

Interstitial Lung Disease Classification Using Feed Forward Neural Networks

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Abstract: This paper presents a classification scheme for Interstitial Lung Disease (ILD) pattern using Patch based approach and ANN classifier. Various methods are proposed for classification of ILD patterns but still accuracy can be improved when ILD cases are complex. In this paper, we have extracted features from (31×31) size patch using histogram of Local Binary Patterns (LBP) and second order statistics such as Grey level co-occurrence matrix (GLCM), Grey level run length matrix (GLRLM). A two layer Feed-Forward Neural Network trained with Scaled Conjugate Gradient Back-propagation algorithm is used for classification. Accuracy of the work carried out in this paper is 93.41 %. Results are verified and compared with different classifiers such as k-NN and SVM. This study has been carried out on publicly available database of ILD cases. ILD patches have been collected from 2-D Region of interest (ROI) marked by expert radiologist. Five frequently seen ILD patterns: Normal, Emphysema, Fibrosis, Ground Glass and Micronodule are considered in this study. Experimental results with proposed scheme outperforms in classification of ILD patterns.

Keywords: *ILD classification · second order statistics · Feed Forward Neural Networks · SVM · K-NN*

1 Introduction

Now a days, interstitial lung disease (ILD) is a very commonly seen disorder, which includes near about 130 categories. There is a possibility that, if a person is suffering from shortness of breath may have ILD disorder. Various forms of ILD has different durability, some of them are short lived while many of them are constantly recurring and irreversible. Thus, accurately classification of ILD is most important. Various methods are applicable for acute diagnosis of ILD, among which imaging scans are preferred more frequently.

Computed Tomography is nothing but detailed image created by computer by taking information from multiple X-rays of the lungs and surrounding structures. Since last three decades Computed Tomography scan of lungs are becoming very famous because of its discriminative information for different ILDs [1], [2]. There are two stages in computer aided diagnosis system. First stage corresponds to segmentation of lung, whereas in second stage, ILD pattern classification takes place.

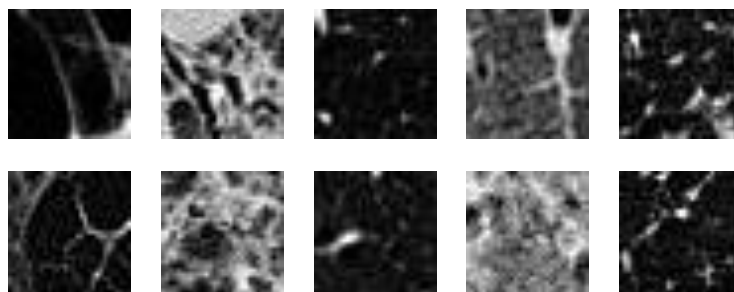


Fig. 1. Patches of each tissue category. Left to right: Emphysema, Fibrosis, Normal, Ground Glass, Micronodule.

Talbar et. al. [19] proposed texture classification, based on wavelet features. Also various study has been carried out on classification of ILD patterns using textural information [3]–[5][6], [7]. Information from HRCT scan can be used to accurately classify the ILD patterns. Renuka Uppaluri et.al.[3] described adaptive multiple feature method, using AMFM they have shown ability of their proposed system to differentiate between the normal and emphysematous whole lung slices. Extension of AMFM to differentiate the normal lung from subtle pathological tissues has been proposed by Ye. Xu. et. al. [7].

Emphysema classification using textural features has been introduced by Renuka Uppaluri et. al. [8]. Along with discriminative features many researchers have tried different classifiers to improve ILD classification. In a very short period of time Support vector machine (SVM) becomes a famous classifier because of its discriminative classification power. Kiet T. Vo et.al. [9] has used k-nearest neighborhood (k-NN) classifier in comparison with SVM, in classification of diffuse lung diseases. Also, Michinobu Nagao et.al. [5] proposed Histogram features followed by bayes classifier for ground glass and micronodule detection. To get more and more accurate classification many researchers have used artificial neural networks (ANN). In combination with grey level distribution and geometric patterns, Yoshikazu Uchiyama et.al.[6] used ANN for classification of diffuse lung disease. To improve Computer aided detection Lilla Boroczky et.al. [10] proposed a method based on genetic algorithm and combined it with support vector machine for Ground glass detection.

