

A SURVEY ON INHERENT SELECTION OF TUBERCULOSIS USING CHEST RADIOGRAPHS

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Abstract— Tuberculosis is a second major health disease prevailing in today's modern world. It is an infectious disease caused by various strains of Mycobacteria called Mycobacterium tuberculosis. Tuberculosis naturally affects the lungs, it also affects the other parts of the body. It is spread through the air when infected people cough, sneeze etc. Generally tuberculosis cause more deaths in the world rather than any other infectious disease 2 billion worldwide, 15 million in the United States, it kills 60% of the people when not treated. 3 million deaths worldwide occur every year. Diagnosing tuberculosis remain still a challenge when it is left undiagnosed the people with mortality rate becomes higher. Early ways of diagnosing tuberculosis are slow and unreliable. In an effect to reduce this disease this paper presents an automated approach for detecting tuberculosis in conventional posterior anterior chest radiographs. Unfortunately, the interpretation of CXRs is subject to human error. In addition, mass screening of a large population is a time-consuming and deadly task, which requires a large effort when done manually. For this reason, there is large curiosity in developing computer-aided diagnostic systems (CAD) that can detect TB automatically in CXRs. These systems have the possibility to decrease the hazard of detecting errors and increase the efficiency of mass screening efforts.

Keywords— Diagnosing, Posteroanterior, Radiographs, Mortality Rate, Computer-Aided Diagnostic Systems (Cad).

I. INTRODUCTION

Tuberculosis is a global health disease [1]. It is an infectious disease caused by mycobacterium tuberculosis. It is estimated that 9 million new cases occur worldwide every year. Unlike other disease TB spreads when infectious people sneeze, cough etc. Widespread of poverty and malnutrition is the important factor for this disease. In clinical trials, cure rates over 90% have been documented [1]. Unfortunately, diagnosing TB is still a major challenge.

The definitive test for TB is the identification of Mycobacterium tuberculosis in a clinical sputum or pus sample, which is the current gold standard method [2][3]. However, it may take several months to identify this slow growing organism in the laboratory. Another techniques sputum smear microscopy, in which bacteria in sputum samples are observed under a microscope.

However, skin tests are not always reliable. The latest development for detection is molecular diagnostic tests that are fast and accurate, and that are highly sensitive and specific. Therefore radiographs are the main portion of any medical assessment for TB [4][5], among microbiological smears, cultures, and skin tests

In this paper, we present an automated approach for detecting TB manifestations in chest X-rays (CXRs), based on our earlier work in lung segmentation and lung disease classification. An automated approach to X-ray reading allows mass screening of large populations that could not be managed manually[6][7].

II. PROBLEM DEFINITION

However TB is a wide spreading disease and many tests has been conducted to test the occurrence of TB. Those test are very time consuming and unreliable therefore in this paper we use an automated approach for detecting tuberculosis using chest radiographs[8][9].

The chest radiograph includes all thoracic anatomy and provides a high yield given the inexpensive and solitary source. The target platform for our automated system is portable X-ray scanners, which allow screening of large parts of the population in rural areas[10][11].

III. RELATED WORK

3.1 Detecting Tuberculosis in Radiographs Using Combined Lung Mask [2012]

This paper focuses to reduce the burden of TB and to improve the detection system for diagnosing TB. So this paper uses the following methods such as lung figure model, a segmentation mask, and a simple power model for segmenting the lung and to improve the ROC more than 83%.

One of the feature of this paper is that is to make use of Dynamic model alignment instead of static model alignment.

3.2 Graph Cut Based Automatic Lung Boundary Detection in Chest Radiographs [2012]

This paper focuses on the chest X-rays(CXRs). It also uses the lung segmentation method in order to detect the flaws or any abnormalities in the chest region. The method consists of two stages: (a) average lung shape model calculation, and (b) lung boundary detection based on graph cut.by using these above two methods it obtains an segmentation accuracy of about 91%.the proposed method is to make use of dynamic method.

3.3 Automated Pulmonary Nodule Detection System in Computed Tomography Images-A Hierarchical Block Classification Approach

This paper presents a novel pulmonary nodule detection method where it uses 3-D block images and it applies an entropy analysis to identify the nodule candidates. Based on the entropy analysis the nodules are split into informative wand non informative blocks. Presentation of the proposed system is assessed by the Lung Image Database Consortium database. This method is mainly used to reduce the false positives in the nodule candidates. It attained 95.28% understanding with only 2.27 false positives per scan.

3.4 Segmentation of anatomical structures in chest radiographs using supervised methods: a comparative study on a public database [2004]

This study segments the lungs, heart, and clavicles in chest radiographs using active shape models (ASM), active appearance models (AAM), and multi-resolution pixel classification (PC). Clavicle segmentation was the most hard of the three segmentations. The best method for clavicle segmentation is ASM. To overcome the challenge of imprecise ends of the clavicles, this group only segmented the portions of the clavicles that were superimposed on the lungs and the rib cage.

3.5 Segmentation of anatomical structures on chest radiographs [2010]

This study segmented the clavicle by creating predefined clavicle templates and fitting them to the chest radiograph. The templates matched the pure incline and stark convex curvature of the clavicle to the image.

IV. METHODS AND MATERIALS

4.1 Sputum test

In this test samples of sputum are tested under a microscope and therefore it is long process takes about 6 to 8 weeks of time[12].

