International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-6 Issue-5, June 2017

Automatic Detection and Localization of Tuberculosis in Chest X-Rays

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Abstract: Tuberculosis is a major health threat in many regions of the world. Opportunistic infections in immune compromised HIV/AIDS patients and multi-drug-resistant bacterial strains have exacerbated the problem, while diagnosing tuberculosis still remains a challenge. When left undiagnosed and thus untreated, mortality rates of patients with tuberculosis are high. Standard diagnostics still rely on methods developed in the last century. They are slow and often unreliable. In an effort to reduce the burden of the disease, this thesis work presents an automated approach for detecting and localizing tuberculosis in conventional postero -anterior chest radiographs. A set of features are extracted from the lung region, which enable the X-rays to be classified as normal or abnormal using a binary classifier. Then if the chest x-ray is classified as abnormal again a set of local features are extracted to localize the affected regions . Thus it become easy to diagnose and treat the disease. An accuracy of 90% is achieved by this method.

Index Terms: Graph cut segmentation, Classification, Local feature extraction.

I. INTRODUCTION

Tuberculosis (TB) is the second leading cause of death from an infectious disease, worldwide, after HIV. With about one-third of the world's population having latent TB, and an estimated nine million new cases occurring every year, Tuberculosis is a major global health problem. Tuberculosis is an infectious disease caused by the bacillus Mycobacterium tuberculosis, which affects the lungs. It spreads through the air when people with active TB cough, sneeze, or otherwise expel this infectious bacteria. TB is mostly found in sub-Saharan Africa and South east Asia, where wide spread poverty and malnutrition reduce resistance to this disease. Moreover, opportunistic infections in immune compromised HIV/AIDS patients have exacerbated this problem. The increasing appearance of multi-drug resistant TB has created an urgent need for a cost effective screening technology to monitor progress during treatment. For treating TB there are many existing antibiotics. While mortality rates are so high when left untreated, treatment with antibiotics greatly improves the chances of survival. Unfortunately, diagnosing TB is still a major problem. The definitive test for Tuberculosis is the identification of Mycobacterium tuberculosis in a clinical sputum or pus sample, which is the current gold standard. However, it may take many months to identify this slow-growing organism in the lab. Another method is sputum smear microscopy, in which bacteria in sputum samples are observed under a microscope. This method was developed more than 100 years ago. In addition, several skin tests based on immune response are available for identifying whether an individual has contracted TB. However, skin tests are not reliable always. The latest developments for detection are molecular diagnostic tests that are very fast and accurate, and that are highly sensitive. However, further economic support is Required for these tests to become common place. This paper, present an automated approach for Tuberculosis detection and localization of the affected area in the chest X-rays (CXRs) using lung segmentation and lung disease classification. An automated approach to X-ray reading allows mass screening of very large populations that could not be managed manually. A postero-anterior radiograph (X-ray) of a patient's chest is a major part of every evaluation for Tuberculosis. The chest radiograph includes all thoracic anatomy and provides a very high yield, given the low cost and single source. Therefore, almost reliable screening system for Tuberculosis detection using radiographs would be a major critical step towards more powerful Tuberculosis diagnostics.

Figure 1.1: Examples of normal CXRs in the MC dataset

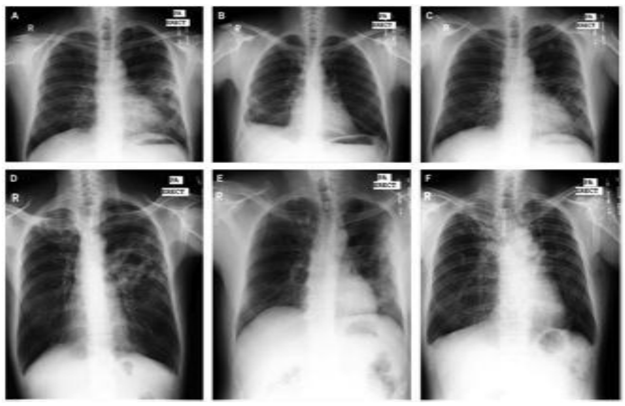

Figure 1.2: Examples of abnormal CXRs in the MC dataset

Manuscript published on 30 June 2017.
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Fig.1shows examples of normal CXRs without signs of TB. These examples are from Montgomery County (MC) dataset. Fig.2 shows positive examples with manifestations of Tuberculosis, which are from the same dataset. Typical manifestations of TB in chest X rays are infiltrations, cavitations, effusions or millary patterns. For instance, CXR A and C in Fig.2 have infiltrates in both lungs. CXR B is a good example of pleural TB, which is indicated by the abnormal shape of costophrenic angle of the right lung. CXR D the irregular infiltrates in the left lung with a large area of cavitation. There is scarring in the right apical region. CXR E shows the peripheral infiltrates in the left lung. Finally, CXR F shows TB scars resulting from an older Tuberculosis infection. This paper describes how to discriminate between normal and abnormal CXRs with manifestations of Tuberculosis, using image processing techniques.

