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Medical Imaging through Machine Learning Technique

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Abstract: ***In this analysis propose and evaluate the convolution neural network designed for classification of ILD patterns. The 7outputs of ILD patterns: healthy, ground glass opacity (GGO), micro nodules, consolidation, reticulation, honeycombing and a combination of GGO/reticulation. To train and evaluate the CNN, we used first deep CNN designed for the specific problem. Finally we classify the performance (91%) demonstrated the potential of CNNs in analyzing lung patterns. We proposed a deep CNN to classify lung CT image patches into7classes, including 6 different ILD pattern sand healthy tissue. The method can be easily trained on additional textural lung patterns while performance could be further improved. The slight punctuation of the results, for the same input, due to the random initialization of the weights. Data or class imbalance in the training set is also a significant issue in medical image analysis this refers to the number of images in the training data being skewed towards normal and non-pathological images. Rare diseases are an extreme example of this and can be missed without adequate training examples. This data imbalance effect can be ameliorated by using data augmentation to generate more training images of rare or abnormal data, though there is risk of over fitting. Aside from data-level strategies, algorithmic modification strategies and cost sensitive learning have also been Analysis.***

Keywords: ILD, CNN, Deep Learning, Machine Learning, Neural Network

1. Introduction

A Convolution Neural Network (CNN) is a powerful machine learning technique from the field of deep learning. CNNs are trained using large collections of diverse images. From these large collections, CNNs can learn rich feature representations for a wide range of images. These feature representations often outperform hand-crafted features such as HOG, LBP, or SURF. An easy way to leverage the power of CNNs, without investing time and effort into training, is to use a pre-trained CNN as a feature extractor[5][12][10] CNN algorithms, which are algorithms used to solve computer vision tasks, are part of a hierarchy of terms under the "umbrella" of Artificial presents a Venn diagram schematic representation of this hierarchy of terms. AI is a broad term that describes the computer science field that is devoted for creating algorithms that solve problems which usually require human intelligence. Machine learning is a subclass of AI that gives computers the ability to learn without being explicitly programmed. In classic machine learning, human experts try to choose imaging features that appear to best represent the visual data (for example, Hounsfield units histograms or the acuteness of masses) and statistical techniques are used to classify the data based on such features. Deep learning, a subtype of machine learning, is a type of representation learning in which no feature selection is used. Instead, the algorithm learns on its own which features are best for classifying the data. With enough training data, representation learning could potentially outperform hand-engineered features.[6][4]

2. Deep Learning for Feature Extraction

Convolution neural network gives better results of accuracy of medical image analysis. Convolution Neural Network (CNN) is a model of deep learning as classic example of deep learning. Convolution neural networks (CNN) are fully and locally connected to hidden layers unlike traditional neural network because for all fully connected networks, the operation becomes computationally intensive. CNNs use parameter sharing, pooling and dropout also which reduce the number of common features to large extent and hence addressing the computational issues [7]9][16].

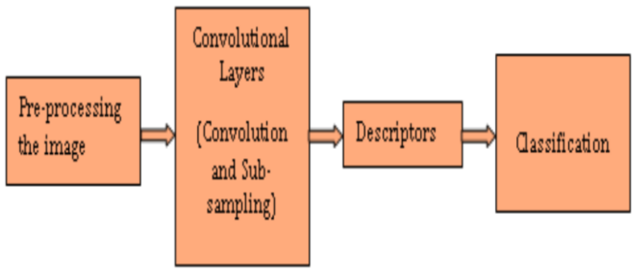

Figure 1: Convolution neural networks

First convolution layer extracted features which are usually low-level features such as edges and lines and Subsequent layers extracted high-level features Size of input is N x N x D and this has to be convolved with kernels whose size k x k x D separately. Convolution of an input with one kernel produces one output feature, and with H kernels independently produces H

Features Each feature in the output consists of (N-k+1) x (N-k+1) elements. For each position of the kernel in a sliding window process, k x k x D elements of input and k x k x D elements of kernel are multiplied and added.

