International Journal of Pure and Applied Mathematics
Volume 117 No. 21 2017, 57-67
ISSN: 1311-8080 (printed version); ISSN: 1314-3395 (on-line version)
url: http://www.ijpam.eu
Special Issue

ijpam.eu

ANN-Back Propagation Network

A.Rajesh[1] and Dr. Mohan Ellappan[2]

[1]Associate Professor, Department of ECE, CVR college of Engineering, Hyderabad, Telangana, India
[2] Principal,P.T.Lee Chengalvaraya Naicker College of Engineering & Technology,Kanchipuram,Tamilnadu,India.

ABSTRACT

Lung infections are the scatters that influence the lungs, the organs that permit us to inhale and it is the most well-known restorative conditions overall particularly in India. The infections, for example, pleural radiation and typical lung are distinguished and characterized in this work. This paper exhibits a PC supported grouping Method in Computer Tomography (CT) Images of lungs created utilizing ANN-BPN. The motivation behind the work is to identify and arrange the lung infections by powerful component extraction through Dual-Tree Complex Wavelet Transform and GLCM Features. The whole lung is sectioned from the CT Images and the parameters are ascertained from the fragmented picture. The parameters are ascertained utilizing GLCM. We Propose and assess the ANN-Back Propagation Network intended for grouping of ILD examples. The parameters give the greatest order Accuracy. After outcome we propose the Fuzzy bunching to portion the injury part from irregular lung.

Keywords: Segment lesion, Fuzzy Clustering, DTCWT, ANN-BPN.

1. INTRODUCTION

The interstitial lung illnesses cause dynamic scarring of lung tissue, which would in the end influence the patients' capacity to inhale and get enough oxygen into the circulation system. High-determination figured tomography (HRCT) is the standard in-vivo radiology imaging instrument for envisioning ordinary/unusual imaging examples to recognize the particular kind of ILD [16], and to create proper treatment arranges. Cases of these lung tissue examples are appeared in Fig. 1. PC helped identification/characterization frameworks are required for accomplishing higher reviews on ILD evaluation [1]. Specifically, the sums and anatomical places of anomalous imaging designs (alongside patient history) can help radiologists to streamline their indicative choices, with better quantitative estimations.

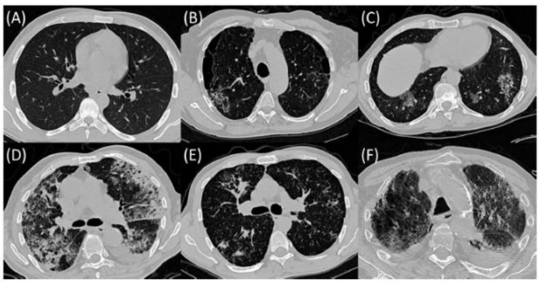


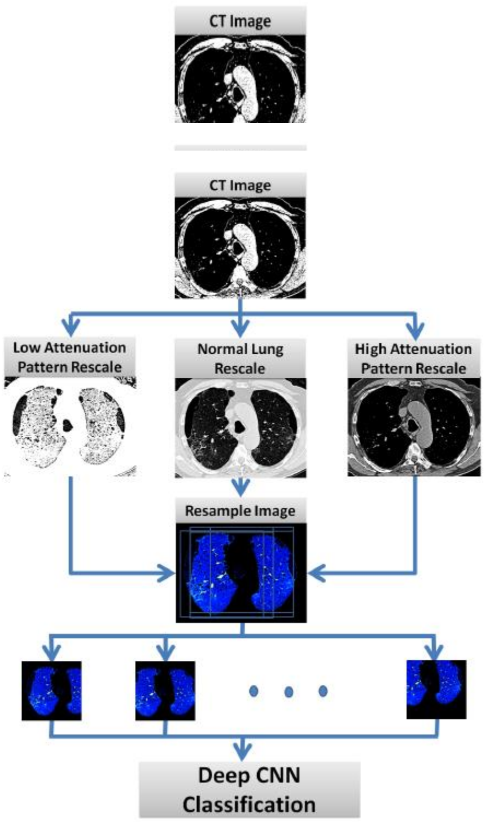
Fig. 1. Example images(segment of HRCT axial slices) for each of the six lung tissue types. (A) Normal (NM). (B) Emphysema (EM). (C) Ground Glass (GG). (D) Fibrosis (FB). (E) Micronodules (MN). (F) Consolidation (CD).

