LUNG NODULE ANALYSIS AND DIAGNOSIS OF PULMONARY FIBROSIS THROUGH DEEP LEARNING

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АНАЛИЗ ЛЕГОЧНЫХ УЗЕЛКОВ И ДИАГНОСТИКА ЛЕГОЧНОГО ФИБРОЗА С ПОМОЩЬЮ ГЛУБОКОГО ОБУЧЕНИЯ

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Аннотация. *Цель работы заключается в разработке алгоритма для выявления патологических образований, вызванных фиброзом в легких человека. Основой алгоритма является модель PSPNet, позволяющей сгруппировать множества наборов данных в соответствии с их сходством на основе диагностических признаков для выявления фиброза легких. Простая и эффективная структура алгоритма использует метод манипулирования пикселями с абразивными процессами на краях сегментов легких и приводит к локализации областей фиброза с высокой точностью.*

Introduction. The field of medical science is an ever-progressing area, where specialists of computer engineering constantly pursue perfection in the diagnosis of various diseases. Over the years, diagnosis of various lung diseases [1] has been difficult, and sometimes even impossible due to the lack of equipment. Pulmonary fibrosis is a condition where lungs are damaged or scarred by several factors, leading to even the death of the patient. Although radiologists have been involved in the detection process, certain abnormalities in the lungs can never be detected with the naked eye. Therefore, a system has been proposed for the automatic detection of pulmonary fibrosis based on CT images [2], to assist radiologists in this process even at a chance of 0.01% of occurrence.

Previously, in an attempt to detect fibrosis [3], a system was created to use a 2D convolutional neural network [4]. The datasets were trained to recognize images in its original size, and then convert them to a bitmap format. During the pre and post processing techniques, the Laplacian of Gaussian 5*5 filter was used to isolate pixels and identify if fibrosis occurs at the edge of the lung or in its cavity. This attempt, though successful, failed to produce results if the image pixilation was weak, and if the lung CT image [2] had more nodules and abrasions.

Therefore, a new algorithm using a PSPNet with a pyramid pooling module [5] is now proposed to enhance the previous system of detecting pulmonary fibrosis with more accuracy.

Methods and Technologies. The system takes a training dataset as an input. This dataset contains High Resolution CT images [2]. Approximately CT images of 60 to 70 patients whose pathological conditions include pulmonary fibrotic regions [3], and normal regions have been used for diagnosis. The pixilation of these images is modelled to provide different features of the lung. These modelled images are then separated into various subsets according to their similarities.

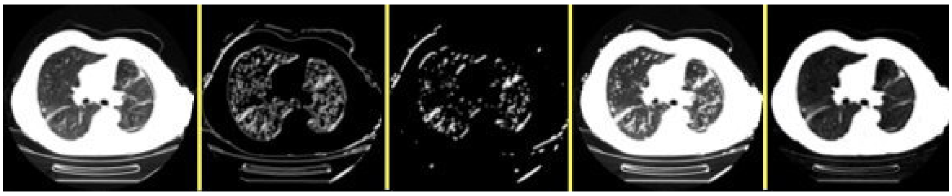

Fig.1. CT Scans with Different Textures and Variations with Various Pathological Conditions

The Pyramid Scene Parsing Network (PSPNet) is used since all subsets are fed in at once into the neural network. In this method, datasets with different textures (as shown in Fig 1) identify features in four different scales. Each scale forms a pyramid level, and each pyramid level reduces in size from bottom to top to form a single pyramid. The size of pyramid is maintained by a 1*1 convolutional layer after every pyramid level. Hence, if the size of the lower most pyramid level is N, it reduces by $1/N$ as it moves layer by layer upwards. During deconvolution, by using the bilinear interpolation technique, the size of the output image obtained is the same as that of the input image.

The network architecture is simple (as seen in Fig 2). The input image is first converted into a bitmap image. It is at the feature extraction stage [6,7] where the Neighbouring algorithm identifies every pixel in the bitmap and manipulates it as black and white pixels to display any nodules. The subsets of similar datasets that are grouped are then finally gathered in the pyramid pooling module. The four levels of the pyramid help to find the fibrotic regions in detail, which is then concatenated with the original image and convolved to determine the final output.

Binary Image Morphing [8,9] is used to remove any extra blobs or uncertainties in the image. In addition to this, Fuzzy Logic technique [9,10] is used to detect fuzziness [11] Fnear the edges of lung images. The blur of the fuzzy border is corrected by using the equation $B=I*k$, where I is the local patch and k is the point spread function of the blur of the image. The k nearest Neighbour algorithm [12,13] is then applied to identify the next fuzzy border pixels.

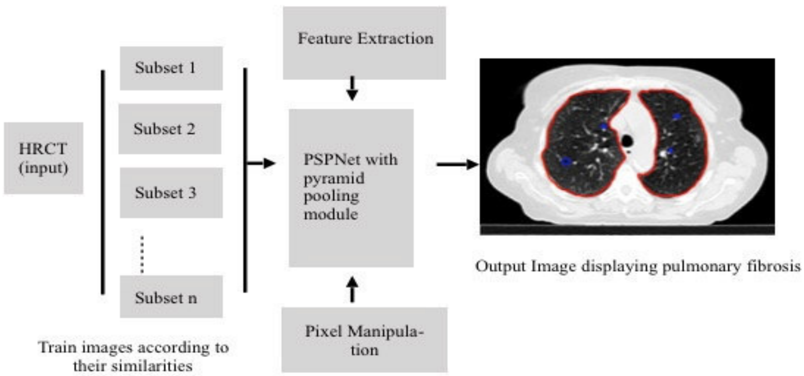

Fig. 2. Network Structure of the Overall Working Process

Conclusion. The above method helps to deal with different textures and data sets. By using Binary Image Morphing techniques [8] and Fuzzy Logic techniques, blurred edges [9,10] caused by pulmonary fibrosis are identified. With the help of PSPNet [5] as the convolutional neural network, fibrosis with various anomalies can be detected more accurately.

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