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Pneumonia Detection using Convolutional Neural Network

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Abstract: *Pneumonia is a life-threatening infectious disease affecting one or both lungs in humans commonly caused by bacteria called Streptococcus pneumonia. One in three deaths in India is caused due to pneumonia as reported by World Health Organization (WHO). Chest X-Rays which are used to diagnose pneumonia need expert radiotherapists for evaluation. Thus, developing an automatic system for detecting pneumonia would be beneficial for treating the disease without any delay particularly in remote areas. Due to the success of deep learning algorithms in analyzing medical images, Convolutional Neural Networks (CNNs) have gained much attention for disease classification. In addition, features learned by pre-trained CNN models on large-scale datasets are much useful in image classification tasks. In this work, we appraise the functionality of pre-trained CNN models utilized as feature-extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. We analytically determine the optimal CNN model for the purpose. Statistical results obtained demonstrates that pretrained CNN models employed along with supervised classifier algorithms can be very beneficial in analyzing chest X-ray images, specifically to detect Pneumonia.*

Keywords: Pneumonia

I. INTRODUCTION

Pneumonia is inflammation of the tissues in one or both lungs that usually caused by a bacterial infection. In the USA annually more than 1 million people are hospitalized with the gripe of pneumonia. Unfortunately, 50.000 of these people die from this illness. Fortunately, pneumonia can be a manageable disease by using drugs like antibiotics and antivirals. Pneumonia is a disease caused by various bacteria and viruses and thus, X-rays are the major diagnosis tool to detect Pneumonia. It is often a difficult task to detect pneumonia outright at an early stage by analyzing the various chest X-rays. With the advent of technology there have been an enormous growth in the healthcare sector. However, Chest X-Rays are considered to be effective, examining Chest X-rays can be ambiguous to detect pneumonia as it can be misinterpreted to be a heart failure or various lung cancers. Various Machine Learning models fail to detect such kind of diseases due to their limitations and thus, urging us to employ advanced and more accurate Deep Learning Models, particularly a densely connected Convolutional Neural Networks (CNN) which helps in feature extraction process. The models can be pretrained to improve the efficiency and accuracy. The main challenge is to build an efficient algorithm that identifies whether a particular patient is suffering from pneumonia or not, by examining his chest X-ray. As the lives of the people are at stake, utmost importance must be given so that the algorithm is extremely accurate. The Convolutional Neural Network (CNN) is one of the most used deep learning neural network and it uses numerous layers along with the max pooling layer. The layers help in automatic image recognition of the X-rays. It also contains the Rectified Linear Unit called ReLU layer which help to improve non-linearity. It is an optimized structure to handle 2D as well as 3D images effectively. It posits a similarity to the fixed network of trial and error system. The paper aims to detect patterns for patients and classifies whether they are affected by pneumonia or not. In addition, in 2015 worldwide, pneumonia was the top killer of children under five yearsold. Moreover, the death rate of pneumonia is highly related to age, and the prevalenceof pneumonia increases dramatically with age, especially in people older than 65. Thelarge number of child deaths by pneumonia alarms scientists worldwide to propose moreeffective and acute methods to detect pneumonia. With technology developing, moreand more measures are developed, in which radiology-based methods are most popularand useful. Diagnostic radiological techniques for pulmonary disease include chest X-rayimaging, computed tomography (CT), and magnetic resonance imaging (MRI), amongwhich chest X-ray imaging is most effective and economical as it is more available andportable in hospital and has lower exposures of dose radioactivity for patients. However, even for very professional and experienced doctors, the diagnosis of pneumonia through X-ray images is still a tremendous task because X-ray images have similarregion information for different diseases, such as lung cancer. Therefore, it is very time-consuming and energy-consuming to diagnose pneumonia through traditional methodsand impossible to diagnose whether a patient suffers pneumonia through a standardizedprocess. Hence, in this study, we propose a Convolutional Neural Network to diagnosepneumonia through X-ray images automatically and obtain results of accuracy 96.07% an Area Under Curve (AUC) 0.9911.

