POTENTIAL NODULE DETECTION FROM POSTERIOR AND ANTERIOR CHEST RADIO GRAPH USING RESTRICTED BOLTZMANN MACHINE AND SVM CLASSIFIER

[1]Dr.T.Satya Savithri, [2]S.K.Chaya Devi
[1]Professor, Dept.of.ECE,JNTU Hyderabad, Telangana state,India

Abstract-The most common techniques used to examine lung tumors include chest radiography, computerized tomography scans though the last one is more sensitive and precise in detecting nodules but costlier, chest radiography is most commonly used and cost–effective diagnosis tool to find lung tumors. But interpreting a chest radiograph is difficult, even experienced radiologists facing trouble in finding abnormalities in chest radiograph. The clinical importance of chest radiographs, combined with their complicated nature, explains the interest to develop a computer aided diagnosis scheme that alerts radiologists to the location of highly suspect lung nodules, will allow the number of diagnostic errors to be reduced. Different methods are proposed in the literature for finding tumors, but none showed the correct result, i.e because of more subtlety of the nodule (not visible),and complexity of anatomical structure presented in the image. In this paper a method is proposed to find more subtle potential nodules in Posterior and Anterior Chest Radiographic images. Nodules find by, delineating lungs from the chest radiograph by using standard mask available at JSRT data base. To locate potential nodule Restricted Boltzmann machine and SVM classifier is used. Here Restricted Boltzmann is used for finding the features from ROI (region of interest), ROI is classified as nodule (or) non nodule by using linear SVM classifier.

Keywords: Restricted Boltzmann machine, potential nodule, and computer aided diagnosis

1. INTRODUCTION

Lung cancer is primary cause of cancer death in the world. Lung cancer mainly occurs in older people about 2 out of 3 people diagnosed with lung cancer are at the age 65 years (or) older, fewer than 2% of all cases are found in people younger 45.

Survival rate of the patient can be improved greatly, if the disease is identified at the earliest. Performing posterior and anterior chest radiograph is the first step in the diagnosis, if a patient shows symptoms that may suggest lung cancer, because of its simplicity low cost, low X-Ray dose. Computer tomography scans can also be used, but it is not recommended because of high radiation dose and high cost. Despite its advantages interpreting abnormalities in a PA chest radiograph is difficult; sometimes even radiologists can fail to detect nodules on chest radiographs, because of its complexity:

The complexities in detecting lung nodules from radiographs are:

(1) Nodule size will vary widely in radio graphs. Nodule diameter ranging from few millimeters to several centimeters.
(2) Some nodules are only slightly denser than the surrounding lung tissue (less visible).
(3) Nodules can appear anywhere in the lung field, and can be obscured by ribs and structures below the diaphragm and heart

(radiographs are projection images contains superimposed structures).

(4) Nodules attached to the vessels and look like vessel

Particularly for the above said reasons, from past decades various computer algorithms have been developed. System developed by using these algorithms is called computer aided diagnosis system. These CAD systems help the radiologists in detecting abnormalities in chest radiographs by highlighting suspicious regions.

The first step in computer aided diagnosis schemes of lung tumor proposed in the literature is the segmentation of the lung field, because segmentation will restrict the processing area of subsequent algorithms. Lung segmentation is the definition of the lung area to be detected and delineated.

Methods presented for segmentation of the lungs, in the literature followed two main approaches rule based segmentation and pixel based classification. Rule based methods apply a sequence of image processing operations, such as filtering, thresholding and morphological operations to delineate the lung field boundary. Rule-based schemes have been proposed by Armato *et al.* [13], Xu *et al.*[14], X. W. Xu and K. Doi, [15], J. Duryea and J. M. Boone [16], E. Pietka [17], and M. S. Brown, L. S.Wilson, B. D. Doust, R.W. Gill, and C. Sun. [18]. In pixel classification each pixel in the image is individually classified as lung/no lung based on features such as image data magnitude, location and local texture measures. Pixel classification using neural networks has been investigated by M. F. McNitt-Gray, H. K. Huang, and J. W. Sayre. [19] and Tsujii *et al.* [20]. Vittitoe *et al.* [21], [22] developed a pixel classifier for the identification of lung regions using Markov random field modeling. Van Ginneken and Haar Romeny proposed a hybrid method improved Active Shape Modeling Technique) that combines a rule-based scheme with a pixel classifier [23]. Lung fields can also be segmented manually by selecting region of interest, (or) by using lung masks available at JSRT databases [1].

