ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network

Namrata Bondfale[1], Shweta Banait [2]

PG Student, Department of E&TC, Indira College of Engineering and Management, Savitribai Phule University, Pune, India[1]

Professor, Department of E&TC, Indira College of Engineering and Management, Savitribai Phule University of Pune, India[2]

ABSTRACT: Automated tissue characterization is one of the most crucial components of a computer aided diagnosis (CAD) system for interstitial lung diseases (ILDs). Although much research has been conducted in this field, the problem remains challenging. Deep learning techniques have recently achieved impressive results in a variety of computer vision problems, raising expectations that they might be applied in other domains, such as medical image analysis. In this paper, we propose and evaluate a convolutional neural network (CNN), designed for the classification of ILD patterns. The proposed network consists of 5 convolutional layers with 2 2 kernels and LeakyReLU activations, followed by average pooling with size equal to the size of the final feature maps and three dense layers. The last dense layer has 7 outputs, equivalent to the classes considered: healthy, ground glass opacity (GGO), micronodules, consolidation, reticulation, honeycombing and a combination of GGO/reticulation. To train and evaluate the CNN, we used a dataset of 14696 image patches, derived by 120 CT scans from different scanners and hospitals. To the best of our knowledge, this is the first deep CNN designed for the specific problem. A comparative analysis proved the effectiveness of the proposed CNN against previous methods in a challenging dataset. The classification performance demonstrated the potential of CNNs in analysing lung patterns. Future work includes, extending the CNN to three-dimensional data provided by CT volume scans and integrating the proposed method into a CAD system that aims to provide differential diagnosis for ILDs as a supportive tool for radiologists.

KEYWORDS*:* Convolutional neural networks, interstitial lung diseases, texture classification.

I. INTRODUCTION

The term interstitial lung disease (ILD) alludes to a group of more than 200 chronic lung disorders characterized by inflammation of the lung tissue, which regularly prompts to scarring usually referred to as pulmonary fibrosis. Fibrosis may progressively cause lung stiffness, diminishing the capacity of the air sacs to capture and carry oxygen into the bloodstream and eventually leads to permanent loss of the ability to breathe. ILDs accounts for 15 percent of all cases seen by pulmonologists and can be caused by autoimmune diseases, genetic abnormalities and long-term exposures to hazardous materials. In 2002, an international multidisciplinary consensus conference, including the American Thoracic Society (ATS) and the European Respiratory Society (ERS), proposed a classification for ILDs, in order to establish a uniform set of definitions and criteria for their diagnosis.

The diagnosis of an ILD includes 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 protocol, d because of the 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 micronodules (Fig.1).

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

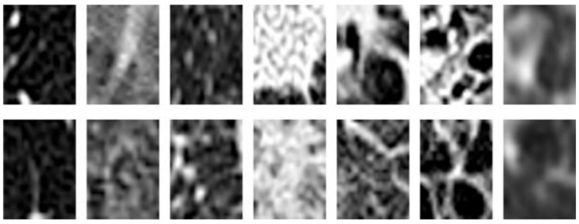


Fig.1:Examples of healthy tissue and typical ILD patterns from left to right: healthy, GGO, micronodules, consolidation, reticulation, honeycombing, combination of GGO and reticulation.

To avoid the dangerous histological biopsies, much research has been conducted on computer aided diagnosis systems (CAD) which could help radiologists and increase their diagnostic accuracy. A CAD system for lung CT scan assessment typically consists of three stages: (a) lung segmentation, (b) lung disease quantification and (c) differential diagnosis. The first stage refers to the identification of the lung border, the separation of the lobes and in some cases the detection and removal of the bronchovascular tree. The second stage includes detection and recognition of the different tissue abnormalities and estimation of their extent in the lung. At last, the third stage combines the previous results to suggest a probable differential diagnosis. In this review, we concentrate on the second stage and especially on the classification of lung tissue with different ILD irregularities. This paper is organized as follows. Section III gives an overview of the previous studies on ILD pattern classification. In Section IV ,we first describe the dataset used in the study, followed by the proposed CNN. Section V dedicates to describe the proposed CNN, and finally Section VI gives the conclusion.