In this work, we have presented, a patch based approach for the classification of ILD patterns using 2-D textural features and two layer feed-forward neural networks. We have focused on most commonly seen ILD patterns: Emphysema, Fibrosis, Ground Glass, Normal and Micronodule. Fig. 1 shows ILD tissue patterns. It can be seen that, tissue patterns are having different textures amongst themselves.

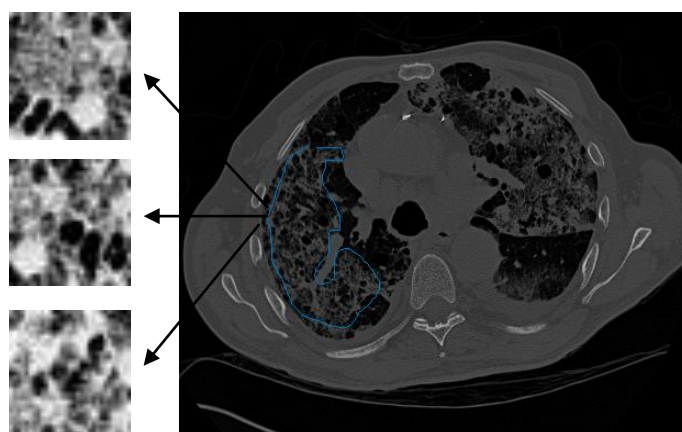


Fig. 2. Division of ROI into patches. From left to right: Obtained (31×31) size patches, Marked ROI

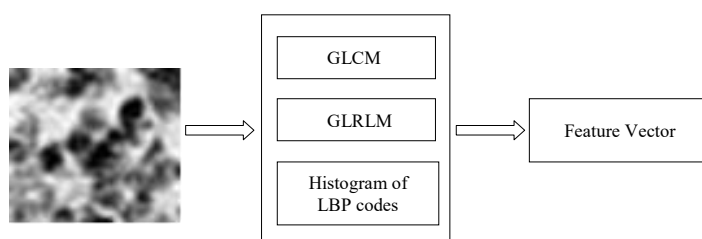


Fig. 3. Illustration of feature extraction. As shown, features have been extracted from image.

Sometimes it is easy for computer to recognize tissue patterns. It is difficult when ILD patterns are more complex. Although it is a very challenging task to recognize interclass pattern variation. So, to design an automatic system which can classify ILD patterns correctly by considering interclass and intra-class variations is a quite challenging task.

2 Proposed Method

In this work, we have divided region of interest (ROI) into half overlapping patches of size 31×31 . Each patch has 75 % overlap with marked ROI. It can be understood from the work [4], [5], [11], [12] that GLCM, GLRLM and histogram of local binary patterns can give more discriminative information about ILD patterns. Fig. 2 shows division of ROI into patches. From left to right: Generated patches of size 31×31 pixels, Marked ROI of fibrosis class.

2.1 Feature Extraction

Proposed feature extraction scheme is shown in Fig. 3. In this study, we have extracted features from (31×31) size patch (as shown in Fig. 2) using gray level co-occurrence matrix, gray level run length matrix and histogram of LBP codes. The gray level co-occurrence matrix (GLCM) [13] gives information about spatial distribution of grey levels. For a given distance d , GLCM matrices gives two dimensional histograms of the occurrence of pairs of grey-levels. An element at any location (p, q) in GLCM, denotes joint probability density of the frequency of occurrence of grey-tone p and q in a specified direction. Hence, we have evaluated GLCM along four directions (0, 45, 90, 135) and distance ($d = 1$). From each of these GLCM, we have extracted four features: Energy, contrast, correlation and Homogeneity. In total, 16 GLCM features has been taken out in this study.

