A Systematic Review on Interstitial Lung Disease

Anni U. Gupta
Research scholar, Department of E&TC, UIT-RGPV, Bhopal
Dr. Sarita Singh Bhadauria
Professor, School of Information Technology, RGPV, Bhopal.

Abstract:
The different diseases including interstitial lung diseases (ILD) diagnosis are done with the help of automated tissues characterization. The various types of diseases present in the lungs where few of the may lead to leave the scars. Detected scars may have different pattern. Depending on pattern occurred in the image various features and classifiers are used to categorize the different layers. To diagnosis the diseases done with the help of an efficient classifier are used. This paper, survey for the various researches regarding to the segmentation, feature extraction, classification of the different pattern from the lung images is presented.

Keywords - Automated tissues characterization; interstitial lung diseases.

I Introduction:

An inside view of human body in a noninvasive way provides to clinicians by Medical imaging. Moreover, it provides a more detailed view of the anatomy affected by the disease, enabling a more accurate, rapid diagnosis and precise treatment options. Therefore, medical imaging has become the standard approach to assessing all significant medical conditions and diseases. Interstitial lung disease (ILD) or diffuse parenchymal lung disease (DPLD) is a condition that outcomes in dynamic powerlessness to keep up typical blood oxygen levels because of disabled exchange of gas over the alveolar-slender film [1]. Interstitial lung illness might be brought about by long haul presentation to risky materials, for example, asbestos or coal residue, or it tends to be brought about by an auto-invulnerable sickness, for example, rheumatoid joint inflammation. When lung scarring happens, it's commonly irreversible. Manifestations incorporate a dry hack. Shortness of breath can happen either very still or after effort. Treatment relies upon the fundamental reason however frequently incorporates steroids.

It also causes stiffness in the lung tissues, reduces ability to carry oxygen to blood stream and remove carbon dioxide [2]. However, ILD subtypes have different prognoses and treatments, so a correct diagnosis is essential [3].

Continuously requires a restorative determination, Lab tests or imaging. Chest radiography is typically the main test to recognize interstitial lung illnesses; however the chest radiograph can be ordinary in up to 10% of patients, particularly at an early stage the malady procedure. X-ray is limited in the diagnosis of some diseases due to the superimposition of different structures. Computer aided diagnosis (CAD) of lung CT (computer tomography) image has been a revolutionary step in the early as well as premature detection of lung abnormalities. Now a day's the HRCT (High resolution computer tomography) provides more resolution than the conventional CT chest, allowing the HRCT to elicit details that cannot otherwise be visualized [4]. Other imaging techniques such as positron emission tomography (PET)-CT and magnetic resonance imaging (MRI) may be used. Downsides with these strategies as MRI has a poor signal to noise ratio proportion in the lung and utilization of PET can require an on location cyclotron and radioisotope with short half-life. Imply that they are not generally utilized, and are right now eclipsed by HRCT as the imaging strategy of decision for ILD indicative and prognostic purposes.

The ILD is classified into four clinically distinct groups: (1) ILD of known association (e.g., collagen vascular disease, hypersensitivity pneumonitis secondary to exposures), (2) granulomatous ILD (e.g., sarcoidosis), (3) other rare ILDs (e.g., lymphangioleiomyomatosis, pulmonary Langerhans cell histiocytosis), and (4) idiopathic diseases (idiopathic interstitial pneumonias [IIPs]) [5, 6].

The Fig. 1 shows different ILD patterns. ILD patterns typical in CT images are: reticulation, honeycombing, ground glass opacity (GGO), consolidation and micronodules. Different feature extraction methods are used right from the beginning of ILD classification.

