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A review of Automated Screening for Tuberculosis of Chest Xray and Microscopy Images

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Abstract— Tuberculosis is a major health issue people are facing all around the world. Tuberculosis is a prevalent, deadly infectious and penetrating disease basically triggered by Mycobacterium Tuberculosis. Mostly lungs are affected from Tuberculosis. The screening process for tuberculosis detection and diagnosis requires time and is susceptible to human errors. The interpretation of tuberculosis is tiresome and hardworking task requiring highly trained workers. The microscopy method for screening includes the Ziehl-Neelsen and fluorescence stained specimen's microscopy. The diagnostic field has been revolutionized by the discovery of X-ray radiology. Chest X-rays radiology is another tool for detecting tuberculosis. The objective of this survey is to review different automated tuberculosis detection approaches using chest X-ray and microscopic images. The paper presents a summary of different automated systems designed. Many clinical and diagnostic applications utilize computationally designed algorithms that help in clinical diagnostic analysis by acquisition of images. It was concluded that Digital image is an important medium for analyzing, annotating, patient's demographics reporting in screening of tuberculosis through chest radiography and microscopy. Using different approaches automated screening of tuberculosis provides an accurate, speedy and cost effective detection system to a manual system of slide analysis for workers. Algorithms designed for chest X-ray or Microscopy images will improve the efficiency and accuracy of the system. In future these approaches can be used to other laboratory based techniques of tuberculosis screening e.g. Drug Susceptibility test, Line Probe Assay and culturing.

Index Terms— *CAD*, *CXR*, *RGB*, *TB*, *AFB*, *HSI*, YCbCr.

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1 Introduction

Computer vision is a widely growing field applied to a variety of real world problems and applications. Medical imaging is one of such application. Different image processing techniques are used to design algorithms that can detect diseases and the severity of the disease. Tuberculosis is an infectious disease and is one of the major problems all around the world. Mostly developing countries suffer from tuberculosis due to poor health conditions. There are different analog techniques for the screening of tuberculosis e.g. microscopy, Genexpert, culture testing and drug susceptibility test and line probe assay detection. However, different automated techniques had been developed for the detection of severity of tuberculosis disease.

2 Microscopy images & tuberculosis screening

The algorithms designed for tuberculosis screening integrates the existing and prevailing analog Ziehl-Neelsen, fluorescence microscopy and chest radiograph methods. Images of sputum sample in different field of view are captured using digital camera strapped on the microscope. The digitized image is processed and the presence or absence of abnormality is recognized. The system will count the total number of bacilli on each slide and report on the findings including the current load in each field of view.

3 Chest radiography & tuberculosis Screening

Medical imaging technology is an information managing and integrated system designed for the screening of tuberculosis patients. The equipment used includes microscope, computer, digital camera for capturing images and the software that will be used for identifying the disease. However for Chest Radiographs the X-Ray images are used as input to algorithm. The algorithms interpret the images. The results generated are used to analyze the sensitivity and specificity of the designed system. Automated systems are used to gain better results in less time. The data of these images can be used as medical record to review and analyze the previous history of a patient. Automated detection system speed up the process by incrementing the bulk of slides screened. The screening process is improved by making the reviewing process faster by reducing eye fatigue.

4 Different automated approaches

This paper describes different chest radiography and microscopy images approaches used in the automated screening of tuberculosis patients.

4.1 Scalar selection technique and filter post processing

The report of Global TB control 2013 according to [26] Indicate that, "Tuberculosis (TB) continues to be a noteworthy worldwide medical issue. An expected 8.6 million individuals suffered from TB in the year 2012 and 1.3 million kicked the bucket from the illness. The fundamental microscopy procedures are utilized for tuberculosis analysis that includes Ziehl-Neelsen and fluorescence microscopy. Fluorescence microscopy is a diagnostic strategy that utilizes high expenses on microscopy unit and its support therefore, Ziehl-Neelsen microscopy is more appropriate for use. Ziehl-Neelsen sputum smear microscopy is used for automated screening of tuberculosis in two main steps that are bacillus segmentation and post processing. Segmentation is a process of dividing an image

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into multiple parts and regions for obtaining the required information. Segmentation identifies objects present in an image. Post processing restores image after segmentation is performed. A scalar selection technique is used for choosing input variables from an image using the classifiers of segmentation. Segmentation classifier uses four color spaces that are RGB, HSI, YCbCr and Lab for the classification of pixels in an image. For segmentation process a total of thirty features were utilized by subtracting the color components of various color spaces. In the post processing step bacilli are separated from artifacts by using a rule based, a size and a geometric filter by using the components of the RGB space. Fig.1 below shows the image containing high density and low density background images. The graph shows the number of pixels of low and high density contrast images. The percentage of high density pixels lies between the values of 61-120 and the low density pixels lies between 1-60 ranges in the graph c mentioned below.

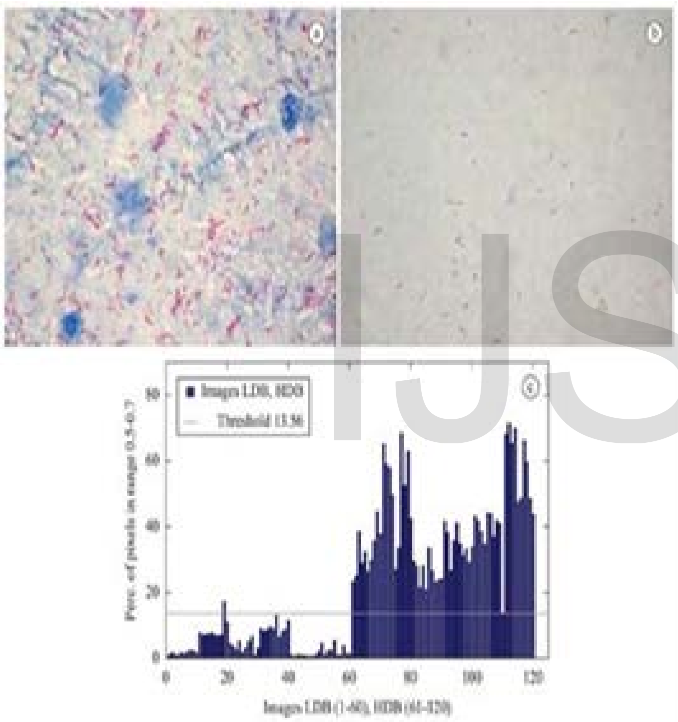

Fig. 1.
(a) High density background image (HDB);
(b) Low density background image (LDB);
(c) The percentage of image pixels represented by bar graph.

In the identification of bacillus an error rate of 3.38% was obtained. The overall sensitivity of the designed system was 96.80%. A total of 120 slide images were taken from 12 patients. Three types of objects were identified that includes bacillus, agglomerated bacillus and artifacts. The best outcome was acquired with a support vector machine algorithm using three post processing filters and segmentation.[1]

4.2 Region based active segmentation

Chest radiographs is an essential apparatus for battling against TB. In high population existing methods are less reliable. For performing mass screening of tuberculosis of chest radiographs another important algorithm was developed. Distinguishing depressions from x-beam samples of chest is a productive strategy for diagnosing TB. The algorithm will scan chest X-ray images with less effort. Region based active segmentation is utilize for the segmentation of lung field. The classification of extracted features are done using support vector machine as either normal or abnormal. Fig.2 below shows the major steps involved in processing images for screening of tuberculosis disease.

