

Lung Cancer Detection Using Artificial Neural Network

Tina Pawar¹, RajeshwarDass²

¹M.Tech Scholar, ECED, DCRUST, Murthal, Sonapat (HR)

²Assistant Professor, ECED, DCRUST, Murthal, Sonapat (HR)

Corresponding Author: Tina Pawar

ABSTRACT

Lung Cancer is the most debilitating sort in one of the deadliest malignancies type of tumor. Over the most recent couple of years the event of destructive tumor has always extended, in light of the fact that the fix of the illness relies upon its underlying judgment. Non-small cell & small cell are two specific sort of lung cancer. The lungs are typically expansive in measure; subsequently tumors can develop in them for quite a while before they are found. Notwithstanding when the manifestations, for example, fatigue and coughing happen, individuals think they are because of different causes. The approach of new ground-breaking equipment and programming strategies has activated endeavors to create personal computer helped symptomatic frameworks for Cancer identification in help of reasonable mass screening in creating nations. In this paper an efficacious feature techniques for detection of lung cancer is presented. The Scaled conjugate gradient back propagation algorithm (SCG-BPNN) mainly utilized for training work. The fact that the SCG-BP performs faster convergence than primary back propagation differ them from one another. The efficiency of neural network is estimated by MSE. The accuracy is achieved up to 97.3 %.

Keywords: CT scan, Lung Cancer, ANN, SCG-BPNN, Mean Square Error

Date of Submission: 28-02-2019

Date of acceptance: 25-03-2019

I. INTRODUCTION

Lung Cancer (LC) is an irresistible ailment produced by bacillus mycobacterium lung cancer, which influence lungs [1-3, 35]. The rise of new medication safe strains is starting to fuel the issue, rendering the current medications incapable, and requiring steadfast represent exertion to dispose of the affliction. Furthermore, extensive quantities of patients through HIV/cancer co-diseases need to be screened for dynamic cancer to affirm a fitting treatment of their infection(s). Taking CT scans is a cheap method to screen for the nearness of cancer. Appallingly, the elucidation of CXRs is at risk to human oversight and depends upon the aptitude of per user [2-5]. Additionally, mass screening of a generous people is a tedious and dull task, which requires impressive exertion when done physically. Consequently, there is extensive enthusiasm for creating CADs that can identify cancer naturally in CXRs. These frameworks can possibly lessen the danger of discovery blunders and increment the effectiveness of mass screening efforts [6].

Lung cancer left over main reason of disease connected demises in US. There were roughly 2, 29,447 new instances of lung cancer & 1, 59,124 linked demises in 2012[3]. Early conclusion can enhance the adequacy of treatment and increment the patient's shot of survival [31]. Computed tomography (CT), Positron emission

tomography (PET), Contrast-enhanced computed tomography (CE-CT) & Low-dose computed tomography (LDCT) are most widely recognized noninvasive imaging modalities for identifying and diagnosing lung knobs. PET sweeps are utilized to separate among harmful and good lung knobs. Early recognition of the knobs can be founded on LDCT and CT filters that take into consideration reproducing the life systems of & identifying anatomic variations in chest. CE-CT considers reproducing the life structures of the chest and surveying the identified knob's qualities. An abundance of known productions has examined the advancement of CAD frameworks for lung cancer from a large group of various picture modalities [7, 9]. The achievement of a specific CAD framework can be estimated as far as precision of conclusion, speed, and robotisation level. The division of lung tissues on chest pictures is preprocessing venture in building up CAD framework so as to diminish look space for lung knobs. Detection & segmentation of lung knobs from the obtainable search space are compulsory phases [8].

Contribution of a CAD framework in medical pictures got utilizing a suitable methodology. A lung division step is utilized to diminish scan space for lung knobs. Knob identification is utilized to recognize the areas of lung knobs. The recognized knobs are sectioned. At that point, an applicant set of highlights, for

example, volume, shape, & additionally features are utilized for determination [9].

The remaining paper is as a survey with previous work is described in section II. Section III explains the proposed methodology. Analysis of results given in section IV while in section V conclusion is done.

II. RELATED WORK

The brief description, contribution, remarks and factors of the work done by the researchers is given below in table 1.

