

Computer Aided Automatic Detection of Tuberculosis in Chest Radiographs

N. Noorul melena

*Ultra College Of Engineering and Technology for Women,
Madurai, Tamil Nadu, India*

S. Anusha

*Ultra College Of Engineering and Technology for Women,
Madurai, Tamil Nadu, India*

G. Chitra

*Ultra College Of Engineering and Technology for Women,
Madurai, Tamil Nadu, India*

C.Sujatha

*Assistant Professor
Ultra College Of Engineering and Technology for Women,
Madurai, Tamil Nadu, India*

Abstract

Tuberculosis (TB) is a common disease with high mortality and morbidity rates worldwide. Automatic systems to detect TB on chest radiographs (CXR) can improve the efficiency of diagnostic algorithms for pulmonary TB. The noise reduction performed in chest X-ray image to detect and remove the impulse noises in the image. The features are extracted from the chest image and trained and classified using SVM (Support vector machine) classifier. The performance of the proposed system is analyzed in terms of sensitivity, specificity and accuracy. Computer aided detection (CAD) system was developed which combines several subscores of supervised subsystems detecting textural, shape, and focal abnormalities into one TB score. A general framework was developed to combine an arbitrary number of sub-scores: subscores were normalized, collected in a feature vector and then combined using a supervised classifier into one combined score. TB score allows for a necessary adaptation of the CAD system to different settings or different operational requirements.

Keywords: Subsystem, subscore, shape, texture, and focal analysis Chest radiographs, computer-aided diagnosis

I. INTRODUCTION

TUBERCULOSIS is an infectious disease caused by the bacillus *Mycobacterium tuberculosis*, which typically affects the lungs. TUBERCULOSIS (TB) remains one of the world's major health concerns. In 2011 an estimated 8.7 million new cases and 1.4 million deaths were reported. The majority of the TB burden is located in Africa, followed by the Asian countries. Although the overall incidence of TB in the Western World has been decreasing in the past decades, an increase in TB rates has been reported in selected high-risk populations especially in urban settings. An automated access for detecting TB in chest X-rays (CXRs), based on lung segmentation and Feature Extraction. In this study we focus on three categories of abnormalities: textural abnormalities, characterized by diffuse changes in appearance and structure of a region; focal abnormalities, which are isolated circumscribed changes in density; and shape abnormalities, where disease processes, have altered the contour of normal anatomical structures. Most of the previously developed systems for automatic analysis of chest radiographs have focused on single task. In this paper we propose an innovative combination of individual subsystems in a structured manner to address the problem of developing a CAD system with good generalization properties. For automatic TB detection there are two main reasons to combine systems. The first, mentioned before, is that it is not likely that a single system will suffice in a multitude of settings. A combination of multiple systems can be adapted to the specific setting, for example by weighing the output of a specific abnormality detection system higher when it is strongly associated with TB in a particular population. The second reason is a general beneficial effect of system combination on the performance of supervised systems. This effect has been extensively studied in the field of pattern recognition. Niemeijer showed that combination of independently developed systems, addressing the same task, improved the performance of CAD. In contrast to that work, we propose a combination of heterogeneous systems, addressing difference.

II. METHODS

The proposed combined CAD system consists of several subsystems; each of them producing one or more subscores indicating the presence of textural, focal, and shape abnormalities. All the subsystems are aggregated into one score by combination of the subscores. The subsystems depend on the segmentation of anatomical structures, preprocessing of the chest radiograph and computation of features, and these tasks are described first

A. Segmentation:

The lungs and clavicles were segmented to limit the analysis by the subsystems to the lung fields and provide them spatial context. The segmentation is based on supervised pixel classification and requires a set of features to be computed for each pixel. Two different segmentations were produced: (1) lung-PC, the post-processed output of a pixel classification stage and (2) lung-HAP, which combines pixel classification and shape model information to improve segmentation of lungs containing gross abnormalities

1) Local Feature Computation:

Local characteristics of each pixel in the image were computed. Three types of features were calculated: texture features based on Gaussian derivatives, features derived from the Hessian matrix, and position features. These features were computed at images resampled to a width of 256 pixels

2) Lung Segmentation

Lung segmentation is required to limit the analysis to the region inside the lung fields, where TB primarily manifests itself.