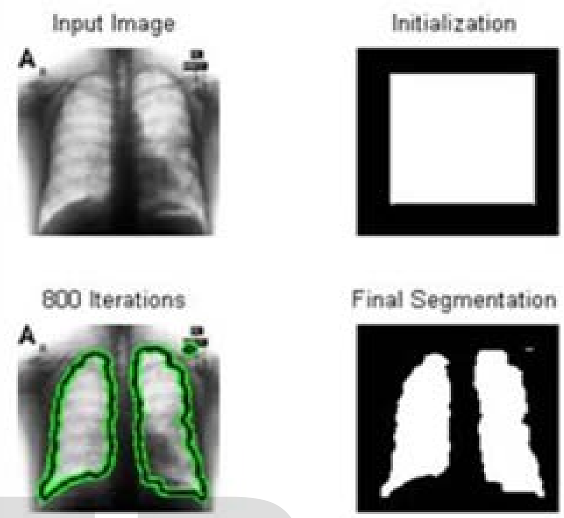

Fig.2. Methodology for identifying abnormality.

The totals of 138 chest X-ray images were taken from which 80 were normal and 58 were abnormal. These chest X-rays images were contained in the Montgomery County Data Set. The images were captured through a Eureka stationary x-ray machine and all images were in 12-bit gray scale. The chest X-ray images depicting abnormalities includes effusions and military patterns. [2]

4.3 Stepwise Classification algorithm

Another important algorithm designed for tuberculosis screening is a stepwise classification algorithm. For classification expansion on Boolean function was performed based on the Shannon cofactor. Different types of false positives are removed from the designed algorithm and identify the concentrations of TB bacilli. TB Bacilli is identified and classified into different categories e.g. beaded, small bright and dim elongated type of objects. Clinical information is used in identifying morphological and contrast features. The step wise classification algorithm is based on few individual classifiers. Adaptive algorithm is utilized for increasing the bacilli counts based on a microbiologist's statistical heuristics decision process. For the reduction of false positives the minimization from a binary decision tree is done to classify different types of true and false positives on the basis of feature vectors. The performance of algorithm was done using a receiver operating characteristic method by using binary class task analysis method. Fig.3 below shows the graph describing total positive and negative cases. The sensitivity is shown on Y-axis and False positive rate on X-axis. The sensitivity and false positive rate at different points is mentioned in the graph. The specificity was calculated from negative cases and the sensitivity was calculated from positive cases. The sensitivity parameter only shows positive cases so it was taken on x-axis in the graph below. The receiver operating characteristic curve (ROC) is used to identify the performance of step wise classification algorithm. A total of 74 positive cases were utilized to generate ROC plot. From a total of 74 positive cases 25 scanty and 49 high concentration cases were used for the development of algorithm. The P1, P2 and P3 are the high concentration regions detected in the plot. Other 102 negative and 74 positive cases were not used in the development of the algorithm. The frequencies of false positives were removed in a sequential fashion. The area under the curve shows high concentration cases by superior detection performance value of 0.913 and the value of 0.878 was obtained from high concentration cases mixed with scanty cases.

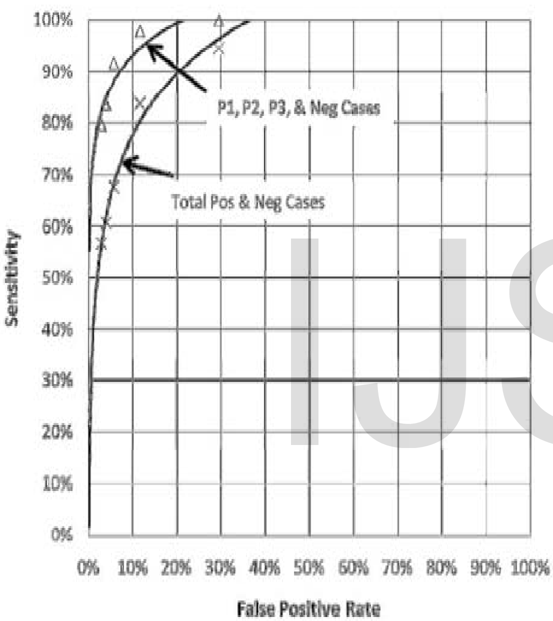

Fig. 3. ROC plot for Total positive and negative cases.

The analysis shows the high concentrations, scanty and negative as 97.96%, 56.00% and 88.24% respectively. [3]

4.4 Support vector machine classification

The identification of rod shaped TB bacilli screening in low resource areas is through the analysis of microscopy images of sputum smear. The digital microscope called the cellscope was used for gathering the required amount of images. Cellscope is one of the novel portable devices that will be used for capturing the required data. The algorithm designed will apply template matching and morphological operations with a Gaussian kernel for the identification of TB objects. The characterization of objects is done by geometric and photometric features, histograms of oriented gradients and Hu moments. After this support vector machine classification is performed. A total of 594 images were taken from a total of 290 patients from the clinics of Uganda. The performance of the algorithm was accurate and the average precision was 89.2%. [4]

4.5 Color Based Bayesian segmentation

Another important method for tuberculosis diagnosis is color based Bayesian segmentation. The method of segmentation identifies possible TB Objects. The artifacts are removed by shape comparison and TB objects are color labeled. The color labeled objects is identified as 'possible', 'non TB' and 'definite' by performing photo micrographic calibration and it is shown in fig.4 below labeling TB bacilli.

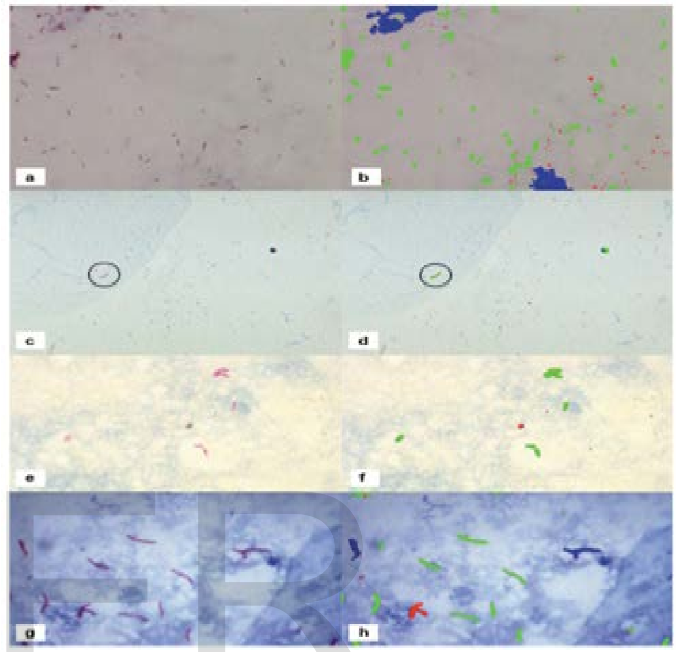

Fig. 4. Result of automated method for labeling TB Bacilli. In the left column are the original images and the right column are automated detected images.

