

# Detection of Thoracic Diseases using Deep Learning

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**Abstract—** The study of using deep learning for detection of various thoracic diseases has been an active and challenging research area. Chest X-rays are currently the most common and globally used radiology practices for detecting thoracic diseases. Patients suffering from thoracic diseases need to take Chest X-Rays which are read by radiologists and a report is generated by them. However, today with the increase in the number of thoracic patients, a quick method to classify the disease and generate the report has become necessary. Also, patient history has to be considered for diagnosis. This paper offers a comparative study on the various deep learning techniques that can process chest x-rays and are capable of detecting the different thoracic diseases. Also, a technique has been proposed to classify 14 diseases namely Atelectasis, Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Pleural thickening based on the given X-rays using Residual Neural Network.

## 1. INTRODUCTION

The thorax, also called chest, is the upper part of the trunk located between the neck and the abdomen. It gets support from the rib cage, the girdle of the shoulder and the spine that also protects it. It is the region of the body formed by the sternum, the thoracic vertebrae, and the ribs. It resides between the neck and diaphragm excluding the upper limb. The heart and lungs reside in the thoracic cavity, as well as many blood vessels which play a vital role in feeding (oesophagus), breathing, and pumping the blood to all parts of the body.

Chest pain is the most frequent reason for consultation and emergency room visits. Chest radiography is the most common imaging examination globally, critical for screening, diagnosis, and management of many life-threatening thoracic diseases. Today, knowledge and observation skills of radiologists are imperative to read CXRs. However, the pathologies have complex structures, and the lesions in images of the lungs have very slight differences wherein some miniscule details can be missed out by experts. Also, there is a lack of trained and expertise radiologists. Hence, in recent years there has been a lot of research to develop systems that can detect thoracic diseases as well as generate reports. In all these researches, the researchers have used deep learning, and neural networking models. This paper aims to explore these models.

## 2. BACKGROUND WORK

Pranav Rajpurkar\* et. al., this paper proposed the development of a deep learning algorithm called CheXNet, a 121-layer convolutional neural network trained on Chest Xray14 [7], currently the largest publicly available dataset. The model CheXNet inputs a chest X-Ray image and outputs the probability of pneumonia along with a heatmap localizing the areas of the image most indicative of pneumonia. Simple modifications to

CheXNet were made to detect all 14 diseases in Chest Xray14, it was found that CheXNet outperforms results on all 14 diseases [1]. Pulkit Kumar et. al., presented a cascaded deep neural network which could diagnose 14 pathologies. [2]. Xiaosong Wang et. al., proposed a novel Text Image Embedding network (Tienet) that extracts image and text representations distinctly. [3]. Qingji Guan et. al., in this paper, a 3-branch guided CNN (AG - CNN), is used. It reduces noise and enhances the alignment of the particular affected region in the X-ray image. [4]. Imane Allaoui et. al., this paper documents the extraction of relevant features from CXRs using pre-trained CNN and then classifying the extracted features with multi label problem transformation methods that transform the multi label problem to single-label classification [5]. Mohammad Tariqul Islam et. al., this paper detected and localized abnormalities in chest X-rays from different datasets using deep convolutional neural networks. As a measure of localization in the CXRs (Chest X-rays), heat maps are used. Trained classifiers were used to conduct localization experiments that proved to be greatly successful for abnormalities like cardiomegaly and pulmonary edema which are spread out spatially [6]. Xiaosong Wang et. al., this paper presents the chest X - Ray dataset, which comprises 108,948 frontal X - Ray images. Importantly it demonstrates the detection and localization of the commonly occurring thoracic diseases [7]. Jeremy Irvin et. al., presented CheXpert, a large dataset that contains 224,316 chest radiographs of 65,240 patients. A labeler is designed to automatically detect the presence of 14 observations in radiology reports, capturing uncertainties inherent in radiograph interpretation [8]. Juan Manuel et. al., this paper demonstrates an automatic normality/pathology classification of posteroanterior (PA) digital chest radiographs. The proposed method is not specialized in a given set of types of lesions or diseases but is able to detect anything that differs from normality [9]. Paras Lakhani et. al., recognizing the potential displayed by DCNN, a practical, result-based, statistical study was performed to determine DCNN efficiency by applying

GoogLeNet and AlexNet DCNNs in the classification of images as displaying pulmonary TB or healthy [10]. The model used by Li Yao et al. is an end-to-end, two stage neural network model. It is a combination of an image

encoder with dense connections, and a decoder with recurrent neural networks [11].

