International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249 – 8958 (Online), Volume-9 Issue-5, June 2020

Automatic Detection of Tuberculosis from Chest X-Rays using Convolutional Neural Network

K. G. Satheeshkumar*, V Arunachalam

Abstract*: Tuberculosis is one of the single infectious diseases which is one among the top ten causes of deaths. Eradication is only possible by timely diagnosis of disease and treatment at its early stage. But unfortunately, timely detection is lagging due to many reasons. In this angle we present a novel scheme for automatic detection of tuberculosis from chest X-ray images. The proposed method accurately detects the malady by performing graph cut segmentation followed by classification using convolutional neural network. The classifier facilitates the chest X-rays to be classified as normal or abnormal. Simulation results show that the accuracy of 94%, sensitivity of 96% and specificity of 84% obtained from the proposed system are comparable and even better than the existing reported methods.

Keywords* : Chest x-ray (CXR), Convolutional Neural Network (CNN),deep learning, graph cut.

I. INTRODUCTION

Tuberculosis (TB) is one of the single infectious diseases which cause high death rates and is one among the top ten causes of deaths. The UN has suggested having immediate steps for eradicating TB by 2030. On similar lines, the World Health Organization (WHO) report on TB has reiterated the millennium development goal by 2030 to reduce its incidence by 80% and resulting death by 90%. The WHO report of 2017 [1] cites the death of 1.3 million people annually to TB. It also attributes the fresh incidence of TB in 5.8 million men, 3.2 million women and 1 million children in 2017. Two thirds of the total new TB cases occurred in eight countries, with India having 27% of them. Tuberculosis is a chronic bacterial infection caused by a rod-shaped bacterium, Mycobacterium tuberculosis. It primarily affects the lungs, but can also affect several other areas like bones, intestines, urinary tract and the skin. Hence, the detection of this disease at an early stage is crucial to a suitable line of treatment. Existing methods of detection are steeply priced, take time [2] and are often inaccurate with low sensitivity or specificity. Accurate detection is essential in eradicating TB [3-4]. CXR is one of the diagnostic methods to detect pulmonary disorders [5]. Presently, diagnosis depends on the ability of the physician who reads the CXR image manually [6] and is affected by human fatigue and other errors. With correct diagnosis, proper treatment will enable quick recovery. TB is spread through sputum and sneeze of affected people. Several tests have been developed for the detection of TB. Common tests include the Skin test [7], Sputum test, Interferon-gamma release assay (IGRA) and the CXR. The Skin test does not confirm correctly. The Sputum test is more accurate. However, it is time consuming and depends on the patient's ability to provide a sputum sample. Further, the sample has to be destroyed after microscopic analysis, as it may be contagious. IGRA is expensive, poor sensitivity and is time consuming [8]. The CXR is an inexpensive and fast method, but its accuracy depends on the diagnostic ability of the physician. Keeping in mind these methods; this paper describes automatic TB detection from CXR using CNN. Initially image is segmented using graph cut method followed by image classification as TB or Non-TB by using CNN classifier. Among the commonly used segmentation methods graph cut based segmentation provides better result for biomedical images [9]. In this method energy function is constructed from the information of regional and boundary, hence providing optimal segmentation. The proposed method permits accurate detection with high accuracy, sensitivity and specificity. The trained CNN classifier can classify the image as malignant or benign occurrence.

Section II describes the literature review of existing methods, and Section III details the proposed method for TB detection. Section IV expounds results and discussions and a lucid conclusion together with a plan for future work in Section V.

II. LITERATURE REVIEW

With the advancement in image processing techniques, computer aided diagnosis assumed a vital role in medical image processing. CXR which relies heavily on Image analysis has also developed new techniques. The papers discussed in the subsequent paragraphs focuses on areas of computer aided diagnosis (CAD). The need of CAD for TB diagnosis has been reviewed in our survey paper [10], where concepts related to the various image processing and ANN classification methods have been alluded. J. Melendez, *et al.*,[11] have used supervised and multiple instance learning (MIL) CAD systems that are easier to retrain. After training the system is likely to provide right labels of unidentified data according to lesion annotations. On the basis of four moments of intensity distribution of the test category of input data, texture feature extracted and classified by K-nearest

Revised Manuscript Received on May 15, 2020.

* Correspondence Author

KG Satheeshkumar*, SENSE,VIT University, Vellore, Tamil Nadu, India. Email:kg.satheeshkumar2013@vit.ac.in.

