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# Review on Pneumonia Detection from Chest X-Ray using Deep Learning Approach

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**Abstract:** Machine Learning (ML) provides various techniques and tools that can help solving diagnostic and prognostic problems in a variety of medical fields. Machine learning is being used for the analysis of the importance of clinical parameters and their combinations for diagnosis, e.g. prediction of disease progression, extracting medical information for outcome analysis, therapy planning and support, and for the patient management. ML is often used for data processing, such as data regularity identification by careful handling of imperfect data, continuous data analysis used in the Intensive Care Unit, and smart alarming resulting in accurate and efficient monitoring. ML can detect patterns of certain diseases in patient electronic healthcare records, and inform physicians of any anomalies. Chest X-rays are used to diagnose various diseases. Multiple diseases can be diagnosed from pneumonia to lung nodules using Deep Learning. A pre-trained ResNet-50 model is re-trained with the use of different datasets of chest x-ray images. Notwithstanding major differences in datasets, ResNet-50 based diagnostic model is considered useful for pneumonia diagnosis. The trained model has achieved a 96.76 % accuracy. RSNA dataset, containing five times as many images as the Chest X-ray Image dataset, took very little time to prepare. In addition, both models were able to learn the significant features of pneumonia with a data set size of just % preparation, due to the use of the Transfer Learning technique. Still using deeper networks, the model can be improvised. The research may be expanded to identify and diagnose pneumonia with X-ray images.

**Keywords:** Artificial Intelligence, Machine Learning, Deep Learning, Pneumonia, Chest X-ray, ResNet.

## I. INTRODUCTION

Pneumonia constitutes a large proportion of death rates among the patients. Early pneumonia diagnosis and treatment is critical for avoiding complications including death. The WHO reports more than 4 million premature deaths from household air pollution-related diseases like pneumonia occur annually. More than 150 million people get infected with pneumonia annually, especially children under the age of 5. Due to the shortage of medical services and staff, the issue can be further complicated in these areas. Chest X-rays are the most popular imaging exam method that is used in practice, essential to screening, diagnosing, and treating a variety of diseases including pneumonia. However, according to an estimate by the World Health Organization, two thirds of the world's population lack access to radiology diagnostics. There is a lack of specialists who, even though imaging equipment is available, can interpret X-rays, contributing to increased mortality from treatable diseases. For many, the risk of pneumonia is immense, particularly in developing countries where billions face energy poverty and rely on polluting forms of energy.

Medical X-rays are images that are usually used to treat certain delicate parts of the human body, such as arms, face, teeth, skull, etc. This approach has been used by medical experts to identify and imagine defects or abnormalities in body organs for several periods. It is because, in addition to its non-invasive characteristics and economic implications, X-rays are very real diagnostic methods in disclosing the pathological modifications. In CXR images, chest diseases can be shown in the form of cavitation, infiltrations, blunted phrenic angles and small, wide - spread nodules. Radiologists can diagnose many conditions and diseases such as pleurisy, effusion, pneumonia, bronchitis, infiltration, nodule, atelectasis, pericarditis, cardiomegaly, pneumothorax, fractures, and many others by analyzing the chest X-ray image. A number of research work on the diagnosis of chest diseases using methodologies for artificial intelligence has been carried out. Multilayer, probabilistic, learning vector quantization, and generalized neural regression networks for chest disease diagnosis have been used. The diagnosis of chronic disruptive pulmonary and pneumonia diseases was implemented using neural networks and artificial immune system. The histogram equalization in image segmentation was applied for image pre - processing, and feed forward neural network is used for classification purpose. The above research works were used efficiently in the classification of medical diseases; however, their performance in terms of accuracy, computation time, and minimum square error was not as effective as the deep networks attained. In order to increase the accuracy of image classification, deep learning systems have been applied. Such deep networks displayed extraordinary accuracy in the execution of these tasks. This

success encouraged researchers to apply these networks to medical images for classification problems related to diseases, and the results indicated that deep networks can effectively extract useful features that distinguish different image classes. CNN has been applied to various medical images classification because it has a power to extract different level features from images.

