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Computer-aided diagnosis of tuberculosis using chest radiographs

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ABSTRACT
Tuberculosis (TB) also referred as Phthisis Pulmonalis is a contagious disease caused by Bacillus Mycobacterium Tuberculosis that affects the lungs. But when left untreated, the infection spreads through the bloodstream and affects the bones, liver and kidneys. The bacteria which cause Tuberculosis infection are communicable, when people with Active Tuberculosis infection sneeze, cough or transmit respiratory fluids in the air. There are several tests to diagnose the Tuberculosis bacterial infection. But, the standard tests are slow, less accurate and more expensive. This paper details an automated approach developed by the author, for Tuberculosis diagnosis which is more accurate and less expensive. The automated approach makes use of Chest radiography to diagnose the disease. The lung region is extracted using Graph cut lung segmentation method for identifying the ribs and clavicles, which are needed for the diagnosis. The Graph cut lung segmentation method provides better accuracy and then the Classification is performed between normal and abnormal X-ray patterns. Finally, performance of the method is analyzed.

Index Terms:- Computer Aided Diagnosis, Purified Protein Derivative, Mantoux test, Lung segmentation, Image processing, Postero-anterior radiograph.

1. INTRODUCTION
The people, who are affected by Tuberculosis infection, do not have any symptoms until the immune system weakens. When the immune system weakens, the Tuberculosis bacteria cause death of tissue in the organs and it is referred as Active Tuberculosis. The symptoms of Active Tuberculosis infection includes chronic with blood-tinged sputum and weight loss. If the Active Tuberculosis infection is not diagnosed periodically, it can be fatal. In the year 2014, according to World Health Organisation survey on Tuberculosis disease, 9.6 million people

was affected by Tuberculosis infection and 1.5 million people died due to the disease [10]. The people who are infected by HIV more often gets infected by Active Tuberculosis infection. People who consume Tobacco and attribute to smoking are more likely to have the risk of Tuberculosis infection. More than 20% of Tuberculosis cases worldwide are attributable to smoking [1]. The mortality rates are high, when the patients with Active Tuberculosis are not periodically diagnosed. Thus it is necessary to provide periodical diagnosis for the patients infected by Tuberculosis infection and antibiotics treatment is provided to increase the chance of survival. Several tests exist for diagnosing the Tuberculosis infection. The standard test to diagnose Tuberculosis infection is using clinical sputum sample, which takes several months to diagnose the growth of Mycobacterium Tuberculosis. Sputum smear microscopy is a technique to diagnosis Pulmonary Tuberculosis infection, in which sputum samples are observed under a microscope. It is a simple and inexpensive technique which involves diagnosing the infectious patients. Sputum smear microscopy has certain limitations in its performance. Mantoux test is a used to diagnose Latent Tuberculosis, which involves injecting Purified Protein Derivative (PPD) Tuberculin into the skin. It is also called as Tuberculin Skin Test. The result of the test depends on the size of swelling caused in the skin. But the Tuberculosis Skin Test is slow and not reliable test for diagnose of Tuberculosis infection.

Serological test are carried out on the sample of blood, and they claim to diagnose Tuberculosis by detecting antibodies in the blood. The World Health Organisation has warned not to conduct Serological test and diagnose Active Tuberculosis. So, some Countries have banned the use of Serological tests for Tuberculosis diagnosis. The standard tests are slow, less accurate and more expensive. Thus Computer aided approach is developed to diagnose the Tuberculosis infection. In this paper, an automated approach is developed to diagnose Tuberculosis manifestations in Chest radiographs. The Chest radiography is ubiquitous radiological investigation which includes the breast anatomy and an important step for Tuberculosis diagnosis due to the low cost. This paper is organized as follows. Section II, briefly summarizes the related work. Section III, provides the description of the System overview. Section IV, describes the proposed framework in detail. Section V, presents the Experimental results and analysis. Conclusions and future work are given in Section VI.