V Arunachalam, Department of Micro and Nano Electronics, SENSE, VIT University , Vellore, Tamil Nadu, Indi. .Email:varunachalam@vit.ac.in.

neighbour classifier. The procedure has several limitations, including the uncertainty due to incomplete labelling scheme during training. Candemir, *et al.*, [12] deals with a robotic detection of TB and is performed using CXRimage.
The input image is filtered by a Gaussian filter to remove noise. The graph cut segmentation algorithm is applied to get the desired lung region. The segmented lung portion is then divided into four lobes. The infected region is again segmented; the feature values of this region are recalculated. These values are used to classify the regions as normal or abnormal by using the AdaBoost classifier. It provides a decent accuracy, but is sensitive to noisy data and outliers.

S.Jaeger, *et al.*, [13], in his study presents TB detection in which a combination of statistical lung, intensity and Log Gabor mask are used to segment the desired lung field. From the lung region, a set of features are extracted for curvatures, shapes and textures. Based on the extracted features, the support vector machine distinguishes between normal and abnormal CXR. However, it suffers from the drawback that a wider range of spectral information needs to be obtained without losing maximum spatial localisation. B.Ginnekanet, *et al.*,[14] concluded their analysis as pixel classification gives superior performance among the different segmentation techniques akin to active shapes and pixel classifications. R.Shenet, *et al.*,[15], used hybrid knowledge based Bayesian classification to detect TB cavities automatically. In this work, circularity and gradient inverse coefficient of variation measures are used to categories identified features and to confirm right cavities. This approach gains high accuracy with low false positive rate in identifying cavities when compared with classical active contour techniques and the non-hybrid approach used for feature extraction in CXR. The Bayesian methodology is very complex which also limits the reach of the work.

L.Hogeweg, *et al.*,[16] in their paper developed a CAD system that combines a number of sub-scores into one detecting textural, shape and focal irregularities in the image. This process was analysed on two data sets and stated that combination method outperforms better than individual methods with limitations of time consumption. Ramana, *et al.*, [17] describe the procedure of taking CXR in the form of Mass Miniature Radiographs (MMR) in which both the lungs and the shadow of the heart in between them are used to recognize the onset of the malady. The extracted features are the white gap, shadow and structures. An Artificial Neural Network (ANN) is constructed and trained for the accurate detection of pulmonary TB. The ANN relies heavily on back propagation algorithm. The major drawback is that in order to evaluate optimal neural network, different combinations of multi-layer perceptrons with different parameters are required, leading to increased computational effort.

Omar, *et al.*, [18] reports that the overall appearance of the infected area on the digital CXR image for pulmonary TB, does not confirm to benchmark shapes, sizes or configurations. Phase congruency (PC) values are used to collect information from the transition of adjacent pixel values. PC values are used as features to represent known disease types. The feature vector consists of its average, variation and maximum values which were found to be able to identify the PTB with higher accuracy. PC is sensitive to parameter changes such as image illumination, blurring and magnification. The PC-based model is a frequency-based model, which obviates the search for specific points. Rather, it considers both amplitude and phase of the individual frequency elements in a signal. Finally, three groups are being detected using a Euclidean distance method such as pulmonary tuberculosis, healthy tissues as well as rib bones.

Karargyris, *et al.*, [19] present a unique approach for the detection of lungs and ribs in CXRs. The unified method combines two detection schemes to reduce the cost. Instead of using pixel-wise techniques, region-based features are used. These features are computed as wavelets which consider the orientation of various anatomic structures. It includes the identification of TB infection from lung region. The approach has a drawback that the Gabor filter used to obtain large spectral information has bandwidth limitation. Noor, *et al.*, [20] describe the statistical interpretation of CXRs for the detection of PTB. Each region of interest (ROI) is represented by the vector form of wavelet texture measures. It is multiplied with the orthogonal matrix Q. Primary elements of the transformed vector displayed a bivariate normal distribution. The study discusses the detection of PTB by constructing a discriminant function. This procedure yielded a correct classification rate of about 94%.

