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Detecting Tuberculosis in Chest Radiographs Using SVM Classifier

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Abstract: Tuberculosis (TB)and HIV/AIDS are the main causes of mortality in adults aged 15-49 years in Sub Saharan Africa (SSA). The interaction between tuberculosis and HIV/AIDS makes the diagnosis and management of the confection difficult. A cross sectional hospital based study was conducted at Haydom Lutheran Hospital (HLH) to assess the interaction between tuberculosis, HIV/AIDS and coinfection in relation to the CD4 T cells. Furthermore, CD4 T cell counts in healthy subjects in different age groups were determined for the purpose of establishing reference values. Physical examination and investigation including sputum for fluorescence microscopy and culture, tuberculosis drugs susceptibility testing and Chest X-Ray (CXR) were done for all tuberculosis and HIV/AIDS patients. Sputum samples were stained using aura mine and examined by fluorescence microscopy. Sputum culture was done using Lowenstein Jensen media and sensitivity to the first line TB drugs was tested. The proposed computer-aided diagnostic system for TB screening, which is ready for field deployment, achieves a performance that approaches the performance of human experts achieve an area under the ROC curve (AUC) of 87% (78.3%accuracy) for the first set, and an AUC of 90% (84% accuracy)for the second set. For the first set, compare the system performance with the performance of radiologists. When trying not to miss any positive cases, radiologists achieve an accuracy of about 82% on this set, and their false positive rate is about half of system's rate.

Index Terms— *Chest radiographs, computer-aided diagnosis, lung pattern recognition and classification, segmentation, tuberculosis (TB), X-ray imaging.*

I. Introduction

TUBERCULOSIS (TB) is the second leading cause of death from an infectious disease worldwide, after HIV, with a mortality rate of over 1.2 million people in 2010 [1].With about one-third of the world's population having latent TB, and an estimated nine million new cases occurring every year, TB is a major global health problem [2]. TB is an infectious disease caused by the bacillus Mycobacterium tuber culosis, which typically affects the lungs. It spreads through the air when people with active TB cough, sneeze, or otherwise expel infectious bacteria. Moreover, opportunistic infections in immunocompromised HIV/AIDS patients have exacerbated the problem. The increasing appearance of multi-drug resistant TB has further created an urgent need for acost effective screening technology to monitor progress duringtreatment.Several antibiotics exist for treating TB. While mortalityrates are high when left untreated, treatment with antibioticsgreatly improves the chances of survival. In clinical trials, curerates over 90% have been documented. Unfortunately, diagnosing TB is still a major challenge.The definitive test for TBis the identification of Mycobacterium tuberculosis in a clinicalsputum or pus sample, which is the current gold standard. However, it may take several months to identify thisslow-growing organism in the laboratory. Another techniqueis sputum smear microscopy, in which bacteria in sputumsamples are observed under a microscope.

This technique was developed more than 100 years ago. In addition, several skin tests based on immune response are available for determining whether an individual has contracted TB. However, skin testsare not always reliable. The latest development for detectionare molecular diagnostic tests that are fast and accurate, and that are highly sensitive and specific. However, further financialsupport is required for these tests to become common place. Thus the rest of the paper organized in such a way that the Section 2 describes Methods, Section 3 shows proposed system, section 4 ends with conclusion.

II.METHOD

This section presents our implemented methods for lung segmentation, feature computation, and classification. Fig. 1 shows the architecture of our system with the different processing steps, which the following sections will discuss in more detail.

A. 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.

B.Graph Cut Segmentation

We model lung segmentation as an optimization problem that takes properties. of lung boundaries, regions, and shapes into account [4]. In general, segmentation in medical images has to cope with poor contrast, acquisition noise due to hardware constraints, and anatomical shape variations. Under most formulations of such problems in computer vision, the minimum energy solution corresponds to the maximum a posteriori estimate of a solution.

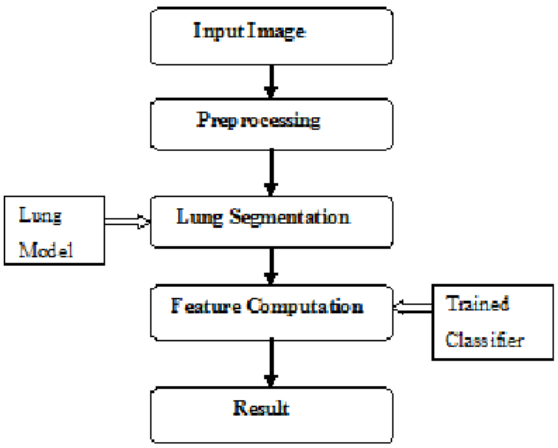

Fig 1: System Overview. The system takes a CXR as input and outputs a confidence value.

