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Lung Pattern Classification for Interstitial Lung Diseases Using an Artificial Neural Network

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ABSTRACT: Lung is the organ that allows us to breathe and lung disease are the disorders that affect the lungs. This paper presents a computer aided classification Method in Computer Tomography (CT) Images of lungs developed using ANN-BPN. The purpose of the work is to detect and classify the lung diseases by effective feature extraction through Dual-Tree Complex Wavelet Transform (DTCWT) and Gray Level Co-occurrence Matrix (GLCM) Features. The entire lung is segmented from the CT Images and the parameters are calculated from the segmented image. The parameters are calculated using GLCM. We Propose and evaluate the Artificial Neural Network -Back Propagation method designed for classification of Interstitial Lung Disease (ILD) patterns. We collect different types of CT images of lung and train artificial neural network. The parameters give the maximum classification Accuracy. After the result we propose the Fuzzy clustering to segment the lesion part from abnormal lung.

This data imbalance effect can be ameliorated by using data augmentation to generate more training images of rare or abnormal data, though there is risk of over fitting. Aside from data-level strategies, algorithmic modification strategies and cost sensitive learning have also been Analysis accuracy for different classes like AUC $AUC_{alexnetp}$, $AUC_{alexnet}$, $AUC_{soresen}$, AUC_{vgg} the potential of CNNs in analyzing lung patterns. Finally classify the performance and trained and evaluated the CNN by MATLAB simulation and simulation result carried out 91% accuracy.

I. INTRODUCTION

Lung diseases are the disorders that affect the lungs, the organ allow us to breathe and it is the most common medical conditions worldwide especially in India. The evidence has showed uncontrollable cell growth in tissues of the lung resulting in lung disease. The term interstitial lung disease caused in the interstitium (a part of the lung).They are also called as diffuse parenchymal lung disease(DPLD).This paper proposes the components of the lung pattern classification for early detection of lung disease. The dual tree complex wavelet transform (DTCWT) is important to generate two filter bandswhich will generate four sub-bands such as LL, LH, HL, HH frequencies and it is divided further. The DTCWT is important because it provides contrast, shape, texture features. Threshold segmentation is used to segment the lungs. The classifier used is artificial neural network -back propagation network which is used to classify the lung disease such as normal andabnormal. lung disease cause many problems such that disease like pleural effusion. Recent studies have shown that there are two types of cancer these include small cell lung carcinoma (SCLC) and non- small cell lung carcinoma (NSCLC).However lung disease is considered as one of the dangerous in the sense that is harmful and get slowly increased. Lung disease is strongly correlated with cigarette smoking. Researchers think that the disease requires early detection and prevention. First we have to identify the symptoms of the lung disease which will be helpful for further purpose. But it is unpredictable because they vary withdifferent types of cancers. But still it can be diagnosed by taking necessary steps and proper measures.

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II. BLOCK DIAGRAM

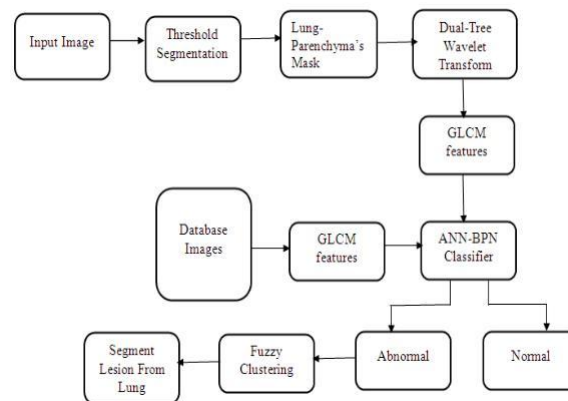


Figure 1: Block diagram of lung pattern classification of ILD

A. Threshold Segmentation

Lung parenchyma mask

Image segmentation is a fundamental step in computerized image analysis and it deals with separating classes in an image into continuous and separate regions. For example, a CT slice from a thoracic scan may contain chest wall, heart segments in addition to lung tissues. The goal of segmentation in this case is to isolate the lung tissue

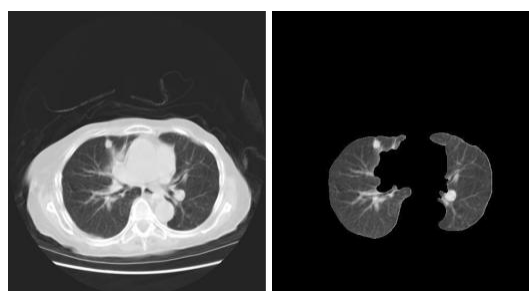


Figure 2: Illustration of the segmentation process. Left: a CT slice from a thoracic scan. Right: segmentation output, showing the isolated lung tissue.