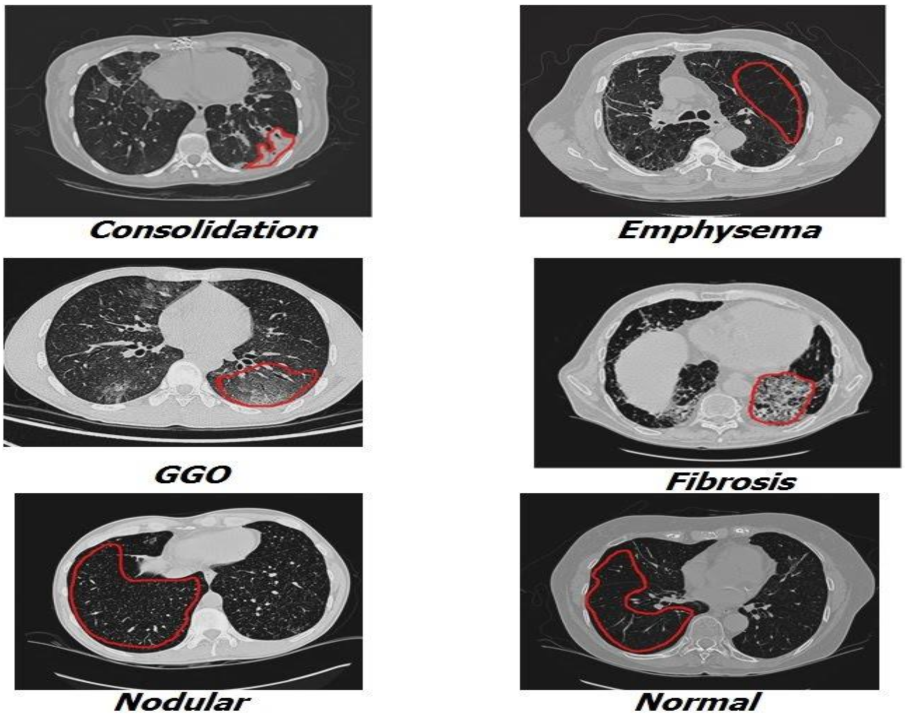

Figure 1: Different ILD patterns

II Methodology:

The overview of the detection of the ILD from the database is shown in the Fig.2

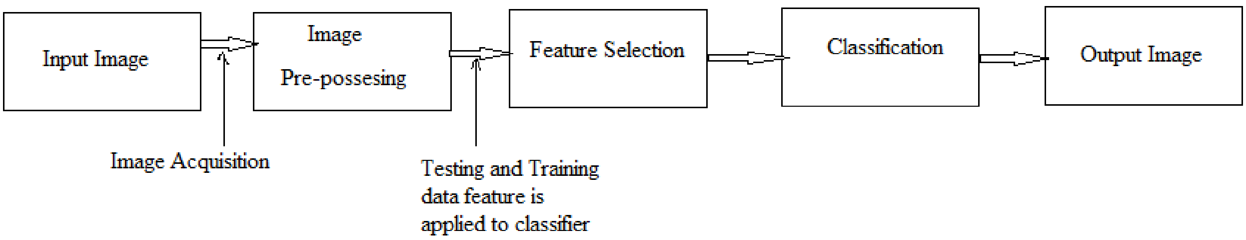

Figure 2: Overview of the detection of the ILD

For performing the classification the test image (input image) having ILD patterns are used. With reference to width and height the rescaling of images is done. Further operations performed on the preprocessed image. Preprocessing is the decisive step of every image processing applications. It is needed to enhance the image generally by removing the noise and adjusting the contrast in it. Firstly, the region of interest selection (ROI) for diagnosis is done. By choosing a rectangular shape this is possible. The feature extractions from the patches formed are done. Next step is the classification section done by using efficient classifier.

III Lung segmentation:

Region of interest (ROI) determine by lung segmentation. The segmentation of lungs is a very challenging problem due to inhomogenities in the lung region, pulmonary structures of similar densities such as arteries, veins, bronchi and bronchioles [7].

