher performance. VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition".

```
In [74]: 1 from tensorflow.keras.applications.vgg16 import VGG16
2 model_vgg16 = VGG16(weights='imagenet',
3                       include_top=False,
4                       input_shape=(64, 64, 3))
5 model_vgg16.trainable = False
6 model_vgg16.summary()
```

Model: "vgg16"

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 64, 64, 3)]	0
block1_conv1 (Conv2D)	(None, 64, 64, 64)	1792
block1_conv2 (Conv2D)	(None, 64, 64, 64)	36928
block1_pool (MaxPooling2D)	(None, 32, 32, 64)	0
block2_conv1 (Conv2D)	(None, 32, 32, 128)	73856
block2_conv2 (Conv2D)	(None, 32, 32, 128)	147584
block2_pool (MaxPooling2D)	(None, 16, 16, 128)	0
block3_conv1 (Conv2D)	(None, 16, 16, 256)	295168
block3_conv2 (Conv2D)	(None, 16, 16, 256)	590080
block3_conv3 (Conv2D)	(None, 16, 16, 256)	590080
block3_pool (MaxPooling2D)	(None, 8, 8, 256)	0
block4_conv1 (Conv2D)	(None, 8, 8, 512)	1180160
block4_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block4_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block4_pool (MaxPooling2D)	(None, 4, 4, 512)	0
block5_conv1 (Conv2D)	(None, 4, 4, 512)	2359808
block5_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block5_conv3 (Conv2D)	(None, 4, 4, 512)	2359808
block5_pool (MaxPooling2D)	(None, 2, 2, 512)	0
=====		
Total params: 14,714,688		
Trainable params: 0		
Non-trainable params: 14,714,688		

```
In [78]: 1 vgg_model = models.Sequential()  
2 vgg_model.add(model_vgg16)  
3 vgg_model.add(layers.Flatten())  
4 #vgg_model.add(layers.Dense(64, activation='relu'))  
5 vgg_model.add(Dropout(0.2))  
6 vgg_model.add(layers.Dense(128, activation='relu'))  
7 #vgg_model.add(layers.Dense(256, activation='relu'))  
8 vgg_model.add(layers.Dense(64, activation='relu'))  
9 vgg_model.add(layers.Dense(1, activation='sigmoid'))  
10 vgg_model.compile(loss='binary_crossentropy',  
11                   optimizer='RMSProp',  
12                   metrics=['acc'])
```

```
In [79]: 1 history = vgg_model.fit_generator(train_set,
2                                           epochs= 20,
3                                           steps_per_epoch = train_size//BATCH_SIZE,
4                                           validation_steps = val_size//BATCH_SIZE,
5                                           validation_data= val_set,
6                                           class_weight=class_weight,
7                                           callbacks=callbacks
8                                           )
```

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1940: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.

warnings.warn("`Model.fit_generator` is deprecated and "

Epoch 1/20

163/163 [=====] - 53s 320ms/step - loss: 0.2451
- acc: 0.6921 - val_loss: 0.2671 - val_acc: 0.9167

Epoch 2/20

163/163 [=====] - 52s 317ms/step - loss: 0.1522
- acc: 0.8317 - val_loss: 0.4300 - val_acc: 0.8125

Epoch 3/20

163/163 [=====] - 52s 317ms/step - loss: 0.1373
- acc: 0.8719 - val_loss: 0.3038 - val_acc: 0.8854

Epoch 4/20

163/163 [=====] - 51s 316ms/step - loss: 0.1219
- acc: 0.8687 - val_loss: 0.1936 - val_acc: 0.9479

Epoch 5/20

163/163 [=====] - 50s 309ms/step - loss: 0.1192
- acc: 0.8731 - val_loss: 0.2481 - val_acc: 0.9271

Epoch 6/20

163/163 [=====] - 50s 310ms/step - loss: 0.1191
- acc: 0.8875 - val_loss: 0.1952 - val_acc: 0.9479

Epoch 7/20

163/163 [=====] - 50s 307ms/step - loss: 0.1115
- acc: 0.8907 - val_loss: 0.1880 - val_acc: 0.9479

Epoch 8/20

163/163 [=====] - 51s 312ms/step - loss: 0.1067
- acc: 0.8863 - val_loss: 0.1743 - val_acc: 0.9583