This work first extract the lung region using a graph cut segmentation method. From this lung region, compute a set of texture and shape features, which enable the X-rays to be classified as normal or abnormal using a binary classifier. Also using different filter bank localization of TB affected area is also done.

This paper utilize the Graph cut segmentation method for the lung segmentation . Graph cuts has emerged as a preferred method to solve a class of energy minimization problems such as Image Segmentation in computer vision. The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. It can identify the regions of interest in a scene or annotate the data. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic/s. Two set of features are extracted and using SVM classifier the CXR is classified as normal or abnormal. If the CXR is abnormal it again segmented into collection of pixels with simiar colour and spatial location called splats. Then features of each splats are extracted using filter banks .Then again using SVM classifier affected splates are identified thus the affected area in the lung region.

II. LITERATURE REVIEW

As literature survey, a study about different segmentation techniques specially focused on graph cut and watershed segmentation method. Also different feature extraction methods in medical images are done.

[Sema Candemir1, Stefan Jaeger2, Kannappan Palaniappan1, Sameer Antani2, and George Thoma2, 2012] [1] describes the method of lung boundary detection. The system described in this paper has two main stages. It first computes an average shape model using training images. Then it uses a graph cut segmentation algorithm to detect the lung regions with the help of the calculated shape model. Segmentation in medical imaging has challenges such as poor contrast, distortions caused by the acquisition equipment, and anatomical shape variations due to diseases. A segmentation algorithm without a priori knowledge about the objects may not produce satisfactory results on medical images.This paper describe a method for accurate lung segmentation . In this paper image segmentation using a graph cut method and model the segmentation problem with an objective function is done. The max flow min-cut algorithm minimizes the objective function to find the global minimum which corresponds to foreground and background labelling of the pixels. The paper explain in detail the graph cut segmentation algorithm.

[Ramya R, Dr. Srinivasa Babu P 2015][2] describes methods for segmenting lung region.This paper mention about cavity segmentation and grah cut.It propose a two step method to segment the cavity borders. First, a pixel classifier is trained to detect the border pixels of the cavity. Cavity border typically has a distinct fuzzy appearance on the chest radiograph. The pixel classifier assigns each pixel a likelihood of belonging to the cavity border. This likelihood map is then used as input cost image for dynamic programming to trace the optimal path in the polar transformed image space. This constructed path corresponds to the cavity border in image space. Graph cut segmentation is A graph cut segmentation can be employed computer vision problems that can be formulated in terms of energy minimization. "graph cuts" is applied specifically to those models which employ a max-flow/min-cut optimization.

[Sema Candemir, Kannappan Palaniappany, and Yusuf Sinan 2013][3] describes multiclass boosting algorithm for the classification scheme. The multi-class regularization labelling system consist of three main stages: (i) The system first learns labels by training a boosting algorithm with local feature vectors of the training images. (ii) The trained system predicts a map for the test image. (iii) An energy-based segmentation algorithm uses the predicted map to segment the test image.

[Wai Yan Nyein Naing, Zaw Z. Htike 2014] [4] This paper describes the chest radiography in tuberculosis This paper is surveyed with the analysis of a CAD system for automated analysis of chest x-ray for identification of pulmonary TB. This paper emphasizes to give the steps of TB classification from X-ray images such as pre-processing, feature extraction and classification. Most of researches are going on in this area from several years. This paper is based on all these researches and experiments for detecting the possibility of TB in a chest radiograph. This will substantially reduce the effort of Medical officer and radiologist.

[Stefan Jaeger*, Alexandros Karargyris, Sema Candemir, Les Folio, Jenifer Siegelman, Fiona Callaghan,Zhiyun Xue, Kannappan Palaniappan, Rahul K. Singh, Sameer Antani, George Thoma, Yi-Xiang Wang,Pu-Xuan Lu, and Clement J. McDonald 2014][5] describes an automated approach to classify a chest x-ray as abnormal(TB affected) or normal.I t describes about two types of feature set such as CBIR feature set and Object Detection Inspired Feature set to classify the chest x-ray as TB positive or not. The methodology used in this paper is first segment the chest x-ray image by using graph cut segmentation ,then feature extraction and finally classification using the SVM classifier. [Laurens Hogeweg, Clara I. S´anchez, Pragnya Maduskar, Rick Philipsen, Alistair Story, Rodney Dawson, Grant Theron,

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Keertan Dheda, Liesbeth Peters-Bax IEEE Transactions on Medical Imaging][6] In this paper textural, focal, and shape abnormality subsystems are combined into one system to deal with the heterogeneous abnormality expression in different populations. The performance is evaluated on a TB screening and a TB suspect database using both an external and a radiological reference standard. 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, pre-processing of the chest radiograph and computation of features.

[Amani Al-Ajlan, Ali El-Zaart 2009] [7] describes Entropy-based image thresholding ,it is an important concept in the area of image processing.It propose a new method which is derived from Pal (1996) method , that used minimum cross-entropy thresholding method for estimating optimal threshold value based on Gamma distribution. Moreover,this method is applicable to processes bi-modal and multimodal images.

