Pneumonia Diagnosis Using Chest X-Ray Images

The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).

Performance Metrics :

```
1. Confusion Matrix
2. Precision, Recall
```

Precision also cannot be taken as single metric and has less significance than recall for this dataset because we want to minimize false negative.

False negative has to be intuitively minimized because falsely diagnosing a patient of pneumonia as not having a pneumonia is a much larger deal than falsely diagnosing a healthy person as a pneumonia patient which is our major concern . That is why we are making this model . To reduce the mistakes done by doctors accidentally .

Importing the libraries

In [2]:
```
import numpy as np
import pandas as pd
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Activation, Dropout, Flatten, D
ense, BatchNormalization, Input
from keras import backend as K
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import glob
from pathlib import Path
import cv2
from keras import backend as K
from keras.utils import plot_model
import pydot, graphviz
from IPython.display import Image
from keras.optimizers import Adam
from keras.callbacks import ModelCheckpoint
import warnings
warnings.filterwarnings("ignore")
from keras.models import load_model
from keras.utils import to_categorical
from sklearn.metrics import confusion_matrix
from mlxtend.plotting import plot_confusion_matrix
from sklearn.metrics import precision_recall_fscore_support
```

We will first go through the training data and do some analysis on that like number of samples per class,etc. The training directory has two another sub-directories:

- Pneumonia : This directorty has all samples X-ray images which descibes pneumonia.
- Normal : These are the images which describes normal cases.

In [4]:
```
# Get the path for pneumonia and normal sub-directories
pneumonia = 'Data/train/PNEUMONIA'
normal = 'Data/train/NORMAL'
pneumonia1 = Path(pneumonia)
normal1 = Path(normal)

pneumonia_name = pneumonia1.glob('*.jpeg') #listing all the images names from
 pneumonia class
normal_name = normal1.glob('*.jpeg') #listing all the images names from non-pn
eumonia class

training_data = [] #Empty list to combine

for img in pneumonia_name:
    training_data.append((img, 0))
for img in normal_name:
    training_data.append((img, 1))
```

In [5]:
```
df = pd.DataFrame(training_data, columns = ['image_name', 'label'], index = No
ne)
df.head()
```

Out[5]:

	image_name	label
0	Data\train\PNEUMONIA\person1000_bacteria_2931....	0
1	Data\train\PNEUMONIA\person1000_virus_1681.jpeg	0
2	Data\train\PNEUMONIA\person1001_bacteria_2932....	0
3	Data\train\PNEUMONIA\person1002_bacteria_2933....	0
4	Data\train\PNEUMONIA\person1003_bacteria_2934....	0

In [6]:
```
df.tail()
```

Out[6]:

	image_name	label
5211	Data\train\NORMAL\NORMAL2-IM-1406-0001.jpeg	1
5212	Data\train\NORMAL\NORMAL2-IM-1412-0001.jpeg	1
5213	Data\train\NORMAL\NORMAL2-IM-1419-0001.jpeg	1
5214	Data\train\NORMAL\NORMAL2-IM-1422-0001.jpeg	1
5215	Data\train\NORMAL\NORMAL2-IM-1423-0001.jpeg	1

