ISSN 2348-1218 (print)
International Journal of Interdisciplinary Research and Innovations ISSN 2348-1226 (online)
Vol. 7, Issue 2, pp: (100-104), Month: April - June 2019, Available at: www.researchpublish.com

Diagnosing Child Pneumonia using Transfer Learning

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Abstract: **Pneumonia kills more children compared to AIDS, measles and malaria combined, pneumonia is detected using chest X-rays diagnosis or also called as Thorax X-rays diagnosis, including the location of the infection and its cause. The following paper discusses the performance of four major transfer learning algorithms such as Mobile Net and Inception V3 on front X-ray images of children of 0 to 5 years of age and classifying the input X-ray. Dataset comprises of 5,000 frontal X-ray images which were augmented to produce 15,000 images to increase the training and testing set. Algorithms are compared with their loss and validation accuracy on how accurately they could classify on a given X-ray image as Normal, Bacterial Pneumonia and Viral Pneumonia after 400 training steps.**

Keywords: **Pneumonia, TransferLearning, Radiology, Chest, X-Ray.**

I. INTRODUCTION

It occurs between the part of the body between the clavicle and the abdomen containing the organs of circulation and respiration and which also include the cavity enclosed by the rib cage, breastbone and vertebral column is called as thorax [2]. There are 14 types of thorax diseases out of which pneumonia is mostly occurring Diseases around 1 million are hospitalized Every year in USA. India contributes to 20% of deaths by Pneumonia. Pneumonia in young children under age of 5 is caused by poor nutrition of the children, lack of birth weight, not breast-feeding infants and also air pollution. Thus Pneumonia has highest number of deaths in India. Pneumonia is lung inflammation caused by infection with virus,bacteria, fungi or other pathogens.

Figure 1.1 Normal

Figure 1.2 Bacterial Pneumonia

Figure 1.3 Viral Pneumonia

According to World Health Organization the data reveals that about 2 million children die with pneumonia and statistics shows that 1 out of 5 children die with pneumonia [16].

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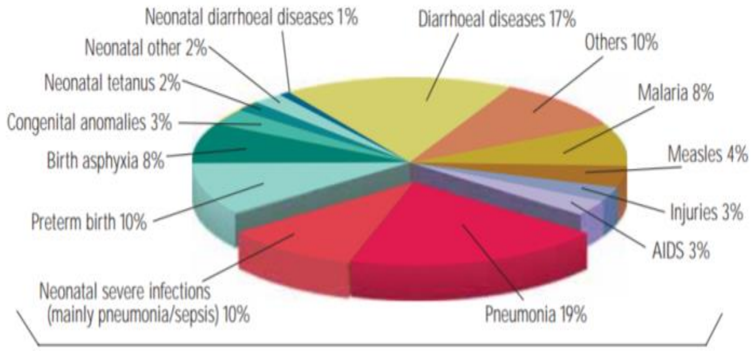

Figure 1.4 Pie chart of deaths by Pneumonia in children

The different symptoms of pneumonia are seen in children according to the infancy and source of infection. The symptoms noticed in children due to bacterial pneumonia are severely illness with high fever and rapid breathing. Similarly the symptoms of viral pneumonia in children are difficult breathing, cough, fever, chills, headaches, loss of appetite and wheezing. Severe cases of child pneumonia are struggling in breathing with their chests moving or lower chest wall indrawing .viral pneumonia often come on gradually and get worse by time .However, if detected early Pneumonia is curable[15].We utilize various transfer learning algorithm as an approach for detecting whether the child has pneumonia or not.

In transfer learning we first the network is trained on a basic dataset and task, and then we adapt the network to use in a different purpose to skilled features, or allocate them, to another target network to be trained on the marked dataset and task.[1]. This process will work if the features are general [17].

In many deep neural networks[11], the networks are schooled on natural images they exhibit an interesting phenomenon in common. In the first layer, they attain features which are similar to Gabor filters and colour blobs. These type of primary-layer features is not to specific to any specific dataset or task. In fact they are in general for many datasets or tasks [18].

II. RELATED WORK

In this section, we have listed the paper which have done related work in pneumonia and transfer learning:

In paper [19] Proposed CAD system for discrimination of ILD, non-ILD and normal lungs with data analysis procedure. Optimal LDF and QDF discriminate functions were developed for pair-wise discrimination procedure ROC curves were used as indicator of performance. Feature extraction method should be improve to obtain better result.

The authors in paper [13]. In this paper, thorax X-ray are used for deep learning algorithm to classify common thorax diseases, data contents of 32,717 unique X-rays and can predict 8 diseases.

This paper [22] uses spectral domain analysis on CNN used for diagnosing human thyroid from OCT image segmentation.

The authors of the paper [13] explains the experimental results showed better accuracy (0.8048±0.0202) and sensitivity (0.7755±0.0296) in extracting features by DCNN (Deep Convolution Neural network) with transfer learning . The values of AUC varied from 0.6937 to 0.8234. And an ensemble of different kinds of features slightly improved the AUC value from 0.8160±0.0162 to 0.8234±0.0014.

III. PROPOSED METHOD

The methodology of the proposed system is mentioned below. The important steps are data gathering and segregation, model training and saving the model and the utilization of saved model for prediction.

A. Data Gathering

Chest X-ray images used are from retrospective cohorts of paediatric patients which were from age one to five years old from Guangzhou Women and Children’s Medical Centre, Guangzhou[10,17].