There are incomprehensible measures of applicable writing on creating CAD frameworks of pneumonic maladies, however the vast majority of them concentrate on distinguishing and evaluating a solitary example, for example, union or knobs [2]. For PC helped ILD grouping, all past reviews have utilized a fix based picture representation with the characterization aftereffects of direct achievement [4, 8, 13, 14]. There are two noteworthy downsides for the picture fix based techniques: 1), The picture fix sizes or scales in studies [13, 14] are moderately little pixels where some visual subtle elements and spatial setting may not be completely caught. The all encompassing CT cut holds a great deal of points of interest that might be ignored in the fix based representation. 2), More critically, the cutting edge strategies accept the manual comment as given. Picture patches are thus examined inside these ROIs. Picture fix based methodologies, which rely on upon the manual ROI data sources, are less demanding to unravel, yet shockingly less clinically alluring. This human requesting procedure will get to be distinctly infeasible for the substantial scale medicinal picture preparing and investigation.

2. Existing Methods

2.1 CNN Architecture:

The design of our CNN is like the convolutional neural system proposed by Krizhevsky, et al. [7]. CNNs with



ower
tly to
itains
ayers
s and
inged
It is
l pre-
y the
iable
when

icker
lizing
e CT
ering

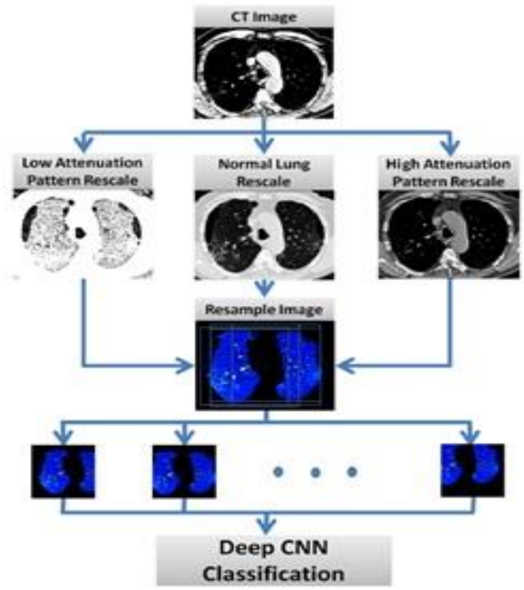


Fig. 2. Flowchart of the training framework.

The yield of the last FC layer is framed into a six-route softmax to produces a dissemination over the six class names (with six neurons). We begin the preparation through stochastic slope plummet (SGD) at a learning rate of 1/tenth of the underlying pre-preparing rate [7] expect for the yield softmax layer. The balanced learning rate permits proper tweaking progress without destroying the instatement. The yield layer still needs an expansive learning rate for merging to the new ILD arrangement classifications.

2.2 KNN Algorithm:

KNN is a nonparametric apathetic learning calculation. That is a truly succinct articulation. When you say a method is nonparametric, it implies that it doesn't make any suspicions on the basic information conveyance. This is entirely helpful, as, in this present reality, a large portion of the viable information don't comply with the regular hypothetical suspicions made (eg gaussian blends, directly detachable and so on).

2.2.1 KNN for Classification:

Lets perceive how to utilize KNN for characterization. For this situation, we are given a few information focuses for preparing and furthermore another unlabelled information for testing. Our point is to discover the class name for the new point. The calculation has diverse conduct in view of k.

Case 1: k = 1 or Nearest Neighbour Rule:

This is the least complex situation. Give x a chance to be the indicate be marked. Discover the guide nearest toward x. Give it a chance to be y. presently closest neighbor manage solicits to dole out the mark from y to x. This appears to be excessively oversimplified and a few circumstances significantly nonsensical. In the event that you feel that this technique will come about a colossal mistake , you are correct – yet there is a catch. This thinking holds just when the quantity of information focuses is not expansive. In the event that the quantity of information focuses is substantial, then there is a high possibility that mark of x and y is same. An illustration may help – Lets say you have a (possibly) one-sided coin. You hurl it for 1 million time and you have head 900,000 circumstances. At that point in all probability your next call will be head. We can utilize a comparable contention here.