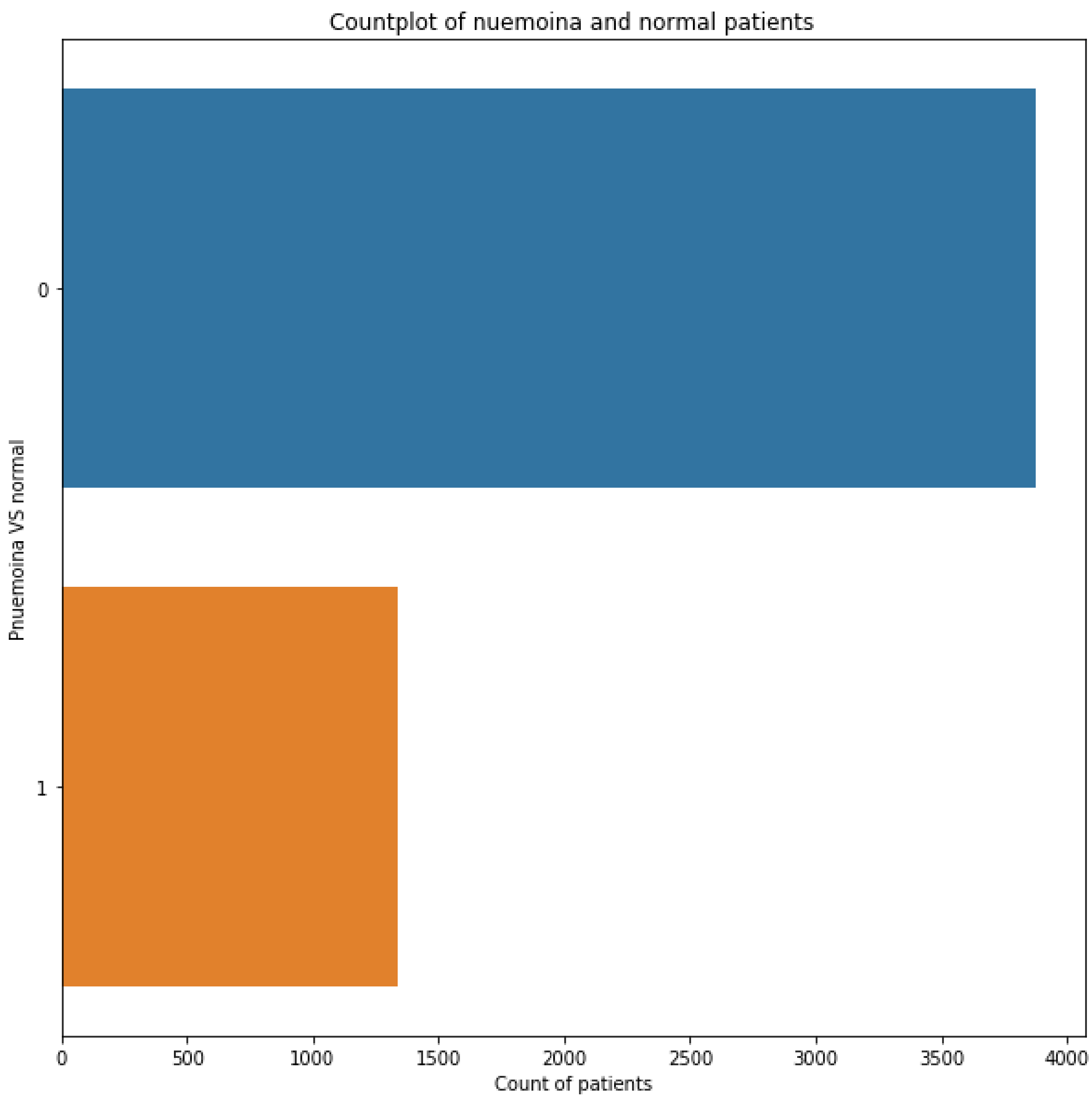
In [7]:
```
df['label'].value_counts()
```

Out[7]:
```
0    3875
1    1341
Name: label, dtype: int64
```

There are 3875 X-ray images of pnuemonia and 1341 images of normal patients.

In [8]:
```
plt.figure(figsize = (10, 10))
sns.countplot(y = 'label', data =df)
plt.title('Countplot of nuemoina and normal patients')
plt.xlabel('Count of patients')
plt.ylabel('Pnuemoina VS normal')
```

Out[8]:
```
Text(0,0.5,'Pnuemoina VS normal')
```



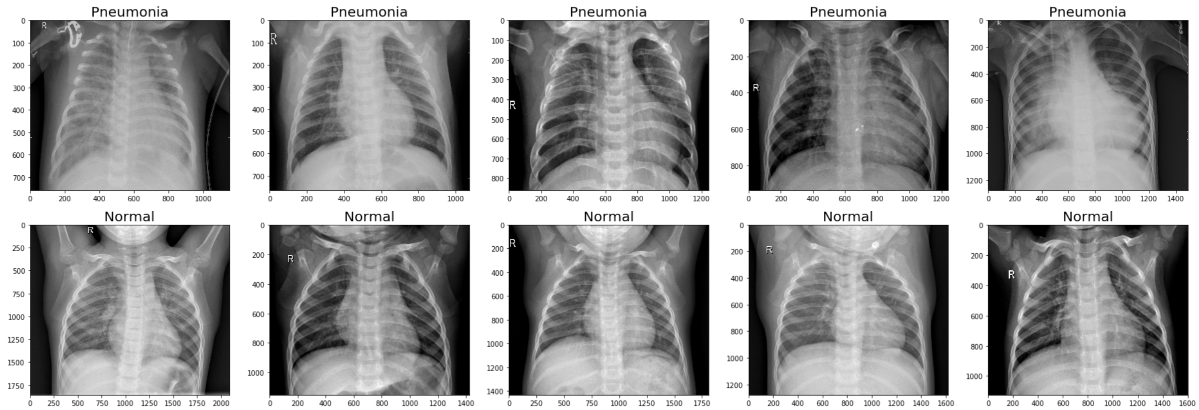
As you can see from above plot the count of pnuemonia patients are almost 3 times more than the normal patients. So this is imbalanced dataset. Therefore validation accuracy won't be a good metric to analyze the model performance