Table 3.1: Distribution of Images in the Dataset

Sr. No	Disease	Number of Images
1	Bacterial Pneumonia	2,700
2	Viral Pneumonia	1,200
3	Normal(No Pneumonia)	1,100

The dataset available to us is not in proportion. From the Table 3.1 it is observed that number of images in corresponding to Bacterial Pneumonia is more than double compared to Viral Pneumonia and Normal category. Augmentation of images is carried out to increase the number of images in the database.

B. Augmentation

Augmentation is used in order to increase our dataset, which helps the transfer learning algorithms to learn efficiently [9]. Augmented images are obtained by flipping, rotating and shifting the current images to produce new images. Table 3.2 provides the detail of augmented set of dataset.

Table 3.2: Distribution of Images After Augmentation

Sr. No	Disease	Number of Images
1	Bacterial Pneumonia	5000
2	Viral Pneumonia	5000
3	Normal(No Pneumonia)	5000

C. Train and Test Split:

For training and evaluation purpose the images are split into proportion of 80:20. 80% of images are fed to the transfer learning algorithm for training and testing is done on the remaining 20%. Each algorithm is tested for 4000 steps. Table 3.3 shows number images used in training and testing respectively.

.Table 3.3: Number of Images split into Training and Testing

Sr. No	Disease	Training Images	Testing Images
1	Bacterial	4000	1000
2	Viral	4000	1000
3	Normal	4000	1000

IV. METHODOLOGIES

A. MobileNet Architecture:

The architecture of mobile net model is based on depth wise convolution and 1x1 convolution which is also called as point wise convolution [3, 6]. Mobile net architecture is majorly used for embedded based vision applications, which lack computer power. This basically means that it will perform a single convolution on each and every channel rather than combining all the channels. In depth wise convolution single filter is used for each channel. The depth wise convolution is performed on each and every input channels. The process is carried out as follows- firstly depth wise convolution is preferred as it is extremely efficient in comparison to standard convolution. But in depth wise convolution only filters each and every input channel and does not combine all these channels to create new features. In order to create new features 1x1 convolution is used. 1x1 convolution uses the output of the depth wise convolution to create new features. This combination of depth wise convolution and 1x1 convolutions is called as depth wise separable convolution. The structure of mobilenet is dependent on depth wise separable convolution. In standard convolution there is 3x3 data set which has a BN and ReLu whereas in depth wise convolution the 3x3 dataset will have a BN and ReLu, also 1x1 convolution will have its BN and ReLu. Mobilenet uses depth wise separable convolution because it uses almost 7-8 times less computation than the standard convolution and makes only a small reduction in the accuracy. Coming to the uses of depth wise separable convolution so it's used in Fine Grained Recognition, Object detection, Face attributes and Face Embeddings. The advantages of depth wise separable convolution are there is no need of large training dataset. Faster process and not much computational power are needed.

B. Inception V3 Architecture:

Inception V3 is combination of several symmetric and asymmetricbuilding blocks. These building blocks includes layers such as max pooling, average pooling, dropouts, concats, fully connected layers where batchnorm is most extensively used. Inception mainly consists of two parts, the feature extraction part is carried out with a convolutional neural network and the classification part is depended on the softmax layers. Inception V3 has pre trained model which can easily classify 1000 classes which may have animals, flowers or be it non living things. In the first parth the model only extracts the general features for the input images and the classification part is done in the second.

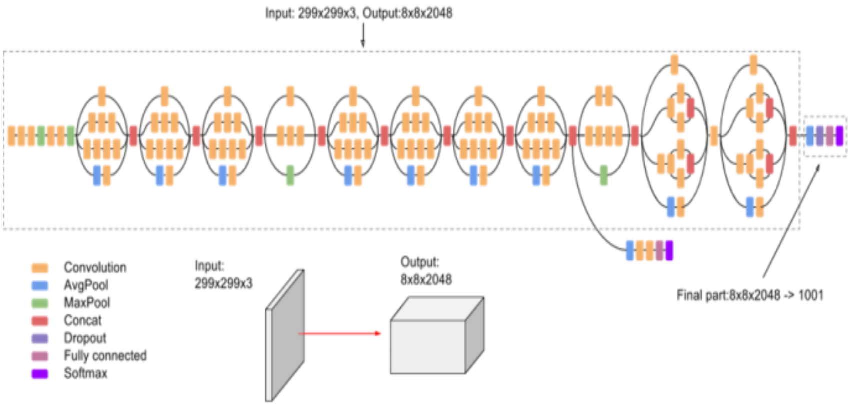

Figure 4.1: Inception V3

V. RESULTS

Table 5.1 Accuracy of MobileNet and Inception V3

SrNo.	Algorithm	Final Test Accuracy(%)
1	Mobile Net	81.4
2	InceptionV3	78.4

Figure 5.1, 5.2 and 5.3 shows the output obtained after execution of the algorithms providing the classification of the images.

Figure 5.1 Model detecting Bacterial Pneumonia

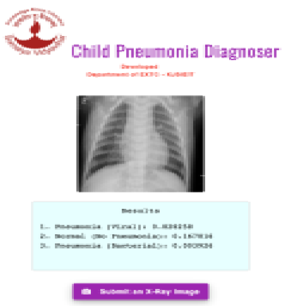

Figure 5.2.2 Model detecting Normal

Figure 5.2.2 Model detecting Viral Pneumonia

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