The figure is divided into two columns. The left column shows the original images and the right column shows the automatically identified TB objects. The green objects are possible TB objects identified by passing through a series of step that includes bayesian segmentation, shape segmentation and size analysis. Red objects are detected by bayesian segmentation but they are rejected on the basis of their shape. Blue objects are those identified as possible TB objects by bayesian and shape segmentation but have an incorrect size. The limitations of bayesian segmentation method were extreme stain variation, low depth of field and superimposed AFB clusters. The method designed is used in developing countries where fluorescence microscopy is unaffordable and inaccessible. [5]

4.6 Particle swarm optimization

The treatment and diagnosis of tuberculosis is still a major challenge with increased mortality rates when left untreated and undiagnosed. For detecting and analyzing the severity of tuberculosis, Particle swarm optimization is another computer aided approach designed. In less time the severity of the disease is analyzed. [6]

4.7 Lung decease classification

Different computer aided diagnosis techniques have become popularized nowadays. By using MATLAB image processing techniques automated tuberculosis screening systems are becoming more and more reliable. The input image is preprocessed. Then segmentation is performed and features from the images are extracted. The algorithm detects tuberculosis in chest X-ray images using different MATLAB functions. Table 1 and 2 below shows some of the results for the left and right lungs. Lungs are detected as normal or abnormal based on the parametric values identified by the designed algorithm. Different statistical features as mentioned below in table I and table II are used to interpret the results. The normal chest radiographs shows lower values of entropy, variance and third moment. The value for mean was higher. In tuberculosis chest radiographs the value of mean was lower. The values of variance, entropy and third moment were higher. In tuberculosis mostly infection spreads asymmetrically and affects both of the lungs. In the tuberculosis chest radiographs on every feature value there is a greater inconsistency found between the right and left lung. [23]

TABLE I
FEATURE VALUES FOR BOTH NORMAL AND ABNORMAL OF THE RIGHT LUNG

Features	Normal	Abnormal
Mean	110.36	104.77
Variance	1237.3	1247
Third Moment	847.34	11353
Entropy	0.8	0.98

TABLE 2
FEATURE VALUES FOR BOTH NORMAL AND ABNORMAL OF THE LEFT LUNG

Features	Normal	Abnormal
Mean	129	102
Variance	1028.6	1140.7
Third Moment	-3394	16180
Entropy	0.78	0.99

4.8 Smoothening sharpening and ridge detection algorithm

The tiny nodules of tuberculosis present in lung area are detected by using two image processing techniques. A repetitive smoothening sharpening technique and ridge detection algorithm are used to detect tuberculosis. The impact of smoothening sharpening technique is determined for enhancing X-ray lung images. The ridge detection techniques further diagnose the indeterminate nodules correctly and identify malignant nodules at earlier stages. The mortality and morbidity for benign nodules surgery is avoided. The technique enhances the image contrast and the results help in classifying and detecting tuberculosis. In table 3 below the number of diagnostic samples tested is mentioned with their aggregate status of the disease and diagnostic results. Theses resultant numerical figures are used to calculate the accuracy, sensitivity and specificity of the designed algorithm. The accuracy rate of 91.25%, specificity rate of 92.11% and sensitivity rate of 90.48% was obtained. [7]

TABLE 3
RESULT OF DIAGNOSTIC SAMPLES TESTED

Diagnostic result	Status of disease		Total
	TB	Non-TB	
TB	38	03	**41**
Non-TB	04	35	**39**
Total	**42**	**38**	**80**

The accuracy of automated classification for tuberculosis process was enhanced to 16.18% by using this method.

4.9 Sobel algorithm and neural network classifiers

Automated detection of tuberculosis is done by using image processing techniques and neural network classifiers. The input image is extracted and morphological operators are applied. Different features are extracted using edge detection process by Sobel algorithm and back propagation neural network is designed. The screening process is done in two main steps that are either by color identification or by shape identification. The detailed methodology is shown in fig.5 below.

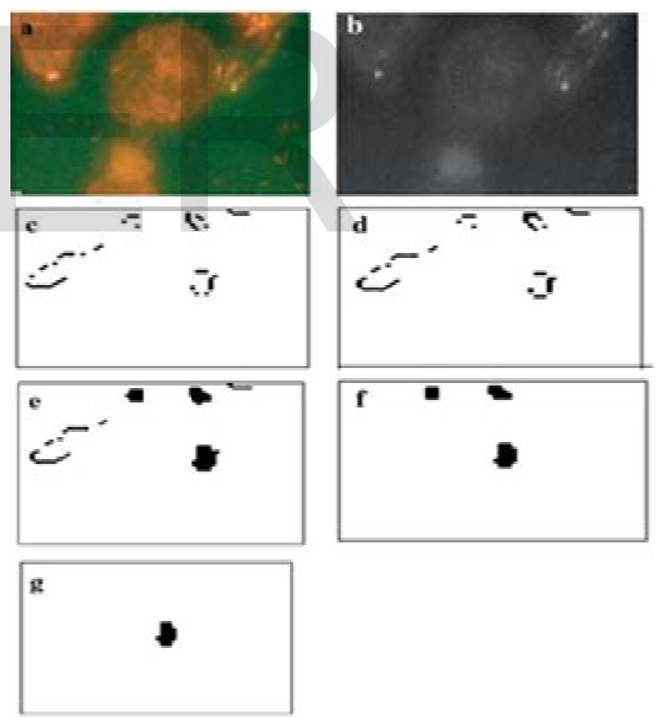

Fig. 5. Detailed methodology of the automation process.

The system designed shows 93.5% sensitivity for the identification of bacilli. [8]

4.10 Local binary pattern classifiers

A Graphics processing unit was designed for processing the images using image processing algorithms. The computer aided diagnosis system designed is used for the identification of suspected tuberculosis nodules and their analysis using local binary pattern classifiers. Different stages of processing algorithm are performed that includes identification of macrostructure and microstructure, rib suppression and nodule accentuation. The classifier is tested using feature histogram. The area, size and density of the lungs can be used to detect nodules of tuberculosis. Different radiographic images are explored using the graphics processing unit with increased efficiency. [9]

4.11 Tubeness filtering and Otsu Thresholding

The manual process of tuberculosis detection performed by pathologist and lab technicians is a time consuming process. This manual detection process requires human efforts and there are higher chances of error as the bacterium has to be search in different field of view. Another automated microscopy system was designed which eliminates limitations of manual system to much extent. Tubeness filtering was used in conjunction with Otsu Thresholding. The input RGB image is converted into grayscale and tubeness filtering is applied for enhancing an image. The components of foreground are separated from background using Otsu global Thresholding. Each connected foreground region in the image is label as separate object by connected component analysis. The noisy regions are removed. The number of bacterium is identified by the number of connected regions. The designed system reduces high false negative rate and human effort. The automatic detection system designed was accurate when comparison was done with two average manual counts as shown in table 4 below. [10]

