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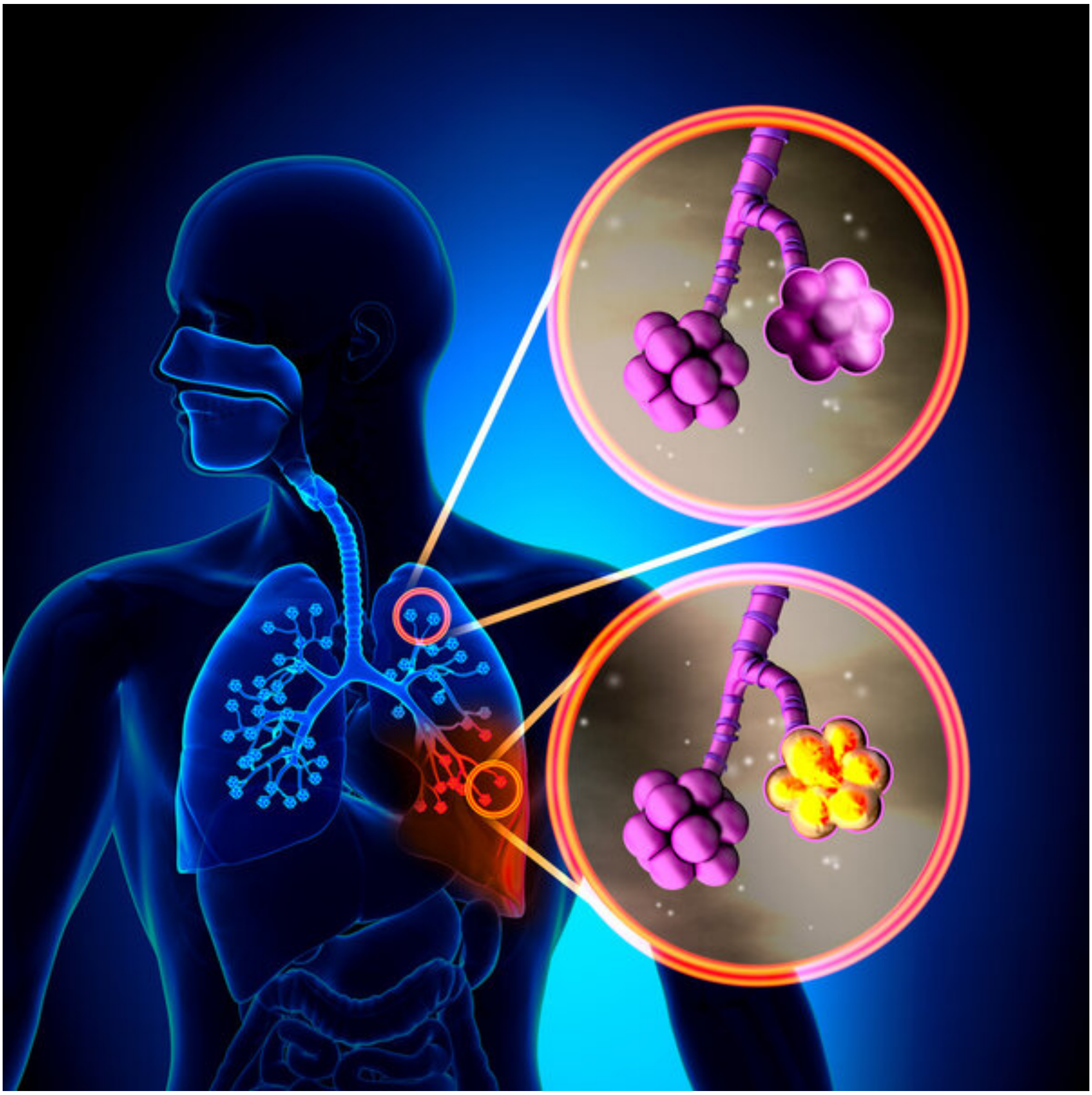
Project Name

Detection of Pneumonia from Chest X-Ray Images using ConvolutionalNeural Network and Transfer Learning.



Dataset Details

Dataset Name : Chest X-Ray Images (Pneumonia)

Number of Class : 2

Number/Size of Images : Total : 5863 Training : 5216 Validation : 16

Business Problem:

Building a model that can classify whether a given patient has pneumonia, given a chest x-ray image.

Stakeholer: Imaging labs/ Hospitals.

Business Questions: How can a successful model help save medical professionals time, money and promote better accuracy in patient diagnosis.

Background:

Pneumonia is an infection that inflames your lungs' air sacs (alveoli). The air sacs may fill up with fluid or pus, causing symptoms such as a cough, fever, chills and trouble breathing. Bacteria and viruses are the main causes of pneumonia. Pneumonia-causing germs can settle in the alveoli and multiply after a person breathes them in. Pneumonia can be contagious. The bacteria and viruses that cause pneumonia are usually inhaled. Commonly affected are Infants, children and people over 65 years in age.

Chest X-rays are used for detecting the Pneumonia infection and to locate the infected area in the lungs. So, To detect the the pneumonia radiologist have to observe the chest xray and he/she has to update the doctor correctly. The main objective of this model is to identify if the person has Pneumonia or not with high accuracy so that the person can get treatment as soon as possible. Deep Learning models which are trained correctly by using good datasets can be helpful for doctors.

To train the model for detecting whether the person has pneumonia or not, A Convolutional Neural Network(CNN) is used. The CNN can train the images of chest xrays and then it can predict with high accuracy.

Data Structure, Selection & Transformation:

The dataset we recieved in Kaggle is actually distributed into 3 folders (train, test, val) and individually, they contain subfolders for each image category (Pneumonia/Normal).

There are a total of 5,863 X-Ray images (in JPEG Format) distributed into 2 categories (Pneumonia/Normal).

Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children’s Medical Center, Guangzhou. All chest X-ray imaging was performed as part of patients’ routine clinical care. For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans. The diagnoses for the images were then graded by two expert physicians before being cleared for training the AI system. In order to account for any grading errors, the evaluation set was also checked by a third expert.

Methods

Cleaning and Feature Engineering

This project uses data cleaning and feature engineering to also addressed the class imbalance between classes we have used Data Augmentation.

Data augmentation in data analysis are techniques used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. It acts as a regularizer and helps reduce overfitting when training a machine learning model.

In order to avoid overfitting problem, we need to expand artificially our dataset. We can make your existing dataset even larger. The idea is to alter the training data with small transformations to reproduce the variations. Approaches that alter the training data in ways that change the array representation while keeping the label the same are known as data augmentation techniques. Some popular augmentations people use are grayscales, horizontal flips, vertical flips, random crops, color jitters, translations, rotations, and much more. By applying just a couple of these transformations to our training data, we can easily double or triple the number of training examples and create a very robust model.

Models Development

We have implemented versions of CNN's with different parameters,dense layers,dropout layers to see how results varies with each change in the parameters. Results Our model,CNN came back with a confusion matrix that produced a 91% accuracy score and a 99% recall score. For our purposes, we were looking to minimize recall as we want to reduce the amount of False positives (False negatives: Patients got negative results but has actually has Pneumonia).

