Identification of Pneumonia Using Deep Learning

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Abstract- *Pneumonia is an infection caused by bacteria, fungi or virus that primarily affects the lungs causing the pulmonary alveolus to be filled with fluid. This pus or fluid makes it hard for oxygen taken in by the lungs to reach the blood stream. The infection can be life-threatening especially to infants. According to UNICEF about 22,000 infants under the age of five die due to pneumonia every year.*

Chest radiographs are now the primary method for diagnosis of pneumonia. Due to this reason the diagnosis of pneumonia is generally delayed in rural areas. Hence, an automated system for the reading of chest radio graphs is needed to help speed up the recovery process from this preventable and treatable disease. Deep Learning algorithms have proven to be quite useful in analysis of X-Rays and Convolutional Neural Networks have been proven to be some of the most efficient models for image classification problems.

Convolutional Neural Networks can automatically detect important features in an image without human supervision. This means that CNNs can be trained to classify and differentiate between a pneumonic and a non-pneumonic lung image. Hence after being trained to give accurate outputs the Neural Network model can be used for pneumonia detection from paediatric X-Rays.

Keywords- Pneumonia, Pulmonary Diseases, Convolutional Neural Networks, X-Rays, Deep Learning.

I. INTRODUCTION

Pneumonia is particularly dangerous in children and is rated as one of the top three causes of child mortality in developing countries like India. Statistics suggest that about 16% of all deaths of children is caused by pneumonia.

Pneumonia can be caused due a variety of reasons of which bacteria and viruses are the most common. While fungi and other parasites are less common. Bacteria like *streptococcus pneumoniae* have been accounted to have caused 50% of all pneumonia cases. Bacteria once in the lungs invade the spaces between the alveoli causing the white blood cells present to start attacking the bacteria. This causes secretions form the surrounding cells to get trapped within the alveoli causing pneumonia. Viruses invade the linings in the cess of the lungs causing cell death. Viruses also make the body more susceptible to bacterial infections, hence viral pneumonia can in turn also cause bacterial pneumonia.

Since the symptoms and causes for viral and bacterial pneumonia are different a quick and accurate diagnosis of the cause of pneumonia can help the patient get the necessary treatment required for the type of pneumonia, aiding in a quick recovery and lower mortality rate caused by the disease. In recent times pneumonia has become even more threatening due to complications caused by COVID-19 (Corona Virus 19). Detection of pneumonia is done by the examination of chest radiograph by radiologists. Pneumonia in an X-ray image is generally characterised by an area of increased opacity within the lungs, hence manually detecting pneumonia from a CSR is complicated as other conditions in the lungs such as bleedings or lung cancer can make the identification harder.

Algorithmic approaches to image analysis such as handcrafted image segmentation or statistical classifiers or computational machine-learning classifiers that are designed for specifically to classify each class of objects are time consuming and computationally expensive and are generally unreliable for pneumonia detection.

Among the existing classifiers Convolutional Neural Networks have proven to be significantly better regarding extracting features and detect objects in a picture. Convolutional Neural Networks (CNN) work by extracting important features from the given input image and assigning weights to these features that are extracted. The learned weights are then used to identify objects or patterns in the given image allowing the model to differentiate one image from the other.

CNNs can obtain abstract features as the input image propagates into the deeper layers of the neural network. Further, techniques such as pooling, data augmentation optimizations etc. can be used to enhance the effectiveness of the model.

This makes creating a framework using these Convolution Neural Networks can lead to accurate and computationally cheap alternative for detection of pneumonia allowing to compensate for the lack of radiologists who can interpret X-rays.

II. LITERATURE SURVEY

"IDENTIFYING MEDICAL DIAGNOSES AND TREATABLE DISEASES BY IMAGE-BASED LEARNING" This paper mainly deals with Transfer Learning. This method of learning can be used to train a model for a given task by using a pre-existing model that was developed for a similar task. That is in case of a domain lacking sufficient data for image based deep learning, a model trained on a similar domain can be used by using transfer learning. The Neural Network Model is trained on the ImageNet dataset after which transfer learning is used in order to train the model for Paediatric chest radio graphs for detection of pneumonia. This allows for training of a highly efficient model in a shorter span of time when compared to training a blank network from scratch.

