Research Article

Classification of Healthy Control and Abnormal Lung Chest Radiography images using CBIR and Atlas-Based Graph cut Segmentation by Transfer Learning CNNs

Jeevitha Sivasamy[a], and T.S. Subashini[b]

[a] Department of Computer and Information Science, Annamalai University, jeevithamca06@gmail.com

[b] Department of Computer Science and Engineering, Annamalai University, rtramsuba@gmail.com

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Abstract: The prominent aim of systematic lung pathologies detection is to improve health outcomes among people with pulmonary diseases and decrease thorax diseases disseminating among the peoples through improved lung abnormality detection, reduction in diagnostic delays and early treatment. Today technological breakthroughs have led to the discovery of various invasive clinical imaging methods for the analysis of lung diseases. In this work, an integrated Computer-Aided Diagnoses (CAD) based on Deep Learning (DL) to diagnosis of lung diseases on chest radiographs was proposed. In this paper we have used JSRT datasets it contains 247 images are employed atlas-based graph-cut segmentation algorithm for extract the lung regions and segmented regions are input to the Convolutional Neural Network (CNN) with augmentation techniques that are provides the training accuracy is 97% and 89% for testing accuracy.

Keywords: Atlas-Based Segmentation, Graph Cut, Convolutional Neural Network (CNN), Deep Learning, Lung Diseases, Chest radiograph.

1. Introduction

In medical fields various modalities have been used for diagnosis of diseases. Generally, the medical X-rays are used to diagnose sensitive human organs such as knee, chest, teeth skull and so on by medical specialists. Particularly, lung pathologies explore to diagnosis by the Chest radiographs. This is because chest X-rays are one of the most efficacious diagnostic tools in the detection of lung pathological changes and beyond their harmless properties and economic considerations.Chest radiograph are the most common film taken in radiography and performed frequently preliminary in the assessment of a vast number sick patients. The benefits of the chest X-rays are quick accessible, wide range of pathology can be identified, simple, low cost it is affordable even poor people, sensitive excellent resolutions. Standard projections of chest views are Posteroanterior (PA) view, Anteroposterior (AP) view and Lateral views.

Digital chest X-rays allow the use of computer vision techniques to automatically lesions segment, detect and diagnose various chest related diseases. Fig 1(a). Shows the Posteroanterior view digital chest X-rays and fig 1(b) is anteroposterior view of chest radiograph.

Fig.1(a), (b) Digital chest X-rays PA and AP view

Classifying and detection of chest X-ray abnormalities is considered a complicated task for radiologists; therefore, several methods have been proposed by the researchers to make this task more accurate. Over the past several decades, computer-assisted diagnostics systems have been developed to obtain beneficial information from X-rays. However, these CAD systems cannot reach a censorious stage in making decisions about the conditions of an X-ray disease [1-3]. Thus, their role was left as a visualization process to assist doctors in decision making. Numerous researches have been done on the detection and diagnosis of chest pathologies using ArtificialIntelligence (AI) methods. Multilayer,learning vector measurement, probabilistic, and general regressions neurological networks has been used to diagnose disease in chest. In [4], chest radiographs are considered to diagnose lung abnormalities such as tuberculosis (TB), pneumonia and lung cancer. The Histogram Equalization (HE) in the image segment was used for image pre-processing, and the Feedforward Neural network (FFNN) was wielded for classification purposes. Natheless, their performance is not as capable as that of deep networks based on accuracy, calculation time and Minimum Square Error (MSE). These deep networks showed extraordinary accuracies in performing such a task. Research on the use of these networks for medical imaging fields for disease classification tasks has been successful, and outcome results has shown that depth networks can effectively excoriate beneficial features that discriminate between different types of images [5-8].

Recent short time ago, some studies based on deep learning models [9] have provided well options to other convolutional machine learning methods classification methods. The CNN plays breakthrough transfer learning methods for diseases detection, object detection in various fields, Natural Language processing, forensic image processing and so on. Combining pre-trained CNN and multiple instance learning algorithms to increase the ability of CNN to recognizedistinguish types of symptoms in chest X-rays proposed in [10]. Transfer learning (TL) to ameliorate the TB screening [11] and convolutional deep network to extract high- and low-level features automatically for improving detection accuracy [12]. These methods refrain from the issue of manually extracting parameters by automatically extracting high-level hierarchical features for TBidentifications directly from the input source data [9]. However, these systems take entire CXRs as classification tasks. This result in the drawback of low effectual information density. In the feature extrication process, this is not easy anymore to get the most useful features directly from the input data information, which leads up to incorrect classifications due to unclear result ranges.

