AN IMPROVED METHOD FOR DIAGNOSIS OF TUBERCULOSIS USING K-MEANS CLUSTERING ALGORITHM AND COMBINED BLUR AND AFFINE MOMENT INVARIANTS

[1]Durga Prasad Kolluru, [2]Dr.M.B.Rama Murthy
[1]Research Scholar of Rayalaseema University – Kurnool, Andhra Pradesh , India.
[2]Retd. Professor, E.C.E Dept, IIIT Basara , Telangana , India.

***Abstract*:** Tuberculosis is a major infectious disease in many regions of the World. Detection of Tuberculosis is the most efficient solution for prevention of this disease. Chest radiography is the most common method adopted for screening this disease and the success of this method depends on the experience and interpretation of the skilled radiologist. This paper presents Computer Aided Diagnosis (CAD) system for detection of Tuberculosis using K-means clustering algorithm and Combine Blur and Affine Moment Invariants (CBAMI). K-means clustering is a method of grouping data objects into different groups, such that similar data objects belong to the same group and dissimilar data objects to different clusters. K-means algorithm is used in this paper to identify the effected portion. The CAD method accelerates the process of active case finding as well as second medical opinion to radiologist. The CBAMI are used as features for the affected portion which was extracted using K-means algorithm. The CBAMI are selected in this work because they are invariant to both affine distortions as well as blur. Simulation results are carried out by considering The Montgomery County X ray dataset and the results are compared with Geometric Moment Invariants. It is observed from the results that the proposed method provided better accuracy.

Keywords: Tuberculosis, **K-Means Clustering**, Combine Blur and Affine Moment Invariants

I. INTRODUCTION

Tuberculosis is one of the leading diseases in the worldwide which will be caused by bacillus mycobacterium tuberculosis [1]. With early detection and proper treatment can reduce TB incidence. It is believed that pulmonary TB can be diagnosed by using chest radiography only. Physicians also make decision based on both radiologic results and with clinical data. So this paper introduces CAD system, will relieve partial work load on radiologists and improves reading efficiency, it is an intensive tool that provides radiologists with a "second opinion" to improve the sensitivity and specificity of their diagnostic decision-making. According to annual report 2018, Tuberculosis remains one of the world's deadliest communicable diseases and 9.0 million people developed TB and 1.5 million died from the disease. India and China alone accounted for 24% and 11% of total cases, respectively [1].Various tests are used to diagnose tuberculosis (TB), depending on the type of TB suspected. There are different methods available for screening of TB namely (i) The Sputum smear microscopy (ii) Tuberculin skin test (iii) Rapid molecular test and (iv) Chest radiography test. Sputum smear microscopy is a screening method in which sputum samples are examined under a microscope to see if bacteria are present or not. Its sensitivity is reduced in patients with HIV co-infection [2]. In Tuberculin skin test, a small amount of tuberculin is injected into the skin and the size of swelling is observed. This method is not reliable as it causes misclassification [1]. Latest rapid molecular tests are fast and accurate. But, their availabilities and cost is a big primary concerned. The WHO recommended chest radiography (CXR) for screening proposes for early detection of TB. Early detection leads to success of anti TB therapy. It also helps to control over transmission of infection as well as development of drug resistant TB. CXR diagnostic method improves TB detection [3,4] can be used for screening large population and can identify active TB cases with a reasonable amount of time. This method is also low cost effective manner. Further, in areas having limited resources, the confirmatory diagnostic test like sputum smear test are not available , CBX can be used as most powerful diagnostic tool for TB detection.

Especially in developing countries, because of lack of skilled radiologists and other resources, it becomes difficult for effective diagnosis. Hence, Computer Aided Diagnosis (CAD) tool can gain lot of significance because they not only reduce diagnostic errors but also increases the efficiency of mass screening in poor resource setting. CAD method provides second opinion to the radiologists for their finding. It provides better diagnosis of cancer and other diseases including TB.
In the literature, for object recognition applications, Histogram of Oriented Gradients (HOG) are used as features. Sivaranjani [6] proposed a method for analysis of TB with HOG as features and SVM as classifier. Ankitha et al [7] proposed a method to extract the lung field by an interactive lung field segmentation based on active contour models. After segmentation process, they analyzed the pixel data within region of interest using first order statistics to extract textural properties in classifying image as TB and non TB. A method using HOG Features in Computer-Aided Diagnosis of Tuberculosis without Segmentation was proposed in [8]. Pallavi et al. [9] used first order statistical properties such as mean and entropy for diagnosis of TB.

