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Effective Pneumonia Detection using Res Net based Transfer Learning

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Abstract:
Pneumonia is a deadly lungs disease known as silent killer is due to bacterial, viral, or fungal infection and causes lung alveoli to fill with pus or fluids. The most common diagnostic tool for pneumonia is Chest X-rays. However, due to several other medical conditions in the lungs, such as volume loss, bleeding,lung cancer,fluid overload,post-radiation or surgery, the diagnosis of pneumonia using chest X-rays becomes very complicated. Therefore, there is a dire need for computer-aided diagnosis systems to assist clinicians in making better decisions. This work proposes an effective, deep convolutional neural network with ResNet-50 architecture for pneumonia detection.ResNet has performed quite well on the image recognition task and was a winner of the ImageNet challenge.A pre-trained ResNet-50 model is re-trained with the use of Transfer Learning on two different datasets of chest x-ray images. ResNet-50 baseddiagnostics model is found useful for pneumonia diagnostics despite significant variations in two datasets. The trained model has achieved an accuracy of 96.76%, which is at par with state-of-the-art techniques available. RSNA dataset, with five times more images than the Chest X-ray Image dataset, took very little time for training. Also, because of the use of the Transfer Learning technique, both the models were able to learn the significant features of pneumonia with only 50% training dataset size.However, the model can be improvised by using more deeper networks. Work can be extended to detect and classifyboth lung cancer and pneumoniausing X-ray images.

Keywords: ResNet, convolutional neural network,Pneumonia detection, chestX-ray, Transfer learning.

Article History

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I. Introduction

Pneumonia has highest mortality rate among young children and old aged people around the world. It is "the silent killer, disease" that shows little political and social awareness as compared to other diseases, and the number of infections is increasing multifold every year. Childhood pneumonia is a disease that finds its roots in poverty. Its leading causes are inappropriate childcare and poor education on top of the unavailability of access to primary healthcare. Adult pneumonia can be considered as a public health problem and needs more active involvement to cure it.

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In the South-East Asia (SEA), the estimated rate of occurrence of pneumonia is 0.36 episodes per child year as compared to the world average of 0.26in children under five years of age. In the context of developing countries, the average is found to be 0.29, while 0.05 episodes per child year is for developed countries. Yearlynew cases of childhood pneumonia are foundin the SEA region are over 61 million, which is out of 156 million worldwide cases. In the SEA region, the mortality rate is over 19% of the under-five population. The 3.1 million deaths occur because of pneumonia in the SEA region. Importantly these deaths do not include pneumonia cases among neonatal infections [1].

In the context of childhood pneumonia, India needs special mention. If we go for numbers, India is ranked globallyamong the top 15 countries, with 43 million infections every year. Morbidity rate is between 0.2 to 0.5 episodes per child year, severity of these infections is in between 10 to 20 percent. Mortality vs high burden countries shows, India has a rate of 322 per hundred thousand, under-five population compared to China's 86 per hundredthousand [2-4].

Accurate diagnosis of pneumonia is hard to accomplish. It needs a review by expert radiologist for chest X-rays (CXR), confirmation through vital sign, clinical history and laboratory examination. Thepneumonia infected areasappear higher in opacity in CXR [5]. The defense mechanism of body against this infection fill the lungs with pus or other liquids, which reduces air holding ability of lungs, and causes choking sensation, cough, and fever, among other symptoms among pneumonia patients. However, because of several other conditions in the lungs such as volume loss (atelectasis or collapse), bleeding, fluid overload (pulmonary edema), lung cancer or surgical changes,or post-radiation the diagnosis of pneumonia in CXR becomes very complicated. Fluid outside the lungs such as in the pleural space (pleural effusion) can also appear more opaque on CXR. A pneumonia opacity is a part of the lungs that looks darker on a radiograph and has a shape that indicates that pneumonia is (or maybe) present. If available, a comparison of CXRs of the patient at different points of time and its correlation with clinical history and symptoms are helpful in the diagnosis of pneumonia.