Metrics used:

1. Accuracy
2. Recall

Here, "Recall" is the most significant metric even more than accuracy and precision. False negative has to be minimized because falsely diagnosing a patient of pneumonia as not having pneumonia is a much larger concern than falsely diagnosing a healthy person as a pneumonia patient. By minimizing false negative, which is in the denominator, we can increase 'Recall' .This model achieves a Recall of 99%.

Import Packages and Functions

We'll make use of the following packages:

numpy and pandas is what we'll use to manipulate our data.

matplotlib.pyplot and seaborn will be used to produce plots for visualization.

util will provide the locally defined utility functions that have been provided for this assignment.

We will also use several modules from the keras framework for building deep learning models.

Run the next cell to import all the necessary packages.

In [3]:
```
#Importing all the necessary libraries:
#we will be using keras for the Neural net stuff.
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import keras
from keras.models import Sequential
from keras.layers import Dense, Conv2D , MaxPool2D , Flatten , Drc
from keras.preprocessing.image import ImageDataGenerator
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,confusion_matrix
from keras.callbacks import ReduceLROnPlateau
import cv2
import datetime
```

Reading the data images

Creating a helper function to pull in the data.Using CV2 for this.We will pull in the images in a 150*150.

In [4]:
```
#helper function:
labels = ['PNEUMONIA', 'NORMAL']
img_size = 150
def get_data(data_dir):
    data = []
    for label in labels:
        path = os.path.join(data_dir, label)
        class_num = labels.index(label)
        for img in os.listdir(path):
            try:
                img_arr = cv2.imread(os.path.join(path, img), cv2.
                resized_arr = cv2.resize(img_arr, (img_size, img_s
                data.append([resized_arr, class_num])
            except Exception as e:
                print(e)
    return np.array(data)
```

In [5]:
```
os.listdir("chest_xray")
```

Out[5]:
```
['.DS_Store', 'test', 'chest_xray', '__MACOSX', 'train', 'val']
```

In [6]:
```
len(os.listdir("chest_xray/train/PNEUMONIA"))
```

Out[6]:
```
3875
```

Loading the dataset.

In [7]:
```
#Using get_data function to load the dataset.
train = get_data('chest_xray/chest_xray/train')
test = get_data('chest_xray/chest_xray/test')
val = get_data('chest_xray/chest_xray/val')

print("Train set:\n========================================")
num_pneumonia = len(os.listdir("chest_xray/train/PNEUMONIA"))
num_normal = len(os.listdir("chest_xray/train/NORMAL"))
print(f"PNEUMONIA={num_pneumonia}")
print(f"NORMAL={num_normal}")

print("Test set:\n========================================")
num_pneumonia = len(os.listdir("chest_xray/test/PNEUMONIA"))
num_normal = len(os.listdir("chest_xray/test/NORMAL"))
print(f"PNEUMONIA={num_pneumonia}")
print(f"NORMAL={num_normal}")

print("Val set:\n========================================")
num_pneumonia = len(os.listdir("chest_xray/val/PNEUMONIA"))
num_normal = len(os.listdir("chest_xray/val/NORMAL"))
print(f"PNEUMONIA={num_pneumonia}")
print(f"NORMAL={num_normal}")

```

```
OpenCV(4.5.5) /private/var/folders/_x/m6lx8cs124q78tmfkx9svwzw0000gn
/T/pip-install-fecr2822/opencv-python/opencv/modules/imgproc/src/res
ize.cpp:4052: error: (-215:Assertion failed) !ssize.empty() in funct
ion 'resize'

OpenCV(4.5.5) /private/var/folders/_x/m6lx8cs124q78tmfkx9svwzw0000gn
/T/pip-install-fecr2822/opencv-python/opencv/modules/imgproc/src/res
ize.cpp:4052: error: (-215:Assertion failed) !ssize.empty() in funct
ion 'resize'

OpenCV(4.5.5) /private/var/folders/_x/m6lx8cs124q78tmfkx9svwzw0000gn
/T/pip-install-fecr2822/opencv-python/opencv/modules/imgproc/src/res
ize.cpp:4052: error: (-215:Assertion failed) !ssize.empty() in funct
ion 'resize'

OpenCV(4.5.5) /private/var/folders/_x/m6lx8cs124q78tmfkx9svwzw0000gn
```

```
/T/pip-install-fecr2822/opencv-python/opencv/modules/imgproc/src/res
ize.cpp:4052: error: (-215:Assertion failed) !ssize.empty() in funct
ion 'resize'

Train set:
========================================
PNEUMONIA=3875
NORMAL=1341
Test set:
========================================
PNEUMONIA=390
NORMAL=234
Val set:
========================================
PNEUMONIA=8
NORMAL=8
```

In [8]:

```python
pneumonia = os.listdir("chest_xray/train/PNEUMONIA")
pneumonia_dir = "chest_xray/train/PNEUMONIA"
```

Let us try to see how well is the data distributed.

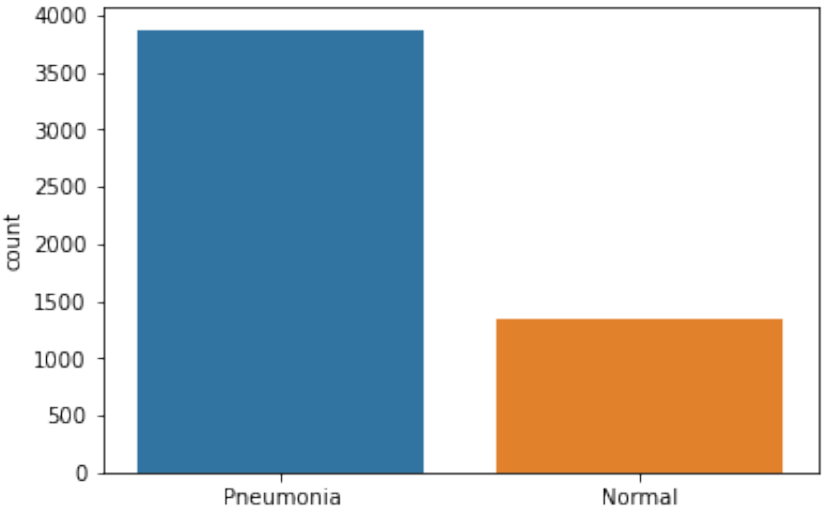
In [9]:

```
#plot to check the distribution.
l = []
for i in train:
    if(i[1] == 0):
        l.append("Pneumonia")
    else:
        l.append("Normal")
sns.countplot(l)
```

```
/Users/Ravinder/opt/anaconda3/envs/learn-env/lib/python3.8/site-pack
ages/seaborn/_decorators.py:36: FutureWarning: Pass the following va
riable as a keyword arg: x. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[9]:

```
<AxesSubplot:ylabel='count'>
```



We can see that we have an imbalanced dataset.Hence,we will be using Data Augmentation to increase the no of training samples.

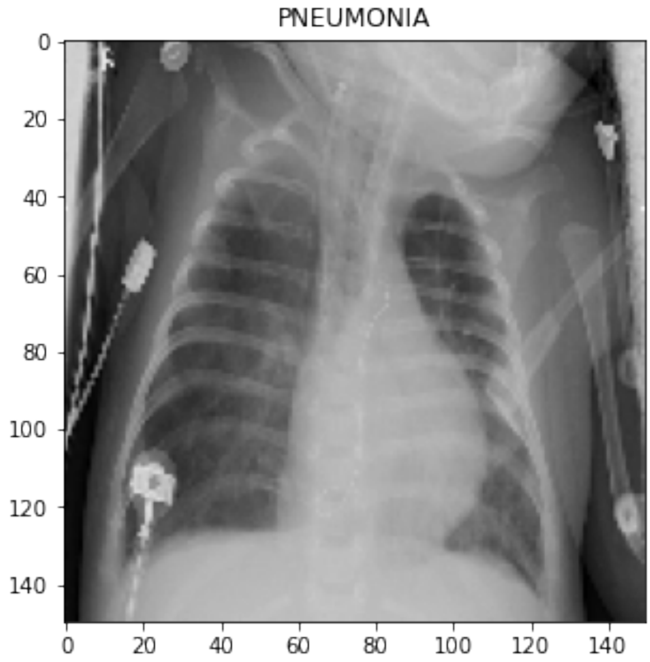
Previewing the images of both the classes.

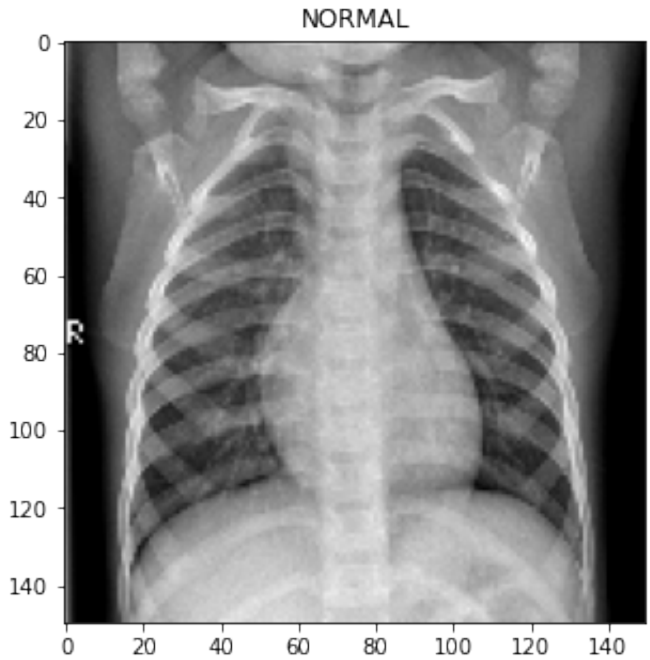
In [10]:

```
#plot to view images of both Pnumeonia & Normal class.
plt.figure(figsize = (5,5))
plt.imshow(train[0][0], cmap='gray')
plt.title(labels[train[0][1]])

plt.figure(figsize = (5,5))
plt.imshow(train[-1][0], cmap='gray')
plt.title(labels[train[-1][1]])
```

Out[10]:

```
Text(0.5, 1.0, 'NORMAL')
```





Data Preparation :

- In image classification we pull in images into an array of numbers. These numbers represent the pixel intensity, and it's a number between 0 and 255, 255 being white and 0 being black.

Points to be considered:

- We need to pair the arrays of the image with their labels (if pneumonia or not)
- In a neural net, there's a lot of math that happens in the backend. If we use numbers like 255 the computer is forced to work with really huge numbers which may increase computational power as well as slow down the epochs. To rectify this we can just divide every pixel by 255 that way we're left with numbers between 0 and 1, 1 being white and 0 being black.
- Lastly when we feed the images to keras, we need to reshape our dimensions. So we'll use the x_train.reshape(-1, image_size, image_size, 1). The numbers mean [batch_size, height, width, channels]. The -1 means that the length in the dimension is inferred so we don't have to specify it. The 1 is because we're using a black and white picture so we'll only have one layer image.

In [ ]:

```
#checking shape of data.
training_set, label = train.__getitem__(0)
print(training_set.shape)
```

In [12]:

```
#Pairing the array of the image with their labels(if pneumonia or
x_train = []
y_train = []

for feature, label in train:
    x_train.append(feature)
    y_train.append(label)
#print(x_train)
x_val = []
y_val = []

for feature, label in val:
    x_val.append(feature)
    y_val.append(label)

x_test = []
y_test = []

for feature, label in test:
    x_test.append(feature)
    y_test.append(label)
```

In [13]:
```
# Normalize the data
x_train = np.array(x_train) / 255
x_val = np.array(x_val) / 255
x_test = np.array(x_test) / 255
```

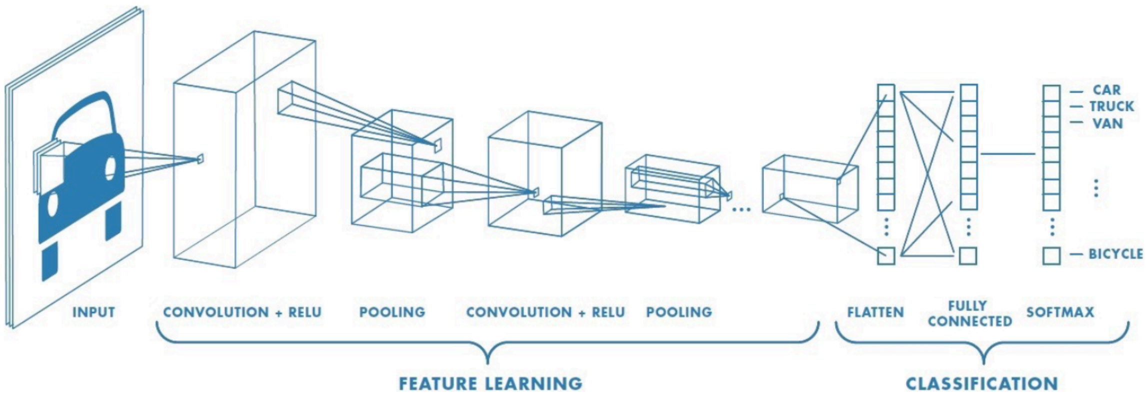
In [14]:
```
#Resizing the data for deep learning
x_train = x_train.reshape(-1, img_size, img_size, 1)
y_train = np.array(y_train)

x_val = x_val.reshape(-1, img_size, img_size, 1)
y_val = np.array(y_val)

x_test = x_test.reshape(-1, img_size, img_size, 1)
y_test = np.array(y_test)
print(x_train[0][0].shape)
```

```
(150, 1)
```

What is CNN ?

CNN stands for Convolutional Neural Network which is a specialized neural network for processing data that has an input shape like a 2D matrix like images. CNN's are typically used for image detection and classification.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.



In [15]:
```
# Build a baseline fully connected model
from keras import models
from keras import layers
#np.random.seed(123)
model = models.Sequential()
model.add(layers.Dense(20, activation='relu', input_shape=(150,150
model.add(layers.Dense(7, activation='relu'))
model.add(layers.Dense(5, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

Fixing data imbalance: Data Augmentation

- We will create duplicates of the images we have by doing certain changes to the images,which can include rotating,flipping,zooming,shifting etc.
- We will not be performing flipping as all the x-Rays will be vertical so doing that might be confusing for the computer.

In [17]:
```
m the data augmentation, here the ImageDataGenerator class provided by
ImageDataGenerator(
aturewise_center=False,
mplewise_center=False,
aturewise_std_normalization=False,
mplewise_std_normalization=False,
a_whitening=False,
tation_range = 30,
om_range = 0.2,
dth_shift_range=0.1,
ight_shift_range=0.1,
rizontal_flip = True,
rtical_flip=False)
t(x_train)
```

In [18]:
```
#timing the model:
original_start = datetime.datetime.now()
start = datetime.datetime.now()
```

CNN1 with a dropout layer.

