ANALYSIS AND DIAGNOSIS OF CYSTIC FIBROSIS OF THE LUNGS WITH IMPROVED DEEP LEARNING TECHNIQUES

N.J. Francis, N.S. Francis, M. Saqib
Scientific Supervisor: Asst Prof. S.V. Axyonov
Tomsk Polytechnic University, Russia, Tomsk, Lenin ave., 30, 634050
E-mail: natzina_92@yahoo.com

АНАЛИЗ И ДИАГНОСТИКА ЦИСТИЧЕСКОГО ФИБРОЗА ЛЕГКИХ С УЛУЧШЕННЫМИ МЕТОДАМИ ГЛУБОКОГО ОБУЧЕНИЯ

Н.Дж. Франсис, Н.С. Франсис, М. Сакиб
Научный руководитель: доцент, к.т.н. Аксёнов С.В.
Национальный исследовательский Томский политехнический университет
Россия, г. Томск, пр. Ленина, 30, 634050
E-mail: natzina_92@yahoo.com

Аннотация. *Целью работы является разработка алгоритма выявления патологического образования при муковисцидоз.. Основой алгоритма является модель PSPNet с потерей очага, которая позволяет вводить наборы данных в соответствии с их сходством на основе диагностических признаков для выявления муковисцидоз легких. Простая и эффективная структура алгоритма использует метод группировки аннотированных изображений, которые затем обрабатываются в CNN, что помогает с высокой точностью локализовать области муковисцидоз в легких.*

Introduction. Cystic fibrosis (CF) [1] of the lungs usually occurs hereditarily. It is a condition where the body produces mucus and thus clogs the lungs. This leads to obstruction of the lungs which is life-threatening, where respiratory failure is the most common way of death for a person suffering from CF. The most known fact of CF is that there is no cure for the disease and the patient is prone to further lung diseases like pneumonia and bronchitis. Thus, detecting the disease at an early stage will help to reduce the impact it has on the person identified with CF. The initial diagnosis of CF involves a sweat test where the presence of an invariantly high chloride level plays a key role in indicating the disease. High Resolution Computer Tomographic (HRCT) images [2] are used in CF for the purpose of identifying supervening complications and further more for the purpose of research. Radiologists play a key role when it comes to CT images. However, diagnosis can be made easy and more accurately to aide radiologists in the purpose of research. The main objective of the researchers is to produce high quality output results to increase the rate of diagnosing CF and thereby increase the therapeutic options in the treatment for patients suffering from CF.

In a recent attempt to detect pulmonary fibrosis, PSPNet [3] is used along with a pyramid pooling module to distinguishably identify the disease. This was made possible by dividing the HRCT images subjectively in various subsets by training the dataset. The dataset that is inputted purely contains patients suffering from pulmonary fibrosis. The module helps divide images accordingly and the output is successfully diagnosed. However, a more advanced training dataset is required to further more compare the output obtained to the output produced.

Thus the algorithm is extended to produce an output with CF. This is done by applying a focal loss [4] and cross entropy[5] along with the PSPNet. This helps in improving the overall output as the HRCT images inputted helps to deal with the problem of identifying mucus and tumours in the images.

Methods and Technologies. The PSPNet is trained with images obtained from the database of the Belarus Medical Centre [6]. CT images of 80 to 90 patients are taken out of which healthy slices of 40 patients were taken for observational purposes.

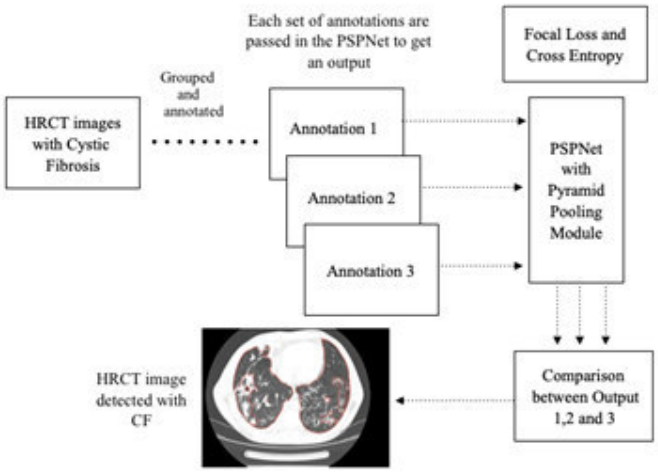

Fig. 1: The overall working architecture for the detection of Cystic Fibrosis

The Pyramid Scene Parsing Network (PSPNet) in the process of high computational segmentation process [7, 8] of the brain has produced results with accuracy and precision. Thus we combine the PSPNet along with pyramid pooling module [9] with focal loss and cross entropy. This pyramid pooling module is known for its region based contextual aggregation [10] which is inputted at various input scales. The pooling kernels are applied to the final network layer of the feature map. The CF cysts are detected by considering the final layer of the convolutional network consisting of a feature obtained in the feature map. Thus it is an element of the feature map to which average pooling is applied. The output of the average pooling applied to the feature map is divided into feature map sizes such as 1X1, 2X2, and so on. Thus the final output of this pyramid pooling module is obtained by using a 1X1 Convolutional Neural Network to each and every feature map. Upsampling and Bilinear Interpolation [10] are used to produce an image of equal weights and the dimensions are enabled to that of the final feature map. The inputted final layer of the feature map is then concatenated with the feature maps that are derived previously from the pyramid pooling module.

The networks are also trained with cross entropy and the loss function. The focal loss is given by,

$$f(a,b) = -b(1-a)^{\gamma}\log(a) - (1-b)a^{\gamma}\log(1-a)$$

Where, f is the focal loss and γ is the focus on the down weight of the samples classified. The cross entropy loss is given by,

$$e(a,b) = -tb\log(a) - (1-t)(1-b)\log(1-a)$$

Where, e is the cross entropy loss and t is the weights.

These functions help to focus on less confidently classified examples and produce output with less loss in the image. The overall working procedure also uses the Fuzzy logic technique for detecting the mucus that is seen in the CT images of lungs with CF. The Binary Image Morphing process [11] is also used in the pre

processing [12] to obtain HRCT images without the blood vessels and veins that might be confused with the abnormality. When a focal loss of $\gamma = 1$ is used in the PSPNet, the model performance is improved. Thus, the overall working involves a single slice of the HRCT image that is annotated thrice and fed into the PSPNet. The images are then passed individually into the system and the output is compared. The comparative results help in accurately detecting CF.

Conclusion. Thus the detection of Cystic Fibrosis is successfully identified by the use of a PSPNet incorporated with the pyramid pooling module. The Cross Entropy and Focal Loss help to retain the loss that takes place during image processing. The images are annotated invariably thrice and fed into the system which on comparison produces relatively accurate results.

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