Give me a chance to attempt a casual contention here - Assume all focuses are in a D dimensional plane . The quantity of focuses is sensibly substantial. This implies the thickness of the plane anytime is genuinely high. At the end of the day , inside any subspace there is satisfactory number of focuses. Consider a point x in the subspace which likewise has a ton of neighbors. Presently let y be the closest neighbor. On the off chance that x and y are adequately close, then we can accept that likelihood that x and y have a place with same class is genuinely same – Then by choice hypothesis, x and y have a similar class. The book "Design Classification" by Duda and Hart has an incredible discourse about this Nearest Neighbor run the show. One of their striking outcomes is to acquire a genuinely tight blunder bound to the Nearest Neighbor run the show. The bound is

$$P^* \leq P \leq P^*\left(2 - \frac{c}{c-1}P^*\right)$$

Where is the Bayes blunder rate, c is the quantity of classes and P is the mistake rate of Nearest Neighbor. The outcome is without a doubt extremely striking (in any event to me) since it says that if the quantity of focuses is genuinely expansive then the blunder rate of Nearest Neighbor is less than double the Bayes mistake rate. Entirely cool for a straightforward calculation like KNN.

Case 2: k = K or k-Nearest Neighbor Rule:

This is a direct augmentation of 1NN. Essentially what we do is that we attempt to discover the k closest neighbor and do a dominant part voting. Regularly k is odd when the quantity of classes is 2. Suppose k = 5 and there are 3 cases of C1 and 2 occurrences of C2. For this situation, KNN says that new indicate has named as C1 as it structures the dominant part. We take after a comparable contention when there are numerous classes.

One of the direct augmentation is not to give 1 vote to every one of the neighbors. An extremely basic thing to do is weighted kNN where every point has a weight which is normally figured utilizing its separation. For eg under backwards separate weighting, every point has a weight equivalent to the reverse of its separation to the indicate be characterized. This implies neighbouring focuses have a higher vote than the more distant focuses. It is quite obvious that the accuracy *might* increase when you increase k but the computation cost also increases.

2.3 k-implies bunching calculation:

k-means is one of the least difficult unsupervised learning calculations that take care of the outstanding bunching issue. The strategy takes after a straightforward and simple approach to arrange a given information set through a specific number of bunches (expect k groups) settled apriority. The principle thought is to characterize k focuses, one for every bunch. These focuses ought to be set in an ent result. Along these lines, the better decision is to sly route as a result of various area causes contrast bind them however much as could reasonably be expected far from each other. The following stride is to take every direct having a place toward given information set and partner it to the closest focus. At the point when no point is pending, the initial step is finished and an early gathering age is finished. Now we have to re-figure k new centroids as bary focal point of the bunches coming about because of the past stride. After we have these k new centroids, another coupling must be done between similar information set focuses and the closest new focus. A circle has been created. Accordingly of this circle we may see that the k focuses change their area well ordered until no more changes are done or at the end of the day focuses don't move any more. At long last, this calculation goes for limiting a target work know as squared mistake work given by:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2$$

where,

'$\|x_i - v_j\|$' is the Euclidean distance between x_i and v_j.

'c_i' is the number of data points in i^{th} cluster.

'c' is the number of cluster centers.

2.3.1 Algorithmic steps for k-means clustering:

Let $X = \{x_1,x_2,x_3,\ldots\ldots..,x_n\}$ be the set of data points and $V = \{v_1,v_2,\ldots\ldots.,v_c\}$ be the set of centers.

1) Randomly select 'c' cluster centers.

2) Calculate the distance between each data point and cluster centers.

3) Assign the data point to the cluster center whose distance from the cluster center is minimum of all the cluster centers..

4) Recalculate the new cluster center using:

$$v_i = (1/c_i) \sum_{j=1}^{c_i} x_i$$

where, 'c_i' represents the number of data points in i^{th} cluster.

