ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

IARJSET

International Advanced Research Journal in Science, Engineering and Technology
National Conference on Emerging Trends in Engineering and Technology (NCETET'16)
Lourdes Matha College of Science & Technology, Thiruvananthapuram
Vol. 3, Special Issue 3, August 2016

Advanced Tuberculosis Detection System Using Chest Radiographs

Ambalekshmi R Chand[1], Gopakrishna M Raj[2]

PG Scholar, Electronics and Communication, Rajadhani Institute of Engineering and Technology, Trivandrum, India [1]

Assistant Professor, Electronics and Communication, Rajadhani Institute of Engineering and Technology, Trivandrum, India[2]

Abstract: Automated tuberculosis detection systems will help radiologists to diagnose the disease easily. The proposed system implements an advanced detection system using chest radiographs. The system uses a minimum cross entropy segmentation for extracting the lung regions from chest radiographs. After the segmentation process several features are extracted for the classification stage. A probabilistic neural network was used for the classification. The images are classified as normal or abnormal by the classifier.

Keywords: Tuberculosis, minimum cross entropy, computer aided diagnosis, chest X-ray, tamura.

I. INTRODUCTION

Tuberculosis is a serious disorder due to the bacterium Mycobacterium tuberculosis. It will spread through the air and it generally affects the lungs but if kept untreated it should affect other parts of the body also. So the early detection of Tuberculosis helps to avoid such serious effects caused due to this. TB can be diagnosed by different methods such as culture of body fluids, based on chest X-rays (CXR) etc. Taking chest radiographs is an inexpensive method for detecting TB. The careful examination of the CXR is necessary in order to prevent errors due to prediction by directly looking into the X-rays. So computer aided diagnosis systems are very useful for reducing such kind of errors and it will be very helpful for radiologists for the exact prediction of the results. Computer aided diagnosis was used in many biomedical applications and it was very useful for the medical specialists for diagnosing many diseases. The main task during this is to extract the lung boundaries from the CXR by suitable segmentation methods. Segmentation is an important stage for examining tuberculosis. There are different segmentation methods that are existing and are using in several image processing systems. The minimum cross entropy segmentation is a more fast and reliable algorithm for segmentation

Here the proposed system implements a minimum cross entropy segmentation method to extract the lung region. The minimum cross entropy segmentation method is a fast and reliable algorithm for segmenting the lungs from chest X-rays .After the segmentation stage, the features such as histogram of gradients (HoG) ,Gray level co-occurrence matrix (GLCM),local binary patterns (LBP) ,tamura features are extracted .The features thus extracted are used to train the classifier. The classifier used is probabilistic neural network and predicted the output to be either normal or abnormal.

II.PROPOSED SYSTEM

The proposed system consists of a pre processing stage, segmentation, feature extraction and classification.

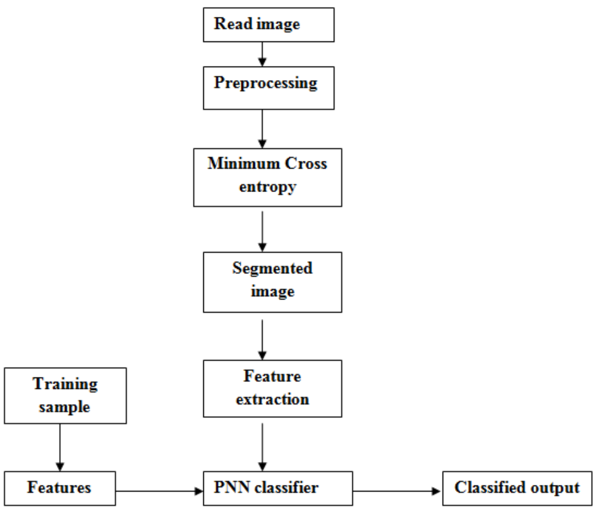

Fig 1 Architecture of the proposed system

The image is first processed in order to extract the features, which describe its contents. Preprocessing involves removing low-frequency background noise, normalizing the intensity of the individual particles images, removing reflections, and masking portions of images. The resulted image has been resized with specified output size.
Then the image is segmented using a minimum cross entropy method. Minimum cross entropy is a fast algorithm for the extraction of lung regions from chest radiographs. Computer aided diagnosis is very much useful for detecting lung regions from chest X-rays.
The threshold selection problem is solved by minimizing the cross entropy between the image and its segmented

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version. The cross entropy is formulated in a pixel-to-pixel basis between the two images and a computationally attractive algorithm employing the histogram is developed. The image and the histogram is loaded and then normalization of the histogram is made done. For each threshold value compute the entropy for low value and high value and cross entropy is calculated. Finally, a threshold value is calculated for minimum cross entropy.