In [9]:
```
pneumonia_data = df[df['label'] == 0]['image_name'].iloc[:10].tolist()
normal_data = df[df['label'] == 1]['image_name'].iloc[:10].tolist()
```

Visualizing some images of both the categories.

In [10]:
```
fig = plt.figure(figsize = (30, 10))
plt.subplot(2,5,1)
image = cv2.imread(str(pneumonia_data[0]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,2)
image = cv2.imread(str(pneumonia_data[1]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,3)
image = cv2.imread(str(pneumonia_data[2]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,4)
image = cv2.imread(str(pneumonia_data[3]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,5)
image = cv2.imread(str(pneumonia_data[4]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,6)
image = cv2.imread(str(normal_data[0]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)

plt.subplot(2,5,7)
image = cv2.imread(str(normal_data[1]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)

plt.subplot(2,5,8)
image = cv2.imread(str(normal_data[2]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)

plt.subplot(2,5,9)
image = cv2.imread(str(normal_data[3]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)

plt.subplot(2,5,10)
image = cv2.imread(str(normal_data[4]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)
```

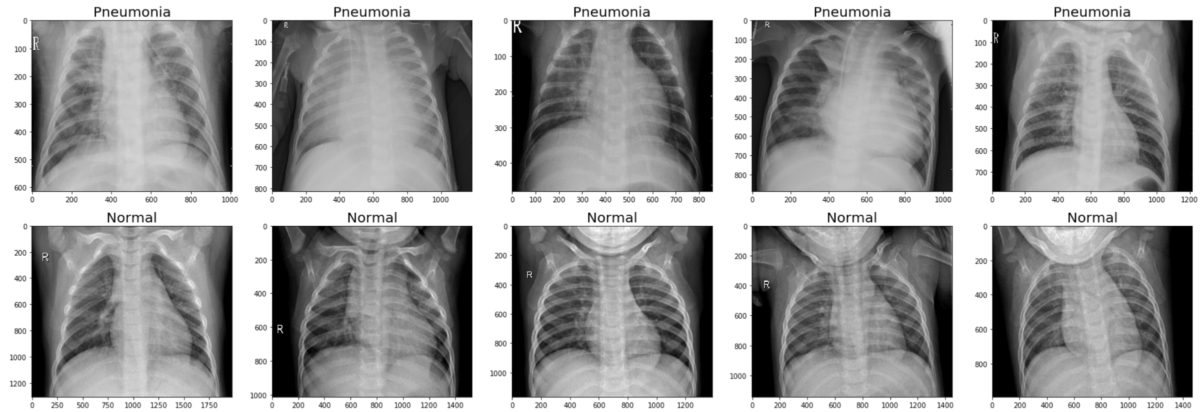
Out[10]: Text(0.5,1,'Normal')



If you look carefully in above plots there are some cases where we won't be able to classify between a normal case and pneumonia case with our naked eyes but of course the expert peoples in medical domain can figure out difference between them.

In [11]:
```
fig = plt.figure(figsize = (30, 10))
plt.subplot(2,5,1)
image = cv2.imread(str(pneumonia_data[5]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,2)
image = cv2.imread(str(pneumonia_data[6]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,3)
image = cv2.imread(str(pneumonia_data[7]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,4)
image = cv2.imread(str(pneumonia_data[8]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,5)
image = cv2.imread(str(pneumonia_data[9]))
plt.imshow(image, aspect="auto")
plt.title('Pneumonia', fontsize = 20)

plt.subplot(2,5,6)
image = cv2.imread(str(normal_data[5]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)

plt.subplot(2,5,7)
image = cv2.imread(str(normal_data[6]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)

plt.subplot(2,5,8)
image = cv2.imread(str(normal_data[7]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)

plt.subplot(2,5,9)
image = cv2.imread(str(normal_data[8]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)

plt.subplot(2,5,10)
image = cv2.imread(str(normal_data[9]))
plt.imshow(image, aspect="auto")
plt.title('Normal', fontsize = 20)
```

