JCSE International Journal of Computer Sciences and Engineering Open Access

Research Paper Volume-5, Issue-11 E-ISSN: 2347-2693

A Deep Learning Approach For the Detection and Classification of Interstitial Lung Diseases Using Convolutional Neural Network

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Available online at: www.ijcseonline.org

Received: 02/Oct/2017, Revised: 15/Oct/2017, Accepted: 10/Nov/2017, Published: 30/Nov/2017

***Abstract*—** Interstitial Lung Diseases (ILD) effects the lung intestitium part will leads to breathing problems and gradually leads to death. A deep learning technique convolutional neural network have been proposed to aid computer aided diagnosis system which enhances the accuracy of diagnosis of ILDs by physician because automatic tissue characterization is a crucial component of CAD system. Deep Convolutional Neural Network (CNN) concept raise the accuracy of medical image analysis for the lung pattern classification.CNN designed for the interstitial lung diseases, consist of five convolutional layers with 2×2 kernels and LeakyReLU activation functions. The CNN use the Adaptive moment estimation optimizer algorithm as a weight updation mechanism in back propagation a process. Experimental results prove superior performance and efficiency of the proposed approach through the comparative analysis of CNN against previous methods.

***Keywords*—** Convolutional Neural Network, Computer Aided Diagnosis, Interstitial Lung Diseases, 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 breathing.ILD'pattern's:reticulation,honeycombing,ground glassopacity(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. Since interstitial lung disease can caused due to several different lung patterns it is difficult for physicians to diagnose the cause of such diseases. As a computer aided diagnosis method the convolutional neural network will aid the doctors to detect interstitial lung diseases more effectively and its early detection is also possible.

The term interstitial lung disease (ILD) refers to a group of more than 200 chronic lung disorders characterized by inflammation of the lung tissue, which often leads to pulmonary fibrosis. Fibrosis may progressively cause lung abnormalities and, reducing the ability of the air sacs to capture and carry oxygen into the bloodstream and eventually leads to permanent loss of the breathing ability. ILDs are the main reason for all cases seen by pulmonologists and can be caused by autoimmune diseases, genetic abnormalities and long-term exposures to non-organic materials. However, the cause of ILDs is mostly unknown and the lung abnormalities mainly described as idiopathic interstitial pneumonia (IIP). The diagnosis of an ILD involves questioning the patient about their clinical history, a thorough physical examination, pulmonary function testing, a chest X-ray and a CT scan. High resolution computed tomography (HRCT) is generally considered to be the most appropriate for the disease detection because of its specific radiation attenuation properties of the lung tissue. The imaging data are interpreted by assessing the extent and distribution of the various ILD textural patterns in the lung CT scan. Typical ILD patterns in CT images are: reticulation, honeycombing, ground glass opacity (GGO), consolidation and micro nodules (Figure.1).

II. RELATED WORK

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

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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 pre-processing 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].

III. METHODOLOGY

This study uses dataset from Swiss university hospital. This section describes the details of data used and the design of convolutional neural network along with the desired output.

DATA

The dataset used for training and evaluating the system was made using the databases of ILD CT scans from a Swiss university hospital: the publicly available multimedia database [16] of ILDs from the University Hospital of Geneva, consists of 109 HRCT scans of different ILD cases. 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.

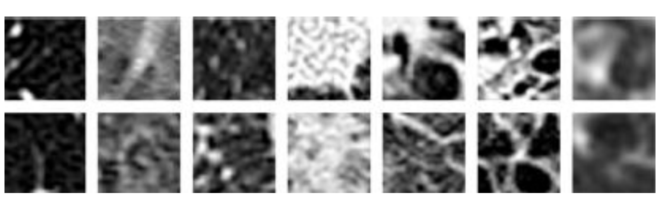

Figure1: healthy, GGO, micro nodules, consolidation, reticulation, honeycombing, combination of GGO and reticulation.

*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 1st layer and it is increased by 1 in each layer added, focused to an area of (L+1)2 for Lth layer and kernel developed will be K (L+1)2. Average pooling layer has size equal to output of the last convolutional layer (figure2). 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.

