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Detection and Identification of Lung Tissue Pattern in Interstitial Lung Diseases using Convolutional Neural Network

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ABSTRACT

Automatic tissue classification is most critical parts of computer aided diagnosis (CAD) system for interstitial lung diseases (ILDs). In computer aided diagnosis, Deep learning strategies offers good results in computer vision problems such as analysis of medical picture. In this paper, we plan and develop a convolutional neural network (CNN) for the categorization of interstitial lung disease (ILD) patterns. The proposed system contains 5 convolutional layers, followed by two fully connected layers. The final layer has different outputs, corresponding to the classes of ILDs like healthy, micronodules, reticulation, honeycombing and ground glass opacity (GGO) etc. We used a dataset of 100 HRCT scans to train the system and evaluation of it. In future, we will extend CNN to three-dimensional data (information) and integrating the proposed system into CAD framework so that differential diagnosis for ILDs will be easier for radiologists.

I. INTRODUCTION

Lung is a vital organ for breathing. Lung Diseases refers to failure of proper lung functions. Interstitial Lung Diseases are ordinary and it is frequently referred as irritation, swelling of lung tissue. It refers to a group of more than 150 lung diseases. It causes lung stiffness and reduces ability of lung tissues to capture and carry oxygen to bloodstream. This may cause permanent failure of air sucking ability of lung. Interstitial Lung Diseases can be cause due to genetic abnormalities, long term exposure to the death-defying materials and in some cases due to autoimmune diseases. Diagnosis of Interstitial Lung Diseases (ILDs) is a long process which consists physical inspection, inquiring patient about their medical history, a x-ray test of chest , a CT scanning of chest and in some critical cases a surgical biopsy. Most appropriate tool for ILD diagnosis High Resolution Computed Tomography (HRCT). To avoid dangerous clinical biopsies, Computed Aided Diagnosis is more useful and it also increases the accuracy of diagnosis. A CAD system includes three stages: (a) lung border identification (b) Abnormalities detection and identification and (c) differential diagnosis. Here we focus on detection and identification of lung tissue abnormalities. Figure 1 shows some examples of ILD tissue patterns like Micronobules, Normal, Ground Glass Opacity (GGO), Honeycombing, Reticulation etc. Each highlighted area is labeled as one of the ILD patterns

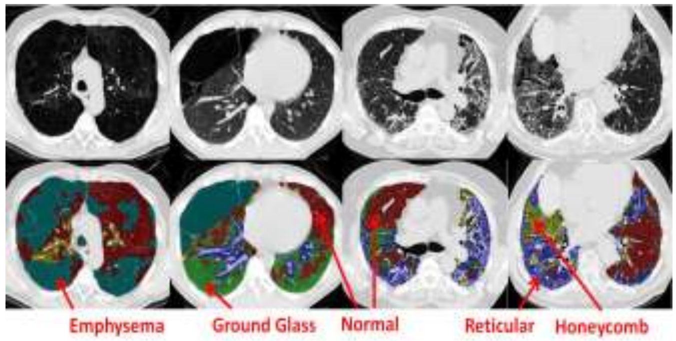

Figure 1: Examples of ILD patterns.

II. LITERATURE REVIEW

In this section we will have an overview of the previous studies on tissue pattern classification of Interstitial Lung Diseases (ILDs), we will also have an outline of the past reviews convolution neural network (CNN), which are used in the proposed study.

A. Tissue Pattern Classification in Interstitial Lung Disease (ILD)

Interstitial Lung Diseases (ILDs) are mainly referred as textural variations in the lung parenchyma i.e. variations in the lung tissues. Therefore main aim of our proposed system is texture classification on region of interest (ROIs). The primary attributes of such a framework are the interested region set and the classification strategy. The first CAD frameworks for ILDs had established feature extraction methods to represent 2D surface, for example, run-length networks (RLM), fractal examination, gray level co-occurrence matrices(GLCM) and first order gray level statistics [1].These characters were later combined and called as the adaptive multiple feature method (AMFM) [6].