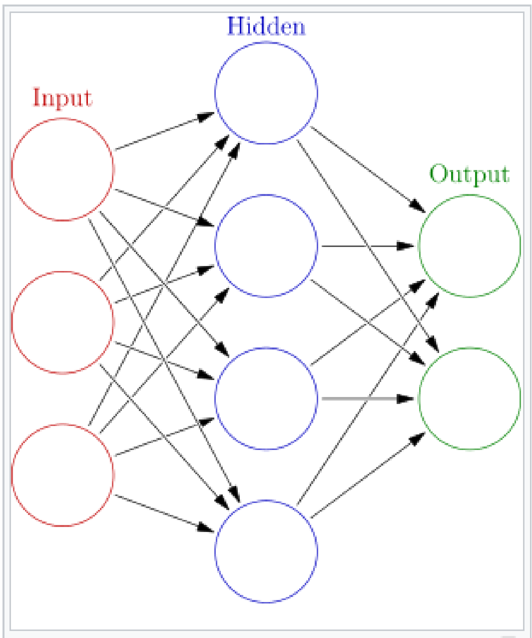
5) Recalculate the distance between each data point and new obtained cluster centers.

6) If no data point was reassigned then stop, otherwise repeat from step 3).

3. Proposed system

3.1 ANN classifier:

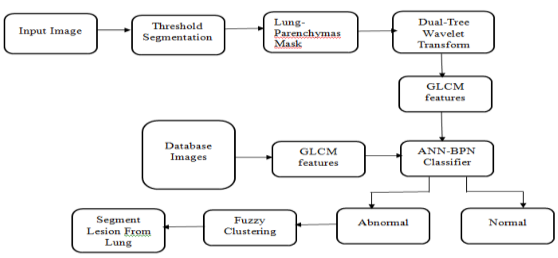
Networks are a Neural the way an organic cerebrum takes care of issues with expansive groups of natural neurons associated by axons. Each neural unit is computational approach which depends on a huge gathering of neural units freely demonstrating associated with numerous others, and connections can implement or inhibitory in their impact on the initiation condition of associated neural units. Every individual neural unit may have a summation capacity which consolidates the estimations of every one of its information sources together. There might be an edge capacity or constraining capacity on every association and on the unit itself to such an extent that it must outperform it before it can proliferate to different neurons. These frameworks are self-learning and prepared instead of unequivocally customized and exceed expectations in ranges where the arrangement or highlight recognition is hard to express in a conventional PC program.



•

Neural systems regularly comprise of different layers or a shape outline, and the flag way navigates from front to back. Back proliferation is the place the forward incitement is utilized to reset weights on the "front" neural units and this is now and again done in blend with preparing where the right outcome is known. More advanced systems are sans more streaming as far as incitement and hindrance with associations cooperating in an a great deal more disorderly and complex design. Dynamic neural systems are the most exceptional in that they progressively can, in light of guidelines, frame new associations and even new neural units while debilitating others.

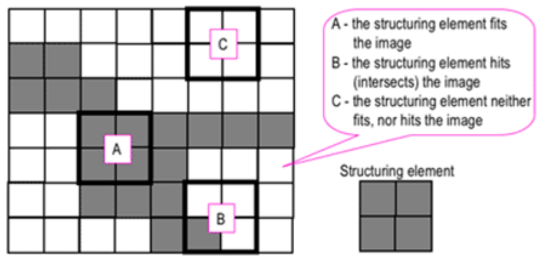
Block diagram:



3.2 MORPHOLOGICAL PROCESS:

Morphological picture handling is an accumulation of non-straight operations identified with the shape or morphology of elements in a picture. Morphological operations depend just on the relative requesting of pixel qualities, not on their numerical qualities, and accordingly are particularly suited to the preparing of double pictures. Morphological operations can likewise be connected to dark scale pictures with the end goal that their light exchange capacities are obscure and hence their total pixel qualities are of no or minor intrigue.

Morphological methods test a picture with a little shape or format called an organizing component. The organizing component is situated at all conceivable areas in the picture and it is contrasted and the relating neighborhood of pixels. A few operations test whether the component "fits" inside the area, while others test whether it "hits" or meets the area:



A typical practice is to have odd measurements of the organizing network and the source characterized as the focal point of the grid. Structuring components play in morphological picture handling an indistinguishable part from convolution pieces in direct picture sifting.

