

# Comparative Study of Pneumonia Detection Using Deep Learning Techniques

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**ABSTRACT:** Pneumonia is one of the largest infectious disease that causes death in children and elderly people across the globe. Pneumonia impacts families and children everywhere but is most prevalent in Sub-Saharan Africa and south Asia. We develop a model that is an ensemble of several well-known models, which achieves high accuracy. Here we discuss an approach to create a model for training X-ray images from ChestX-ray14 data set, the largest known data set containing around a hundred thousand front view X-Ray images that classify into a variety of 14 diseases.

**KEYWORDS:** Pneumonia, Deep Learning, Convolutional Neural Network, CheXNet, ResNet, U-net, EfficientNet-B4.

## I. INTRODUCTION

A pneumonia outbreak was observed by the entire world in the city of Wuhan, China. But not clear by everyone the reason behind the outbreak. Later the doctors were able to identify the disease as a new species of coronavirus also currently known as COVID-19. The main motivation behind this research was to identify pneumonia just by using the x-ray images of the patients. The doctors have to do a lot of certain tests to identify if the patient has pneumonia or not, to solve the cumbersome problem we decided to develop a machine learning model to make the work of the doctors simpler.

With the high growth in popularity of neural networks, engineers and researchers have been able to find a large number of world-changing products for computer vision. Deep learning now provides us with the mechanism to easily create artificial intelligence to create automated analysis techniques previously thought impossible for computers. The exposure to pneumonia is quite high for many people, mainly in economically underdeveloped and developing countries where majority are deprived of nutritious diet. The World Health Organisation states that more than 4 million untimely deaths per year occur from diseases caused by air pollution, like pneumonia. More than 0.15 billion people are suffering from pneumonia on a yearly basis, especially kids under 6 years of age. In such areas, the situation may be exacerbated mainly because of lack of medical resources.

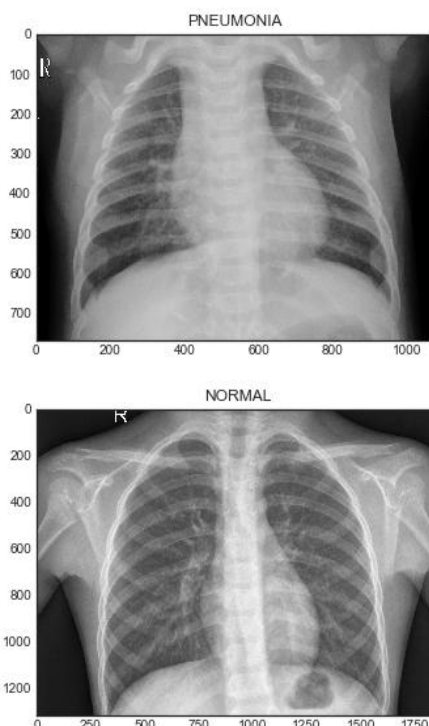


Figure 1: Pneumonia and Normal X-ray Image

In the Figure 1, it is difficult for us to determine which has pneumonia and which is a normal x-ray. The only difference which can be observed by anyone who is not a doctor is that the X-ray image with pneumonia is a bit blurry as compared to the normal X-ray image. Using just this knowledge we cannot determine the target value. It is also difficult for a doctor to determine the outcome just by glancing at an X-ray image. In the past it has been observed that the doctors undergo testing or get an X-ray and give a False positive or a false negative result (Type 1 or Type 2 error), which resulted in bad medical conditions of the patients. Hence, we believe that such solutions can help the medical fields to reduce such errors and save lives.

## II. RELATED WORKS

There are a lot of research papers trying to solve the problem involving the detection of pneumonia and many of them have provided their improvement in the model, we are trying to use these papers to analyse and get a subtle understanding of what solutions have been used and how we can use them to make our new model.

### Xception [1]

Xception proposes an architecture called depthwise separable convolution which is similar to the VGG-16 architecture. According to the paper depthwise separable convolution uses a residual connection mapping of spatial correlation and cross-channel correlation can be dropped entirely. Xception which is an extreme inception contains 36 convolution layers. The end of the convolution base is followed by a logistic regression layer. Talking about architecture 36 convolution layer is organized into fourteen modules. They all have a residual connection around them except the last layer and the first layer. The dataset used contains 14000 images of about 6000 classes. Concluding all depthwise separable and convolution lie at corners of a discrete spectrum with inception being an intermediate in between [1].