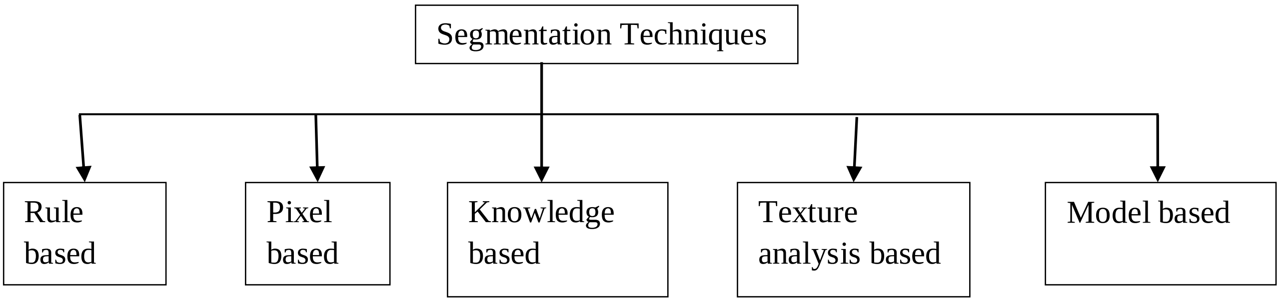

Figure 3: Different types of segmentation techniques

Under the category of rule based approach Region growing, thresholding and component analysis techniques come. Most techniques incorporate edge control as one of the fundamental systems. An investigation that demonstrated the first computerized division which drew much consideration [8]. Different strategies incorporate yet not restricted to watershed method [9], [10] dynamic shapes or snakes [11], graph cut methods [12].

Region growing method projected by [13] works well in presence of noise and can correctly separate the regions having the same properties but it is unreliable in high attenuation patterns like ILD. In [14] developed a thresholding method which selects optimum threshold to separate lung region from background, produces high accuracy and the overall segmentation results are good due to high contrast in attenuation between the foreground and background of CT image. However it cannot detect some normal structures inside the lungs and found to be very complicated for ILD.

As [15], Fuzzy method is used for segmentation which requires less iteration time to converge to global optimal solution but fails to segment images corrupted by noise, outliers and other artifacts.

In case of segmentation by registration method proposed by [16], the pathologies can be easily segmented with better accuracy whereas largest border positioning error may occur and can be applicable to clinical practice only after testing with many scans.

It is found that the model based method works well in the presence of pathological lung due to its lower execution time and increased accuracy. In paper [17] utilized a shape model called dynamic forms or snakes which are independent and self-adjusting as they continued looking for an insignificant vitality and they can be utilized to follow dynamic items in transient just as the spatial measurements. On the other hand snakes can often get stuck in local minima states and requires longer computation time. Later, level set method is introduced by [18] that finds out the object boundaries by means of energy minimization procedures yet develops irregularities during the level set evolution. An automatic scheme of lung segmentation using active contour with distance regularized level set method is proposed [7], has ability to segment the dense tissue patterns occurring even in the lung walls.

IV Methods of Feature extraction:

Visual features of lung tissues can be described numerically in a number of ways. Adaptive Multiple Feature Extraction Method (AMFM) was the initial method used for feature extraction. It includes the methods such as first order gray level statistics as since the intensities well represent the physical properties of lung tissues., Gray Level Co-occurrence Matrices (GLCM), Run Length Matrices (RLM) and fractal analysis [19], [20]. This was followed by wavelet and contourlet transforms to highlight specific image features such as edges., histogram of oriented gradients [21], local binary patterns [22] describes the spatial structure of local image texture, and can be easily configured to be multi-resolution and rotation-invariant. However, the LBP feature might capture too many image details, and introduce large degree of unnecessary feature variations within the same tissue category, bag of word approach [23], [24], [25] and sparse representation models [26], [27], [28] Such element descriptors are exhaustive in removing small image details, but then they give multi-resolution and histogram quantization properties that are particularly valuable for obliging element variety. For extracting the features, Restricted Boltzmann Machine (RBM) a generative fake neural system that catches and repeat the measurable structure of information.

V Methods of classification:

To classify ILD patterns the different classification methods such as, K Nearest Neighbor (KNN), Convolution Neural Network (CNN), Deep Convolution Neural Network (Deep CNN), Support Vector Machine (SVM).

A method adopted by CAD system for classifying the ILD patterns is defined as lung pattern classification. After extracting the features of the input data, next step is to categorize the features. Initially linear discriminant classifier [29] and bayesian classifier [30] were utilized for playing out the characterization. Then artificial neural network (ANN) classification [31] was introduced. It consists of mainly two layers, i.e, input layer and output layer. The test data features are fed to the input layer of ANN classifier. The best possible features are selected from the texton feature selection obtained for the test data. By looking at the test and train information highlights utilizing ANN, the ordered outcome is gotten.

Then next KNN classifier [32] was used for performing the classification. KNN classifier groups the information highlights dependent on closest neighbor data, which is calculated using the distance vector [33]. For distance measurement, Euclidean distance is used. In KNN classification, the output is the class membership. The classification of object is done by majority votes of its neighbors, with the item being allotted to the class most regular among its K closest neighbors.