Table: 1 Major finding by the researchers

Ref.	Investigator	Type of Image	No. of Images	Research Methodology used	Major Findings
[1]	L.A. Haryanto	CT Images	50	The GLCM feature extraction consequences then trained utilizing ANN. Technique used is back propagation network	GLCM Co-occurrence parameter calculated
[2]	Moffy Vas et.al	CT Images	216	Feed forward-NN with back propagation algo. was utilized	Accuracy calculated
[3]	Shubhangi Khobragade et.al	X- Ray Images	80	Feed forward neural network used 7 input neuron of chest radiographs 3 hidden layer signifies lung diseases as LC	Accuracy calculated
[4]	S.KalaivaniPramitet.al	CT- Diagnosis database	70	Feed forward back propagation NN. 3 Layers.	Efficiency calculated
[5]	Shraddha Deshmukhet.al	MRI Images	32	Fuzzy min- max neural network	Accuracy calculated
[6]	Qing Wu et.al	CT Images	12	Entropy Degradation Technique	Accuracy calculated
[7]	Fatma Taheret.al	Sputum Color Images	100	ANN & Support Vector Machine (SVM)	Accuracy calculated
[8]	Rachid Sammouda, et.al	CT Images	10	ANN of Hopfield model (HNN) & GA	Eliminate isolated pixel
[9]	Lei Fan, Zhaoqing, et.al	CT Images	1500	Convolution neural network	Accuracy calculated
[10]	Taolin Jin ¹ , Hui Cui, Shan Zeng, Xiuying Wang	CT Images	1397 1035 – Cancer 362 – non Cancer	3D CNN model	Accuracy calculated
[11]	Ryota Shimzu et.al	CT Images	57	Supervised deep learning neural network	Accuracy calculated
[12]	Hao Tanget.al	CT Images	600	Deep convolutional neural network	CPM score calculated
[13]	Emre et.al	CT Images	128	Multi-layer FF perceptron model was used in ANN.	Accuracy calculated
[14]	Sridevi et.al	X- Ray	5	Levenberg marquardt back propagation algorithm	Boundary region identified
[15]	Allison et.al	CT Images	1500	Convolution neural networks	Accuracy calculated
[16]	Zirong L et.al	X – Ray	626	Residual network based on CNN	Recall estimated
[17]	Sheng Chenet et.al	CT Images	233	Massive-training artificial neural networks	Sensitivity calculated

[18]	Chaofng Liet et.al	JSRT CT Images	93	Outline of ensemble of convolutional NN	Sensitivity calculated
[19]	Hewon Chung et.al	CT Images	42	Global LC extraction with Chan Vese model	Performance parameter calculated
[20]	Mathew S et.al	CT Images	31	Fuzzy & refined fuzzy set	Shape feature calculated
[21]	Arnaud et.al	CT Images	1018	False positive reduction	Sensitivity calculated
[22]	Nikolas Lessmann et.al	CT Images	1744	Deep neural networks with dilated convolutions	Sensitivity calculated
[23]	Sandeep et.al	CT Images	12	Machine learning & multinomial Bayesian	Abnormality calculated
[24]	Kingsley Kuan et.al	LUNA dataset CT Images	16	Nodule classifier patient classifier	Sensitivity calculated
[25]	Mehdi FatanSerj, Bahram Lavi, Gabriela Hoff	CT Images	10	Deep convolutional neural network	Sensitivity, specificity and F1 score calculated
[26]	Aqeel Mohsin Hamad	CT Images	4	GLCM neural network classifier	GLCM Parameter
[27]	M Lavanya, P Muthu Kannan	CT Images	20	Fuzzy Local Information Cluster Means Back Propagation Network Classification	Accuracy calculated
[28]	Gurpreet Kaur, Jaspreet Kaur	X- Ray	10	Fuzzy Logic based Multi Thresholding	Accuracy calculated
[29]	JinsaKuruville K Gunavathi	CT Images	10	FISANFIS Modified ANFIS	Accuracy calculated
[30]	Atin et.al	CT Images	10	Fuzzy Logic	Accuracy calculated

Above table 1 demonstrates the research methodology used by various researchers along with their major findings i.e. sensitivity, efficiency, accuracy etc. Accuracy is the most calculated parameter to measure the efficiency of the proposed techniques by the researchers.

III. PROPOSED METHODOLOGY

JSRT CT Scan80 Images are taken out. This technique comprises of three primary advances: an extraction advance to distinguish the lungs; a detachment venture to isolate the privilege & left lungs; & a discretionary smoothing advance to flat lung limits. Every one of these means is portrayed in part straightaway.

1. **Lung Extraction:** The objective of lung extraction step is to isolate voxels relating to lung tissue from voxels comparing to encompassing life systems. As opposed to utilizing a settled edge to fragment the lungs, rather utilize ideal thresholding to consequently choose a division edge for picture volume. Availability & topological examination are utilized to further refine locales that speak to removed lungs [11-15].

i) **Threshold Selection:** Optimal thresholding is a programmed edge determination technique [32] that enables to accommodate the little varieties in tissue thickness expected over a populace of subjects and two kinds of voxels are:

- voxels inside extraordinarily thick body & chest divider structures
- low-thickness voxels in lungs or discernible all around including the body of the subject. This will use perfect thresholding to pick a division limit to disconnect the body from the voxels, and after that recognize the lungs as the low-thickness cavities inside the body.