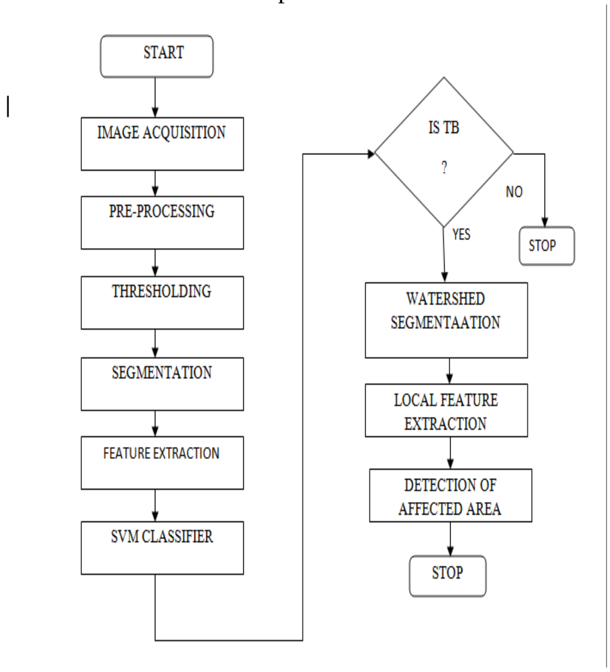
[Bram van Ginneken*, Shigehiko Katsuragawa, Bart M. ter Haar Romeny, Kunio Doi, and Max A. Viergever, 2002][8] describes about texture analysis,which is an active research field. One method is filter bank method, in which statistics from filtered images are used as features. This paper explain the choice to use moments of histograms extracted from regions in the image after filtering with a multi scale filter bank consisting of the Gaussian and its derivatives. The approach in this paper is to divide the lung fields in parts and analyze each part separately, with a classifier trained with texture features extracted solely from these parts. In this way, the classifier should capture knowledge regarding the normal variation within that particular part. Overlapping regions of various sizes are used so that not only the texture features are extracted at multiple scales, but also from multiple "apertures."

[Manik Varma and Andrew Zisserman][9] this paper investigate texture classifcation from single images obtained under unknown viewpoint and illumination. A statistical approach is developed where textures are modelled by the joint probability distribution of filter responses. This distribution is represented by the frequency histogram of filter response cluster centres (textons). Recognition proceeds from single, un calibrated images and the novelty here is that rotationally invariant filters are used and the filter response space is low dimensional. It also discuss the effects of various parameters on classification algorithm such as the choice of filter bank and rotational invariance, the size of the texton dictionary as well as the number of training images used. Finally, it present a method of reliably measuring relative orientation co-occurrence statistics in a rotationally invariant manner, and discuss whether incorporating such information can enhance the classifier's performance.

[Manuel J. Marín-Jiménez and Nicolás Pérez de la Blanca 2005][10] The aim of this work is the evaluation of different multi-scale filter banks,mainly based on oriented Gaussian derivatives and Gabor functions, to be used in the generation of robust features for visual object categorization. In order to combine the responses obtained from several spatial scales, it use the biologically inspired HMAX model. The aim of this work is to carry out an experimental study in order to propose a new set of simpler filter banks, comparing the local features based on a Gabor filter banks with the ones based on Gaussian derivative filter banks. These features will be applied to the object categorization problem.

III. PROPOSED METHOD

The Framework of the entire process is shown below



This section presents implementation methods for lung segmentation, feature computation, and classification. The above figure shows the block diagram of the system with the different processing steps .First, the system segments the lung of the input CXR using a graph cut optimization method . For the segmented lung field, the system then computes a set of features as input to a pre-trained binary classifier. Then, using decision rules and thresholds, the classifier outputs its confidence in classifying the input CXR as a TB positive case, for example.

Now, if the CXR is classified as abnormal , the lung region is segmented using watershed segmentation. The features of each segmented region is extracted. Using ttest algorithm predominant features for TB positive is selected. Again using a classifier the affected areas are detected and shaded.

Step by step procedure is as described below

1. Image Acquisition

The data is taken from the publically available JSRT set. It contain 247 CXRs out of which 93 CXRs are normal and 154 CXR are abnormal . The JSRT data is the result of a study investigating the detection performance of radiologists for solitary pulmonary nodules . The data was collected from 14 medical centers. All CXR images have a size of 2048 x2048 pixels and a grayscale color depth of 12 bits. Each of the abnormal CXRs contains one pulmonary nodule classified into one of five degrees of subtlety, ranging from extremely subtle to obvious. However,

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In the JSRT images, the nodules hardly affect the lung shapes. The nodules are either well within the lung boundary or they are so subtle that the effects on lung shape are minor. Therefore take advantage of the entire JSRT database to train our shape model for a typical normal lung.

In this work the user can select their CXR. The program is coded in MATLAB 2013a ,a dialogue is displayed on the screen so that the user can select their image. If the image selected is not correct an error is produced. This image file is then converted into grayscale image.