The steps in KNN classification of ILD patterns are as follows.

• Initially place the train data features and labels obtained in a 2 dimensional space.
• Then clustering or grouping of the train data features are done.
• The test data is then placed on to the same space.
• For obtaining the nearest neighbor information corresponding to test data, calculate the distance of train data vectors to test vectors using Euclidean distance.
The distance calculation is given by d_E (x,y) where the (x,y) is x = {x1, x2,.xN} and y = {y1,y2...yN}. Then, d_E (x,y) = $\sqrt{xi^2-yi^2}$
• Choose the closest distance vector with respect to both test and train data.
• Find the closest distance by voting or averaging the majority of data points. Voting is the method of arranging the data in ascending order (sorting the data points). The orchestrated information is then contrasted with marked prepared information with return the related class. Consequently the grouped outcome is acquired.

SVM was utilized for playing out the arrangement which is a straight grouping strategy utilized for characterizing the two unique classes, trailed by Multiclass Multiple bit learning classifier (m-MKL). It upgrades the mix of highlight space acquired utilizing less number of bits.
Given a few information focuses, each having a place with one of two classes and the objective is to choose to which class another information point have a place. In help vector machines, an information point is seen as an n-dimensional vector, in n-dimensional space Rn and need to know whether separate such focuses with a Canonical plane [34]. At that point arbitrary Random forest classifier [35] was utilized for performing ILD design grouping.

A RF is a combination of decision trees with each tree depending on the values of a randomly sampled feature vector. To classify a new input vector, each tree "votes" for a class and the forest chooses the class having the majority of votes over all the trees in the forest. RFs have been used successfully in numerous machine learning applications yielding classification performances at least comparable to SVM and ANN while being much faster, especially in the prediction phase. But RFs can handle very large numbers of input variables and they are fully parallelizable and easily implemented.

Afterwards, classification performed with CNN [36] that produces more prominent exactness in characterizing ILD designs. Convolutional Neural Networks (CNN) [37] are feed-forward Artificial Neural Network (ANN) similar to biological actions and developed to recognize patterns specifically from pixel images, by integrating feature extraction and categorization. A Convolutional Neural Network (CNN) made up of four layers:
(1) convolutional layer, (2) activation layer, (3) pooling layer and (4) fully-connected layers. A convolutional layer is made up of sparse local connectivity and weight sharing. Every neuron of the layer is linked with a small input. Different neurons respond to different local areas of the input, which merge with each other to get a better representation of the image. Lung image patches are more surface like that have no particular structures, consequently profound layers in CNN would really not perform well on such information. Profound CNN [38] is a changed strategy utilized for playing out the ILD design grouping. Profound CNN comprise of five convolution layers contrasted with four convolution layers of CNN that empowers it to choose the most ideal highlights than CNN.

It comprises of normal pooling layer that down sample the info picture as for width and height. The three completely associated layers (thick layer) will create the arranged outcome. The yield layer is called as softmax layer. This layer thinks about the test and train information highlights to create the grouped yield designs.

Deep CNN delivers more exactness contrasted with all the characterization techniques talked about previously. Among these classifiers, the superiority of SVMs for texture classification. However, because of their simple implementation, Bayesian and nearest-neighbor classification methods are still in use.

Table 1: Different types of classifier

Classifier	Advantages	Disadvantages
CNN	Greater accuracy.	deep layers would actually not perform well on lung images
Deep CNN	More accuracy. It to select the best possible features than CNN	need a lot of training data
k-NN	Gives consistent classification results. Consistency increases with the amount of data.	Finding an optimal value for "k" is challenging. A large dataset is needed.
ANN	Have ability to learn complex input-output relationships, and have low dependence on domain specific knowledge.	Need various parameters to tune classifiers. Computational complexity is high, and overtraining is often inevitable.
SVM	Globally optimal.	Algorithmic complexity is high. Unbalanced training may cause overriding minority class by majority class.

VI Related work:

In this section different recent research is studied and compared along with advantages and disadvantages of method as well as their performance parameters are mention.