Different learning approaches based on Artificial Intelligence, including shallow learning and deep learning, replace the step of extracting features and classifying diseases in conventional CAD systems. Artificial Intelligence also played an important role in the suppression of bone and the segmentation of CXR images. The commonly used classification methods for disease diagnosis use methods such as shallow learning but their performance depends mostly on the extraction of manually designed features. If the CXR images are complex, the manual extraction of features that are helpful for effective CAD tool and its performance requires a lot of time and effort. But Deep Learning algorithms, especially the Convolution Neural Networks (CNN), can extract features on their own based on input data, following a supervised training process without human interference. The ability of neural networks to learn on their own has opened new perspectives in the interpretation and analysis of chest radiography. Deep learning is growing tremendously in various fields such as segmentation, image classification, and great thrust has been developed for applying deep learning to medical images. In various tasks and applications, numerous studies have verified the usefulness of deep learning algorithms and their efficiency at the same or superior level to humans. The development in computer vision applications is not limited to the task of image classification but also improvised for various other tasks such as object detection, segmentation is just to name a few. In particular, the development of ever more powerful GPUs coupled with the availability of large data sets are driving factors for improvising learning rates. CNN like Deep Learning methods are dominant technology among researchers for the detection and prediction of diseases from medical images.

## II. LITERATURE REVIEW

Machine-based learning methods can also be described as pixel-based methods. Each pixel is assigned to a corresponding anatomical structure for chest x-rays, such as the lung, heart, mediastinum, diaphragm, etc. The classifier can use various features, such as the pixel's gray value, spatial location information, and statistical data about texture. Some classifier features, such as a k-nearest neighbor (KNN) classifier, support vector machine (SVM), Markov random field (MRF) model, or neural network (NN), are inputted to train the classifier. The method can be subdivided into methods based on shallow machine learning and deep learning based methods. The active field of research has been for the detection and diagnosis of diseases for several decades. Several researchers performed pneumonia detection and diagnosis using a variety of modalities. Abeyratne et al. [16] proposed an automated algorithm for diagnosing pneumonia using cough sounds. For the development of the proposed method, a database of cough sound from 91 patients was made using bedside microphones. The distance between the patient's mouth and the microphone ranged from 40 cm to 70 cm depending on the location. The cough sounds obtained mathematical information, and it was used to train a Logistic Regression Classifier. Finally, a comparative study was conducted between the three techniques of classification, namely reasonable clinical diagnosis, the WHO algorithm and the proposed method of logistic regression. The method has achieved % and % specificity and sensitivity, respectively. Pingale and Patil [17] used a similar approach to the diagnosis using cough sound analysis for the identification of pneumonia. Cough samples from infants aged 6 months up to teens aged 15 years were collected. "Continuous Wavelet Transform" (CWT) was used to analyze the cough samples. CWT coefficients are compared with Power Spectral Density (PSD), and the threshold values for skewness and kurtosis were used for classification of pneumonia. Following Deep Learning and Computer Vision's success in image recognition tasks, numerous researchers have used CXR to detect and diagnose pneumonia. In 2017, Rajpurkar P. et al[11] developed CheXNet, a 121-layer, convolutional neural network trained on the Chest X-ray14 dataset. The network performance was evaluated with that of expert radiologists, and it was found that CheXNet's f1 score was 0.435 compared to an average of 0.387 for radiologists. Antin et al.[18] did the classification task for pneumonia using the NIH dataset. Application was made of a convolution neural network like CheXNet. The model, however, managed to achieve an AUC of 0.684 compared to CheXNet's 0.828. Ayan and Unver [19] used two deep learning algorithms for the pneumonia classification, namely the CXR model VGG16 and Xception. Model was fine-tuned in the training process after Transfer learning. The two networks' efficiency has been tested on varying metrics. VGG16 achieved 87 % accuracy compared to the 82 % accuracy of the Xception model. It was found that Xception model performance high in pneumonia detection cases while VGG16 model performed well in normal case detection. Liang and Zheng [20] suggested a novel49 network architecture with convolution layers. Transfer learning has been used to speed up training on neural networks and to resolve the question of inadequate data. The model reached a 90.5 % accuracy, which was higher than other early CNN models.

Raheel Siddiqi [24] presented a model trained by Kermany et al on the dataset given. The model developed was a deep sequential, convolution neural network of 18 layers. The model proposed performed the classification function with 94.39 per cent accuracy.

The model also attained a high sensitivity of 0.99. Yet the model's specificity was quite low. Chakrabhardy S. A model was also developed by et al [23], using convolution neural networks. The network was composed of 17-layers with 3 convolution layers, accompanied by 5 dense layers and the output layer. For the reduction of dimensionality, the architecture has implemented a set of max-pooling layers. The model developed has been able to achieve 95.62 % with 95 percent recall and 96 % accuracy, respectively. The goal in the current research is to develop an effective model for pneumonia detection based on CXR. Using transfer learning on ResNet-50 the model is retrained for pneumonia detection. Ultimately, the analysis was performed for learning performance and the accuracy of the qualified models.