The k x k x D multiply-accumulate operations are required for producing one output feature. Analysis and Comparison .Analyze the medical images based on features extracted in previous stage using suitable classifiers. The results will be finally compared with few results of conventional method of

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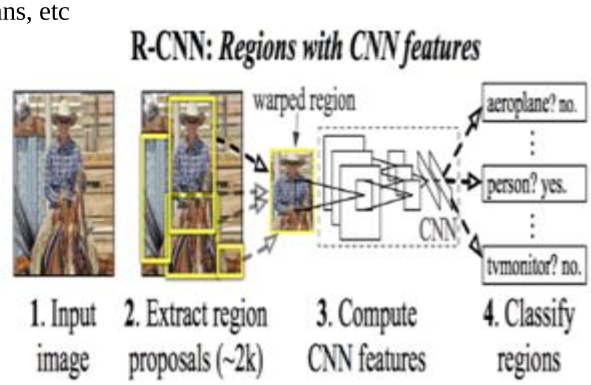
machine learning that may be ordinary neural network based learning technique. Even though the problems are superficially similar, research on image analysis for natural and medical images has traditionally been separated. Natural image analysis often refers to problems such as object detection, face recognition and 3D reconstruction, using images from normal RGB cameras. Medical image analysis entails tasks like detecting diseases in X-ray images, quantifying anomalies in MRI, segmenting organs in CT scans, etc



3. Proposed System

The scans were produced by different CT scanners with slightly different pixel spacing so a pre-processing step was applied. The image intensity values were cropped and segmented the images.

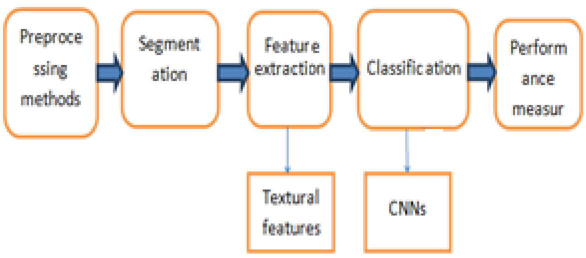


Figure 2: System Architecture

The six most relevant ILD patterns, namely GGO, reticulation, consolidation, micro nodules, honeycombing and a combination of GGO and reticulation. Healthy tissue was also added, leading to 7 classes

4. Module Explanation

- Pre-processing
- Segmentation
- Feature extraction
- Classification

a) Pre-Processing

Pre-Processing Stage The watershed based image segmentation produces mostly an over-segmentation of the image. Pre-processing and post-processing of an image is performed to overcome this problem. Pre-processing is mainly applied to the image before the watershed segmentation. As shown in, pre-processing includes first stage of noise removal using median filter, second stage of morphological gradient calculation and last stage of thresholding a gradient image. The purpose of this phase is to make the image ready for further processing because the image may contain many noise need to apply filtering. These phases consist of the following steps:

- To read a graphics file format image use imread.
- To write a graphics file format image, use imwrite.
- To obtain information about the nature of a graphics file format image, use imfinfo.

b) Cropping

The Crop Image tool blocks the MATLAB command line until you complete the operation. Using the mouse, draw a rectangle over the portion of the image that you want to crop. Perform the crop operation by double-clicking in the crop rectangle or selecting Crop Image on the context menu.

c) Segmentation

Image segmentation is the process of dividing an image into multiple parts. This is typically used to identify objects or other relevant information in digital images. There are many different ways to perform image segmentation.

d) Soft Threshold Algorithm

Image thresholding is a simple, yet effective, way of partitioning an image into a foreground and background. This image analysis technique is a type of image segmentation that isolates objects by converting gray scale images into binary images. Image thresholding is most effective in images with high levels of contrast.

e) Feature Extraction

Local features and their descriptors are the building blocks of many computer vision algorithms. Their applications include image registration, object detection and classification, tracking, and motion estimation. These algorithms use local features to better handle scale changes, rotation, and occlusion. Computer Vision System Toolbox algorithms include the FAST, Harris, and Shi &Tomasi corner detectors, and the SURF and MSER blob detectors.

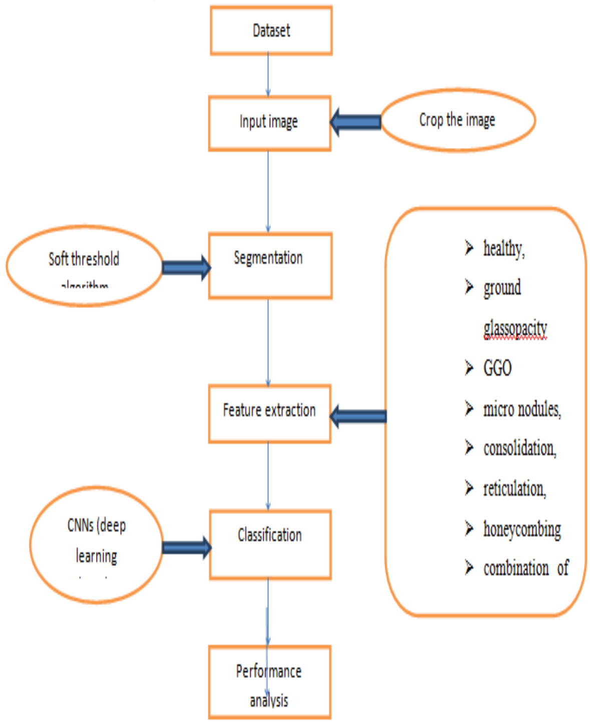


Figure 3: Proposed Flow Chart

f) 7 Classes

- Healthy,
- Ground glass opacity
- GGO
- Micro nodules,
- Consolidation,
- Reticulation,
- Honeycombing
- Combination of GGO/reticulation