As in image processing, image segmentation is extremely rich area in the image analysis and computer vision literature. Yet, broadly speaking, image segmentation methods may be classified into three distinct approaches, a) statistical, b) geometric, and c) variation. Statistical methods model the image information and cast the region process as mapping from raw images. Geometric methods exploit object shape descriptions in order to separate the image contents into classes. Variation methods(e.g., level sets) create an implicit description of class boundaries in terms of a curve/surface that evolves and cuts the particular object at its boundary (zero-level set).Variation approaches uses implicit models (e.g. level sets), and explicit models (e.g., snakes and gradient vector flow). Under each category, there exists an enormous body of theoretical and algorithmic foundation.

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B. DTCWT

For many applications it is important that the transform be perfectly invertible. Some authors, including Lawton [Law93], have experimented with complex factorization of the standard Daubechies polynomials selectivity properties. DTCWT comes with a different approach in order to overcome this and obtained perfect reconstruction (PR) complex filters, but these do not give filters with good frequency drawback.

a) One-dimensional DTCWT

Kingsbury first introduced the DTCWT which relies on the observation that approximate shift invariance can be achieved with a real DWT by doubling the sampling rate at every level of the tree. For this to figure, the samples should be equally spaced. The sampling rates can be doubled by eliminating the down-sampling by 2 after the level 1 filter. This is equivalent to having two parallel fully-decimated trees a and b, like in fig. 3.4, provided that the delays of H0b and H1b are one sample offset from H0a and H1a. Kingsbury found that, to induce uniform intervals between samples from the two trees below level one, the filters in one tree must provide delays that are half a sample different (at each filter input rate) from those within the alternative tree. This statement is additionally supported by Selesnick who, in [Sel01], gives an alternative derivation and explanation of the same result. The implementation of such a transform is completed using two mother wavelets, one for every tree, and one amongst them being (approximately) the Hilbert transform of the other. On one hand, the dual-tree DWT is viewed as an over complete wavelet transform with a redundancy issue of two. On the other hand, the dual-tree DWT is also a complex DWT, where the first and second DWTs represent the important and unreal parts of one complicated DWT. The first implementation projected had the constraint of linear phase, and to accomplish this, the implementation required odd-length filters in one tree and even-length filters within the other. Bigger symmetry between the two trees happens if every tree uses odd and even filters alternately from level to level, but this is not essential. In another implementation proposed in [Kin01], the condition of linear phase is dropped, resulting the so-called Q-shift dual tree. In this case all the filters beyond level 1 are even length and are designed to have a group delay of approximately 1

b) Shift Invariance

In order to examine the shift invariance properties of a transform, Kingsbury [Kin01] proposes a method based on the retention of only one type (details or approximations), from just one level of the decomposition tree. For example one may favor to retain only the level-3 detail coefficients and set all the others to zero. If the signal y reconstructed from simply these coefficients, is freed from aliasing then it is aforesaid that the transform is shift invariant at that level. The degree of shift invariance of two implementation schemes (one for the DTCWT and the other for the classical DWT) is presented in fig.4.

c) Two-dimensional DTCWT

Extension of the DTCWT to two dimensions is achieved by dissociable filtering on Columns and so rows. However, if column and row filters both suppress negative frequencies, then only the first quadrant of the 2-D signal spectrum is preserved. It is well known, from 2-D Fourier transform theory, that two adjacent quadrants of the spectrum are required to represent fully a real 2-D signal. Therefore in the DT CWT it is also filtered with complex conjugates of the row (or column) filters in order to retain a second (or fourth) quadrant of the spectrum. This then gives 4:1 redundancy in the transformed

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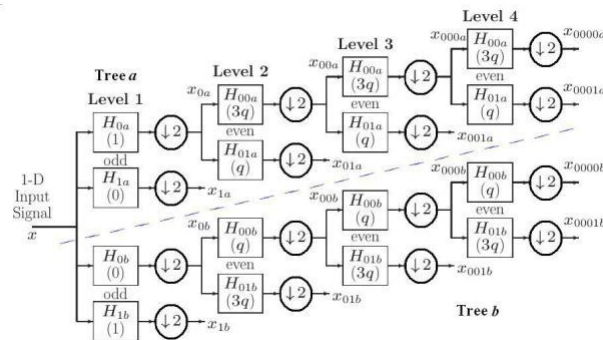


