Pneumonia Detection Using Deep Learning Approaches

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***Abstract*— Pneumonia is among the most prevalent diseases, and due to lack of experts it is difficult to detect. This paper focuses on surveying and comparing the detection of lung disease using different computer-aided techniques and suggests a revised model for detecting pneumonia, which will then be implemented as part of our future research. In this survey, we also tried to familiarize ourselves with the different image pre- processing techniques used to convert raw X-ray images into standard formats for analysis and detection, machine learning techniques such as CNN, RESNET, CheXNet, DENSENET, ANN and KNN, which is an important phase in accurate pneumonia detection.**

Keywords—pneumonia detection, CNN, Chest radiography, deep learning, machine learning, lung segmentation

I. INTRODUCTION

Around 450 million people worldwide (7% of the population) are affected by pneumonia and result in about four million deaths each year [10]. Pneumonia is the most serious illness in children younger than 5 years of age [9]. India, with 158,176 deaths in 2016, continues to have the highest number of pneumonia infant deaths in the world. The report, released on World Pneumonia Day, found that by 2030 nearly 11 million children under five were likely to be killed by the infectious disease [8]. In the 19th century, William Osler considered pneumonia to be "the captain of the men of death."

Physical examination, medical history, clinical examinations such as sputum or blood test, chest X-rays, and some other imaging techniques are the various ways in which doctors diagnose pneumonia in hospital patients. Chest X-rays, which is now becoming cheaper due to technological advances in bio-medical equipment, is the most common technique used for detection of pulmonary diseases such as cheese pneumonia. This problem of availability of experts can be solved by computer aided diagnosis. Current development in the field of artificial intelligence can be lot useful. Convolution neural networks can be used to classify chest X-ray images to detect if pneumonia is present or not.

II. RELATED WORK

A. Techniques using artificial intelligence

In [1] researchers have tried to apply different techniques for minimizing dimensionality. The dataset used is a JSRT dataset comprising 247 X-ray images of 154 lung nodules and 93 lung nodules-free events. The JSRT dataset data study reveals that this tiny dataset is an unbalanced dataset considering the presence and absence of nodules, nodule type (malignant / benign), nodule size, degree of subtlety, nodule size distribution, etc. Several datasets from the current JSRT dataset are extracted. After removal of bone shadow, BSE-JSRT data set (dataset #02) was obtained. Segmented JSRT (dataset #03) and segmented BSE-JSRT (dataset #04) were obtained after JSRT and BSE-JSRT segmentation, i.e. cutting sections of the right and left lung in standard CXRs. T-SNE technique is used to remove outliers, i.e. abnormally small lungs and heart area inclusion, as given by dataset #5. The multiple data sets collected were used to perform multiple learning and validation runs. Highest accuracy was obtained when most of the processed data set #05 was used, which is 0.71, and the lowest data set #04, which is 0.56, was obtained. The bone shadow exclusion dataset #02 showed no great improvement with accuracy that was 0.65 compared to the original dataset #01.

Authors in [2] provided the aid of the artificial neural network a tool for detecting lung diseases like those of TB, pneumonia and lung cancer. Pre-processing methods of image are used here to delete irrelevant data. Equalization of the histogram improves the image and filtering of the image reduces noise and sharpens the image with a high pass filter. Area of interest is used for the creation of lung segmentation. Diagnostic features such as perimeter, area, irregularity index and equal diameter and irregularity index are extracted as well as statistical features such as standard deviation, mean and entropy. Feed-forward and back-propagation neural network are used for image classification to detect lung diseases. The dataset used was from Sasoon Hospital of 80 patients. Accuracy of 92% was achieved using the feed-forward neural network. Its limitation is that it not robust when there are changes in the position and size of the CXR.

