Pneumonia Detection using chest X-Rays

Mini-Project Report

Rutvik Patel
Dept. of Information and Communication Technology
PDPU, Gandhinagar, India
rutvik.pict17@sot.pdpu.ac.in
(17BIT048)

Parth Shah
Dept. of Information and Communication Technology
PDPU, Gandhinagar, India
parth.sict17@sot.pdpu.ac.in
(17BIT051)

***Abstract*—We have attempted to develop a model that can detect pneumonia from chest X-rays at a level exceeding practicing radiologist. Our algorithm is a 4-layer convolutional neural network trained on ChestXRay2017 of Mendeley Data, dataset of validated OCT and Chest X-Ray images described and analyzed in "Deep learning-based classification and referral of treatable human diseases". The images are split into a training set and a testing set of independent patients. The images are labeled as (disease)-(randomized patient ID) - (image number by this patient) and further split into 2 directories: PNEUMNIA and NORMAL. This dataset contains over 5800 frontal-view X-ray images which we have separated into train, validation and test sets. We have tried to extend the algorithm to detect viral and bacterial pneumonia in ChestXRay2017 and achieve significant results on the same.**

Keywords—Convolutional Neural Networks, Pneumonia classification, MaxPooling, Deep Learning, Bacterial and Viral Pneumonia, Recall (Sensitivity) in healthcare domain

I. Introduction

The risk of pneumonia is immense for many, especially in developing nations where billions face energy poverty and rely on polluting forms of energy. The WHO estimates that over 4 million premature deaths occur annually from household air pollution-related diseases including pneumonia. Over 150 million people get infected with pneumonia on an annual basis especially children under 5 years old. In such regions, the problem can be further aggravated due to the dearth of medical resources and personnel. For example, in Africa's 57 nations, a gap of 2.3 million doctors and nurses exists. For these populations, accurate and fast diagnosis means everything. It can guarantee timely access to treatment and save much needed time and money for those already experiencing poverty. Chest X-rays are currently the best available method for diagnosing pneumonia, playing a crucial role in clinical care and epidemiological studies. However, detecting pneumonia in chest X-rays is a challenging task that relies on the availability of expert radiologists. In this work, we present a model that can automatically detect pneumonia from chest X-rays with significant accuracy. Our model is a 4-layer convolutional neural network that inputs a chest X-ray image and classifies it as suffering from pneumonia or not. We train our model on the ChestXRay2017 dataset of Mendeley Data which contains 5856 frontal-view chest X-ray images individually labeled with up to 3 different causes of pneumonia. We have used dense connections and batch normalization to make the optimization of such a deep network tractable.

II. Motivation

Some of the most popular methods for Pneumonia detection, currently, include Sputum tests, Blood tests and CT Scan. Methods like Blood tests take longer time to give out results. Whereas, methods like Sputum test is comparatively inaccurate and lastly, methods like CT Scan are very expensive for a common man. These factors inspired us to consider this project where a patient can get a rough idea about his health, thus decreasing costs for common man and number of tests required.

III. Literature Survey

A systematic literature review was performed to examine various methods employed, to detect Pneumonia cases. In recent time, exploration of Machine learning (ML) algorithms in detecting thoracic diseases has gained attention in research area of medical image classification. Some have proposed a method of detecting pulmonary tuberculosis following the architecture of different DCNNs like Alex Net and Google Net. Performance of different variants of Convolutional Neural Networks (CNNs) for abnormality detection in chest X-Rays was proposed. Today, many datasets are available for these types of tasks.

In recent times, CNN-motivated deep learning algorithms have become the standard choice for medical image classifications although the state-of-the-art CNN-based classification techniques pose similar fixated network architectures of the trial-and-error system which have been their designing principle. U-Net, SegNet, and Cardiac Net are some of the prominent architectures for medical image examination. To design these models, specialists often have a large number of choices to make design decisions, and intuition significantly guides manual search process. Models like evolutionary-based algorithms and reinforcement learning (RL) have been introduced to locate optimum network hyperparameters during training. However, these techniques are computationally expensive, gulping a ton of processing power.

As an alternative, considering computational constrains, we have formulated a much simpler CNN deep neural network, with minimal impact on performance.