In [19]:
```
nstantiating the model
del = Sequential()
dding the first layer
tep1: Convolution
del.add(Conv2D(32,(3,3),strides =1,padding='same',activation ='relu',in
tep2:Pooling
del.add(MaxPool2D((2,2)))

dding a second convolutional layer
```

```
del.add(Conv2D(64,(3,3),strides =1,padding='same',activation ='relu'))
del.add(Dropout(0.1))
oolinh
del.add(MaxPool2D((2,2)))

dding a third convolutional layer
del.add(Conv2D(128,(3,3),strides =1,padding='same',activation ='relu')
del.add(Dropout(0.3))
ooling
del.add(MaxPool2D((2,2)))

dding a fourth layer
del.add(Conv2D(128,(3,3),strides =1,padding='same',activation ='relu')
del.add(Dropout(0.2))
del.add(MaxPool2D((2,2)))

dding a fifth layer
del.add(Conv2D(256,(3,3),strides =1,padding='same',activation ='relu')
del.add(Dropout(0.2))
del.add(MaxPool2D((2,2)))

tep3: Flattening
del.add(Flatten())
del.add(Dense(units =128,activation = 'relu'))
del.add(Dropout(0.3))

tep4: Full connection
del.add(Dense(units=1,activation ='sigmoid'))
ompling the CNN
del.compile(optimizer = "adam",loss ='binary_crossentropy',metrics =['a
isplay model summary.
del.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 150, 150, 32)      320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 75, 75, 64)        18496
_________________________________________________________________
dropout (Dropout)            (None, 75, 75, 64)        0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 37, 37, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 37, 37, 128)       73856
_________________________________________________________________
dropout_1 (Dropout)          (None, 37, 37, 128)       0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 18, 18, 128)       0
_________________________________________________________________
```

```
conv2d_3 (Conv2D)            (None, 18, 18, 128)       147584
_________________________________________________________________
dropout_2 (Dropout)          (None, 18, 18, 128)       0
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 9, 9, 128)         0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 9, 9, 256)         295168
_________________________________________________________________
dropout_3 (Dropout)          (None, 9, 9, 256)         0
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 4, 4, 256)         0
_________________________________________________________________
flatten (Flatten)            (None, 4096)              0
_________________________________________________________________
dense_4 (Dense)              (None, 128)               524416
_________________________________________________________________
dropout_4 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 129
=================================================================
Total params: 1,059,969
Trainable params: 1,059,969
Non-trainable params: 0
_________________________________________________________________
```

In [64]:

```
#Fitting the CNN ro the images using fit_generator
history = model.fit(datagen.flow(x_train,y_train,batch_size=32),epoc

# end timer
end = datetime.datetime.now()
elapsed = end - start
print('Training took a total of {}'.format(elapsed))
```

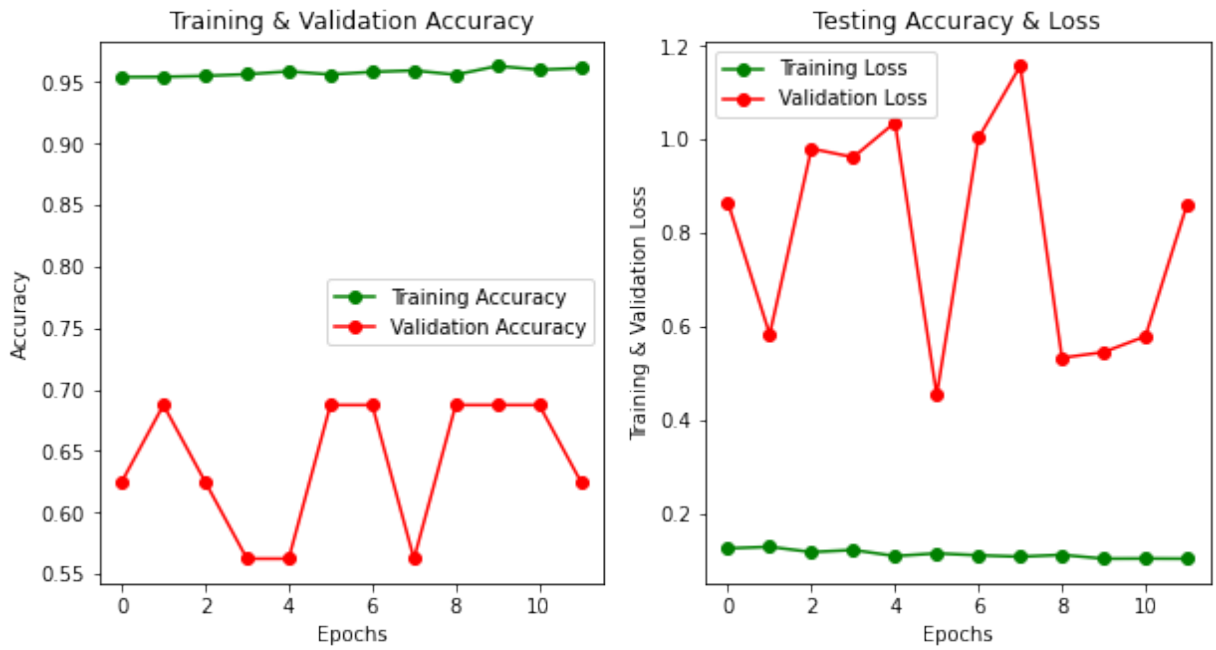
```
Epoch 1/12
163/163 [==============================] - 210s 1s/step - loss: 0.12
41 - accuracy: 0.9542 - val_loss: 0.8646 - val_accuracy: 0.6250
Epoch 2/12
163/163 [==============================] - 177s 1s/step - loss: 0.12
75 - accuracy: 0.9544 - val_loss: 0.5824 - val_accuracy: 0.6875
Epoch 3/12
163/163 [==============================] - 191s 1s/step - loss: 0.11
62 - accuracy: 0.9551 - val_loss: 0.9804 - val_accuracy: 0.6250
Epoch 4/12
163/163 [==============================] - 222s 1s/step - loss: 0.12
07 - accuracy: 0.9565 - val_loss: 0.9620 - val_accuracy: 0.5625
Epoch 5/12
163/163 [==============================] - 202s 1s/step - loss: 0.10
77 - accuracy: 0.9588 - val_loss: 1.0364 - val_accuracy: 0.5625
Epoch 6/12
163/163 [==============================] - 228s 1s/step - loss: 0.11
34 - accuracy: 0.9563 - val_loss: 0.4528 - val_accuracy: 0.6875
Epoch 7/12
163/163 [==============================] - 209s 1s/step - loss: 0.10
92 - accuracy: 0.9584 - val_loss: 1.0031 - val_accuracy: 0.6875
Epoch 8/12
163/163 [==============================] - 204s 1s/step - loss: 0.10
64 - accuracy: 0.9595 - val_loss: 1.1574 - val_accuracy: 0.5625
Epoch 9/12
163/163 [==============================] - 212s 1s/step - loss: 0.11
03 - accuracy: 0.9561 - val_loss: 0.5323 - val_accuracy: 0.6875
Epoch 10/12
163/163 [==============================] - 170s 1s/step - loss: 0.10
21 - accuracy: 0.9632 - val_loss: 0.5444 - val_accuracy: 0.6875
Epoch 11/12
163/163 [==============================] - 170s 1s/step - loss: 0.10
24 - accuracy: 0.9601 - val_loss: 0.5786 - val_accuracy: 0.6875
Epoch 12/12
163/163 [==============================] - 171s 1s/step - loss: 0.10
20 - accuracy: 0.9615 - val_loss: 0.8618 - val_accuracy: 0.6250
Training took a total of 5:31:46.546904
```