2. RELATED WORK

Chest radiography plays an important role in the detection and diagnosis of the disease related to lungs. The Chest radiograph specifies the thoracic anatomy and provides high yield, at the low cost [1]. There are some challenges in processing Chest X-ray images. For example, in lung Segmentation, the strong edges at the rib cage and clavicle region cause local minima for most minimization approaches. Segmenting the lung apex is also a nontrivial problem because of the changing intensity at the clavicle bone [18]. Examples of normal Chest X-ray and abnormal Chest X-ray i.e., with and without Tuberculosis infection are shown in Figure 1 and Figure 2 respectively.

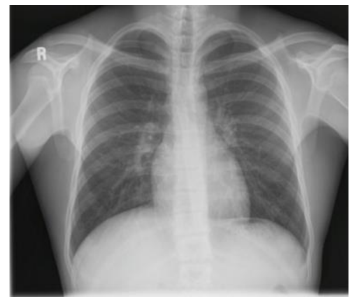

Figure 1 Normal Chest X-ray

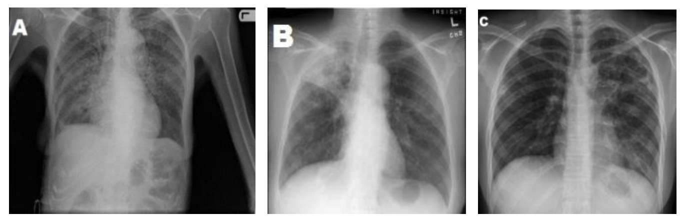

Figure 2 Abnormal Chest X-ray; (A) Chest X-ray A, represents Signs of Tuberculosis; (B) Chest X-ray B, represents Cavitary Tuberculosis and; (C) Chest X-ray C, represents Pulmonary Tuberculosis

Computer Aided Diagnosis (CAD) has been popular for Tuberculosis detection and lung disease classification. Detecting the lung regions in Chest X-ray images is an important step of Computer Aided Diagnosis applications such as Tuberculosis or Pneumoconiosis screening. Computer Aided Diagnosis (CAD) scheme for detecting lung nodules in Chest radiograph consist of three major steps: 1) Segmentation of Lung field based; 2) Feature analysis and 3) Classification of the nodule candidates into nodules or non-nodules by use of a nonlinear Support Vector Machine (SVM) classifier. Automatic Segmentation of anatomical fields is the first steps in Computer Aided Systems. Some of the diagnostic information can be extracted from the anatomical boundaries such as Total Lung Capacity which aids in detection of Pneumonia, Pulmonary Atelectasis or Obstructive Airways diseases. Tuberculosis classification needs anatomical boundaries for the classification of further stages [9]. There are several anatomical challenges in Segmenting the lung region which involves segmenting the lung apex, because of the varying intensities in the upper clavicle bone region. Other Challenges includes segmenting the costophrenic angle and X-ray image in-homogeneitics [2]. Segmentation methods for segmenting the chest radiograph are classified as (i) rule based methods (ii) pixel classification-based methods (iii) deformable model based methods and (iv) hybrid methods.

In rule based method, segmentation is based on certain rules such as Threshold operations. These methods have mostly heuristic assumptions and compute approximate solutions that can be far from the global optimum. Therefore, rule based methods are generally used as an initialization stage of more robust segmentation algorithms. Pixel classification-based methods are more general than rule-based segmentation methods [3]. The segmentation in pixel classification-based method is based on the feature vector for each pixel in the input image and the intensities of the lung region. Deformable models are used in medical image segmentation due to its shape flexibility. Active Shape Models (ASM) and Active Appearance Models (AAM) have been applied to segment the lung region. Although Active Shape Models and Active Appearance Model approach have become popular for biomedical applications, they have several limitations and shortcomings including: (i) they can become trapped at local minima in Chest x-rays due to high contrast and strong rib cage edges, (ii) segmentation performance relies on the accuracy of the initial model to the actual boundary, and (iii) they have many internal parameters which produces highly variable solutions. Hybrid methods aim to produce better results by fusing several techniques. In [3], the lung region is extracted using a combination of an intensity mask, a lung model mask derived from a training set. Fusing deformation-based (Active Shape Model, Active Appearance Model) and pixel classification methods provides best performance compared to other approaches [3]. Thus, hybrid approach is applied to detect, register and robustly segment lung organ boundaries across the large patient population [3].The lung region is extracted using the intensity mask and the long model mask derived from training data set.