3.3 DUAL TREE COMPLEX WAVELET TRANSFORM (DTCWT):

Nick Kingsbury [11] recommended that double tree complex wavelet change is utilized to beat hindrances of customary wavelet change. The complex wavelet transform (CWT) is mind boggling esteemed expansion to standard DWT. CWT utilize complex esteem sifting that breaks down the genuine/complex flag into genuine and nonexistent parts in change area. The genuine and nonexistent coefficient is utilized to process sufficiency and stage data. DTCWT have isolate sub groups for positive and negative introductions. DTCWT ascertain complex change of flag utilizing two separate discrete wavelet change (DWT) disintegration. DWT deterioration produces two parallel trees [11]. We utilize 1D DTCWT, consider (hx + jgx) where, hx is the arrangement of channels {h0 , h1}, and gx is the arrangement of channels {g0 , g1} both sets in just x-heading (1-D). The channels h0 and h1 are the genuine esteemed lowpass and highpass channels individually for genuine tree. The same is valid for g0 and g1 for nonexistent tree. DTCWT has great directional selectivity as contrast with different techniques. Additionally it has decreased move variation property [11]. Following are features of DTCWT:

- Approximate shift variant.
- Good directional selectivity.
- Perfect reconstruction using short linear filters.
- Limited redundancy.
- Efficient order n computations.

3.4 GLCM:

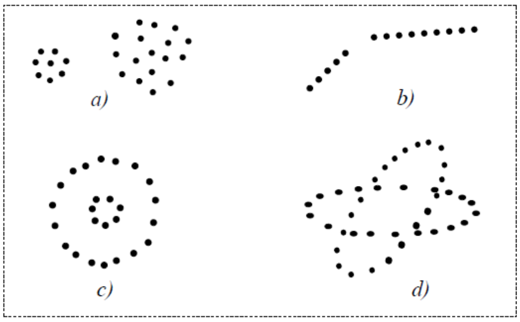
A co-occurrence matrix or co-occurrence distribution is a matrix that is defined over an image to be the distribution of co-occurring pixel values (grayscale values, or colors) at a given offset.

$$C_{\Delta x,\Delta y}(i,j)=\sum_{x=1}^{n}\sum_{y=1}^{m}\begin{cases}1, & \text{if } I(x,y)=i \text{ and } I(x+\Delta x,y+\Delta y)=j\\ 0, & \text{otherwise}\end{cases}$$

The 'value' of the image originally referred to the grayscale value of the specified pixel, but could be anything, from a binary on/off value to 32-bit colour and beyond.

3.5 Fuzzy Clustering:

Many clustering algorithms have been introduced in the literature. Since clusters can formally be seen as subsets of the data set, one possible classification of clustering methods can be according to whether the subsets are *fuzzy* or *crisp* (hard).



Hard grouping techniques depend on traditional set hypothesis, and require that a question either does or does not have a place with a bunch. Hard grouping implies apportioning the information into a predetermined number of totally unrelated subsets.

Fluffy grouping techniques, be that as it may, permit the items to have a place with a few bunches at the same time, with various degrees of participation. Much of the time, fluffy grouping is more normal than hard bunching. Protests on the limits between a few classes are not compelled to completely have a place with one of the classes, yet rather are doled out participation degrees in the vicinity of 0 and 1 showing their halfway enrollment. The discrete way of the hard parceling likewise causes troubles with calculations in light of diagnostic utilitarian, since these useful are not differentiable. Another grouping can be identified with the algorithmic approach of the distinctive methods (Bezdek, 1981).

Agglomerative various leveled strategies and part progressive techniques frame new groups by reallocating enrollments of one point at once, in light of some appropriate measure of similitude. With diagram theoretic strategies, Z is viewed as an arrangement of hubs. Edge weights between sets of hubs depend on a measure of similitude between these hubs. Bunching calculations may utilize a target capacity to gauge the allure of parcels. Nonlinear streamlining calculations are utilized to look for nearby optima of the goal work. The rest of this section concentrates on fluffy grouping with target work. These techniques are moderately surely knew, and numerical outcomes are accessible concerning the merging properties and group legitimacy appraisal.

4.EXPERIMENTAL SETUP AND RESULTS

INPUT IMAGE:

We taken one abnormal input image and calculating performance.

Fig1: abnormal lung pattern input image.