TABLE 4
COMPARISON OF AUTOMATIC VERSES MANUAL IDENTIFICATION OF TB BACTERIA

Observation	Expert Manual Count1	Expert Manual Count2	Automatic Count
1	13	15	14
2	12	14	
3	14	15	
Average	13.0	14.6	

4.12 Color filtering and fuzzy segmentation

Segmentation is an important step in the identification of the target object. Shape is not only the discriminant feature for identifying tuberculosis bacterium because there are different other types of microorganisms having the same shape. Chromatic information was used in designing different other methods. Color filtering and fuzzy segmentation are based on chromatic information. In color filtering a comparison is done between the blue channel and the product of other two channels. Blue channel is obtained by taking inverse of yellowish stained bacteria. Fuzzy segmentation of color images is done by obtaining information from each separate chromatic histogram. Another important method designed is an achromatic segmentation in which gray level morphological operators are applied only to the green channel. Segmentation can also be done by extracting signatures from the images and provides information about all aspects e.g. color, shape and texture. Projections of logarithmic polar mapping are drawn onto ID vectors for extracting signatures. The analysis of different methods designed shows that they are reliable, fast and accurate for the screening of tuberculosis. [11]

4.13 De-correlation stretching and hidden layer neural networks

Another researcher used neural networks and color segmentation techniques as a key factor for the automated screening of tuberculosis bacteria. The fluorescence microscopy images are taken as an input to the algorithm. Segmentation of the input image is performed based on two important features of intensity value that are similarity and discontinuity. De-correlation stretching is done to discriminates different features and for better visual interpretation. Information is modified and extracted by morphological process. In morphology process dilation and erosion of the image is performed. When features are extracted neural network is used to find patterns and desired information in the data. Eccentricity and compactness is performed for applying neural network to the data that is taken as input. An input layer, hidden layer and output layer is taken as a construction apparatus for detecting tuberculosis bacteria. Two types of data is taken for input to neural network that is trained data and the data that is never been trained. The segmentation results of some of the images are shown in fig.6. An accuracy of 88% is obtained by using 15 hidden layer neural networks for automated screening of tuberculosis bacteria. [12]

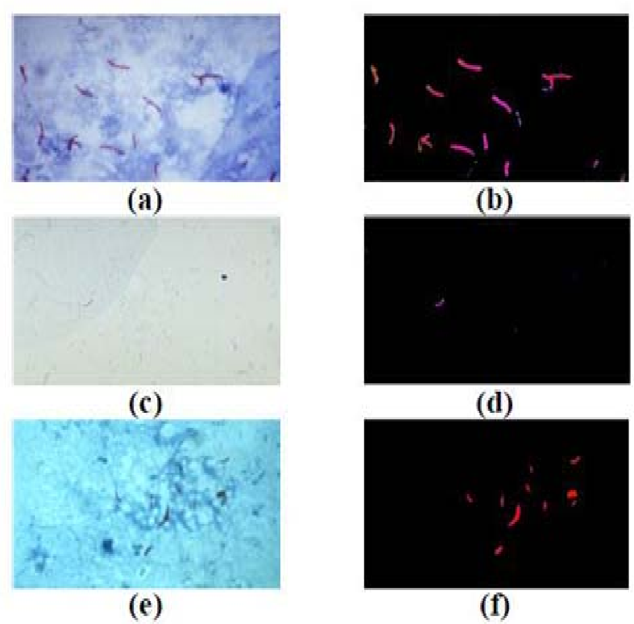

Fig. 6. Different results of image segmentation, (a), (c), and (e) are the original images and (b), (d), and (f) are images of the automation segmentation result.

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4.14 Kohlar illumination and pixel classifiers

Another important automated tuberculosis detection system was developed using pixel classifiers. Images are acquired using digital camera with kohler illumination technique used for standardizing the slides. Segmentation was performed using pixel classifiers. After performing segmentation and validating it feature extraction is done. The selection and optimization of feature set is done by feature subset selection and fisher transformation. Tuberculosis bacteria are identified as objects in fisher transformation. The fig.7 below shows the output of the designed algorithm in which red colored images are bacillus objects and blue colored images are non-bacillus objects. The touching bacilli are labeled as nonbacilli. Different types of classifiers were used to identify tuberculosis bacteria. Different classifiers used with different selection procedures were evaluated based on cross validation and comparison.

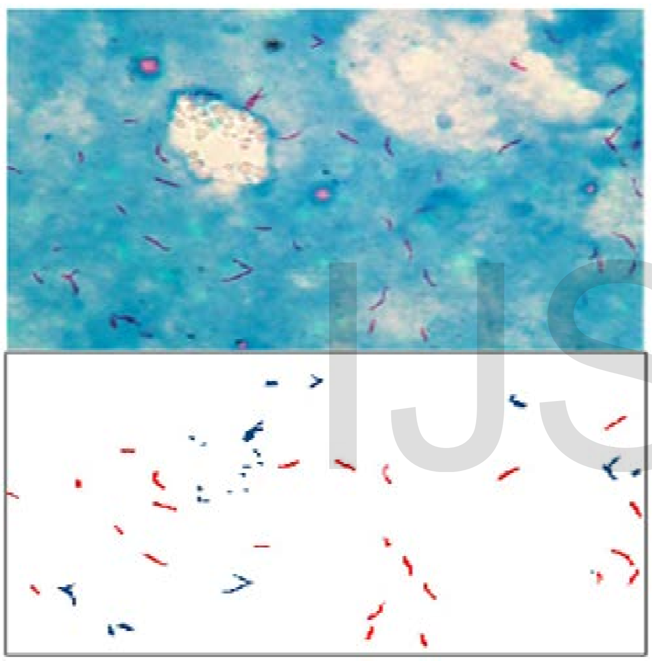

Fig. 7. Output of the resulted image obtained after working on an algorithm.

The sensitivity and specificity of all classifiers used for the identification of tuberculosis bacteria was above 95%. [13]

4.15 Watershed segmentation

An important computer aided diagnosis system was designed for examining chest x-ray images by medical doctors. The algorithm can mark suspected areas on chest x-rays for identification of abnormalities present. Chest x-rays are identified on the basis of knowledge of anatomical features. X-ray images are carefully examined based on the knowledge of pathology and physiology. Lung isolation is performed to isolate lung from background image for performing desired analysis and detecting abnormalities. The chest x-rays are darker and are easy to identify but there are some issues regarding chest x-rays examinations due to the existence of shoulders, ribs and blood vessels making boundaries difficult to identifiable. Watershed segmentation is performed to isolate two lungs and dark background. To reduce limitations modifications are done in watershed segmentation. Lung boundaries detection algorithm is designed for detecting lung objects. Thoracic diameter measurement is done using thoracic diameter measurement algorithm. Lung volume and nodules are detected showing abnormality. The system detects abnormalities related to lungs of different types including tuberculosis, lung collapse, congestive heart failure and lung cancer efficiently. [14]

4.16 Otsu Thresholding and support vector machine algorithm

Support vector machine algorithm identifies and counts tuberculosis bacteria. Color segmentation of the microscopy images is done by extracting the saturation channel of NTSC color model. Otsu method is used for Thresholding the segmented images. The identification of tuberculosis bacteria is done by feature extraction by two important parameters that are compactness and eccentricity. The object recognition and training is done using support vector machine algorithm. The results of the testing process are shown in the fig.8 below. The bacteria's are detected and indicated by green color in the testing process.