Hu [10] introduced geometric moments based on monomials . He derived a set of seven moment invariants which are invariant with respect to change in image translation, rotation and scale. Jan Flusser et al [11] derived blur invariants which are invariant with respect to blurring on the acquired image. Blur invariants are required because real imaging systems as well as imaging conditions are imperfect. Blur may occur in the captured image during the image acquisition process because of the factors such as lane aberration, diffraction, wrong focus and atmospheric turbulence. They proposed an approach which describes images by features that are invariant with respect to blur and recognize images in the feature space. In order to obtain features which are invariant to blur as well as affine distortion, The same authors [12] derived combined blur and affine moment invariants. Combined invariants are capable of recognizing objects in the degraded scene without any restoration.

Clustering is a method of grouping data objects into different groups, such that similar data objects belong to the same group and dissimilar data objects to different clusters. Current research increasing interest in digital image searching, classification, identification, management and storage. Some common but important applications of are person identification in movie clips and festive home videos, recognition in biometric system, natural scene classification for robot vision, commercials filtering, segmentation of important topics in lectures and meetings. The image clustering, an important technology for image processing, has been actively researched for a long period of time and explosive growth of the Web, image clustering has even been a critical technology to help users digest the large amount of online visual information. Clustering approach is widely used in biomedical image segmentation and it is application are used for brain tumor detection as the normal and abnormal to find out the tumor on the brain [13]. The many different segmentation techniques are used in the image mining and image segmentation approaches can be divided into many parts as: clustering, edge detection, thresholding and region extraction. In this paper, we used the clustering concept in the image to identify the affected portion of chest. Many of things and real situation, like image, restricting an object into only one cluster will be take on the different tasks. A technique which is handles the mining of information, association of the image data or additional patterns not unambiguously stored in the image data base of the image segmentation process [14]. The methods are handling with the image processing, image stored and retrieval, data mining, machine learning, database on the image to be stored and artificial intelligence. A huge amount of image databases have being implements with as rule mining concept. It handles with several features of very huge image databases which comprises of indexing methods, image storages, and image retrieval, all regarding in an image mining system.

Most of the methods discussed above for diagnosis of Tuberculosis is based on histogram of oriented features, calculation of mean, variance, third moment and entropy features as well Geometric moment invariants. All these methods do not take care into account of blur as well as affine distortion present in the Tb X-ray image. Further, K-means algorithm is used to segment the X-ray image into three regions namely background, chest and affected cavities. In order to solve this problem and to obtain better accuracy, we propose an efficient method for detection of Tuberculosis in this Paper. The proposed method computes Combined Blur and Affine Moment Invariants (CBAMI) on X-ray image and uses them as feature for detection of tuberculosis.

This paper is organized into five sections. Details about the Geometric moment invariants, K-means algorithm as well as CBAMI are presented in section II. Proposed method is presented in section III. Simulation results are presented in section IV. The last section presents the conclusions about the work.

II. Overview on K-means Algorithm and Moment Invariants

In this section, we present details about K-means algorithm, Geometric moments and Combined Blur and Affine Moment Invariants.