Out[11]: Text(0.5,1,'Normal')



In [21]:
```
img_height, img_width = 256, 256
epochs = 32
batch_size = 16
train_dir ='Data/train'
validation_dir = 'Data/val'
test_dir = 'Data/test'
nb_train_samples = 5216
nb_validation_samples = 16
```

In [13]:
```
if K.image_data_format() == 'channel_first':
    input_shape = (3, img_height, img_width)
else:
    input_shape = (img_height, img_width, 3)
```

Building Convolutional Nueral Network architecutre.

In [14]:
```
model = Sequential()

#first convolutional layer
model.add(Conv2D(32, (3,3), input_shape = input_shape, padding ='same'))
model.add(Activation('relu'))

#second convolutional layer
model.add(Conv2D(64, (3,3), activation = 'relu', padding ='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size = (2,2)))

#third convolutional layer
model.add(Conv2D(64, (3,3), activation = 'relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size = (2,2)))
model.add(Dropout(rate = 0.5))

#fourth convolutional layer
model.add(Conv2D(64, (3,3), activation = 'relu',padding = 'same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size = (2,2)))
model.add(Dropout(rate = 0.5))

#flatten
model.add(Flatten())

#first dense layer
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(rate = 0.5))

#second dense layer
model.add(Dense(32))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Dropout(rate = 0.5))

#output layer
model.add(Dense(2))
model.add(Activation('softmax'))
```

In [15]:
```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_1 (Conv2D)            (None, 256, 256, 32)      896       
_________________________________________________________________
activation_1 (Activation)    (None, 256, 256, 32)      0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 256, 256, 64)      18496     
_________________________________________________________________
batch_normalization_1 (Batch (None, 256, 256, 64)      256       
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 128, 128, 64)      0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 126, 126, 64)      36928     
_________________________________________________________________
batch_normalization_2 (Batch (None, 126, 126, 64)      256       
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 63, 63, 64)        0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 63, 63, 64)        0         
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 63, 63, 64)        36928     
_________________________________________________________________
batch_normalization_3 (Batch (None, 63, 63, 64)        256       
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 31, 31, 64)        0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 31, 31, 64)        0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 61504)             0         
_________________________________________________________________
dense_1 (Dense)              (None, 64)                3936320   
_________________________________________________________________
activation_2 (Activation)    (None, 64)                0         
_________________________________________________________________
dropout_3 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_2 (Dense)              (None, 32)                2080      
_________________________________________________________________
activation_3 (Activation)    (None, 32)                0         
_________________________________________________________________
batch_normalization_4 (Batch (None, 32)                128       
_________________________________________________________________
dropout_4 (Dropout)          (None, 32)                0         
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 66        
_________________________________________________________________
activation_4 (Activation)    (None, 2)                 0         
=================================================================
Total params: 4,032,610
Trainable params: 4,032,162
Non-trainable params: 448
_________________________________________________________________
```

In [16]:
```
#compiling the model
model.compile(optimizer =Adam(lr = 0.001, decay = 1e-4), loss = 'categorical_c
rossentropy', metrics = ['accuracy'] )
```

In [17]:
```
train_datagen = ImageDataGenerator(
                rescale = 1. / 255,
                shear_range = 0.2,
                zoom_range = 0.2,
                horizontal_flip = True,
                rotation_range = 40,
                width_shift_range = 0.2,
                height_shift_range = 0.2)

test_datagen = ImageDataGenerator(rescale=1. / 255)
```

In [18]:
```
train_generator = train_datagen.flow_from_directory(
                train_dir,
                target_size=(img_width, img_height),
                batch_size=batch_size,
                class_mode='categorical')
```

```
Found 5216 images belonging to 2 classes.
```

In [19]:
```
for data, labels in train_generator:
    print(data.shape)
    print(labels.shape)
    print(labels)
    break
```

```
(16, 256, 256, 3)
(16, 2)
[[0. 1.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [1. 0.]
 [0. 1.]]
```

In [22]:
```
validation_generator = train_datagen.flow_from_directory(
                        validation_dir,
                        target_size=(img_width, img_height),
                        batch_size=batch_size,
                        class_mode='categorical')
```

```
Found 16 images belonging to 2 classes.
```