Fig. 8. Results of the testing process for different images.

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The number of development count bacteria is equal to the manual counting result in support vector machine and is used to apply in identifying and counting the amount of bacteria present in the microscopy image. [15]

4.17 K-means clustering and Otsu Thresholding approach

Another important work was done in which a comparison was performed between clustering and Thresholding to find out improved method for tuberculosis bacilli segmentation. The method designed is based on k-means clustering and Otsu Thresholding approach. The interpretations and performance of Thresholding and clustering approach for tuberculosis bacilli segmentation is compared. The developed system shows that an improved segmentation performance had been achieved by using clustering approach as compared to Thresholding approach. This comparison also shows that k-mean clustering is highly sensitive to the TB pixels. The results of different algorithms are shown in table5. [16]

TABLE 5
RESULTS OF DIFFERENT SEGMENTATION ALGORITHMS

Segmentation method	Accuracy	Sensitivity	Specificity
K-means clustering	98.91	99.22	98.73
Otsu Thresholding	98.36	99.02	98.02

4.18 Graph cut lung segmentation

Tuberculosis is a contagious disease that when left untreated spreads from the lung through the bloodstream to bones, kidney and liver. An initial diagnosis is done by using chest X-ray analysis to confirm the presence of the disease. An automated approach was developed for the detection of tuberculosis using chest X-ray images as input and the methodology is shown in fig.9. The region of lung was extracted by using graph cut lung segmentation. Ribs and clavicles are identified for the purpose of diagnosis by performing segmentation. The graph cut lung segmentation gives accuracy and classifies x-ray patterns as abnormal and normal for detecting the performance of an algorithm. The features were computed and classification of the input X-ray images was classified as either normal or abnormal chest X-ray with the presence or absence of tuberculosis. [25] The experimental results after feature extraction and support vector machine classification step are shown in fig.10.

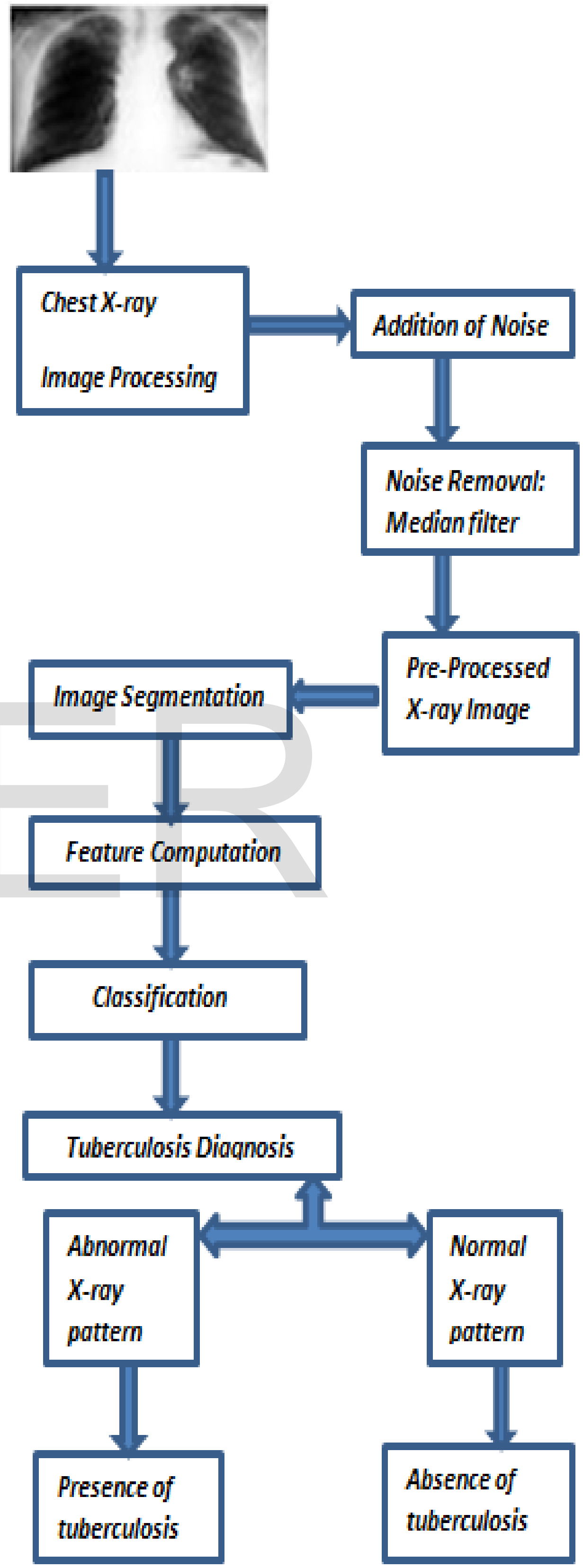

Fig. 9. Systematic overview of the system designed

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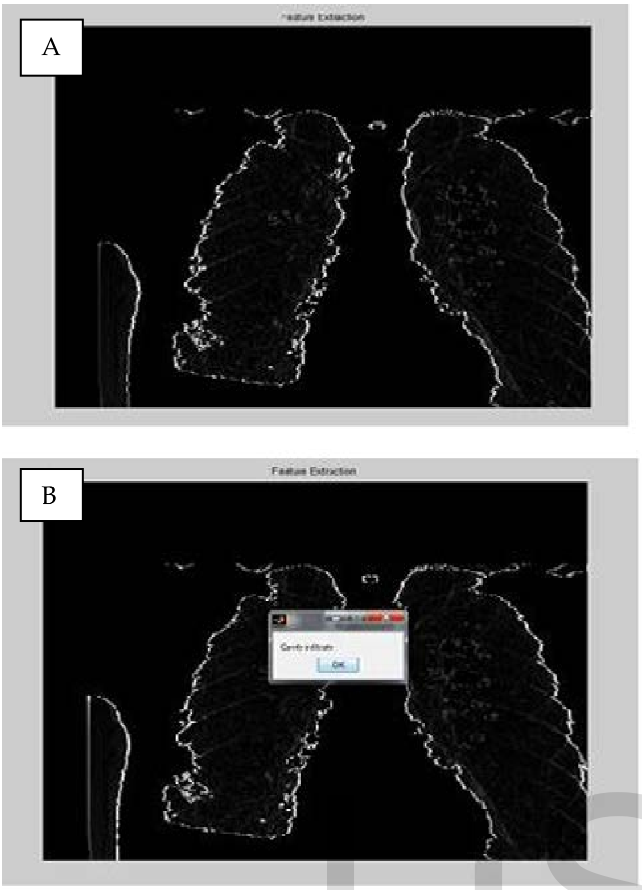

Fig. 10. Experimental Results of feature extraction (A) and support vector machine classification (B).