In some technique, a arrangement of texture atoms is recognized by using k-means and k-SVD, on described interested tissue patches. The resulting set of Textron’s i.e. texture atom constitutes a issue-specific dictionary and every local structure in the image is represented by the closest Textron or a linear combination of the entire set. Restricted Boltzmann machine (RBM) is used for extracting learned features. RBMs are generative artificial neural networks (ANNs) that are able to capture and reproduce the statistical structure of the input and were utilized in [9] for learning multi-scale filters with their responses as the features. A few activities have been made to utilize deep learning (DL) procedures and mostly CNNs, after their remarkable performance in colour image characterization [3]. Dissimilar to other learning methods that build information representation models in an unsupervised way, CNNs learn elements and prepare an ANN classifier, by limiting the classification error. Despite the fact that deep learning uses numerous sequential learning layers, the primary activities on lung CT pictures received shallow structures.

B. Convolutional Neural Networks(CNN)

CNNs means Convolutional Neural Networks which are feed-forward ANN i.e. Artificial Neural Network encouraged by biological actions and intended to recognize designs specifically from pixel images, by integrating both feature extraction and classification. A Convolutional Neural Network (CNN) consists of four layers: convolutional, activation, pooling and fully-connected layers. A convolutional layer is described by sparse local connectivity and weight sharing. Every neuron of the layer is linked with a small the input, which look like the receptive field in the human visual system. Different neurons respond to different local areas of the input, which merge with each other to get a better representation of the image. Although the concept of CNNs has existed for decades, training such deep networks with multiple stacked layers was accomplished just as of late. This is mainly due to their extensive parallelization properties, which have been coupled with massively parallel GPUs, the huge amounts of available data, and several design tricks, such as the rectified linear activation units (ReLU). In this paper, we propose a CNN for the classification of ILD patterns that uses the descriptive potential of neural networks. The technique has assessed on a dataset from local radiology center.

III. METHODS

In this section, we are going to see the actual framework, algorithm used for the identification and classification of ILDs tissues pattern. A network with good efficiency and performance is chosen for this application. It contains 5 convolutional layers, trailed by two fully connected (FC) layers and at last a softmax layer. We had modified it according to our application i.e. for detecting and classifying ILDs tissue patterns, as shown in Figure 2.

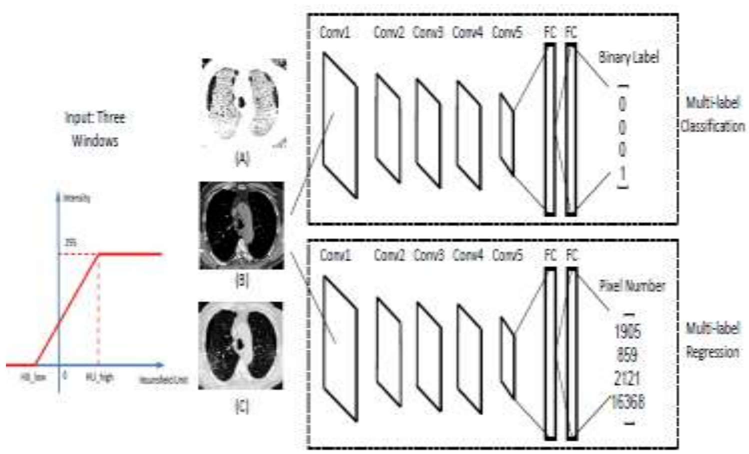

Figure 2: Multi-label CNN models

As shown in above Figure 2, the input image is a RGB image so it is converted into Gray image. After doing some preprocessing steps it is given to the Convolutional Network. There are 5 Convolutional layers trailed by 2 fully connected layers. The output of FC i.e. Fully Connected layers may be in binary label for Multi-label Classification or in pixel number for Multi-label Regression.

A. Database

The database used for the processing of this proposed system is taken by the local radiology center. It consists of 100 HRCT scans of the different patients. The database was studied by experienced radiologists by drawing polygons around some frequently appearing ILD pattern. Some of those are reticulation, GGO(ground glass opacity), micronobules honeycombing, etc.

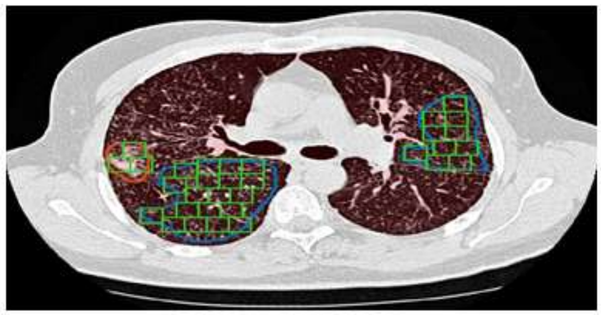

Figure 3: Example of generating image patches through a CT slice.

