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Convolutional Neural Network for Detection and Identification of Interstitial Lung Diseases

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Abstract: **Automated tissue characterization is standout amongst the most essential parts of computer aided diagnosis (CAD) system for interstitial lung diseases (ILDs).Deep learning strategies provides impressive results in variety of computer vision problems such as medicinal picture investigation. In this paper, we plan and evaluate a convolutional neural network (CNN) for the classification of ILD patterns. The proposed system comprises of 5 convolutional layers, trailed by two fully connected layers. The last thick layer has different outputs, equivalent to the classes like ground glass opacity (GGO), micronodules, consolidation, reticulation, honeycombing etc. Future work incorporates extending CNN to three-dimensional data (information) gave by CT volume scans and integrating the proposed method into CAD framework that intends differential diagnosis for ILDs as a strong device for radiologists.**

***Index Terms*— Convolutional neural networks, interstitial lung diseases, texture classification.**

I. INTRODUCTION

Lung is essential organ for breathing. Lung Diseases refers to malfunctions of lung. Interstitial Lung Diseases are very common and it is often referred as lung tissue inflammation. It refers to a cluster of more than 150 lung diseases. It reduced ability of lung tissues to capture oxygen and it may lead to permanent loss of air sucking ability of lung. ILDs can be cause due to long term exposure to the perilous materials and in some cases due to genetic abnormalities. ILD diagnosis is a lengthy process which consists physical examination, questioning to the patient about their clinical history, x-ray test , CT scan and in some cases a surgical biopsy. Best way for ILD diagnosis is HRCT i.e. High Resolution Computed Tomography. Computed Aided Diagnosis is very useful to avoid dangerous clinical biopsies and which of increases the Diagnosis accuracy. 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 typical ILD tissue patterns like Ground Glass Opacity (GGO), Reticulation, Honeycombing, Micronobules etc.

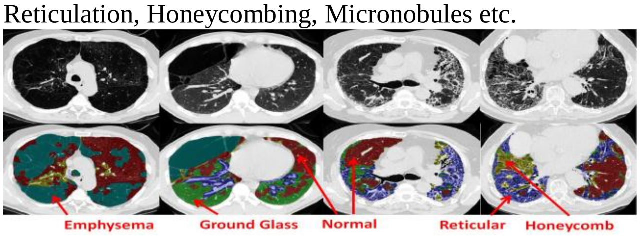

Figure 1: Examples of ILD patterns. Each highlighted area is labeled as one of the ILD patterns.

II.RELATED WORK

In this section we give an overview of the previous studies on ILD pattern classification, we give an outline of the past reviews on ILD design arrangement and a short introduction to convolution neural network (CNN), which are used in the proposed procedure.

A. ILD Pattern Classification

ILDs are mostly characterized as textural changes in the lung parenchyma, so the most of the part of our proposed frameworks is surface categorization on areas of interest (ROIs) or volumes of interest (VOIs). The primary attributes of such a framework are the picked include set and the arrangement strategy. The chief CAD frameworks for ILDs proposed established component extraction methods to depict 2D surface, for example, first request dark level insights, dim level co-event lattices (GLCM), run-length networks (RLM) and fractal examination [1].These features were later merged and alluded as the adaptive multiple feature method (AMFM) [6]. AMFM was generally accepted as the state of the art until new systems appeared that utilized more modern texture description techniques and gave a new perspective to the issue.

In this technique, a arrangement of texture atoms or Textron's is recognized by using k-means and k-SVD, on already described local patches. The resulting set of Textron's constitutes a problem-specific dictionary and every local structure in the image is represented by the closest Textron or a linear combination of the entire set. The final global descriptor usually consists of the histogram of Textron's appearing in the image. Another device which has be used for extracting learned features is the restricted Boltzmann machine (RBM). 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 events have as of late additionally been made to utilize profound learning (DL) procedures and particularly CNNs, after their noteworthy execution in substantial scale shading picture characterization [3]. Dissimilar to other element learning strategies that construct information portrayal models in an unsupervised way, CNNs learn elements and prepare an ANN classifier in the meantime, by limiting the arrangement mistake. Despite the fact that the term DL infers the utilization of numerous sequential learning layers, the primary endeavors on lung CT pictures received shallow structures.

B. Convolutional Neural Networks

CNNs are feed-forward ANN inspired by biological procedures and intended to perceive designs specifically from pixel images (or other signals), by incorporating both feature extraction and classification. A typical CNN involves four types of layers: convolutional, activation, pooling and fully-connected (or dense) layers. A convolutional layer is characterized by sparse local connectivity and weight sharing. Every neuron of the layer is just associated with a small local area of the input, which resemble the receptive field in the human visual system. Different neurons respond to different local areas of the input, which overlap with each other to get a better representation of the image.

The preparation of CNNs is performed comparably to that of different ANNs, by limiting a loss function using gradient descent based methods and back propagation of the error. 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 deep CNN for the classification of ILD patterns that exploits the outstanding descriptive capability of deep neural networks. The technique has been assessed on a dataset from local radiology centre.

III. METHODS

Here, we are going to see the actual framework, algorithm used for the identification and classification of ILDs tissues. Basically CNN is a very vast and it has many variations like AlexNet, GoogLeNet, VGGNet and deep residual networks. Each one of above network has its own benefits and they are applicable for specific application. 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.