In [39] HRCT scan images of ILD and methods Multilayer perceptron, k-nearest neighbor, naïve Bayes, J48 decision trees, and SVM classifier used. Found SVM has better tradeoff between blunder rates and group the superior to anything different classifiers yet the execution isn't made in 3D pictures. Context-sensitive support Vector machine (csSVM) [40] strategy can be connected to multiclass order issues yet increment in computational burden likewise proposed technique connected to 2D image. Author in [41] Automatic segmentation of lung field by Active contour with distance regularized level set method (ACDRLS) proposed which fully automatic segmentation techniques using CAD and performs well in the presence of dense tissue patterns. But the value of sigma is small, the regularized limit of Gaussian smoothing will be feeble thus the estimation of Area Error

Measure (AEM) will be enormous. In [42] CT Scan ILD images used with Convolutional Neural Network (CNN) classifier with highest area under the curve(AUC) and average F-score over the different classes having huge number of parameters and slow training (typically a few hours) Slight fluctuation of the results, for the same input, due to the random initialization of the weights.

In paper [43] Texture patterns included ground-glass opacity (GGO), reticulation and consolidation DECT (dual-energy CT) joined with example examination is helpful for breaking down DILD (Diffuse interstitial lung disease) and anticipating survival by arrangement of morphology and upgrade. Patients with definite Honeycombing findings of typical IPF/UIP who did not need to undergo surgical biopsy were not included in the study. In [44] used texture image with multi-resolutional feature-based CBIR (Content Based Image Retrieval) system method proposed. The proposed highlight extraction strategy is turn invariant, and the highlights are removed from the most extreme recorded square inside the region of interest (ROI), but the invariant to orientation of the texture and shape of the ROI limitation of proposed method.

As ultrasound wave is reflected from the lung surface in view of the air inside the lung tissue, in paper [45] ultrasound imaging used and proposed noninvasive lung ultrasound surface wave elastography (LUSWE) technique. Proposed method is a safe and noninvasive technique for generating and measuring surface wave propagation on the lung. Confinement of technique difficult to straightforwardly apply a vibration excitation on the lung surface and measure surface wave velocities of the lung. Author applied support vector machine (SVM)[46] method on HRCT images .The result is compared with the existing method and this provides the better result, also helps for supporting decision for clinical. CAD-based system proposed in [47] applied on HRCT scans images with 3D processing, gives a more accurate lung volume helpful for diagnostic and analytic Purposes. Method is only applied to the little dataset. 3D performance evaluation from global Database still required. Ensemble classifiers in [48] applied on HRCT images, ensemble classifiers such as bagging and stacking performed better than the individual classifiers in both the ROI-based classification and whole lung quantification, but technique is not applied to the 3D volumetric images, which provides the more information about diseases. [49]CT image of lungs classified with ANN, KNN and Deep CNN, Hybrid kernel based SVM. The proposed Hybrid kernel based SVM classification produces more performance in ILD pattern classification compared to all other classification methods. This method is done with the approximately equal number of image patches for training and testing sets, if the training is set low and testing is set high then the accuracy is reduced.

High Resolution Computed Tomography images in [50] independently reclassified by idiopathic interstitial pneumonia the correlation relation between the reticulation, traction bronchiectasis and architectural distortion to the decrease survival. This method is only applied to the little dataset. In [51] CNN and Support Vector Machine (SVM) method applied on CT scan images. CNN gives more accuracy for ILD Detection and CT images are resized in fix size, classify 2D lung images. Convolutional Neural Network (CNN) [37] Proper lung images classification applied on HRCT scan images No need of a dangerous biopsies. It is an invasive method so easy or simple for patients Provide a reliable diagnosis three- dimensional images of the CT scans. ILD database HRCT images classified with Radial Basis Function (RBF) Support Vector Machines (SVMs) [52] provide the better accuracy due to different patch selection and evaluation method.

In [53] new programmed division calculation of lung areas. It acquires the ideal edge an incentive by utilizing the iterative techniques which have diminished the impact that limit determination to the split. In every CT cut, evacuate the foundation impedance and acquire the lung district limit by utilizing the limit following calculation. At long last fix the lung district limit by utilizing the numerical morphology technique. The investigation demonstrates that the programmed division calculation can dispose of the foundation obstruction and the impedance of the trachea bronchus inside the chest. [54] Give a basic examination of the present methodologies to lung division on CT images to help clinicians in settling on better choices when choosing the instruments for lung field division. Partitioned the lung field division strategies into general classifications, with an outline of relative points of interest and disservices of the techniques having a place with each gathering.

