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Detection of Pneumonia from X-Ray Images Using Convolutional Neural Networks

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Abstract. Pneumonia is an infection which is caused by bacteria or viruses. Early diagnosis is critical to treat the disease successfully without delaying the treatment much. In most of the cases and as per the usual process the patient with pneumonia-like symptoms can be dragonized via frontal and lateral chest x-ray images, which are then seen over by the naked eye by doctors or radiologists. The diagnoses can be misleading and confusing as the appearance of the disease can be unclear in X-ray images and can put the doctor in a dilemma, as the features may not be visible clearly via naked eyes. That is why computer-aided diagnosis is generally required to guide clinicians. The model is based upon the convolutional neural network architecture, wherein pre-processed images are fed to the developed network layers and trained to provide us results with high accuracy of 94.3%, a precision rate of 93.18%, recall of 98.20% and an F1 score of 95.63%. The objective of the work is to design a model that can provide fast and accurate analysis which not only may save diagnosis cost, but also provide invaluable time for the doctors to begin the treatment if the disease is detected early.

Keywords. Pneumonia; CNNArchitecture; RunModel; deep learning; transfer learning.

1. Introduction

Pneumonia is a disease that is caused by inflammation of single or both of the disease afflicted individual's lungs either by bacteria or by a virus. It is a fairly common condition, with more than 3 million cases per year in Asia itself. Although the cure for Pneumonia is available, it can quickly become deadly if not diagnosed early.The World Health Organization (WHO) says that over 3 million people lose their lives annually due to this disease, especially children below 7 years of age. In certain regions of the world, the potency of the disease increases exponentially due to the unavailability of basic medical facilities and/or absence of proper experienced medical personnel who can attend to the diseased. For instance, in Africa's 57 nations, there is a per capita shortage of at least 2.3 million doctors per person. For these populations, accurate and fast diagnosis is of utmost importance. Our model can ensure speedy medical diagnosis, services and access to medical facilities and not only help in saving important time but also resources of both the doctor and patient; who are already below the poverty line in these nations.

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2. Related Work

In recent years, Machine Learning & Artificial Intelligence have been used extensively to detect cure and prevent various diseases.Many researchers have worked in this area and classified images to detect diseases by using various deep learning techniques.CNN [13] along with feature extraction has been used in this study to differentiate between healthy lungs and diseased ones via frontal chest x-ray images. They have implemented pre-trained CNN models and used them for feature extraction followed by classification of normal and diseased chest x-rays. They use models like AlexNet, Xception which are pre-trained via Imagenet. DenseNetarchitecture [9] contains 169 layers and has been used for classification purposes [1].In another study, a relatively small dataset of 1093 images has been used. The author used conventional machine learning techniques such as SVM and Random Forest to classify healthy and diseased chest x-ray images. Imputation techniques such as K-nearest neighbor and Feature median are used for pre-processing. Elastic Net and Sparse Linear Discriminant Analysis is used for feature selection [2].The purpose of another study was to demonstrate that Lymph nodes can be efficiently detected even in the presence of sparsely populated substructures. They use the CADe system for the detection of LN feature candidates and use SVM for classification of the same. The images are decomposed to 2.5D before classification to reduce the number of irrelevant features and compensate overfitting. The neural network consists of various layers for classification [3].In another study, an attempt has been made to classify multiple diseases from chest x-ray (frontal) images. These diseases include Chronic obstructive pulmonary disease, pneumonia, asthma, tuberculosis, and lung cancer. Probabilistic Neural Network was used in this study. They use MLNN with BPPwMi.e Multi-layered Neural Network to classify amongst the six classes (tuberculosis, COPD, pneumonia, asthma, lung cancer and normal) [4].In this study, their goal is to successfully anticipate future events to make intelligent or premediated decisions about the same. They deploy Instance Segmentation with R-CNN[10] to separate and segregate important features from the instances captured by a video camera and those are passed through a decision tree for prediction purposes [5].In another study, the authors compared some previously defined deep models, namely Xception, Vgg16, Densenet121, InceptionV3 along with their own proposed model for the classification of images. The proposed network is implemented by using Keras deep learning framework. They used transfer learning to get already trained weights and then use those weights in their proposed model. They used pre-trained weights from the chestxray-14 dataset, which has 112,120 frontal chest x-ray images [12].

3. Proposed Work

We try to build a simple model to automatically be able to perform optimal and efficient classification tasks upon the input images from the dataset with deep neural networks. The proposed convolutional neural network architecture is designed keeping in mind the task of pneumonia image classification. Our technique is based on the convolutional neural network algorithm, which itself is a part of a large number of deep learning methodologies; using a set of neurons to convolve on a given image and extract features from them. Demonstration of high accuracy along with various other parameters of our proposed model with the minimization of the cost of computing the weights is the main agenda of our study when compared with the existing pneumonia models. Figure 2 shows the architecture flow chart of our model

3.1. The Dataset

The dataset used by us in our study is taken from Kermany et al. [11]. It has about 5852 fontal x-ray images of the chest region, which mainly are taken from patients from 1 year to 5 years old. We train our proposed model on 4832 of these images and use 396 images as or validation set.The remaining 624 images, having 390 Pneumonia inflicted images and rest 234 normal lung images; are used as test set. We test various parameters, such as recall, precision, accuracy, F1 score of our model on the given test set. The Figure 1 shows 2 images from the dataset, the first one from the left is normal lung image and the second one is pneumonia infected image.