In [23]:
```
test_generator = test_datagen.flow_from_directory(
                        test_dir,
                        target_size=(img_width, img_height),
                        batch_size=1,
                        shuffle = False,
                        class_mode='categorical')
```

```
Found 624 images belonging to 2 classes.
```

In [24]:
```
for data, labels in test_generator:
    print(data.shape)
    print(labels.shape)
    print(labels)
    break
```

```
(1, 256, 256, 3)
(1, 2)
[[1. 0.]]
```

In [25]:
```
print(test_generator.class_indices)
```

```
{'NORMAL': 0, 'PNEUMONIA': 1}
```

Making Checkpoint each epoch to check and save the best model performance till last and also avoiding further validation loss drop due to overfitting.

In [26]:
```
checkpointer = ModelCheckpoint(filepath = 'model.h5',
                               verbose = 0,
                               mode = 'auto',
                               save_best_only = True,
                               monitor='val_loss')
```

In [210]:
```
history = model.fit_generator(
    train_generator,
    steps_per_epoch = nb_train_samples // batch_size,
    epochs = epochs,
    validation_data=validation_generator,
    validation_steps=nb_validation_samples // batch_size,
    callbacks=[checkpointer])
```

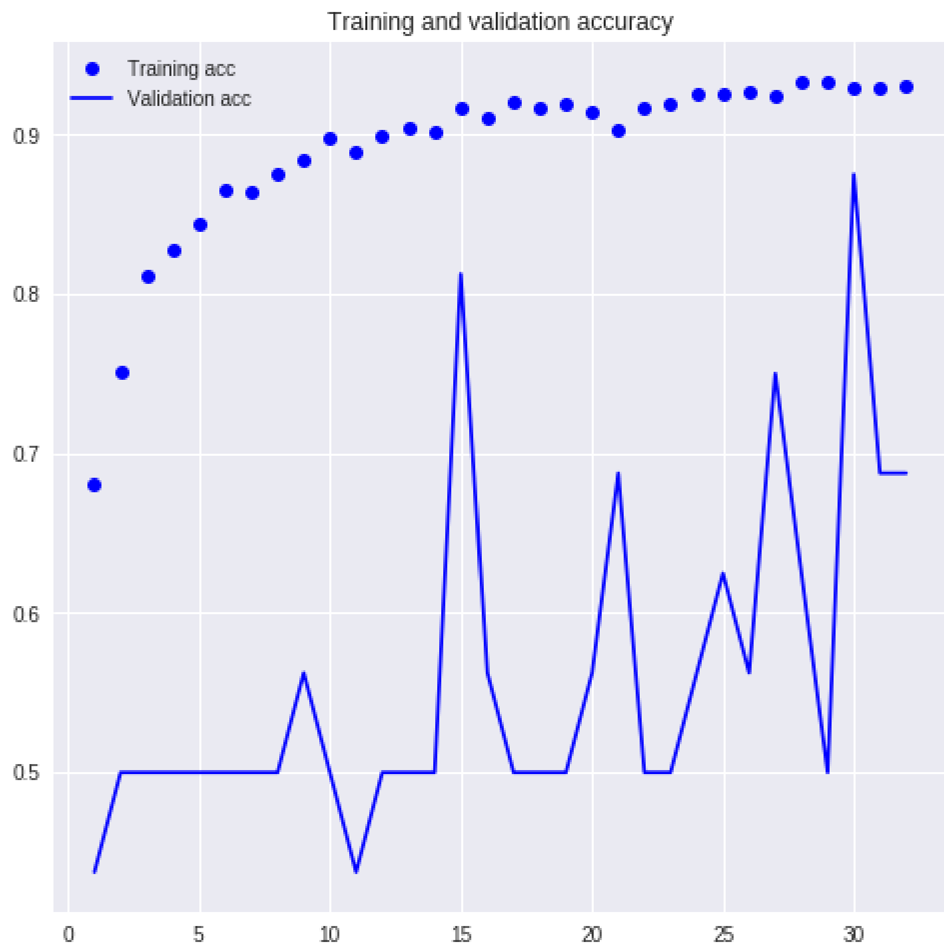
```
Epoch 1/32
326/326 [==============================] - 185s 568ms/step - loss: 0.7488 - a
cc: 0.6810 - val_loss: 0.8473 - val_acc: 0.4375
Epoch 2/32
326/326 [==============================] - 173s 529ms/step - loss: 0.5310 - a
cc: 0.7490 - val_loss: 1.5904 - val_acc: 0.5000
Epoch 3/32
326/326 [==============================] - 177s 542ms/step - loss: 0.4172 - a
cc: 0.8119 - val_loss: 1.3519 - val_acc: 0.5000
Epoch 4/32
326/326 [==============================] - 176s 541ms/step - loss: 0.3858 - a
cc: 0.8246 - val_loss: 1.3293 - val_acc: 0.5000
Epoch 5/32
326/326 [==============================] - 176s 539ms/step - loss: 0.3465 - a
cc: 0.8439 - val_loss: 1.5958 - val_acc: 0.5000
Epoch 6/32
326/326 [==============================] - 176s 539ms/step - loss: 0.3211 - a
cc: 0.8650 - val_loss: 1.0229 - val_acc: 0.5000
Epoch 7/32
326/326 [==============================] - 176s 539ms/step - loss: 0.3078 - a
cc: 0.8637 - val_loss: 1.5265 - val_acc: 0.5000
Epoch 8/32
326/326 [==============================] - 175s 537ms/step - loss: 0.2843 - a
cc: 0.8761 - val_loss: 2.8878 - val_acc: 0.5000
Epoch 9/32
326/326 [==============================] - 174s 534ms/step - loss: 0.2732 - a
cc: 0.8844 - val_loss: 1.1513 - val_acc: 0.5625
Epoch 10/32
326/326 [==============================] - 175s 536ms/step - loss: 0.2420 - a
cc: 0.8982 - val_loss: 1.4589 - val_acc: 0.5000
Epoch 11/32
326/326 [==============================] - 174s 535ms/step - loss: 0.2658 - a
cc: 0.8865 - val_loss: 1.2996 - val_acc: 0.4375
Epoch 12/32