Next step in computer aided diagnosis for chest radiographs is tumor detection. So many researchers have proposed different methods in the literature for finding tumor; none showed the perfect results, because of anatomical structure complexity in the radiograph.

The complexity anatomical structure(rib crossings, rib and vessel crossings, and rib and clavicle crossings and also due to end on vessels) and subtlety of the nodule in the image are reasons for getting more number of false positives per image.False positive finding is not a nodule but it is interpreted as a nodule (or) lesion.

For nodule detection in the literature pixel based classification and feature based classification methods has been proposed. In feature based classification method, initially suspicious nodule regions are segmented from the chest radiograph. Based on features from each suspicious region; regions are classified in to potential nodule (or) non nodule regions. In pixel based classification directly pixels values of chest radiograph are used for finding potential nodule. In these methods since pixel values used directly for finding nodules, these methods avoids errors caused due to segmentation of suspicious regions and feature calculations.

Feature based classification methods proposed by J.Wei,Y.Hagihara *et al. [30]* , Rui teixeiro Ribeiro [31], Junji Shiraishi Qiang Li *et al*, [32], Russell C. Hardie *et al*, [35].

Rui teixeiro Ribeiro [31], proposed a method where suspicious nodule regions are found by using multi scale blob detection method later potential nodule is found by using SVM classifier with the help features calculated from each suspicious region.

Junji Shiraishi Qiang Li *et al*, [32] developed CAD scheme where entire chest radio graph divided in to blocks of fixed size called Region of interest. By using average radial-gradient filtering technique, initial nodule candidates are enhanced, features are calculated from original image, nodule enhanced image and contra lateral subtraction image. Resultant features are used for detecting potential nodule by using ANN.

Russell C. Hardie *et al*, [35] presented a scheme, in which new weighted-multi scale convergence index nodule candidate detector is proposed for nodule candidate detection. Adaptive distance-based thresholding was used for nodule segmentation. For each segmented nodule candidate features are calculated .Fisher linear discriminate classifier is used for finding potential nodule candidate using features calculated earlier.

The CAD system which uses pixel based classification proposed by Zhenghao Shi *et al [33],* Kenji Suzuki *et al[34]*

Zhenghao Shi *et al [33],* presented a scheme where nodule candidates are suspected by using Eigen values of Hessian matrix. Rule based classifier and Multi Massive trained SVM classifier was proposed to reduce the number of false positives and to find potential nodule.

Kenji Suzuki *et al [34]* proposed a method, in which difference imaging technique and multiple gray-level thresholding technique has been used to find initial nodule candidates. Rule based and linear-discriminant classifiers were used for reducing false positives. Later for reducing false positives further and to find potential nodule candidate Multi Massive Trained ANN has been employed. In this scheme at the beginning feature based classifier were used to find the potential nodule candidate, later MTANN pixel based classification method has been used to reduce number of false positives and to find potential nodule candidate.

Some methods in the literature make use of subtraction technique for nodule detection, in these methods initially nodule enhanced image is obtained, by filtering the image with nodule like filter, later back ground is subtracted, subsequently nodules are found by muti level thresholding [29].

In this paper attention paid to find nodule candidates including subtle and more subtle nodules from posterior and anterior chest radiographs using Restricted Boltzmann machine and SVM classifier.