4.19 One class pixel and object classifier

Different classifiers are used to automate the detection process of tuberculosis. Two types of one class classifiers are used to design a system for the identification of bacterium. The classification process is done in two stages. In first stage a one class pixel classifier is implemented and geometrically transformed invariant features are extracted. In second stage one class ject classification is implemented. Classifiers are used to extract feature and all classifiers are compared. The sensitivity of tested classifiers was above 90%. The accuracy of classifiers on different features was evaluated by the area of the ROC curve and their different values are shown in table 6 below. In the evaluation process mixture of Gaussian classifiers performed well. [17]

TABLE 6
PERFORMANCE OF CLASSIFIERS

Features	Gaussian	Mixture of Gaussians	PCA	kNN
Set of all extracted features	0.9424	**0.9810**	0.9069	0.8934
Linear Fisher mapping	0.9759	**0.9801**	0.5000	0.9748

4.20 Binary classifier system

Tuberculosis is a health risk in various regions of the world. Lung region is mainly extracted by segmentation for automated screening using chest radiography. Another system was designed that performs segmentation using a graph cut segmentation method. The schematic approach is shown in the fig.11 below representing the system taking a CXR as input and outputs a confidence value indicating the degree of abnormality for the input image.

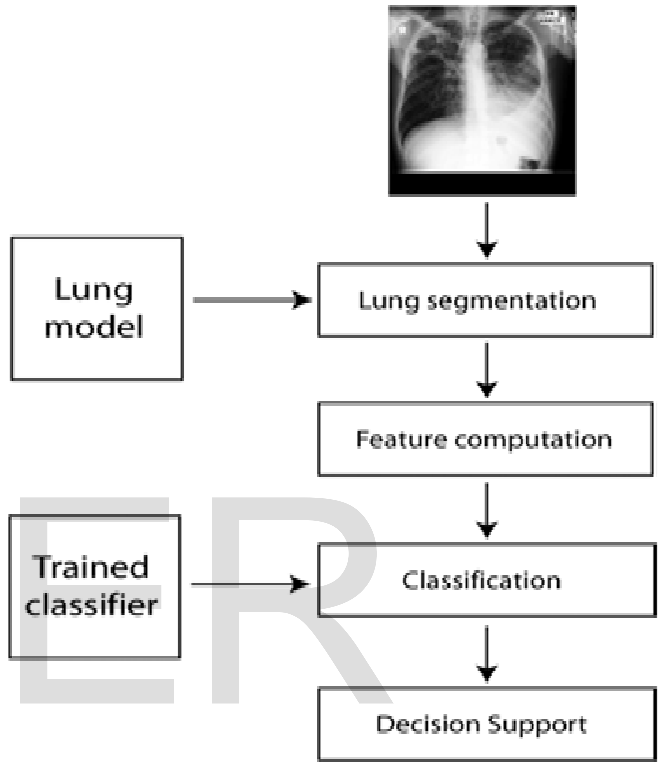

Fig. 11. Flow diagram showing the schematic approach of algorithm design.

A binary classifier system is used to extract a set of shape and texture feature to classify x-rays as either normal or abnormal. The performance of system was detected by a collection of two datasets. For the first dataset the accuracy obtained was 78.3% and for the second dataset the accuracy obtained was 84%. The first set was compared with the performance of radiologists. The performance achieved approaches the performance of radiologist. [18]

4.21 Test Scores based CAD system

A computer aided system was developed which combines several subscores detecting focal, textural and shape abnormalities into one TB score. The arbitrary numbers of subscores are combined in a framework. The subscores are normalized and then collected in a feature vector. This collection is then combined using a supervised classifier into a framework. The designed method was evaluated on two databases each consisting of a total of 200 digital images. The two databases include a western high risk group screening and a TB suspect screening in Africa. The combined scores and individual test scores were compared with a radiological reference determined by a human expert and an external non radiological reference. The performance of the system was determined using receiver operator characteristic analysis. The results of combined subscores were better than individual subscores except for external reference used for database containing African screening samples. This was one of the limitations of the proposed CAD system designed that the performance of individual test scores was slightly higher for external reference from database of TB suspect screening in Africa. [19]

4.22 Scores based abnormality detection system

An important abnormality detection system was designed for fluids and infection related to the lungs. The chest radiographs were taken as input. The abnormality features are given different abnormality scores. The sharpness of costophrenic angle is Scoreθn, the area of the lung is scorearea, the lung level is scorelevel and symmetrical lung area is assigned scoreLp. The radiograph will be abnormal if the score of any of the abnormality features is 1. A total of 177 images are detected as normal. The numbers of disease images are 35 respectively. The image level results shows that 78% of infection images are correctly detected as abnormal. The fluid images show 100% results detecting abnormality. [20]

4.23 Costophrenic angle based measurement system

Different automated systems designed for tuberculosis screening mainly focus on parenchymal abnormalities and ignored pleural effusion related imaging designing. However, costophrenic angle is mostly used for detecting pleural effusion tuberculosis. The proposed system for costophrenic angle measurement discussed earlier has some limitations as discussed earlier. Another system was designed that detects pleural effusion in the right and left hemithoraces. A total of 638 CXRs were used for evaluation. Lung segmentation is performed initially. Chest wall contour structure was used to localize the costophrenic region. The information of intensity and morphology are extracted to design region descriptors around the costophrenic region. The classification of left and right hemithoraces is done based on random forest classifiers. The performance is evaluated on the basis of receiver operating curve and recess localization accuracy. The system shows improvement as compared to systems designed using the costophrenic angle and lung segmentation only. [21]

4.24 Infiltrate feature region extraction and binarization

Infiltrates appears on the lung of patient's suffering from tuberculosis. Infiltrates are mostly condensed, uncircumcised or liquid in appearance and whitish in color. The liquid mainly emerges from suppuration or blood. The existence of infiltrate is mostly detected clinically by radiologists. Analysis of infiltrates is a long and time consuming process. Infiltrates are assumed objects for automated detection. The infiltrate object was detected using segmentation morphology process consisting of dilation and erosion. Side detection is done by decreasing the value of erosion and dilation morphology. The infiltrate object is extracted by feature region analysis and binarization. The infiltrate region extracted is calculated for width and number on sides of each lung by feature region analysis. The number of infiltrates objects detected on right lung was 36 spots, however no infiltrate object was present in the left lung. For comparison two x-ray thorax images on healthy patients were also done and there were no infiltrates detected in the left and right lung for healthy patients. [22]

4.25 Multiple classification approach

Automated tuberculosis screening of chest radiographs can also be detected by finding abnormal signs of a diffuse textural nature. Segmentation of the lungs was performed using active shape models. The segmentation approach is used for subdividing the lung fields into overlapping regions of different sizes. From each region textural features are extracted using multiple classification approach. In addition 'difference features' are acquired by the subtraction of feature vectors from corresponding regions in the right and left lung field. For each identified region a real time collected training set is used. The kernel pixel parallel classifier is used for classifying all regions. The pixel and LBP process leads to a clean classification. The results of classifications are then combined by using a multiplier. The regions with more supported classification reliable weigh more heavily and produces an abnormality score for each image. Abnormality threshold is used to classify abnormal and normal lungs. [24] The graphical representation showing performance of the combined lung mask and automated approach is shown in fig.12 below. The performance of automated approach improves the robustness, accuracy and speed of the diagnosis. In this way the diagnosis and treatment can be done at right time.