### Focal Loss [2]

This paper [2] proposes an approach to deal with class imbalance. To address the class imbalance problem, the model [2] reduces the log loss that results in the drastic reduce of the loss assigned to a well-classified instance. An elementary dense detector called retina-net [2] is used for estimating the successfulness of the forfeiture. Here they recognize class imbalance as the main hurdle hindering one-stage object detectors from striking top-performing, two-stage procedure. To deal with this, they proposed focal loss [2] which put in a harmonized term to the log loss in order

to cynosure learning on the hard-negative instance. They demonstrated its success by scheming an entirely convolutional one-stage detector [2].

#### **CheXNet [3]**

CheXNet [3] is an algorithm based on a 121 layered Convolutional Neural Network (CNN, DenseNet). This algorithm is used to find and locate any presence of Pneumonia in front view XRay Images. The dataset used to train CheXNet [3] has around 100,000 images (ChestXray-ray14) that classify into a variety of 14 diseases. CheXNet gives a binary output, (0,1) representing the lack or existence of Pneumonia in the given Chest X-ray Image. CheXNet [3] scores a higher average F1 score than of an everyday Radiologist on the standard Pneumonia detection job [3] [4].

#### **Pneumonia Detection with Supervised Learning [5]**

To diagnose diseases in the proximity of chest area physicians use X-rays. It is a cheaper alternative than CT scan or MRI scan. It is difficult to diagnose with chest X-rays compared to CT scan or MRI scan. With advanced computer-aided tools, physicians can create chest X-rays and diagnose more quickly and accurately. Pneumonia, which is diagnosed only by chest X-ray, takes around 50,000 people's lives each year. With computer-aided tools available Pneumonia detection, physicians can accurately and efficiently diagnose the disease. Input is again a front view Chest X-ray image and the result is classified as Pneumonia free or not. [5].

#### **Deep Learning Approach to Pneumonia Classification [6]**

In this paper [6], a Convolution Neural Network was designed from square one unlike in other papers where researches have used transfer learning to achieve a good score comparable to transfer learning techniques. The model proposed in the paper [6] is a CNN consisting of 2 primary components i.e. feature extractors and activation functions. The feature extractor comprises of multiple conv2D, conv3D layers with max-pooling layers stacked up with a RELU activator this output is flattened and then passed through a 2- layer ANN (Artificial Neural Network) which uses an activation function of RELU, a sigmoid function that performs classification tasks. After tuning the parameters and hyperparameters, the researchers were able to achieve a higher validation accuracy as compared to other approaches [6].

#### **Jointly Learning Convolutional Representations to Compress Radiological Images and Classify Thoracic Diseases in the Compressed Domain [7]**

This paper [7] has tackled the problem of information loss that occurs when the researcher down samples the high-definition medical image data by using interpolation before feeding into the neural network. This paper [7] has presented a solution to the problem. They have used a Convolution Neural Network (CNN) based approach in which the resolution of the image using autoencoders and simultaneously classify it using a CNN. This method [7] helps in extracting essential features from the high dimension image. They have used high-definition images of a public dataset of a chest x-ray and have outperformed state of the art solutions [7].

### **IV. PROPOSED MODEL**

After a certain evaluation of the previous papers, we were able to develop a model which can be seen in Fig 1. The problem that we had to tackle while we develop the model is class imbalance i.e. our data is more biased towards the negative class (X-ray images without pneumonia) than the positive class (X-ray images with pneumonia). Looking at the problem in hand we had to come up with such an architecture which will be able to tackle the problem.

The architecture that we have proposed is an ensemble of two deep learning models. The first model is a "ResNet-34 based U-net" which is ensembled with our second model which is an "EfficientNet-B4 based U-net". On this architecture we will use a range optimizer, BCE (Binary cross entropy) and Dice Loss with progressive scaling.