In this proposed method, initially PA chest Radiographs are enhanced, because of low contrast of the original image. Later visible lung fields are extracted from chest radiographic image by using mask available in JSRT data base this is done to restrict the processing area of the original image. In this work lung regions obscured by the mediastinum, the diaphragm are not considered, where nodules also present. After these preprocessing steps entire image divided in to 64×64 fixed size patches. Each patch is called Region of interest (ROI).Patch which contains nodule is called nodule patch, which doesn't contain nodule is called non nodule patch. Each Image patch was classified in to nodule (or) non nodule patch by using Restricted Boltzmann machine and SVM classifier.

In this scheme for training and testing, pixel values of the image patches were used. During training process, from each image patch, with the help of Restricted Boltzmann machine features are obtained. These features are used to train SVM classifier. Restricted Boltzmann machine is parameterized model; it can learn probability distribution of target, based on samples from the unknown target distribution. Training RBM means adjusting its parameters in such a way that probability distribution of the machine represents training data distribution. Parameters changed during training are weights and biases of visible and hidden neurons. These parameters were used as features for classification, in this paper visible unit bias values considered as features from RBM.

For testing image patches i.e. to differentiate image patch as nodule patch and non nodule patch. Each patch of particular image is given as input to the RBM. Visible neuron bias values of the RBM considered as features for the patch. Using SVM classifier, by using above obtained features particular patch is classified as nodule (or) non nodule patch.

The whole proposed method has been developed and tested on the radiographs of the standard database acquired by the Japanese society of radiological Technology. Initially images have been down sampled to dimension 512*512 pixels. This size has been chosen in order to reduce computational costs of the algorithms without losing any much details of the image.

The enhancement and Segmentation are discussed in section 2.Lung patch feature extraction and classification described in section 3. Results and conclusion are discussed in section 4 and 5.

2. ENHANCEMENT AND SEGMENTATION

Images for processing chosen from JSRT data base.

Original image having low contrast, further processing on the same image will give undesired result; contrast of the image must be enhanced. For increasing the contrast of the image, local contrast enhancement method is used. Which normalize the contrast within the image and across all the images [35]

$$y(m;n) = \underline{x(m;n) - \mu(m;n)} \text{ ------ } \quad (1)$$

σ(m;n)

$x(m;n)$ is the input image.
$y(m;n)$ is the local contrast enhanced image.
μ(m;n) is the local mean estimate.
σ($m;n$) is the local standard deviation estimate.

μ(m;n) is calculated by

$$\mu(m;n) = x(m;n) * h(m,n); \text{-------} \; (2)$$

$h(m;n)$ is the Gaussian low pass filter response with standard deviation 16.
The local standard deviation is computed by

$$\sigma(m;n) = \sqrt{X^2(m;n) * \mathrm{h}(\mathrm{m},\mathrm{n}) * \mu^2(m,n)}$$
(3)

Next step in nodule detection is segmentation of the lung region from chest radiographic images. Lungs are segmented in order to reduce the processing area of the image. Segmented lungs obtained by multiplying original image with standard mask (shown in Fig 1b) available at JSRT data base. Segmented lungs are shown in Fig: 1c
In this proposed method region based classification is employed so entire segmented lung region (visible lung region) is divided in to fixed 64*64 size ROI's. After dividing the lung region in to image patches (ROI's).each ROI classified in to nodule (or) non nodule patch, as explained in the following section.

3. LUNG PATCH FEATURE EXTRACTION AND CLASSIFICATION

Each Image patch was classified in to nodule (or) non nodule patch by using Restricted Boltzmann machine and SVM classifier.