g) Classification

A Convolution Neural Network (CNN) is a powerful machine learning technique from the field of deep learning. CNNs are trained using large collections of diverse images. From these large collections, CNNs can learn rich feature representations for a wide range of images. These feature representations often outperform hand-crafted features such as HOG, LBP, or SURF. An easy way to leverage the power of CNNs, without investing time and effort into training, is to use a pre-trained CNN as a feature extractor.

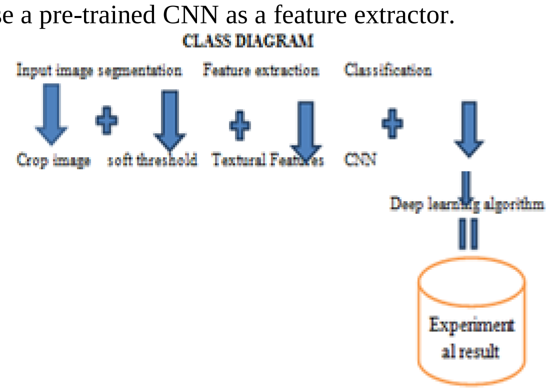


Figure 4: Class Diagram

5. Experimental Setup

Evaluation: The evaluation of the different ILD patch classification approaches is based on a train-validation-test scheme. The actual training of the methods was carried-out on the training set, while the validation set was used for fine tuning

Implementation:

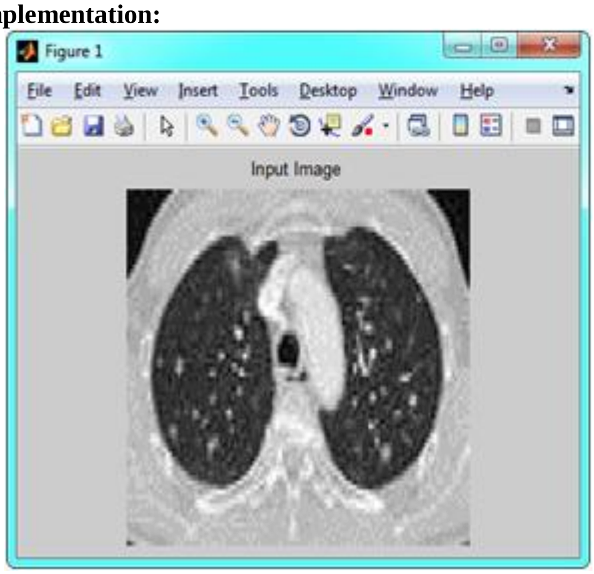


Figure 5: Input Image

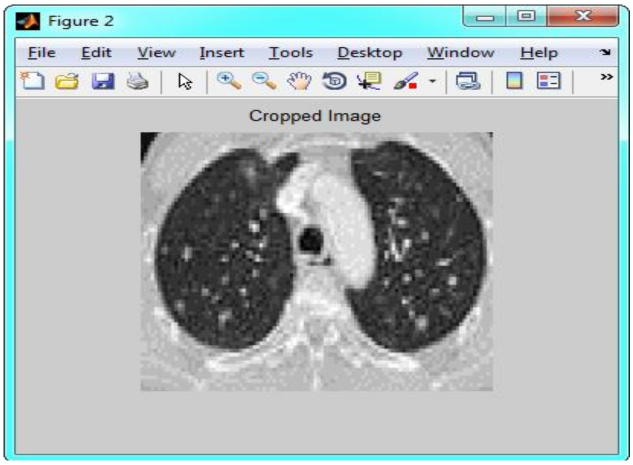


Figure 6: Cropped Image

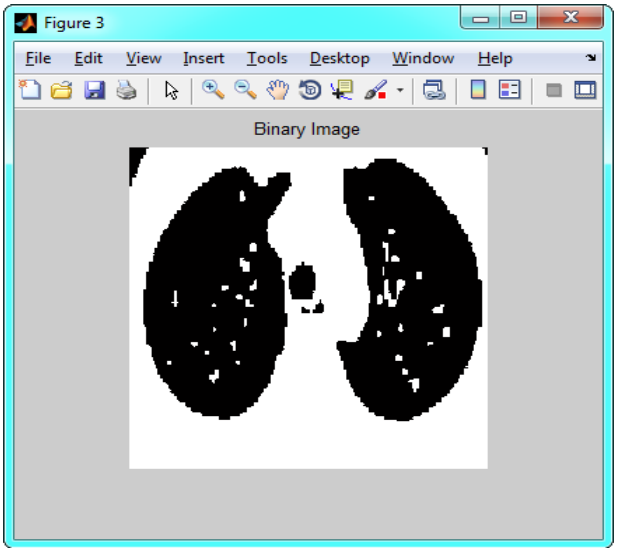


Figure 7: Binary Image

a) Image Segmentation

Image segmentation means division of an image into meaningful structures. It is process of extracting and representing information from the image to group pixels together with region of similarity [11]. Sonka et al. define the goal of segmentation as "to divide an image into parts that have a strong correlation with objects or areas of the real world contained in the image" [7]. Figure 3.1 shows a basic example of the image segmentation where Figure 3.1.is an original gray scale image and Figure 2.1b is a segmented image [19]. All the objects of the original image can be identified in segmented image with their boundaries. There are many techniques available for the image segmentation. Examples are, threshold based segmentation, edge based segmentation, region based segmentation, clustering based image segmentation, markov random field based segmentation and hybrid techniques

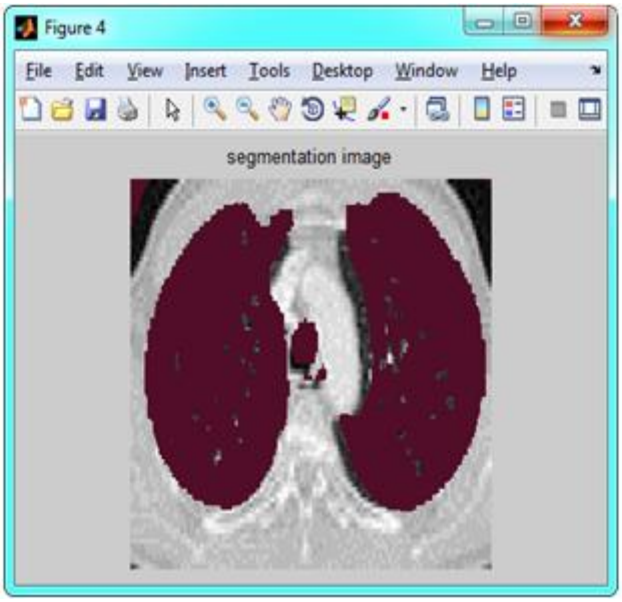


Figure 8: Segmented Image

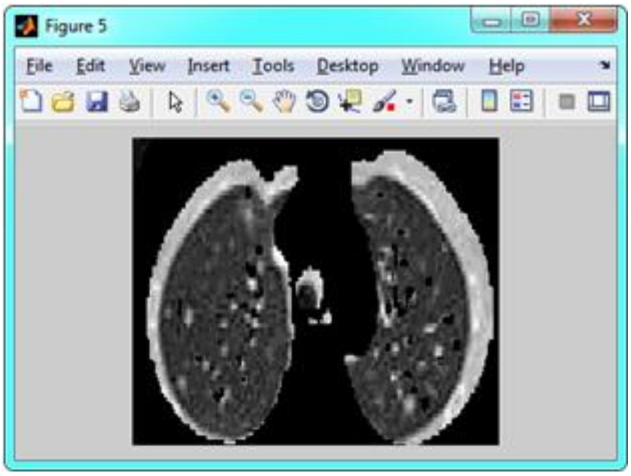
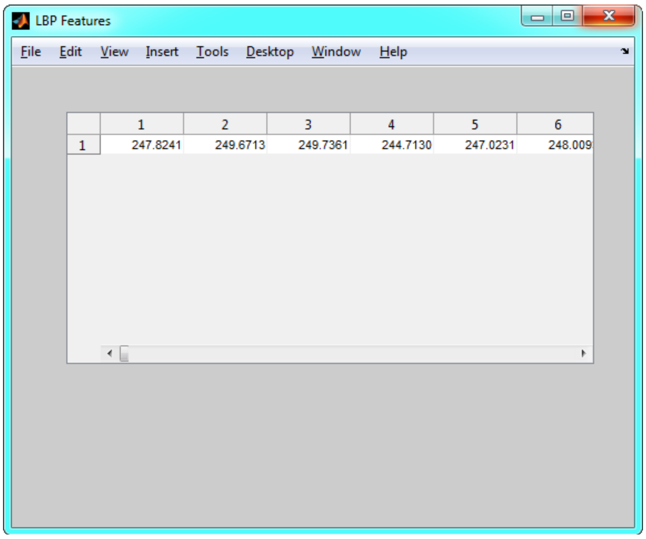