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In [3] researchers present a lung cancer identification method using X-ray images from the chest. The solution takes place in two stages. In the first step, a sequence of image processing techniques is used to eliminate noise and minimize the region of interest that is a nodule that is a suspected nodule area of 65x65 squares. The square pixels were taken as device data. The pixel intensity values are stored in the file. To train the system it is used in the next stage. The database is categorized into different categories and the information it contains is used to train and check the process. Two types of pixel-based and numerical feature-based inputs are performed in the second stage of the neural network learning. For pixel-based intensity vector outputs, purelin and tansig transfer functions were used and two tansig transfer functions were used for input vectors for the numerical feature base. Using a pixel-based technique, 96 percent accuracy was achieved in this method and 88 percent accuracy was achieved using feature-based technique.

In paper [4], a carefully controlled CNN, the modified version of CNN, was used to diagnose chest X-ray thorax disease. A thorax infection normally occurs in disease-specific small (localized) areas. Network performance is impaired due to poor CXR alignment. This issue is addressed in this paper by proposing three-branch AG-CNN. It learns to avoid noise and improve alignment from disease-specific regions. It also incorporates a global branch to reduce the local branch's lost discriminatory signs. In particular, they first use global photos to know a regional CNN division. Instead, directed by the global branch's attention heat map, they infer a mask from the global image to crop a discriminative area. Local region trains a local branch of the CNN. Eventually, the final pooling layers of the global and local branches are concatenated to fine-tune the fusion component. The data set used is the dataset of ChestXray14. They get a good global baseline first, with ResNet-50 generating an average AUC of 0.841 as backbone. After convergence of local signals with global information, AG-CNN raises the average AUC to 0.868, while average AUC 0.871 is obtained by using DenseNet-121.

The researchers in[5] developed a cheXNet algorithm, which is a CNN of 121 layers (DenseNet) . It takes the chest-Xray images as input and produces the likelihood of pneumonia including a heat-map that locates the most likely area of pneumonia. They change the end layer with one that has just a single output and then add a sigmoid nonlinearity. They randomly divide the data set into practice (98637 images, 28744 patients), validation (6351 images, 1672 Patients), and testing (420 images, 389 patients) for training the model. Before inputting the images into the network they resize the images to 224x224 and normalize it and training data is augmented with random horizontal flipping. They compared their model with four radiologists on F1 metric. cheXNet earns a score of 0.435 higher than the average of 0.387 for radiologist.

In [6] the authors obtained the data from three separate hospital system and asses how CNNs generalized across three hospital system for pneumonia detection. For this, they use 158,323chest radiograph from NIH, MSH and IU institution. For classification, they reproduce Rajpurkar and Colleagues cheXNet model. To classify frontal radiographs in the IU and MSH datasets they use ResNet-50 CNNs. For model training they use torchvision and PyTorch 0.2.0. All images are resized to 224x224. CNN's used in this were trained with DenseNet-121 architecture with an added dense layer (n=15). It used sigmoid activation (for binary classification) and softmax activation (for n> 2 multiclass prediction). Through this they find that on internal test set the model perform better rather than external. The model performance decreases on the external test set.

In[7] the researchers test the efficacy of the neural deep convolution network to detect tuberculosis using chest x-rays. AlexNet and GoogleNet, two separate DCNNs, were used to identify pulmonary or healthy objects. Both untrained and pre-trained networks on ImageNet were used. The dataset consisting of 1007 chest radiograph is used which were split into 68%, 17.01% and 14.9% for training, validating and testing respectively. The radiographic images of the chest were resized to a 256x 256 matrix and converted to images in Portable Network Graphics format were loaded to a computer with a deep learning framework for linux os. All images have been improved by using 227x 227 pixel random cropping, mean subtraction, and mirror images, which are pre-constructed choices within the Caffe system in this finding that DCNNs can identify TB with 0.99 AUC. They found that ImageNet's pre-trained DCNNs performed better than untrained networks with daily images.