2.1 Introduction to K-means clustering-algorithm

The K-means clustering algorithm comprised of three steps, they distance, minimum-distance cluster assignment and cluster centroid update. These three steps are repeatedly executed until convergence meet or number of iteration end. The main features are

- The K-means algorithm splits the given dataset (image) into K number of clusters or groups
- It assigns a member(pixel) into a cluster (group) based on minimum distance between the pixel and all cluster centroids
- The algorithm is not complex and iterative procedure steps
- The high speed convergence but stayed on local minimum at most of times

Unsupervised Clustering: The K-means algorithm has no training phase. The dataset (image pixels) to be clustered is not attached with class or target variables.The K-means algorithm should starts with K number of clusters, however actual number of cluster exist in an image is unknown. Image segmentation results of K-means algorithm depends on initial cluster centroid values. If There is changes in the initial cluster's centroid values while executing the algorithm, The members(pixels) belonging to the clusters and image segmentation results will be changed. The objective of K-means clustering is to minimize sum of squared distance between cluster members and cluster centroids

K-Means Clustering:

It's the on the techniques for the clustering concept in the data mining process and is very famous algorithm for the K-means clustering, because it is similar or simpler and easier in computation of an efficient K-means clustering algorithm it is the simplest unsupervised learning algorithms that solve the well known clustering problems[12]. It's the K-means algorithm is an unsupervised clustering algorithm that classified in the input data points into multiple classes based on their intrinsic distance from other dataset points of his cluster [7].

Its assume that the data features from a vector space and tries to find natural clustering.

Hierarchical Clustering: Hierarchical clustering is any valid measure of distance can be used for a traditional clustering method that can be generates a tree structure or a dendrograms and it's a matrix of distance.

Here, x, y is a set of two elements in the cluster and d(x,y) denote the min-distance between the two elements of x and x.

Complete linkage clustering: Its calculate the maximum distance between the large set of clusters. Formula as

$$d(x,y) = \max_{x \in X, y \in Y} d(x,y)$$

where x, y is a set of two elements in the cluster and d(x, y) denote the max-distance between the two elements of x and x.

Its calculate the minimum distance between the large set of clusters.

$$d(x,y) = \min_{x \in X, y \in Y} d(x,y)$$

where x, y is a set of two elements in the cluster and d(x, y) denote the min-distance between the two elements of x and x.

$dis(x,y) = \sum_{i=1}^{d} \|x_i - c_i\|$

The feature vectors are grouped into k means clusters using a selected distance measure such as Euclidean distance may be calculated.

K-Means Algorithms:

The principle of the k-medoids algorithm (its same for the k-means algorithm) for cluster the data and k-medoids algorithm is the one of the best unsupervised learning clustering algorithm [10].

Clustering the image is according to the group of pixels and the k-medoids algorithm is initially we have to a number of cluster k, then k-cluster center are chosen randomly. The distance between the each pixel to each cluster centers are calculated. The distance may be of simple Euclidean function. Single pixel is compared to all cluster centers using the distance formula.

$$\sum c(j) = k||Xj - Xi||_2^2$$

To calculate the number clustering in the equation of the k is medoids point of cluster.

$$\sum_{k=1}^{k} \sum_{\mathrm{C(i)=k}} \big||Xi - Ck|\big|_2^2$$

Minimum cover of C

For each $i=1....n$, to find the cluster center of c_k closest to x_i,

and let $c_{(i)}=k$

Algorithm: the main steps in the algorithm are as follows

1. Give the no of cluster value as k.
2. Randomly choose the k cluster centers
3. Calculate mean or center of the cluster
4. Calculate the distance between each pixel to each cluster center

5. If the distance is near to the center then move to that cluster.
6. Otherwise move to next cluster.
7. Re-estimate the center.

2.2 Geometric Moments and Their Invariants

The Geometric moments of order (p, q) for an image $f(x,y)$ are defined [10] as

$$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)\,dx\,dy \qquad (1)$$

where $p,q = 0,1,2,........,\infty$

To keep the dynamic range of M_{pq} consistent for different size images, the N x M image plane is first mapped onto a square defined by $x \in [-1,+1]$, $y \in [-1,+1]$. Then M_{pq} can be written as

$$M_{pq} = \int_{-1}^{1}\int_{-1}^{1} x^p y^q f(x,y)\,dx\,dy \qquad (2)$$

The discrete form representation of the above expression is given by

$$M_{pq} = \sum_{i=0}^{N-1}\sum_{j=0}^{M-1} x_i^p y_j^q f(x_i, y_j)\,\Delta x\,\Delta y \qquad (3)$$

where (x_i, y_j) is the centre of (i, j) pixel and $\Delta x = x_i - x_{i-1}, \Delta y = y_j - y_{j-1}$ are the sampling intervals in the 'x' and 'y' directions respectively. N x M corresponds to the size of the image.