II. LITERATURE SURVEY

They describe the objectives and the most recent results of the TALISMAN project which aims to carry out image-based diagnostic aid for interstitial lung diseases (ILDs) with secondary data integration. Prototypes of the computer tools are implemented. High correct classification rates of lung tissue regions in high-resolution computed tomography (HRCT) based on a high-quality dataset built from clinical routine recommends that the computerized analysis of HRCT image with integration of the clinical context is ready to be utilized for computer-aided diagnosis of ILDs[1]. Visual investigation of diffuse lung disease (DLD) patterns on high-resolution computed tomography (HRCT) is troublesome as a result of their high complexity. They[2] proposed a bag of words based method on the classification of these textural patters in order to improve the detection and diagnosis of DLD for radiologists. Six kinds of typical pulmonary patterns were considered in this work. They were consolidation, ground-glass opacity, honeycombing, emphysema, nodular and normal tissue. Since they were characterized by both CT values and shapes, we proposed a set of statistical measure based local features calculated from both CT values and the Eigen-values of Hessian matrices. The proposed method could accomplish the recognition rate of 95.85%, which was higher comparing with one global feature based method and two other CT values based bag of words strategies.

In this work[3], They have designed a customized Convolutional Neural Networks (CNN) with shallow convolution layer to classify lung image patches with interstitial lung disease (ILD). While many feature descriptors have been proposed over the past years, they can be quite complicated and domain-specific. The same architecture can be generalized to perform other medical image or texture classification tasks. A modified RBM was utilized for both element extraction and classification of lung tissue, incorporating some features of CNNs. Weight sharing was utilized among the hidden neurons, which were densely connected to label (output) neurons, while the whole network was trained in a supervised manner, using contrastive divergence and gradient descent[4]. The pre-trained deep CNN of [5] (AlexNet) was utilized in [6] to classify whole lung slices after fine-tuning with lung CT data. In [4], an adjusted RBM was utilized for both element extraction and grouping of lung tissue, joining a few components of CNNs. Weight

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

sharing was utilized among the shrouded neurons, which were thickly associated with name (yield) neurons, while the entirety.

III. PROPOSED WORK

In this section we give an overview of the previous studies on ILD pattern classification, followed by a brief introduction to convolutional neural networks (CNN), which are utilized in the proposed methodology.

A) ILD Pattern Classification

Since ILDs are generally manifested as textural alterations in the lung parenchyma, most of the proposed systems employ texture classification schemes on local regions of interest (ROIs) or volumes of interest (VOIs), depending on the 2D or 3D capabilities of the CT imaging modality employed. By sliding a fixed-scale classifier over pre-segmented lung fields, an ILD quantification map of the entire lung is generated. The latter can be used – either by physicians or CAD systems – to attempt the final diagnosis. The main characteristics of such a system are the chosen feature set and the classification method. The principal CAD systems for ILDs proposed classical feature extraction techniques to describe 2D texture, such as first order gray level statistics, gray level co-occurrence matrices (GLCM), run-length matrices (RLM) and fractal analysis. These features were later merged and alluded as the adaptive multiple feature method (AMFM). 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.

B) Convolutional Neural Networks

CNNs are feed-forward ANN inspired by biological procedures and ntended 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 backpropagation 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).

IV. METHODS

In this section, we first describe the dataset used in the study, followed by the proposed CNN. The definition of the input data and desired outputs prior to the actual methods gives a better definition of the problem and thus a better understanding of the methods.

A) Data

The dataset used for preparing and assessing the proposed strategy was made utilizing two databases of ILD CT scans from two different Swiss university hospitals:

- The first is the openly accessible multimedia database of ILDs from the University Hospital of Geneva [30], which consists of 109 HRCT scans of different ILD cases with 512×512 pixels per slice. Manual annotations for 17 different lung patterns are additionally given, along with clinical parameters from patients with histologically proven diagnoses of ILDs.
- The second database was given by the Bern University Hospital, “Inselspital”, and consists of 26 HRCT scans of ILD cases with resolution 512×512.

Healthy tissue was additionally included, leading to 7 classes. The annotation concentrated on typical instances of the considered ILD patterns, excluding ambiguous tissue areas that even experienced radiologists find difficult to classify. Subsequently, tissue outside the polygons may belong to any pattern, including that considered. In addition, the annotators tried to avoid the bronchovascular tree which (in a complete CAD system) should be segmented and

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

removed, before applying the fixed-scale classifier. Annotation of the lung fields was also performed for all scans. The considered classes appeared in the annotations of 94 out of the 109 scans of the Geneva database, to which the 26 cases from "Inselspital" were included, giving a total of 120 cases. On the premise of the ground truth polygons of these cases, we extracted in total 14696 non-overlapping image patches of size 32×32, unequally distributed across the 7 classes.

B) Visualizing the Learned Features

Unlike the traditional fully-connected neural networks, which behave like a black box learning machine, features learned by CNN can be easily visualized and understood. The kernel matrices in the convolutional Layer represent sets of features learned by the network. It is interesting that the feature filters look similar to two dimensional discrete cosine transformation (DCT) kernel functions. Based on this observation, it is clear that 2D special frequency information has been learned by the network as good discriminative features to distinguish the texture-like lung image patches.