326/326 [==============================] - 174s 533ms/step - loss: 0.2342 - a
cc: 0.8997 - val_loss: 8.0590 - val_acc: 0.5000
Epoch 13/32
326/326 [==============================] - 174s 535ms/step - loss: 0.2499 - a
cc: 0.9009 - val_loss: 4.5712 - val_acc: 0.5000
Epoch 14/32
326/326 [==============================] - 175s 535ms/step - loss: 0.2414 - a
cc: 0.9020 - val_loss: 3.0419 - val_acc: 0.5000
Epoch 15/32
326/326 [==============================] - 174s 533ms/step - loss: 0.2185 - a
cc: 0.9172 - val_loss: 0.4918 - val_acc: 0.8125
Epoch 16/32
326/326 [==============================] - 175s 537ms/step - loss: 0.2227 - a
cc: 0.9103 - val_loss: 1.0133 - val_acc: 0.5625
Epoch 17/32
326/326 [==============================] - 175s 538ms/step - loss: 0.2013 - a
cc: 0.9206 - val_loss: 1.4082 - val_acc: 0.5000
Epoch 18/32
326/326 [==============================] - 175s 537ms/step - loss: 0.2098 - a
cc: 0.9174 - val_loss: 2.7193 - val_acc: 0.5000
Epoch 19/32
326/326 [==============================] - 175s 537ms/step - loss: 0.2092 - a
cc: 0.9168 - val_loss: 3.0196 - val_acc: 0.5000
```

```
Epoch 20/32
326/326 [==============================] - 175s 535ms/step - loss: 0.2120 - a
cc: 0.9137 - val_loss: 0.7965 - val_acc: 0.5625
Epoch 21/32
326/326 [==============================] - 177s 544ms/step - loss: 0.2433 - a
cc: 0.9036 - val_loss: 0.4845 - val_acc: 0.6875
Epoch 22/32
326/326 [==============================] - 176s 539ms/step - loss: 0.2154 - a
cc: 0.9164 - val_loss: 3.1636 - val_acc: 0.5000
Epoch 23/32
326/326 [==============================] - 177s 542ms/step - loss: 0.2088 - a
cc: 0.9197 - val_loss: 1.3670 - val_acc: 0.5000
Epoch 24/32
326/326 [==============================] - 176s 541ms/step - loss: 0.1991 - a
cc: 0.9229 - val_loss: 1.0191 - val_acc: 0.5625
Epoch 25/32
326/326 [==============================] - 177s 543ms/step - loss: 0.1957 - a
cc: 0.9254 - val_loss: 2.0066 - val_acc: 0.6250
Epoch 26/32
326/326 [==============================] - 177s 543ms/step - loss: 0.1941 - a
cc: 0.9264 - val_loss: 1.1397 - val_acc: 0.5625
Epoch 27/32
326/326 [==============================] - 174s 535ms/step - loss: 0.1965 - a
cc: 0.9245 - val_loss: 0.4120 - val_acc: 0.7500
Epoch 28/32
326/326 [==============================] - 175s 536ms/step - loss: 0.1788 - a
cc: 0.9335 - val_loss: 0.7486 - val_acc: 0.6250
Epoch 29/32
326/326 [==============================] - 175s 536ms/step - loss: 0.1762 - a
cc: 0.9333 - val_loss: 2.7526 - val_acc: 0.5000
Epoch 30/32
326/326 [==============================] - 175s 538ms/step - loss: 0.1931 - a
cc: 0.9262 - val_loss: 0.3567 - val_acc: 0.8750
Epoch 31/32
326/326 [==============================] - 175s 536ms/step - loss: 0.1908 - a
cc: 0.9298 - val_loss: 0.5894 - val_acc: 0.6875
Epoch 32/32
326/326 [==============================] - 173s 532ms/step - loss: 0.1964 - a
cc: 0.9275 - val_loss: 0.7655 - val_acc: 0.6875
```