In [66]:

```
#Calculating loss & accuracy of the model.
print("Loss of the model is - " , model.evaluate(x_test,y_test)[0]
print("Accuracy of the model is - " , model.evaluate(x_test,y_test
```

```
20/20 [==============================] - 5s 249ms/step - loss: 0.287
5 - accuracy: 0.9071
Loss of the model is -  0.28754690289497375
20/20 [==============================] - 5s 228ms/step - loss: 0.287
5 - accuracy: 0.9071
Accuracy of the model is -  90.70512652397156 %
```

In [67]:
```
#plotting the Training accuracy and loss
epochs = [i for i in range(12)]
fig , ax = plt.subplots(1,2)
train_acc = history.history['accuracy']
train_loss = history.history['loss']
val_acc = history.history['val_accuracy']
val_loss = history.history['val_loss']
fig.set_size_inches(10,5)

ax[0].plot(epochs , train_acc , 'go-' , label = 'Training Accuracy
ax[0].plot(epochs , val_acc , 'ro-' , label = 'Validation Accuracy
ax[0].set_title('Training & Validation Accuracy')
ax[0].legend()
ax[0].set_xlabel("Epochs")
ax[0].set_ylabel("Accuracy")

ax[1].plot(epochs , train_loss , 'g-o' , label = 'Training Loss')
ax[1].plot(epochs , val_loss , 'r-o' , label = 'Validation Loss')
ax[1].set_title('Testing Accuracy & Loss')
ax[1].legend()
ax[1].set_xlabel("Epochs")
ax[1].set_ylabel("Training & Validation Loss")
plt.show()
```



Predictions

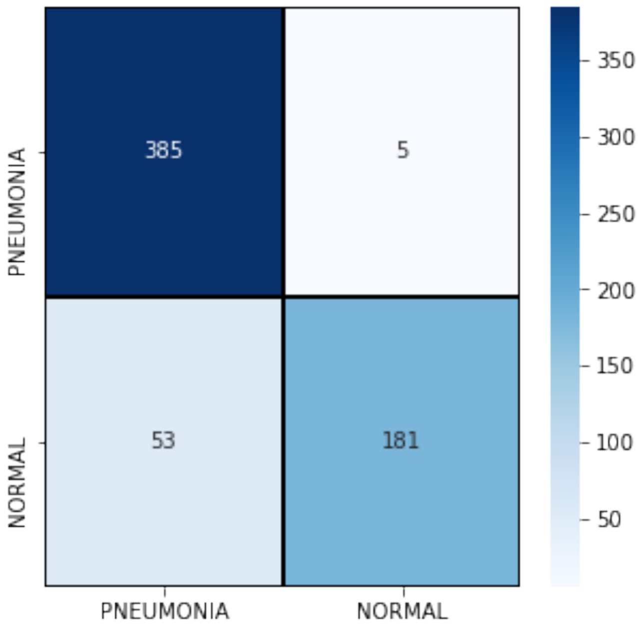
In [68]:
```
predictions = model.predict_classes(x_test)
predictions = predictions.reshape(1,-1)[0]
predictions[:15]
```

Out[68]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int32)
```

In [69]:
```
cm = confusion_matrix(y_test,predictions)
cm = pd.DataFrame(cm , index = ['0','1'] , columns = ['0','1'])
```

In [70]:
```
lt.figure(figsize = (5,5))
ns.heatmap(cm,cmap= "Blues", linecolor = 'black' , linewidth = 1 , annc
```

Out[70]: <AxesSubplot:>



In [71]:
```
print(classification_report(y_test,predictions,target_names = ['Pr
```

```
                     precision    recall  f1-score   support

Pneumonia(class 0)       0.88      0.99      0.93       390
   Normal(Class 1)       0.97      0.77      0.86       234

          accuracy                           0.91       624
         macro avg       0.93      0.88      0.90       624
      weighted avg       0.91      0.91      0.90       624
```

In [72]:
```
#save the model
model.save("model.h5")
```

Results:

Model with dropout layers has an accuracy of %, and recall of 99% on Recall.

Now's let build a CNN without drop out layer:

We want to see how our model behaves without dropout layers.

CNN2

In [24]:
```
Buildign the CNN2 model
odel2 = Sequential()
Adding the first layer
Step1: Convolution
odel2.add(Conv2D(32,(3,3),strides =1,padding='same',activation ='relu',
Step2:Pooling
odel2.add(MaxPool2D((2,2)))

Adding a second convolutional layer
odel2.add(Conv2D(64,(3,3),strides =1,padding='same',activation ='relu')
model.add(Dropout(0.2))
Poolinh
odel2.add(MaxPool2D((2,2)))

Adding a third convolutional layer
odel2.add(Conv2D(64,(3,3),strides =1,padding='same',activation ='relu')
model.add(Dropout(0.3))
Pooling
odel2.add(MaxPool2D((2,2)))

Adding a fourth convolutional layer
odel2.add(Conv2D(128,(3,3),strides =1,padding='same',activation ='relu'
model.add(Dropout(0.3))
Pooling
odel2.add(MaxPool2D((2,2)))

Adding a fifth convolutional layer
odel2.add(Conv2D(128,(3,3),strides =1,padding='same',activation ='relu'
model.add(Dropout(0.3))
Pooling
odel2.add(MaxPool2D((2,2)))

adding a sixth  layer
odel2.add(Conv2D(128,(3,3),strides =1,padding='same',activation ='relu'
model.add(Dropout(0.2))
odel2.add(MaxPool2D((2,2)))

Step3: Flattening
odel2.add(Flatten())
odel2.add(Dense(units =256,activation = 'relu'))
odel2.add(Dropout(0.3))

Step4: Full connection
odel2.add(Dense(units=1,activation ='sigmoid'))
Compiling the CNN
```

```
ompiling the CNN
odel2.compile(optimizer = "adam",loss ='binary_crossentropy',metrics =[
display model summary.
odel2.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_5 (Conv2D)            (None, 150, 150, 32)      320
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 75, 75, 32)        9248
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 37, 37, 32)        0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 37, 37, 64)        18496
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 18, 18, 64)        0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 18, 18, 64)        36928
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 9, 9, 64)          0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 9, 9, 128)         73856
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 4, 4, 128)         0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 4, 4, 128)         147584
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 2, 2, 128)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 512)               0
_________________________________________________________________
dense_6 (Dense)              (None, 256)               131328
_________________________________________________________________
dropout_5 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 257
=================================================================
Total params: 418,017
Trainable params: 418,017
Non-trainable params: 0
_________________________________________________________________
```

In [25]:

```
#Fitting the CNN ro the images using fit_generator
history = model2.fit(datagen.flow(x_train,y_train,batch_size=32),e