Feature extraction is an important step in image processing. such as histogram of gradients, local binary patterns, tamura features are extracted and was used for training the PNN classifier. PNN was a supervised classifier and weights are calculated by feeding the extracted features to the input stage of the classifier. Classifier was trained by using training datasets. The classifier predicted whether the image is normal or abnormal.

III. SYSTEM IMPLEMENTATION

A. Pre processing stage

After reading the images a pre processing stage is made done. In image processing pre processing is an important step in order to reduce the noise and to enhance the image quality thereby improving the performance of the stages of the processing. Histogram equalization is made done in the pre processing stage in order to enhance the contrast of the image. After histogram equalization the image looks brighter than before.

B. Minimum cross entropy segmentation

Segmentation is an important method for extracting the lung regions from the chest x-rays. The proposed system implements a minimum cross entropy based segmentation method. Thresholding is done by selecting a threshold value which having a minimum cross entropy .A minimum cross entropy is found out between the segmented and original image. So a threshold value can be selected according to cross entropy and thereby segmentation can be done according to that threshold value.

Let I be the original image and h(i), i = 1, 2,...,L, be the corresponding histogram with L being the number of gray levels. Then the thresholded image, denoted by It, using t as the threshold value is constructed by

$$I_t(x,y)=\begin{cases} \mu(1,t), I(x,y) < t \\ \mu(t, L+1), I(x,y) \geq t \end{cases} \quad (1)$$

$$\mu(a,b) = \sum_{i=a}^{b-1} ih(i) \Big/ \sum_{i=a}^{b-1} h(i) \quad (2)$$

Cross entropy can be calculated by

$$D(t) = \sum_{i=1}^{t-1} ih(i) \log\left(\frac{i}{\mu(1,t)}\right) + \sum_{i=1}^{t-1} ih(i) \log\left(\frac{i}{\mu(t,L+1)}\right)$$

The MCET determines the optimal threshold t* by minimizing the cross entropy.

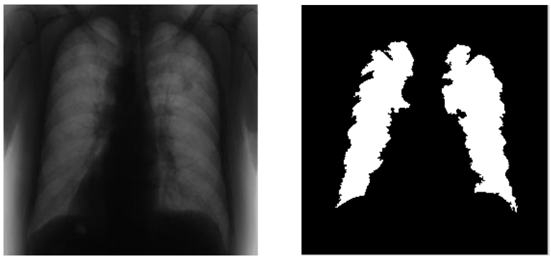

Fig 2 a) original image b) Segmented image

C. Feature extraction

After the segmentation stage several features such as gray level co occurrence matrix, histogram of gradients, local binary patterns, tamura features are extracted. The extracted features are then fed to the input of the classifier for training process.

1) Gray Level Co occurrence Matrix(GLCM)

Gray level co-occurrence matrix (GLCM) is used for examining the texture features of an image. The gray level co-occurrence matrix is also known as gray level spatial dependence matrix. Several statistical features of an image can be extracted from the GLCM.A GLCM can be created by calculating how often the pairs of pixel with particular value and that is specified in the relationship occur in an image and after creating the GLCM different statistical measures such as contrast, energy, correlation and homogeneity can be determined. Contrast determines the local variations in the GLCM. Correlation calculates the joint probability occurrences of the specified pixel pairs. The sum of squared elements in the GLCM is determined by calculating energy. Homogeneity determines the distribution closeness of elements in the GLCM to the diagonal of GLCM.

2) Histogram of oriented gradients

The Histogram of Gradients (HoG) is a feature descriptor used in several computer aided processes and also in image processing for the detection of objects in an image. It has several advantages than other descriptors. Since HoG operates on local cells. It is also invariant to geometric and photometric transformations except for object orientation .HOG calculate the gradient values and then cell histogram was created.

Implementation of the HOG descriptor algorithm is as follows:

- Divide the image into small connected regions called cells, and for each cell compute a histogram of gradient directions or edge orientations for the pixels within the cell.
- Discretize each cell into angular bins according to the gradient orientation.
- Each cell's pixel contributes weighted gradient to its corresponding angular bin.
- Groups of adjacent cells are considered as spatial regions called blocks

The grouping of cells into a block is the basis for grouping and normalization of histograms.

- Normalized group of histograms represents the block histogram.
- The set of these block histograms represents the descriptor.