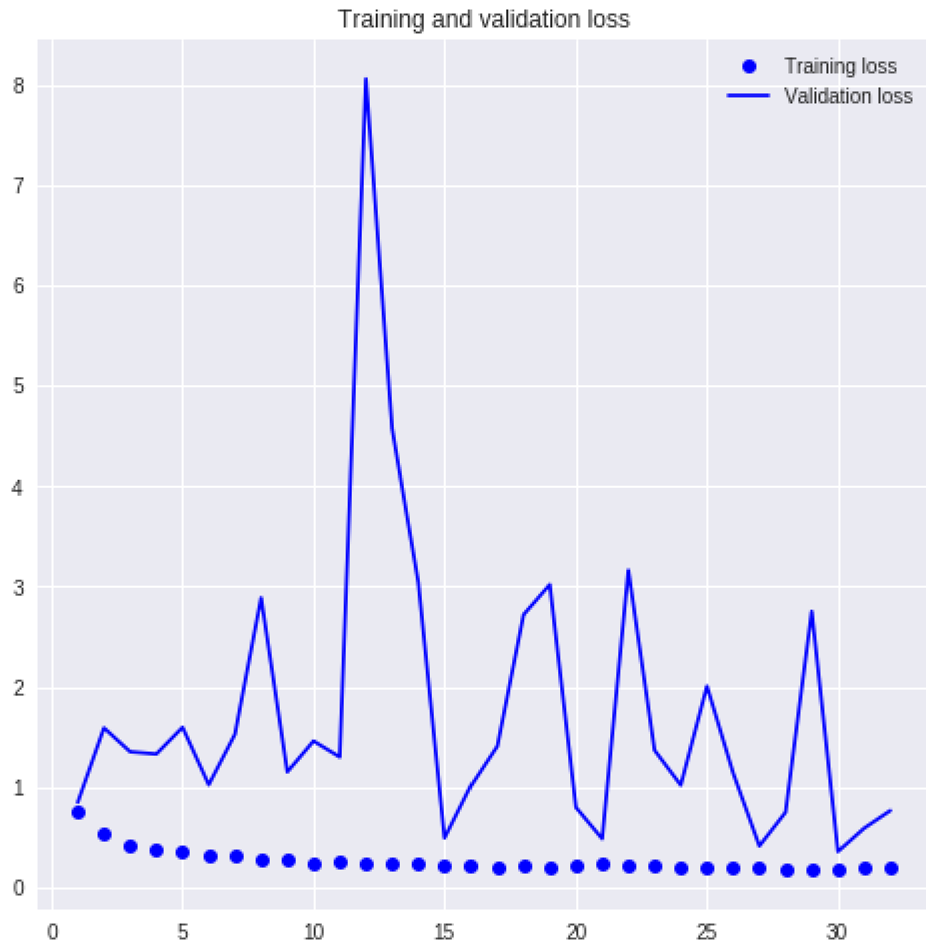
Visualizing training and validation performance on dataset.