II. DEEP LEARNING

Most modern deep learning models are based on artificial neural networks, specifically convolutional neural networks (CNN)s, although they can also include propositional formulas or latent variables organized layer-wise in deep generative models such as the nodes in deep belief networks and deep Boltzmann machines. In deep learning, each level learns to transform its input data into a slightly more abstract and composite representation. In an image recognition application, the raw input may be a matrix of pixels; the first representational layer may abstract the pixels and encode edges; the second layer may compose and encode arrangements of edges; the third layer may encode a nose and eyes; and the fourth layer may recognize that the image contains a face. Importantly, a deep learning process can learn which features to optimally place in which level on its own. This does not completely eliminate the need for hand-tuning; for example, varying numbers of layers and layer sizes can provide different degrees of abstraction.

The word "deep" in "deep learning" refers to the number of layers through which the data is transformed. More precisely, deep learning systems have a substantial credit assignment path (CAP) depth. The CAP is the chain of transformations from input to output. CAPs describe potentially causal connections between input and output. For a feedforward neural network, the depth of the CAPs is that of the network and is the number of hidden layers plus one as the output layer is also parameterized). For recurrent neural networks, in which a signal may propagate through a layer more than once, the CAP depth is potentially unlimited. No universally agreed-upon threshold of depth divides shallow learning from deep learning, but most researchers agree that deep learning involves CAP depth higher than 2. CAP of depth 2 has been shown to be a universal approximator in the sense that it can emulate any function. Beyond that, more layers do not add to the function approximator ability of the network.

III. RELATED WORK

Over the last decade, several machine learning based automated methods for identifying different types of pneumonia have been widely studied Fiszman et al used a natural language processing (NLP) tool to identify acute bacterial pneumonia-related disease in chest X-ray. Performance of this type of resource intensive application is very much comparable to that of the human expert . Chapman et al demonstrated three computerized methods using a rule base, a probabilistic Bayesian network, and a decision tree to diagnose the chest X-ray report associated with acute bacterial pneumonia**.** In “Journal of Biomedical Iinformatics” a study of feasibility of an NLP-based monitoring system is done to identify healthcare-associated pneumonia in neonates. However, practical clinical applications of these types of methods are limited due to the dependency on the information extracted from the narrative reports of the patients. Parveen et al reports an unsupervised fuzzy c-means classification learning algorithm to detect pneumonia infected X-ray images. This approach improves classification accuracy as fuzzy c-means allocate weights to all the pixels of the input X-ray images. Rajpurkar et al demonstrated ChexNet, a 121-layer deep convolutional neural network (CNN), that provides the probability of detecting or identifying pneumonia using a heatmap to localize the area of the infection.

IV. OBJECTIVES

Create the dataset for different conditions of lungs.Develop a deep learning model which can accurately classify the X-ray image for healthy and affected lungs.Develop an model to identify the type of PNEUMONIA.Generate report for X-Ray image.

V. PROPOSED METHDOLOGY

This is mainly divide in to 2 parts one is front-end and back end. In the front end part, we will focus on user interaction and will be using language such as HTML CSS. In the front end part, we will mainly focus on designing and

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user interaction. This front is designed in such a way that the user can upload his Chest x-ray scan image. Further, this image is sent back to the server. In the server, there will be some evaluation based on which output will be generated which contains either disease found or not found. This result is sent back to the user web application and displayed to user.