2. Pre-processing

The following steps are done in the preprocessing stage.

3. Image Rotation

In the dataset images are laying horizontally. To get a vertical position the image is rotated clock wisely to 90 degree.

4. Image Resizing

The data is taken from the publically available JSRT set. It contain 247 CXRs out of which 93 CXRs are normal and 154 CXR are abnormal. The data was collected from 14 medical centers. All CXR images have a size of 2048 x2048 pixels and a grayscale color depth of 12 bits. This image is resized into an image of size 256x256.

5. Histogram Equalization

The image contrast is enhanced by histogram equalization. Here adaptive histogram equalization is done. In adaptive histogram the image is divided into tiles and contrast of each tile is enhanced.

6. Image Smoothing

Coherence filter is used to smooth the image so that unwanted edges can be blurred out.

7. Thresholding

Image segmentation refers to the process of subdividing a digital image into multiple regions or objects. The goal of segmentation is to simplify or change the representation of an image into a form that is more meaningful and easier to analyze. Image thresholding is an efficient technique for image segmentation applications and for pattern recognition. The important step in thresholding is the choice of the threshold. There are two different approaches for thresholding: global and local thresholding. Global thresholding techniques segment the entire image by using a single global threshold based on gray level values. On the other hand, local thresholding techniques segment the image into smaller sub-images then the thresholds will be calculated for each sub-image depending on local properties of the point or its position as well as its graylevel values .

Entropy is "the measure of information content in probability distribution" . Entropy could be used also as "a measure of separation that separates the information into two regions, above and below an intensity threshold" . A number of entropy based thresholding methods are exist in the literature. These methods can be categorized into three groups: entropic thresholding, cross-entropic thresholding and fuzzy entropic thresholding. Entropic thresholding considers "the image foreground and background as two different signal sources, so that when the sum of the two class entropies reaches its maximum, the image is said to be optimally thresholded". Cross-entropic thresholding considers "the thresholding as the minimization of an information theoretic distance". Fuzzy entropic thresholding considers "the fuzzy memberships as an indication of how strongly a grey value belongs to the background or to the foreground".

This work used the minimum cross entropy thresholding method.

Consider an image function f: N x N→G, where N is the set of natural integers and G={1,...L} ϵ N the set of gray level. Segmentation process is a construction of the function g:N x N→S where S ={μ_1,μ_2} ϵ R ,where R is a real number. The segmented image g(x,y) is constructed as follows:

$$g(x,y) = \begin{cases} \mu 1, & f(x,y) < t \\ \mu 2, & f(x,y) \geq t \end{cases} \text{ ---------------- } 8$$

The segmented image g(x,y)uniquely determined from f(x,y) by the specification of three unkown parameter t, μ_1, μ_2.A criteria has to constructed to find the optimal value of t, μ_1,μ_2 So that g is resemble as close as f. That is

$$\eta(g)=\eta(t, \mu_1,\mu_2).\text{-- } 9$$

Thus a set of value G={g_1,g_2.....g_N},where N is the number of pixel in the image has to be inferred from the observed image F={f_1,f_2...f_N} together with the use of suitable constraints. G contain image having only two values μ_1 and μ_2 which are yet unknown. F gives the constraints on the values of μ_1 and μ_2 such that total intensity in the reconstructed image is identical to the observed image in both categories. The constraints can be summarized

1) ,μ_2} g_i ϵ{ μ_1

2) $\sum_{fi<t} fi = \sum_{fi<t} \mu 1$

3) $\sum_{fi\geq t} fi = \sum_{fi\geq t} \mu 1$

Which allows the determination of μ_1 and μ_2 by the following equations:

$\mu_1(t) = \sum_{fi<t} fi/N1$ and $\mu_2(t) = \sum_{fi\geq t} fi/N2$,

where N_1 and N_2 are number of pixels smaller in the two region. Combining the equations

$$\eta(t) = \sum_{fi<t} fi \log\left(fi/\mu 1(t)\right) + \sum_{fi\geq t} fi \log\left(fi/\mu 2(t)\right) \text{------------------------------- } 10$$

The threshold is then selected by

$$t0 = \min\left(\eta(t)\right) \text{ -- } 11$$

where to is the required threshold.

Thus threshold is selected to minimize the cross entropy between the thresholded image and the original image.

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8. Graph Cut Based Lung Segmentation

The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. It can identify the regions of interest in a scene or annotate the data. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. Image segmentation is useful in many applications such as Medical Imaging (Tumor Detection), Face Recognition, Machine Vision etc.