### III.METHODOLOGY

The approach followed for the creation of the model is discussed in this section. Firstly, a brief overview is given of the used datasets. The working modules will be discussed in more detail later. Specific modules to be addressed include preprocessing, classifier preparation, and classification using ResNet-50. Artificial neural networks (ANNs) are models of computations inspired by the human brain. We consist of a large number of connected nodes, each doing a simple mathematical operation. This operation specifies the output of each node, as well as a collection of parameters which are unique to that node. By linking these nodes together, and setting their parameters carefully, it is possible to learn and measure very complex functions.

#### A. Data

Three publicly available datasets are used for study in this work

- 1) *ChestX-ray14 Dataset*: ChestX-ray14 dataset which contains images of 30,805 specific patients with 112,120 front-view X-rays used. Dataset is splitted randomly into the validation and test preparation. There is no overlap between the sets of patients. Images are downscale to 224 / 224 and normalize before it inputs into the network in the ImageNet training set based on the mean and standard deviation.
- 2) *RSNA Dataset*: This dataset has been published by Radiological Society of North America (RSNA). The dataset is maintained and publicly available for use by the scientific community. This dataset contains 26684 samples and is a subsection of larger dataset made by the National Health Institute (NIH). The NIH dataset consists of 112000 samples and consists of three mark groups, lung opacity (31%), no lung opacity (40%) and normal (29%). Although the RSNA dataset is part of the NIH dataset, a lot of differences exist between the two datasets. RSNA dataset is developed primarily for pneumonia cases and provides the necessary and accurate information to classify and detect the disease.
- 3) *Chest X-Ray Image (CXI) Dataset*: The dataset is being established in Guangzhou, China. Guangzhou Women and Children's Medical Center. The X-ray images are taken from pediatric patients under the age of five. The Chest X-rays in the datasets are actually part of routine healthcare for patients. Pre-processing is conducted on all images within the dataset to delete scans of poor quality. To prevent some kind of misclassification, photos are reviewed and identified by two specialist physicians and a third party radiologist further. The dataset includes a total of 5856 X-ray images in the format of. JPEG. Every of the two photos is Types: Non-pneumonia / normal pneumonia. Further, the dataset is divided into three folders: Training, testing and validation sets. Each folder has Pictures from both categories: normal and pneumonia.
- 4) *Convolution Neural Network using ChestX-ray14 Dataset*: Wang et al. ( 2017) released ChestX-ray14 dataset containing 112.120 front-view X-ray images of 30.805 unique patients. Wang et al. (2017) annotate each image using automated extraction methods on radiology documents, using up to 14 separate thoracic pathology labels. As one of the annotated pathologies, labeled the images which have pneumonia as positive examples and label all other images as negative examples. For the purpose of pneumonia detection, the dataset is randomly into training (28744 patients, 98637 images), validation (1672 patients, 6351 images), and testing (389 patients, 420 images). There is no patient overlap between the sets. CheXNet is a 121-layer Dense Convolutional Network (DenseNet), trained on dataset ChestX-ray 14 (Huang et al., 2016). DenseNets facilitates information and gradient flow across the network, enabling the optimization of very deep networks to be tractable. After the sigmoid nonlinearity is added, the final fully connected layer is replaced by one with a single output. The weights of the network are initialized on ImageNet using weights from a pre-trained model (Deng et al. , 2009) .The network is trained end-to - end using Adam ( $\beta_1 = 0.9$  and  $\beta_2 = 0.999$ ) as standard parameters (Kingma & Ba, 2014).The model is trained using minibatches of Size 16. The initial learning rate of 0.001 is used which decays by a factor of 10 each time the validation loss plateaus after an epoch, and the model with the lowest validation loss was chosen.
- 5) *DenseNet121 Architecture*: The design in DenseNet needs fewer parameters than a traditional CNN. DenseNet layers only use 12 filters with a limited collection of new characteristic maps. Another issue with DenseNet is the training time, as each layer has

its input from previous layers. However, DenseNet solves this problem by providing access to the gradient values from the loss function and the input image. This greatly reduces the cost of computation and allows a better choice for this model.