Figure 9: CNN Image

b) Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighbourhood of each pixel and considers the result as a binary number The LBP algorithm parameters control how local binary patterns are computed for each pixel in the input image. **Local Binary Pattern** (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhoods of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.



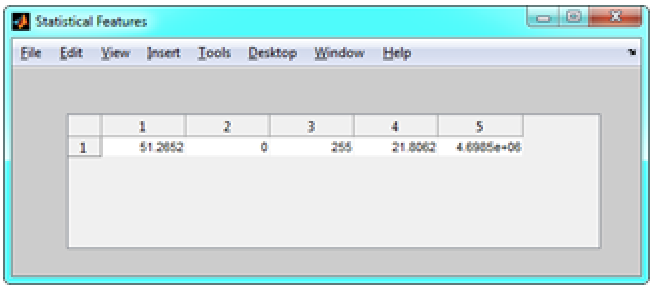
LBP Features

	1	2	3	4	5	6
1	247.8241	249.6713	249.7361	244.7130	247.0231	248.009

Figure 10: LBP Features

c) Statistical Feature

Texture analysis techniques describe texture of regions in an image through higher order moments of their grayscale histograms. The most commonly used method for texture analysis is based on extracting various textural features from a gray level co-occurrence matrix (GLCM). The GLCM approach is based on the use of second-order statistics of the grayscale image histograms. Structural texture analysis techniques describe a texture as the composition of well-defined texture elements such as regularly spaced parallel lines. The properties and placement rules of the texture elements define the image texture. Model based texture analysis techniques generate an empirical model of each pixel in the image based on a weighted average of the pixel intensities in its neighbourhood. The estimated parameters of the image models are used as textural feature descriptors. Transform based texture analysis techniques convert the image into a new form using the spatial frequency properties of the pixel intensity variations. The success of this type lies in the type of transform used to extract textural characteristics from the image. The image processing of citrus fruit images using statistical and transform based texture analysis is explained here.



Statistical Features

	1	2	3	4	5
1	51.2852	0	255	21.8062	4.6985e+06

Figure 11: Statistical Features

d) Gray-Level Co-Occurrence Matrix (GLCM)

Texture Analysis Using the Gray-Level Co-Occurrence Matrix (GLCM The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

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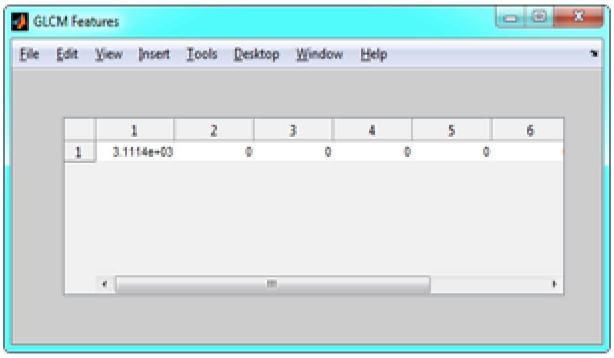

Figure 12: GLCM Features

Proposed CNN In order to decide on the optimal architecture and configuration of a CNN, one should first comprehend the nature of the problem considered - in this case - the classification of ILD patterns. Unlike arbitrary objects in colour images, which involve 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 available definitions in the literature [31]. Here, we define texture as a stochastic repetition of a few structures (textons) with relatively 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.

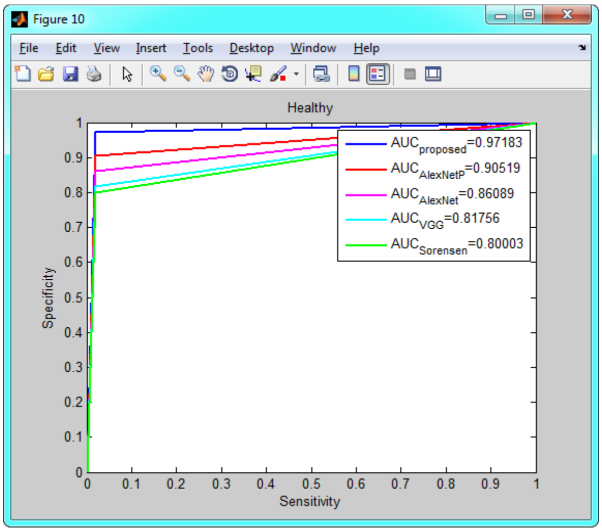

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Figure 12: Healthy Class graph