To employ a graph cut approach and model the lung boundary detection with an objective function. To formulate the objective function, we define three requirements a lung region has to satisfy:

1) the lung region should be consistent with typical CXR intensities expected in a lung region,

2) neighboring pixels should have consistent labels, and

3) the lung region needs to be similar to the lung model we computed. Mathematically, we can describe the resulting optimization problem as follows:

Let $f=\{f_1,f_2\ldots\ldots f_N\}$ be a binary vector whose components f_P correspond to foreground (lung region) and background label assignments to pixel p ϵ P, where P is the set of pixels in the CXR, and N is the number of pixels. According to the method, the optimal configuration of is given by the minimization of the following objective function:

$$E(f) = E_d(f) + E_s(f) + E_m(f) \quad \text{---------------------------- } 12$$

where E_d , E_s and E_m represent the region, boundary, and lung model properties of the CXR, respectively. The region term considers image intensities as follows:

$$Ed(f) = \frac{1}{Imax}\left[\sum_{(p,s\in C)} |Ip - Is| + \sum_{(p,T)\in C} |Ip - IT|\right] \quad \text{------------------------------------ } 13$$

Where I_p is the intensity of pixel p and C is the set of edges representing the cut. <u>$I_s$and I_T are</u> the intensities of foreground and background regions. These intensities are represented by using a source (S) and terminal node (T).I_{max} is the maximum intensity value of the input image. (2) ensures that labels for each pixel are assigned based on thepixel's similarity to the foreground and background intensities.

The boundary constraints between lung border pixels and are formulated as follows:

$$Es(f) = \sum_{(p,q)\in C} \exp\left(-(Ip - Iq)2\right) \quad \text{---------- } 14$$

This term uses the sum of the exponential intensity differences of pixels defining the cut. The sum is minimum when the intensity differences are maximum.

The average lung model is a 2-D array which contains the probabilities of a pixel being part of the lung field. Based on this model, we define the lung region requirement as follows:

$$Em(f) = \sum_{(p,T)\in C} \mathrm{Prp} + \sum_{(p,s)\in C}(1 - \mathrm{Prp}) \quad \text{----- } 15$$

where P_{rp} is the probability of pixel being part of the lung model. This term describes the probability of pixels labeled as lung belonging to the background, and the probability of pixels labeled as background belonging to the lung, according to the lung model. The aim is to minimize both probabilities.

Using the three energy terms given above, minimize the objective function with a fast implementation of min-cut/max-flow algorithm .

9. Feature Extraction

To describe normal and abnormal patterns in the segmented lung field, two different feature sets are considered. The motivation is to use features that can pick up subtle structures in an CXR.

1) Object Detection Inspired Features—Set A:

As the first set, the features that successfully applied to microscopy images of cells for which classified the cell cycle phase based on appearance patterns are taken. This set is versatile and can also be applied to object detection applications. The first set is a combination of shape, edge, and texture descriptors . For each descriptor, it compute a histogram that shows the distribution of the different descriptor values across the lung field. Each histogram bin is a feature, and all features of all descriptors put together form a feature vector that input to the classifier. Through empirical experiments, it is found that using 32 bins for each histogram gives us good practical results. In particular, the following shape and texture descriptors are used.

- Intensity histograms (IH).
- Gradient magnitude histograms (GM).
- Shape descriptor histogram (SD)

$$SD = \arctan\left(\frac{\lambda 1}{\lambda 2}\right) \quad \text{------------------------------------- } 16$$

where λ_1 and λ_2 are the eigenvalues of the Hessian matrix, with $\lambda_1 \le \lambda_2$.

- Curvature descriptor histograms (CD)

$$CD = \tan^{-1}\left(\frac{\sqrt{\lambda 1^2 + \lambda 2^2}}{1 + I(x,y)}\right) \quad \text{--------------------------------- } 17$$

With $0 \le CD \le \frac{\pi}{2}$, where I(x,y) denotes the pixel intensity for pixel(x,y) . The normalization with respect to intensity makes this descriptor independent of image brightness.

- Histogram of oriented gradients (HOG)

is a descriptor for gradient orientations weighted according to gradient magnitude. 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. HOG has been successfully used in many detection systems .

- Local binary patterns (LBP)

is a texture descriptor that codes the intensity differences between neighboring pixels by a histogram of binary patterns . LBP is thus a histogram method in itself.

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The binary patterns are generated by thresholding the relative intensity between the central pixel and its neighboring pixels. Because of its computational simplicity and efficiency, LBP is successfully usedin various computer vision applications, often in combination with HOG.

With each descriptor quantized into 32 histogram bins, our overall number of features is thus 6*32=192.

2) CBIR-Based Image Features—Set B

For the second feature set, Set B, it contain a group of low-level features motivated by content-based image retrieval (CBIR) . This feature collection includes intensity, edge, texture and shape moment features, which are typically used by CBIR systems. The entire feature vector has 594 dimensions, which is more than three times larger than the feature vector of Set A, and which allows to evaluate the effect of high-dimensional feature spaces on classification accuracy. Most of the features are extracted, except for Hu moments and shape features, based on the Lucene image retrieval library, LIRE . In particular, Feature Set B contains the following features.