Figure 3: one dimensional DTCWT

III. RESULT



Figure 4: Output of the block diagram

The analysis was performed per class (one-vs-all) while the average over all classes is also presented. For each ROC, the AUC is given and the 95% confidence interval is plotted. Comparing on the most difficult patterns i.e., consolidation, reticulation, honeycombing and reticulation/GGO. For the rest of the patterns (healthy, GGO and micronodules) the difference between the proposed method and the pre-trained AlexNet was not considered significant, while for GGO the difference from VGG-Net was also non-significant (). Finally, the superiority of the proposed method after averaging over all considered classes was also found to be statistically significant

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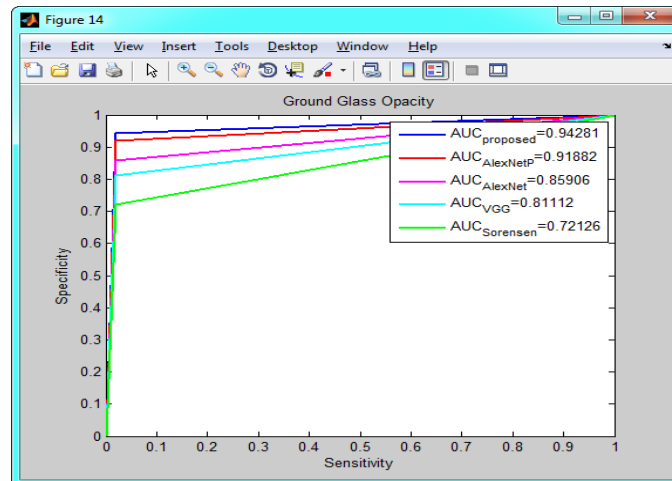


Fig. 5 Ground Glass Opacity Class Graph

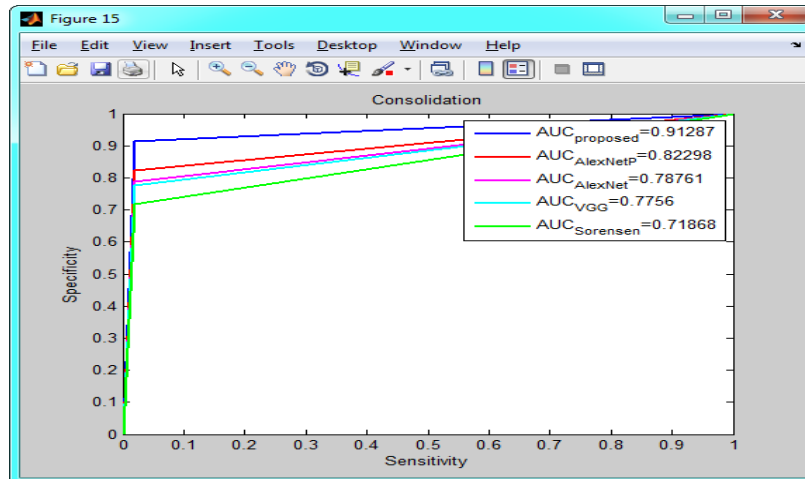


Fig. 6 Consolaidation

In this we have to compare the input CT image with the database image. This can be done by validation process Comparison is done by the parameters like entropy, correlation function, mean and so on. If result is normal, then the process will be stopped. If result is abnormal, then we have to find where the disease is present exactly. The disease will be identified with the help of watershed segmentation. The affected part will be in the color. The output image will be clear and gives the detail about the lesion part.

IV. CONCLUSION

However, the segmentation algorithm proves to be simple and effective. Gray scale Co-occurrence matrix performed well in BPN. Better texture and edge representation Segmentation provides better clustering efficiency. Computer aided Diagnosis system for interstitial lung diseases in medical Application.

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REFERENCES

- [1] SOCIETY, BT. "The diagnosis, assessment and treatment of diffuse parenchymal lung disease in adults." Thorax 54, no. Suppl 1 (1999):
- [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 tomography scans of the lung: A survey," IEEE Trans. Med. Imaging, vol. 25, no. 4, pp. 385–405, 2006.
- [4] K. R. Heitmann, H. Kauczor, P. Mildenerger, 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–
- [5] Delorme, Stefan, Mark-Aleksi Keller-Reichenbecher, pneumonia: quantitative assessment of high-resolution Investigative radiology 32, no. 9 (1997):566-574. Ivan Zuna, Wolfgang Schlegel, and Gerhard Van Kaick. "Usual interstitial computed tomography findings by computer-assisted texture-based image analysis."
- [6] R. Uppaluri, E. a Hoffman, M. Sonka, P. G. Hartley, G. W. Hunninghake, and G. McLennan, "Computer recognition of regional lung disease patterns," Am. J. Respir. Crit. Care Med., 160 (2) , pp. 648–654, 1999.
- [7] 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.
- [8] 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.
- [9] 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.
- [10] 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.
- [11] 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.
- [12] 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
- [13] 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.