The division limit is chosen through an iterative methodology. Give T^i a chance to be the division limit at step i. To pick another division limit, T^i applied to the picture to isolate voxels into body & non-body voxels. Let μ_b and μ_n be mean dark level of body voxels & nobody voxels after division with limit T^i as shown in eq. 1. At that point the new limit for step $i + 1$ is [14]

$$T^{i+1} = \frac{\mu_b + \mu_n}{2} \quad \text{eq.1}$$

This iterative limit refresh technique is repeating until there is no adjustment in the edge, i.e., $T^{(i+1)}=T^i$. The underlying edge T^0 is chosen dependent on the CT number for perfect air (1000 HU) and the CT number for voxels inside the chest divider/body (0 HU).

ii) Network and Topological Analysis:

Subsequent to applying the perfect edge, the non body voxels will contrast with the air enveloping the body, lungs, and other low-thickness regions inside the image volume. 3-dimensional related parts naming is used to recognize the lung voxels. The establishment air is wiped out by deleting districts that are related with the edge of the image. Little, withdrew areas are discarded if the region volume is too little [15-16]. To recognize the lungs, we hold the fundamental the two greatest sections in the volume, with the additional basic that each part ought to be greater than a fated minimum volume. In this paper, we hold only the portions with a volume more critical than one percent of the total picture voxel count. The high-thickness vessels in the lung will be named as body voxels in the midst of the perfect thresholding step. In this way, the 3-D lung regions will contain unwanted inside melancholies. Topological examination, similar to that used in, is used to fill the lung areas and take out within pits [17].

iii) Division of the Large Airways: To perform quantitative examinations on the lung tissue, the trachea and considerable flying courses must be perceived and separated from the left and right lungs. This movement is moreover critical to energize the left and right lung division delineated [18].

The trachea and left and right fundamental stem bronchi are recognized in the main dull

dimension image data using a close space expansion with a unit extend divide. This procedure is proportionate to facilitate cut by-cut territory creating. To instate the close scattered enlarging, the region of the trachea is normally perceived by means of chasing down the broad, round, air-filled region near the point of convergence of the underlying couple of cuts in the enlightening file. Territories in the present cut give potential seed coordinate positions toward the accompanying cut. The cut by-cut creating technique is ended when the proportion of the district on another cut augmentations definitely, demonstrating that the avionics courses have merged into the low-thickness lung tissue [19].

Fig. 1 shows the proposed working of lung nodule segmentation and classification based on neural network. At the point when seen on transverse CT cuts, front & back intersections between left & right lungs might be thin with frail differentiation [18].

Much of the time, dark scale thresholding neglects to isolate left & right lungs close to these intersections, Objective of the lung partition step is to find these intersection lines and totally isolate the privilege and left lungs. Utilizing a method like that utilized in, dynamic writing computer programs is connected to locate the greatest cost way through a chart with weights corresponding to pixel dim level. The greatest cost way compares to the intersection line position. Be that as it may utilize an alternate methodology to locate the dynamic programming seek areas. In this strategy, a hunt area is found on a 2-D cut and it is proliferated to progressive cuts. In light of the smooth pneumonic life systems, the intersection line position differs gradually through the informational index [20-22].

PRE PROCESSING

NO

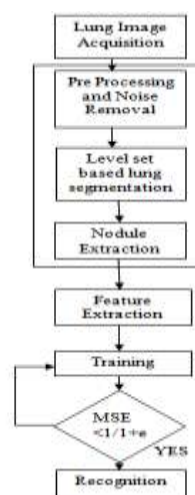


Fig: 1 Flowchart showing the methodology used.

To find the region for applying dynamic programming look for on one cut, 2-D morphological breaking down is associated with detach the benefit and left lungs. An unforeseen growth is then used to restore the harsh exceptional limit shape, without re-partner the two lungs yet again. Let address the plan of lung pixels on a singular cut. To disconnect the left and right lungs to enroll another set S using a n-overlay breaking down [22] as shown in eq. 2.

$$S = A \ominus nB_4 \quad \text{eq. 2}$$

where \ominus is a parallel morphological disintegration and B_4 is a four-associated (precious stone molded) paired organizing component. The scaling term is chosen with the goal that nB_4 is the slightest homothetic that outcomes in A and S having an alternate number of 2-D associated parts. Subsequent to isolating the lungs by disintegration to frame S, the limit is reestablished utilizing a restrictive enlargement. The restrictive widening continues iteratively. Effect of contingent expansion at step $i+1$ is [24] as shown in eq. 3.

$$C^{i+1} = C^i \cup \{p\} \oplus B_4 \quad \text{eq. 3}$$

where \oplus is a parallel morphological widening & $p \in C^i \cap A$, with choice of additional compelled so C^i & C^{i+1} have a similar no. of 2D associated parts [18-19].

$C^0 = S$ is utilized to introduce the contingent widening. This plan ensures that lung limit is recuperated without responding left & right lung parts. The restrictive expansion in eq. 1 is reshaped until no pixels $p \in C^i \cap A$ are left that can be included deprived of altering the network of districts is C^i .