3) Clavicle Segmentation

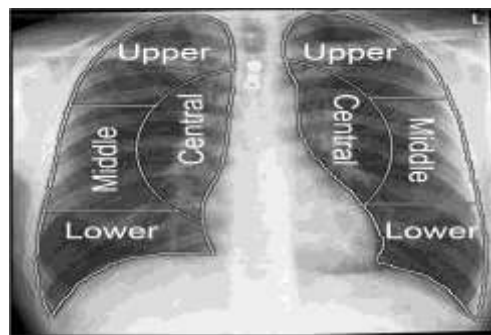
The presence of many overlapping structures renders the upper lung region the most difficult to analyze in the chest radiograph and can lead to a high rate of false positives

B. Preprocessing:

A CAD system usually applies a series of pre-processing steps to an input image. The main goal of pre-processing is to enhance the image quality so that objects of interest, such as nodules or linear opacities consistent with scarring/fibrosis, become more evident. The quality of the pre-processing therefore strongly affects the performance of the subsequent processing steps. For X-ray screening, typical pre-processing steps are contrast enhancement, bone suppression, and lung boundary detection. A bounding box around the lungs was determined from lung-HAP and the image was cropped to. A 5% margin was added to the width and the height of to compensate for possible undersegmentation and to reduce border effects in feature computation. The cropped image was then resized to a width of 1024 pixels

C. Abnormality Detection Subsystems:

A number of subsystems were used to detect textural, focal, and shape abnormalities in chest radiographs. One or more subscores were generated by each subsystem. The subscores were afterwards combined into one overall abnormality score. afterwards combined into one overall abnormality score. The different subsystems and subscores are summarized in. From some subsystems more than one subscore is derived. The original input features for the subsystems are not included into the combination



1) Shape Analysis:

When large abnormalities close to the lung walls are present, the normal shape of the lungs is corrupted and difficult to determine, because of similar densities of abnormalities and extra-pulmonary structures. This causes the boundaries of the detected lung fields to be displaced with respect to the true lung boundary. Therefore, an abnormal shape of the projected lung fields indicates the presence of abnormalities and can be used to detect abnormal images.

2) TexturAnalysis:

Textural abnormalities in CXRs commonly occur in TB and typically reflect inflammatory changes in the lung parenchyma, but can also be the result of fluid or fibrotic

3) FocusLesion Detection:

Isolated well defined focal lesions, such as nodules, can occur in TB cases. This type of lesion is less well detected by texture analysis. Focal lesions were automatically detected with a commercially available software package for module detection (ClearRead+Detect v5.2; Riverain Technologies, Miamisburg, Ohio). The software outputs for each image a list of suspicious locations with a likelihood score.

D. Combination:

With all the subsystems and subscores available the key issue is how to combine this information into one score that reflects the overall probability of the image containing abnormalities related to TB. From each individual subsystem the subscores S_i , with and the total number of subscores, are collected into a vector .

III. SYSTEM ARCHITECTURE

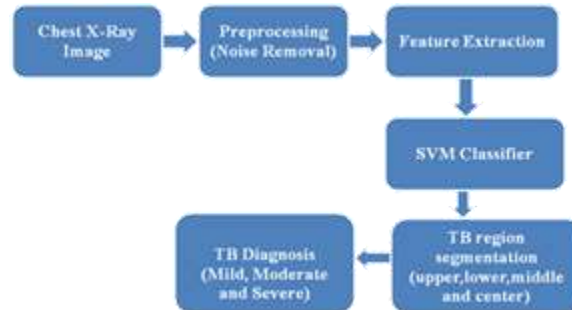


Fig. 1: System Overview. The system takes a CXR as input and outputs a confidence value.