Chest radiography being inexpensive and easy-to-use, is the most common medical imaging and diagnostic technique.Machines forModern Digital Radiography (DR) are readily available in underdeveloped areas at reasonable costs. Therefore, CXRs are widely used in the diagnosis of diseases such astuberculosis, pulmonary nodules, pneumonia, early lung cancer, to list few.

A large amount of information is concealed in CXR, about the patient's health, but correct interpretion of the available information is non-trivial for the doctors and radiologists. The complexity increases with the overlapping of the tissue structures in the CXR. For instance, when thecontrast between the surrounding tissue and lesion is very low, or there is an overlap in the ribs, the large pulmonary blood vessels or lesion, detection becomes challenging. Even for the experienced doctor, it's not easy to differentiate between similar lesions or to find nodules which are very obscure. Consequently, the examination of CXR results in a certain degree of missed detection.

This inconsistency in the interpretation of medical images gives rise to a paradigm shift from a completely manual system of interpretation by human professionals to CAD (Computer-Aided-Diagnosis) systems for better interpretation and diagnosis to minimize human errors. Also, systems assist in training of novice technicians, practitioner having less experience and makes reading and interpretation of CXRs in standardized manner.

Different Artificial Intelligence based learning methods including shallow learning and deep learning, replaces in the traditional CAD systems the step of feature extraction and disease classification. Artificial Intelligence has also played a significant role in bone suppression and image segmentation of CXR. The commonly used classifiersin the detection of diseases uses methods like shallow learning, but their performance mostly depends on the manually designed features extraction. If the CXR images are complex, it takes a lot of time and effort in manual extraction of features that are helpful for effective CAD tool and its performance. But Deep Learning algorithms, especially Convolutional Neural Networks (CNN), can extract features by themselves based on input data, after a supervised training process without human interference. The ability of neural networks to learn by itself has opened new prospects in the analysis of radiographic images and its interpretation. There is tremendous growth of deep learning in various fields such as semantic segmentation [8-9],image classification [6-7] andgreat thrust has generated for the applying deep learning to medical images.

Various studies have confirmed effectiveness of deep learning algorithms and their performance at par or superior to humans in various tasks and applications. A very famous case in 2015 was documented during ImageNet challenge, a model overtook performance of human levelfor classification of images [10]. This was a starting point, from there, the Deep Learning models and algorithms are continued to improve. The improvement in computer vision applications is not limited to the task of image classification but also in improvised for various other tasks such as object detection,segmentation are just to name a few.

In particular, the development of increasingly powerful GPUs coupled with the availability of large datasets are driving factors to improvise the learning rates. Advances in hardware made the resource-intensive models possible with performance better than the human professionals, for various tasks of medical imaging, including pneumonia diagnosis [11], arrhythmia detection [14], skin cancer classification [13], diabetic retinopathy detection [12], and bleeding identification [15]. Therefore, CNN like Deep Learning methods are dominant technology among researchers for disease classification and diagnosis from medical images.

II. LITERATURE REVIEW

For several decades the active area of research has been detection and diagnosis of diseases. In our context, several researchers carried out detection and diagnosis of pneumonia, using a multitude of modalities. Abeyratne et al. [16] proposed an automated algorithm using cough sounds to diagnose pneumonia. For the development of the proposed method, a database of cough sound from 91 patients was made using bedside microphones. Depending on the position, distance between the patient'smouth and the microphone was varying between 40 cm to 70 cm. Mathematical features were collected from the cough sounds, and it was used to train a Logistic Regression Classifier. Finally, a comparative study was performed between the three classification techniques, namely, reasonable clinical diagnosis, the WHO algorithm, and the proposed Logistic Regression method. The method has achieved a specificity and sensitivity of 75% and 94%, respectively. A similar approach for the diagnosis was made by Pingale and Patil [17] using cough sound analysis for pneumonia detection. The cough samples were collected from infants of age 6 months up to teens of 15 years. To analyze the cough samples, "Continuous Wavelet Transform" (CWT) was used. CWT coefficients are compared with Power Spectral Density (PSD), and the skewness and kurtosis threshold values were used for the pneumonia classification.