- Tamura texture descriptor: The Tamura descriptor is motivated by the human visual perception. The descriptor comprises a set of six features. This work use three of these features, which have the strongest correlation with human perception: contrast, directionality, and coarseness.
- CEDD and FCTH: CEDD (color and edge direction descriptor) and FCTH (fuzzy color and texture histogram) incorporate color and texture information in one histogram. They differ in the way they capture texture information.
- Hu moments: These moments are widely used in image analysis. They are invariant under image scaling, translation, and rotation . The DISCOVIR system (distributed content-based visual information retrieval) to extract Hu moments.
- CLD and EHD edge direction features: CLD (color layout descriptor) and EHD (edge histogram descriptor) are MPEG-7 features . CLD captures the spatial layout of the dominant colors on an image grid consisting of 8x 8 blocks and is represented using DCT (discrete cosine transform) coefficients. EHD represents the local edge distribution in the image, i.e., the relative frequency of occurrence of five types of edges (vertical, horizontal, 45 diagonal, 135 diagonal, and nondirectional) in the sub-images.
- Primitive length, edge frequency, and autocorrelation: These are well-known texture analysis methods, which use statistical rules to describe the spatial distribution and relation of gray values .
- Shape features: We use a collection of shape features provided by the standard MATLAB implementation (regionprops) , such as the area or elliptical shape features of local patterns.

10. Classification

To detect abnormal CXRs with TB, a support vector machine (SVM) is used , which classifies the computed feature vectors into either normal or abnormal. An SVM in its original form is a supervised non probabilistic classifier that generates hyperplanes to separate samples from two different classes in a space with possibly infinite dimension. The unique characteristic of an SVM is that it does so by computing the hyperplane with the largest margin; i.e., the hyperplane with the largest distance to the nearest training data point of any class. Ideally, the feature vectors of abnormal CXRs will have a positive distance to the separating hyperplane, and feature vectors of normal CXRs will have a negative distance. The larger the distance the more confident in the class label. Therefore use these distances as confidence values to compute the ROC curves.

If the CXR is classified as normal,then no further verification is needed. The result is displayed as normal. If the CXR is classified as abnormal the next step is to localize the affected area. For that the following steps are done.

11. Watershed Segmentation

Watershed segmentation results in a very stable segmentation results including connected segmentation boundaries. Watershed based image segmentation algorithms are less computational complex and provide very good segmentation result.

Watershed transformation also called, as watershed method is a powerful mathematical morphological tool for the image segmentation. It is more popular in the fields like biomedical and medical image processing, and computer vision . In geography, watershed means the ridge that divides areas drained by different river systems. If image is viewed as geological landscape, the watershed lines determines boundaries which separates image regions. The watershed transform computes catchment basins and ridgelines (also known as watershed lines), where catchment basins corresponding to image regions and ridgelines relating to region boundaries . Segmentation by watershed embodies many of the concepts of the three techniques such as threshold based, edge based and region based segmentation. Watershed algorithms based on watershed transformation have mainly two classes. The first class contains the flooding based watershed algorithms and it is a traditional approach where as the second class contains rain falling based watershed algorithms. Many algorithms have been proposed in both classes but connected components based watershed algorithm shows very good performance compared to all others. It comes under the rain falling based watershed algorithm approach. It gives very good segmentation results, and meets the criteria of less computational complexity for hardware implementation.

12. Local Features Extraction

Textures are modelled by the joint distribution of filter responses. This distribution is represented by texton (cluster centre) frequencies, and textons and texture models are learnt from training images. Classification of a novel image proceeds by mapping the image to a texton distribution and comparing this distribution to the learnt models.

In the learning stage, training images are convolved with a filter bank to generate filter responses. Filter responses are chosen as textons and are used to label each filter response, and thereby every pixel, in the training images. The histogram of texton frequencies is then used to form models corresponding to the training images.

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Model generation.: Given a training image, its corresponding model is generated by first convolving it with a filter bank and then labelling each filter response with the texton which lies closest to it in filter response space. The histogram of textons, i.e. the frequency with which each texton occurs in the labelling, forms the model corresponding to the training image.

In the classification stage, the same procedure is followed to build the histogram corresponding to the novel image. This histogram is then compared with the models learnt during training and is classified on the basis of the comparison. A nearest neighbour classifier is used and the t test is applied. Now the rotationally invariant filter sets that are used in the classification algorithm in this work are described as follows:

a) The Leung-Malik (LM) set

The LM set consists of 48 filters, partitioned as follows: first and second derivatives of Gaussians at 6 orientations and 3 scales making a total of 36; 8 Laplacian of Gaussian filters; and 4 Gaussians. The scale of the filters range between σ= 1 and σ = 10 pixels.