IV. OVERVIEW

A. Feature Extraction:

Feature extraction is a special form of dimensionality reduction. Feature extraction starts from an initial set of measured data and builds derived values.

B. SVM Classifier:

SVM classifies each row of the data in sample, A matrix of data using the information in support vector Machine classifier. High accuracy level and low detection time

C. TB Severity Diagnosis:

TB diagnosis for three levels that are Mild, Moderate, and severe. The X-ray images have Three layers that are upper, middle, and lower. Lower layer affected by cold means that is the severe level of TB.

D. Proposed system:

The lung images are first preprocessed. In preprocessing noise removal is done in the images. Then feature is extracted. To implement the CT lung abnormality detecting by the SVM classifier. To implement the CT lung abnormality detection by the SVM classifier. Initially remove the noise from the images. For filtering the images using the Wiener filter for denoising. In a second step, we employ a graph cut approach and model the lung boundary detection with an objective function. "Graph cuts" is applied specifically to those models which employ a max-flow/min-cut optimization. After lung segmentation we extract three features such as LBP, HOG, and Tamura features are extracted. Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity. HOG counts occurrences of gradient orientation in localized portions of an image. It also computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy. And finally extract the Tamura features. These features are given to the SVM classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. The trained classifier will predict about the CT lung images. And finally analyze about our classifier performance with the existing system.

V. CONCLUSION

TB has diverse manifestations and to analyze CXRs automatically, algorithms that focus on different manifestations need to be combined. When using only a single subsystem, different subsystems were found to perform best for two datasets from different populations, but the combined approach outperforms each single subsystem in both cases. The combined system is close in performance to an independent human observer. Although the system presented combines multiple detectors, certain types of abnormalities are still missed. These can be addressed using the general framework proposed in this paper, where adding more subsystems is expected to further improve the versatility of an automated detection system.

REFERENCES

- [1] Laurens Hogeweg, "Automatic Detection of Tuberculosis in Chest Radiographs Using a Combination of Textural, Focal, and Shape Abnormality Analysis", *IEEE TRANSACTIONS ON MEDICAL IMAGING*, VOL. 34, NO. 12, DECEMBER 2015.
- [2] D. Zachary et al., "Changes in tuberculosis notifications and treatment delay in Zambia when introducing a digital x-ray service," *Public Health Action*, vol. 2, pp. 56–60, 2012
- [3] A. Story, S. Murad, W. Roberts, M. Verheyen, and A. C. Hayward, "Tuberculosis in London: The importance of homelessness, problem drug use and prison," *Thorax*, vol. 62, pp. 667–671, 2007.
- [4] G. de Vries, R. A. van Hest, and J. H. Richardus, "Impact of mobile radiographic screening on tuberculosis among drug users and homeless persons," *Am. J. Respirat. Crit. Care Med.*, vol. 176, pp. 201–207, 2007.
- [5] K. Siddiqi et al., "Clinical diagnosis of smear-negative pulmonary tuberculosis in low-income countries: The current evidence," *Lancet Infectious Diseases*, vol. 3, p. 288, 2003..
- [6] M. S. Glickman and W. R. Jacobs, Jr., "Microbial pathogenesis review of mycobacterium tuberculosis: Dawn of a discipline," *Cell*, vol. 104, pp. 477–485, 2001
- [7] A. N. Leung, "Pulmonary tuberculosis: The essentials," *Radiology*, vol. 210, pp. 307–322, 1999.
- [8] G. A. Agrons, R. I. Markowitz, and S. S. Kramer, "Pulmonary tuberculosis in children," *Seminars Roentgenol.*, vol. 28, pp. 158–172, 1993.
- [9] C. Chan, J. Woo, K. Or, R. Chan, and W. Cheung, "The effect of age on the presentation of patients with tuberculosis," *Tubercle Lung Disease*, vol. 76, pp. 290–294, 1995.
- [10] A. Leung, N. Müller, P. Pineda, and J. FitzGerald, "Primary tuberculosis in childhood: Radiographic manifestations," *Radiology*, vol. 182, pp. 87–91, 1992.