B.Van G, *et al.*, [21] in their work describes different ways to detect irregularities signs in textural character. In this work, the lung area is partitioned into several overlap in regions. Diverse features are extracted from every region. In order to detect the different textural nature, the moments are given to a filter bank and the difference between left and right lung fields are taken. By voting and weighted integration, classification is done from extracted features. JunmingJ, [22] has proposed an automatic segmentation scheme using fully connected CNN for segmenting colorectal tumors from magnetic resonant images (MRI) and got better result than other methods. This result further strengthened our inference that CNN-based system could be a better choice for classification of CXR image. SemaCandemir, *et al.*, [23] has stated CXR is one of the imaging techniques and segmenting the lung region is essential for more accurate classification. The various lung boundary detection methods and their accuracy levels have been elaborated. The recent studies discussed in the preceding paragraphs urges the need for new rapid and accurate diagnostic techniques by which more accurate classification can be performed. This could in turn control the disease and minimize the mortality rates. Hence, a new method of classification based on CNN is proposed and is discussed in this paper.

III. PROPOSED METHOD

The section details the implementation of the proposed system. The image is initially segmented and subsequently classified as normal or abnormal.

A Segmentation:

Segmentation method can be broadly classified into five broad groups [9] based on the methodology employed.

These include threshold-based, edge-based, region-based [24] watershed-based and energy-based. Among these, graphs cut segmentation that takes the regional and boundary information to create energy function, is one of the apt energy-based segmentation, which gives global optimal result and is also widely accepted for medical images.
Hence, is used as a segmentation method in this work. In graph cut segmentation method [25], basics of graph theory is applied on image and represents a set of pixels as vertices or nodes. The colour or intensity difference between any two pixels is considered as an edge, with a weight attached. A normal cut along with second smallest Eigen value and Eigen vector divides the image into two different portions as shown in Fig. 1 [25]

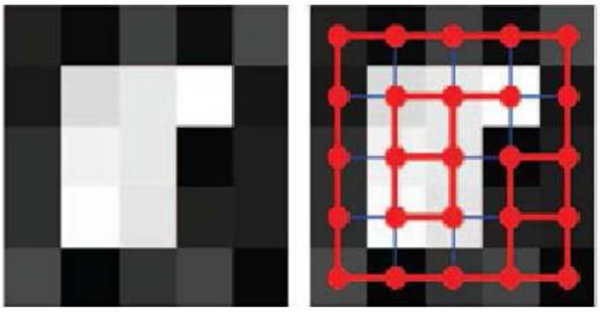


Fig. 1. [25]An example of normalized cut (a) Original and (b) Connected Graph

In the figure, first one is original and second one is connected graph. The thick and thin edges are used to represent strong and weak similarities between two pixels. Ultimately the image is divided into two regions of strong and weak similarity.

Procedure for Normalized Cut Algorithm is detailed as illustrates.

i. For a given image or image sequence, set up a weighted graph, G = (V, E) where V and E denote the set of vertices and edges of G respectively.

ii. Find weights between vertices I_1 and I_2 ,

$$w = \exp\left(\frac{\log 0.01}{MAXVAL} * abs(I_1 - I_2)\right) \quad (1)$$

where $MAXVAL$ is the maximum value of the input image.

iii. Build the weight matrix 'WM'.

iv. Solve (D - WM) for Eigen vectors with the smallest Eigen values, where D is the diagonal matrix.

v. Use Eigen vector with second smallest Eigen value to bipartition the graph.

B.CNN Classification

Here, we used five-layer CNN architecture**.** Input layer is of size 200X200, the output of which is fed to convolution layer having kernel size of 3X3. Output of this is given to a Rectified Linear unit (ReLu) employing *tanh* activation function. The processed data from the ReLu layer is given to the max pooling layer and subsequently fed to convolution layer 2 with ReLu, using sigmoid activation function. The output from this layer fed to fully connected layer and finally to the SoftMax layer to classify the given image as TB or Non-TB. The learning rate of the system is taken as 0.01 as larger values results in faster operation with lower accuracy and smaller values provides higher accuracy with very computation time.

As with any CNN models, a resized image of a predefined size needs to be given to the input layer and all the features are extracted as it progresses through the different layer of the CNN model. The training task of the model becomes more and more time critical when

i. The number of training images are increased which will increase accuracy and reduced errors due to over fitting

ii. The epoch levels are increased, where higher accuracies are observed at higher epochs

These parameters are requirements of an efficient CNN model but impose lot of computational requirements. To reduce the computational requirements, instead of providing a complete image, a graph cut segmented lung region is provided as the input to the CNN. In order to reduce the effect of over fitting regularization term in the form of L1 norm has been added into the objective function, which is basically the sum of all model parameters.