After the success of Deep Learning and Computer Vision in image recognition tasks, many researchers have used CXR for pneumonia detection and diagnosis. In 2017, Rajpurkar P. et al.,[11] developed CheXNet, a convolutional neural network with 121-layers, which was trained on Chest X-ray14 dataset. The performance of the network was assessed with that of expert radiologists, and it was found that f1 score ofCheXNet was 0.435 compared to the radiologist average of 0.387. Antin et al. [18] performed the pneumonia classification task using the NIH dataset. A convolutional neural network like CheXNet was used. However, the model was able to achieve an AUC of 0.684 compared to 0.828 of CheXNet.

Ayan and Unver [19] used two deep learning modelsfor classification of pneumonia, namely VGG16 and Xception model from CXR. Model was fine-tuned after Transfer learning in the training phase. The performance of the two networks was tested on different metrics. VGG16 achieved an accuracy of 87% as compared to the Xception model accuracy of 82%. It was observed that Xception model performancehigh in detection of pneumonia cases whereas VGG16 modelgave good performance in the detection of normal cases.

Liang and Zheng [20] proposed a novel49 convolutional layers network architecture. Transfer learning was used to accelerate neural network training and to overcome the problem of insufficient data. The model achieved an accuracy of 90.5%, which was better than most of the early CNN models.

Raheel Siddiqi[24] presented a model trained on the dataset provided by Kermanyet al. The model developed was an 18-layer deep sequential convolutional neural network. The proposed model performed the classification task with an accuracy of 94.39%. Also, the model achieved high sensitivity of 0.99. However, the specificity of the model was quite low.

Chakraborthy S. et al. [23] also developed a model by leveraging convolutional neural networks. The network consisted of 17-layers with 3 convolutional layers, which was followed by 5 dense layers and the output layer. For the dimensionality reduction, a series of max-pooling layers have been introduced in the architecture. The model developed was able to achieve an accuracy of 95.62 % with recall and precision of 95% and 96 %, respectively.

In the present work, aim is to design an effective model for the CXR based detection of pneumonia. The model is re-trained for pneumonia detection using transfer learning on ResNet-50. Finally, the investigation was carried out for the effectiveness of learning and the accuracy of trained models.

III. METHODOLOGY

In this section, the methodology followed to develop the model is discussed. Firstly, a brief description of the datasets used are given. Later, the working modules are discussed in detail. Various modules to be discussed are pre-processing, training the classifier, and classification using ResNet-50.

A. Data

Two publicly available datasets are used for study in this work.

RSNA dataset:Radiological Society from North America(RSNA)has published this dataset.The dataset is maintained and publicly available to be used by the scientific community.This dataset contains 26684 samples and is a subset of larger dataset made by the National Institute of Health(NIH). NIH dataset consists of 112000 samples and consists of three classes of labels, lung opacity(31%), no lung opacity/ not normal(40%) and normal (29%). Even though RSNA dataset is part of NIH dataset, there are a lot of differences between the two datasets. RSNA dataset is mainly developed for cases of pneumonia and provides necessary and accurate information for classification and detection of the disease.

Chest X-Ray Image (CXI) dataset:This dataset has been taken from Kermany et al.,[21].This dataset is developed in the Guangzhou Women and Children's Medical Center Guangzhou, China. The radiographic images are taken from pediatric patients under five years of age. The Chest X-rays in the datasets are in fact part of patients routine health care. The pre-processing is performed on all the images within the dataset to remove low quality scans. Images are checked and classified by two specialist clinicians and further by a third party radiologist to avoid any kind of misclassification. In total the dataset contains 5856 X-ray images in the .JPEG format. Images are either of the two types: pneumonia and non-pneumonia/normal as shown in Fig1. The dataset is further subdivided into three folders: training , validation and test sets. Each folder contains images from both categories: pneumonia and normal.