V. PROPOSED CNN

In order to decide on the optimal architecture and configuration of a CNN, one ought to first appreciate the way of the issue considered – for this situation – the classification of ILD patterns. Unlike arbitrary objects in color images, which include complex, high-level structures with specific orientation, ILD patterns in CT images are characterized by local textural features. Although texture is an intuitively easy concept for humans to perceive, formulating a formal definition is not trivial, which is the reason for the many accessible definitions in the literature. Here, we define texture as a stochastic repetition of a few structures (textons) with moderately small size, compared to the whole region. Image convolution highlights small structures that resemble the convolution kernel throughout an image region, and in this way the analysis of filter bank responses has been successfully used in many texture analysis applications.

This encourages the utilization of CNNs to perceive texture by identifying the optimal eproblem-specific kernels; however some key aspects stemming from our definition of texture have to considered: (i) The total receptive field of each convolutional neuron with respect to the input (i.e., the total area of the original input "seen" by a convolutional neuron) should not be larger than the characteristic local structures of texture, otherwise non-local information will be captured, which is irrelevant to the specific texture, (ii) since texture is characterized by fine grained low-level features, no pooling should be carried out between the convolutional layers, in order to prevent loss of information, (iii) each feature map outputted by the last convolutional layer should result in one single feature after pooling, in order to gain some invariance to spatial transformations like flip and rotation. Unlike color pictures that usually have high-level geometrical structure (e.g., the sky is up), a texture patch should still be a valid sample of the same class when flipped or rotated.

1) Architecture

On the premise of these standards, we designed the network. The input of the network is a 32×32 image patch, which is convolved by a series of 5 convolutional layers. The size of the kernels in each layer was selected to be minimal, i.e., 2×2. The use of small kernels that lead to very deep networks was proposed in the VGG-net, which was ranked at the top of ILSVRC 2014 challenge by employing 3×3 kernels and up to 16 convolutional layers. Here, we go one step further by shrinking the kernel size even more to involve more non-linear activations, while keeping the total receptive field small enough (6×6) to capture only the relevant local structure of texture. Each layer has a number of kernels proportional to the receptive field of its neurons, so it can handle the increasing complexity of the described structures.

The size of the rectangular receptive field is 2×2 for the first layer and is increased by 1 in each dimension, for each layer added, leading to an area of $(L+1)2$ for the Lth layer. Hence, the number of kernels we utilize for the Lth layer is $k(L+1)2$, where the parameter k depends on the complexity of the input data and was set to 4 after relevant experiments. An average pooling layer follows, with size equal to the output of the last convolutional layer (i.e., 27×27). The resulting features, which are equal to the number of features maps of the last layer i.e., f=36k, are fed to a series of 3 dense layers with sizes 6f, 2f and 7, since 7 is the number of classes considered.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

2. Training Method

The training of an ANN can be viewed as a combination of two components, a loss function or training objective, and an optimization algorithm that limits this function. In this review, we utilize the Adam optimizer to minimize the categorical cross entropy. The cross entropy represents the uniqueness of the approximated output distribution (after softmax) from the true distribution of labels. Adam is a first-order gradient-based algorithm, designed for the optimization of stochastic objective functions with adaptive weight updates based on lower-order moments. Three parameters are associated with Adam: one is the learning rate and the other two are exponential decay rates for the moving averages of the gradient and the squared gradient. After relevant experiments, we left the parameters to their default values namely, learning rate equal to 0.001 and the rest 0.9 and 0.999, respectively.