C. Receiver Operating Characteristics (ROC):

Classifier quality can be checked using ROC. The y-coordinate indicates the sensitivity (recall) of the system and the x-coordinate denotes the false positive rate. The quality of a classifier is determined by its classification performance. ROC specifies how healthy a classifier can classify an image. Misclassification can lead to degraded performance. Accuracy, specificity and sensitivity are the measures used to evaluate the quality of a classifier. Table I lists the confusion matrix developed for the evaluation.

Accuracy is used to indicate the accuracy of the test in reducing classification error and is given by,

$$Accuracy = \frac{TP+TN}{TotalSamples} * 100\ \% \quad (2)$$

Sensitivity indicates the correctness of the test among the affected people.

$$Sensitivity = \frac{TP}{TP+FN} * 100\ \% \quad (3)$$

Specificity indicates the correctness of the test among the impervious people.

$$Specificity = \frac{TN}{TN+FP} * 100\ \% \quad (4)$$

Table I. Confusion Matrix

Condition	Predicted Condition Positive	Predicted Condition Negative
Test Positive	True Positive (TP)	False Positive (FP)
Test Negative	False Negative (FN)	True Negative (TN)

D. Dataset and Implantation Tools.

This work uses the data set from JSRT with a standard image format which is used for educational and research purpose of image processing, image compression and computer aided diagnosis by many researchers. 93 images of non-nodule and 154 CXR images with lung nodules were examined, which included 100 malignant case and 54 benign case for analysis, training and testing purposes. The same set was used for comparing the existing SVM classifier with the proposed CNN classifier.

All images had a size of 2048 x 2048 pixels with a 12-bitgrey scale depth. The work was carried out on a Lenovo Intel core i3 processor with 4 GB RAM and MATLAB 2018b.

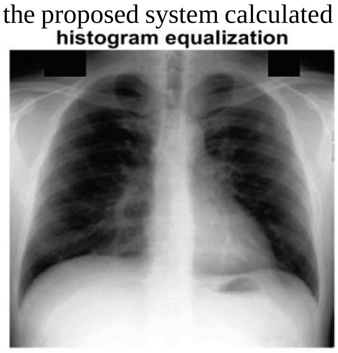
IV. RESULT AND DISCUSSION

A.Result

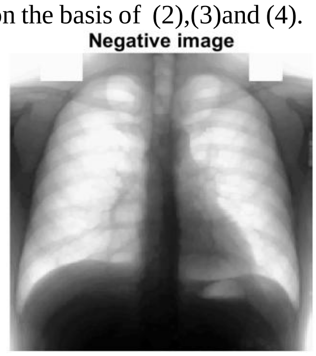
The experiment was carried out on images available on JSRT database of 247 CXR images which contained 154 nodule and 93 non nodule images. The same data base was used for training and testing. 60 % of the dataset used for training and 40% is used for testing. Results of pre-processing steps are presented in Fig. 2 for a sample image, Histogram equalization image in Fig. 2(a), its negative image in Fig. 2(b), sharpened image in Fig. 2(c), Enhanced image in Fig. 2(d) and binary segmented in Fig.2(e).

The images are classified as normal and abnormal. For getting a better picture on the effectiveness of the proposed system, it has been compared to a SVM based classifier and a CNN model which is trained on an unsegmented image. The feature using training the SVM model are shape descriptor histogram, curvature descriptor histogram, intensity histogram, gradient magnitude histogram, histogram of oriented gradient, local binary pattern and CBIR Based features.

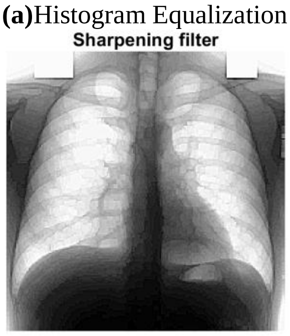
From 93 test samples, 88 samples were classified correctly using segmented CNN 83 by unsegmented CNN and the SVM classifier was able to classify 80. Table II and III details the confusion matrix used for CNN and SVM respectively. Table IV shows the performance evaluation of the proposed system calculated on the basis of (2),(3)and (4).