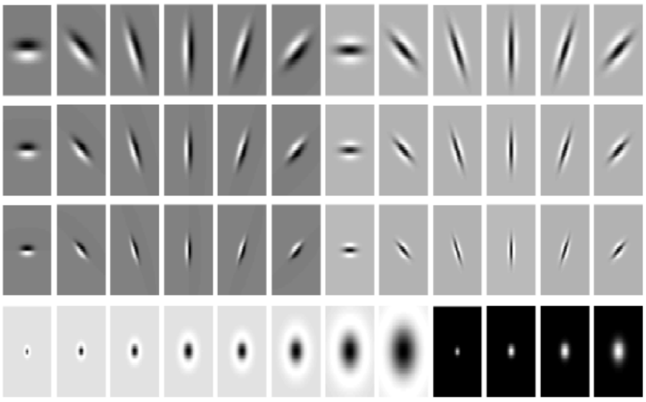

Figure : The LM filter bank: has a mix of edge, bar and spot filters at multiple scales and orientations. It has a total of 48 filters - 2 Gaussian derivative filters at 6 orientations and 3 scales, 8 Laplacian of Gaussian filters and 4 Gaussian filters.

b) The Schmid (S) set

The S set consists of 13 rotationally invariant filters of the form

$$F(r,\sigma,t) = F0(\sigma,t) + \cos\left(\frac{\pi t r}{\sigma}\right) e^{\frac{-r2}{2\sigma 2}} \qquad \text{-------------- } 18$$

where $F0(\sigma,t)$ is added to obtain a zero DC component with the (σ,t) pair taking values (2,1), (4,1), (4,2), (6,1), (6,2), (6,3), (8,1), (8,2), (8,3), (10,1), (10,2), (10,3) and (10,4).

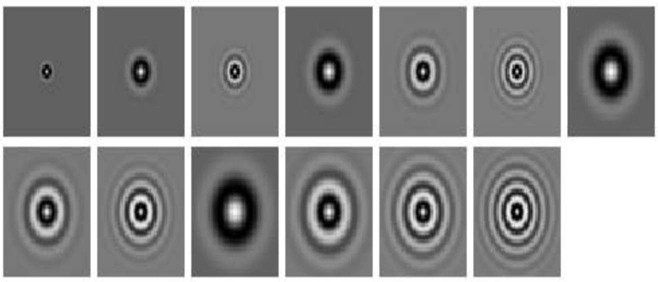

Figure 3.8: The S filter bank :is rotationally invariant and has 13 isotropic, \Gabor-like" filters.

c) The Steerable Filters

The term “Steerable filter” is used to describe a class of filters in which a filter of arbitrary orientation is synthesized as a linear combination of a set of’ basis filters’. Oriented filters are used in many vision and image processing tasks, such as texture analysis, edge detection ,image data compression ,motion analysis and image enhancement.

IV. EXPERIMENTAL RESULTS

This section contain the images obtained at various stages of the work. The section is divided into two parts as classification section and Localization section.

1. Classification Section

This section presents the practical evaluation of the work. First the input image is selected and rotated to 90^0.The input image is as shown. The Chest X-ray image is taken as an input image.

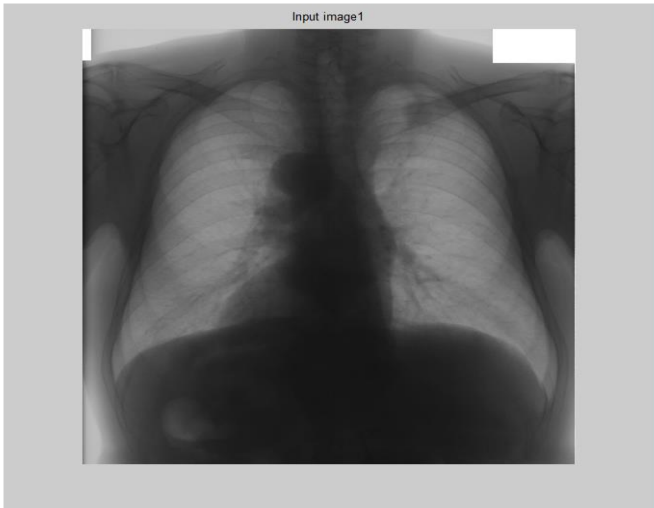

Figure 1: Input Chest X-ray

Fig 2 shows the pre-processing of the chest radiograph include the image resizing and histogram equalization. The input image of size 2048X2048 and it is resized to 256X256,then the contrast of the input image is enhanced using adaptive histogram equalization. Then fitering is done. Coherence filter is used for this. The function COHERENCEFILTER will perform anisotropic diffusion of a2D gray/color image or 3D image volume, which will reduce the noise in an image while preserving the region edges, and will smooth along the image edges removing gaps due to noise. These are as shown.

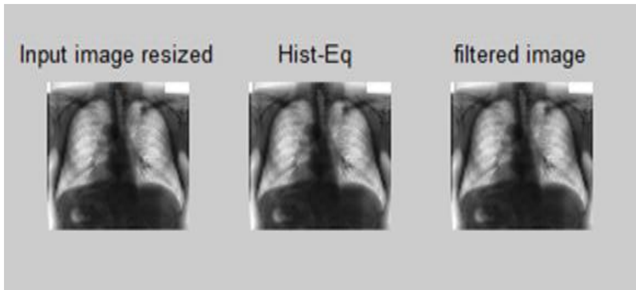

Figure 2: pre-processed images

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Then thresholding of the image is done. The minimum cross entropy thresholding is used in this work.
The function min CEP is used which perform the thresholding of nonblank space of the image. Then Graph cut lung segmentation is performed and after morphological operation lung regions are segmented out. It is shown in fig 3.