VI. RESULT

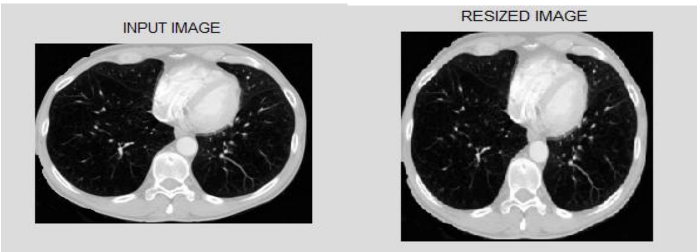


Fig 2: Original Image Fig 3: Resized Image

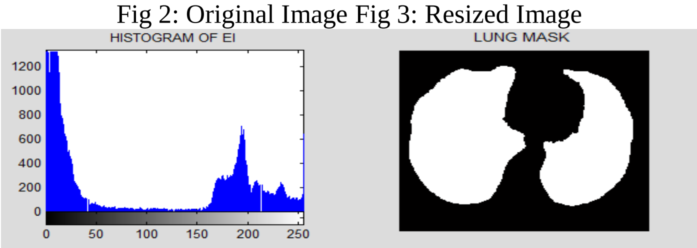


Fig 4: Histogram Of RI image   Fig 5: Lung mask

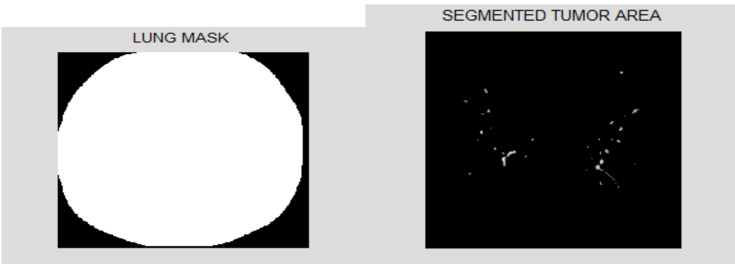


Fig 6: Lung maskFig 7: Segmentation

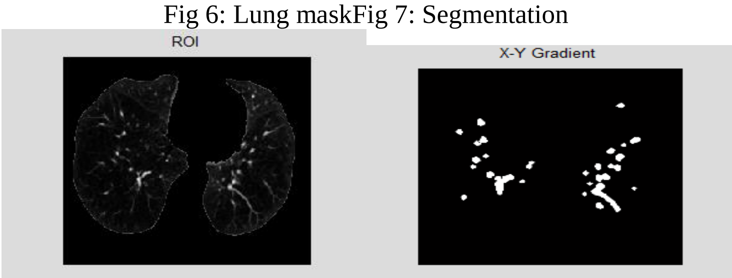


Fig 8: Region of Interest

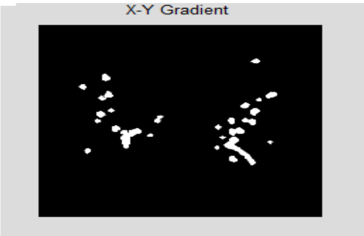
ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

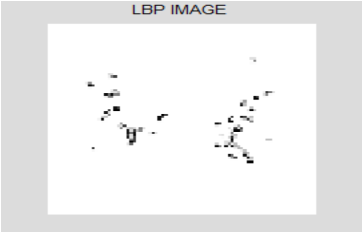
International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017





VII. CONCLUSION

In this paper, we proposed a deep CNN to classify lung CT image patches into 7 classes, including 6 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 with 2×2 kernels and LeakyReLU activations, followed by just one average pooling, with size equal to the size of final feature maps and three dense layers. The training was performed by limiting the categorical cross entropy with the Adam optimizer. The proposed approach gave promising results, outperforming the state of the art on a very challenging dataset of 120 CT 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 a more extensive investigation of the involved parameters. In future studies, we plan to extend the method to consider three dimensional data from MDCT volume scans and finally to integrate it into a CAD system for differential diagnosis of ILDs.

REFERENCES

[1] K Doi, Current status and future potential of computer–aided diagnosis in medical imaging, British Journal of Radiology 78, pp. 3–19, 2005
[2] R. Xu et al., "Classification of diffuse lung disease patterns on high-resolution computed tomography by a bag of words approach," Proc. MICCAI, vol. 14, pt. 3, pp. 183–90, 2011.
[3] Q. Li et al., "Medical image classification with convolutional neural network," in Proc. 13th Int. Conf. Control Automat. Robot. Vis., Dec. 2014, vol. 2014, pp. 844–848.
[4] G. Van Tulder and M. de Bruijne, "Learning features for tissue classification with the classification restricted Boltzmann machine," Med. Comput. Vis., Algorithms for Big Data, pp. 47–58, 2014.
[5] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," Adv. Neural Inf. Process.Syst., p. 9, 2012.
[6] M. Gao et al., "Holistic classification of CT attenuation patterns for interstitial lung diseases via deep convolutional neural networks," in 1st Workshop Deep Learn. Med. Image Anal., 2015, pp. 41–48.
[7] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in Int. Conf. Learn.Represent., 2015.
[8] G. Hinton, "Dropout : A simple way to prevent neural networks from overfitting," J. Mach. Learn. Res., vol. 15, pp. 1929–1958, 2014.
[9] D. P. Kingma and J. L. Ba, "Adam: A method for stochastic optimization," in Int. Conf. Learn. Represent., 2015, pp. 1–13.
[10]B. T. Society, "The diagnosis, assessment and treatment of diffuse parenchymal lung disease in adults," Thorax, vol. 54, no.Suppl 1, p. S1.