3.*1Restricted Boltzmann Machine*

RBM is a probabilistic artificial neural network, which can learn a probability distribution of its input datasets .RBM'S are effective feature extractors from images, for classification. In this scheme RBM is used to learn the probability distribution of the lung image patches.
RBM consists of two layers of neurons, namely visible layer and hidden layer. Each neuron in one layer connected to neuron in other layer, but neurons in the same layer are not connected. Connections between the layers are symmetrical and bidirectional that means information flows in both directions during usage of the network. Connection between the layers associated with weights. Each neuron in both the layers consists of bias values.
Training of the RBM performed using contrastive divergence algorithm. Training RBM means adjusting its parameters in such a way that probability distribution of the machine represents training data distribution. Parameters changed during training are weights and biases of visible and hidden neurons. Training starts by locale the states of the visible units to a training vector. Then states of the hidden units are calculated parallel by using following equation

$$P(h_j=1|v) = \sigma(\, b_j+\textstyle\sum_i v_i.w_{ij}) \text{ ------------}(1)$$

where σ(x) is the logistic sigmoid function

$$\sigma(x) = 1/(1 + \exp(-x)) \text{ ---------------}(2)$$

Once states of the hidden units are calculated, a reconstruction is produced by setting states of visible units with a probability given by the following equation.

$$P(v_i=1|h) = \sigma(\, a_i+\textstyle\sum_j hj.w_{ij}) \text{ ----------------}$$
(3)

Then change in a weight is then given by

$$\triangle W_{ij}=€(<v_ih_j>data \; -<v_ih_j>recons) \text{ ----------}(4)$$

A simplified learning rule which uses states of the individual units is used for updating biases.

Where vi are the states of visible unit i , hj are the states of the hidden unit j, ai, bj are their biases and wij are the weights .And the updated weight matrices and bias matrices of the RBM networks are the features.

3.2 Image patches training and testing

The size of the lung patch used for classification is 64*64.This size for the patch chosen based on investigational results.RBM constructed with 64 visible and 16 hidden neurons. Here visible neuron bias values considered as features. During training RBM trained with different nodule and non nodule patches. As said above training means changing the weights and biases. Linear SVM classifier trained with features (visible neuron bias values) obtained from RBM. For testing image patches, same RBM is used.RBM is trained with image patch to be tested. With the help of features obtained from RBM by using SVM classifier image patches classified as nodule and non nodule patch.

3.3 SVM classifier

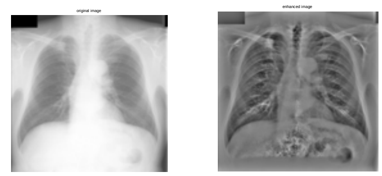
Support vector machine is based on statistical learning theory; it is a supervised learning algorithm. SVM was introduced by vapnik 1979.mostly used for data analysis and pattern recognition.SVM creates a hyper plane between the classes of data indicating which class particular set of data belongs to. Initially machine is trained to understand the structure of the input data. Input data is classified based on training examples. Largest margin between the two classes indicates the best hyper plane for SVM. If data is linear a separating hyper plane used to divide the data. For inseparable data nonlinear kernels are used to separate the data. Different kernel functions are.

4. RESULTS

This proposed method has been tested on JSRT data base. The results obtained are equivalent to results mentioned at the JSRT database. This technique can work even with low contrast images. In this proposed algorithm initially as a preprocessing step, size of the image reduced to 512*512.After that visible lung region segmented from Posterior and Anterior chest radiograph by using mask available at JSRT database(shown in Fig 1d). Each image is divided in to 64*64 fixed size lung patches (shown in Fig 1e). Proposed scheme trained initially with nodule patches and non nodule patches. Using the trained system images patches in the image, tested to find a patch contains potential nodule (Final result shown in Fig 1(f)). Fig (1) shows the entire process of nodules detection.

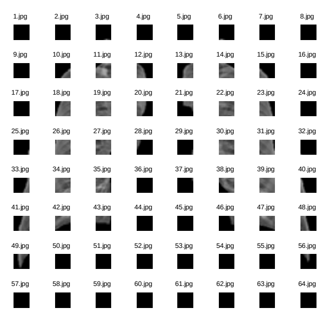
With this scheme 54 images from JSRT data base used for testing. Out of 54 images, we could able to detect potential nodule from 34 images with 8 false positives per image. System works with sensitivity of 62.96% with 8 F.P /image. For training the scheme, 22 nodule patches and 49 non nodule patches from different images has been used.