The Geometric central moments [10] are defined as

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x - \bar{x})^p \,(y - \bar{y})^q f(x,y)\,dx\,dy \qquad (4)$$

where $\bar{x} = \frac{M_{10}}{M_{00}}$ and $\bar{y} = \frac{M_{01}}{M_{00}}$ (5)

For a digital image, the Geometric central moments can be written as

$$\mu_{pq} = \sum_{i=0}^{N-1}\sum_{j=0}^{M-1} (x_i - \bar{x})^p (y_j - \bar{y})^q f(x_i, y_j)\,\Delta x\,\Delta y \qquad (6)$$

The normalized central moments [10] are defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \qquad (7)$$

where $\gamma = \frac{p+q}{2} + 1$ for $p + q = 2,3,.....$

Hu [10] derived moment invariants using Geometric moments which are invariant to image rotation, translation and scale. These invariants are given below [10].

$\varnothing_1 = \eta_{20} + \eta_{02}$ (8)

$\varnothing_2 = (\eta_{20} - \eta_{02})^2 + 4\,\eta^2_{11}$ (9)

$$\varnothing_3 = (\eta_{30} - 3\,\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (10)$$

$$\varnothing_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (11)$$

$$\varnothing_5 = (\eta_{30} - 3\,\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} - \eta_{12})^2 - 3(\eta_{21} - \eta_{03})^2 + (3\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} - \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (12)$$

$$\varnothing_6 = (\eta_{20} - 3\,\eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 + 4(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (13)$$

$$\varnothing_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})(\eta_{30} - \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 + (\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \quad (14)$$

2.3 Combined Blur and Affine Moment Invariants

Jan Flusser et al. [12] derived combined blur and affine moment invariants. Combined invariants are capable of recognizing objects in the degraded scene without any restoration. The Combined Blur and Affine Moment Invariants (CBAMI) are given below [12].

$$Set_1 = \mu^2_{30}\,\mu^2_{03} - 6\,\mu_{30}\,\mu_{21}\,\mu_{12}\,\mu_{03} + 4\,\mu_{30}\,\mu^3_{12} + 4\,\mu^3_{21}\,\mu_{03} - 3\,\mu^2_{21}\,\mu^2_{12}) / \mu^{10}_{00}. \quad (15)$$

$$Set_2 = \mu^2_{50}\,\mu^2_{05} - 10\,\mu_{50}\,\mu_{41}\,\mu_{14}\,\mu_{05} + 4\,\mu_{50}\,\mu_{32}\,\mu_{23}\,\mu_{05} + 16\,\mu_{50}\,\mu_{32}\,\mu^2_{14} - 12\,\mu_{50}\,\mu_{14}\,\mu^2_{23} + 16\,\mu^2_{41}\,\mu_{23}\,\mu_{05} + 9\,\mu^2_{41}\,\mu^2_{14} - 12\,\mu_{41}\,\mu^2_{32}\,\mu_{05} - 72\,\mu_{32}\,\mu_{41}\,\mu_{14}\,\mu_{23} + 48\,\mu^3_{23}\,\mu_{41} + 48\,\mu_{14}\,\mu^3_{32} - 32\,\mu^2_{32}\,\mu^2_{23}) / \mu^{14}_{00}. \quad (16)$$