Let C signify outcome after restrictive widening. While left & right lungs had been isolated now, the division was expert utilizing district shape properties (by means of the morphological administrators) without counting dim scale qualities of front & back intersection lines. Since intersection lines are marginally more brilliant than encompassing LC, dim scale data can be utilized to all the additional precisely characterize division between 2 lungs [25].

IV. RESULT ANALYSIS

The toolboxes used for proposed work are image processing toolbox and wavelet toolbox. These tool stash give specialists and researchers a broad suite of hearty computerized picture handling and investigation capacities. Picture handling tool stash is intended to free specialized experts from the tedious undertakings of coding and investigating essential picture preparing and examination activities sans preparation. This converts into huge efficient and cost decrease ~~benefits, empowers~~ to invest less energy coding calculations and additional time investigating and finding answers for various issues. The tool stash underpins an extensive variety of picture handling tasks, including the accompanying:

- a) Displaying and exploring images
- b) Spatial transformations
- c) Morphological operations
- d) Analyzing and enhancing images
- e) Linear filtering and filter design
- f) Neighborhood and block operations
- g) Image deblurring
- h) Region based processing



Fig. 2 Original Lung Image



Fig. 3 CLAHE Image of Proposed Lung Image

Fig. 2 & 3 represents original Lung Image & CLAHE image. These image are enhanced by preprocessing of the image.

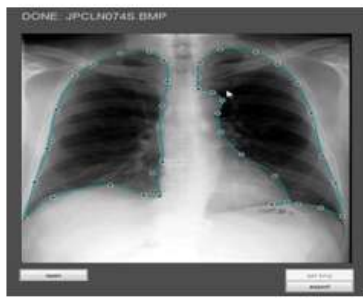


Fig. 6 GUI Image Import Section

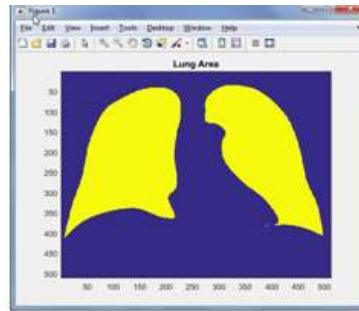


Fig. 7 Lung Area Detection

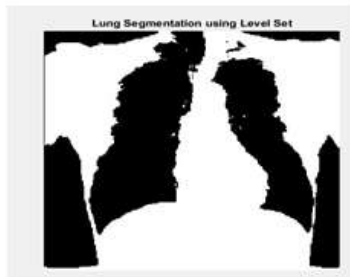


Fig. 8 Lung Area Segmentation using level set

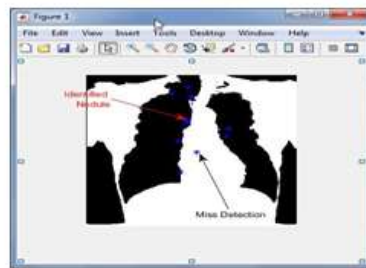


Fig. 9 Identification of Nodule and Miss Detection

Fig. 8 Lung Area Segmentation using level set Fig. 9 Identification of Nodule and Miss Detection

Fig. 4 & 5 represents CLAHE & NBPC Image and ROC of lung image. The tumor area is find out from these images. The lung cancer is detected after import the given CT scan images,

The dataset of CT images are import in GUI import section as shown in Fig.6. The Lung area detection as shown in Fig. 7.

Lung area segmentation using level set algorithm is shown in Fig. 8. Level Set [33-34] algorithm is used for segmentation. Identification of nodule and miss detection is arranged in Fig.9.

Table 2 Performance Parameter of Lung Image

Sr. No.	Performance	Mean	Standard Deviation
1.	Orientation	21.91421	55.34241
2.	Perimeter	178.2021	38.42679
3.	Solidity	0.902295	0.070057
4.	Entropy	0.201344	0.033201
5.	Eccentricity	0.6240096	0.16005135
6.	Area	0.6987201	0.9875214
7.	Convexa	0.728954	0.875412

Table 2 gives the performance parameter of lung images. The parameter like orientation, solidity and entropy, eccentricity etc. are shape parameters.