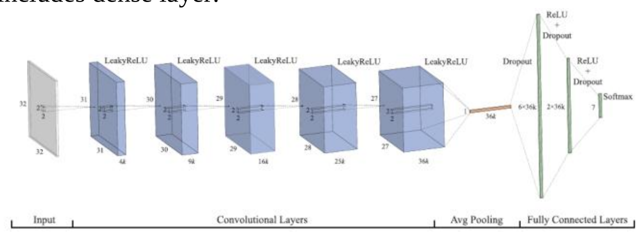

Figure 2: Architecture of proposed CNN

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 as,

$$|f(x)| = \begin{cases} x, & x > 0 \\ ax, & else \end{cases}$$

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 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 squad 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.

Adaptive Moment estimation Algorithm (Adam): Adam involves the following steps:

Step 1.Compute the gradient and its element-wise square using the current parameters.
Step 2.Update the exponential moving average of the 1st-order moment and the 2nd-order moment.
Step3.Compute an unbiased average of the 1st-order moment and 2nd-order moment.

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Step 4.Compute weight update: 1st-order moment unbiased average divided by the square root of 2nd-order moment unbiased average (and scale by learning rate).
Step 5.Apply update to the weights.

Adam involves 3 parameters: the learning rate, the decay rate of 1st-order moment, and the decay rate of 2nd-order moment. It can be view from the paper that the final weight update is approximately bounded by the learning rate that makes it relatively easier to choose the scale of the learning rate, especially in some scenarios where the region of optimal solution can be estimated in advance. The exponential moving average is biased towards zero when starting from zero, so it is divided by a term based on the decay rate to get an unbiased estimate.

IV. Results and Discussion

In this section, presents the results of the performed experiments, and analyse the performance of the proposed method.

The evaluation of interstitial lung disease is done on different ild pattern images obtained from databases of ILD CT scans from the University Hospital of Geneva which consists of 109 HRCT scans of different ILD cases with 512×512 pixels per slice. The classification and detection process is did on established CNN structure. The training process was carried out on the training set and overall performance is assessed on test test.The input of the system is a grey level image from ILD dataset.
This section presents the results for the proposed deep convolutional neural network system based classification system using Adaptive moment estimation algorithm with the parameters chosen as explained in previous section. The input given to the cnn architecture will be a grey level image from the ILD dataset which will be an interstitial lung disease pattern used to train the convolutional neural network for obtain better results from cnn for detection and classification of interstitial lung diseases.

After the preprocessing stage of the given input image obtain the dilated and binary image corresponding to the given input. The convolutional neural network will detect the disease affected areas in the interstitium part of lung based on the trained values and also recognize the pattern of lung interstitium which cause interstitial lung disease so that a radiologist can diagnose the disease.

The training state graph (fig.3) shows the variations in the gradient factor with respect to the number of iterations (epoch) taken by the neural network during training process. Thus we can analyse at which time the gradient factor shows minimum value and this graph also plot the validation fail conditions for each epoch. It varies on epoch based on its gradient value.

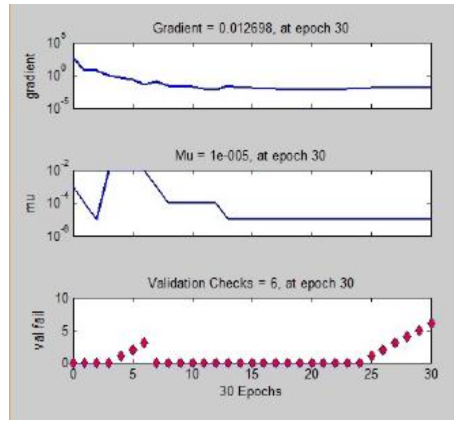

Figure 3: Training state graph

The plotted performance graph (fig.4) shows the performance of the proposed method. The graph plot error value on y axis against x axis which plots the number of epoch and shows the best performance at corresponding epoch.

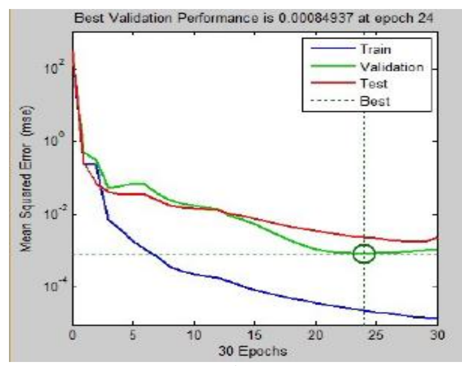

Figure 4: Performance graph

V. 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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