- 6) *Classification using ResNet-50 Architecture:* Our algorithmic method for defining possible pneumonia causes is developed by Faster-RCNN. We have tried many other object detection techniques such as You Look Only Once (YOLO3) and U-Net image detection architectures but it fails to make better predictions, from our tests, we find that MaskRCNN performing better in prediction tasks. Training a complete DenseNet-121 took longer to train but yielded similar results to VGG16's. The deeper network may be a consequence of using such a deep network architecture. He et al., he explains, a model with too many layers will begin to degrade precision when it is overloaded as the model's depth increases. For this reason, the middle ground between the two was evaluated as a new base model, and that was ResNet-50 The ResNet architecture proposed by [22] is a deep, 50-layer, neural network architecture that uses Residual research. He et al. hypothesize that instead of learning the mapping function  $H(x)$  directly, it will be better for the model to learn the residual  $F(x) = H(x) - x$  (this mapping is typically re-cast as  $H(x) = F(x) + x$ ) ResNet uses residual blocks with connections connecting the input of one layer to the output of another layer, also known as "shortcut connections". The shortcut connections add to the output of the stacked layers  $F(x)$  the identity function  $x$  (i.e. the function which returns its input as output). The benefit of these residual blocks is that layers can be skipped, thus alleviating the question of degradation that occurs when the model has many layers. The ResNet architecture performed better than other state-of-the-art models and has won many competitions in the classification, such as the ILSVRC 2015 competition.

#### IV. RESULT AND DISCUSSION

The results of the study can be summarized as follows: there were 26,684 images in the RSNA dataset, and 5856 images in the Chest X-Ray Image dataset. If we look at the precision table, the highest accuracy for both datasets is achieved with the 80-20 splitting ratio. The model trained on the RSNA dataset was 96.76 percent, with 94.06 % respectively for the Chest X-ray Image dataset. 80-20 is found to be the highest test-ratio preparation.

- 1) The model trained on the RSNA dataset did better for accuracy than the Chest X-ray Image dataset. It indicates that pneumonia illness has major features to be learned from the x-ray picture of the lung. And for this task a bigger dataset worked well. It is found that it's easier to use a larger dataset to know the features of pneumonia effectively.
- 2) If we look at the 50-50 splitting ratio in both cases and compare it with the best accuracy, the accuracy is observed to be insignificantly improved. Due to Transfer Learning, the trained ResNet model will learn the required features with a training dataset of only 50 %. So we can train model with just over % training sample in case of urgent market development needs and save a significant amount of time to train the model, without sacrificing the accuracy.
- 3) Careful evaluation indicates that 90% of training is less reliable than 80% of training, but it should be the reverse because further training is more effective. We could not find out the reason for this situation. In order to find the reason for this case we need to experiment in a dedicated area.
- 4) Comparing the two datasets, the RSNA dataset includes five times more images than the CXI dataset, but given the training time RSNA dataset takes just twice the training time for the Chest X-ray Image data collection. It is found that pneumonia features are learned faster by the RSNA dataset than the CXI data collection. As previously stated, the RSNA dataset also performed well in terms of precision. The RSNA dataset is well suited for pneumonia detection and treatment compared to CXI dataset.
- 5) ResNet-50 model has been evaluated in the present work on both the RSNA and CXI datasets. The proposed model with CXI dataset achieved the highest 94.06 % which is better than the model Xception and VGG16. Although some CNN models have delivered better results than the model proposed. The model ResNet-50 tested on RSNA dataset gave a 96.76 % which is the best among all state-of-the-art models.

RSNA dataset worked better on ResNet-50 architecture than CXI dataset. The model based on the RSNA dataset took less time to train than the CXI dataset and was able to learn the pneumonia features January-February 2020 ISSN: 0193-4120 Page No. 15146-15153 15152

Above Table shows that the efficiency of SVM exceeds all other machine learning classification algorithms including Logistic Regression. So we can conclude that with SVM we obtain the highest accuracy rate compare to all other classification algorithms for this particular datasets.

## V. CONCLUSIONS

All of these reasons make chest X-ray detection of pneumonia complex. Therefore a algorithm is required to interpret radiographic images accurately. Recently, due to great advances in deep learning, it is possible to develop improvised patient care, reduce the workload of radiologists and assist them in making better decisions. Various datasets are chosen to build an effective model for the pneumonia disease classification task. The efficiency and effectiveness of these algorithms was compared in terms of accuracy, precision, sensitivity and specificity, order to find the best classification algorithm as a result of implementation. Furthermore, in-depth research is carried out on the best image classification tasks architecture. Many architectures have been used but it is found that ResNet architecture is the best one for the technology proposed. ResNet -50 has been chosen as the base architecture, and is trained using two separate datasets to pass learning.

Also, the model is prepared for various training ratios and test sets. The accuracy obtained for the proposed model was 96.76 %. The precision obtained is on par with cutting-edge research work.

Although the model has achieved relatively good accuracy in classification and prediction of pneumonia, some areas of progress have been observed. Therefore a program is required to interpret radiographic images accurately. Recently, due to great advances in the field of Deep Learning, automated patient care can be created, the workload of radiologists reduced and helped to make better decisions.

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