DeepMedic and U-Net neuronal network architectures for lung segmentation in CT scans

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***Abstract*—This work examines the DeepMedic and the U-Net architectures of neuronal nets for segmentation of lung structures in computed tomography scans. The application of the algorithms will be evaluated on the LUNA16 dataset.**

I. Introduction

Since hardware specifications and computational power increased dramatically in the last years machine learning approaches can be applied in various disciplines today. On top of that the progress in research on convolutional neuronal networks (CNN) made it a very powerful tool for image processing where information is gained from image data.
One challenging application is medical image computing (MIC). The main goal of MIC is to extract clinically relevant information or knowledge from medical images. Furthermore Segmentation is the process of partitioning an image into different meaningful segments (e. g. organs, bones, ...).
In this project the goal is to segment the lung of a human body from a computed tomography (CT) scans.
The used dataset is from the LUNA16 challenge [1] and each scan contains a number of slices which are 512 x 512 pixel greyscale images. The algorithm creates a 512 x 512 pixel label map for each slice marking every pixel that is part of the lung. An example of one scan and the corresponding labeling is shown in figure 1.

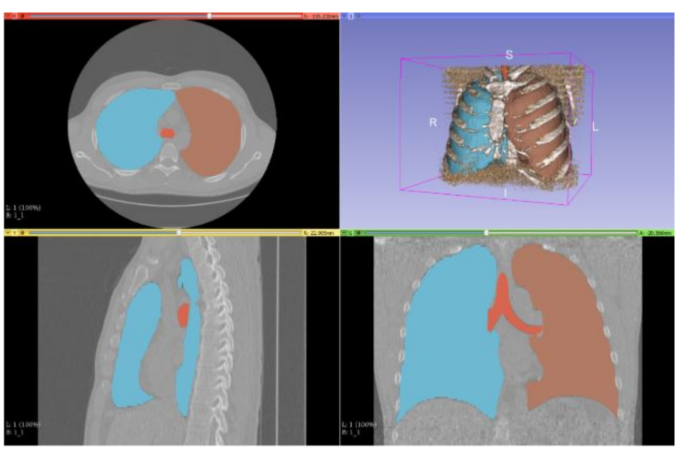

Fig. 1. CT scan of the lung and labeled parts

The segmentation of the lung from the rest of the picture is the first step for further image processing. In the LUNA16 dataset the final goal for example is to detect nodules of the lung indicating cancer. Machine learning approaches can be a powerful support for the doctors who treat patients with suspected cancer. The algorithms can reduce human errors and . It might even have the potential to outperform human capabilities and could automatizes the process of cancer detection. This could have a positive effect on health care quality and costs.
In this work two different neuronal networks will be trained and tested to segment the lung on the above described dataset. Furthermore they will be examined and compared under different metrics.
First a short overview on the DeepMedic Network and the U-Net will be given and will be related to other approaches for medical image segmentation. After that the process and implementation will be explained and in the end the results of the two algorithms examined and compared.

II. Background

A. DeepMedic architecture

DeepMedic is a 3D Neural Network. It has been initially used for segmentations in biomedical 3D scans, especially for detecting brain anomalies such as injuries, tumors and lesions. In this project we have been able to try this algorithm on lung segmentations.
A DeepMedic model consists of detecting a particular pattern in an image. This is achieved by convolution at following layers of the network. We distinguish two components in the model. First there is a three-dimension Convolutional Neural Network (CNN) model used for dense segmentation, then a three-dimension fully connected conditional random field (CRF) model for deeper predictions. (Might we only use the first component?)
Each layer of the CNN model contains channels called feature maps, i.e. a group of neurons identifying a feature in the previous layer. Then a feature is defined by associated kernel weights. Number of inputs, outputs, feature-maps and kernels are tunable.

B. U-Net architecture

Semantic segmentation is partition of an image in coherent parts. For end to end encoding decoding network unet is used for semantic segmentation. Unet is mostly used for biomedical image segmentation. The following image shows how unet works.

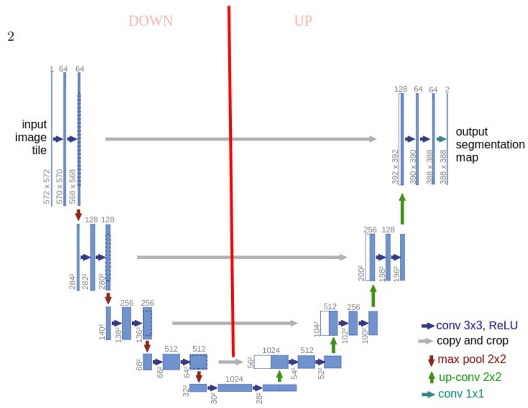

Fig. 2. CT scan of the lung and labeled parts

This is a U-net architecture . Each bluebox corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.
The first part is called down or encoder part where we will apply convolutional blocks followed by maxpool downsampling to encode the input image into feature representations at multiple different levels. The second part of the network consists of upsample and concatenation followed by regular convolution operations. We are going to expand the future dimensions from left to meet the same size with concatenation blocks. The grey and green arrows tell from where to concatenate future maps together. The main feature of unet in comaprison to other fully convolutional segmentation networks is that while upsampling and going deeper in the networks we are concatinating the higher resolution features from downpart with upsampled features in order to better localize and learn representation with upcoming convolutions. As upsampling is sparse we need to be good prior from beginning stages to get the better localization representation. In order to get consistent size we applied padded convolutions to keep dimensions consistent across concatination. Localization is one of the most important feature in case of biomedicalimage processing. In order to localize, high resolution from the contracting path are combined with upsampled output. By this the successive convolution layer can then learn to assemble a more precise output. The main modification in our architecture was that in the upsampling part we have a large number of feature channels, which allows the network to propogate context information to high resolution layers. To predict the pixels in the border region of the image, the missing context is extrapolated by mirroring the input image.

III. Related Work

text and subsections

IV. Process

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V. Evaluation

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VI. Conclusion

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References

[1] “Lung nodule analysis 2016.” [Online]. Available: https://luna16.grand-challenge.org/