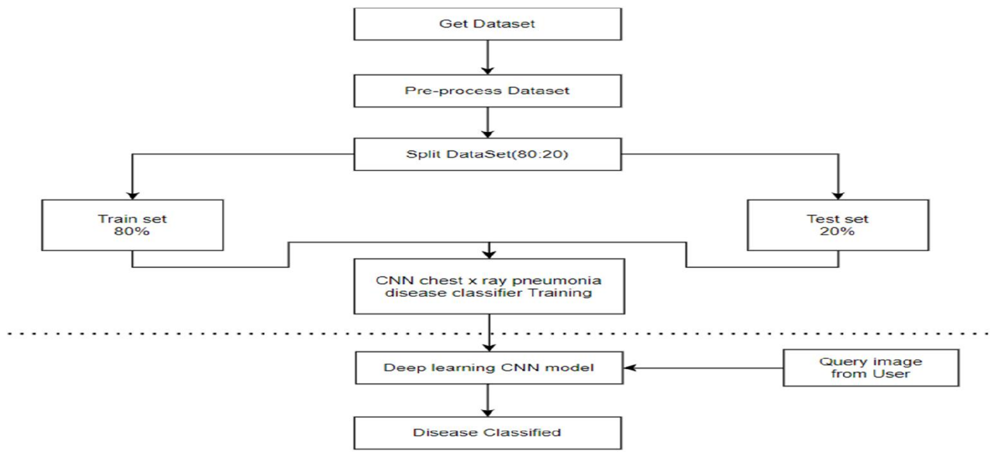

Figure 2: Proposed Methodology

We will be using deep learning to classify whether the given chest X-Ray image consists of pneumonia disease or no. To do this classification we should first train our model. here we'll using a model based on CNN convolutional neural network. To train this model will be using a dataset having 100 to 1000 images. These data sets have main 2 classes one is pneumonia disease and another one is normal. These data sets are mainly divided into two parts it is 80:20. 80% part can be considered as training the model and 20% should be considered as evaluating the model. First, step his to preprocess the dataset, then divide data sets into two-part train part and test part (80:20). Then we will use the train data set and feed that data in CNN. This training process can be carried out for 2 hours to 12 hours this training time depends on the system CPU and GPU. If the system has a good CPU and GPU it will take less time and vice versa. once the training step as been completed. we will then evaluate the model by using test datasets. Then this CNN model is used to detect upcoming chest x-ray data and classify whether scan as pneumonia disease or no. This model is then loaded onto the server by using a flask. Whenever a user uploads his chest X-ray scan image. we will be able to detect whether pneumonia disease affected that person or no.

VI. DATASET

The dataset used for all the diagnosis is based on a Chest X-ray dataset which is released by the radiological department/society on the Kaggle website. All the images are X-rays consisting of the RGB format. The Keras open-source deep learning framework along with the TensorFlow backend is employed to build and train the Convolutional Neural Network.

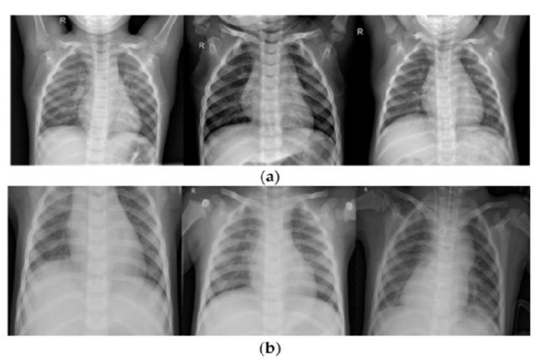

Figure 1: Examples from the dataset. (a) Normal cases, (b) Pneumonia cases.

The dataset obtained consisted of the training, testing and validation images each divided by the Pneumonia and Normal chest X-rays. A total of approximately 6000 images of anterior posterior are present. The data is modified into the training and validation set to enhance the system and increase efficiency. A total of around 5216 images are included in the training set and similarly, a total of 624 images are allocated to the validation set in order to improve the overall accuracy.

V. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks Recent developments in deep learning field, especially convolutional neural networks (CNNs) showed great success in image classification. The main idea behind the CNNs is creating an artificial model like a human brain visual cortex. The main advantage of CNNs, it has the capability to extract more significant features from the entire image rather than handcrafted features. Researchers developed different CNN based deep networks and these networks achieved state of results in classification, segmentation, object detection and localization in computer vision. Besides the natural computer vision problems, CNNs achieved very successful results in solving medical problems such as breast cancer detection, brain tumour segmentation, Alzheimer disease diagnosing, skin lesion classification etc. Pneumonia Detection Using CNN .The detailed reviews presented here about deep learning in medical image analysis. As far as, we are realized that there are a few studies about the detection of pneumonia using deep learning. In 2017, Antin et al. used a DenseNet-121 layer with utilizing transfer leaning method and they achieved 0.60 % area under the curve (AUC) value. In 2017, Rajpurkar, et al. proposed a 121-layer convolutional neural network based on DenseNet and named as CheXNet. They trained their network with 10.000 frontal view chest X-ray images with 14 different diseases. They assessed the performance of their network with four expert radiologists on the f1 score metric which is the harmonic average of the precision and recall metrics. CheXNet achieved a f1 score of 0.435 (95% CI 0.387, 0.481), higher than the radiologist average of 0.387 (95% CI 0.330, 0.442). Based on this information, we create CNN for classifying pneumonia from chest X-ray images. Convolutional Neural Networks (CNN) are everywhere. It is arguably the most popular deep learning architecture. The recent surge of interest in deep learning is due to the immense popularity and effectiveness of convnets. The interest in CNN started withAlexNet in2012and it has grown exponentially ever since. In just three years, researchers progressed from 8 layer AlexNet to 152 layer ResNet. CNN is now the go-to model on every image related problem. In terms of accuracy they blow competition out of the water. It is also successfully applied to recommender systems, natural language processing and more. The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself.CNN is also computationally efficient. It uses special convolution and pooling operations and performs parameter sharing. This enables CNN models to run on any device, making them universally attractive.

All in all this sounds like pure magic. We are dealing with a very powerful and efficient model which performs automatic feature extraction to achieve superhuman accuracy (yes CNN models now do image classification better than humans). Hopefully this article will help us uncover the secrets of this remarkable technique. Over the years, research on convolutional neural networks (CNNs) has progressed rapidly, however the real-world deployment of these models is often limited by computing resources and memory constraints. What has also led to extensive research in Conv Nets is the accuracy of difficult classification tasks that require understanding abstract concepts in images. Another reason why CNN are hugely popular is because of their architecture the best thing is there is no need for feature extraction. The system learns to do feature extraction and the core concept of CNN is, it uses convolution of image and filters to generate invariant features which are passed on to the next layer. The features in next layer are convoluted with different filters to generate more invariant and abstract features and the process continues till one gets final feature / output (let say face of X) which is invariant to occlusions.

Also, another key feature is that deep convolutional networks are flexible and work well on image data. As one researcher points out, convolutional layers exploit the fact that an interesting pattern can occur in any region of the image, and regions are contiguous blocks of pixels. But one of the reasons why researchers are excited about deep learning is the potential for the model to learn useful features from raw data. Now, convolutional neural networks can extract informative features from images, eliminating the need of traditional manual image processing methods.

VI. CONCLUSION

It primarily aims to improve the medical adeptness in areas where the availability of radiotherapists is still limited.Our study facilitate the early diagnosis of Pneumonia to prevent adverse consequences (including death) in such remote areas. Developing a automatic detection of pneumonia in energy-efficient medical systems is important to improve the quality of healthcare with reduced cost and time response.It is concluded that the deep learning model proposed above classifies the Chest X-rays for Pneumonia diagnosis in a very accurate manner. Therefore, it is concluded that the deep learning model proposed above classifies the Chest X-rays for Pneumonia diagnosis in a very accurate manner. The loss of the model is minimized while training and the accuracy simultaneously increases through each epoch stages in order to yield distinct results for classifying the Pneumonia affected and non-affected individuals. The data augmentation and preprocessing stages help to ensure that the performance of convolutional neural networks and deep neural networks is not subjected towards overfitting, thus the results obtained will always remain coherent. With a smaller number of convolutional layers, the proposed model predicts adroitly whether a given sample of Chest X-ray has pneumonia, or is normal. This is immensely helpful in the medical field for early and accurate diagnosis for Pneumonia in patients. Early diagnosis is of paramount importance in saving a person's life, by ensuring effective and timely treatment of the patient.

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