Xiaoou Tang [14] proposed grey level run lengths for textural analysis. In a coarse texture, relatively long grey level runs would occur, rather in fine texture many a times short grey level run occurs. Given a patch, a run-length matrix $r(l, m)$ is defined as the number of runs with pixels of grey level l and run length m . Various texture features can then be derived from this run length matrix out of which, we have taken out: long run emphasis (LRE), run length non-uniformity (RLN), run percentage (RP), Short Run Low short run emphasis (SRE), Grey-Level Emphasis (SRLGE), Low Grey-Level Run Emphasis (LGRE), Short Run High Grey-Level Emphasis (SRHGE), gray level non-uniformity (GLN), Long Run Low Grey-Level Emphasis (LRLGE), Long Run High Grey-Level Emphasis (LRHGE), High Grey-Level Run Emphasis (HGLR).

Local binary patterns (LBP) proposed by Ojhal et. al.[15] is a very strong textural feature descriptor. LBP gives both statistical as well as structural information by histogram of LBP patterns. We have evaluated LBP codes by taking radius equal to one, which actually corresponds to micro-structures in given image patch. LBP operator gives one binary pattern to every pixel in an image by thresholding its grey level intensity with reference to circularly symmetric neighbor set for predefined radius R . Another important issue in LBP codes is to set number of bins. In this study, we have set number of bins by taking cube root of total number of pixels in an image. In this work, we have extracted histogram of LBP patterns with 10 bins.

This study includes in total (1×37) dimensional feature vector corresponds to one (31×31) size patch. Out of which 16 features are from GLCM matrix, 11 are from GLRLM and features of histogram of LBP pattern.

2.2 Classification

2.2.1 Data Pre-Processing:

Any classifier aimed to predict class of test sample based on model which is built with training data. Inputs for building the model must be pre-processed to get proper trained model. Scaling (or Normalization) is a common approach in data pre-processing. Specially with SVM, data vector given to SVM must be real valued and normalized. In this study we have normalized our feature set by z-score normalization method.

Table 1. Database Information

Tissue Category	# Patches Generated	#Training	#Testing
Emphysema(TE)	344	258	86
Fibrosis(TF)	1362	1022	340
Ground Glass(TG)	684	514	170
Normal(TN)	1269	949	320
Micronodule(TM)	5256	3942	1314

2.2.3 *k*-Nearest Neighbor (*k*-NN)

k-NN is a non-parametric approach for classification. *k*-NN performs well when data given for classification is normalized and less complex. Consider an example of 3-NN($k=3$) classifier, it will give 3 instances from training data those are nearest to test data sample based on distance measure. The test patch is then assigned to the class which has the greatest frequency amongst the 3 instances. It gives classification decision based on majority. Various distance measures are available to measure the similarity between query and training data samples. Selection of *k* can be done empirically. In our work, we have used 3-NN classifier for comparison with ANN.

2.2.4 Support Vector Machine(SVM) :

SVM is a nonlinear classifier which creates a hyper plane, to classify the input samples. Various kernels are available for SVM such as RBF, Linear, Polynomial (or quadratic) etc. Among these, RBF kernel comparatively gives good results when feature dimension are less. In case of higher dimensional feature vector, one may go with linear Kernel. SVM is originally designed for binary class problem. To use it for multiclass classification various methods are proposed, including one-versus-all [16], one-shot multiclass classification [17] etc. To extend SVM for multi-class classification we have used one-versus-all method and RBF kernel.

Table 2. Confusion matrix of Patch wise tissue classification by proposed method

Ground Truth	TE	TF	TG	TN	TM
Emphysema(TE)	81	0	0	4	1
Fibrosis(TF)	2	320	9	1	8
Ground Glass(TG)	2	4	145	9	10
Normal(TN)	4	2	7	264	43
Micronodule(TM)	8	14	2	17	1273

2.2.5 Artificial Neural Networks (ANN):

ANN is a very superior and famous classifier used in pattern recognition as well as in medical diagnosis[6], [11], [18]. Trained ANN with optimum initial weight parameters has the ability to classify the given data with great accuracy. In this work, we have used two layered Feed-forward Back Propagation Neural Network trained with Scaled Conjugate Gradient Back-propagation for classification of ILD patterns. Features extracted from patch are given to Input layer. Number of Input layer neuron equals to 37, which is a feature dimensionality. Output layer has five neurons which indicates five classes of ILD patterns. Classification results are compared with 3-NN and SVM. Input data given to input layer was normalized using z-score normalization.