Epoch 9/20

163/163 [=====] - 50s 307ms/step - loss: 0.1087
- acc: 0.8869 - val_loss: 0.1886 - val_acc: 0.9583

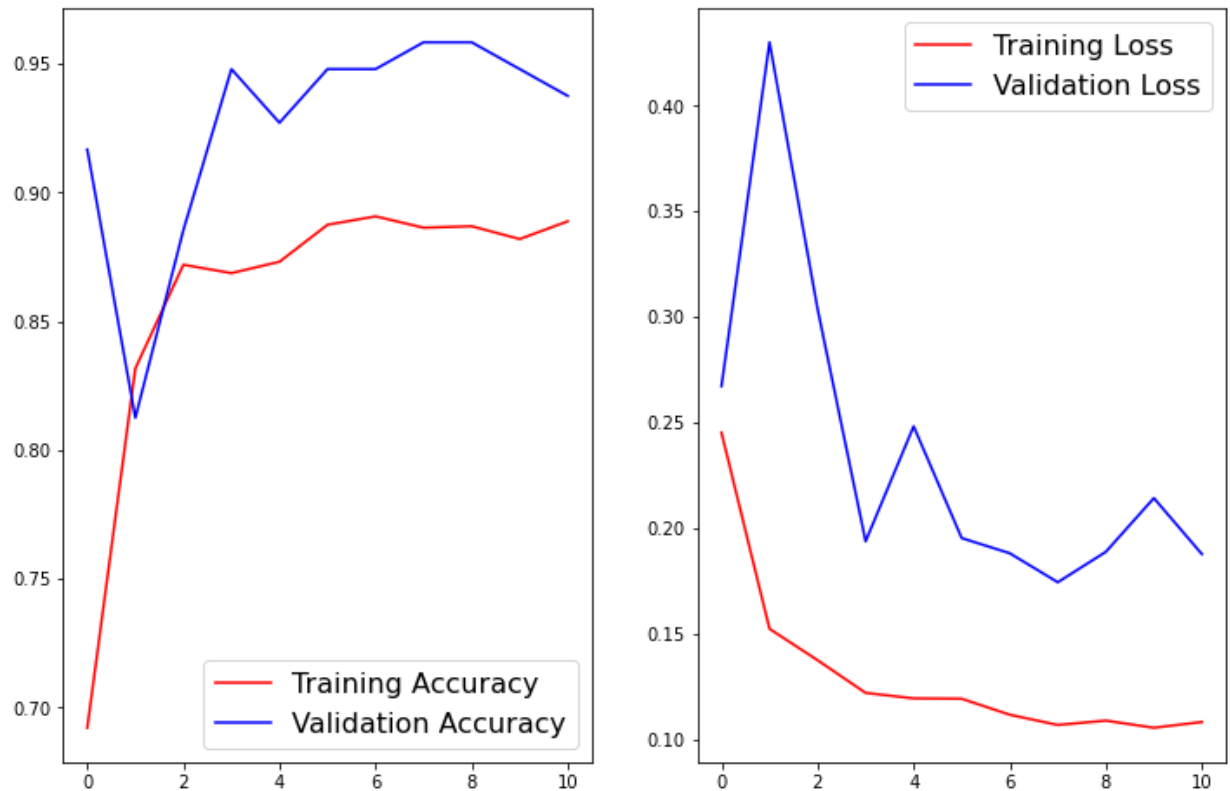
Epoch 10/20

163/163 [=====] - 50s 310ms/step - loss: 0.1053
- acc: 0.8819 - val_loss: 0.2141 - val_acc: 0.9479

Epoch 11/20

163/163 [=====] - 50s 310ms/step - loss: 0.1081
- acc: 0.8888 - val_loss: 0.1876 - val_acc: 0.9375

```
In [80]: 1 model_evaluate(vgg_model, history)
```