"PNEUMONIA DETECTION USING CONVOLUTIONAL NEURAL NETWORKS", in this paper by Samm V. Mitatnte and Brandon G. Sibbaluca et al. various pre-trained neural networks models particularly, Convolutional Neural Network models are compared for their performance on feature-extraction and their learning of generic features on largescale datasets. The models compared in this study were AlexNet, LeNet, GoogleNet, VGGNet, DenseNet-121 and ResNet-50. It is concluded in the paper that DenseNet and ResNet-50 show the most optimal performance on chest X-ray images while using SVM classifiers.

"CHEXNET: RADIOLOGIST-LEVEL PNEUMONIA DETECTION ON CHEST X-RAYS WITH DEEP LEARNING" An algorithm developed by Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu et al. for detecting pneumonia in chest X-Rays. The model was trained on a dataset containing over 1,00,000 images on it's 121-layer deep architecture. The algorithm as mentioned also detects 13 other diseases including pulmonary tuberculosis.

"DEEP LEARNING FOR AUTOMATIC PNEUMONIA DETECTION" This paper an effective model for detection of opacities in chest radiographs. The model developed is heavily established on pre-existing models, namely RetinaNet with Se-ResNext101 and applies several improvements to the model. The improvements on the model are very resource heavy and does not involve test-time augmentations.The model was trained at different levels of augmentation and the data with the highest number of modifications was perceived to have had the highest mean average precision score.

"PNEUMONIA DETECTION USING CONVOLUTIONAL NEURAL NETWORKS (CNNs)" This paper is aimed at creating four convolutional neural network models with multiple feature selection, data augmentation and pooling techniques. Each model is trained separately and the performances are compared against each other. It is concluded that models with higher number of convolutional layers show better performance than model with a single or 2 convolutional layers. The CNN model with 3 convolutional layers is shown to have the best performance at 92.31% validation accuracy and 98 Recall score.

III. SYSTEM DESIGN

3.1 Architecture

Convolutional Neural Networks are a branch of deep neural networks that contain a convolution operation in at least one of the model's layers in place of a general matrix multiplication. Convolutional Neural Networks have proven to be one of the best Neural Network models when it comes to the field of image classifications.

The amount of data required for the accurate training of a Convolutional Neural Network is generally too large and hence, the dataset present must be augmented in a manner such that the images can be duplicated by creating small changes to the attributes of the image but not changing the overall image itself.

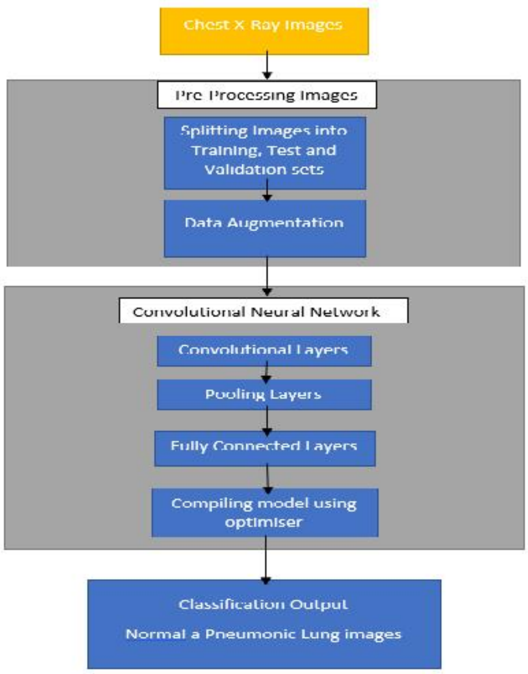

Figure 1: Architecture for Pneumonia detection

3.2 Convolutional Neural Network Model

The Convolutional Neural Network model developed consists of 5 Convolution layers and 5 Max Pooling Layers. The network is then connected to two dense layers. The dataset used to train the model contains 5232 chest radiographs, mostly paediatric in nature. Of these images about 3900 are labelled to contain some form of pneumonia while the rest do not contain any characteristics which can point towards the presence of pneumonia. The neural network model was trained for 12 epochs after which the accuracy achieved by the model stagnates.