B. Pre-processing

In this section we will focus on the actions applied on the dataset samples as a primary step before these models are fed for the classification during training and prediction process. There are three types of pre-processing we considered for our data: addition, removal and transformation of attributes in the data. Within the addition of attributes, dummy attributes, transformed attributes and missing data were considered. Removing attributes from the data also helps in the boost of model accuracy. Transformations of training data helped reduce the skewness of data as well as the prominence of outliers in the data. In the next step, the dataset is divided into three sets: training, validation and test sets.

A. Training the classifier

The problem consists of binary classification where input is an image, and the classifier gives output either as "0" (Non-pneumonia) or "1" (Pneumonia). The method used is the transfer learning technique for training purposes.

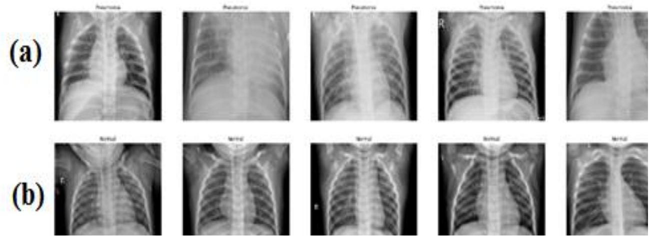


Fig. 1: Data samples from CXI [21], dataset, (a) pneumonia cases, (b) normal cases.

Transfer learning is a technique where a model trained on one task is re-purposed on a second related task.

The focus here is on the pre-trained model approach, which consists of the following important steps:

1) *Select the Source Model*. Research institutions and large technological companies release models on large and challenging datasets. A pre-trained model is chosen from the available models that matches the problem under consideration
2) *Reuse Model*.The pre-trained model selected in the previous step can be used for the task in interest. Re-use of the model may consist of using all or specific parts of the model. It mainly depends on the type of modelling used.
3) *Tune Model*. Optionally, the model may need to be refined or adapted on the input-output pair data available for the task of interest.

In the present work, a pre-trained ResNet-50 model on the ImageNet dataset is used as a classifier for pneumonia classification. The selected deep learning model is trained on ILSVRC (ImageNet Large Scale Visual Recognition Challenge) dataset comprising of 1000-class photograph classification competition. The pre-trained approach is useful in our case because the pre-trained model is trained on a large database of images of 1000 classes. The features learned in the previous task can easily be applied in the problem concerned to learn the significant features of the disease pneumonia.

The generation of a new model through transfer learning is explained here. Figure 2 shows a ResNet model that is trained using the weights of the ImageNet dataset. The steps are summarized below:

- First few layers of a Deep Learning model identify simple shapes, middle layers identify more complex shapes and patterns and the final layers are used to make predictions.
- In the pre-trained ResNet-50 model most of the layers are untouched. Only the final prediction layer is replaced by a new prediction layer.
- As seen in Figure 3 last layer contains information in the form of a vector which consists of a series of nodes.
- We add a new prediction layer consisting of two nodes, which predicts if the image has pneumonia or not as shown in Figure 4.

TABLE I gives the hyper parameters used during CNN training forCXI dataset and TABLE II gives the set of hyper parameters used for training the CNN for RSNA dataset. In both the cases, binary cross entropy is chosen as the loss function to solve the binary classification problem. SGD (Stochastic Gradient Descent) optimizer is used in case of CXI dataset whereas Adam optimizer is used in case of RSNA dataset.

In both the cases learning rate is kept same. As both the models were trained using transfer learning so increasing the number of epochs did not improved the accuracy. So, to save time number of epochs was set at 4.

