

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.

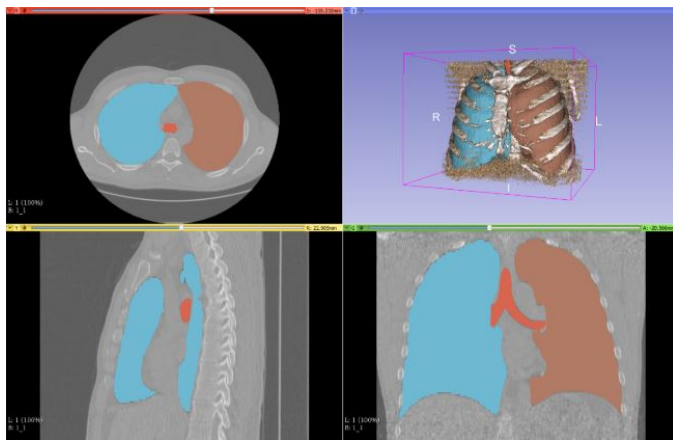


Fig. 1. CT scan of the lung and labeled parts

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 will try this algorithm for lung segmentations.

A DeepMedic model consists of detecting a particular pattern in an image. This is achieved by multi-layer convolution in 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. U-Net is mostly used for biomedical image segmentation. In figure 3 the structure of the U-Net is shown.

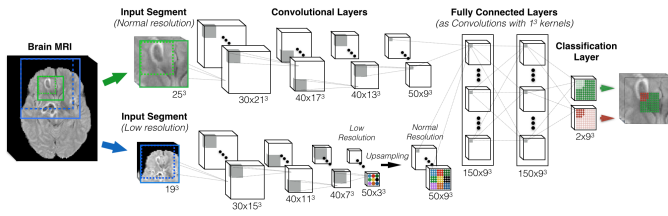


Fig. 2. Overview of DeepMedic architecture

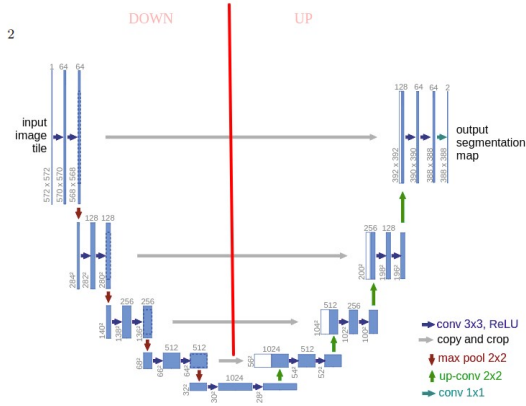


Fig. 3. Structure of U-Net architecture

Each blue box 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. 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 layers to encode the input image into feature representations at multiple different levels. The second part of the network consists of upsample and concatenation layers followed by regular convolution operations. We are going to expand the dimensions from left to meet the original image size. The grey and green arrows tell from where to concatenate future maps together. The main feature of U-Net in comparison to other fully convolutional segmentation networks is that while upsampling and going deeper in the networks it also concatenates the higher resolution features from the down sampling part with upsampled features in order to better localize and learn representation.

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 concatenation. Localization is one of the most important feature in case of biomedical-image 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 propagate 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.

C. Metrics

III. RELATED WORK

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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/>