### 3. COMPARATIVE STUDY

**Table 1.** Comparative study of available literature.

Reference Paper No.	Aim/Objective	Model Used	Building Data	Target	Architecture Details	Result
1	To detect Pneumonia from Chest X-rays as well as 14 thoracic diseases at a level exceeding practicing radiologists.	121-layer Convolutional Neural Network	ChestX-ray14, National Institute of Health [7]	Thoracic Disease Label	DenseNet-121 [16] layer deep convolutional neural network replacing the fully connected network with single output.	The model was able to classify 14 different pathological diseases.
2	To build Computer Aided Diagnosis (CAD) systems by using deep convolutional neural networks.	Desnet-161 [16] Architecture with Boosted cascading	Chest X-ray14 [7]	Thoracic Disease Label	Cascaded network that uses Binary Relevance approach with Softmax loss and PWE loss.	The combination of boosted cascaded approach increased the performance compared to the single classifier for BR with cross entropy and PWE loss. However, the performance of classifier and localization needs improvements.
3	To extract the distinctive image and text representation of Chest X-rays using Text-Image Embedding Network (TieNet).	CNN-RNN model (Modified Resnet 50 model), Long Short Term Memory Network	ChestX-ray14, OpenI [17], Hand-labelled data	Thoracic Disease Label	End to end trainable CNN-RNN model Attention Encoded Text Embedding. Saliency Weighted Global Average Pooling. Joint Learning. Medical Image Auto-Annotation.	An accuracy of over 0.9 on average in AUCs was seen for the assignment of labels of the disease in the evaluation dataset.
4	To perform the task of thorax disease classification using Attention Guided Convolutional Neural Network.	Attention Guided Convolutional Neural Network	ChestX-ray14 Dataset [7]	Thoracic Disease Label	Attention Guided Convolutional Neural Network (CNN) Global branch as well as the local branch make use of Resnet-50 [12]. The local branch is used to focus on the lesion.	Average AUC 0.841 with ResNet-50. [12] AUC is improved to 0.868 by AG-CNN on combining the local cues and global information. Average AUC 0.871 with DenseNet.-121 [16].
5	To improve the performance of CAD systems for diagnosing thoracic diseases by proposing a new method comprising the use of CNNs for extracting	Convolutional Neural Network (Densenet-121 [16]) utilizing Multi-label Softmax Loss	ChestXRy14 Dataset [7], CheXpert Dataset [8]	Thoracic Disease Label	Last 14D fully connected, sigmoid activated layer removed. Adam optimizer is used.	The results show that the proposed method showed an average AUC of 0.882