In [9] researchers worked with various deep learning models and introduced a cascade deep neural network diagnosing all 14 diseases. They use the data set of ChestXray14. They train DenseNet with a basic approach to BR, lose pairwise error (PWE) and compare results. They design boosted architecture of classification specifically designed for the task of classification of multi-labels. They designed their cascade network in which predictions from all previous levels were received as input by each successor level in the cascade network. For both PWE loss and cross-entropy, they used 6-level cascading. Increasing degree of cascading consists of two layers that are completely connected. They used non-linearity of RELU and a 0.5 dropout between layers that were fully connected. They found that a boosted approach to cascade increased performance compared to single classifiers trained with loss of PWE and cross-entropy.

In [10] researchers, using ResNet CNN template to differentiate between benign and malignant nodules to detect lung cancer. The template will identify radiographs with a sensitivity of 92 percent and 86 percent precision as a nodule or non-nodule. It can also determine the regions of the general nodule, but cannot determine the exact positions of the nodule. To determine if the JSRT dataset is benign / malignant. The diameter of the nodules ranges from about 30 to 170 pixels. The JSRT dataset also contains the size and coordinate of the center of the lung nodule, if present. They measure the model’s ability to classify radiographs by examining the classification accuracy on the test set.

In [11] the authors used the ChestX-ray8 of 108,948 frontal view X-ray images of 32,717 unique patients with the text mined eight disease image labels. They prove that these frequently occurring thoracic diseases can be identified and also located spatially through a unified, weakly supervised multi-label image classification and disease localization system, verified using their proposed dataset. They provide a unified weakly-supervised multi-label image classification and pathology localization system for detecting and localizing common thoracic diseases, capable of detecting presence of multiple pathologies and then generate boundary boxes around the respective pathologies. They detect whether one or more pathologies are presented in each X-ray image in the Unified DCNN system, and locate them using Multi-label configuration, Transition Layer, and Multi- label Classification Loss Layer activation and weights extracted from the network. They also use Global Pooling Layer Weakly-Supervised Pathology Localization and Bounding Box Generation Prediction Layer.

In [12], the authors centered on the advanced calculations for tackling the issue of programmed demonstrative of thorax illnesses based on X-ray pictures. Approaches are utilized for the advancement of an unused calculation for the programmed demonstrative of therapeutic pictures. It incorporates 4 steps: Picture preprocessing in which it essentially distinguishes classifies and move forward by and large accuracy of determination. Lung field's division which permits Location of pathologies found interior lung borders conjointly distinguish pathology due to organs shape changes. Highlights calculation can be done amid therapeutic pictures discovery. Calculated highlights can be separated into three categories - textural, geometric, differentiate. Classification is utilized for calculation classification. It's investigation of commonly utilized calculations for diagnosing thorax infections. The main point of view is MIL-based approach for preparation of the classification algorithm.

Authors in [13] described how the machine learning became the leading technology for tackling CAD in the lungs by doing rule-based study. For tackling CAD in the lungs machine learning is the dominant technology. It is a rule-based study on Deep learning in image analysis, Rib detection and suppression in chest radiographs, feature extraction from CT, Airway segmentation in CT, Nodule detection in CT, Nodule classification and characterization in CT. Rule-based image processing is used for finding candidates, followed by feature extraction and classification for each candidate in the computer-aided detection system. Deep learning is an excellent technology.

Authors in [14] test, visualize and clarify the quality of tailored CNNs for pneumonia detection and further distinguish in pediatric CXRs between bacterial and viral forms. They present a unique visualization technique to locate the region of interest, which is deemed important to model predictions in all the inputs that are from the class predicted. They evaluate the quality of the models to the underlying tasks statistically. The conclusion is that in detecting the disease and differentiating between bacterial and viral pneumonia, the modified VGG16 model achieves 96.2 percent and 93.6 percent accuracy. In all performance metrics, the model outperforms the state of the art and demonstrates improved generalization and reduced bias.