CLASSES CNN

Statistics of the Database. (H: Healthy, GGO: Ground Glass Opacity, Micronodules, Cons: Consolidation, Ret: Reticulation, Hc: Honeycombing)problem considered – in this case –the classification of ILD patterns. Unlike arbitrary objects in color images, which involve 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, The two networks were designed for the classification of 224 -224 colour images, so in order to make our data fit, we rescaled the 32- patches to 224 -224 and generated 3 channels by considering 3 different HU windows according to [32]. First, we tried training the AlexNet from scratch on our data. However, the size of this kind of networks requires very large amounts of data, in order to be trained properly. The achieved accuracy was in the order of 91% and the and noisy low-detailed filters obtained from the first convolution layer .the size, as well as the scale of the network, are too large for our problem. To overcome the problem of insufficient data we fine-tuned the already trained (on Image Net) AlexNet, which is currently the most common technique for applying it to other problems. the size of the used set can be more important than the type of data. However, by looking at the filters of the first layer .. Finally, we tested the pre-trained (on ImageNet) VGG-Net after fine-tuning it, since training a network with that size from scratch would need even more data than AlexNet. The network achieved an improvement of about 2% compared to AlexNet probably due to the smaller size of kernels that permit the use of more convolution layers, however the result is still inferior to that proposed.

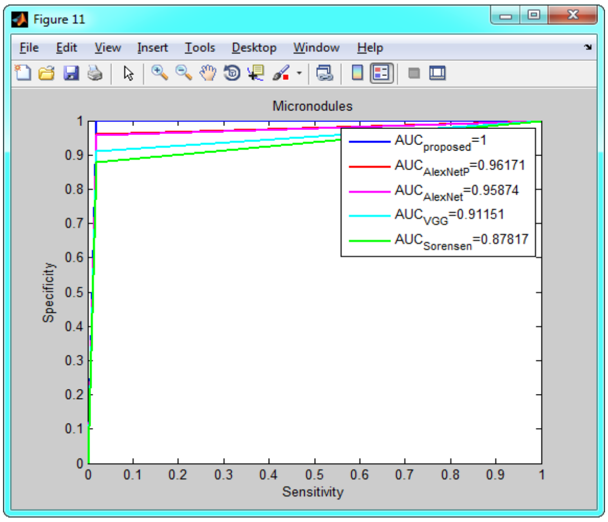

Figure 13: Micronodules Class Graph

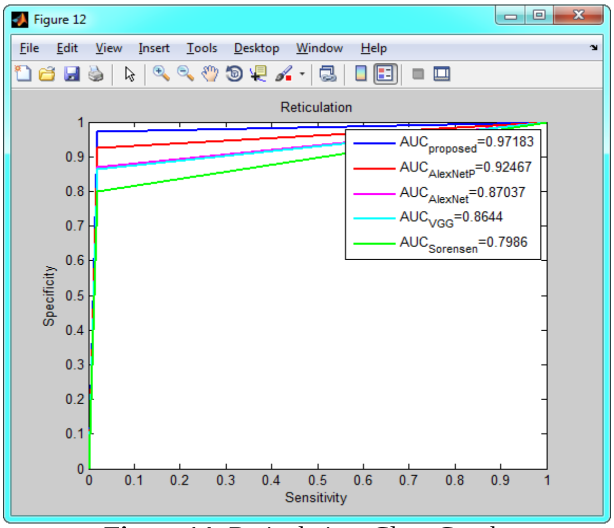

Figure 14: Reticulation Class Graph

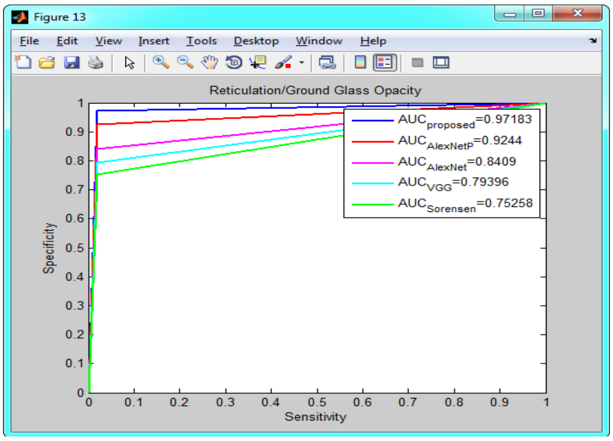

Figure 15: Reticulation / ground glass opacity class graph

analysis for AlexNet, AlexNet pre-trained (AlexNetP), VGG-Net, the method by Sorensen et al. [13] and the proposed CNN., the area under the curve (AUC) was computed and the 95% confidence interval was plotted according to [14]. The comparison showed that the proposed method achieved the highest AUC on each of the 7 classes. To test the statistical significance of the AUC differences,