	features from images as well transformation methods used in multi label classification.					
6	To localize and detect abnormalities in chest X-rays. Deep CNN is used on different datasets.	AlexNet [13], VGG-16 [15], VGG-19 [15], ResNet-50 [12], ResNet-101[12] and ResNet-152 [12]	Indiana Dataset [17], JSRT Dataset [18,19], Shenzhen Dataset [20]	Thoracic Disease Label	<b>DCNN Models:</b> AlexNet [13], VGG-Net [15] and ResNet [12]. <b>Localization:</b> Black level occlusion showed better results than the grey one as chest X-rays are grey.	Deep learning method improves the accuracy by 17 percent as compared to rule based methods. Localization of abnormalities that were spatially spread out like cardiomegaly were successful; however, it failed for features that were pointed like lung nodules.
7	To spatially locate and detect the eight common thoracic diseases.	DNorm [21], MetaMap [22], AlexNet [13], GoogleNet [14], VGGNet-16 [15], ResNet-50 [12]	ChestXray8 Dataset [7]	Thoracic Disease Label	<b>Unified DCNN layer</b> - transition layer, global pooling layer, prediction layer and loss layer. <b>Pre-trained models:</b> AlexNet [13], GoogLeNet [14], VGGNet-16 [15] and ResNet-50 [12], The FC layers and the final classification layer were left out. <b>Multi-label setup.</b>	The model used (ResNet-50 [12]) was able to classify the eight diseases. Localization was achieved by creating heatmaps with the help of transition layer's activation functions and the weights obtained by the prediction layer.
8	To present and analyse the CheXpert dataset and to design a labeler which would automatically detect the presence of 14 diseases.	Automated rule-based labeler	CheXpert Dataset [8]	Thoracic Disease Label	Uses self training approach, 3 class classification approach. Adam Optimizer is used. Labeler follows 3 distinct stages: 1) Mention extraction 2) Mention classification 3) Mention aggregation	Comparison to NIH Labeler: The labelling algorithm achieves a higher F1 score.
9	To perform an automatic normality/pathology classification of digital chest radiographs.	LBP feature extraction. GDAV, DV & CV classifiers	48 high resolution DICOM chest radiograph images (HGURS, Spain)	Thoracic Disease Label	Feature Extraction: LBP Classification: GDAV: Greater Difference in Absolute Value. DV: Discrete Voting. CV: Continuous Voting.	The CV method produces the best result among the 3 methods by giving 87% correct classifications.
10	To detect tuberculosis (TB) on chest radiographs, and thereby evaluate the efficacy of deep convolutional neural networks (DCNNs).	AlexNet [13], GoogleNet [14]	NIH ChestX-ray14 dataset[7], Shenzen dataset[20], Belarus Tuberculosis Portal[23], Thomas Jefferson University Hospital	Thoracic Disease Label	Training Augmentations: Rotations of 90°, 180°, and 270°, Contrast Limited Adaptive Histogram Equalization processing. Pre-trained networks were trained on images from ImageNet. GoogleNet [14], AlexNet [13] were used	AlexNet [13] and GoogLeNet [14] DCNNs were used together to make a classifier that had an AUC of 0.99.

					in both pre-trained and untrained forms.	
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#### 4. PROPOSED SYSTEM

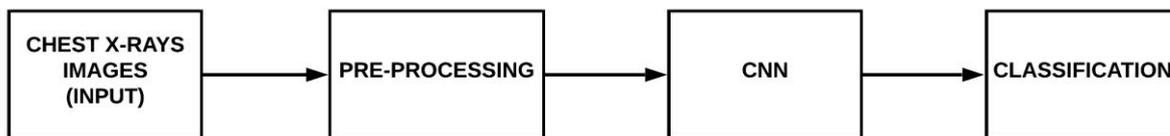


Fig. 1. Block Diagram of Proposed System.

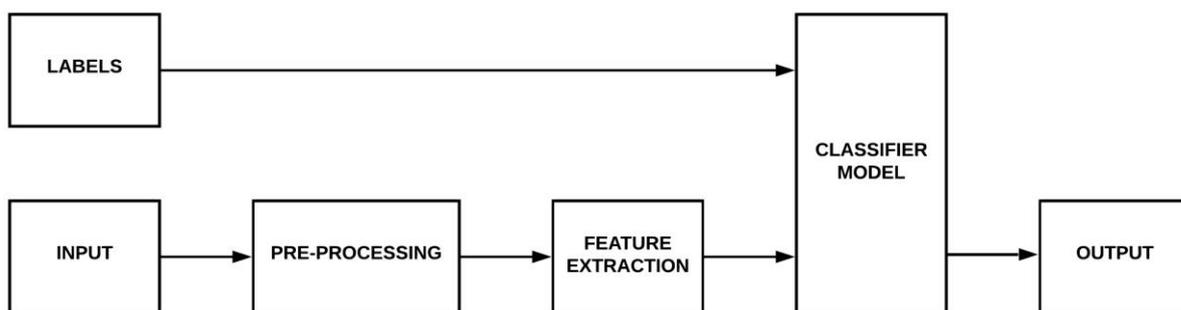


Fig. 2. Block Diagram of Training Phase.