3.3 Input Images

The input images comprise of a Chest X-Ray images of patients around five years of age. These images are categorised into two class labels: Normal and Pneumonic as shown in Figure 2.

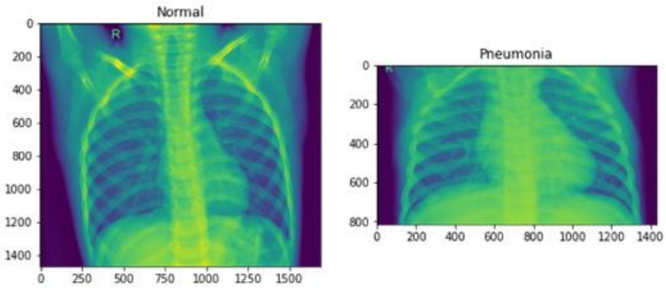

Figure 2: Chest X-Ray images classified into Normal and Pneumonia classes.

Initially the images are in a three channel RGB format and are changed into a single channel grayscale format to decrease the computational power required as shown in Figure3.

Figure 3: X-Ray image in Grayscale

Every image in a neural network is considered as a three-dimensional matrix with parameters Height x Width x Depth, since the image given is in two dimensions only, the depth here is considered as the number of channels in the image. Here we change the dimensions of the input image into 150 x 150 and since the images are taken in grayscale, they only have one channel hence each image is considered as a 150 x 150 x 1 matrix.

The dataset taken contains 5856 such images which are segmented into a training set, a validation set and finally a testing set, in order to prevent overfitting. The training set contains of 4,192 images of which 1082 belong to normal disease-free lungs and 3110 belong to pneumonic lungs. The Test set consists of 624 images of which 234 and disease-free and 390 are pneumonic. The validation set consists of 8 images each.

The amount of images in the given dataset is insufficient to train an accurate Convolutional Neural Network model and hence the dataset needs to be augmented. The idea behind data augmentation is to make modifications to the data images which are strong enough to cause variations but do not alter the fundamental characteristics of the image. Augmentation is necessary in order to create a larger dataset from a pre-existing smaller data set, by applying enough augmentations the amount of data can be effectively doubled.

Images are selected randomly, and the following augmentations are applied to these selected images:

- Rotate by 30 degrees
- Magnify by 20%
- Pan the image horizontally by 10%
- Pan the image vertically by 10%
- Mirror the image along a horizontal edge

3.4 Convolution Layer

Convolution is a mathematical operation in which each portion of the image is taken and multiplied by the corresponding portion of a**kernel** matrix and the values obtained are added and are now used to represent that part of the image.

The kernel matrix is chosen as per requirements of the features being obtained. A set of kernel matrices used is called a kernel filter or a filter. Each of these filters extract different features from the image and can be used individually or can be used together but in different layers of the neural network.

3.5 Stride

The stride value of a layer is the number of steps the convolutional filter takes when moving from the left to right of the image. The number of parameters in a convolved feature can be either increased or decreased by decreasing or increasing the stride value. In this model we use the stride value of 1.

3.6 Padding

The process of convolution removes the outer boundaries of the images which can result in some information getting lost from the image; this can be prevented by using a **Zero Padding** around the border of the image. This allows the filter to pass through the edges of the images and extract features and the zero-padding does not create any noise. When zero-padding is used in a convolution layer it is called as a Same Padding, and when no such padding is used it is called Valid Padding. Valid padding can be used to reduce the size of the matrix obtained after convolution, while Same Padding returns an equal sized output.