The analysis was performed per class (one-vs-all) while the average over all classes is also presented. For each ROC, the AUC is given and the 95% confidence interval is plotted. Comparing on the most difficult patterns i.e., consolidation, reticulation, honeycombing and reticulation/GGO. For the rest of the patterns (healthy, GGO and micronodules) the difference between the proposed method and the pre-trained AlexNet was not considered significant, while for GGO the difference from VGG-Net was also non-significant ( ). Finally, the superiority of the proposed method after averaging over all considered classes was also found to be statistically significant

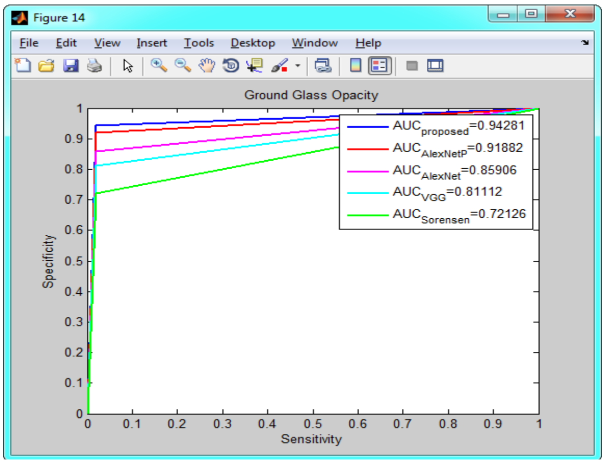

Figure 16: Ground Glass Opacity Class Graph

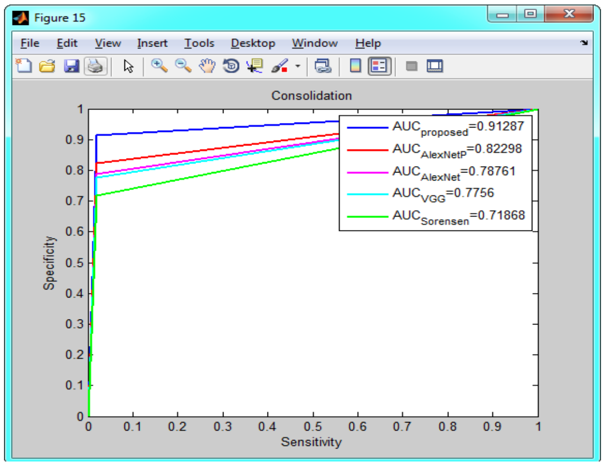

Figure 17: Consolaidation

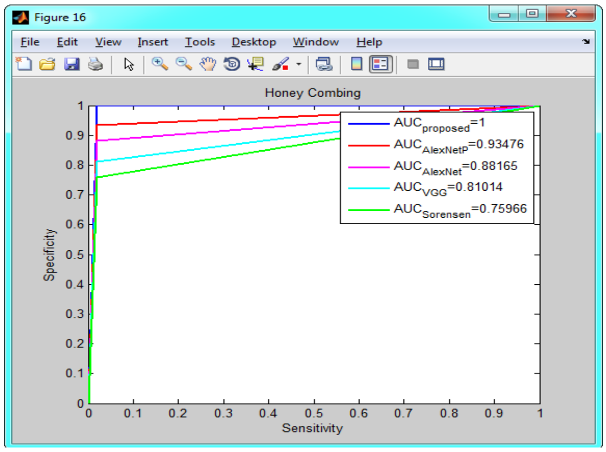

Figure 18: Honey Combing Class Graph

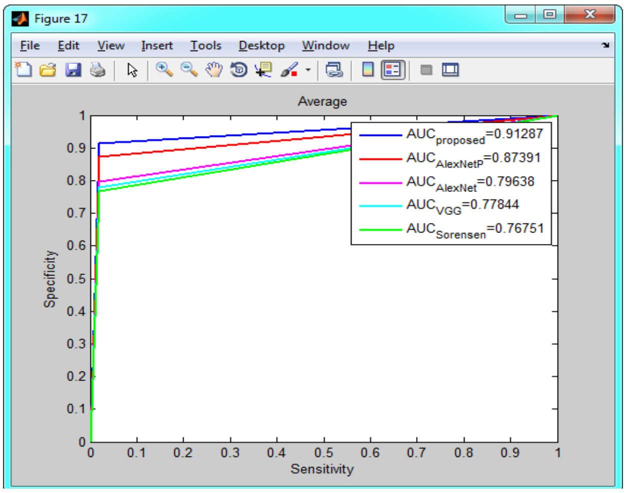

Figure 19: Accuracy graph

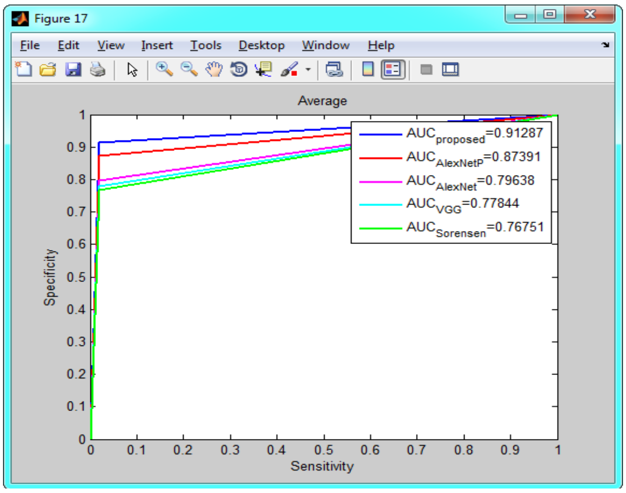

Figure 20: Sensitivity graph

In Deep Learning, an epoch is a hyper parameter which is defined before training a model. One epoch is when an entire dataset is passed both forward and backward through the neural network only once. ... For example: If we divide a dataset of 2000 training examples into 500 batches, then 4 iterations will complete 1 epoch.

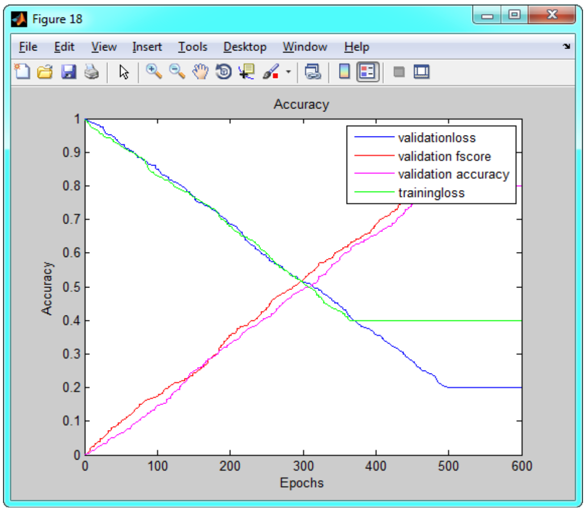

Figure 21: Epochs graph

6. Conclusions