B. Classification using ResNet-50

The choice of ResNet-50 has a big reason behind it. Although several other architectures were used previously, none of them gave a satisfactory result. For example, VGG16 is a comparatively smaller network. It may not be able to find features needed to classify pathologies in chest x-rays. This smaller network could be a factor in its poor performance.

At the same time, training a full DenseNet-121 took a longer time to train but gave comparative results to that of VGG16. The deeper network could be a consequence of using such a deep network architecture. He et al., explains, a model with too many layers can start degrading accuracy as it gets saturated when the depth of the model increases. For this reason, a new base model was tested as a middle ground between the two, and that was ResNet-50.

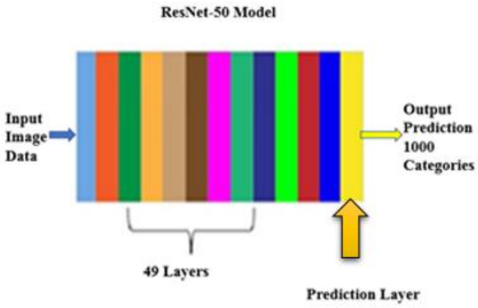


Fig. 2: Image showing the ResNet-50 model

The ResNet architecture proposed by [22] is a deep neural network architecture with 50 layers that uses residual learning.

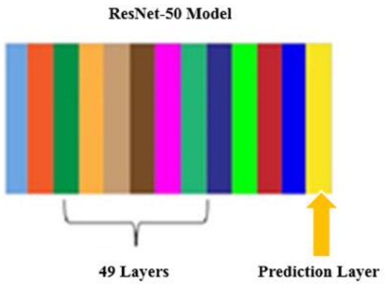


Fig. 3: Image showing the removal of last layer for training

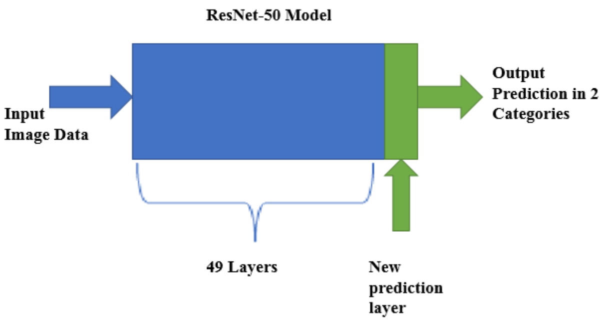


Fig. 4: Image showing the addition of the new prediction layer.

TABLE I
HYPER PARAMETERS OF CNN TRAINING FOR CXI DATASET

Loss Function	Binary Cross-Entropy
Optimizer	StochasticGradient Descent
Learning Rate	0.01
Number of Epochs	4
Batch size	16

TABLE II
HYPER PARAMETERS OF CNN TRAINING FOR RSNA DATASET

Loss Function	Binary Cross-Entropy
Optimizer	Adam
Learning Rate	0.01
Number of Epochs	4
Batch size	20

He et al. hypothesize that instead of learning the mapping function H(x) directly, it would be easier for the model to learn the residual F(x) = H(x) - x (this mapping is usually re-casted as H(x) = F(x)+ x).

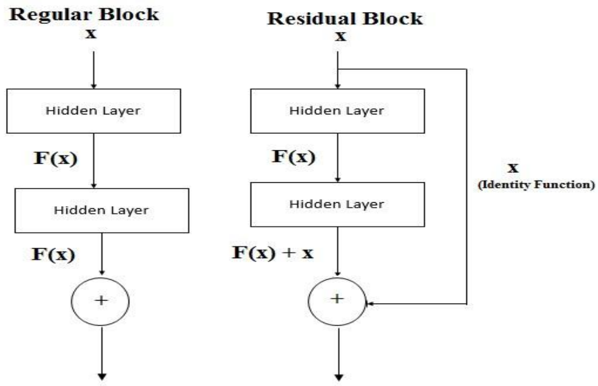


Fig. 5: A standard block in a regular stacked network (left) and a residual block in the ResNet architecture (right).