In paper[55] gives information that are inferred from an enormous tentatively enlisted partner appearing that age, kind of ILD, BALF and physiologic discoveries in the five most basic types of ILD impact anticipation.[56] The exploration centers on the division of the reticular example on the contaminated area dependent on the evaluations given by the ILD scoring file; grade 0 - missing, grade 1 – fine intralobular fibrosis prevailing, grade 2 – microcystic design with airspace under 3mm in width, and grade 3 – bigger growths 3-6mm in distance across also examined the two division strategies, watershed division calculation and Fuzzy C-Means (FCM). The investigation demonstrates that the two techniques ready to section the reticular example for grade 2 and grade 3 of the ailment. FCM yielded better outcome contrasted with the watershed in term of having higher exactness of sore location and less over-sectioned area.

A completely programmed plan for surface examination of lung fields in chest radiographs in [57]. The technique depends on surface examination on nearby areas in the picture, which are divided consequently. Highlights are extricated from histograms of the reactions of a multi-scale channel bank. Every district is prepared autonomously with an alternate - NN classifier. The outcomes recommend that this strategy might be useful to radiologists for perusing mass chest screening pictures.[58] Utilizing the GMLVQ calculation, the pertinence of surface highlights was evaluated in their capacity to arrange sound and sick lung designs in chest CT pictures. In test with genuine world information, the capabilities chosen by the GMLVQ approach had a fundamentally better order execution contrasted and include sets chosen by a common data positioning. This approach estimates the importance of single highlights.

Below Table 1, gives the summary of various recent work related to ILD.

Table 2: Comparison of different methods

Author	Input image	Method	Advantage	Limitation	Performance Parameter
Ranveer Joyseeree, et.al.© 2018 Elsevier Ltd	ILD database HRCT	Radial Basis Function (RBF) Support Vector Machines (SVMs)	Provide the better accuracy due to different patch selection and evaluation method.	The misclassification of the pattern occurs in the annotated area and causes to reduce in accuracy	Multicast tissue classification accuracy = 80.31 %.

Namrata Bondfale,et.al. ©2018 IEEE	HRCT scans	Convolutional Neural Network (CNN)	Proper lung images classification No need of a dangerous biopsies It is a invasive method so easy or simple for patients Provide a reliable diagnosis	three- dimensional images of the CT scans	accuracy of 0.82
Pratiksha Hattikatti ©2017 IEEE	CT Scan Images	CNN and Support Vector Machine (SVM)	CNN gives more accuracy for ILD Detection	CT images are resized in fix size ,classify 2D lung images	CNN accuracy =94% SVM accuracy = 86%
Hanna M. Nurmia, et.al.© 2017 Elsevier Ltd	High Resolution Computed Tomography	Independently reclassified by idiopathic interstitial pneumonia	the correlation relation between the reticulation, traction bronchiectasis and architectural distortion to the decrease survival	This method is only applied to the little dataset.	Hazard ration GGO=1.079 Reticulation=1.144 Traction bronchiectasis=1.184 Architectural distortion=1.094
Ajin M, Mredhula L,© 2017 Elsevier B.V	CT image of lungs	ANN, KNN and Deep CNN, Hybrid kernel based SVM	Hybrid kernel based SVM classification produces more performance in ILD pattern classification compared to all other classification methods.	This method is done with the approximately equal number of image patches for training and testing sets, if the training is setlow and testing is set high then the accuracy is reduced.	confusion matrix, recall rate, precision, Faverage and accuracy ANN=57.5% KNN=72.94% Deep CNN=84.14% Hybrid kernel based SVM=90.52%
Sanghoon Jun,et.al.© Society for Imaging Informatics in Medicine 2017	HRCT images	ensemble classifiers	ensemble classifiers such as bagging and stacking performed better than the individual classifiers in both the ROI-based classification and whole lung quantification	This technique is not applied to the 3D volumetric images, which provides the more information about diseases	SVM=0.62, NB = 0.54, RF = 0.58
SangHoon Jun, et.al.© Society for Imaging Informatics in Medicine 2017	HRCT image	support vector machine (SVM)	The result is compared with the existing method and this provides the better result, also helps for supporting decision for clinical	This methods categorized into two diseases	Average accuracy = 81 %
Xiaoming Zhang, et.al.©2017 IEEE	ultrasound imaging	noninvasive lung ultrasound surface wave elastography (LUSWE) technique	Proposed a safe and noninvasive technique for generating and measuring surface wave propagation on the lung.	impossible to directly apply a vibration excitation on the lung surface	surface wave speeds of the lung were 3.30 ± 0.37 m/s at 100 Hz, 4.38 ± 0.33 m/s at 150 Hz, and 5.24 ± 0.44 m/s at 200 Hz