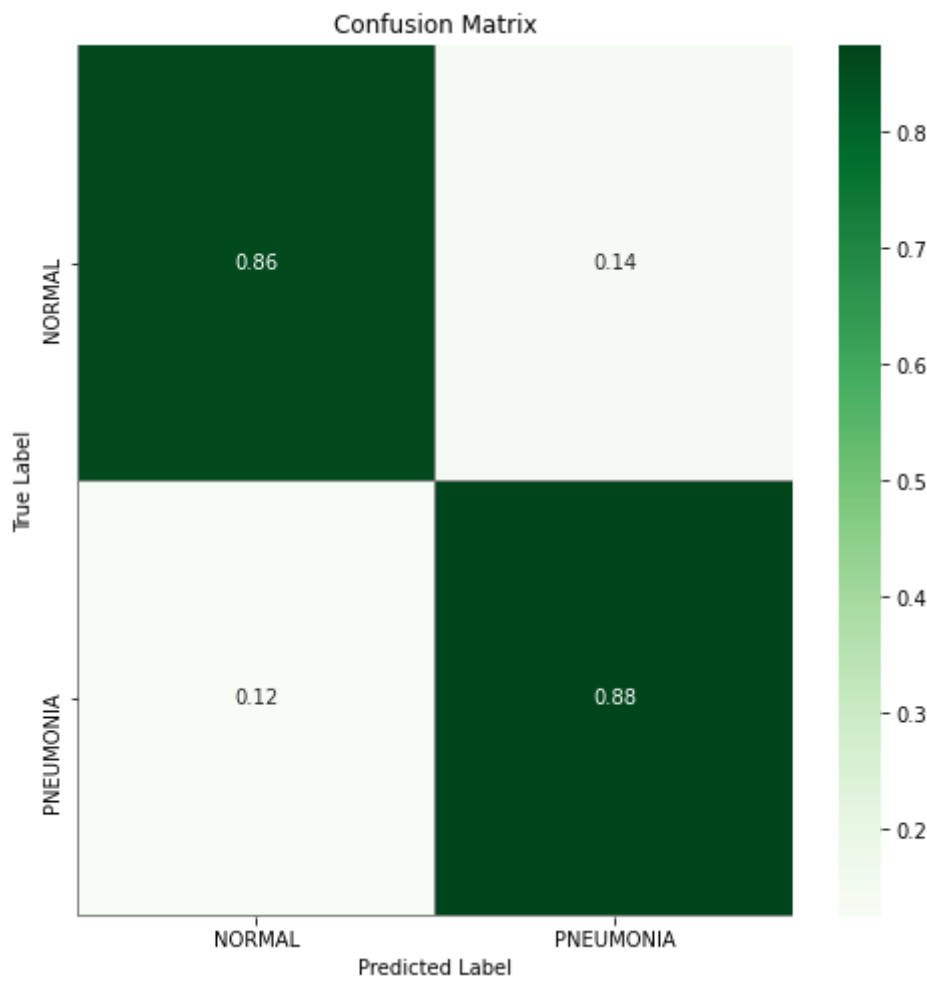


```
*****
Classification Report
*****
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:2001: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
```

```
warnings.warn("`Model.predict_generator` is deprecated and "
```

	precision	recall	f1-score	support
NORMAL	0.81	0.86	0.83	188
PNEUMONIA	0.91	0.88	0.89	312
accuracy			0.87	500
macro avg	0.86	0.87	0.86	500
weighted avg	0.87	0.87	0.87	500



Looking at the results it is clear that VGG16 is a great model to accurately predict chest x-rays. Similar to what I obtained with my CNN architecture of model 2, VGG16 also shows a 87% accuracy and it can also distinguish very well between normal and pneumonia x-rays.

1.5 VI. Model Analysis

1.5.1 Saving the Model

Looking at all the models, it seems that the best CNN model that I have built is Model 2 run with balanced data and the early stop callback, which is able to predict 91% of pneumonia while still able to predict a high proportion of normal x-rays (81%).

```
In [84]: 1 model2_path = "/content/drive/MyDrive/model2.hd5"
2 model2_path
```

```
Out[84]: '/content/drive/MyDrive/model2.hd5'
```

```
In [85]: 1 #Balance_model_2.save(model2_path)
```

```
INFO:tensorflow:Assets written to: /content/drive/MyDrive/model2.hd5/assets
```

```
In [86]: 1 # Reload model
2 best_model = models.load_model(model2_path)
```

While this has one of the best accuracy of the models that I have built, looking at the accuracy and loss curves it is obvious that the model can be improved to become more robust as there is a high degree of variability both in loss and in accuracy through the different epochs. Fine-tuning of the CNN architecture including fine-tuning of the hyperparameters within each layer of the neural network are likely to yield an improved and more robust model.