In [17], the researchers experimented with bone shadow and lung segmentation techniques to detect cancer. For 7 layers of convolution, they used CNN. They took JSRT data set to perform bone elimination, lung segmentation by applying UNet-based CNN to 512* 512 pixel image, and then compared CPU and GPU training model and found that GPU performed 7 times better than CPU, and obtained pre-processing software like bone shadow to remove segmentation.

In [18], researchers used a two-stage model, the first stage was chosen to learn high-resolution medical images, and the second stage was designed to enable the model to exploit statistical dependencies between labels to improve predictive accuracy. We use LSTM to estimate 14 chest x-ray trends in pathology. They use 2d convent to encode and decode using RNN-based activation function in which they use sigmoid. We do densely connected image encoder in this model first, predict the tag, and then train with MLE. This was done on a dataset which contains total 112120 chest x-rays in PNG format of 1024*1024 pixel.

Authors developed the CNN-based model for various interstitial lung diseases in [19], which can be a lung tissue inflammatory condition. They used a dataset of 14696 image patches extracted from 120 CT-Scan from different hospitals, including cancer, pneumonia, TB, etc. Also known as AlexNet, they proposed deep CNN. That consists of five layers with activation of LeakyReLU. They compared various techniques such as VGG-Net and LeNet. And with 85.5 percent, they get the best result with CNN. And their model can train on more lung patters easily as well.

In [15], the authors used a computer for presenting experiments and results on the identification of lung tuberculosis (TB). They attempt to minimize patient waiting time in obtaining X-ray diagnosis, outcome of lung TB disease due to the mismatch of the ratio of the patients to the number of radiologist. To make the diagnosis, Radiologist makes visual examination on the textural feature of thoracic X-ray images. They take advantage of textural features determined by the machine to be used as a criterion in the classification of objects as TB or non-TB. Five variables are measured using a statistical function of picture histograms: mean, standard deviation (STD), skewedness, kurtosis, and entropy. Using the Principal Component Analysis process, the measured features are then reduced to two and one main feature. Used as a descriptor the minimum distance classifier method based on two and one main feature. The consequence of the experiment is the identification of non-TB and TB images based on statistical features on the object histogram.

B. Other miscellaneous techniques

In [8], the researchers built a simple tool to use cough sound analysis to diagnose pneumonia. Patient cough sound is captured using a mobile phone recorder and then wavelet sound decomposition is performed and statistical criteria for classifying cough into pneumonia or healthy are found. The programming is performed in MATLAB R200a. First they perform signal segmentation using FFT (Fast Fourier transformation).after that they perform wavelet decomposition using continuous wavelet transformation. Next, Power spectral density (PSD) is performed after the discovery of these numerical parameters. CWT (continuous wavelet transformation) coefficients that give threshold values are determined for skewness and kurtosis. After the signal analysis threshold values are used to classify the signal into pneumonia or not.

In [16], the researchers used image processing methods to detect pneumonia in chest X-rays. They found a 40 CXR dataset and worked on it using Python 2.7 and the same image processing libraries as OpenCV etc. They created their own resizing algorithm, histogram equalization, abdomen region cropping, ling boundary, threshold calculation, ratio calculation, compute a ratio for each lung. Their original image was 2048* 2048 pixels, so they resized various pixel sizes and compared the time and result, finding that 800* 800 was the best pixel size, using resize feature. They use histogram equalization to improve contrast by equalizing their feature. The abdomen is cropped in the cropping area below the lung. Lung boundary is then identified by dividing CXR into half and drawing 100 horizontal lines. And last they do thresholding to separate healthy part of the lung, they have used Otsu thresholding techniques. In this paper, they can only detect lung boundary and compute on that region.