2.3 Dataset

In this work, we have used publicly available dataset of ILD cases[1]. This database has 2062 Region of Interest (ROI) marked by three experienced radiologists. Dataset has 113 sets of high resolution computed tomography (HRCT) images with (512×512) size having resolution 12 bit/pixel. Along with ROI, pattern label is also provided, which includes in total 17 different patterns. In this study, we have used only five frequently seen patterns: Emphysema, Fibrosis, Ground Glass, Normal, Micronodule. A brief summary of dataset used is shown in Table 1. Dataset also includes images with more than two ILD patterns. Some more details about scanning protocol: Spacing between the slices is 10–15 mm, Slice thickness is 1–2 mm, Scan time between two slices is 1–2 s. In this study, we have divided image slice into half overlapping image block having (31×31) pixel size. Image patches which are having 100 % overlap with lung field and 75 % overlap with marked ROI were selected for feature extraction. Fig. 2. shows obtained patches from marked region of interest, blue line indicates marked ROI. In order to increase the number of patches, we have applied transformations like transpose, horizontal flip, vertical flip etc. on original patches.

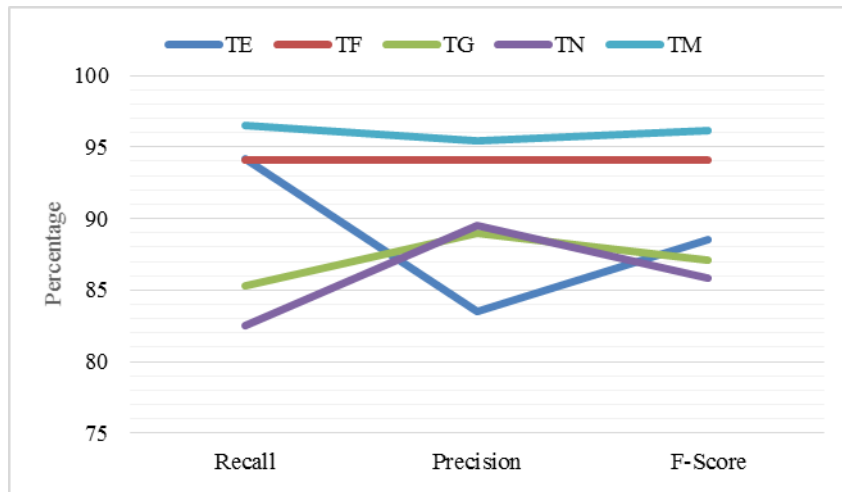


Fig. 4 .Performance Measure Of Proposed Method

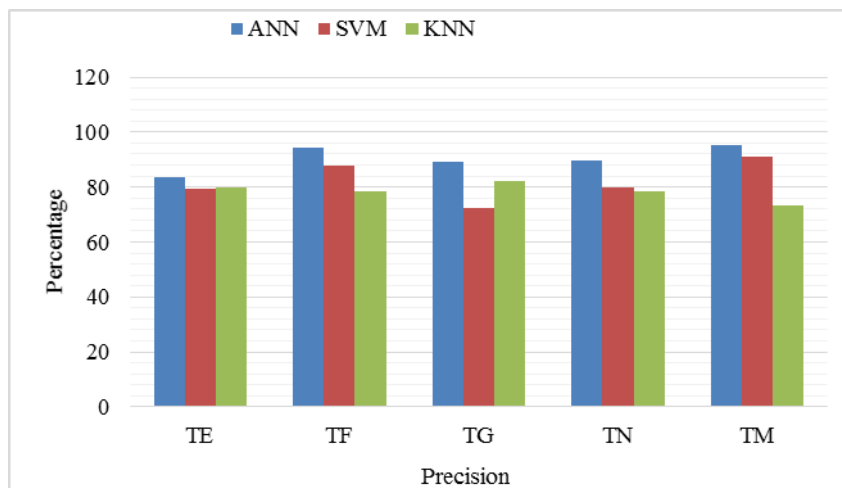


Fig. 5. Comparison of Proposed Method with SVM and k-NN

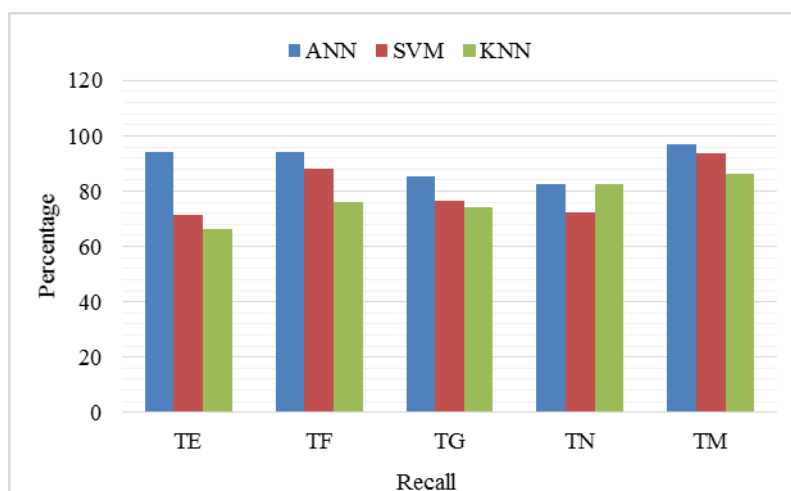


Fig. 6 .Comparison of Proposed Method with SVM and k-NN

3 Result and Discussion

The performance measures used in our work are Recall, F-score and Precision, formulated below.

$$\text{Recall} = \frac{\text{Samples correctly classified as } c}{\text{Samples of class } c} \quad (1)$$

$$\text{Precision} = \frac{\text{Samples correctly classified as } c}{\text{Samples of class } c} \quad (2)$$

$$F - \text{score} = \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (3)$$

$$\text{Accuracy} = \frac{\text{Total number of correctly classified samples}}{\text{Total number of samples}} \quad (4)$$