This model has ‘Same Padding’ in all convolutional layers.

3.7 Pooling Layer

The pooling layers in a model are designed to reduce the spatial size of the image at every step in the model. This reduction of spatial size allows for extraction of dominant/powerful features from the image while using less computational power.

Pooling is done by 3 ways: Min pooling, Average Pooling and Max Pooling. Max pooling is the most used type of pooling.

In Max Pooling, parts of the image are covered with a kernel matrix and the maximum value of the portion of the image covered by this kernel is taken. In this way less powerful features are effectively removed from the images and only the powerful features are extracted. Hence, noise pooling not only helps in extraction of features but also acts as a noise suppressant.

Max pooling was used in all pooling layers of the model

3.8 Dense Layer

The dense layer is a neural network layer that is fully connected to its previous layer, that is all neurons in the dense layers are each connected to all neurons in the previous layers. The dense layers perform matrix multiplication on the given data and can be trained and updated by using back-propagation.

The first dense layer in the model is connected to a max pooling layer and outputs a vector of length 128. This vector is fed into the next dense layer which converts the matrix and gives an output value of 1 vector length.

3.9 Activation Function

The outputs of each layer need to be adjusted for the model to perform accurately. This is done by imparting nonlinearity to the network. Nonlinearity can be used to adjust or cut-off the generated outputs allowing the neurons to only be activated over a certain threshold.

The model uses ReLU activation function on most of its layers. The ReLU activation function, as show in formula 3.1only activates the neuron if the value of the output from the neuron is over zero; else the neuron is not activated.

$$f(x) = \max(0, x)$$

Formula 1: ReLuActivation Function

The final dense layer or the output layer of the neural networks uses a sigmoid activation function.

$$S(x) = \frac{1}{1+e^{-x}}$$

Formula 2: Sigmoid Activation Function

Sigmoid activation functions are used in the final dense layer of the neural networks when the expected output is binary in nature. The output of the dense layer in this model is 0 for Normal Lung image and 1 for a Pneumonic lung image.

3.10 Optimizer

The optimizer used in the model is the Adam Optimizer. The Adam Optimizer is an algorithm that is a combination of two methodologies often used in gradient descent: Momentum and Root Means Square Propagation.

Adam Optimizer is one of the most efficient methods for problems with a large number of parameters.

The loss function used with the optimizer is **Binary Cross-Entropy.**

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i.\ log(p(y_i)) + (1 - y_i).\ log(1 - p(y_i))$$

Formula 3: Binary Cross-Entropy Loss Function

Here y is the label (1 for pneumonic and 0 for normal) and p(y) is the predicted probability if the p(y) is the Probability of the image being pneumonic for all N images.

IV. RESULTS

The model was trained using the images processed by the “ImageDataGenerator”, which supplies images for training and validation separately.

The model summary depicted in Figure 4 shows the status of the image in each layer of the neural network along with the number of parameters that were included in the training of the network in that layer. The output of each layer is different from the previous and the image is effectively compressed into smaller versions of the image containing only the important features that the model deems to be important.

The neural network divides the dataset into batches of 32 files each and runs each batch through the neural network 12 times. Totalling 164 such batches for 12 epochs.

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 150, 150, 32)	320
max_pooling2d_10 (MaxPooling	(None, 75, 75, 32)	0
conv2d_11 (Conv2D)	(None, 75, 75, 64)	18496
max_pooling2d_11 (MaxPooling	(None, 38, 38, 64)	0
conv2d_12 (Conv2D)	(None, 38, 38, 64)	36928
max_pooling2d_12 (MaxPooling	(None, 19, 19, 64)	0
conv2d_13 (Conv2D)	(None, 19, 19, 128)	73856
max_pooling2d_13 (MaxPooling	(None, 10, 10, 128)	0
conv2d_14 (Conv2D)	(None, 10, 10, 256)	295168
max_pooling2d_14 (MaxPooling	(None, 5, 5, 256)	0
flatten_2 (Flatten)	(None, 6400)	0
dense_4 (Dense)	(None, 128)	819328
dropout_8 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 1)	129

Total params: 1,244,225
Trainable params: 1,244,225
Non-trainable params: 0

Figure 4: Summary of the model

After training, validation is performed on a validation set which contains only 16 images hence the validation accuracy does not form a smooth curve.

