IDENTIFICATION OF BRONCHOPULMONARY LUNG SEGMENTS THROUGH SHADOWING AND CONVENTIONAL NEURAL NETWORKS

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ИДЕНТИФИКАЦИЯ БРОНХОЛЕГОЧНЫХ СЕГМЕНТОВ В ЛЕГКИХ С ПОМОЩЬЮ ЗАТЕНЕНИЯ И СВЕРТОЧНЫХ НЕРОННЫХ СЕТЙ

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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. Radiologists contribute an enormous amount of time to identify various diseases from lung images. Technology can be used to analyze and accelerate the pathosis discerning process of a patient. Identifying bronchopulmonary lung segments during pathology analysis [5] provides doctors with an advantage to work only with the particular affected segments.

Although many researchers have performed segmentation [1] on lung CT images, these segmentation techniques are only shaped to detect veins [8], blood vessels or pathologies. In the recent years, scientists have found more profound segmentation methods [1] to identify lung lobes, but research is still carried on to identify bronchopulmonary segments.

Previously, in an attempt to perform segmentation on CT images, Canny Edge Detection algorithm along with various filters were used. This approach was not very effective as only one or two segments could be detected.

Taking the latest segmentation methods into consideration, a convolutional neural network proves efficient to identify multiple bronchopulmonary segments. R Mask CNN [2] has proved to be an exceptional neural network for segmentation [1] purposes. U-Net and Keras are used with R Mask CNN [2] every time the neural network repeats its cycle in training the dataset.

Furthermore, in order to reduce the size of the training dataset, shadowed and highlighted segments of the image are identified using a Ridge based Distribution Analysis method (RAD).

Training Data and Functionality. For the purpose of bronchopulmonary segmentation [3,5], the dicom image [4,7] obtained from Belarus Medical Centre should be first converted into a .jpeg or .png format. The lung image is then analyzed for different shadowed regions using RAD. During the RAD process, dominant structure points are first identified within the lung image. From theses structure points, ridge points or points that distinguish one region from the other are identified. Connecting ridge points are then identified to form a histogram Ω(x) using the formula:

$$S(x, \sigma) = N(x, \sigma i) * (\nabla\Omega(x, \sigma d) \cdot \nabla\Omega t(x, \sigma d))$$

Where σi is the size of the symmetric neighbourhood [11] forming the region within the lung image, x is the centre point of the field S, $\sigma = \{\sigma i, \sigma d\}$ and also the calculus of the vector field is given by a gaussian kernel. Using this formula, the various shadowed regions are first detected and sent as the dataset into R Mask CNN [1,6] for training as seen in Fig1.

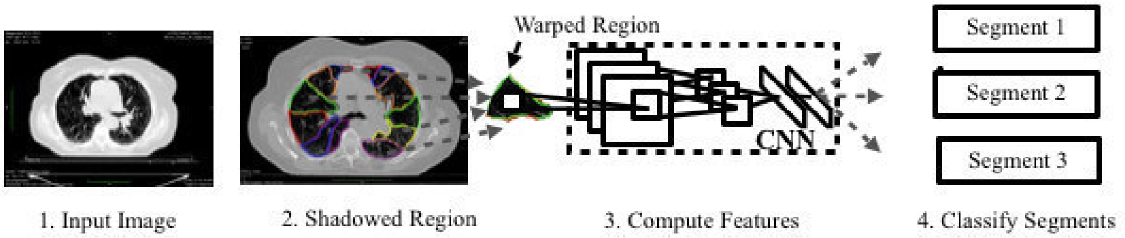

Fig 1. Mask R CNN Effective Functioning

The deep convolutional neural network used during this entire process is the Keras framework, known for its excellent segmentation properties [3,5]. During the first convolution, R Mask CNN is used. When the R Mask CNN repeats training, U-Net is used to simplify the training process and render classified segmented regions.

The softmax detector of U-Net is combined with the bbox regressor of R Mask CNN as seen in Fig2 to provide separate pulmonary lung segments.

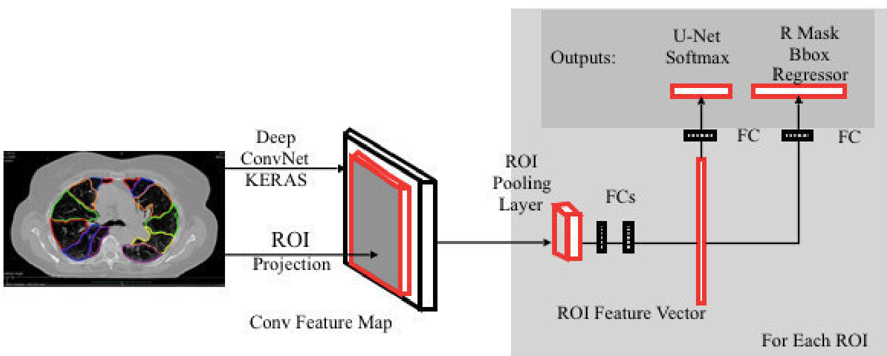

Fig 2. Combination of Two Convolutional Neural Networks

Prediction and Performance. Learning of shadowed regions within the lung helps in identifying segments that may not be visible otherwise. The enormous space occupied by R Mask CNN for the training of images is eliminated with the help of shadowed features as input and U-Net. There is a loss in output pixels due to extraction and convolution. The loss function will include three elements pertaining to R Mask CNN and U-Net [1,6]. It includes:

$$L = L_{CLS(U)} + L_{box(R)} + L_{mask}$$

Where $L_{CLS(U)}$ is the log loss from U-Net's softmax detector [1,6], $L_{box(R)}$ is the loss [10] from R Mask CNN's bbox regressor, and L_{mask} is the loss [10] from the detected mask.

Conclusion. The main purpose for the detection of bronchopulmonary segments is to help radiologists identify pathologies [5] pertaining to the particular segment. Each segment is independent, and any anomaly in one segment does not affect the other segments. In comparison to older segmentation versions, the use of neural networks proves to be more efficient as internal features of the lung can be identified. The use of two different neural networks along with the shadow feature helps the setup to process images clearly and identify each segment more accurately.

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