

Deep Learning for the identification of Interstitial Lung Diseases

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Abstract: The Computer Aided Diagnosis(CAD) system for Interstitial Lung Diseases(ILD) have been proposed to aiming to enhance the accuracy of diagnosis of ILDs by physician because automatic tissue characterization is a crucial component of CAD system. To raise the quality of medical image analysis for the classification of patterns of lung present the concept of Deep Convolutional Neural Network(CNN).CNN designed for the classification of Interstitial lung diseases, consist of five convolutional layers with 2×2 kernels and LeakyReLU activation functions. The CNN use the Adam optimizer algorithm for the classification of ILD patterns. Experimental results prove superior performance and efficiency of the proposed approach through the comparative analysis of CNN against previous methods.

Keywords: Interstitial Lung Diseases, Convolutional Neural Network, texture classification.

I. Introduction

Interstitial lung disease refers to a group of more than 200 chronic lung disorders which frequently leads to pulmonary fibrosis, which finally leads to permanent loss of ability to breathe.ILD textural patterns in lung CT scan are:reticulation,honeycombing,ground glass opacity(GGO),consolidation and micronodules.The diagnosis of ILD is conducted on CAD with increase in diagnostic accuracy by radiologist, CT scan analysis consist of three stages:(a)lung segmentation refer to identification of lung border.(b)lung disease quantification refer to detection and identification of the tissue abnormalities and its estimation of extent in lung.(c)Differential diagnosis combines results to suggest the differential diagnosis. Optimal treatment and prognosis of ILD depend on accurate diagnosis.

II. Existing SYSTEM

The CAD system for ILD pattern classification consist mainly two major stages: (a) lung segmentation and (b) lung pattern quantification. At the first stage extricate the lung borders and in second the ILD pathologies are identified by classifying local image patches. A variety of methods have been proposed for the identification of patches and classification techniques for understanding the recognized data.

The first approach uses the already established statistical tools for the description of lung tissue mainly 1st order statistics, grey live occurrence matrices (GLCM), run length matrices and fractal analysis. These all are together called AMFM.It was proposed by Uppaluri et al [1].

K.R.Heitmann et.al implemented neural networks and experts' rules for the detection of ground glass opacities on HRCT.A hybrid network with three single nets and expert rule was designed for the detection of GG on this study [2].

ATS (American Thoracic Society) and ERS (European Respiratory Society) published a consensus classification which integrates clinical, radiological and pathological definition and classification of whole group of IIP (Idiopathic Interstitial Pneumonias [3].Y.Xu et.al developed a computer aided detection tool which characterize ILD patterns with the help of volumetric features in MDCT image, which mainly used the Bayesian and SVM classifier [4].

Panayiotis D Korfiatis studied an automated method for volumetric quantification of interstitial pneumonia patterns using a multidetector CT(MDCT) dataset.3D automated grey level thresholding with edge highlighting wavelet preprocessing is used for lung classification and vessel tree volume is defined. Then classification is based on 3-class pattern classification of LP [5].A Textron based classification system based on raw pixel representation with radial basis function kernel is proposed by Mardad.J.Ganesh for the classification of emphysema in CT images of lung [6].

Rui Xu developed a bag of words based method for the classification of textural patterns of lungs. This approach depends on CT values and egen values of Hessain matrices [7].Adrien Depeursinge proposed a near-affine-invariant texture descriptors derived from isotropic wavelet frames for the classification of lung tissue pattern [8].

Feature based images patch approximation technique is evaluated by Yang Song for lung tissue classification. It used Rotation Invariant Gabor Local Binary Patterns (RGLBP) texture descriptor and Multi-Coordinate Histogram of Oriented Gradient (MCHOG) gradient descriptor along with Patch Adaptive Sparse Approximation (PASA) for classification [9].

W.Zhao et.al introduced a sparse representation method to classify normal tissue and five types of DLD (Diffuse Lung Disease) patterns. This model composed of dictionary learning, sparse coding and spatial pooling steps [10].Qing Li created a multiscale feature extractors based on unsupervised learning algorithm, obtain the image feature vectors for the classification of lung patterns for ILD [11].

A Restricted Boltzmann Machines (RBMS) is developed Gijis Van Talder for texture based tissue classification. A combination of convolutional classification RBM and classification RBM for feature learning and classification [12].Mingchen Gao presented an algorithm for lung pattern classification which uses the entire image as holistic input [13].

III. Proposed System

Convolutional Neural Networks are feed forward Artificial Neural Network (ANN) which are inspired by the biological events and developed to identify patterns from pixel images directly by integrating feature extraction and classification. In this paper, propose deep CNN for the classification of ILD patterns.CT images of ILD patterns are distinguished by local textural features.ILD textural Patterns in lung CT scan are: reticulation, honeycombing, Ground Glass Opacity (GGO), consolidation and micro nodules.