ResNet uses residual blocks with connections that connect the input of one layer to the output of another layer, also known as "shortcut connections" (see Figure 5). The shortcut connections add the identity function x (i.e., the function that returns its input as output) to the output of the stacked layers F(x). The advantage of these residual blocks is that layers can be skipped, which alleviates the degradation issue that arises when the model has many layers. The ResNet architecture performed better than other state-of-the-art models and has won several classification competitions, such as the ILSVRC 2015 classification competition.

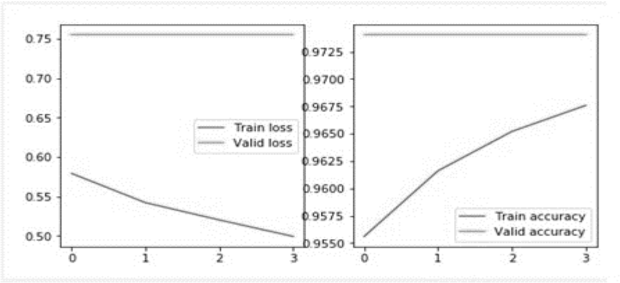
IV. RESULTS AND DISCUSSION

To develop an effective model for pneumonia diagnosis, a series of experiments were performed on both the datasets. Splitting ratios for training and test sets were varied, and the accuracy and loss plots were recorded. Time taken for training was also being recorded. TABLE III gives an analysis of the variation of training and test sets over accuracy and training time for both the datasets.

TABLE III
ANALYSIS OF TRAINING AND TEST SETS SIZE FOR ACCURACY AND TRAINING TIME.

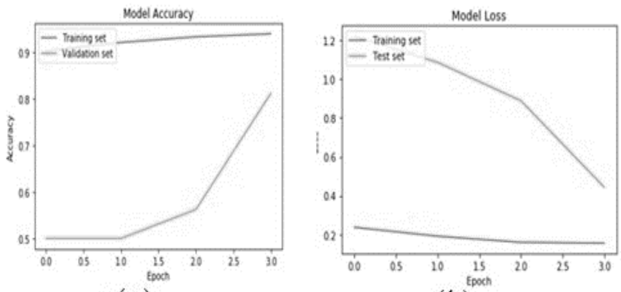
Training and Test ratio	**Accuracy (%)**		**Training Time (minutes)**	
	RSNA	**CXI**	**RSNA**	**CXI**
90% - 10%	96.74	93.96	69.87	28.23
80% - 20%	**96.76**	**94.06**	55.62	28.48
70% - 30 %	96.68	93.63	54.33	27.48
60% - 40%	96.63	93.54	56.88	29.87
50% - 50%	96.64	93.54	53.88	27.38

As seen in the table above, the best splitting ratio is 80:20 for training and test sets. Figure 6 and Figure 7 gives the plots of accuracy and loss for both the datasets for 80:20 training to test ratio.



(a) (b)

Fig. 6: Loss (a) and Accuracy (b) plots of RSNA dataset for 80:20 training and test set



(a) (b)

Fig. 7: Accuracy (a) and Loss (b) plots of Kermany et al., a dataset for 80:20 training and test set

The findings of the work can be summarized as follows:

RSNA dataset contained 26,684 images, and the Chest X-Ray Image dataset contained 5856 images. If we look at the accuracy table, the best accuracy is achieved at the 80-20 splitting ratio for both the datasets. The model trained on the RSNA dataset got 96.76 %, and the Chest X-ray Image dataset got 94.06% accuracy, respectively. It is observed that 80-20 is the best training to test ratio.

1) The model trained on the RSNA dataset performed better than the Chest X-ray Image dataset for accuracy. It shows that pneumonia disease has significant features that are to be learned from the chest x-ray image. So, a bigger dataset performed well for this task. It is observed that to learn the features of pneumonia effectively, it's better to use a bigger dataset.