In[20] a hybrid detection method was used by the researchers to detect tuberculosis. They use data set containing 20 frames, 19 non-cavity, and 110 standard set cavity collection. They first perform image scaling on this dataset and then remove the lower part of the lung as the tuberculosis cavity on the top part of the lung is present. They conducted automated initialization, identification of hybrid data, optimal selection of thresholds, and finally detection of cavities. They compared GICOV, circularity, and hybrid and obtained the best hybrid result with 85.35 percent accuracy.

Table 1 shows the Comparison of various Pneumonia & other lung diseases detection techniques.

Table 1: Comparison of various Pneumonia & other lung diseases detection techniques

Ref.no. Publisher/ Year	**Problem definition**	**Processing techniques**	**Algorithms**	**Tools and technologies used**	**Accuracy**	**Data set**	**Strengths**	**Weakness**
[1] ICACI/ 2018	Detection of lung cancer	Bone shadow exclusion(#2) Segmentation(#3) Segmentation after bone shadow exclusion(#4) Exclusion of outliers by t- SNE method(#5)	CNN	Tensor flow GPU used NVIDIA Tesla K40c card	71%	JSRT	Highly accurate	It uses small dataset which might not contain all the cases
[2] IEEE/ 2016	Detection of lung diseases like Lung Cancer, TB , Pneumonia	Image pre-processing Lung segmentation Feature extraction Image classification	ANN(Feed forward neural network) with sigmoid activation function	NA	92%	Sasoo hospital, Pune (Dataset of 80 patients)	It can detect multiple lung diseases	It is not robust when there are changes in the size and position of CXR images
[3] International Journal of image-processing/ 2011	Detection of lung cancer	Pre-processing(Median filtering, Sharpening and histogram equalization) Binary image(thresholding) Lung region segmentation	ANN	NA	96%(Pixel based technique) 88 %(Feature based technique)	JSRT	It is earliest approach to detect lung cancer nodules	Nodules identification is complicated by contrasting outlines of blood vessels and ribs
[4] arXiv 2018	Detection of thorax diseases	Global branch takes input Local branch is trained after discovering local lesion region and cropping Finally global and local branches are combined to fine tune	Attention guided CNN (sigmoid function)	NA	AUC(0.871)	Chest X-ray 14	It yields better accuracy compared to other methods	Relatively insensitive to parameter changes
[5] Stamford University/ 2017	Detection of Pneumonia	Image downscaling to 224*224 Normalize based on standard deviation and mean Random horizontal flipping	DCNN (DenseNet)	NA	AUC(0.76)	ChestX-ray14	indicating absence or presence of 14 different pathology classes	Only frontal radiograph were present