# end timer
end = datetime.datetime.now()
elapsed = end - start
print('Training took a total of {}'.format(elapsed))
```

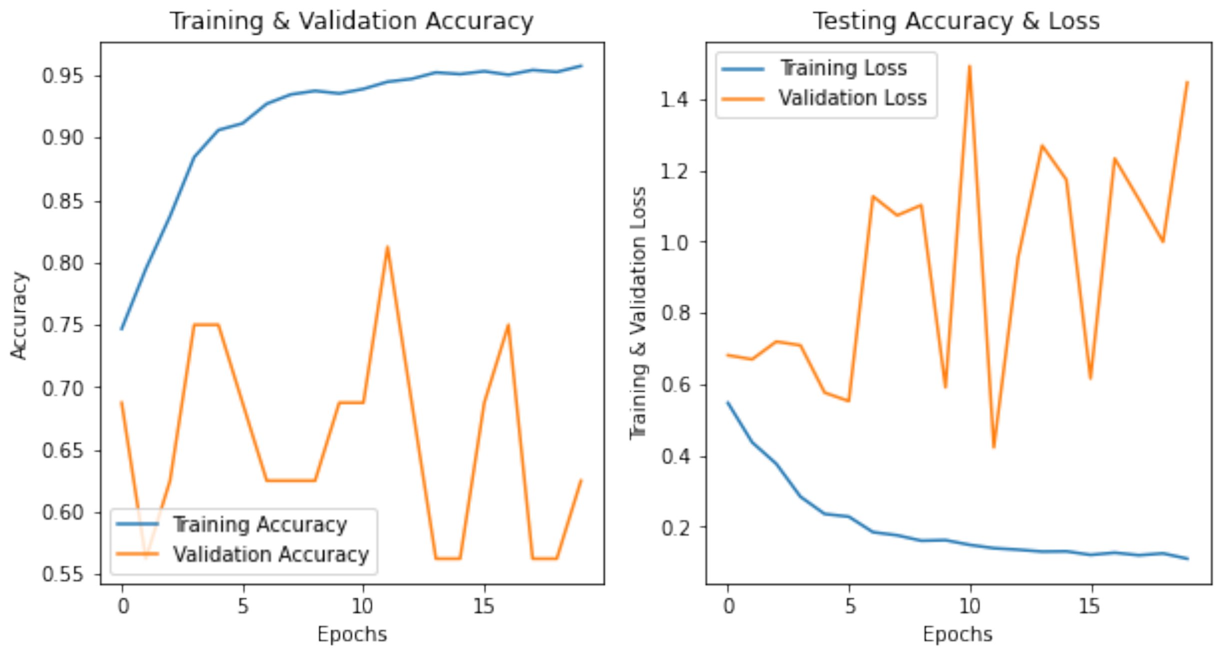
```
Epoch 10/20
163/163 [==============================] - 97s 594ms/step - loss:
0.1623 - accuracy: 0.9354 - val_loss: 0.5906 - val_accuracy: 0.687
5
Epoch 11/20
163/163 [==============================] - 98s 598ms/step - loss:
0.1490 - accuracy: 0.9390 - val_loss: 1.4920 - val_accuracy: 0.687
5
Epoch 12/20
163/163 [==============================] - 97s 597ms/step - loss:
0.1397 - accuracy: 0.9448 - val_loss: 0.4222 - val_accuracy: 0.812
5
Epoch 13/20
163/163 [==============================] - 98s 600ms/step - loss:
0.1356 - accuracy: 0.9471 - val_loss: 0.9536 - val_accuracy: 0.687
5
Epoch 14/20
163/163 [==============================] - 98s 599ms/step - loss:
0.1302 - accuracy: 0.9523 - val_loss: 1.2690 - val_accuracy: 0.562
5
```

In [27]:

```
print("Loss of the model is - " , model2.evaluate(x_test,y_test)[0
print("Accuracy of the model is - " , model2.evaluate(x_test,y_tes
```

```
20/20 [==============================] - 4s 206ms/step - loss: 0.340
8 - accuracy: 0.9119
Loss of the model is -  0.34082722663879395
20/20 [==============================] - 4s 212ms/step - loss: 0.340
8 - accuracy: 0.9119
Accuracy of the model is -  91.18589758872986 %
```

In [28]:
```python
#plotting training& validation accuracy, Traning & validation loss
import matplotlib.pyplot as plt
epochs = [i for i in range(20)]
fig , ax = plt.subplots(1,2)
train_acc = history.history['accuracy']
train_loss = history.history['loss']
val_acc = history.history['val_accuracy']
val_loss = history.history['val_loss']
fig.set_size_inches(10,5)

ax[0].plot(epochs , train_acc  , label = 'Training Accuracy')
ax[0].plot(epochs , val_acc , label = 'Validation Accuracy')
ax[0].set_title('Training & Validation Accuracy')
ax[0].legend()
ax[0].set_xlabel("Epochs")
ax[0].set_ylabel("Accuracy")

ax[1].plot(epochs , train_loss  , label = 'Training Loss')
ax[1].plot(epochs , val_loss , label = 'Validation Loss')
ax[1].set_title('Testing Accuracy & Loss')
ax[1].legend()
ax[1].set_xlabel("Epochs")
ax[1].set_ylabel("Training & Validation Loss")
plt.show()
```



In [29]:
```
predictions = model2.predict_classes(x_test)
predictions = predictions.reshape(1,-1)[0]
predictions[:15]
```

```
WARNING:tensorflow:From <ipython-input-29-e74f08e66a06>:1: Sequential.predict_classes (from tensorflow.python.keras.engine.sequential) is deprecated and will be removed after 2021-01-01.
Instructions for updating:
Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.g. if it uses a `sigmoid` last-layer activation).
```

Out[29]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int32)
```

In [30]:
```
fication_report(y_test, predictions, target_names = ['Pneumonia (Class
```

```
                    precision    recall  f1-score   support

Pneumonia (Class 0)       0.88      0.99      0.93       390
   Normal (Class 1)       0.98      0.78      0.87       234

           accuracy                           0.91       624
          macro avg       0.93      0.89      0.90       624
       weighted avg       0.92      0.91      0.91       624
```

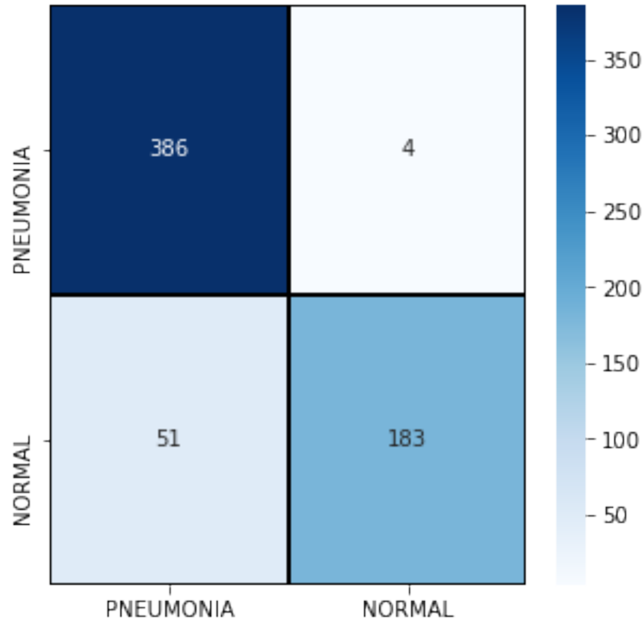
In [31]:
```
#confusion matrix for CNN model2.
cm = confusion_matrix(y_test,predictions)
cm
```

Out[31]:
```
array([[386,   4],
       [ 51, 183]])
```

In [32]:
```
cm = pd.DataFrame(cm , index = ['0','1'] , columns = ['0','1'])
```

In [33]:
```
olor = 'black' , linewidth = 1 , annot = True, fmt='',xticklabels = la
```

Out[33]: <AxesSubplot:>



In [35]:
```
#save the model
model2.save("model.h5")
```

Result:

Model2 without dropout layer and 6 convolutional layers has an accuracy of 91%,and a recall of 99% on Pneumonia.The no of false positives in this model is less than the first one.