2) If we look at the 50-50 splitting ratio in both the cases and compare them with the best accuracy, it is observed that there is an insignificant improvement in the accuracy. It is because of Transfer Learning that the trained ResNet model can learn the necessary features with only 50% training dataset. So, we can train model with just over 50% training sample in case of urgent production needs of the market and can save a significant amount of time spent in training the model, without compromising the accuracy.

3) Careful observation shows, 90% of training gives less accuracy as compared to 80% training, but it should be opposite as more training gives more accuracy. We were unable to find the reason for this case. We needto experiment in a dedicated environment to find the reason for this case.

TABLE IVA COMPARISON OF ACCURACY AMONG DIFFERENT RESEARCH WORKS

Author and Year	**Model**	**Dataset**	**Accuracy**
Ayan and Unver, 2019 [19]	Xception & VGG16	CXI Dataset [24] Kermany et al.	82% & 87%
Liang and Zheng, 2019 [20]	CNN with 49 convolutional layers & 2 dense layers.	CXI Dataset [24] Kermany et al..	90.5%
Chakraborthy S,2019 [23]	17-layer CNN with 3 convolution and 5 dense layers	CXI Dataset [24] Kermany et al..	95.62%
Raheel Siddiqi,2019[24]	18-layer CNN model	CXI Dataset [24] Kermany et al..	94.39%
Proposed work Model-1	ResNet-50	CXI Dataset [24] Kermany et al.	94.06%
Proposed work Model-2	ResNet-50	RSNA Dataset	**96.76%**

4) If the two datasets are compared, the RSNA dataset contains five times more images than the CXI dataset, but if we consider the training time RSNA dataset only takes double the Chest X-ray Image dataset training time. It is observed that the RSNA dataset is learning the features of pneumonia faster than the CXI dataset. Also, as mentioned previously, RSNA dataset performed well in terms of accuracy. So RSNA dataset is well suited for the detection and diagnosis of pneumonia as compared to CXI dataset.

5)In the present work ResNet-50 model was tested on both RSNA and CXI dataset. The proposed model with CXI dataset achieved the highest accuracy of 94.06 % which is better that Xception and VGG16 model. Although some CNN models gave better results than the proposed model. The ResNet-50 model tested on RSNA dataset gave an accuracy of 96.76% which is the best among all state-of-the-art models.

RSNA dataset performed better than CXI dataset on ResNet-50 architecture. The model tested on RSNA dataset took less time for training as compared to CXI dataset and is able to learn the features of pneumonia

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effectively. So RSNA dataset is well suited for detection and diagnosis of pneumonia.

V. CONCLUSION

All these reasons make the detection of pneumonia from chest x-rays complex. Therefore, there is a need for a system for the accurate interpretation of radiographic images. Recently because of great advancements in the field of Deep Learning, it is possible to develop improvised patient care, reduce the workload of radiologists, and assist them in making better decisions.

The main goal of the research to develop an effective model to classify pneumonia using Chest X-ray is achieved successfully. Based on the literature review, two datasets are selected for building an effective model for the classification task of pneumonia disease. Further, in-depth research is carried out over the best architecture in image classification tasks. Several architectures were used, but ResNet architecture is found to be the best model for the proposed model.

ResNet -50 was selected as the base architecture and is trained using transfer learning over two different datasets. The model is also trained for different ratios of training and test sets. The accuracy achieved was 96.76 % for the proposed model. The accuracy achieved is on par with state-of-the-art research works.

Although the model has achieved quite a good accuracy in the classification and prediction of pneumonia, some improvement aspects have been observed. The accuracy achieved can be improved further by using more deeper networks like ResNet-101orResNet-152. The future work could be to extend this work to detect and classify CXR images for lung cancer and pneumonia.

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