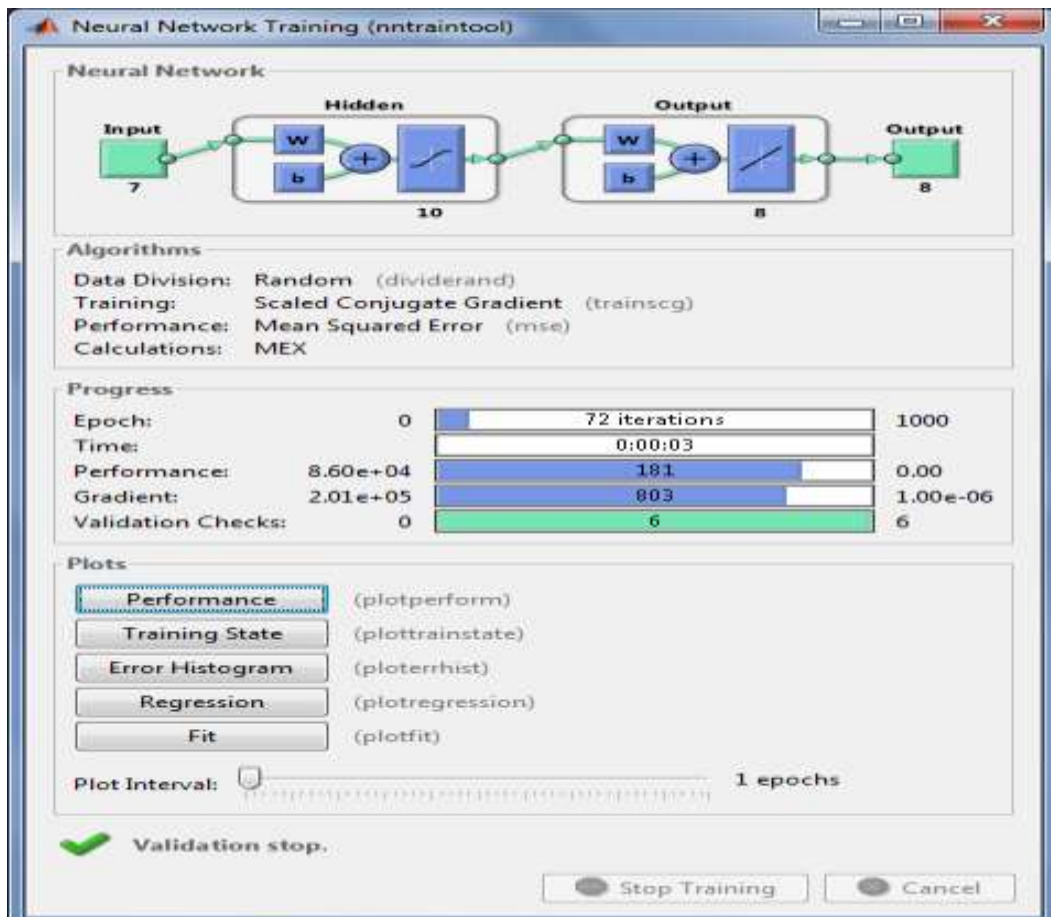


Fig. 10 Neural Network Training tool

Neural network training tool is given in Fig. 10. The back propagation neural network selected with scaled conjugate training function. For 1000

epochs, 72 iteration the performance is calculated. There are 6 validation check points given

Table 4: Network Parameters

Parameters	Value
Input layer	7
No. of epoch	72
No. of error	0.5
Min. learning rate	0.001
Hidden layers	10
Activation function	$1/1+e^x$
Learning rule	Gradient momentum
Training	Scaled conjugate gradient back propagation
Output layer	8