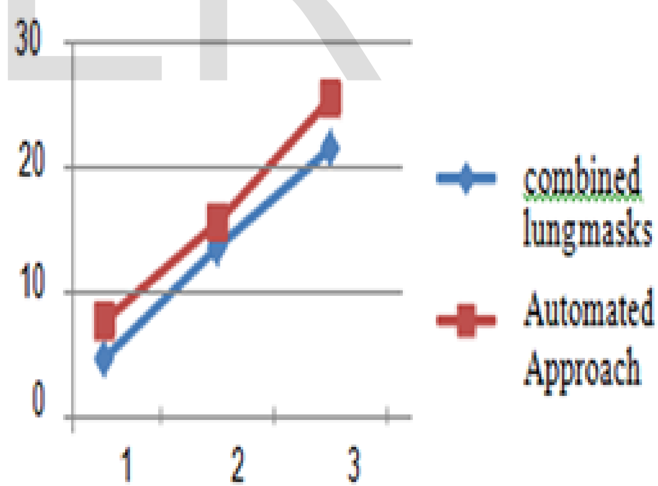

Fig. 12. Graphical representation of combined lung mask and automated approach for performance analysis.

5. Discussion

An ideal system for the screening of tuberculosis is not available. Every system designed has some limitations and advantages. This review shows how automated detection systems designed differ in the proportion of cases detected, false positives and the number of systems detecting a true case of tuberculosis. The paper also describes the variation in performance of different automated systems designed.

6. CONCLUSION

Medical image processing is a widely growing field and various researches are in progress from several years. The computer based algorithms are utilized in medical field to improve patient diagnosis and treatment. The paper summarizes the analysis of different CAD systems designed for the automated screening of tuberculosis through Chest X-Ray and microscopy images. We will first conclude the microscopy imaging results. According to [1], scalar selection technique and filter post processing system designed will improve sensitivity up to 96.80%. In [3], stepwise classification approach was used and an accuracy of scanty detection of 56.00%, high concentration of 97.96% and negative of 88.24% was obtained. Another system [4], used support vector machine classification approach from which an average precision of was obtained. Color based bayesian segmentation was used by [5] for AFB detection however, clusters superimposition, low field depth and variations in stain were challenges. The sensitivity of 93.5% was obtained using Sobel edge detection and neural network classifier system in [8]. Another approach [10] of Tubeness filtering was used with Otsu Thresholding for identifying AFB bacteria. The result of two manual counts was nearly equal to the automatic count result. The automatic count system can be used for detecting AFB bacteria correctly. In [11], fuzzy segmentation combined with color filtering approach was used for detecting tuberculosis bacillus with the specificity of 82% was obtained. The results of [12] showed 88% accuracy in which authors used de-correlation stretching and hidden layer neural networks to identify bacilli. Another important algorithm [13] gave sensitivity and specificity of above 95% using kohlar illumination approach with pixels classifiers. In [15], support vector machine and otsu thresholding approach were used. The number of automatic count bacteria was equal to manual count result. Therefore, this approach can be used for detecting and counting the number of bacilli. The comparison of K-mean clustering and otsu Thresholding approaches was done [16] and it shows that k-mean clustering gave better results as mentioned in table 5. Review is also done on automated chest X-ray radiology. However, most of the designed approaches for
automation of chest X-ray didn't mentioned specificity, sensitivity and accuracy in number values. These algorithms however detected abnormality in different lung regions[2],[6],[9],[14],[19],[21],[22],[23],[24],[25]. Another important algorithm was designed using smoothening sharpening with edge detection method and the algorithm [7] gives the sensitivity, specificity and accuracy of above 90%. In [18], a binary system classifier was used and the accuracy of 82% was obtained. The disease can also be detected on the basis of abnormality scores [20]. The scores can be obtained by symmetrical lung area, the level of the lung, sharpness of costophrenic angle and the area of the lung. Using the values of these scores 78% of the infection can be detected and fluid images are correctly detected up to 100% to be abnormal. In table 7 a review of different techniques used in the automated screening of tuberculosis is summarized. The paper is based on research work done for the automated screening of tuberculosis in microscopy and chest X-ray images. Different screening algorithms will help in reducing the effort and ease for radiologists, microbiologists and medical specialists.

7. RECOMMENDATIONS

For automated microscopy detection scalar selection techniques [1] and K-mean clustering approach [16] gives good results as shown in table 7. However for automated chest radiography detection abnormality scores based method [20] can be used for correct detection especially for fluid images. Another important algorithm [7] in which smoothening sharpening and edge detection approach was used is recommended for screening of chest x-ray radiographs.

8. FUTURE WORK

Medical image processing is an important field of study. Different functions of MATLAB image processing can be used for automation. The designed approaches can be used to detect the severity of the disease at right time. We need to do is to design a single approach for automation of microscopy images on the basis of their shape, size and color so we can maintain the accuracy and specificity of the algorithm. This can be used to improve the sensitivity and specificity of the designed system near to 100%. For chest radiography a system needed to be designed of the basis of abnormality scores so we can easily detect the severity of the disease in different regions of the lungs.