[6] PLOS/2018	Detection of Pneumonia	Deep learning supervised deep learning model ,takes an image as input and predict the probability of predicted class	CNN(DenseNet) ResNet-50	PyTorch0.2.0 torchvision	Internal(AUC 0.931) External (AUC 0.815)	1.NIH(chest Xra y14) 2.IU(Open-I) 3.MSH(mount sinai hospital)	highly accurate	CNNs do no perform well on external data as compare to internal data
[7] RSNA/2017	Detection of Tuberculosis	Images are resized to 256 x 256 Images are augmented using 1..Random cropping(227x227 pixel) 2.mean subtraction 3. mirror images	AlexNet GoogleNet	1.Linux OS 2.Caffe framework	AUC(0.99)	1007 chest radiograph	ImageNet performed better than the untrained networks	This algorithm can only use for TB detection
[8] IEEE/2017	Detection of Pneumonia	Signal segmentation Wavelet decomposition Power spectral density Statistical parameter	Fourier transform Continuous wavelet Transform	MATLAB	NA	NA	This is low cost, non-contact, and noninvasive	Used very less input/refers (22 signals)
[9] Springer/2018	Meltilabel classification of thoracic diseases in chest radiographs	Binary relevence(BR) PairWise Error(PWE) Softmax activation weighted cross entropy loss calculated	Baseline: DensNet161 Boosted cascade network	NA	NA	chestX-Ray14	Boosted cascade approach give increased performance	BR approach it does not model the interclass relation with example
[10] Isabel BushStanford Computer Science353 Serra Mall, Stanford, CA 94305	Distinguish between benign and malignant nodules to detect lung cancer	Localisation and classification	ResNet models with deep CNN	NA	68%	JSRT	Higher accurate	ResNet model is unable to determine its precise location
[11] IEEE/2017	classification of eight common thoracic diseases	Weakly-supervised pathology localization Multi-label disease classification	Unified DCNN Framework	NA	NA	ChestX-ray8	NA	NA
[12] HIKARI ltd/2015	Detection of thorax diseases	Image pre-processing, lung fields segmentation, features calculation, classification	CAD System	NA	NA	No dataset used	Effective methods of image preprocessing, features calculation	Automating thorax diseases detection still remains unsolved due to its complexity
[13] Springerlink February 2017	Dominant technology for tackling CAD in the lungs	Pulmonary image analysis Computer-aided detection Computer-aided diagnosis Image processing	rule-based study	NA	No dataset used	NA	ConvNets are better feature extractor	Computed tomography (CT)
[14] Applied science 2018	Detection of pneumonia	Data Collection and Preprocessing	VGG16	CAM and grad-CAMvisualization tools	96.2% - detecting diseases	chestX-Ray14	Highly Accurate	NA
[15] IEEE/2013	Detection of Tuberculosis	Pre-processing Features Images Extraction Images Identification	Statistical Image Feature PCA for Feature Vector Dimension Reduction Minimum Distance Classifier	NA	95.7%	No dataset used	Pre- processed images used	NA
[16] IEEE/ 2017	Detection of Pneumonia	Indigenous algorithm Resizing Histogram Cropping Lung boundary Thresholding Compute ratio	No algorithm used	Python 2.7 And OpenCV's Library	NA	40 dataset CXR	Identified lung region by rib cage boundary identification	The Otsu thresholding which was not successful
[17] National Technical University of Ukraine	Detection of lung cancer	Bone elimination Lung segmentation Resize to 256*265	UNet-based convolutional neural network	Tesorflow,GPU (NVIDIA tesla K40c)	NA	JSRT	Model has high training accuracy	The trained data set was not accurate

[18] Enlitic/ 2018	computer-assisted diagnosis (CAD)of chest x-rays (CXR)	Lower the resolution	ConvNets as encoders and decoders based on RNNs	NA	NA	112,120 frontal-view chest x- rays in PNG format	Two-stage end-to- end neural network model	Limited dataset was used
[19] IEEE/ 2016	Detection of different lung disease	Resize Convolutional layers Leaky ReLU Avg. pooling Fully connected layers	Deep Learning Proposed CNN	NA	85.5%	14696 image patches from 120 CT-scan	The method can easily trained on additional textural lung patterns	The large no. of parameters and slow training.
[20] IEEE/2010	Detection of Tuberculosis	Scaled Exclude lower part of lung Histogram equalization Gaussian smoothing	Hybrid knowledge guided detection framework	NA	82.35%	Cavity set:20 Non-cavity set:19 Normal set:110	This is best method to detect TB from CXR	It fail to detect cavities

C. Datasets

a. Indiana dataset

In [23] researchers addressed with Indiana University School of Medicine the dataset obtained from hospitals in affiliation. This includes 7470 chest x-rays bearing annotations of disease frontal and later al pictures such as pleural effusion, distortion, pulmonary edema, cardiac hypertrophy.

b. Kit dataset

In [24] the dataset contains 10,848 cases from the Korean Tuberculosis Institute including 3828 cases of abnormalities and 7020 cases of normal.