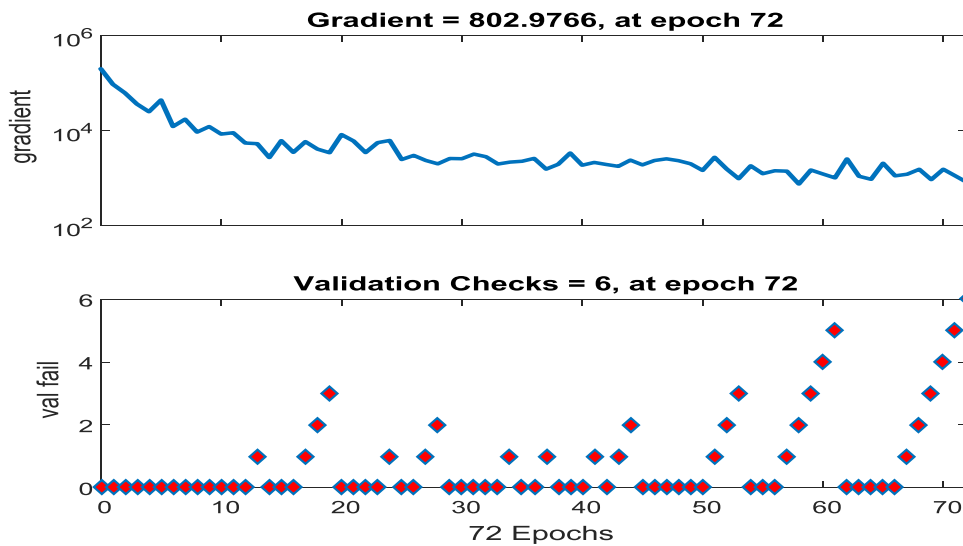


Fig. 11 Validation Check at 72 epochs

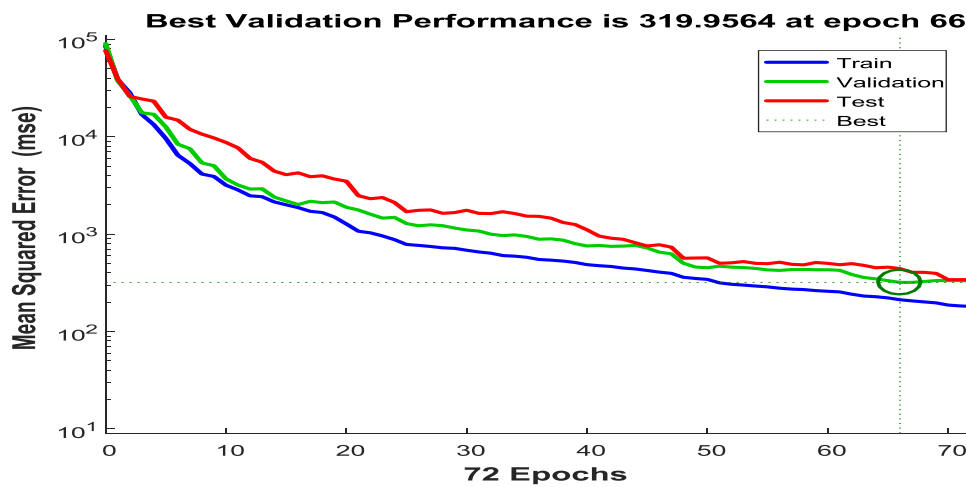


Fig. 12 Validation Performance for different Epochs.

Fig.11 represent validation checks at 72 epochs. In this gradient & validation checks are 802.9766 & 6 respectively.

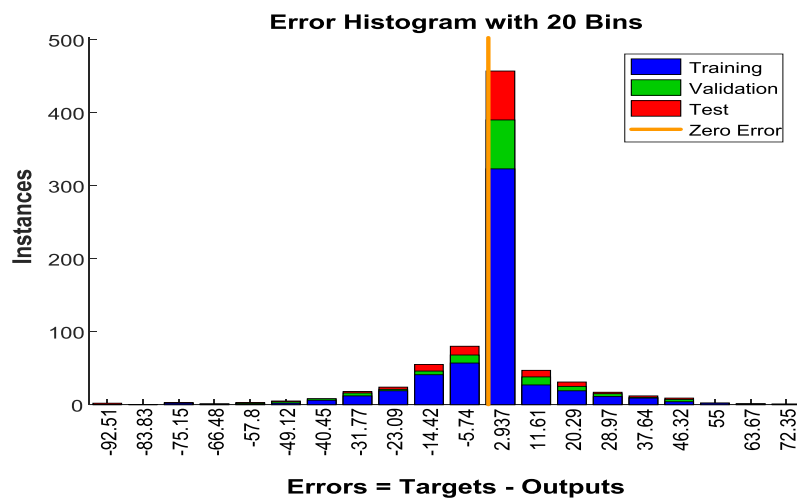


Fig. 13 Error Histogram with 20 bins

For 20 bins error histogram contains training, testing, validation and also zero error index is given above in fig. 13.

Table 3 Comparative Analysis of Accuracy with different Methods

Sr. No.	Dataset	Methodology	Accuracy
1.	216 CT Images	Feed Forward Neural Network 20 hidden nodes	92 %
2.	80 X- Ray Image	Feed Forward Neural Network (7 Neurons)	92 %
3.	70 CT-Diagnosis database	Feed Forward Neural Network (14 Neurons)	80 %
4.	12 CT Scan Image	Entropy Degradation Method	77.8 %
5.	100 sputum color images	ANN & SVM	ANN: 90 % SVM : 97%
6.	1500 CT Scan Image	CNN	65 %
7.	80 CT Scan	SCG-BPNN, 10 hidden layer	97.3 %

Table 3 analyses the comparative analyses of 80 CT Scan image. The accuracy is improved up-to 97.3 %.

Table 5: Network Performance

Parameter	Value
Recognition accuracy	97.3%
Mean square error (MSE)	1.00e-06

Table 5 shows network performance parameters i.e. recognition, accuracy & mean square error. Table 3 represents that proposed method is efficient in comparison to other methods and provides 97.3% recognition accuracy.

V. CONCLUSION

Precise division of objects of intrigue is one of the fundamental prerequisites of any medicinal imaging and CAD framework. At present, a wide range of shape/appearance highlights and choice procedures in light of these highlights are created, tried, and utilized for taking care of utilization particular division issues. The best methodologies consolidate numerous picture/question highlights and information preparing strategies. Be that as it may, however tests bring more precise outcomes, the division frequently turns out to be excessively mind boggling and tedious. The created computerized lung division techniques that give a critical piece of our CAD inquire about for Lung filters. The accuracy is improved up to 97.3 %.