$$Set_3 = (\mu^2_{30}\mu_{05}\,\mu_{12} - \mu^2_{30}\mu_{03}\,\mu_{14} - \mu_{30}\mu^2_{21}\,\mu_{05} - 2\,\mu_{30}\,\mu_{21}\,\mu_{12}\,\mu_{14} + 4\,\mu_{30}\,\mu_{21}\,\mu_{23}\,\mu_{03} + 2\,\mu_{30}\mu^2_{12}\,\mu_{23} - 4\,\mu_{30}\,\mu_{12}\,\mu_{32}\,\mu_{03} + \mu_{30}\mu^2_{03}\,\mu_{41} + 3\,\mu^3_{21}\,\mu_{14} - 6\,\mu^2_{21}\mu_{12}\,\mu_{23} - 2\,\mu^2_{21}\mu_{03}\,\mu_{32} + 6\,\mu_{21}\mu^2_{12}\,\mu_{32} + 2\,\mu_{12}\,\mu_{21}\,\mu_{41}\,\mu_{03} - \mu_{21}\mu^2_{03}\,\mu_{50} - 3\,\mu^3_{12}\,\mu_{41} + \mu^2_{12}\mu_{03}\,\mu_{50}) / \mu^{11}_{00}. \quad (17)$$

$$Set_4 = (2\,\mu_{30}\,\mu_{12}\,\mu_{41}\,\mu_{05} - 8\,\mu_{30}\,\mu_{12}\,\mu_{32}\,\mu_{14} + 6\,\mu_{30}\,\mu_{12}\,\mu^2_{23} - \mu_{30}\,\mu_{03}\,\mu_{50}\,\mu_{05} + 3\,\mu_{30}\,\mu_{03}\,\mu_{41}\,\mu_{14} - 2\,\mu_{30}\,\mu_{03}\,\mu_{23}\,\mu_{32} - 2\,\mu^2_{21}\mu_{41}\,\mu_{05} + 8\,\mu^2_{21}\mu_{32}\,\mu_{14} - 6\,\mu^2_{21}\,\mu^2_{23} + \mu_{21}\,\mu_{12}\,\mu_{50}\,\mu_{05} - 3\,\mu_{21}\,\mu_{12}\,\mu_{41}\,\mu_{14} + 2\,\mu_{21}\,\mu_{12}\,\mu_{32}\,\mu_{23} + 2\,\mu_{21}\,\mu_{03}\,\mu_{50}\,\mu_{14} - 8\,\mu_{21}\,\mu_{03}\,\mu_{41}\,\mu_{23} + 6\,\mu_{21}\,\mu_{03}\,\mu^2_{32} - 2\,\mu^2_{12}\mu_{50}\,\mu_{14} + 8\,\mu^2_{12}\mu_{41}\,\mu_{23} - 6\,\mu^2_{12}\,\mu^2_{32}) / \mu^{12}_{00}. \quad (18)$$

$$Set_5 = (\mu_{30}\,\mu_{41}\,\mu_{23}\,\mu_{05} - \mu_{30}\,\mu_{41}\,\mu^2_{14} - \mu_{30}\mu^2_{32}\,\mu_{05} + 2\,\mu_{30}\,\mu_{32}\,\mu_{23}\,\mu_{14} - \mu_{30}\,\mu^3_{23} - \mu_{21}\,\mu_{50}\,\mu_{23}\,\mu_{05} + \mu_{21}\,\mu_{50}\,\mu^2_{14} + \mu_{21}\,\mu_{41}\,\mu_{32}\,\mu_{05} - \mu_{21}\,\mu_{41}\,\mu_{23}\,\mu_{14} - \mu_{21}\mu^2_{32}\,\mu_{14} + \mu_{21}\,\mu_{32}\,\mu^2_{23} + \mu_{12}\,\mu_{50}\,\mu_{32}\,\mu_{05} - \mu_{12}\,\mu_{50}\,\mu_{23}\,\mu_{14} - \mu_{12}\mu^2_{41}\,\mu_{05} + \mu_{12}\,\mu_{41}\,\mu_{32}\,\mu_{14} + \mu_{12}\,\mu_{41}\,\mu^2_{23} - \mu_{12}\mu^2_{32}\,\mu_{23} - \mu_{03}\,\mu_{50}\,\mu_{32}\,\mu_{14} + \mu_{03}\,\mu_{50}\,\mu^2_{23} + \mu_{03}\mu^2_{41}\,\mu_{14} - 2\,\mu_{03}\,\mu_{41}\,\mu_{23}\,\mu_{32} + \mu_{03}\,\mu^3_{32}) / \mu^{13}_{00}. \quad (19)$$