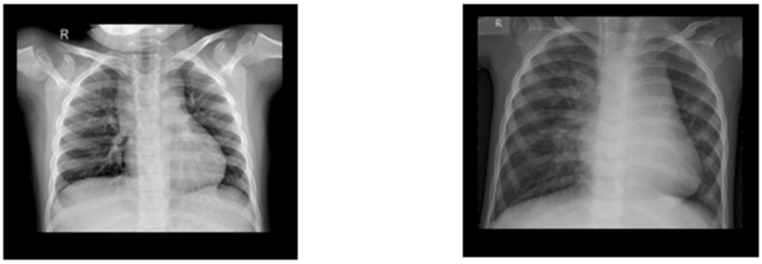

Figure1. Dataset Images with normal and pneumonia lung images

3.2. Data Pre-processing

We take input as the images segregated into folders at the saved location under their respective classes, which are then segregated into separate data generators and classes are used for various computations. The data set is divided into 3 folders labeled as Test, Train, and Val respectively. Each of the test and train folders is bifurcated into Normal and Pneumonia folder, which has healthy and diseased labeled x-ray images. The test folder contains random images of both classes i.e., both healthy and diseased inflicted unlabeled images for prediction purposes.Image transformations such as random zooming, shifting and color shift on images are also applied in this section.

3.3. CNN Architecture

This module is the core CNN architecture of our model.It consists of 6 layers, with each layer having the following components:

1. Firstly, the input image is reduced to 150x150 dimension and is given as input to the first layer of the CNN model [7,8]. The first layer has 32 nodes with a 3x3 feature filter and also has L2 kernel and bias regularizers. The regularizers help in reducing the overfitting of the model which is incurred if the number of epochs or iterations increases over the dataset while the training process is in place.

2. The next five layers take input from the previous layers and each has the number of nodes in them to be doubled i.e. 32→64→128→256→512→512. Rest all parameters are the same as the first layer.
3. As in the convolution process, the number of features decreases, so we use "padding=same" in the function parameters while defining the layer to preserve the matrix shape. This is ensured by adding zeros to the reduced input shape after passing through the convolution layer.
4. After the convolution process, we add a flattening layer, which converts all 2D arrays of features into an end to end contiguous single dimension array.
5. We then add 2 dense layers with 256 nodes followed by a dropout of 0.5. Dropout randomly drops nodes in hidden layers to counter overfitting in the model.
6. Also, we have used Rectified Linear unit (ReLu) activation unit as our activation function. Mathematically it can be shown as y=max (0, x), for all x belonging to the real number domain.
7. In the end, we add a dense layer of 2 nodes with Softmax activation function.
8. Softmax activation function should be used if we have a classification task with more than or equal to 2 classes, or if we use one-hot encoding as the sum of all predictions or weights is 1.

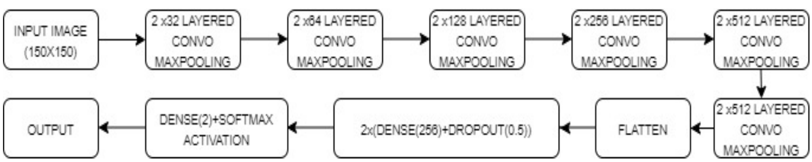

Figure 2. Architecture Flow Chart

4.Results Discussion

We evaluated the model by using 624 frontal chest X-ray images. The test set contains 234 normal and 390 pneumonia cases. The same has been demonstrated in the confusion matrix. TP, TN, FN, FP denote respectively the number of true positive, true negative, false negative, false positive results in our results.The results have been compared with the base paper Liang et al. [6] in Table 1 over the same dataset and the same number of test set images. Result calculation

1. Accuracy = (TP+TN)/(TP+FN+TN+FP)
2. Precision = TP/(TP+FP)
3. Recall = TP/(TP+FN)
4. F1 score = 2*(precision*recall)/(precision+recall)

Variables:

TN = 206, FN = 7, TP = 383, FP = 28

Table 1. Test set results

	Calculated Value	Base Paper Value [6]
Accuracy	**94.3**	90.5
Precision	**93.1**	89.1
Recall	**98.2**	96.7
F1 Score	**95.6**	92.7

5. Conclusion

The analysis of the survey on Pneumonia detection using Convolutional Neural Networks led to various conclusions, including that as we increase the size of our CNN, we may gain efficiency on our test set, but this also has a high chance of overfitting if regularization techniques are not used. Furthermore, a bulky architecture will prevent our goal to implement is as a simple fast product that can evaluate the patient's condition on the go using our developed model.

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