REFERENCES

- [1]. Lilik Anifah et.al, "Cancer Lungs Detection on CT Scan Image Using Artificial Neural Network Back propagation Based Gray Level Co-occurrence Matrices Feature", International Conference on Advanced Computer Science and Information Systems, pp. 327- 331, 2017.
- [2]. Moffy Vas, Amita Dessai, "Lung cancer detection system using lung CT image processing", International Conference on Computing, Communication, Control and Automation (ICCUBEA), pp. 1-5, 2017.
- [3]. Shubhangi Khobragade, Aditya Tiwari, C.Y. Pati and Vi kram Narke, "Automatic Detection of Major Lung Diseases using Chest Radiographs and Classification by Feed-forward Artificial Neural Network", IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems, pp. 1-5, 2016.
- [4]. S.KalaivaniPramit Chatterjee Shikhar Juyal Rishi Gupta, "Lung Cancer Detection Using Digital Image Processing and Artificial Neural Networks", International Conference on Electronics, Communication and Aerospace Technology, pp. 100-103, 2017.
- [5]. Shraddha Deshmukh, Swati Shinde, "Diagnosis Of Lung Cancer Using Pruned Fuzzy Min- Max Neural Network", International Conference on Automatic Control and Dynamic Optimization Techniques, pp. 398-402, July 2016.
- [6]. Qing Wu and Wenbing Zhao, "Small-Cell Lung Cancer Detection Using a Supervised Machine Learning Algorithm", International Symposium on Computer Science and Intelligent Controls", pp. 88-91, July 2017.
- [7]. Fatma Taher, NaoufelWerghe and Hussain Al-Ahmad, "Computer Aided Diagnosis System for Early Lung Cancer Detection", International Conference on systems Signals and Image Processing (IWSSIP)", pp. 5-8, 2015.
- [8]. Rachid Sammouda, "Segmentation and Analysis of CT Chest Images for Early Lung Cancer Detection", Global Summit on Computer & Information Technology, pp. 120-126, July 2016.
- [9]. Lei Fan, Zhaoqiang Xia, Xiaobiao Zhang, Xiaoyi Feng, "Lung Nodule Detection Based on 3D Convolutional Neural Networks", International