Step 1:

At first, Input image is to be segmented

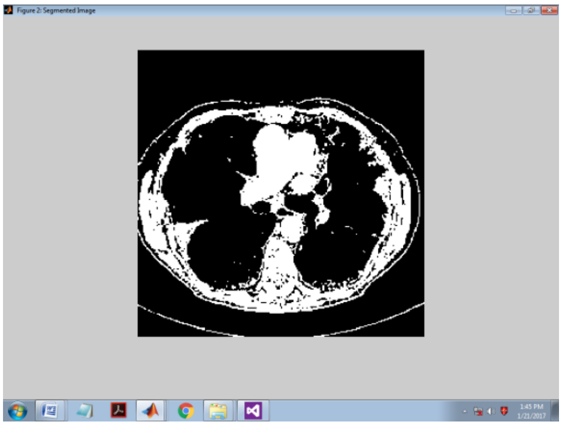


Fig2: segmented image

Step 3:

After performing segmented the object is separated from its back ground.

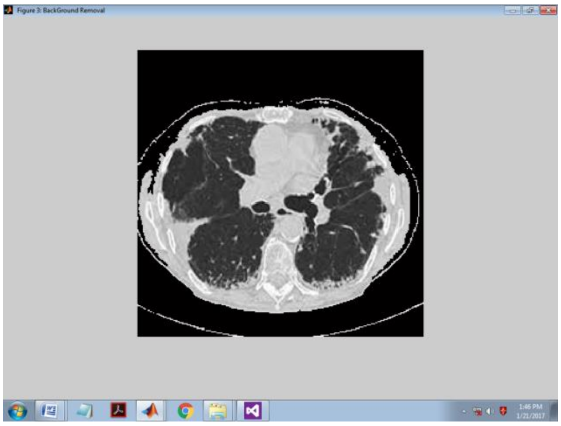


Fig3: Background removal in an segmented image

Step 4:

The step 4 is applying regional mask in the background removal image.

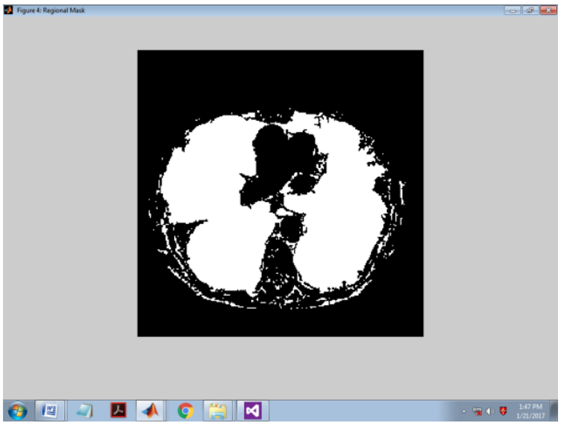


Fig4: regional mask image

Step 5:

In step5 we applying neural network

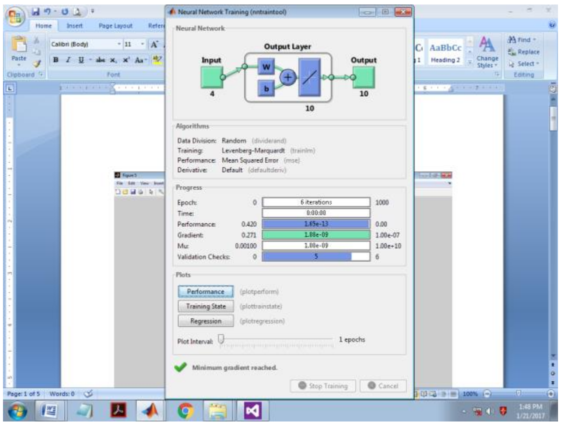


Fig5: neural network

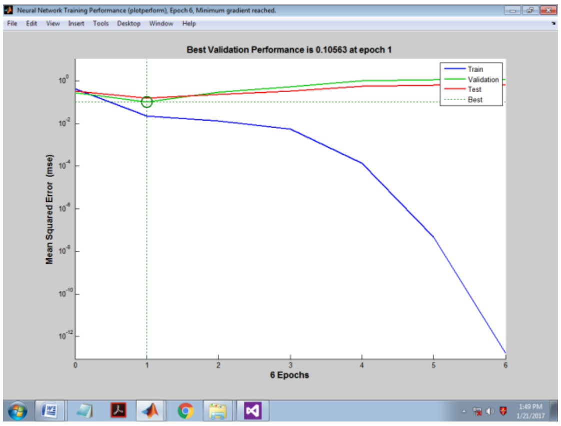


Fig5(a):performance analysics of mse and 6epochs

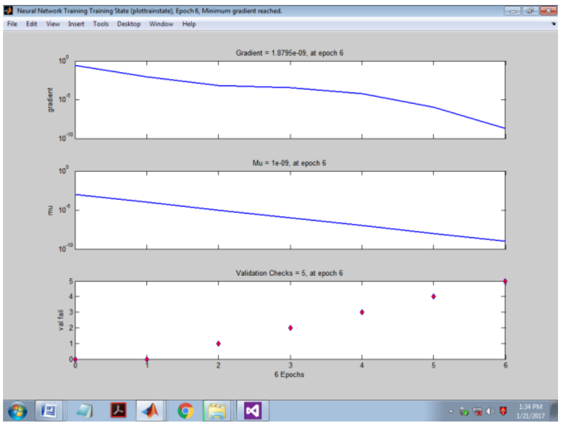


Fig5(b): training state

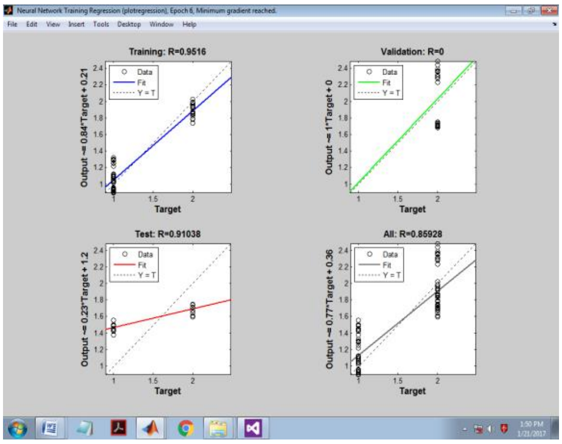


Fig5(c): training regression state

In this section we analyze performance training state and regression. In fig 5(a) we analyse minimum mean square error(mse) of 6 iteration. In fig5(b) represent neural network training training state minimum gradient reached. finally we calculate neural network training regression. Its reached minimum reached.

5. CONCLUSION

In this paper, we display another representation and approach for interstitial lung infection characterization. we proposed a profound ANN to arrange lung CT picture patches into 7 classes, including 6 distinctive ILD designs and solid tissue. There are a few headings to be investigated as future work. The picture highlights gained from the profound ANN system can be coordinated into more refined order calculations. There are a few cases (_ 5%) with numerous malady labels on a similar cut of CT picture. Recognition with different marks at a cut level would intrigue. Understanding the clinical importance and estimation of the components gained from the system would likewise be a bearing that we plan to seek after.

6. REFERENCE

[1] SOCIETY, BT. "The diagnosis, assessment and treatment of diffuse parenchymal lung disease in adults." *Thorax* 54, no. Suppl 1 (1999): S1.

[2] Demedts, M., and U. Costabel. "ATS/ERS international multidisciplinary consensus classification of the idiopathic interstitial

pneumonias."*European Respiratory Journal* 19, no. 5 (2002): 794-796.

[3] I. Sluimer, A. Schilham, M. Prokop, and B. Van Ginneken, "Computer analysis of computed *Trans. Med. Imaging*, vol. 25, no. 4 tomography scans of the lung: A survey," *IEEE*, pp. 385–405, 2006.

[4] K. R. Heitmann, H. Kauczor, P. Mildenberger, T. Uthmann, J. Perl, and M. Thelen, "Automatic detection of ground glass opacities on lung HRCT using multiple neural networks.," *Eur. Radiol.*, vol. 7, no. 9, pp. 1463–1472, 1997.

[5] Delorme, Stefan, Mark-Aleksi Keller-Reichenbecher, Ivan Zuna,Wolfgang Schlegel, and Gerhard Van Kaick. "Usual interstitial pneumonia: quantitative assessment of high-resolution computed tomography findings by computer-assisted texture-based image analysis."*Investigative radiology* 32, no. 9 (1997): 566-574.