Building a CNN3 Model:

with RMSprop optimizer:

In [49]:
```
ilding the CNN2 model
el3 = Sequential()
ding the first layer
ep1: Convolution
el3.add(Conv2D(32,(3,3),strides =1,padding='same',activation ='relu',in
ep2:Pooling
el3.add(MaxPool2D((2,2)))

ding a second convolutional layer
el3.add(Conv2D(64,(3,3),strides =1,padding='same',activation ='relu'))
del.add(Dropout(0.2))
```

```
olinh
el3.add(MaxPool2D((2,2)))

ding a third convolutional layer
el3.add(Conv2D(128,(3,3),strides =1,padding='same',activation ='relu')
el3.add(Dropout(0.3))
oling
el3.add(MaxPool2D((2,2)))

ep3: Flattening
el3.add(Flatten())
el3.add(Dense(units =256,activation = 'relu'))
el3.add(Dropout(0.3))

ep4: Full connection
el3.add(Dense(units=1,activation ='sigmoid'))
mpiling the CNN
el3.compile(optimizer = "rmsp",loss ='binary_crossentropy',metrics =['a
splay model summary.
el3.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_14 (Conv2D)           (None, 150, 150, 32)      320
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 75, 75, 64)        18496
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 37, 37, 64)        0
_________________________________________________________________
conv2d_16 (Conv2D)           (None, 37, 37, 128)       73856
_________________________________________________________________
max_pooling2d_16 (MaxPooling (None, 18, 18, 128)       0
_________________________________________________________________
flatten_3 (Flatten)          (None, 41472)             0
_________________________________________________________________
dense_10 (Dense)             (None, 256)               10617088
_________________________________________________________________
dropout_8 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_11 (Dense)             (None, 1)                 257
=================================================================
Total params: 10,710,017
Trainable params: 10,710,017
Non-trainable params: 0
_________________________________________________________________
```

In [50]:

```
#Fitting the CNN ro the images using fit_generator
history = model3.fit(datagen.flow(x_train,y_train,batch_size=32),epo

```

```python
# end timer
end = datetime.datetime.now()
elapsed = end - start
print('Training took a total of {}'.format(elapsed))
```

```
Epoch 1/20
163/163 [==============================] - 136s 833ms/step - loss: 0
.4969 - accuracy: 0.7697 - val_loss: 1.0052 - val_accuracy: 0.6875
Epoch 2/20
163/163 [==============================] - 145s 887ms/step - loss: 0
.3099 - accuracy: 0.8625 - val_loss: 1.0414 - val_accuracy: 0.6250
Epoch 3/20
163/163 [==============================] - 186s 1s/step - loss: 0.26
29 - accuracy: 0.8825 - val_loss: 1.1217 - val_accuracy: 0.8125
Epoch 4/20
163/163 [==============================] - 180s 1s/step - loss: 0.24
77 - accuracy: 0.8961 - val_loss: 1.3339 - val_accuracy: 0.6875
Epoch 5/20
163/163 [==============================] - 145s 892ms/step - loss: 0
.2159 - accuracy: 0.9158 - val_loss: 0.9723 - val_accuracy: 0.6250
Epoch 6/20
163/163 [==============================] - 167s 1s/step - loss: 0.20
08 - accuracy: 0.9170 - val_loss: 1.0200 - val_accuracy: 0.5625
Epoch 7/20
163/163 [==============================] - 170s 1s/step - loss: 0.19
06 - accuracy: 0.9252 - val_loss: 1.5594 - val_accuracy: 0.6250
Epoch 8/20
163/163 [==============================] - 133s 813ms/step - loss: 0
.1943 - accuracy: 0.9199 - val_loss: 1.0280 - val_accuracy: 0.6250
Epoch 9/20
163/163 [==============================] - 133s 813ms/step - loss: 0
.1719 - accuracy: 0.9323 - val_loss: 1.4464 - val_accuracy: 0.6875
Epoch 10/20
163/163 [==============================] - 132s 811ms/step - loss: 0
.1637 - accuracy: 0.9385 - val_loss: 1.7432 - val_accuracy: 0.5000
Epoch 11/20
163/163 [==============================] - 133s 816ms/step - loss: 0
.1727 - accuracy: 0.9317 - val_loss: 2.6855 - val_accuracy: 0.5625
Epoch 12/20
163/163 [==============================] - 133s 815ms/step - loss: 0
.1546 - accuracy: 0.9411 - val_loss: 0.8739 - val_accuracy: 0.6875
Epoch 13/20
163/163 [==============================] - 133s 814ms/step - loss: 0
.1583 - accuracy: 0.9411 - val_loss: 1.7292 - val_accuracy: 0.6250
Epoch 14/20
163/163 [==============================] - 133s 816ms/step - loss: 0
.1609 - accuracy: 0.9385 - val_loss: 1.0491 - val_accuracy: 0.6250
Epoch 15/20
163/163 [==============================] - 135s 827ms/step - loss: 0
.1448 - accuracy: 0.9431 - val_loss: 1.1583 - val_accuracy: 0.6250
Epoch 16/20
163/163 [==============================] - 133s 814ms/step - loss: 0
.1430 - accuracy: 0.9454 - val_loss: 1.2932 - val_accuracy: 0.6875
```

```
Epoch 17/20
163/163 [==============================] - 133s 816ms/step - loss: 0
.1354 - accuracy: 0.9498 - val_loss: 1.2407 - val_accuracy: 0.6875
Epoch 18/20
163/163 [==============================] - 133s 813ms/step - loss: 0
.1396 - accuracy: 0.9492 - val_loss: 1.9086 - val_accuracy: 0.5625
Epoch 19/20
163/163 [==============================] - 133s 817ms/step - loss: 0
.1424 - accuracy: 0.9456 - val_loss: 1.0312 - val_accuracy: 0.7500
Epoch 20/20
163/163 [==============================] - 2510s 15s/step - loss: 0.
1428 - accuracy: 0.9469 - val_loss: 0.7085 - val_accuracy: 0.7500
Training took a total of 4:46:48.023340
```