Therefore, in this proposed work distinguish from previous tuberculosis and other lung diseases classification detection methods. Instead of using the segmented images to tuberculosis recognition target. The atlas-based graph cut segmentation methods [12] have applied which is reduce the amount calculations in unwanted regions of the whole chest X-ray image and it is reduce the computation time of CNNs training iterations and also to allow us to breed precise results. In the meanwhile, in order to avert the problem of produce feature manually, the CAD based on CNNs is proposed for object detection of tuberculosis in chest radiographs.

The first stage has applied accurate lung boundary segmentationof CXR. The segmentation methods(include survey paper and other segment reference) and detection of diseases is important in CAD. Graph cut segmentation [12] was performed accurately in lung boundary segmentation for chest images, since it could beperformed end-to-end training uses very minimal images and manipulate complex shapes change and the surrounding tissues. The segmented stage has been achieved precisely on JSRT dataset and the segmented images arefed to the transfer learning convolutional neural networks structures. The second stage is proposingeffective tuberculosis classifications in chest X-ray images using CNNs which is exceeds the performance of previous methods. Our proposed systems can efficiently improve the screening of TB by public health organizations and services.

2. Literature Review:

In this section the research seen in the literature review of CXR machine learning segmentation methods and convolutional neural network classification of tuberculosis diagnosis. The segmentation on chest x-rays the literature includes edge-based segmentation, morphological operations[13], region growing algorithms, ridge detections. The successfulness of any CAD based system be dependent on accurate segmentation. An effective development of automated lung segmentation methods and survey is given in [11].A heuristics edge approach [3my seg] and the Connected Component Labeling (CCL) and threshold have used to segment the lungs in [5 my seg].Adaptive thresholding method is employed for medical image segmentation by cheol-Hwan et al (2015)[14]. In [15] abnormal regions of lung segmentation by improved Active Shape Method (ASM). Structured Edge Detector method(SED) which is deployed for lung field segmentation from lung boundary maps in CXR[16].

However, the correct segmentation will lead to accurate classification and detection for diseases diagnosis.Recently, some studies stand on Deep Learning (DL) approachable methods [8] have provided optimal alternatives to other convolutional classification methods. In [8] proposed a method of combining pre-trained CNNs andmulti-level learning algorithm is to increase the ability of CNNs to recognize different types of pathologies or diseases in chest X-rays.Convolutional Neural Networks has been implemented to various medical imaging classifications due to it is ability of extracting different level of features from images [5-8].TB and non-TB cases classification has been done in nine different types of deep CNNs such as ResNet18, ChexNet, Inception V3, VGG19 and so on [17].Using CNN architectures to assist in the successful diagnosis pleural effusions, Lung cancer predictionon chest radiography images in [18].

3. Proposed Methodology:

a) Dataset: This study was evaluated Chest X-rays dataset publicly available on Japanese Society of Radiological Technology (JSRT).This dataset has small number of images. The datasets contained 154 abnormal CXRs and 93 images are healthy controls. These Chest X-rays had pixel resolutions of 2048X2048 with .png extension and grayscale images.

Lung boundary or region segmentation is the predominant task in the detection of plurality categories lesions in computer aided systems (CADx). In segmentation, it is important not only to classify pixels into foreground (FG) or background (BG), but also to conserve their spatial information. Lung boundary segmentation is the prominent task in the detection of lesions and classifying diseases in computer aided systems. In segmentation, it is required not only classify pixels into background and foreground but in addition to keep their spatial information.In this work to classify into CNNseither healthy or abnormal of the lungs [19] using atlas-based graph cut segmentation on chest radiography images. The segmentation methods have three steps are: Content Based Image Retrieval (CBIR) frame work, Creation of lung masks, Segmentation of lung regions. The overall segment diagram is shown Fig 2.