[6] Automatic detection of lung cancer nodules by employing intelligent fuzzy cmeans and support vector machine ", Biomedical Research, August 2016.

[7] Cognitive Computational Semantic for high resolution image interpretation using artificial neural network", Biomedical Research, August 2016.

[8] C. Sluimer, P. F. van Waes, M. a Viergever, and B. van Ginneken,"Computer-aided diagnosis in high resolution CT of the lungs.," *Med.Phys.*, vol. 30, no. 12, pp. 3081–3090, 2003.

[9] Y. Song, W. Cai, Y. Zhou, and D. D. Feng, "Feature-based image patch approximation for lung tissue classification," *IEEE Trans. Med. Imaging*,vol. 32, no. 4, pp. 797–808, 2013.

[10] M. Anthimopoulos, S. Christodoulidis, a Christe, and S. Mougiakakou,"Classification of interstitial lung disease patterns using local DCT features and random forest," *2014 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 6040–6043, 2014.

[11] Y. Uchiyama, S. Katsuragawa, H. Abe, J. Shiraishi, F. Li, Q. Li, C.-T. Zhang, K. Suzuki, and K. Doi, "Quantitative computerized analysis of diffuse lung disease in high-resolution computed tomography," *Med.Phys.*, vol. 30, no. 9, pp. 2440–2454, 2003.

[12] K. T. Vo and A. Sowmya, "Multiple kernel learning for classification of diffuse lung disease using HRCT lung images.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2010, pp. 3085–3088, 2010.

[13] A. Depeursinge, D. Van De Ville, A. Platon, A. Geissbuhler, P. A. Poletti, and H. Muller, "Near-affine-invariant texture learning for lung tissue analysis using isotropic wavelet frames," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 4, pp. 665–675, 2012.

[14] Sørensen, Lauge, Saher B. Shaker, and Marleen De Bruijne. "Quantitative analysis of pulmonary emphysema using local binary patterns." *Medical Imaging, IEEE Transactions on* 29, no. 2 (2010): 559-569.

[15] Y. Xu, E. J. R. van Beek, Y. Hwanjo, J. Guo, G. McLennan, and E. a. Hoffman, "Computer-aided Classification of Interstitial Lung Diseases Via MDCT: 3D Adaptive Multiple Feature Method (3D AMFM)," *Acad. Radiol.*, vol. 13, no. 8, pp. 969–978, 2006.

[16] V. A. Zavaletta, B. J. Bartholmai, and R. a. Robb, "High Resolution Multidetector CT-Aided Tissue Analysis and Quantification of Lung Fibrosis," *Acad. Radiol.*, vol. 14, no. 7, pp. 772–787, 2007.

[17] P. D. Korfiatis, A. N. Karahaliou, A. D. Kazantzi, C. Kalogeropoulou, and L. I. Costaridou, "Texture-based identification and characterization of interstitial pneumonia patterns in lung multidetector CT," *IEEE Trans.Inf. Technol. Biomed.*, vol. 14, no. 3, pp. 675–680, 2010.

[18] I. Mariolis, P. Korfiatis, L. Costaridou, C. Kalogeropoulou, D. Daoussis and T. Petsas, "Investigation of 3D textural features' discriminating ability in diffuse lung disease quantification in MDCT," *2010 IEEE Int.Conf. Imaging Syst. Tech. IST 2010 - Proc.*, pp. 135–138, 2010.

[19] A. Depeursinge, P. Pad, A. S. Chin, A. N. Leung, D. L. Rubin, H. Muller, and M. Unser, "Optimized steerable wavelets for texture analysis of lung tissue in 3-D CT: Classification of usual interstitial pneumonia," in *12th International Symposium on Biomedical Imaging*, 2015, pp. 403–406.

[20] Gangeh, Mehrdad J., Lauge Sørensen, Saher B. Shaker, Mohamed S.Kamel, Marleen De Bruijne, and Marco Loog. "A texton-based approach for the classification of lung parenchyma in CT images." In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2010*, pp. 595-602. Springer Berlin Heidelberg, 2010.