Rahul Das Gupta, et.al.©2016 IEEE	texture image	multi-resolutional feature-based CBIR(Content Based Image Retrieval) system	proposed feature extraction technique is rotation-invariant, and the features are extracted from the maximum-inscribed square inside the region of interest (ROI),	invariant to orientation of the texture and shape of the ROI	individual component intensity (I)+gradient magnitude(GM) +gradient direction(GD)= Average precision (%) ±StandardDeviation=73.40±8.55
Jung Won Moon et.al.© European Society of Radiology 2016	CT image	Texture patterns included ground-glass opacity (GGO), reticulation and consolidation	DECT(dual-energy CT) combined with pattern analysis is useful for analysing DILD(Diffuse interstitial lung disease) and predicting survival by provision of morphology and enhancement	Patients with definite Honeycombing findings of typical IPF/UIP who did not need to undergo surgical biopsy were not included in the study	Overall accuracy = 90.47 %for combined 2D and 3D features
M. R. Daniya Raj et.al. ©2014 IEEE	CT Images	automatic segmentation of lung field by Active contour with distance regularized level set method(ACDRLS)	fully automatic segmentation techniques using CAD performs well in the presence of dense tissue patterns	the value of sigma is small, the regularized capacity of gaussian smoothing will be weak and so the value of Area Error Measure(AEM) will be large which results in noisy segmentation results	parameters timestep=1, sigma=0.8 and u=0.2.
Marios Anthimopoulos et.al. (c) 2015 IEEE	CT Scan Images	Convolutional Neural Network (CNN)	highest area under the curve(AUC) average F-score over the different classes	large number of parameters and slow training (typically a few hours) Slight fluctuation of the results, for the same input, due to the random initialization of the weights.	Favg= 0.8547 Accuracy=0.8561
Chuen Rue Ng et.al.©2017 IEEE	HRCT scans	CAD-based system	3D processing . Gives a more accurate lung volume helpful for diagnostic and analytic Purposes	method is only applied to the little dataset. 3D performance evaluation from global Database required	similarity Coefficient = 98.32%
Namkug Kim et.al.Journal of Digital Imaging · Feb. 2011	HRCT	context-sensitive support Vector machine (csSVM)	method can be applied to multiclass classification problems	increase in computational load ,proposed method applied to 2D image	Accuracy 60.30±13.95%
Adrien Depeursinge et.al.Journal of Digital Imaging Feb.2010	HRCT scans	Multilayer perceptron, k-nearest neighbour, naive Bayes, J48 decision trees, and SVM.	SVM has better tradeoff between error rate and classify the better than other classifiers.	implementation is not made in 3D images.	Accuracy, SVM = 0.8907, Naive Bayes = 0.3778, J48 = 0.7555

Conclusion:

ILD is a method to diagnosis the group of lung disease affecting the tissues, if it is not properly diagnosed it may lead to the severe disease. It difficult for diagnosis the diseases even by the experienced physicians because these kinds of diseases have the similar clinical manifestation with each other making. Many researches are processed in the classification of the diseases. In this paper, the different research for the sorting of the ILD images. ANN is initially used for performing classification. Then KNN classification of ILD patterns are done and it produces more accuracy compared to It is with ANN classification Also the deep CNN and kernel based SVM provides the better classification result compared to the other classifiers. The different research is studied and compared with advantages and limitation with performance parameter of method discussed. Most of the work done on HRCT scan images. There are lots of databases is available for the ILD and some of them are available freely also.

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