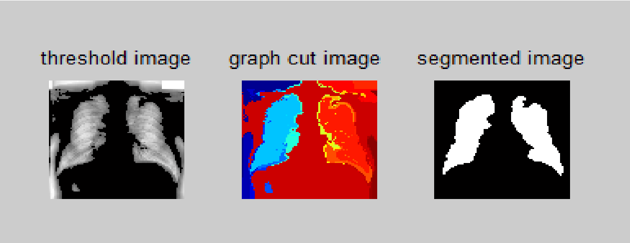

Figure3: Images after thresholding, graph cut segmentation and morphological operations

Feature extraction is performed to extract the feature of Chest radiograph. The features are extracted based on *Object Inspired Features* such as Intensity Histogram, Gradient Magnitude Histogram, Shape Descriptor Histogram, Curvature descriptors Histogram , Histogram of Gradients and Local Binary Patterns. Also *Content Based Image* features such as Tamura , Region properties and GLCM are used. Classification is performed using Support Vector Machine to diagnose the presence and absence of Tuberculosis disease in Chest Radiograph. Features and classification using Support Vector Machine is shown in Figure.

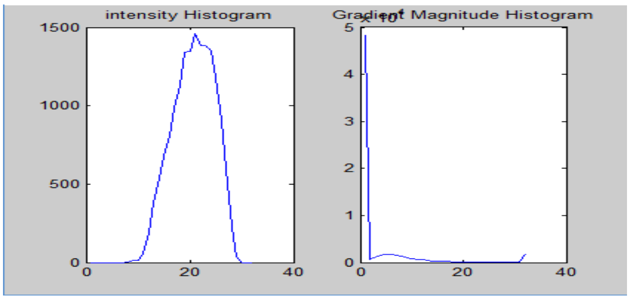

Figure4: Histograms

Table 1

Feature	Value
Coarseness	31.7691
Contrast	0.2111
Direction	7.3700e-09

Tamura feature values are as shown in the table. Properties of gray level co-occurrence matrix are contrast, correlation and energy.

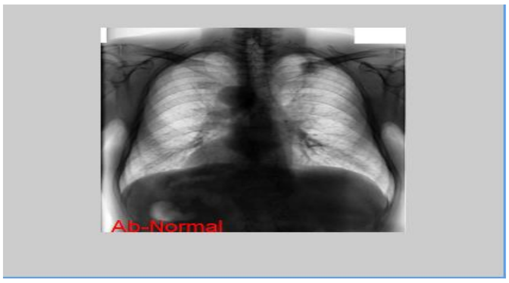

Figure 5: Chest x-ray classified as abnormal

2. Localization Section

If the chest x-ray is classified as abnormal ,then to localization of the affected area is done. For that ,first watershed segmentation is done, then local features of each over segmented region obtained from the watershed is taken. The affected region in the watershed region is put to true and others to false. Then this is multiplied with the input image to get a mask. Then this mask is applied to segmented lung region. The images are as shown.

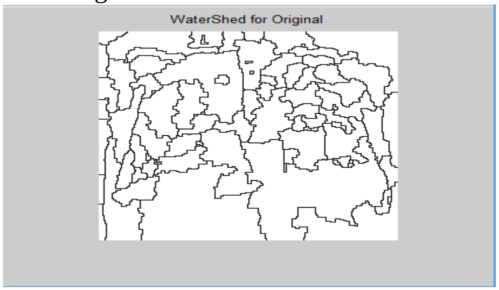

Figure 6: Watershed image

Figure 7: Obtaining the mask (The input image and the shaded watershed image are element by element multiplied to get the mask)

Figure 8: Applying the mask (The lung region and the mask are element by element multiplied to get the nodule region) Thus the final output image is as shown

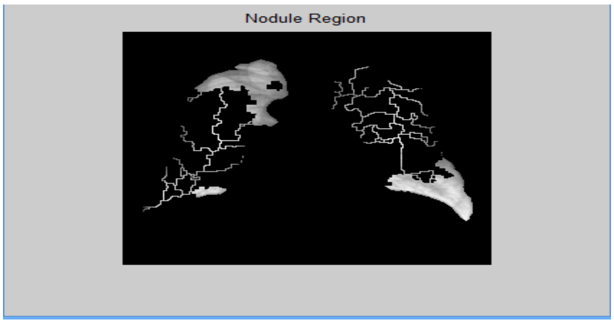

Figure 9: The affected area of the lung region region Fig.c Original image

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V. CONCLUSION

This work aims to develop an automated system that screens CXRs for manifestations of TB and then localize the affected area. When given a CXR as input, this 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. In this work a set of shape, edge, and texture features are computed and given as input to a binary classifier, which then classifies the given input image into either normal or abnormal. If the CXR is abnormal then watershed segmentation is performed and local features are extracted using filter banks. Again the segmented regions are classified using a linear SVM. Then affected areas are found.90% of accuracy is achieved by this method.

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