IV. Methodology

This section deals with the detailed description of the applied methodology. The proposed pneumonia detection system using the ‘Densely Connected Deep Convolutional Neural Network’ is described in Figure 1. The architecture of the proposed model has been divided into two main stages - data preprocessing and augmentation, and classification model.

- Data Pre-processing and Augmentation

  The primary goal of using Convolutional Neural Network in most of the image classification tasks is to reduce the computational complexity of the model which is likely to increase if the inputs are images. The original 3-channel images with varied dimensions were resized into 300×300 pixels and were converted to grayscale, to reduce the heavy computation and for faster processing. All of the further techniques has been applied over these downsized images.

  Further, these images were augmented to get virtually larger dataset and get more samples to help generalize the model. The augmentation techniques used in our project include variations to shear, rotation, width and height shift and horizontal flips.

- Classification Model

  Figure 1 shows the overall architecture of the proposed CNN model which consists of two major parts: the feature extractors and a classifier (sigmoid activation function). Each layer in the feature extraction layer takes its immediately preceding layer's output as input, and its output is passed as an input to the succeeding layers. The proposed architecture in Figure 1 consists of the input, convolution, max-pooling, dense and classification layers combined together. The feature extractors comprise conv3×3, 32; conv3×3, 64; conv3×3, 128; conv3×3, 128, three max-pooling layers of size 2×2, and ReLU activators between them. The output of the convolution and max-pooling operations are assembled into 2D planes called feature maps, and we obtained $298 \times 298 \times 32$, $147 \times 147 \times 64$, $71 \times 71 \times 128$, and $69 \times 69 \times 128$ sizes of feature maps, respectively, for the convolution operations and $149 \times 149 \times 32$, $73 \times 73 \times 64$ and $34 \times 34 \times 128$ sizes of feature maps from the pooling operations, respectively, with an input of image of size $300 \times 300 \times 1$. It is worthy to note that each plane of a layer in the network was obtained by combining one or more planes of previous layers.

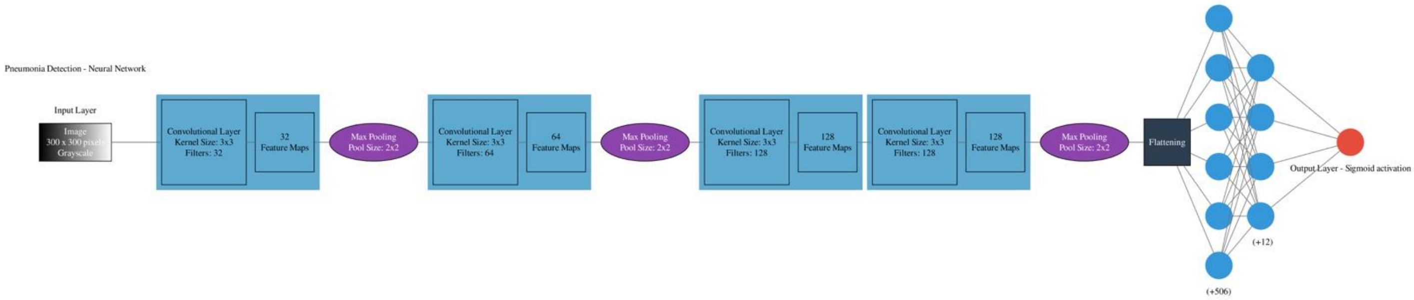


Figure 1

  The classifier is placed at the far end of the proposed convolutional neural network (CNN) model. It is simply an artificial neural network (ANN) often referred to as a dense layer. This classifier requires individual features (vectors) to perform computations like any other classifier. Therefore, the output of the feature extractor (CNN part) is converted into a 1D feature vector for the classifiers. This process is known as flattening where the output of the convolution operation is flattened to generate one lengthy feature vector for the dense layer to utilize in its final classification process. The classification layer contains a flattened layer and three dense layers of size 512, 16 and 1, respectively, a ReLU between the three dense layers and a sigmoid activation function that performs the classification tasks.