$$Set_6 = (\mu^2_{70}\,\mu^2_{07} - 14\,\mu_{70}\,\mu_{61}\,\mu_{16}\,\mu_{07} + 18\,\mu_{70}\,\mu_{52}\,\mu_{25}\,\mu_{07} + 24\,\mu_{70}\,\mu_{52}\,\mu^2_{16} - 10\,\mu_{70}\,\mu_{43}\,\mu_{34}\,\mu_{07} - 60\,\mu_{70}\,\mu_{43}\,\mu_{25}\,\mu_{16} - 234\,\mu_{61}\,\mu_{52}\,\mu_{25}\,\mu_{16} + 40\,\mu_{61}\mu^2_{43}\,\mu_{07} + 50\,\mu_{61}\,\mu_{43}\,\mu_{34}\,\mu_{16} + 360\,\mu_{61}\,\mu_{43}\,\mu^2_{25} - 240\,\mu_{61}\mu^2_{34}\,\mu_{25} + 360\,\mu^2_{52}\mu_{34}\,\mu_{16} + 81\,\mu^2_{52}\,\mu^2_{25} - 240\,\mu_{52}\mu^2_{43}\,\mu_{16} - 990\,\mu_{52}\,\mu_{43}\,\mu_{34}\,\mu_{25} + 600\mu_{52}\,\mu^3_{34} + 600\mu^3_{43}\,\mu_{25} - 375\,\mu^2_{43}\,\mu^2_{34}) / \mu^{18}_{00}. \quad (20)$$

III. PROPOSED METHOD

The first step is proposing which is used to remove background noise. In this work, we used median filtering for smoothing. The processed image is segmented using K-means clustering. Combine blur and affine moment invariants are computed on the segmented image. Combine blur and affine moment invariants are selected as features because they are invariant with respect to image blur and affine distortions. In presence of these distortions also, the computed features are invariants. The extracted features are then applied for classification with and without TB features using Euclidean distance classifier. Finally, the result is evaluated by expert radiologist.

IV. SIMULATION RESULTS

In order to test the proposed approach, we considered The Montgomery County dataset. This dataset is collected online freely from the Department of Health and Human Services, Montgomery County, Maryland, USA. It consists of 138 frontal chest X-rays from Montgomery Countys Tuberculosis screening program, out of which 80 are normal cases and 58 are cases with manifestations of TB. These X-rays were captured with a Eureka stationary X-ray machine (CR), and are provided in Portable Network Graphics (PNG) format as 12-bit gray level images. The size of the X-rays is either 4,020x4,892 or 4,892x4,020 pixels. These images are resized to 450 x 450 pixels. Original and segmented images are shown in Fig.1 K-means energy minimizations is also shown in the fig2. From the results, it is observed that these features are invariant with respect to affine distortions such as rotation, scale, translation as well as blur. The proposed approach is applied on the database images and the the accuracy is calculated. The accuracy is 93%. For comparision, the same experiment is repeated with Geometric moment invariants as features and observed that the accuracy is 89%. Hence, the CBAMI can be effectively used for extracting features of chest X ray images.

V. CONCLUSIONS

In this paper, a method for detection of Tuberculosis using K-means algorithm for clustering, CBAMI as features and Euclidean Distance as classifier is proposed. The proposed method computes Combined Blur and Affine Moment Invariants (CBAMI) on X-ray image after segmentation and uses them as feature for detection of tuberculosis. The CBAMI are selected as features in this paper because they are invariant to both affine distortions as well as blur. It is observed from the simulation results that the detection accuracy is better. Our future work will be directed towards use of neural network classifier for classification.