1.5.2 Lime

To get a sense into what features of the x-ray images were contributing for the improper diagnosis of normal x-rays as pneumonia, I used the Lime package to depict the features that the model found most important in making its predictions.

```
In [87]: 1
2 test = test_val_datagen.flow_from_directory(test_folder,
3                                             target_size=IMG_SIZE,
4                                             subset='training',
5                                             batch_size=500,
6                                             classes = ["NORMAL",
7                                             class_mode='binary
8                                             shuffle=False
9                                             )
```

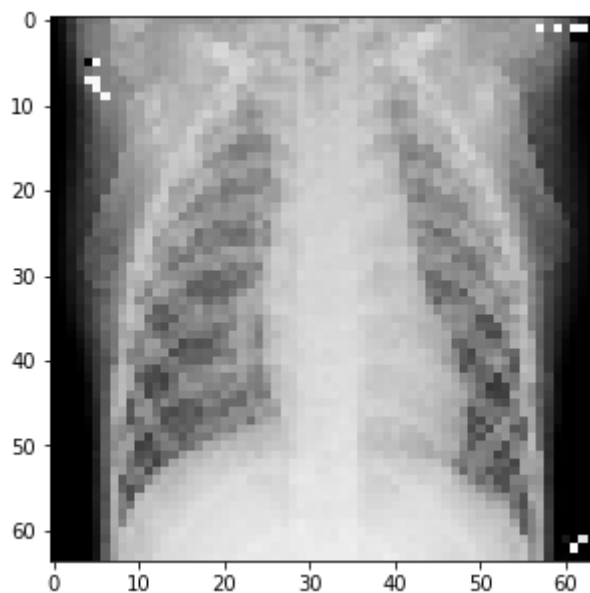
```
Found 500 images belonging to 2 classes.
```

```
In [62]: 1 x_test, y_test = next(test)
```

```
In [88]: 1 # Get image and label for an accurate normal prediction
2 label = y_test[90]
3 img = x_test[90]
4
5 # Get model pred
6 pred = best_model.predict(np.array([img]))
7 pred_class = int(pred.round())
8
9 # Print true class, predicted class and image
10 print('True Class:', label)
11 print('Predicted Class:', pred_class)
12 plt.imshow(img)
13 plt.show()
```

True Class: 0.0

Predicted Class: 1



```
In [64]: 1 explainer = lime_image.LimeImageExplainer()
```

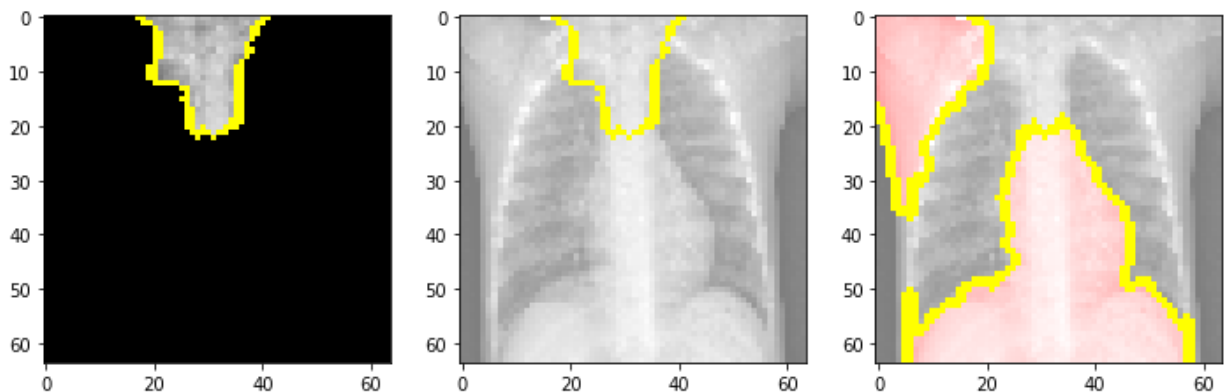
```

In [96]: 1 plt.rcParams['figure.figsize'] = [12, 5]
2 def mask_temp_1(index):
3     label = y_test[index]
4     img = x_test[index]
5
6     pred = best_model.predict(np.array([img]))
7     pred_class = int(pred.round())
8
9     explanation = explainer.explain_instance(img, best_model.predict, top
10
11     temp, mask = explanation.get_image_and_mask(explanation.top_labels[0]
12     fig, ax = plt.subplots(1,3)
13     ax[0].imshow(mark_boundaries(temp, mask))
14
15
16     temp, mask = explanation.get_image_and_mask(explanation.top_labels[0]
17     ax[1].imshow(mark_boundaries(temp / 2 + 0.5, mask))
18
19     temp, mask = explanation.get_image_and_mask(explanation.top_labels[0]
20     ax[2].imshow(mark_boundaries(temp / 2 + 0.5, mask))
21
22
23     #temp, mask = explanation.get_image_and_mask(explanation.top_labels[0]
24     #ax[3].imshow(mark_boundaries(temp / 2 + 0.5, mask))
25
26
27
28     print("label: ", label, "prediction:", pred_class)
29
30     mask_temp_1(2)