An automated nodule detection requires accurate image segmentation 1) to measure the metabolic activity of lesions after precisely detecting them; 2) to track disease progression over time using the Metabolic Tumour Volume (MTV), and the amount of lesion information (i.e., total lesion activity); and 3) to determine spatial extent of lesions pertaining to Pulmonary infections [6]. The Graph cut algorithm, models the segmentation process using an objective function in terms of lung model properties and segments the ribs, heart, and clavicles in the Chest radiograph.The Graph cut algorithm computes a global binary segmentation by minimizing the objective function. In [18],*CandemirS et al*. developed Thresholding Method for object extraction process from its background by determining whether greater or equal to an intensity value T(threshold) for the X-ray image. The pixels are classified as object (pixel) or a background (pixel). In general, thresholding can be categorized into three categories which are global thresholding, local thresholding and dynamic/adaptive thresholding based on pixel values. Chest X-ray image classification is performed on the extracted information from the training set. The Classification algorithm is classified as supervised and unsupervised based on the sample classes. In [12], *Shafeena Basheeret et al*. developed Principal Component Analysis (PCA) as the classification method for classifying the X-ray images and it is used as image recognition. The features are extracted based on the Scale Invariant Feature Transform (SIFT). Scale Invariant Feature Transform is an algorithm to detect and describe local features of the image. Principal Component Analysis identifies features and the components which represents the full object state and termed as Principal Components. So, Principal Components extracted by Principal Component Analysis implicitly present all the features and is a mathematical calculation applied on orthogonal transformation by converting the set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables.

In [43], *Kim Le et al*. proposedWatershed segmentation method for classification, which requires different types of morphological operations and also requires watershed transformation in the segmentation process of the lung regions. Watershed segmentation used in the partition of lung regions .The algorithm is used to adjust the smoothness of regions and boundaries. In [32], *Osman M.K et al*. used neural networks for the classification of Pulmonary Tuberculosis. Neural networks are effective in the support rules of Tuberculosis diagnosis which is developed based on the histo-pathological variables to detect the disease. Two models of clustering is used to classify the patients. The clustering uses a Fuzzy-Art Neural network integrate the fuzzy logic operators and the basic characteristics Adaptive Resonance Theory (ART). In [28], *Quellec G et al*. developed a Decision tree for the classification of disease. The decision tree consists of nodes and branches. Each node specifies the decision. The start node is called as root node. The tree has branches which provide the result based on the conditions provided. The decision tree learning algorithm has high transparency and accuracy. In [1], *Jaeger S et al*. used Support Vector Machine as classification algorithm for finding the best hyper plane in the input space. The purpose of the Support Vector Machine is to find the optimized separator function called as classifier. Support Vector Machine (SVM) is used to diagnose the presence of Tuberculosis based on Chest radiographs.

3. SYSTEM OVERVIEW

This section presents the system overview of Tuberculosis diagnosis in detail. The developed automated approach for the diagnosis of Tuberculosis using Chest radiograph is shown in Figure 3.

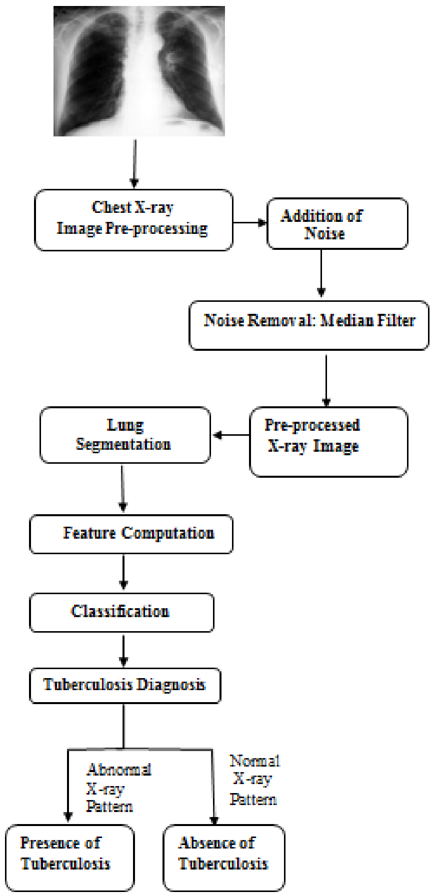

Figure 3 System Overview: Tuberculosis Diagnosis

The steps include Chest radiograph Pre-processing, Lung segmentation, followed by Feature computation and Classification of the input x-ray as normal and abnormal Chest radiograph with the presence and absence of Tuberculosis [1].