B. Flowchart

Tissue pattern detection we are doing with MATLAB software. The flow chart of the system is as shown in figure 4. In this Input image is taken from the dataset. These input images are produced by scanning of the HRCT scan images. The scans were produced by different CT scanners with slightly different pixel spacing so a pre-processing steps are needed applied.

There are two phases, first one is Training and second one is Testing. As we are using CNN so our machine or application need to be trained, so Training is important and done first. In Testing phase the input data is tested with respect to the database which is already trained. In Training phase there are four steps are involved: (a) Pre-processing, (b) Segmentation, (c) Feature Extraction and (d) Storing the data to database. Testing phase includes three steps as follows: (a) Pre-processing, (b) Segmentation, (c) Feature Extraction. In Training phase the image data is first pre-processed, means if the size of the image is larger beyond the memory of the classifier then that image is utilized partially. So here input image which is RGB scaled is converted into Gray scale. After that we have to resize that image depend on the input data. There are the very high resolution data so the image size is very much large so we have to collect all the input data in one fixed size, so resizing is important. Image segmentation is the procedure of partitioning a digital image into various segments. Segmentation is nothing but finding out the border or outline of the image. Segmentation is done to simplify the representation of an image to analyse easily. In feature extraction step, the textural information is used so that we can identify the ILDs tissue pattern. After this three steps all the input HRCT scans are stored as a database. In Testing phase input image is pre-processed, segmented and features are extracted and then it is given to the Convolutional Neural Network. According to the extracted feature and its CNN operation we can classify the ILDs tissue for differential diagnosis.

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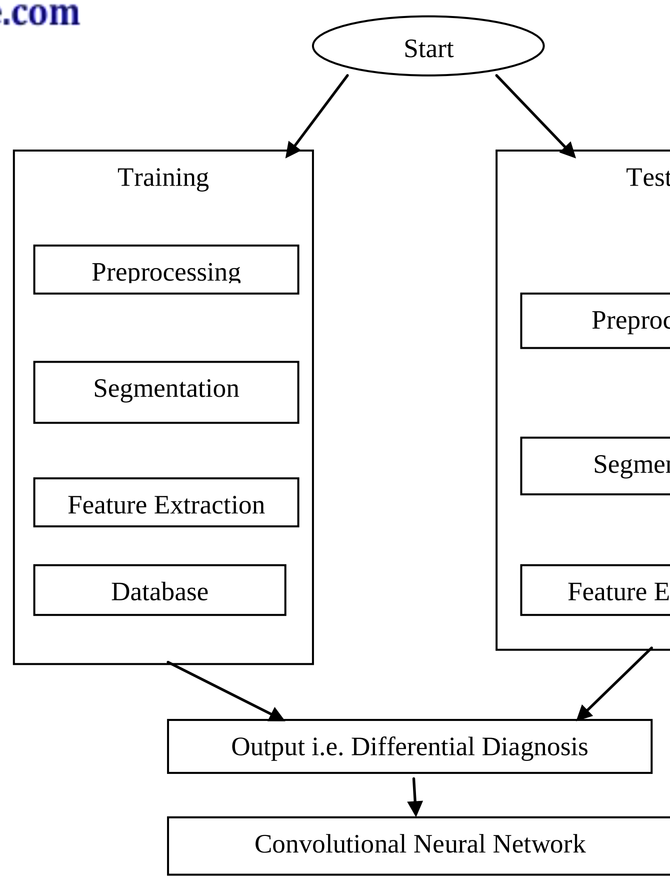

Figure 4: Flowchart

IV. RESULT

In this section, we are going to see the results obtained by the system. Here we are showing the screenshots of the system developed. Firstly we have to train our CNN system, so after clicking on "Training" button system will be trained and ready to classify the lung tissue patterns. After clicking "Browse Image" we can browse and take image as input. In Preprocessing, we are resizing an input image. After resizing, we are enhancing our input image. In segmentation, we will apply thresholding, inversion, masking. After all these three steps we get segmented lung area and ROI i.e. region of interest. We extract the texture of tissue by using LBP (Local Binary Pattern). After clicking on Estimation, we will get the differential diagnosis of the lung tissue pattern.