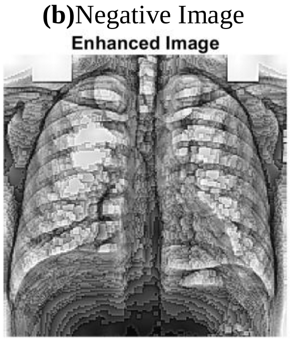
(a) Histogram Equalization



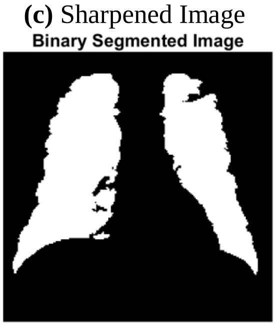
(b) Negative Image



(c) Sharpened Image



(d) Enhanced Image



(e) Binary Segmented Image

Fig. 2. Pre-processing steps for effective segmentation

Table II. Confusion Matrix of CNN Classifier

Condition	Predicted TP	Predicted TN
TP	77	2
TN	3	11

B. *Discussion*

Threshold, region and graph cut-based segmentation were carried out randomly on 100 images that includes both malignant and benign from the JSRT database of 247 CXR images which contained 154 nodule and 93 non nodule images.

Table III. Confusion Matrix of SVM Classifier

Condition	Predicted TP	Predicted TN
TP	69	3
TN	10	11

The segmented images have been scored by two expert radiologists from nearby hospitals. They independently categorised the segmented images on the basis of its percentage of correctness into three groups namely 100%, 75% and below 50% and labeled as A, B and C.

From the classification perspective labels A & B give a higher degree of classification when compared to label C. Hence both labels A & B has been taken as true case and other as false. Then accuracy is calculated on the average of two true case of experts score by using (6) .

$$Accuracy = \frac{True\ Case}{Total\ Images}. \tag{6}$$

Scores have been tabulated for these three methods and shown in Table V. Tabulated score shows that graph cut based segmentation gives better segmentation accuracy than other two. From this approach we could validate the fact that graph cut based segmentation methods can provide optimal segmentation of CXR images.

For the same set of images CNN based classification of graph cut based segmented CXR images provided better classification results than that of other segmentation methods. We compared the performance in terms of accuracy and ROC of CNN classification with and without graph cut segmentation. It was inferred that segmentation improves the classification performance.

On comparing the quality metric scores of the proposed architecture with very recent architectures, it can be seen that the scores are comparable and in certain cases better than the average score(accuracy) of 89% obtained on three CNN architecture AlexNet, ResNet and DenseNet used by Jared A, *et al.*, [26]. Furthermore, the scores are way better than model developed by Sivaramakrishnan R, *et al.*, [27] having an accuracy of 82.4 %. Receiver Operating Characteristics performance is of projected system using CNN classifier shown in Fig. 5 (a) and (b).

Table V. Comparison of Segmentation Accuracy of Threshold Based, Region Based and Graph Cut Based Segmentation Methods. Labels A, B and C corresponds to 100%, 75% and below 50% segmentation quality respectively

Segmentation Methods	Expert 1				Expert 2				Average True Case Accuracy (%)
	A	B	C	True Case (%)	A	B	C	True Case (%)	
Threshold Based	52	18	30	70	48	20	32	68	69
Region Based	60	21	19	81	62	20	18	82	81.5
Graph Cut Based	68	23	9	91	70	22	8	92	91.5

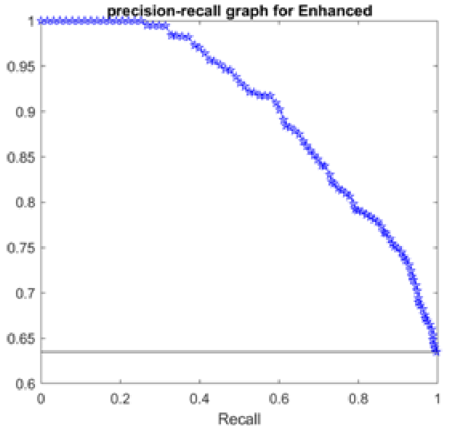
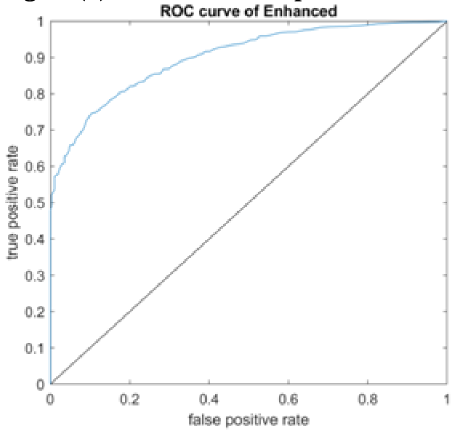


Fig. 5. (a) Characteristics performance



.