- Conference on the Frontiers and Advances in Data Science (FADS), pp. 7-10 , 2017.
- [10]. Taolin Jin, Hui Cui¹, Shan Zeng, Xiuying Wang, “Learning deep spatial lung features by 3D convolutional neural network for early cancer detection”, International Conference on Digital Image Computing: Techniques and Application”, pp. 1-6, 2017.
- [11]. Ryota Shimizu, Shusuke Yanagawa, Yasutaka Monde, Hiroki Yamagishi, “Deep Learning Application Trial to Lung Cancer Diagnosis for Medical Sensor Systems”, International SoC Design Conference, pp. 191-192, 2016.
- [12]. Hao Tang, Daniel R. Kim, Xiaohui Xie, “Automated Pulmonary Nodule Detection Using 3D Deep Convolutional Neural Networks”, 15th International Symposium on Biomedical Imaging, pp. 523-526, April 2018.
- [13]. Emre Dand, Murat Çak, Ziya Ek, Murat Özkan, Özlem Kar Kurt, Arzu Canan, “Artificial Neural Network-Based Classification System for Lung Nodules on Computed Tomography Scans”, International Conference of Soft Computing and Pattern Recognition, pp. 382-386 , 2014.
- [14]. Sridevi A, G.K.D. Prasanna Venkatesan, “Tuberculosis Malady Recognition in Chest Radiographs via Artificial Neural Networks”, International Conference on Electrical, Instrumentation and Communication Engineering, pp. 104-107, 2017.
- [15]. Allison M Rossetto and Wenjin Zhou, “Deep Learning for Categorization of Lung Cancer CT Images”, International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), pp. 272-273, 2017.
- [16]. Zirong Li, Lian Li, “A novel method for lung masses detection and location based on deep learning”, IEEE International Conference on Bioinformatics and Biomedicine, pp. 963-969, 2017.
- [17]. Sheng Chen and Kenji Suzuki, “Computerized Detection of Lung Nodules by Means of Virtual Dual-Energy Radiography”, IEEE Transactions on Biomedical Engineering, Vol. 60, no. 2, pp. 369-378, February 2013.
- [18]. Chaofeng Li, Member, IEEE, Guoce Zhu, Xiaojun Wu, Member, IEEE, Yuanquan Wang, “False-positive Reduction on Lung Nodules Detection in Chest Radiographs by Ensemble of Convolutional Neural Networks”, pp. 1-11 , 2018.
- [19]. Heewon Chung, Hoon Ko, Se Jeong Jeon, Kwon-Ha Yoon and Jinseok Lee, “ Automatic Lung Segmentation with Juxta-Pleural Nodule Identification using Active Contour Model and Bayesian Approach”, IEEE Journal of Translational Engineering in Health and Medicine, Vol. 6 , pp. 1-15, July 2018.
- [20]. Matthew S. Brown, Michael F. McNitt-Gray, Jonathan G. Goldin, Robert D. Suh, James W. Sayre, and Denise R. Aberle, “Patient-Specific Models for Lung Nodule Detection and Surveillance in CT Images”, IEEE Transactions on Medical Imaging, Vol. 20, no. 12, pp. 1242-1250, December 2001.
- [21]. Arnaud A. A. Setio, Francesco Ciompi, Geert Litjens, Paul Gerke, “Pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks”, pp. 1-10
- [22]. Nikolas Lessmann, Bram van Ginneken, Member, IEEE, Majd Zreik, Pim A. de Jong, Bob D. de Vos , Max A. Viergever, “Automatic Calcium Scoring in Low-Dose Chest CT Using Deep Neural Networks with Dilated Convolutions”, IEEE Transactions On Medical Imaging, Vol. 37, no. 2, pp. 615-625, February 2018.
- [23]. Mr. Sandeep A. Dwivedi, Mr. R. P. Borse, Mr. Anil M. Yametkar, “Lung Cancer detection and Classification by using Machine Learning & Multinomial Bayesian”, Journal of Electronics and Communication Engineering , Vol. 9, Issue 1 , pp. 69-75 , Jan 2014.
- [24]. Kingsley Kuan, Mathieu Ravaut, Gaurav Manek, “Deep Learning for Lung Cancer Detection: Tackling the Kaggle Data Science Bowl 2017 Challenge”, International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, pp. 254–261, May 2017.
- [25]. Mehdi Fatan Serj, Bahram Lavi†, Gabriela Hoff, “A Deep Convolutional Neural Network for Lung Cancer Diagnostic”, Journal of Thoracic Oncology, Vol. 9 issue 7, pp. 935–939, 2014.
- [26]. Aqeel Mohsin Hamad, “Lung Cancer Diagnosis By Using Fuzzy Logic”, International Journal of Computer Science and Mobile Computing, Vol. 5, Issue. 3, pp. 32 – 41 , March 2018.
- [27]. M Lavanya, P Muthu Kannan, “Lung Lesion Detection in CT Scan Images Using the Fuzzy Local Information Cluster Means (FLICM) Automatic Segmentation Algorithm and Back Propagation Network Classification”, Asian Pacific Journal of Cancer Prevention, Vol. 18, pp. 3395-3399, 2018.
- [28]. Gurpreet Kaur, Jaspreet Kaur, “Fuzzy Logic Based Multi Thresholding For Lung Cancer Detection”, Proceedings of International Academic Conference on Electrical, Electronics and Computer Engineering, Chennai, pp. 90-93, Sept 2013.
- [29]. Jinsa Kuruvilla and K. Gunavathi, “Lung cancer classification using fuzzy logic for CT images”, Int. J. Medical Engineering and Informatics, Vol. 7, no. 3, pp. 233-249, 2015
- [30]. Atin, C Yilmaz, Kaur, Satayan, “Cancer risk analysis by fuzzy logic approach and performance status of the model”, Turkish Journal of Electrical Engineering & Computer Sciences, Vol 21, pp. 897 – 91, July 2013.
- [31]. Rajeshwar Dass, “Speckle Noise Reduction of US Images using BFO cascaded with Wiener filter and DWT in Homomorphic Region”, Procedia Computer Science Journal Elsevier, Vol. 132, pp. 1543-1551, 2018, ISSN: 1877-0509.
- [32]. Rajeshwar Dass, Vikas, “Comparative Analysis of Threshold Based, K-mean and Level Set Segmentation Algorithms”, International Journal of Computer Science & Technology, vol. 4, issue 1, Jan-March 2013, ISSN: 0976-8491(Online), 2229-4333(print).

- [33]. Poonam Jaglan, Rajeshwar Dass, Manoj Duhan, "A Comparative Analysis of Various Image Segmentation Techniques", Proceedings of 2nd International Conference on Communication, Computing and Networking, Lecture Notes in Networks and Systems, Vol. 46, pp. 359-374, Springer, Singapore, 2018, https://doi.org/10.1007/978-981-13-1217-5_36, ISBN: 978-981-13-1217-5(online), ISBN: 978-981-13-1216-8(print).
- [34]. Rajeshwar Dass, Priyanka, Swapna Devi, "Image Segmentation Techniques," International Journal of Electronics & communication Technology(IJECT), Vol.3 ,Issue1, pp.66-70, Jan.-March2012, ISSN:2230-7109(online),2230-9543(print).
- [35]. Poonam Jaglan, Rajeshwar Dass, Manoj Duhan, "Breast Cancer Detection Techniques: Issues and Challenges", Journal of The Institution of Engineers (India): Series B Electrical, Electronics & Telecommunication and Computer Engineering, Springer, India, 2019, ISSN 2250-2106, Vol. 100, pp. 1-8, DOI [10.1007/s40031-019-00391-2](https://doi.org/10.1007/s40031-019-00391-2), ISSN 2250-2106.

Tina Pawar" Lung Cancer Detection Using Artificial Neural Network" International Journal of Engineering Research and Applications (IJERA), Vol. 09, No.03, 2019, pp. 09-19