Figure 2 nodule and non nodule patches detected by the system. Nodule patches represented here with their number in JSRT database.Figure 2 shows system can able to detect the nodules present anywhere in the patch(irrespective of their position in the patch), it can also detect nodule which are having very dull appearance in the image(JPCLN001). System also can detect the nodule which are attached the vessels (JPCLN023), and it can also detect the nodules which are having different shape (JPCLN016) (i.e. nodule need not be circular).

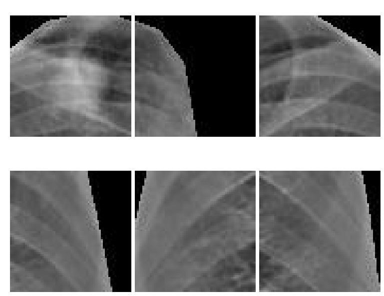


1(a) 1(b)

1(c) 1(d)

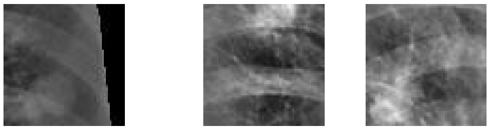


1(e)

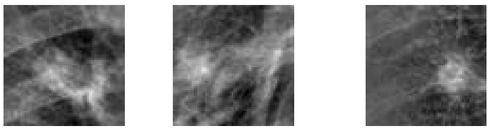


1(f)

Fig 1: shows entire process of nodule detection Fig (1a) original image (PA chest Radiograph), Fig (1b) enhanced version of original image, Fig (1c) lung mask from JSRT data base ,Fig (1d) segmented visible lung from PA chest radiograph Fig(1e) segmented lung divided into fixed 64*64 size blocks ,Fig (1f) resultant output after classification

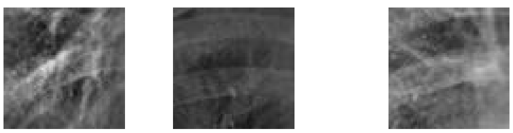


JPCLN001 JPCLN006 JPCLN014

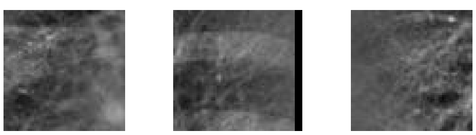


JPCLN016 JPCLN023 JPCLN044

2(a)



JPCLN006 JPCLN001 JPCLN014



JPCLN016 JPCLN023 JPCLN044

2(b)

Fig 2 nodule and non nodule patches detected by the system. Image patches represented here with their number in JSRT database Fig 2(a) nodule patches Fig 2b non nodule patches

6. CONCLUSIONS

The proposed method is tested on subtle and very subtle nodules. Proposed scheme can detect the nodule having different shapes, and even if their appearance very dull in the image. System can also detect the nodules appear anywhere in the patch, it can also detect the nodule attached to the vessels. After processing the image patches, nodule appearance and chaterstics of the nodule in the image patch are not changed. Number of false positives per image occurring in this scheme is due to rib patterns, existing in the patches. We may decrease the number of false positives, by applying this scheme on rib eliminated images and also by choosing the image patches for training the RBM selectively.

REFERENCES

[1] Segmentation of anatomical structures on chest radiographs S. Juhász, Á. HorváthL. Nikházy Gorváth Á. Horváth Budapest University of Technology and Economics/Department of Measurement and Information Systems, Budapest, Hungary

[2] Lung field segmentation in Digital Postero-Anterior Chest Radiographs Paola Campadelli and Elena Casiraghi Universita degli Stdi di Milano ,Computer Science Department ,LAIV Laboratory .s.singh et al(Eds) ICAPR 2005 LNCS3687 pp 1431-1440,2005

[3] A Fully Automated Method for Lung Nodule Detection From Postero-Anterior Chest Radiographs Paola Campadelli, Member, IEEE, Elena Casiraghi*, and Diana Artioli IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 25, NO. 12, DECEMBER 2006

[4] Xin-Wei, Xu, K. Doi, T. Kobayashi, H. MacMahon, and M. L. Giger, "Development of an improved CAD scheme for automated detection of lung nodules in digital chest images", *Med. Phys.*, vol. 24, no. 9, pp. 1395 – 1403, 1997.