In [224]:
```
acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']
plt.figure(figsize = (8, 8))
epochs = range(1, len(acc) + 1)
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()
```

Out[224]: <matplotlib.legend.Legend at 0x7f1d42d9fe48>



In [225]:
```
plt.figure(figsize = (8, 8))
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```



Loading the model with minimum validation loss.

- NOTE : This is model will not be model trained at last epoch becuase we have used the keras callback function to save the best model at intermediate epochs.

In [28]:
```
model = load_model('model.h5')
```

In [29]:
```
scores = model.evaluate_generator(test_generator, steps = 624)
```

In [30]:
```
print("Loss on Test Data is", scores[0])
print("Accuracy on Test Data is", scores[1] * 100,"%")
```

```
Loss on Test Data is 0.35711445524981256
Accuracy on Test Data is 85.73717948717949 %
```

Since we are having unequal number of images in both the classes, therefore we can't take accuracy as metric to measure the model performance.

In [48]:
```
pred = model.predict_generator(test_generator, steps = 624)
```

In [49]:
```
pred[:5]
```

Out[49]:
```
array([[0.8502388 , 0.14976124],
       [0.99770075, 0.00229921],
       [0.95368093, 0.04631906],
       [0.95523727, 0.04476276],
       [0.9716475 , 0.02835254]], dtype=float32)
```

In [50]:
```
pred = np.argmax(pred, axis = 1)
```

In [51]:
```
normal_test_dir = 'Data/test/NORMAL'
pneumonia_test_dir = 'Data/test/PNEUMONIA'

normal_test = Path(normal_test_dir).glob('*.jpeg')
pneumonia_test = Path(pneumonia_test_dir).glob('*.jpeg')

test_labels = []

for img in normal_test:
    label = to_categorical(0, num_classes = 2)
    test_labels.append(label)

for img in pneumonia_test:
    label = to_categorical(1, num_classes = 2)
    test_labels.append(label)

test_labels = np.array(test_labels)
```

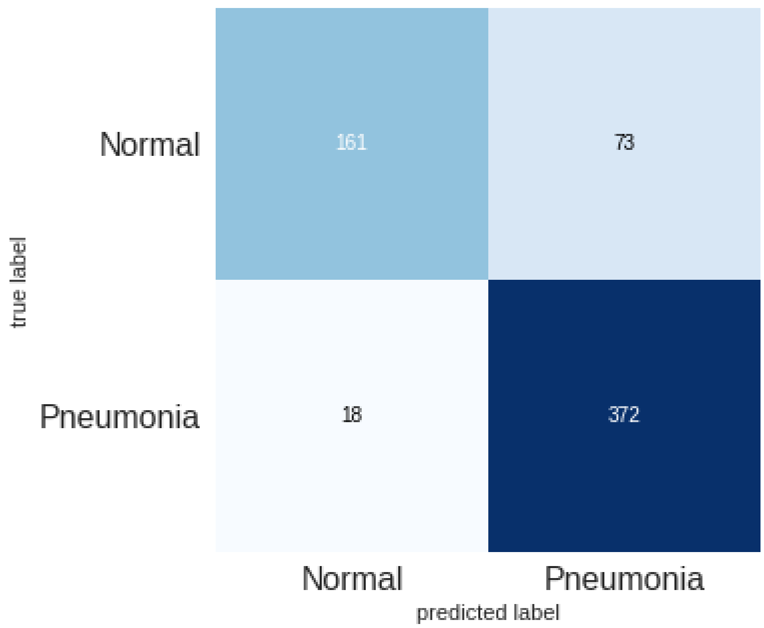
In [229]:
```
test_labels
```

Out[229]:
```
array([[1., 0.],
       [1., 0.],
       [1., 0.],
       ...,
       [0., 1.],
       [0., 1.],
       [0., 1.]], dtype=float32)
```

In [52]:
```
y_true = np.argmax(test_labels, axis = 1)
```

In [218]:
```
cm = confusion_matrix(y_true, pred)
plot_confusion_matrix(cm, figsize = (10, 5 ))
plt.xticks(range(2), ['Normal', 'Pneumonia'], fontsize=16)
plt.yticks(range(2), ['Normal', 'Pneumonia'], fontsize=16)
```

Out[218]:
```
([<matplotlib.axis.YTick at 0x7f1d42eff0b8>,
  <matplotlib.axis.YTick at 0x7f1d4631c160>],
 <a list of 2 Text yticklabel objects>)
```



In [236]:
```
print("Precision : ",372 / (372 + 73))
print("Recall : ",372 / (372 + 18))
```

```
Precision :  0.8359550561797753
Recall :  0.9538461538461539
```

Recall is 95% which is quite good.