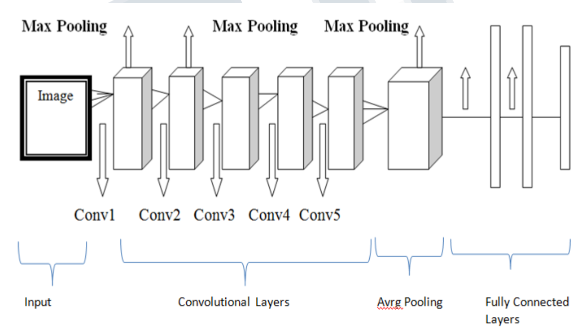

Figure 2: Multi-label CNN model

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.Data

The database used for the processing of this proposed system is taken by the local radiology center. The database of ILDs patterns is given by the Nucleus Diagnostics Center, Pune. It consists of 15 HRCT scans of the different patients. The database was annotated by experienced radiologists by drawing polygons around some frequently appearing ILD pattern. Some of those are micronobules, GGO(ground glass opacity), honeycombing, reticulation etc.

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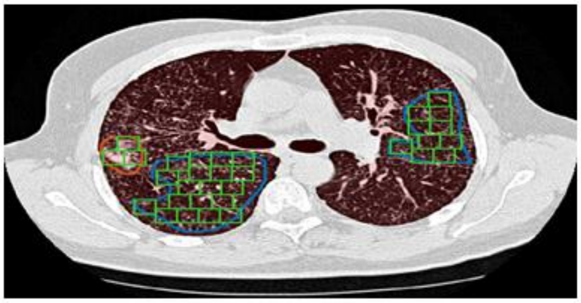

Figure 3: Example of generating image patches through the annotations of a CT slice.

B.Flowchart

ILD detection we are doing with MATLAB software. The flow chart of the system is as shown in figure 5. .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 analyze 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.

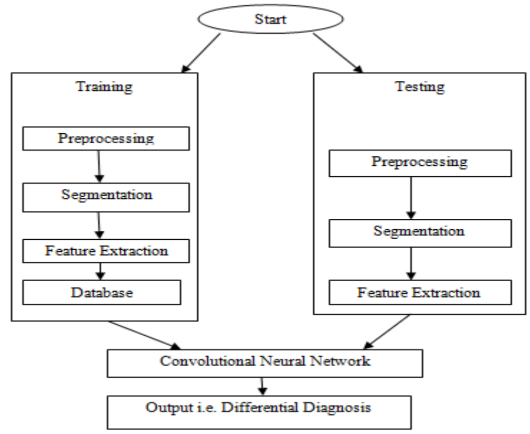

Figure 5: Flowchart

Here, In CNN we are applying three operations as follows: (a) Morphological Operations, (b)Thresholding, (c) Masking. Morphology is a wide collection of image processing operations that process images based on outline. Morphological operations relate a structuring element to an input image and output image is of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image. The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image[10]. Thresholding is applying some limits to differentiate the applicable data. The process of separating an image from its background is masking. Masking is used for highlighting the useful part of an image.

IV. RESULTS

In the result the original lungs image is given as input image. Then resize the image to reduce the pixel value of input image. Taking the histogram of resized image i.e. image enhancement is done. The contrast is matching of RI image. Then there is lungs mask, remove the exterior area. After that segment the image. Then we segment the image

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also use the feature extraction and we detect if any diseases is present.

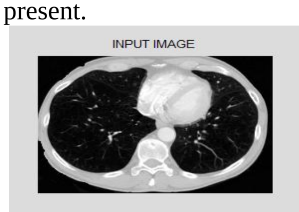

Fig 5: Original Image

Fig 6: Resized Image

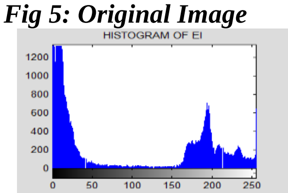

Fig 7: Histogram Of RI image

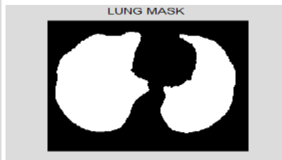

Fig 8 :Lung mask

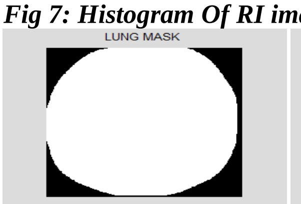

Fig 9:Lung mask

Fig 10: Segmentation

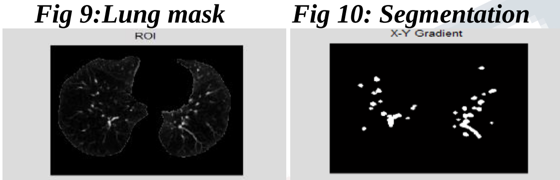

Fig 11: Region of Interest

V. CONCLUSION

In this paper, we proposed a deep CNN to classify lung CT image patches into different classes, including some different ILD patterns and healthy tissue. A novel network architecture was designed that captures the low-level textural features of the lung tissue. The network consists of 5 convolutional layers followed by two fully connected layess. The proposed approach gave good results, performing well on the dataset HRCT scans from various healing centers and scanners. The technique can be effectively prepared on additional textural lung patterns while performance could be further enhanced by investigating the involved parameters.

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