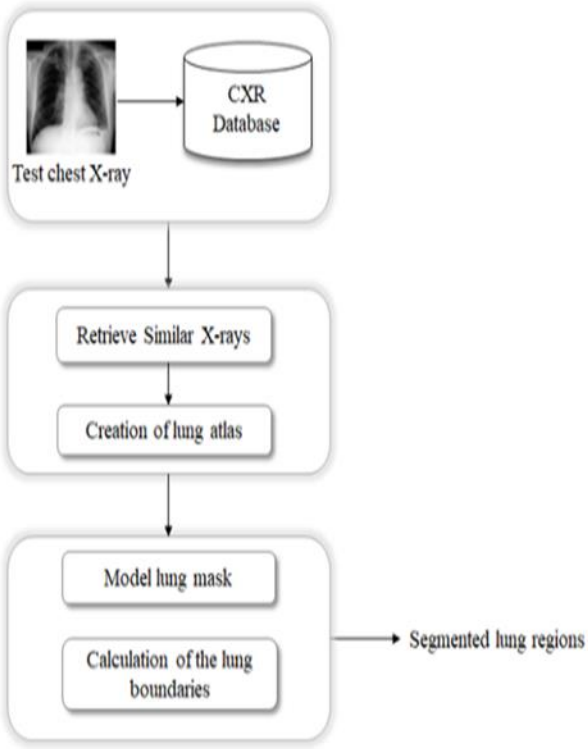

Fig 2. Block diagram of segmentation method using chest X-rays

In the first stage in order create the adaptive lung model to retrieve the similar images using Radon transform [16] and Bhattacharya distance metric from the Chest X-ray database. The retrieved top similar images which are fed to next stage to create correct lung model by using SIFT- Flow based method. Chest X-rays size and shapes can be varying significantly across the patients so it leads to segment complicated. In earlier step retrieve the similar lung images under the investigation with parameter of CBIR framework after the statistical model of the lung model under the investigation of non-rigid image SIFT-Flow image registration algorithm. In this stage average specific model lung masks have been created. Finally, the statistical lung masks obtained in the previous stage this step detects the region of lung boundary of CXR images with help of graph-cut method [19], it was proven to be effective in boosting validation accuracy in Transfer learning CNNs.). The example output of segmented image given below fig2.

Fig2. (a) Input chest X-ray, (b) Created lung mask to the corresponding image, (c) Segmented lung region

b) Transfer Learning (CNNs) in lung healthy and non- healthy classification:In this proposed work described the two-level stage of pipeline for segmenting and classifying lungs in CXR, the complete work flow diagram shows in fig. 2. When the number of training samples will grow, the predictions enormously improve in model-based methods. When a certain amount of data is available, some modifications should be applied to the existing dataset to artificially increase the training set. In this work we used flipping the images left to right. Augmentation techniques help to providessubstantial augmented images from the existing datasets. After augmentation the total number of images are input to the convolutional neural networks to classification of normal and abnormal in X-rays. The screenshot for implementation of augmentation as shown in fig4. CNN has employed to numerous medical image processing classifications due to automatically extracting features from the images. The CNN layers in the network with kernel help in extracting the temporal and spatial features in an image. Transfer learning method can be useful in those applications of Convolutional neural network where the datasets are not large. This CNN also performs efficacy on many publicly available datasets.

The original model processes an input image of size 256 X 256 dimensions. In this work, consists of three convolutional layers, pooling layers, flatten and dense layers are employed to classification of CXRs whether it is normal or abnormal.The segmented images inputs to the first convolutional layer with number of 64 filter (kernel) size3 X 3Every block of the input matrix is separately convolved with the filter and produced a pixel in the output.Convolutional operation performed in all images matrix and have created feature maps with same padding and then Max-Pooling reduce the dimensionality of each feature maps with 2 X 2 size to prevent the over-fitting problem. In each convolutionlayers and Max-pooling layers followed by Rectified Linear Unit (ReLU) activation function to perform extract the features. The last Fully Connected network (FC) layer of this CNN was put back by a single sigmoid node in order to output results the probability of having the specified pathology. Fig 3 is a complete flow of Convolutional Neural Networks (CNNs) to process a segmented chest X-ray images and classify it based on the extracted features by the convolutional and polling layers.