4.2 Skin test

Commonly used diagnostic tool for tuberculosis is a simple skin test. A small amount of a substance called PPD tuberculin is injected just below the skin of your inside forearm. A hand raised red bump means you are likely to have TB infection size of the bump determines whether the test results are significant[13][14].

False positive: It may happen if you have been vaccinated recently with the bacilli ecalmetteguein vaccine.

False negative: It occurs with people who recently affected with TB but whose immune system has not yet reached the bacteria.

4.3 Blood test

A blood test may be useful if you ar4e at high risk of TB infection but have a negative response to the skin test if we have taken the vaccine recently.

4.4 Computer Aided Diagnosis

In Radiology CAD also called as Computer Aided Detection is a procedure in medicine that assists doctors in the interpretation of medical images. Imaging techniques in X-ray, MRI and ultrasound diagnostics yield a great deal of information in which the radiologists have to analyze and evaluate comprehensively in a short time[14].

CAD is relatively young interdisciplinary technology combining elements of artificial intelligence and digital image processing with radiological image processing.

V. SYSTEM DIAGRAM

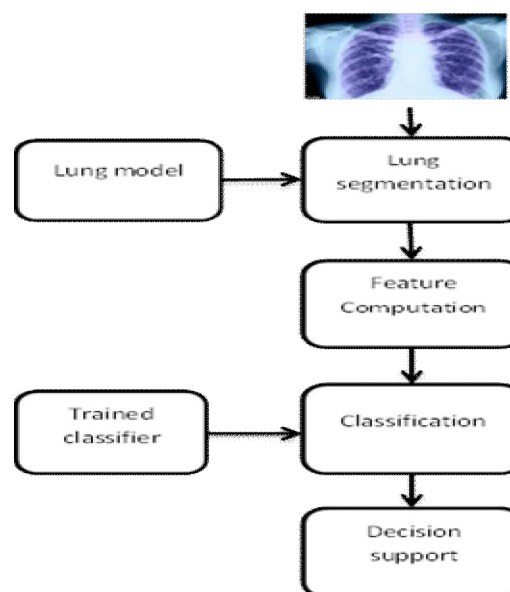


Fig 1: This takes chest X-ray as input and produces an output which indicates the degree of abnormality for the given chest X-ray

VI. FEATURE AND CLASSIFICATION METHOD

6.1 Algorithm Outline

In order to perform a regional analysis of chest images, we propose the following multi-stage approach. The first step is an automatic segmentation of both lung fields [14]. Subsequently, the lung fields are divided into smaller regions of interest (ROIs). Each region is searched for abnormal signs. Because we focus on diffuse abnormalities, we perform texture analysis and extract a set of features from each ROI. In an off-line stage, the results for each region on images with known locations of abnormalities are used to construct a training set of reference cases. In the on-line analysis, a statistical classifier estimates the likelihood that a specific ROI is abnormal. The system could stop here and present the possibly abnormal regions to a radiologist. Optionally, the results of all regions can be pooled in a final stage into a single score for the complete image.

6.2 Graph Cut Segmentation

It is employed to solve a computer vision problems such as image smoothening. This segmentation also takes the properties of lung boundaries, shapes and regions into account [4] currently we employ a modified version of Active Shape Models to extract the lung fields from a chest radiograph. This method is very robust and trainable, making it easy to adjust it to other databases with different image characteristics. The segmentation result is generally sufficiently accurate for our purposes.

We align the entire training mask for the given input CXRs and then perform the horizontal and vertical histogram equalized images. We employ a graph cut approach in which three necessities a lung region has to fulfill: 1) the lung region should be reliable with distinctive CXR intensities expected in a lung region, 2) adjacent pixels should have reliable labels, and 3) the lung region requirements to be similar to the lung model we computed. Let $C=(C_1, C_2, C_3, \dots, C_p, C_N)$ be a binary vector components and C_p is the foreground and background label, $p \in \mathcal{P}$ is the pixel and N is the number of pixels
Therefore

$$E(C) = Ed(C) + Es(c) + Em(C) \quad (1)$$

Ed , Es , Em represents the region, boundary and the lung model

$$Ed(C) = 1/ \text{Imax}(\sum_{p,s \in F}) |I_p - I_s| + \sum_{p,t \in F} |I_p - I_t| \quad (2)$$

I_p is the intensity of pixel P and F is the set of edges. I_s it represents the intensities of foreground and the background images. $IMAX$ is the maximum intensity values.

$$ES(C) = \sum (P, q \in F) \exp(-(|I_p - I_q|)^2) \quad (3)$$

Therefore we compare the segmentation algorithm with the lung boundary detection and obtain

$$\Omega = TP / (TP + FP + FN)$$

Where TP is the True Positive and FP is the False Positive and FN is the False Negative.

VII. CONCLUSION

We have developed an automated system that screens CXRs for manifestations of TB. When given a CXR as input, our system first segments the lung region using an optimization method based on graph cut. This method combines intensity information with personalized lung atlas models derived from the training set. We compute a set of shape, edge, and texture features as input to a binary classifier, which then classifies the given input image into either normal or abnormal. To improve the performance further, we could try to improve the lung segmentation, which provides average performance compared to other systems in the literature. One approach would be to find optimal weights for the terms in the graph cut energy function

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