Fig. 5 gives information about performance measure of proposed method. High precision means number of correctly classified patches are greater than number of misclassified patches. High precision is an indication that, in a designed system misclassification rate is very less, while high recall means in a designed system, correct classification rate is higher. F-score normalization is giving clarification about system ability to correctly classify as well as misclassify. We have compared performance of proposed system with two classifiers (SVM and k -NN). Fig. 5,6 shows comparison between performance measure of ANN, SVM and k -NN. We have divided dataset into training and testing parts. Out of total image patches only one fourth patches were taken for testing and remaining are used to train feed forward neural network. With this trained network, we have classified our test image patches. Confusion matrix of tested image patch classification, by proposed method is shown in Table 2. diagonal elements represents correctly classified patches. In any classification system, there are two major Problems: 1) Less interclass discrimination, 2) Higher variation within the class itself. Same is the case with ILD pattern classification. Normal tissue patterns and patterns with disease micronodule are having somewhat same contrast or gray level distribution. It shows less intra class discrimination.

We can see normal class from Table 2, number of patches misclassified to micronodule pattern are highest amongst total number of misclassified patches of normal tissue pattern. Same is the case with emphysema and micronodule pattern. As seen from Table 2, precision of emphysema pattern decreases as compared with its recall, just because of misclassification taken place with micronodule class. Higher recall in one class automatically contributes to good precision of other classes. We can verify this from Table 2, emphysema pattern having higher recall so as fibrosis and micronodule class having good precision. Overall accuracy of our system is 93.41 %. Fig. 5. Shows graphical representation of comparison between three classifiers. 3-NN gives poor recall but good precision just because of good recall of other classes.

4 Conclusion

In this work, we have classified ILD patterns using patch based approach and feed-forward neural network. Also, we have compared results of proposed method with two classifiers: k -NN and multi class support vector machine. From comparison with different classifiers we can say that well trained feed forward neural network gives good performance. In future, results can be improved by using deep convolutional neural networks.

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