Although many computer vision algorithms involve cutting a graph (e.g., normalized cuts), the term "graph cuts" is applied specifically to those models which employ a max-flow/min-cut optimization. "Binary" problems (such as denoising a binary image) can be solved exactly using this approach; problems where pixels can be labeled with more than two different labels (such as stereo correspondence, or denoising of a grayscale image) cannot be solved exactly, but solutions produced are usually near the global optimum.

C.Features

To describe normal and abnormal patterns in the segmented lung field, we experimented with three different features,such as LBP,HOG and Tamura.

1) Local binary patterns (LBP) is a texture descriptor that codes the intensity ifferences between neighboring pixels by a histogram of binary patterns.[6].

The LBP operator assigned a label to every pixel of a gray level image. The label mapping to a pixel is affected by the relationship between this pixel and its eight neighbors of the pixel. If set the gray level image is I, and Z0 is one pixel in this image. So can define the operator as a function of Z0 and its neighbors, Z1, …, Z8. And it can be written as:

$$T = t (Z0, Z0-Z1, Z0-Z2, \ldots, Z0-Z8).$$

However, the LBP operator is not directly affected by the gray value of Z0, so can redefine the function as following:

$$T \fallingdotseq t (Z0-Z1, Z0-Z2, \ldots, Z0-Z8).$$

To simplify the function and ignore the scaling of grey level, use only the sign of each element instead of the exact value. So the operator function will become:

$$T \fallingdotseq t (s(Z0-Z1), s(Z0-Z2), \ldots, s(Z0-Z8)).$$

2) Histogram of Oriented Gradients (HOG) is feature descriptors used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. The image is divided into small connected regions, and for each region a histogram of gradient directions or edge orientations for the pixels within the region is computed. The combination of these histograms represents the descriptor,[7]. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.

3) Tamura feature descriptor: The Tamura descriptor is motivated by the human visual perception [5]. The descriptor comprises a set of six features. We only use three of these features, which have the strongest correlation with human perception: contrast, directionality, and coarseness. Coarseness relates to distances of notable spatial variations of grey levels, that is, implicitly, to the size of the primitive elements (texels) forming the texture. The proposed computational procedure accounts for differences between the average signals for the non-overlapping windows of different size.

d. Classification

To detect abnormal CXRs with TB, we use a support vector machine (SVM), which classifies the computed feature vectors into either normal or abnormal. SVM maps input vectors to a higher dimensional vector space where an optimal hyper plane is constructed. Among the many hyper planes available, there is only one hyper plane that maximizes the distance between itself and the nearest data vectors of each category. This hyper plane which maximizes the margin is called the optimal separating hyper plane and the margin is defined as the sum of distances of the hyper plane to the closest training vectors of each category.

Expression for hyper plane,

$w.x+b = 0$

x – Set of training vectors

w – vectors perpendicular to the separating hyper plane

b – offset parameter which allows the increase of the margin

III. PROPOSED SYSTEM

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.

IV. CONCLUSION AND FUTURE WORK

An automated system that screens CXRs for manifestations of TB. The system is currently set up for practical use in Kenya, where it will be part of a mobile system or TB screening in remote areas. When given a CXR as input 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. And then 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.

Compare two different established feature sets: one set typically used for object recognition and the other used in image retrieval applications. Both feature sets and most of the classifier architectures tested, To provide a similar performance and improve the performance further, 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. Another possibility would be to use more atlas-based lung models.

FUTURE WORK

In Future, to implement multiclass SVM classifier with other extracting features. A system framework is presented to recognize multiple kinds of activities from videos by an SVM multi-class classifier with a binary tree architecture. The thought of hierarchical classification is introduced and multiple SVMs are aggregated to accomplish the recognition of actions. Each SVM in the multi-class classifier is trained separately to achieve its best classification performance by choosing proper features before they are aggregated. Experimental results both on a home-brewed activity data set and the public Schüldt's data set show the perfect identification performance and high robustness of the system. The results of the experiments indicate that this method has much faster training and testing times than the widely used multi-class SVM methods like "one-against-one" and "one-against-all" while keeping comparable recognition rates.

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