TABLE 7
SUMMARY OF AUTOMATED DETECTION METHODS FOR SCREENING OF TUBERCULOSIS PATIENTS

Authors	**Approach**	**Dataset**	**Method**	**Accuracy**	**Limitation**
Cicero Ferreira Fernandes Costa Filho, Luciana Botinelly Mendonça Fujimoto, Pamela Campos Levy, Clahildek de Matos Xavier, Marly Guimaraes Fernandes Costa.[1]	Scalar Selection technique and filtering.	120 sputum smear images of 12 patients.	Automated Smear Microscopy detection.	96.80% Sensitivity.	Error rate of 3.38%.
Hrudya Das and Ajay Nath.[2]	Region based active contour segmentation and support vector machine.	138 Post-erioanterior Chest X-rays.	Automated Chest X-rays detection.	No accuracy value given just showing detection approach.	When increasing the features selected and when using another segmentation method it may get more accurate result.
Ajay Divekar, Corina Pangilinan, Sean Kennedy, Tarlochan Sondh, Fleming Y. M. Lure and Gerrit Coetzee. [3]	Stepwise Classification approach.	176 Sputum smear microscopy slides.	Automated Smear Microscopy detection.	Accuracy of Negative detection was 88.24%, accuracy of Scanty detection was 56.00%, and accuracy of High-concentration was 97.96%.	Not mentioned.
Jeannette ChangPablo ArbeláezNeil SwitzClay ReberAsa TapleyJ. Lucian DavisAdithya CattamanchiDaniel FletcherJitendra Malik. [4]	Support vector machine classification.	594 images corresponding to 290 patients.	Automated Smear microscopy detection.	Average precision of 89.2% ±2.1% was obtained.	Not Mentioned.
P. Sadaphal, M.F. Beg, G. W. Comstock, and J. Rao. [5]	Color based Bayesian Segmentation.	Not mentioned.	Automated smear microscopy detection.	No Accuracy is mentioned.	Clusters superimposition, low field depth and variations in stain were challenges.
Jhanshy. J, Prof. S. Pushparani. [6]	Particle Swarm Optimization.	Not Available.	Automated Chest X-ray detection.	No Accuracy is mentioned.	Not mentioned.
P. A. Kamble, V. V. Anagire and S. N. Chamtagoudar.[23]	Lung decease classification.	Not available.	Automated chest X-ray detection.	No accuracy is mentioned.	Not mentioned.
Chandrika V, Parvathi C.S., and P. Bhaskar. [7]	Smoothening sharpening and edge detection algorithm.	A total of 80 chest X-ray images.	Automated chest X-ray detection.	Accuracy rate of 91.25%, sensitivity rate of 90.48% and specificity rate of 92.11% was obtained. Accuracy was improved to 16.18% using this method.	The Target error of 0.003 was obtained.
Amarja Adgaonkar , Juhi R. Nath, Aditi Atreya and Akshay D. Mulgund, . [8]	Sobel algorithm and neural network classifier.	Not available.	Automated smear microscopy detection.	93.5% sensitivity.	The work done can be extended in the Hybrid development algorithm.
Joshua M. Leibstein and Andre L. Nel. [9]	Local binary pattern classifier.	Not available.	Automated chest X-ray detection.	Not mentioned.	Not mentioned.
Authors	**Approach**	**Dataset**	**Method**	**Accuracy**	**Limitation**

Ayush Goyal, Mukesh Roy, Prabhat Gupta, Malay Kishore Dutta, Sarman Singh and Vandana Garg. [10]	Tubeness filtering and Otsu Thresholding.	Not available.	Automated smear microscopy detection.	Not mentioned.	Not mentioned.
Manuel Forero-Vargasa,Filip Sroubekd,Josue Alvarez-Borrego, Norberto Malpica,Gabriel Cristobal,Andres Santos,Luis Alcala, Manuel Desco and Leon Cohen. [11]	Color filtering and fuzzy segmentation.	25 Sputum smear images.	Automated smear microscopy detection.	82% specificity.	Not mentioned.
Ibnu Siena , Kusworo Adi , Rahmat Gernowo and Nelly Mirnasari. [12]	De-correlation stretching and hidden layer neural networks	929 TB bacteria shape.	Automated smear microscopy detection.	88% Accuracy.	Improvements required in pattern recognition.
Rethabile Khutlang, Sriram Krishnan, Ronald Dendere, Andrew Whitelaw, Konstantinos Veropoulos, Genevieve Learmonth and Tania S. Douglas. [13]	Kohlar illumination and pixel classifiers.	19 Smear Positive slides were taken and a total of 100 images were obtained from 19 different patients.	Automated smear microscopy detection.	The sensitivity and specificity of above 95% was achieved.	There is a need for Searching descriptive and touching bacillus.
Kim Le. [14]	Watershed Segmentation.	100 CXR's.	Automated Chest X-ray detection.	Not mentioned.	Tuning of the system designed is further in process and can be extended to other chest diseases.
Kusworo Adi,Rahmad Gernowo, Aris Sugiharto, K. Sofjan F, Adi P, Ari B. [15]	Otsu Thresholding and support vector machine algorithm.	929 images are taken.	Automated smear microscopy detection.	Not mentioned	Not mentioned.
Rachna H. B. and M. S. Mallikarjuna Swamy [16]	K-means clustering and Otsu Thresholding approach.	25 positive tissue slides.	Automated smear microscopy detection.	K-means clustering approach gave 98.91% accuracy and Otsu Thresholding approach gave 98.36% accuracy. However clustering is the best method as it is highly sensitive to the TB pixels.	Not mentioned.
R.K.Manisha, K.S.Palanisamy [25]	Graph cut lung segmentation.	Not mentioned.	Automated Chest X-ray detection.	Not mentioned.	Different features are extracted from chest radiograph and classifiers will be used to improve performance of the system.
Authors	**Approach**	**Dataset**	**Method**	**Accuracy**	**Limitation**
Rethabile Khutlang, Sriram Krishnan, Andrew Whitelaw,	One class pixel and	Nineteen ZN-stained spu-	Automated smear mi-	The sensitivity of 97.89% and specificity of 94.67%	Not mentioned.

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and Tania S Douglas [17]	object classifier	tum smear slides.	croscopy detection.	was obtained.	
Stefan Jaeger, Alexandros Karargyris, Yi-Xiang Wang, Sema Candemir, Les Folio, Jenifer Siegelman, Fiona Callaghan, Rahul K. Singh, Zhiyun Xue, Kannappan Palaniappan, Sameer Antani, George Thoma, Pu-Xuan Lu, and Clement J. McDonald [18].	Binary classifier system.	Dataset consisting of 138 CXR's.	Automated chest X-ray detection.	82% accuracy was achieved.	Performed on limited dataset.
Hogeweg L, Sánchez CI, Maduskar P, Philipsen R, Story A, Dawson R, Theron G, Dheda K, Peters-Bax L, van Ginneken B [19].	CAD system with several subscores of supervised subsystems.	Two databases each consisting of 200 digital CXRs.	Automated chest X-ray detection.	Not mentioned	Differences in the performance of the combined TB Score and independent observer were not significant in both databases.
Wan Siti Halimatul Munirah Wan Ahmad, Mohammad Faizal Ahmad Fauzi and W Mimi Diyana W Zaki [20].	Abnormality scores are detected based on symmetrical lung area, sharpness of costophrenic angle, area of the lung and the lung level.	212 normal and with diseased radiographs.	Automated Chest X-ray detection.	78% of the infection and 100% of the fluid images are correctly detected as abnormal.	Not mentioned.
Pragnya Maduskar, Rick H.M.M. Philipsen, Jaime Melendez, Ernst Scholten, Duncan Chanda, Helen Ayles, Clara I. Sánchez and Bram van Ginneken [21].	Random forest based detection classifiers.	A total of 638 CXRs are used.	Automated chest X-ray detection.	Not mentioned.	Not mentioned.
Julius Santony and Jufriadif Na'am [22]	Math Morphology and Feature Region Analysis.	A total of 40 X-ray images are usd.	Automated chest X-ray detection.	Not mentioned.	Not mentioned.
D.Jeevitha, J.Rajasekaran [24]	Histogram based Parallel Pixel Segmentation.	Two different feature sets.	Automated chest X-ray detection.	Not mentioned	Not mentioned.

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