We proposed a deep CNN to classify lung CT image patches into7classes, including 6 different ILD pattern sand healthy tissue. The method can be easily trained on additional textural lung patterns while performance could be further improved. The slight fluctuation of the results, for the same input, due to the random initialization of the weights. Data or class imbalance in the training set is also a significant issue in medical image analysis This refers to the number of images in the training data being skewed towards normal and non-pathological images. Rare diseases are an extreme example of this and can be missed without adequate training examples. This data imbalance effect can be ameliorated by using data augmentation to generate more training images of rare or abnormal data, though there is risk of over fitting. Aside from data-level strategies, algorithmic modification strategies and cost sensitive learning have also been Analysis

Table 1: The proposed method for the seven considered classes

CLASSES	AUC	$Auc_{alexnetp}$	$Auc_{alexnet}$	Auc_{VGG}	Aucsoresen
Honey Combing	1	0.93476	0.88165	0.81014	0.75966
Reticulation /Ground Glass Opacity	0.97183	0.9244	0.8409	0.79396	0.765858
Reticulation	0.97183	0.92467	0.87037	0.8644	0.7986
Consolidation	0.91287	0.82298	0.78761	0.7756	0.71868
Ground Glass Opacity	0.94281	0.91882	0.85906	0.81112	0.72126
Micro nodules	1	0.96171	0.95874	0.911151	0.87817
Healthy	0.97183	0.90519	0.86089	0.81756	0.80003
Accuracy (Proposed)	91%				

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