The proposed system is designed with the aim of automating the process of detection, classification of thoracic diseases with the help of deep learning techniques.

The proposed system will involve use of deep convolutional neural networks for building a classifier that will extract and learn different features of the chest X-ray images along with their labels. Once the model is trained, it would be capable of detecting the thoracic disease given a new chest x-ray image. The system can be further extended to detect any type of thoracic disease.

The block diagram of the proposed system is shown in Fig 1 and Fig 2. and is explained as follows:

1. Input and Labels: The input of the system are frontal-view chest x-ray images with their corresponding thoracic disease as label like pneumonia, pneumothorax. The images will be fed to the convolutional neural network (CNN) in the form of batches and they will also be shuffled. This will make the model even more robust.
2. Pre-processing: The chest x-ray images will be preprocessed using various image processing techniques such as downscaling, normalization, etc. The training data can also be augmented using random horizontal flipping. This will help in improving the performance of the CNN.
3. CNN: The features of the images will be extracted using a deep convolutional neural

network model consisting of convolutional layers, batch normalization, ReLU activation and max pooling layers. The final layer will be a fully connected layer with output features corresponding to the number of classes which will help in classifying the image i.e predicting the disease label.

#### 5. IMPLEMENTATION

##### 5.1 DATASET

The dataset used for training is the ChestX-ray14 dataset [7] which contains 112,120 frontal-view chest X-ray images of 30,805 unique patients. A smaller dataset was created by taking 100 images from each class. Hence, 1500 images along with their labels serve as input to the model.

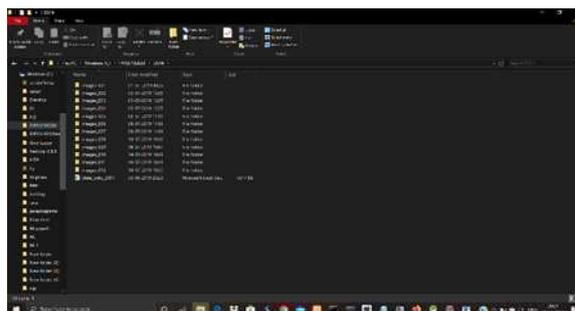


Fig. 3. The Dataset provided by NIH.



Fig. 4. Segregated images per class folders.

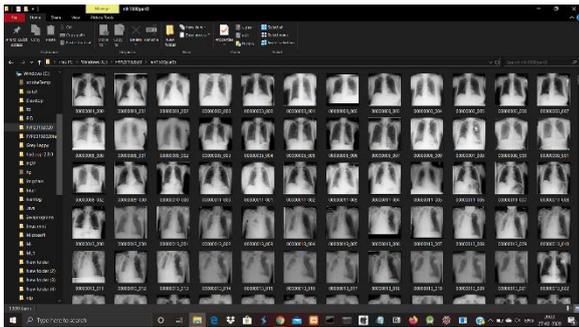


Fig. 5. 1500 images dataset(100 per class).

## 5.2 DATA PREPROCESSING

Input Images: The input images are downscaled to 224x224 so that it can be fed to the network. The images are also normalized based on mean and standard deviation and are also randomly horizontally flipped.



Fig. 6. Input Image.

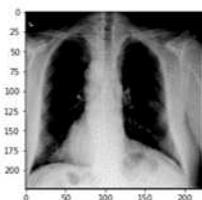


Fig. 7. Output Image after Data Preprocessing.

## 5.3 CLASSES (OUTPUT LABELS)

There are 15 classes(labels) out which 14 are disease labels namely Atelectasis, Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Pleural thickening and the last one is Normal study.

## 5.4 MODEL ARCHITECTURE

ResNet (Residual Neural Network) [12], is a deep neural network model architecture which uses residual blocks as a solution to vanishing gradients problem. The residual block makes use of identity mapping i.e. ‘Skip Connection’. The identity mapping does not contain any parameters, it is solely used to pass the original information from one layer to another layer without being hindered. ResNet has been one of the most successful deep learning neural network architectures.