Fig. 5. (b)Receiver Operating Characteristics of projected system using CNN classifier

Comparison table of SVM and CNN shown in Table VI.

Table VI. Performance Evaluation of Projected System Compared with SVM

Classifier	CNN	SVM
Accuracy	**94%**	**86%**
Sensitivity	**96%**	**87%**
Specificity	**84%**	**80%**

V. CONCLUSION

Automatic tuberculosis detection from CXR using CNN classification has been presented in this paper. We have compared the performance of CNN classifier models that are trained using segmented and unsegmented image. It was observed that the former model provides more accuracy, specificity, sensitivity and ROC.

The proposed work has been compared with the existing SVM classifier in terms of accuracy, specificity and sensitivity. The system gives accuracy of 94% that of 86% of SVM, sensitivity 96% that of 87% of SVM and Specificity of 84% that of 80% of SVM. This result was achieved by using graph cut based segmentation followed by CNN. ROC performance of the proposed system also gave better results. The results clearly show the CNN classification outperforms the existing SVM classification method. Future work is envisaged by identifying the TB as cavity or milary TB and the stage of the disease.

REFERENCES

1. World Health Organisation 2017, "Global Tuberculosis report". Rep. WHO/ HTM / TB/2017.
2. Ruben K et.al "Nanoparticle-Based Biosensing Assay for Universally Accessible Low-Cost TB Detection with Comparable Sensitivity as Culture". Diagnostics 9,222. 2019, pp 1-14.
3. Uplekar M, Weil D, Lonnroth K, Jaramillo E, Lienhardt C, Dias HM, et al ,"WHO's new end TB strategy" Lancet,2015,385.1799-1801.
4. Kahwati LC, Feltner C, Halpern M, Woodell CL, Boland E, Amick HR, et al, "Primary care screening and treatment for latent tuberculosis infection in adults: evidence report and systematic review for the US Preventive Services Task Force", JAMA 316,2016,pp970-83.
5. Suhail R etc, "Interpretation of plain chest roentgenogram", Chest 141(2), 2012, pp544-558.
6. Jonathan K etc, "Chest X ray made easy 3rd edition" , Elsevier Churchill Livingstone, London, 2009,eBook ISBN: 9780702057625
7. Rafaela B et.al, "Cost-effectiveness of QuantiFERON-TB Gold In-Tube versus tuberculin skin test for diagnosis and treatment of Latent Tuberculosis Infection in primary health care workers in Brazil", PLOS ONE,2019,.pp1-24.
8. Diya Lu, etc, "Diagnosis of Tuberculosis Meningitis Using a Combination of Peripheral Blood T-SPOT.TB and Cerebrospinal Fluid Interferon-γ Detection Methods" Laboratory Medicine, Volume 47, Issue 1,2016,pp 6–12.
9. Faliu Yi Inkyu, Moon, "Image Segmentation: A Survey of Graph-cut Methods", Proceedings of International Conference on Systems and Informatics (ICSAI 2012) published by IEEE, Yantai, China,2012, pp1936-1941.