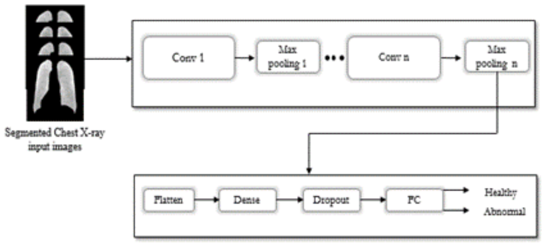

Fig 3. The proposed architecture of CNN

CNN model performance based on under the learnable hyper-parameters which is followed by number of kernels and it size, pooling layers, number of weights, sigmoid activation function s(z)=1\1+e^(-z) is used to calculate the loss function through forward propagation while training datasets and get predict the probability of output with 0/1.RMsprop is an optimizer similar to gradients descent optimizer and is to normalize the large gradients to evict exploding and increase small gradients to evict vanishing. Therefore, we should increase the learning rate of the model and faster computation.

4. Experimental Results

The Japanese Society of Radiological Technology (JSRT) Chest X-rays dataset is used in this research work. The JSRT dataset contains totally 247 images and 154 are nodule and 93 non-nodule images. The matrix size of each image 2048 X 2048 with 0.175 mm pixel size and wide density range is 12-bit 4096 grayscale. The Chest x-rays labelled as either diseased or normal. In this Paper we focused on binary classification of the given input CXRs using Convolutional Neural Networks. Before the sequential model have employedthe augmentation, technique is used for due to small amount of input data.

```
if file.endswith('.png')==True:
    im = Image.open(main_dir+clas+'/'+str(file))
    out = im.transpose(Image.FLIP_LEFT_RIGHT)
    out.save(main_dir+clas+'/'+'1'+str(file))
```

Fig. 4 Implementation of augmentation screenshot

After the augmentation inputs chest X-rays are generated by totally 667 images with size 256 X 256. The complete images set were taken to spilt into 80% training and 10 % considerfor testingand 10 % forvalidation which means 20% for predictions of chest X-rays healthy control or diseases. Below the given table shows training parameter of CNN classification model. Total number of trainable parameter 3,716,290 non-trainable parameter is 0 so, CNN model performed well in training function. Below the table. 1(a) mentioned Generated CNN architecture for our proposed work and table. 2(b) described training parameters for CNN model training function.

Table. 1 (a) CNN architecture for proposed work, Table. 2(b) Training Parameters.

Table. 1(a)

Layer (type)	Output Shape	Param #
conv2d_11 (Conv2D)	(None, 256, 256, 64)	1792
activation_1 (Activation)	(None, 256, 256, 64)	0
max_pooling2d_1 (MaxPooling2	(None, 128, 128, 64)	0
conv2d_12 (Conv2D)	(None, 126, 126, 32)	18464
activation_2 (Activation)	(None, 126, 126, 32)	0
max_pooling2d_2 (MaxPooling2	(None, 63, 63, 32)	0
conv2d_13 (Conv2D)	(None, 61, 61, 32)	9248
activation_3 (Activation)	(None, 61, 61, 32)	0
max_pooling2d_3 (MaxPooling2	(None, 30, 30, 32)	0
flatten_1 (Flatten)	(None, 28800)	0
dense_1 (Dense)	(None, 128)	3686528
activation_4 (Activation)	(None, 128)	0
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 2)	258
activation_5 (Activation)	(None, 2)	0

Total params: 3,716,290
Trainable params: 3,716,290
Non-trainable params: 0

Table. 2(b)

Number_filter	64
Filter_size	3 x 3
Max-pooling size	2 x 2
Optimizer	Rmsprop
Loss calculation	Binary_ crossentropy
Padding	"same"
Total_Epochs	100

(a) (b)

Fig 5. 5(a) Abnormal CXR and 5(b) Normal images (Classified by CNN)

5. Conclusion:

In this work presents a transfer learning approach designed with efficacy of deep CNNs for automatically distinguish between the normal and unhealthy CXRs was experimented with JSRT publicly available digital chest X-rays dataset. The performance of the model was good with accuracy of training 97%, and validation accuracy is 89 %. Segmentation of lungs is very complicated for CADs using radiography images. This state-of- art-performance could be useful and faster with accurate diagnosis. The results disclose that deep neural networks could be successfully implemented for Chest X-rays classification tasks as its manifest efficient accuracies.

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