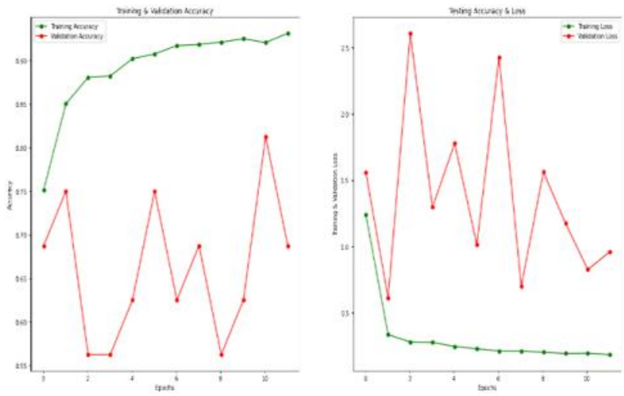

Figure 5: Graphs depicting the training and validation accuracy and losses

The model achieves an accuracy of 96% over the training set over the last epoch.

The model is saved and can be used to perform predictions over input files. The model correctly predicts the output of a pneumonic lung as shown in Figure 6.

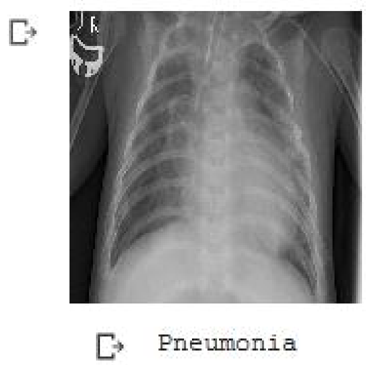

Figure 6: Model correctly predicting the output of an image

V. CONCLUSION

The model has achieved an accuracy of 96% on the dataset. Since the data set of 5400 images is quite small in terms of the amount of data needed for a highly accurate model, it can be concluded that the model slightly overfits over the data.

Regardless, the model proves that Artificial Intelligence, specifically Convolutional Neural Network classifier models can be used by medical personnel for the detection of pneumonia in a quick and accurate way. This can help in finding the presence of pneumonia in the early stages of infection, during which it can be treated easily helping reduce the deaths of young children. An early diagnosis of the infection can allow the patient to be treated with medicines and an admission to the hospital can be avoided. This causes less strain on the healthcare system that is under constant stress due to the raise of lung infections related to Covid-19.

The lack of data required for training an accurate model is a problem that can be solved by using transfer learning. Transfer learning is especially useful in the field of image based classification in the medical field because of the similarities in the data sets. Training a model on a large dataset already present and using that model for predictions of other data sets can be quite useful in cases where the amount of data is not sufficient for an accurate model.

The model of Convolutional Neural Networks that has been trained can be further upgraded to classify imagers based on the stage of pneumonia in the patient which can help the doctors take necessary measures easily. The model can also be further enhanced for the diagnosis of Covid-19 as the Chest Radiographs of both the infections can be similar. This can be used as an alternative to the MRI scans which take longer to produce and require more expertise from the radiologist to efficiently study.

The Chest Radiographs on which the model is trained on can also be used for diagnosis of various other medical conditions which the model can be trained to detect easily by the means of transfer learning. Hence, the neural network model developed for the diagnosis of pneumonia can be extended into several other fields of healthcare making it easier for the health care system in newer and more efficient ways for diagnoses and treatment of patients

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