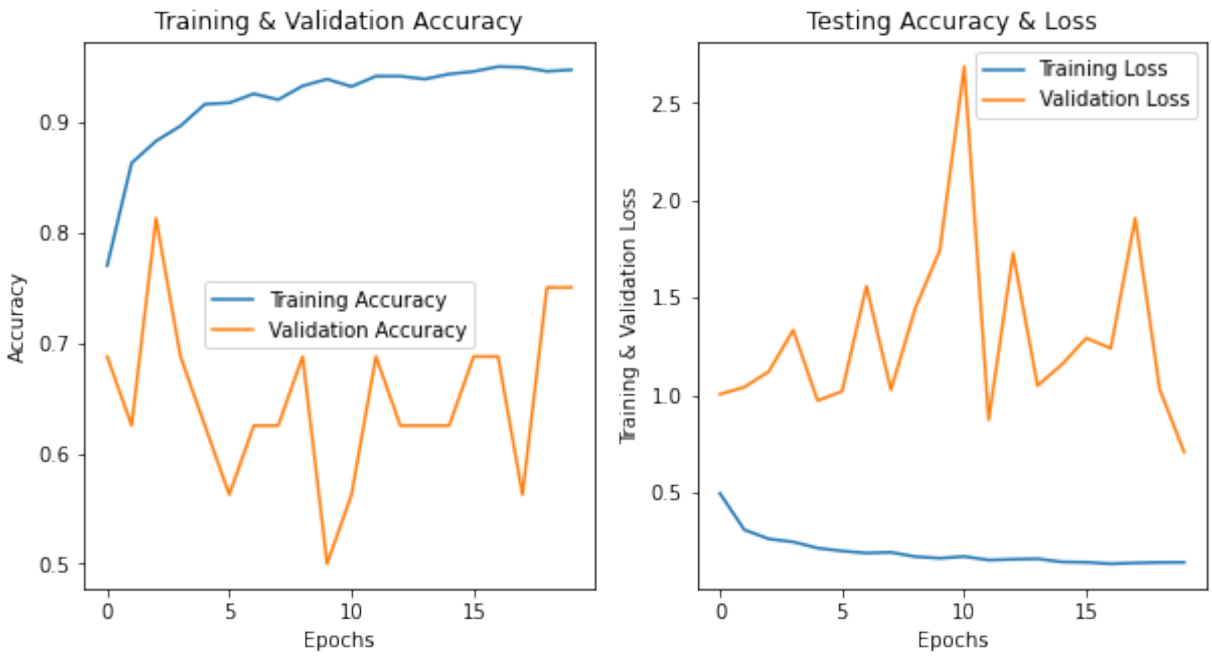
In [51]:

```
#Evaluate on test:
print("Loss of the model is - " , model3.evaluate(x_test,y_test)[0
print("Accuracy of the model is - " , model3.evaluate(x_test,y_tes
```

```
20/20 [==============================] - 4s 190ms/step - loss: 0.228
1 - accuracy: 0.9231
Loss of the model is -  0.22807727754116058
20/20 [==============================] - 4s 187ms/step - loss: 0.228
1 - accuracy: 0.9231
Accuracy of the model is -  92.30769276618958 %
```

In [52]:

```
#plotting training& validation accuracy, Traning & validation loss
import matplotlib.pyplot as plt
epochs = [i for i in range(20)]
fig , ax = plt.subplots(1,2)
train_acc = history.history['accuracy']
train_loss = history.history['loss']
val_acc = history.history['val_accuracy']
val_loss = history.history['val_loss']
fig.set_size_inches(10,5)

ax[0].plot(epochs , train_acc  , label = 'Training Accuracy')
ax[0].plot(epochs , val_acc , label = 'Validation Accuracy')
ax[0].set_title('Training & Validation Accuracy')
ax[0].legend()
ax[0].set_xlabel("Epochs")
ax[0].set_ylabel("Accuracy")

ax[1].plot(epochs , train_loss  , label = 'Training Loss')
ax[1].plot(epochs , val_loss , label = 'Validation Loss')
ax[1].set_title('Testing Accuracy & Loss')
ax[1].legend()
ax[1].set_xlabel("Epochs")
ax[1].set_ylabel("Training & Validation Loss")
plt.show()
```



In [53]:

```
#Printing classification report.
print(classification_report(y_test, predictions, target_names = ['
```

```
                    precision    recall  f1-score   support

Pneumonia (Class 0)       0.88      0.99      0.93       390
   Normal (Class 1)       0.98      0.78      0.87       234

           accuracy                           0.91       624
          macro avg       0.93      0.89      0.90       624
       weighted avg       0.92      0.91      0.91       624
```

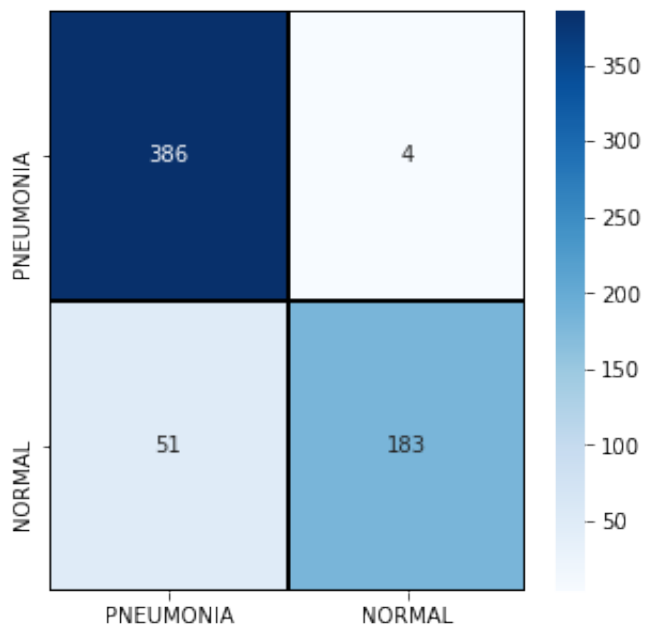
In [54]:

```
#confusion matrix for CNN model3.
cm = confusion_matrix(y_test,predictions)
cm = pd.DataFrame(cm , index = ['0','1'] , columns = ['0','1'])
```

In [55]:

```
#Plotting confusion matrix.
plt.figure(figsize = (5,5))
sns.heatmap(cm,cmap= "Blues", linecolor = 'black' , linewidth = 1
```

Out[55]: <AxesSubplot:>



In [56]:

```
#save the model
model3.save("model.h5")
```

Results:

Comparing scores of the models.

In [61]:
```
model_scores_combined = {'CNN_model': 91.98, 'CNN_model2': 91, 'CN
```

In [62]:
```
model_scores = pd.Series(model_scores_combined)
```

In [63]:
```
model_scores
```

Out[63]:
```
CNN_model     91.98
CNN_model2    91.00
CNN_model3    91.00
dtype: float64
```

In [ ]:
```
are same for all the models,CNN_Model1 is our best performing model w
```

Conclusion:

1. Activation function used was Relu throughout except for the last layer Sigmoid was used as it is a binary classsification problem.
2. Dropout layers have been added to reduce overfitting.
3. Optimizer for the first 2 models is 'adam', for the last model3 'rmsprop' has been used.
4. Loss function used is binary_crossentropy.
5. Max no of epochs used is 20, with batch size of 32.

Future Improvements

1. Training selected models with a a higher no of epochs to try to reach convergence.
2. Gathering more data for a better model.
3. Testing this data on different pretrained models would lead to significant improvement.
4. This work can be extended to detect and classify X-Ray images with lung cancer & Pneumonia.
5. If model's recall and accuracy scores are good it can surely help in reducing patient wait times.

In [ ]:
```

```