```

HBox(children=(FloatProgress(value=0.0, max=1000.0), HTML(value='')))

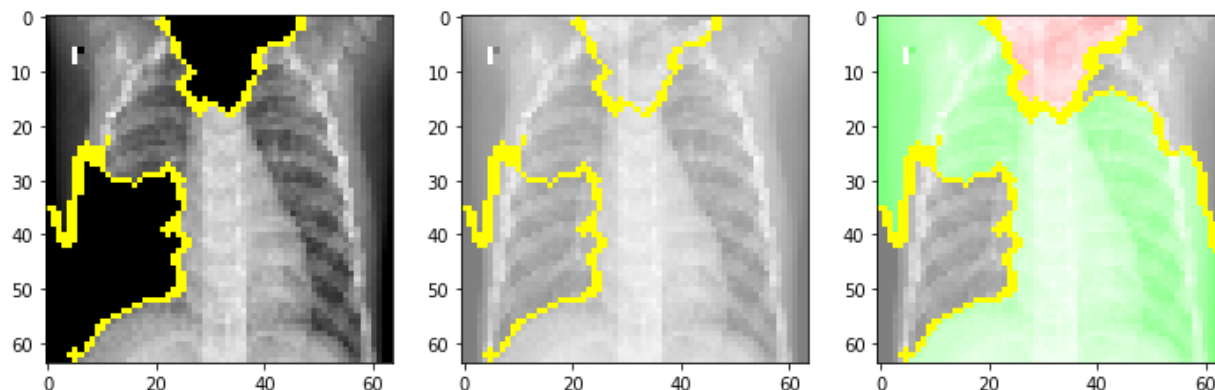
label: 0.0 prediction: 0



```
In [93]: 1 mask_temp_1(6)
```

```
HBox(children=(FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```

```
label: 0.0 prediction: 1
```



The images shown displays the features that the model found the most important in green and the ones found to be less important in red. From this image we can see that the CNN model picked up a large portion of the diaphragm and the sternum as key features in making its incorrect prediction, suggesting that the high intensity pixels coming from these areas may be adding noise to the model. Taking this into consideration, additional pre-processing methods that can remove or suppress the intensity of pixels coming from the diaphragm and sternum areas could also be valuable in improving this model for future clinical use.

1.6 VII.Conclusions

In conclusion, I was able to develop a deep learning model using convolutional neural network that, albeit not perfect, can accurately diagnose pneumonia from chest x-ray images. Through the process of building and analysing this model we learned the following:

- 1) Chest x-ray images can be used to develop AI-based diagnostic models.
- 2) Chest X-rays are a good tool for the diagnosis of pneumonia.
- 3) The diaphragm and sternum areas are a source of noise that affects the ability of model to correctly diagnose patients.

These are important information when implementing this or other AI-based tools for pneumonia diagnoses in the clinic. Therefore, for the implementation of this tool in a clinical setting I would recommend it to be implemented as follows:

- Develop a pre-processing tool that removes the noise coming from the diaphragm and sternum areas which is done automatically as part of the x-ray processing.
- Implement the AI model automatically once the x-ray image is generated and processed as a first step in the diagnosis of pneumonia to help inform the radiologist that interprets the x-ray.

This would help speed up the x-ray analysis and increase efficiency within the healthcare system but still require a doctor to make a final diagnosis based on the diagnosis done by the AI model, the doctor's experience and the patient's symptoms.