V. RESULTS

To evaluate and validate the effectiveness of the proposed approach, we conducted the experiments many times, with several approaches. Parameter and hyperparameters were heavily turned to increase the performance of the model. Different results were obtained, but we decided to consider the result with optimum Accuracy and Recall values.

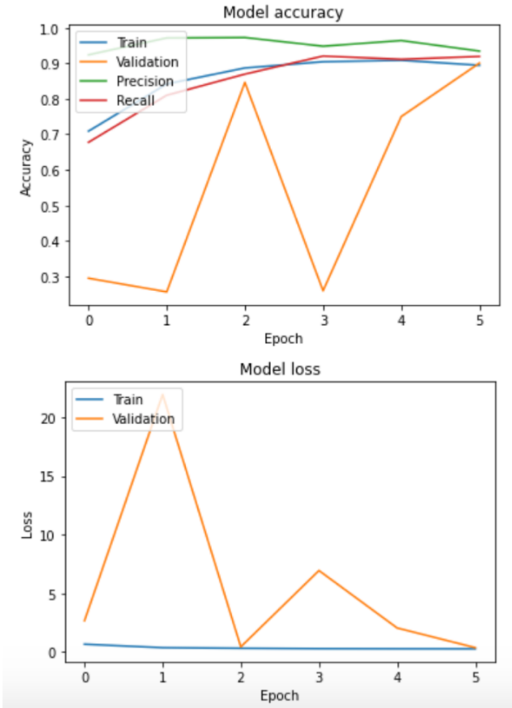
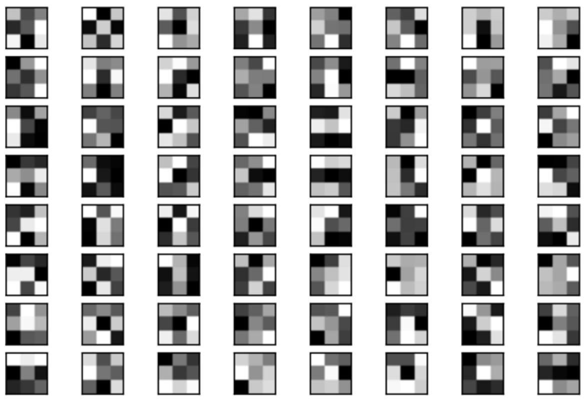


Figure 2

As explained above, methods such as data augmentation, learning rate variation, and annealing were deployed to assist in fitting the small dataset into deep convolutional neural network architecture. Considering all the checkpoints during the training phase, we decided to go ahead with one of the models, for best results. For this particular model, training loss = 0.2283, training accuracy = 0.9102, training recall=0.9455, validation loss=0.2395, validation accuracy=0.9006 and validation recall=0.944. For test set, loss=0.4396, accuracy=0.8429 and recall=0.9436.

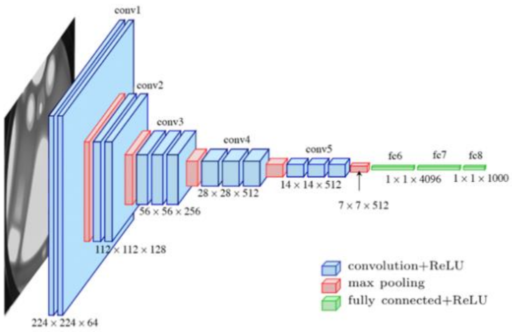


Representation of a few kernels from 2^{nd} convolution layer

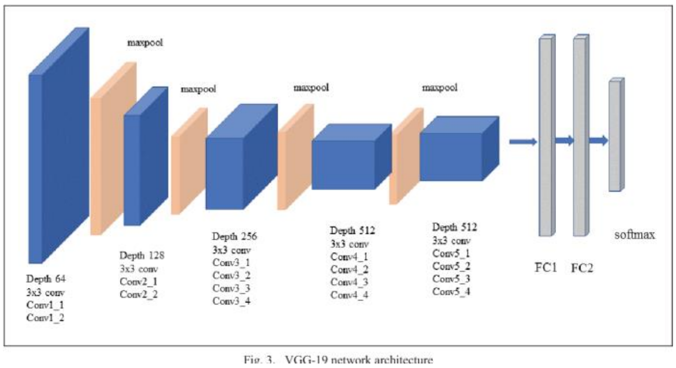
VI. Discussion

For this task, we explored several different types of neural network architectures, before settling with a comparatively smaller architecture which was designed by us. The architectures we explored and tried using include VGG16, VGG19 and Xception.