[5] H. Yoshida and K. Doi, "Computerized detection of pulmonary nodules in chest radiographs: reduction of false positives based on symmetry between left and right lungs", *Proc. SPIE in Medical Imaging 2000*, pp. 97 – 102, 2000.

[6] Y.Wu, M.L.Giger, K.Doi, C.J.Vyboorny, R.A.Schmidt, and C.E.Metz, "Artificial Neural Networks in Mammography: Application to Decision Making in the Diagnosis of Breast Cancer", *Radiology*, vol. 187, pp.81- 87, 1993.

[7] Blob Detection by Scale-Space Filtering. by James Fishbaugh

[8] B.Sahiner, H P Chan, D.Wei, N.Petrick, M.A.Helvie, D.D.Adler, and M.M.Goodsitt, "Image feature selection by a genetic algorithm: Application to classification of mass and normal breast tissue", *Med. Phys.*, vol. 23, no.10, pp.1671-1683, 1996.

[9] M.A.Kupinski, M.L.Giger, "Feature selection and Classifiers for the Computerized Detection of Mass Lesions

in Digital Mammography," *IEEE International Congress on Neural Networks, Houston, Texas*, pp. 2460 - 2463, June 1997.

[10] G.D.Tourassi, E.D.Frederick, M.K. Markey, and C.E.Floyd, Jr., "Application of the mutual information criterion for feature selection in computer-aided diagnosis," *Med. Phys.*, vol. 28, no.12, pp.2394 - 2402, 2001.

[11] Jun Wei, Yoshihiro Hagihara, Akinobu Shimizu, and Hidefumi Kobatake, "Optimal image feature set for detecting lung nodules on chest X-ray images", *CARS / Springer*, 2002.

[12] B. van Ginneken, "Computer aided diagnosis in chest radiography", PhD Thesis, Netherland, 2001.

[13] S. G. Armato, M. L. Giger, and H. MacMahon, "Automated lung Segmentation in digitized postero – anterior chest radiographs," *Academic Rad.*, vol. 4, pp. 245 – 255, 1998.

[14] X. W. Xu and K. Doi, "Image feature analysis for computer – aided diagnosis: Accurate determination of ribcage boundary in chest radiographs," *Med. Phys.*, vol. 22, no. 5, pp. 617 – 626, 1995.

[15] X. W. Xu and K. Doi, "Image feature analysis for computer-aided diagnosis: Detection of right and left hemi-diaphragm edges and delineation of lung field in chest radiographs," *Med. Phys.*, vol. 23, no. 9, pp. 1613 – 1624, 1996.

[16] J. Duryea and J. M. Boone, "A fully automatic algorithm for the segmentation of lung fields in digital chest radiographic images," *Med. Phys.*, vol. 22, no. 2, pp. 183 – 191, 1995.

[17] E. Pietka, "Lung segmentation in digital chest radiographs," *J. Digital Imag.*, vol. 2, pp. 79–84, 1994.

[18] M. S. Brown, L. S.Wilson, B. D. Doust, R.W. Gill, and C. Sun, "Knowledge-based method for segmentation and analysis of lung boundaries in chest X-ray images," *Computerized Med. Imag Graphics*, vol. 22, pp. 463 – 477, 1998.

[19] M. F. McNitt-Gray, H. K. Huang, and J. W. Sayre, "Feature selection in the pattern classification problem of digital chest radiograph segmentation," *IEEE Trans. Med. Imag.*, vol. 14, pp. 537 – 547, June 1995.