10. KG Satheeshkumar, Alex Noel Joseph Raj, "Developments in computer aided diagnosis used for tuberculosis detection using chest radiography: a survey". ARPN Journal of Engineering and Applied Sciences, Vol. 11, No. 9, 2016, pp5530-5539.
11. J. Melendez, et al, "A novel multiple-instance learning-based approach to computer aided detection of tuberculosis on chest x-Rays", IEEE Transactions on Medical Imaging, vol. 34, no. 1, 2015.
12. S. Candemir, S. Jaeger, K. Palaniappan, S.Antani and G. Thoma, "Graph-cut based automatic lung boundary detection in chest radiographs", IEEE Healthcare Technology Conference: Translational Engineering in Health and Medicine. Houston, Texas USA,2012, pp31-34.
13. S.Jaeger, A. Karargyris, S. Antani and G. Thomas, "Detecting tuberculosis in radiographs using combined lung masks", International Conference IEEE Engineering in Medicine and Biology Society. San Diego, California USA,2012, pp 4978-81.
14. B. Van Ginneken, Stegman,Loong M, "Segmentation of anatomical structures in chest radiographs using supervised methods a comparative study on public database", Medical Imaging Anal, vol. 21,2006, pp924-933.
15. R. Shen, I. Cheng, and A. Basu, "A hybrid knowledge-guided detection technique for screening of infectious pulmonary tuberculosis from chest radiographs", IEEE Trans. Biomed. Eng., vol. 57, no. 11,2010,pp2646–2656.
16. L.Hogeweg, et al, "Automatic detection of tuberculosis in chest radiographs using a combination of textural, focal, and shape abnormality analysis", IEEE Transactions on Medical Imaging. 2015, pp 2429-42.
17. Ramana K. V, Khader Basha S. K, "Neural Image Recognition System with Application to Tuberculosis Detection", IEEE International Conference on Information Technology: Coding and Computing. Las Vegas, NV, USA,2004, pp1-5.
18. Omar Mohd Rijal, Hossien Ebrahimian, Norliza Mohd Noor, "Determining Features for Discriminating PTB and Normal Lungs Using Phase Congruency Model", Proceedings of the IEEE- EMBS International Conference on Biomedical and Health Informatics, Hongkong China,2012, .pp 341-44.
19. Karargyris A, Antani S, Thoma G, "Segmenting Anatomy in Chest X-rays for Tuberculosis Screening", ConfProc IEEE Eng Med BiolSoc,2011, pp 7779-82.
20. NorlizaMohd. Noor, Omar Mohd. Rijal, AshariYunus, "A Statistical Interpretation of the Chest Radiograph for the Detection of Pulmonary Tuberculosis", IEEE EMBS Conference on Biomedical Engineering and Sciences, Kuala Lumpur, Malaysi,2010, pp47-51.
21. B.V Ginneken, S Katsuragawa, BMter HaarRomeny, k. Doi and M. Viergever, "Automatic detection of abnormalities in chest radiographs using local texture analysis", IEEE Transactions on Medical Imaging, vol. 21, no.2,2002, pp139-149.
22. Junming, JianFei, XiongWei, XiaRuiZhang JinhuiGu Xiaodong WuXiaochun Meng, "Fully convolutional networks (FCNs) - based segmentation method for colorectal tumours on T2-weighted magnetic resonance images". Australasian Physical & Engineering Sciences in Medicine, Volume 41, Issue 2,2018, pp393–401.
23. Sema C etc. "A review on lung boundary detection in chest X-rays", International Journal of Computer Assisted Radiology and Surgery 14,2019, pp563 – 576.
24. Lu Xiong et al., "Color disease spot image segmentation algorithm based on chaotic particle swarm optimization and FCM", The Journal of Supercomputing,2020,pp 03171-8
25. J.Shi and J.Malik, "Normalized cuts and image segmentation". IEEE Transactions on Pattern Analysis and Machine Intelligence Volume: 22, Issue: 8, 2000, pp 888 – 905.
26. Jared A. Dunnmon, Darvin Yi, Curtis P. Langlotz, Christopher Ré, Daniel L. Rubin, Matthew P. Lungren, "Assessment of Convolutional Neural Networks for Automated Classification of Chest Radiographs", Radiology; Volume 290: Number 2,2019, pp 537–544.
27. Sivaramakrishnan, R., et al., "Comparing deep learning models for population screening using chest radiography". Medical Imaging Computer-Aided Diagnosis Vol. 10575, 2018, pp105751E-1 - E11.

AUTHORS PROFILE

KG Satheeshkumar, Research Scholar in SENSE, VIT, Vellore, Tamil Nadu, India. He has done his M.Tech in Network Communication and Security from Dr,MGR Educational and Research Institute Chennai. Since 2001, he has been a faculty in Department of Electronics and Communication Engineering, Amal Jyothi College of Engineering, Kanjirapally, Kottayam, Kerala, India.

Arunachalam. V received the B.E. degree in Electrical and Electronics Engineering from University of Madras, India, in 1997 and M.E. degree in Power Electronics and Drives from Anna University, Chennai, India, in 2002. Since 2004, he has been a member of faculty in the Department of Micro and Nano Electronics, School of Electronics Engineering, Vellore Institute of Technology University, Vellore, India, where he is currently an Associate professor and head of the department. His research interests are FPGA based system design, HW/SW partitioning, VLSI DSP and reconfigurable architecture. He is serving as IEEE student branch counselor, VIT University, Vellore.