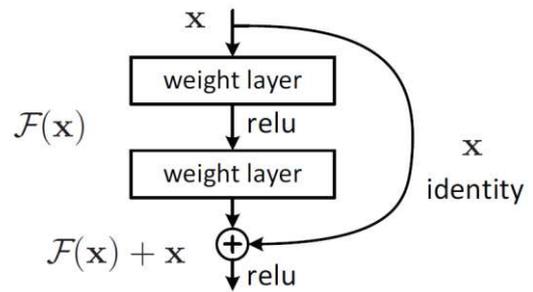


Fig. 8. Residual Learning : A building block [12].

The dataset of 1500 images is trained using ResNet -18 architecture which consists of a series of convolutional layers, batch normalization, ReLU activation layers. All these layers are then followed by an average pooling layer. The final and last layer is a fully connected layer.

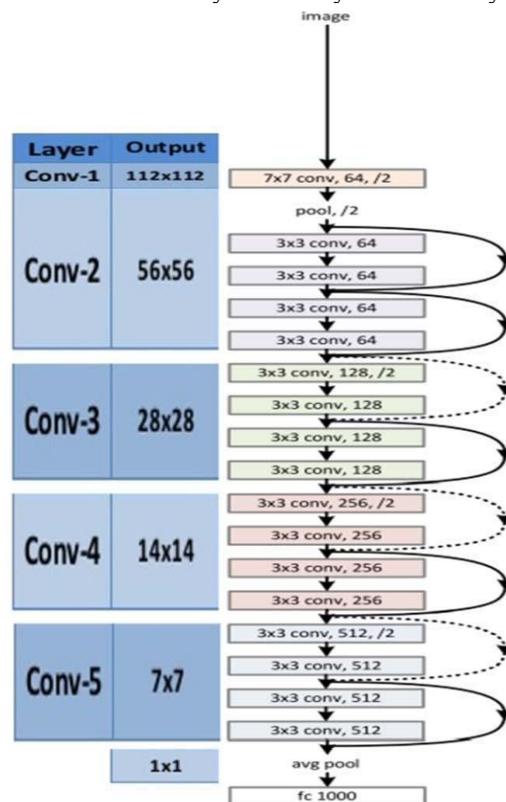


Fig. 9. Architecture of ResNet-18 [12].

## 5.5 TRAINING

The first layer of the architecture is modified to accept gray-scale images as input and the number of output features in the last layer is modified to the required number of classes for output. The model has been trained from scratch, hence, the pretrained model with Imagenet weights is not used. The dataset of 1500 images is split into 70% for training.

The network is trained using Stochastic Gradient Descent as an optimizer with a learning rate of 0.001, in 4 batches for 50 epochs. A training accuracy of 97.99% is achieved.

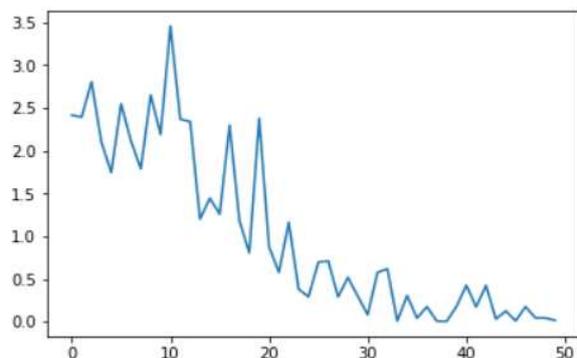


Fig. 10. Plot of loss per epoch.

## 6. CONCLUSION

The use of deep learning techniques in the field of detecting thoracic diseases from chest x-rays is still an active area of research. Thoracic diseases pose a serious, prevailing threat to the health of the global population. Hence timely diagnosis is critical. With the help of deep learning, faster and quicker diagnosis of thoracic diseases could save time. From the comparative study, the different methods used to process chest x-rays as well as detect the thoracic diseases was understood. The model proposed in the paper has been trained and the training accuracy achieved is 97.99%. Further work involves testing the model for different images belonging to each class and obtaining the results.

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