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Figure 5: Training CNN system

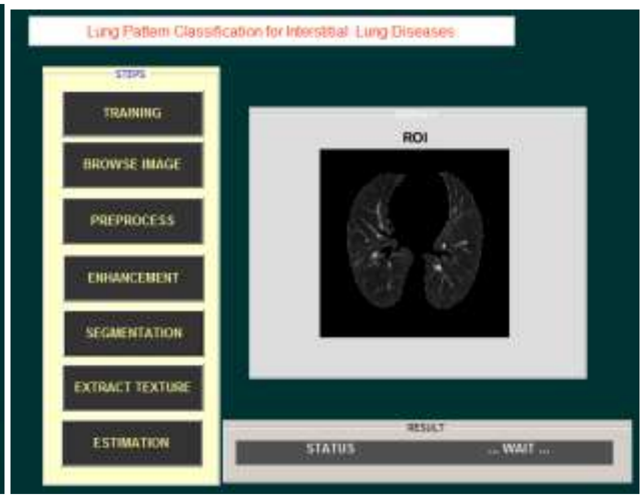

Figure 6: Segmentation Process: ROI (Region of Interest)

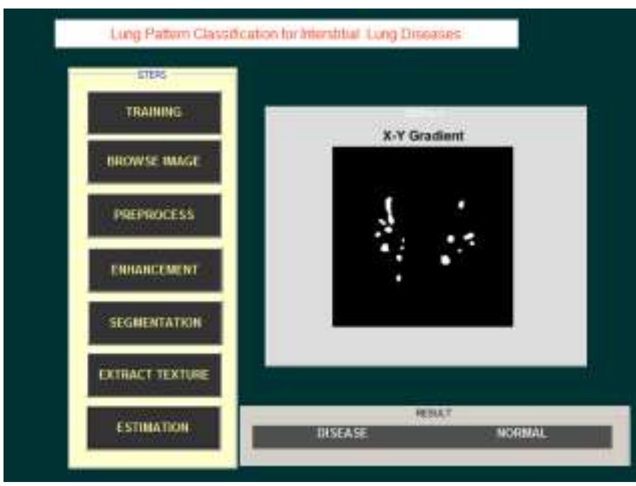

Figure 7: Estimation: Differential Diagnosis Normal

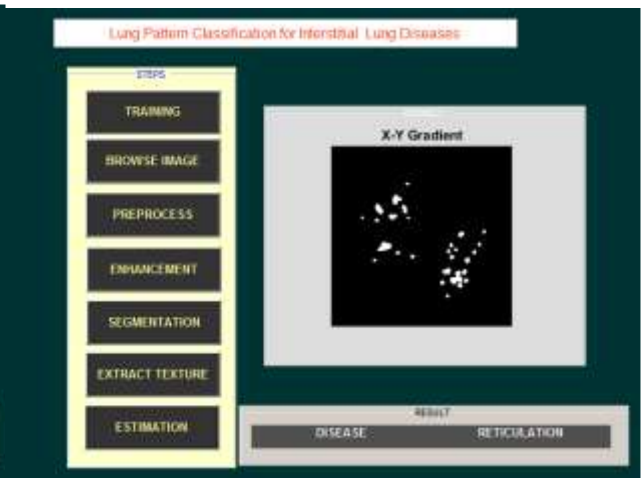

Figure 8: Estimation: Differential Diagnosis:Reticulation class

Accuracy: Accuracy obtained by this system is calculated in following way:

	Normal	Abnormal
Normal	TP (True Positive)	FN (False Negative)
Abnormal	FP (False Positive)	TN (True Negative)

Table 1: Calculation of TP, TN, FN, FP

$$\text{Accuracy} = (TP + TN)/(P + N)$$

Here, TP= 19, TN=22, P=25, N=25. So, Accuracy= 0.82

V. CONCLUSION

In this paper, we developed a CNN framework to classify lung tissue patterns into different classes such as Normal, Reticulation, Ground Glass Opacity, Honeycombing etc. A CNN network architecture was designed that captures textural features of the lung tissue. This framework contains of 5 convolutional layers trailed by two fully connected layess. The develpoed system gave good results accuracy of 0.82, performing well on the dataset of HRCT scans.

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