VGG is an acronym for the Visual Geometric Group from Oxford University and VGG16 is a network with 16 layers proposed by the Visual Geometric Group. These 16 layers contain the trainable parameters and there are other layers also like the Max pool layer but those do not contain any trainable parameters. VGG19 is another variant of VGG16. We were unable to use these architectures due to computational constraints and very long training time.



VGG 16 Architecture

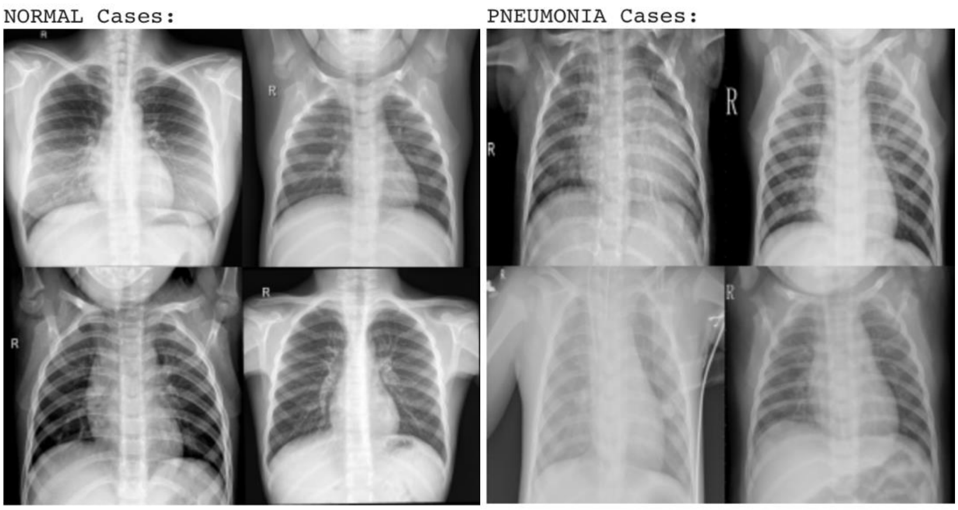


VGG 19 Architecture

VII. Conclusion

We developed a model to detect and classify pneumonia from chest X-ray images taken from frontal views at high recall values. The algorithm begins by transforming chest X-ray images into sizes smaller than the original. The next step involves the identification and classification of images by the convolutional neural network framework, which extracts features from the images and classifies them. Due to the effectiveness of the trained CNN model for identifying pneumonia from chest X-ray images, the validation accuracy of our model was significantly higher when compared with other approaches. To affirm the performance of the model, we repeated the training process of the model several times, each time obtaining the same results. To validate the performance of the trained model on different chest X-ray image sizes, we varied the sizes of the training and validation dataset and still obtained relatively similar results. The study was limited by depth of data. With increased access to data and training of the model with radiological data from patients and nonpatients in different parts of the world, significant improvements can be made.

We have demonstrated how to classify positive and negative pneumonia data from a collection of X-ray images. We build our model from scratch, which separates it from other methods that rely heavily on transfer learning approach. In the future, this work will be extended to detect and classify X-ray images consisting of lung cancer and pneumonia. Distinguishing X-ray images that contain lung cancer and pneumonia has been a big issue in recent times, and our next attempt will be to tackle this problem.



REFERENCES

[1] [Dataset] https://data.mendeley.com/datasets/rscbjbr9sj/2

[2] https://towardsdatascience.com/step-by-step-vgg16-implementation-in-keras-for-beginners-a833c686ae6c

[3] https://machinelearningmastery.com/how-to-visualize-filters-and-feature-maps-in-convolutional-neural-networks

[4] Wasif Khan, Nazar Zaki, and Luqman Ali, “Intelligent Pneumonia Identification from Chest X-Rays: A Systematic Literature Review”.

[5] Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Robyn L. Ball, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, Andrew Y. Ng, “CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning”.