[20] O. Tsujii, M. T. Freedman, and S. K. Mun, "Automated segmentation of anatomic regions in chest radiographs using an adaptive -sized hybrid neural network," *Med. Phys.*, vol 25, no. 6,pp. 998 – 1007, 1998.

[21] N. F. Vittitoe, R. Vargas - Voracek, and C. E. Floyd, Jr., "Identification of lung regions in chest radiographs using Markov Random Field modeling," *Med. Phys.*, vol. 25, no. 6, pp. 976 –985, 1998.

[22] N. F. Vittitoe, "Markov random field modeling in postero – anterior chest radiograph segmentation," *Med. Phys.*, vol. 26, no. 8, pp. 1670 – 1677, 1999.

[23] B. van Ginneken and B. M. ter Haar Romeny, "Automatic segmentation of lung fields in chest radiographs," *Med. Phys.*, vol. 27, no. 10, pp. 2445 – 2455, 2000.

[24] T. F. Cootes, C. J. Taylor, D. Cooper, and J. Graham, "Active shape models: Their training and application," *Comput. Vis. Image Understanding*, vol. 61, no. 1, pp. 38 – 59, 1995.

[25] G. Behiels, D. Vandermeulen, F. Maes, P. Suetens, and P. Dewaele, "Active shape model - based segmentation of digital Xray images," in *Lecture Notes in Computer Science*. Berlin,Germany: Springer -Verlag, vol. 1679, MICCAI'99, pp. 128 – 137, 1999.

[26] Kelemen, G. Székely, and G. Gerig, "Elastic model – based segmentation of 3 - d neuro-radiological data sets," *IEEE Trans. Med. Imag.*, vol. 18, pp. 828 – 839, Oct. 1999.

[27] W. K. Pratt, *Digital Image Processin*, 3rd ed., A Wiley Interscience Publication, Singapore, 2002.

[28] R.C.Gonzalez, R.E.Woods, and S.L.Eddins, *Digital Image Processing Using MATLAB*, LP ed. Delhi, Pearson Education, 2004.

[29] M.L. Giger, K. Doi, H. MacMahon, \Image feature analysis and computer-aided diagnosisin digital radiography: automated detection of nodules in peripheral lung elds", Medical Physics, vol. 15, no. 2, pp. 158 166, 1988

[30] J.Wei,Y.Hagihara and H.kabataki “Detection of cancerous tumors on chest XRay images candidate detection filter and its evaluation ,”International conferemce on Image processing 1999,val.3 pp .397 -401 1999

[31] lung tumor detection in chest radiographs By Rui teixeiro Ribeiro 2008

[32] Junji Shiraishi Qiang Li, Kenji Suzuki, Roger Engelmann, and Kunio Doi Computer-aided diagnostic scheme for the detection of lung nodules on chest radiographs: Localized search method based on anatomical classification,The University of Chicago, 5841 S. Maryland Avenue, MC 2026, Chicago, Illinois 60637 March 2006

[33] Zhenghao Shi1, Minghua Zhao, Lifeng He, Yinghui Wang, Ming Zhangand Kenji Suzuki A Computer Aided Pulmonary Nodule Detection System Using Multiple Massive Training SVMs Appl. Math. Inf. Sci. 7, No. 3, 1165-1172 (2013)

[34] Kenji Suzuki, Junji Shiraishi, Hiroyuki Abe, Heber MacMahon, and Kunio Do False-positive Reduction in Computer-aided Diagnostic Scheme for Detecting Nodules in Chest Radiographs by Means of Massive Training Artificial Neural Network 2005

[35] Russell C. Hardie¤,Steven K. Rogers, Terry Wilson¤¤, and Adam Rogers (Corresponding author) Department of Electrical and Computer Engineering,University of Dayton, 300 College Park, Dayton Performance Analysis of a New Computer Aided Detection System for Identifying Lung Nodules on Chest Radiographs