RESULTS

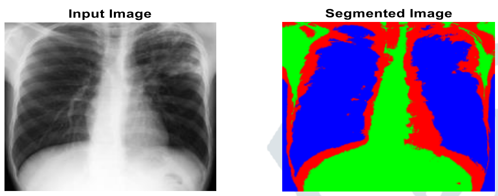


Fig.1. Original and segmented images

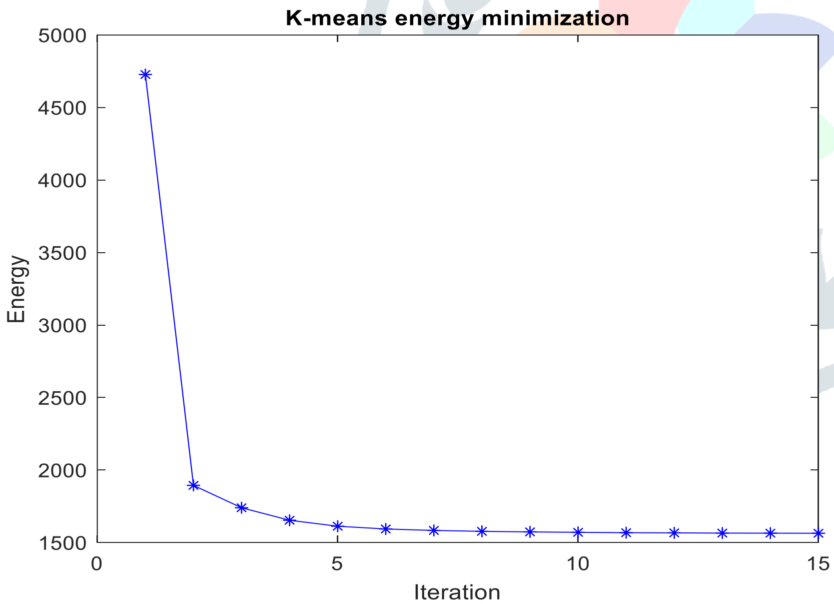
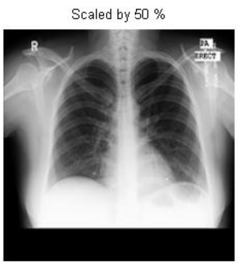
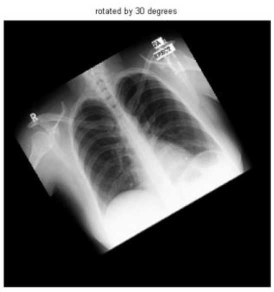
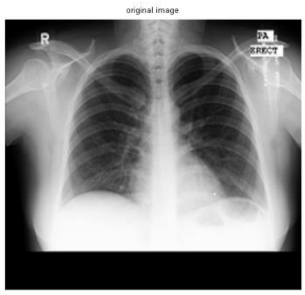


Fig.2. K-means energy minimization versus iteration







Scaled by 50% **Rotated by 30^0** **Original Image**

CBAMI	Original Image	Scaled by 50%	Rotated by 30 degrees	Blurred by variance 0.2
Set1	1.74e-22	1.74e-22	1.74e-22	1.74e-22
Set2	1.58e-32	1.58e-32	1.58e-32	1.57e-32
Set3	7.27e-27	7.29e-27	7.30e-27	7.07e-27
Set4	-1.66e-27	-1.66e-27	-1.66e-27	-1.65e-27
Set5	2.68e-32	2.68e-32	2.69e-32	2.73e-32
Set6	-0.03272	-8.18e-06	-1.76e-02	-0.032

REFERENCES

[1] Anuj, Rahul Hooda and Ajay Mittal, " TB Detection in Chest Radiograph Using Deep Learning Architecture", 5th International Conferenceon Emerging Trends in Engineering, Technology, Science and Managementpp.136-140,, IETE, August 2017

[2] P. Quinco, S. B uhrer-Śekula, W. Branddao, R. Monte, S. L. Souza, V. Saraceni, M. Palaci, R. Dietze, and M. Cordeiro-Santos, "Increased sensitivity in diagnosis of tuberculosis in hiv-positive patients through the small-membrane-filter method of microscopy," *Journal of clinical microbiology*, vol. 51, no. 9, pp. 2921– 2925, 2013.

[3] J. Pouchot, A. Grasland, C. Collet, J. Coste, J. M. Esdaile, and P. Vinceneux, "Reliability of tuberculin skin test measurement," *Annals of internal medicine*, vol. 126, no. 3, pp. 210–214, 1997.