4. THE PROPOSED FRAMEWORK

This section presents the implemented methods for Lung Segmentation, Feature computation, and Classification. The system takes Chest X-ray as the input and segments the lung region of the input Chest X-ray using Graph cut lung segmentation method in combination with a lung model. For the segmented lung field, the system computes a set of features as input to a pre-trained classifier. Finally, the classifier outputs its confidence in classifying the input Chest X-Ray as a Tuberculosis positive case or Tuberculosis negative case based on the computed features.

A. Image Pre-Processing

Image Pre-processing, resample the Chest radiographs by increasing the Grey scale contrast and improve Chest X-ray image quality. Image pre-processing step involves addition of noise and removal of noise to suppress unwanted distortions and enhance the feature of the image for further processing. The reason for the need of image pre-processing includes:

- Noise reduction
- Contrast enhancement
- Elimination of acquisition-specific artifacts

B. Graph Cut Lung Segmentation Algorithm

The Graph cut approach models the lung boundary detection based on the object function. To formulate the objective function, lung region has to satisfy: a) the lung region should be consistent with typical Chest X-ray intensities, b) neighboring pixels should have consistent labels, and c) the lung region needs to be similar to the lung model are computed. Example of lung segmentation in Chest X-ray is shown in Figure.4 respectively.

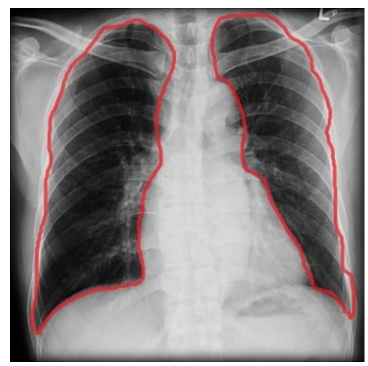

Figure 4 Lung Segmentation

C. Feature Extraction

The normal and abnormal Chest X-ray patterns are identified based on 1) Object detection Inspired features and 2) Content based image retrieval features.

1) Object Detection Inspired Features

In object detection inspired features, features are described based on the appearance pattern. It is the combination of shape, edge, gradient, and texture descriptor. Histogram is computed for each descriptor value distributed across the lung field. The features of the descriptor form a feature vector and the feature vector is used as an input for the classifier. The following shape and texture descriptors are used.

- Intensity Histograms(IH)
- Gradient Magnitude Histograms(GM)
- Shape Descriptor Histograms(SD)

$$SD = \tan^{-1}\left(\frac{\lambda_1}{\lambda_2}\right) \quad (1)$$

Where λ_1 and λ_2 are the Eigen values of the Hessian Matrix, with $\lambda_1 \leq \lambda_2$.

- Curvature Descriptor Histograms(CD)

$$\mathrm{CD} = \tan^{-1}\left(\frac{\sqrt{\lambda_1^2+\lambda_2^2}}{1+I(x,y)}\right) \quad (2)$$

With $0 \leq \mathrm{CD} \leq \pi/2$, where $I(x, y)$ denotes the pixel intensity for the pixel(x, y).

- Histogram of Oriented Gradients (HOG) Histogram of Oriented Gradients is a descriptor for gradient orientations based on gradient magnitude.

2) Content Based Image Retrieval Features

In Content based image retrieval features, low level features are identified. The low level features include edge, shape moments and intensity if the Chest radiograph. Content based image retrieval features include the following descriptors:

- Tamura texture descriptor:

In Tamura texture descriptor, contrast, coarseness and directionality features are identified.

- CEDD and FCTH:

(Color and Edge Direction Descriptor) and (Fuzzy Color and Texture Histogram) incorporate color and texture information in the histogram.

- Hu moments:

Hu moments are invariant under Chest X-ray scaling, rotation and translation.