c. MC and Shenzen dataset

In paper[21] researchers speak about the two datasets made available by the U.S. National Medicine Library, which are the Mountgomery county chest X-ray dataset (MC) and the shenzen chest X-ray dataset made for Tuberculosis detection. The MC Dataset was collected in partnership with the Health and Human Services. Department, Montogmery country, Maryland, USA. It contains 138 frontal X-rays of which 58 are manifestation of TB and 80 are normal cases. It also contains other data like patient's gender, age and abnormalities seen in the lung. The Shenzen dataset was collected in collaboration with Shenzen No.03 People's Hospital. It contains 662 frontal chest X-ray images of which 336 are with manifestation of TB and 326 are normal. It also contains other data similar to MC Dataset. All the images are in PNG format.

d. JSRT dataset

In [25, 26] the dataset is created by Japanese Society of Radiological Technology and contains 247 chest radiographs of which 154 are with nodules and 93 without nodules.

e. Chest X-ray 14 dataset

In [11] the sample was taken from the hospital medical PACS databases associated with the National Institute of Health Medical Center and consisting of approximately 60% of all hospital frontal X-rays.

Table2 below gives the details about the different datasets used in the various research papers.

Table2: Details about the different datasets.

Sr. no.	**Name of Dataset**	**Diseases**	**No. of Images**	**Image size**	**Type of Images**
[23]	Indiana dataset	pleural effusion, opacity, pulmonary edema, cardiac hypertrophy	7470	NA	frontal and lateral
[24]	Kit dataset	Tuberculosis	10848	NA	NA
[21]	MC dataset	Tuberculosis	138	4020*4892	frontal
[21]	Shenzen dataset	Tuberculosis	662	NA	frontal
[25,26]	JSRT dataset	Lung cancer	247	2048*2048	NA
[11]	Chest X-ray 14 dataset	14 Diseases	112120	1024*1024	frontal

III. PROPOSED METHODOLOGY

The proposed pneumonia detection system technique can be conducted in two steps. Image preprocessing techniques will be used in the first step to boost design performance such as resizing and histogram equalization. Then use the t-SNE to exclude outliers that could affect the outcome and improve the accuracy. We will be using lung segmentation in the next stage to obtain the area of interest. At the end classification algorithm will be used to detect the presence or absence of pneumonia using VGG16 as the baseline algorithm which is built on CNN which can be further modified to achieve better accuracy than Rajaraman[14] which used customized VGG16 as the algorithm to and achieved accuracy of 96.2% and 93.6% for detection and classification of pneumonia, as shown in fig1.

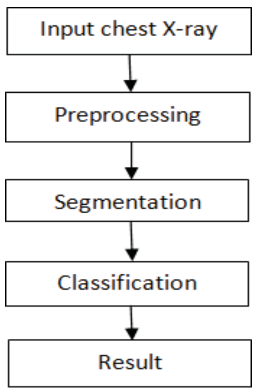

Fig1: The proposed methodology

In the second phase the pre-trained network can be deployed on end devices like smart-phones to achieve portability

IV. CONCLUSION

There are several approaches used to detect lung diseases using computer-aided diagnoses but techniques using machine learning algorithms have proved to be more reliable. CheXNet by Rajpurkar[5] produces good results for detecting various diseases but is then left behind by Attention guided CNN[4] which achieves better accuracy in detecting various lung diseases but fails to do so for a hernia when compared to Rajpurkar but from the later methods used by Rajaraman [14], it is observed that VGG16 achieves the highest accuracy so far. It can also be observed that the speed and accuracy of the network can be increased by various image preprocessing techniques. It is also observed that the exclusion of outliers improves the output result. From various datasets used to train the model, it has come forward that the use of versatile and moderate size dataset with images from different hospitals and radiologist improves the accuracy and gives a better result when tested on images from different datasets. The images in dataset14 where 14 various lung diseases are identified. It can happen that a disease can be detected even when it is not present due to presence of some other disease and this problem of false disease detection has to be solved. We will try to solve this problem by creating a model for a single disease which is pneumonia and the use of a dataset with the presence and absence of a single disease to avoid false detection.

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