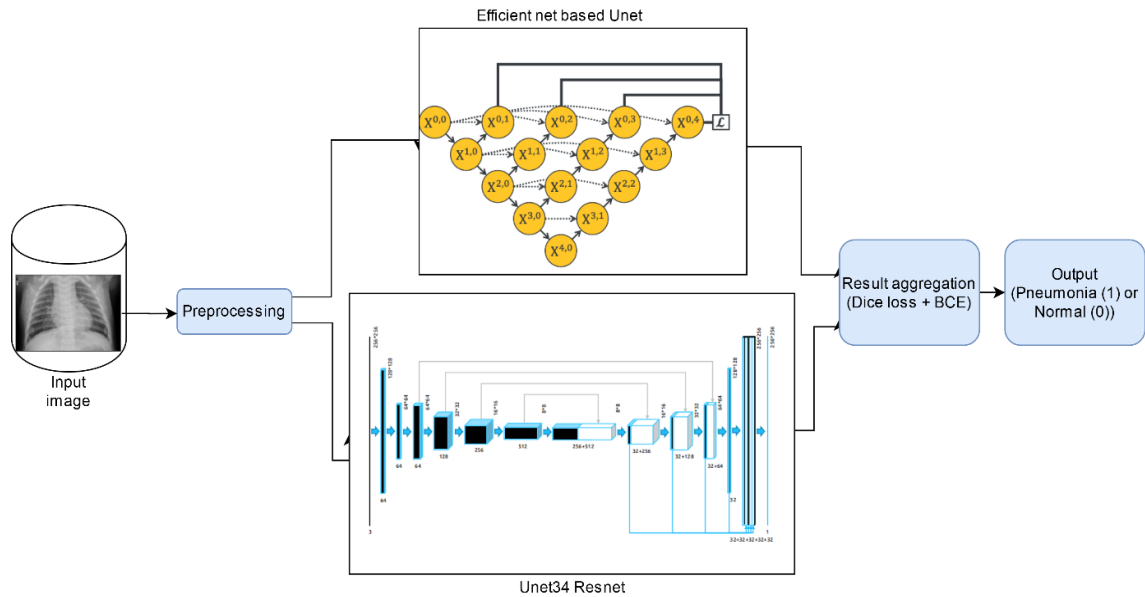


Fig. 2. Model Architecture

Now we will examine our models we have used in the architecture. The ResNet [8] is a serial collection of residual blocks (Res-Blocks) with skip connections unlike CNNs. Resnet was released in 2015 which was a remarkable research the advantage of using such a powerful model is the performance of the model applications. As seen in [8] each block is having a skip connection that acts like a memory with historical data. There is stability when ResNets are used instead of generic CNNs.

This network is in parallel with EfficientNet-B4 based U-net where each block in the U-net is an EfficientNet. Here we propose a new approach that uses the compound model scaling feature of EfficientNets which supports depth, resolution and width scaling, encoding and decoding feature from U-nets, historical memory capability from ResNets, which are ensemble together, to increase the efficiency of the model. A U-net model is mainly used in biomedical Image classification, because of its ability to be used as Encoder-decoder. U-nets are most effective when used in applications that have same input and output dimensions. Therefore, U-nets are helpful in super resolution or colorization.

While training dense detectors, which has large class imbalance, there is a possibility of getting high cross-entropy loss. Due to this we try to use loss functions which tend to perform well even if we have an imbalance of data one of such functions is Dice loss (DL). It has been observed by many data scientists that using this loss can help the model towards imbalance. The Dice loss as given in [11] is defined as:

$$DL(p_t) = 1 - \frac{2 \sum_{pixels} Y_{true} Y_{pred}}{\sum_{pixels} y_{true}^2 + \sum_{pixels} y_{pred}^2}$$

The dice coefficient is calculated for each class (positive or negative) mask. The above formula scoring is repeated all the classes and in the end an average is considered.

$$CE(p, y) = \begin{cases} -\log(p), & \text{if } y = 0 \\ -\log(1 - p), & \text{otherwise} \end{cases}$$

The above equation defines the Cross-Entropy Loss. Here  $p \in [0, 1]$  which is the probability of class with value 1 as its label.

ResNet-34 based U-net ensemble with EfficientNet-b4 based U-net with ranger optimizer and uses BCE (Binary cross entropy) using Dice loss with progressive scaling. Important point to note here is that the number of connections between input layer and first hidden layer should be less and similarly the number of connections between last hidden layer and output layer should be less, this is done to maximize the efficiency.

## V. CONCLUSION

It is great to witness the growth and accuracy of deep learning in such real-world scenarios. In this paper, we have demonstrated a classification of having or not having pneumonia data from a dataset of X-Ray images. The model at the end will provide an architecture that will outperform the model available and will provide an output that distinguishes itself from the other model or methods available.

## VI.FUTURE WORK

In the near future, this project could lead us to identify and locate or pinpoint pneumonia in chest X-Ray images. The problem being faced recently is distinguishing X-Ray images that contain Pneumonia. Our next task should be to handle this issue and other diseases such as lung cancer, neoplasia, lymphoma etc.

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