- Primitive Length, Edge Frequency and Auto-correlation:

These are the texture analysis method which uses statistical rules to describe the spatial distribution relation with grey values.

D. Classification

Support Vector Machine is a supervised learning model used as Classification algorithm for Tuberculosis diagnosis. Support Vector Machine classifies the computed feature vectors into either normal or abnormal. It is a supervised non-probabilistic classifier that generates hyper planes to separate samples from two different classes in a space with possibly infinite dimension.

5. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the practical evaluation of the work. Graph cut lung segmentation and feature extraction is performed. The Chest X-ray image is taken as an input image and the diagnosis of Tuberculosis disease is performed. Chest X-ray image pre-processing is an initial step in the process. Pre-processing of the Chest radiograph includes addition of noise and removal of the noise using Median filter. The addition of noise is based on the noise density in Salt and Pepper noise. In Figure 5, addition of Salt and Pepper noise is shown.

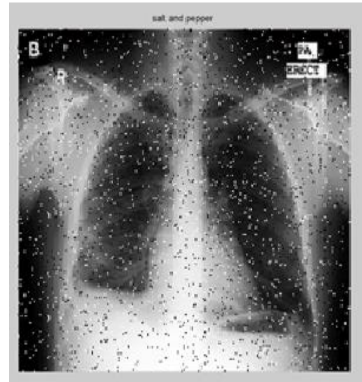

Figure 5 Addition of Salt and Pepper noise

Median Filter is a filtering operation to remove the noise in the Chest radiograph and provides better accuracy to the radiograph. Median Filter is performed on Chest X-ray to remove noise which is shown in Figure 6.

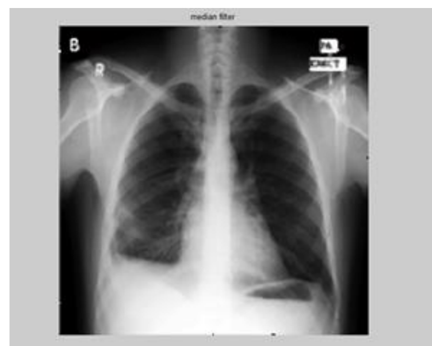

Figure 6 Median Filter

The Chest radiograph is segmented using Graph cut lung segmentation algorithm. The Graph cut lung segmentation algorithm segments the lung region as ribs and clavicles are needed as an input for feature extraction. The Segmented Lung region is shown in Figure 7.

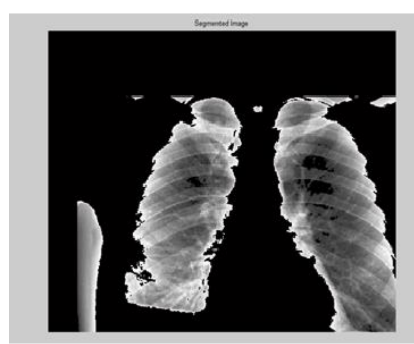

Figure 7 Segmented Lung Regions

Feature extraction is performed to extract the feature of Chest radiograph. The features are extracted based on Intensity

Histogram, Gradient Magnitude Histogram and Shape Descriptor Histogram. Figure 8 represents the Feature Extraction performed on the lung region.

Figure 8 Feature Extraction

Classification is performed using Support Vector Machine to diagnose the presence and absence of Tuberculosis disease in Chest Radiograph. Classification using Support Vector Machine is shown in Figure 9.

Figure 9 Support Vector Machine

Support Vector Machine also classifies the stages of Tuberculosis in the abnormal chest radiograph patterns. It helps the radiologist to analyse and provide treatment for the Tuberculosis affected patients based on the classified stages of Tuberculosis disease.

6. CONCLUSION

The automated approach is developed to diagnose Tuberculosis disease based on Lung Segmentation and Classification. Based on the test conducted, it is observed that the automated approach provides better performance than the manual diagnosis of the Tuberculosis disease. The stages of the Tuberculosis disease are identified using classification algorithm which helps the physician to provide treatment to the patients affected by Tuberculosis. Thereby, the fatality rate caused due to Tuberculosis infection can be minimized. In the Future work, many different features are extracted from the Chest radiographs to provide better diagnosis. The performance of the system are analysed by using different classifiers.

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