[4] A. Harries, N. Hargreaves, J. Kwanjana, F. Salaniponi et al., "Clinical diagnosis of smear-negative pulmonary tuberculosis: an audit of diagnostic practice in hospitals in malawi," *The international journal of tuberculosis and lung disease*, vol. 5, no. 12, pp. 1143–1147, 2001.

[5] J. Day, S. Charalambous, K. Fielding, R. Hayes, G. Churchyard, and A. Grant, "Screening for tuberculosis prior to isoniazid preventive therapy among hiv-infected gold miners in south africa,"*The international journal of tuberculosis and lung disease*, vol. 10, no. 5, pp. 523–529, 2006.

[6] Sivaranjani, " Analysis of Tuberculosis in chest using SVM classifier", National Conference on Research Advances in Communication, Computation, Electrical Sciences and Structures, pp. 18-20, 2015

[7] Ankitha B M , Sanjeev Kubakaddi and Dr.Bharathi S H, "Computer Aided Diagnosis of Tuberculosis usingFirst order Statistical approach", IPASJ International Journal of Electronics & Communication (IIJEC), Volume 3, Issue 4, pp. 22-28, April 2015

[8] Arun Chauhan, Devesh Chauhan and Chittaranjan Rout, "Role of Gist and PHOG Features in Computer-Aided Diagnosis of Tuberculosis without Segmentation", PLOS ONE www.plosone.org 1, Volume 9, Issue 11, , November 2014

[9] Pallavi T. P., Praveen Kumar P. S., " Diagnosis of Tuberculosis by using first order statistics applied to chest radiograph", International Journal of Sciences & Applied Research, IJSAR, 2(8), pp. 16-22, 2015

[10] Hu. M.K, " Visual Pattern Recognition by Moiments Invariants", IRE Transaction on Information Theory, 8, 179-187, 1962

[11] Jan Flusser and Tomas suk et al., " Recognition of Blurred Images by Method of Moments", IEEE Transaction on Image Processing, vol.5, no.3, pp.533-537, March 1996

[12] Tomas Suk and Jan Flusser, "Combined Blur and Affine Moment Invariants and their use in Pattern Recognition",

[13] Dubey, M.Hanmandlu, Sr.Member, ShantaramVasikarla, "Evaluation of ThreeMethods for MRI Brain Tumor segmentation," IEEE, 2011.

[14] Hakeem AejazAslam, TirumalaRamashri, Mohammed Imtiaz Ali Ahsan "A New Approach to Image Segmentation for Brain Tumor detection using Pillar K-means Algorithm" IJARCCE,vol 2,issue 3, March 2013.

[15]K.Durga Prasad, Dr.M.B.Ramanamurthy and Dr. A.Venkataramana, "Diagnosis of Tuberculosis using Combined Blur and Affine Moment Invariants", International Journal of Advance Research Trends in Engineering and Technology, vol.4, issue.12, pp.20-25, December 2017

BIOGRAPHY

1.  Durga Prasad Kolluru, Research Scholar of Rayalaseema University – Kurnool, Reg.No: PP.ECE.0046, ECE Dept. He received his M.Tech (DS&CE) from Jaya Prakash Narayan College of Engg, and B.Tech(ECE) from Nimra Engg college ., Currently he is working as Associate Professor at Jaya Prakash Narayan College of Engg, and has 18 years of teaching Experience. His area of interest include Digital Image Processing , Pattern Recognition , Electromagnetic field, VLSI Design, antenna And Wave Propagation, Communication systems.

2. Dr. M.B.Rama Murthy is in the academic field for the past 36 years and he is retired as Professor in ECE Dept, IIIT – Basara, Telangana. He worked as Professor and Dean Academics in Jaya Prakash Narayan College of Engg,Mahabubnagar. He has 66 publications to his credit in International Journals and conferences. He is senior member IEEE, life fellow IETE, life member IEI and life member ISOI. His area of interest are Electromagnetic field , antenna And Wave Propagation , speech processing , signal processing, Digital Image Processing and Communications.