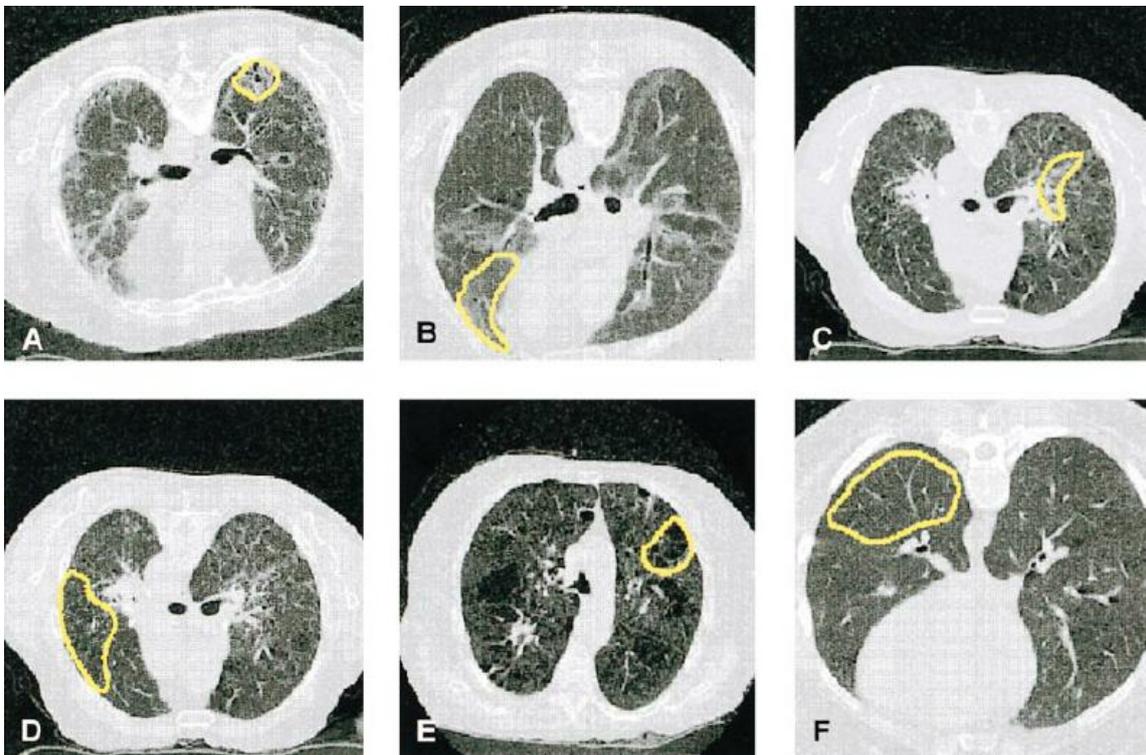


Figure 1: Examples of healthy tissue and ILD patterns [14]

Architecture:CNN architecture consist of five convolutional layers ,where a 32×32 image patch is the input of the network is a minimized size of 2×2 kernels are used at each kernel. The rectangular field size 2×2 for 1^{st} layer and it is increased by 1 in each layer added, focused to an area of $(L+1)2$ for L th layer and kernel developed will be $K (L+1)2$. Average pooling layer has size equal to output of the last convolutional layer. The features obtained will shed to 3 dense layers which will increase the convergence. The dropout layer includes will solves over fitting problem and it includes dense layer.

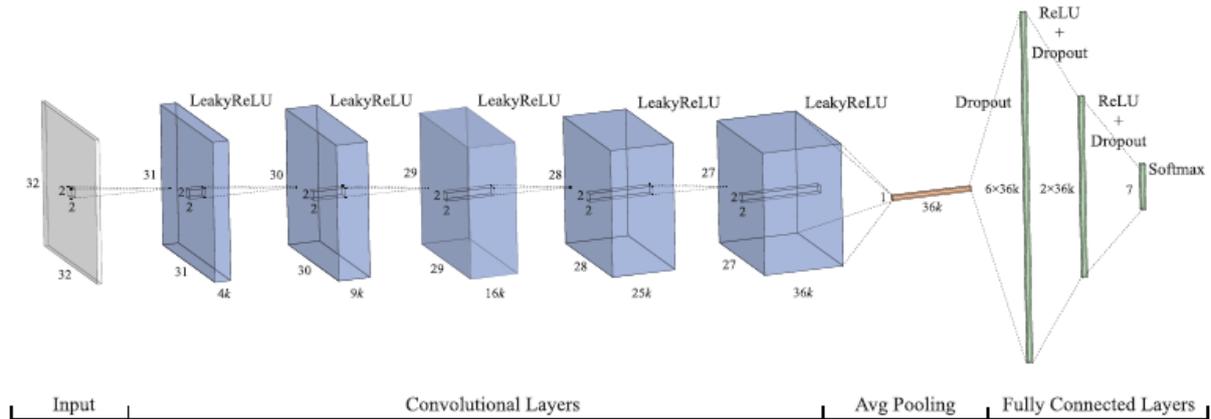


Figure 2: Architecture of proposed CNN [15]

Activation Functions: A variant of ReLU, Leaky ReLU is used for activating each convolutional layer and LeakyReLU assigns a non-zero slope. The activation function can be represented.

$$F(x) = \begin{cases} x, & x > 0 \\ \alpha, & \text{else} \end{cases}$$

Where α is manually set co-efficient. To improve the performance the value of α increased from 0.01 to 0.3. The training objective and an optimization algorithm components are used at the training stage of an ANN. Here we use the Adam first order gradient based algorithm which developed for optimization of stochastic objective functions will minimize the categorical cross entropy. These are three variable quantities used along with Adam: learning rate, exponential decay rates of average of gradient and squared gradient. Initialization of convolutional layer begins with the use of orthogonal matrices multiplied with a scaling parameter. In validation set, performance of the system evaluated on test set. Average F-score method is used due to its increased sensitivity and accuracy.

IV. Conclusion

A deep CNN is proposed for the classification of lung images into 7 classes consists of 6 ILD patterns and the healthy tissue. The put forward CNN is based on 5 convolutional layers having 2×2 kernels and Leaky ReLU activation functions with the inclusion of a pooling layer and dense layer. This system is implemented with the Adam optimizer algorithm, which minimizes the categorical cross entropy. This procedure can be easily trained on textural lung patterns by improving its performance by enhancing the properties of the used parameters.

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