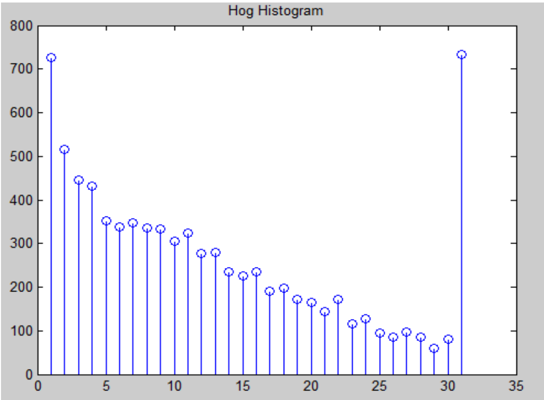

Fig 3HOG histogram

3) Local binary patterns

Local binary pattern is a simple and efficient texture descriptor and its computational complexity is also low. The input image is labelled by a value which is got by thresholding neighbourhood of the pixel with centre pixel value. The result is then considered as binary number i.e., either 0 or 1.Different labels are used and all these labels are thereby combined to form a texture descriptor.

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Optionally normalize the histogram.

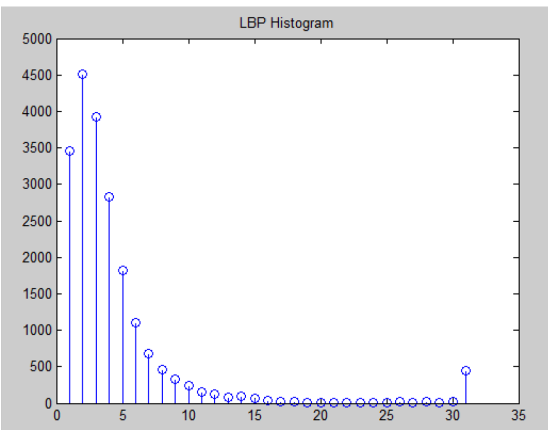

Fig 4 LBP histogram

- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 256-dimensional feature vector.
- Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

4) Tamura features

Tamura feature includes coarseness, contrast, directionality, line likeness, regularity and roughness. The features such as coarseness, contrast and directionality are used here since they are correlated higher with human perception. The textures of an image can be described effectively by the tamura features and it is widely used in image retrieval applications. Coarseness relates to distances of notable spatial variations of gray levels. Contrast measures how gray levels vary in the image. Directionality is measured using the frequency distribution of oriented local edges against their directional angles.

D. Probabilistic neural network

A probabilistic neural network classifier (PNN) was used for classification and it senses the features that are extracted. It is a supervised classifier. The classifier was trained by using JSRT databases.

After the training process the classifier predict the output as either normal or abnormal according to the features that it senses during the training stage.

The features from the training dataset are compared with the features extracted from the test image and classified by the PNN classifier.

IV.EXPERIMENTAL RESULTS

The proposed system was experimentally tested on JSRT databases. JSRT databases are publically available and the segmentation results are very accurate and we got better segmentation of the lungs from the chest radiographs using the minimum cross entropy. Several features such as HoG, LBP, tamura, GLCM are extracted. These features show the textural and statistical properties in the images. The chest X-ray images are classified as normal or abnormal by using a PNN classifier. The results show 95 percent accuracy in the images

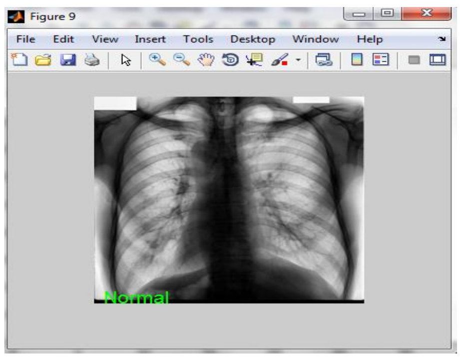

Fig 5 Classifier prediction

DOI 10.17148/IARJSET

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V. CONCLUSION

In this work we proposed a minimum cross entropy segmentation for extracting the lung regions from the chest X-rays and it was found to be very fast and accurate .Tuberculosis can be easily detected through this and we incorporate minimum cross entropy for getting fast and better results by finding out the threshold value for segmentation. Tuberculosis can be easily detected through this proposed method. By using this method lung regions can be easily extracted from the chest X-rays by the minimum cross entropy segmentation and it is found to be more accurate and faster than the existing algorithms. We also incorporated a probabilistic neural network for classification of the chest X-ray images as normal or abnormal after training and testing of the classifier. So the proposed system must be very much useful for medical experts to diagnose tuberculosis using the chest X-rays. As a future work several other features can be also extracted for further medical applications and can be done using other classifiers for a comparison study.

APPENDIX

The chest X-ray datasets are publically available .Submit the request on the webpage: http://archive.nlm.nih.gov/ for research purposes.

ACKNOWLEDGMENT

The authors would like to thank JSRT for providing the chest X-ray databases and the reviewers and editors for their constructive feedback.

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