Segmentation of costa in 2d MRI scans utilizing the U-Net convolutional network architecture

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Segmentation of costa (rib bones) in magnetic resonance images is not a widely researched area. However, it may have significant clinical value, since it can act as a stable reference for multiple analysis and quantification tasks (Xu, Bagci, Jonsson, Jain, & Mollura, 2014). As such, we consider this problem to be an appropriate starting point for benchmarking the applicability of the U-Net architecture in 2d MRI scans. The main concept of the U-Net network pipeline is the heavy reliance on data augmentation combined with up sampling to allow connection between convolution and deconvolution layers (Litjens et al., 2017; Ronneberger, Fischer, & Brox, 2015).

We performed a series of tests on MRI scans, where we trained a U-Net CNN architecture utilizing a subset of 30 512x512 monochrome MRI images from a single 3d axial scan of the chest region consisting of 344 images. Masks for the training images were created by labelling pixels either as background or as costa cross-sections. Each image and mask in the training set contained from 4 to 10 of labelled costa cross-sections, varying in size, location, and orientation. Augmentation was supported by the utilizing the preprocessor module in Keras. The model was trained using 600 epochs with 30 steps per epoch, and with a constant learning rate of $3 \cdot 10^{-5}$.

An initial test was performed on another subset of 30 images from the same MRI scan to see if the algorithm would be able to detect the structures in an equal environment than initially trained upon. Results, which were produced as output masks with a probability measure between 0 and 1 in each pixel, were quite promising. In Figure 1, we see one of the test results, where the left image is the original and the right is a color mapped overlay of the produced probability mask. For validation purposes we utilized the trained model on 4 other samples from an axial MRI scan slightly skewed and with another cross-section size compared to the scan originally trained on. Results from this test showed that the model performed equally well (see Figure 2).

Our ambition is to transfer the successful implementation to include other tasks that may aid radiologists in detecting various lesions and give input to volumetric calculations. To achieve this, we need to extend the segmentation in 3d which may be achieved by exploring the V-net architecture (Milletari, Navab, & Ahmadi, 2016).

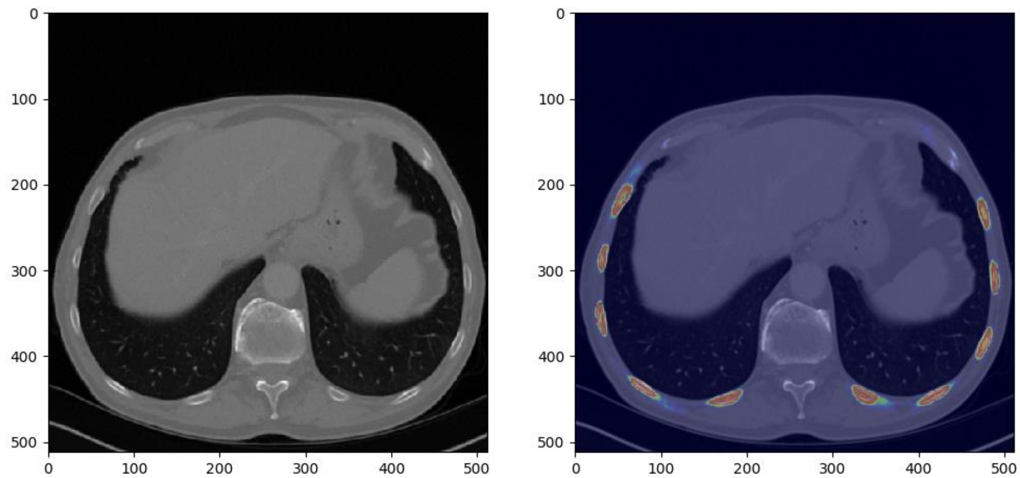

Figure 1: Segmentation of costa in an image taken from the same scan as the original training images.

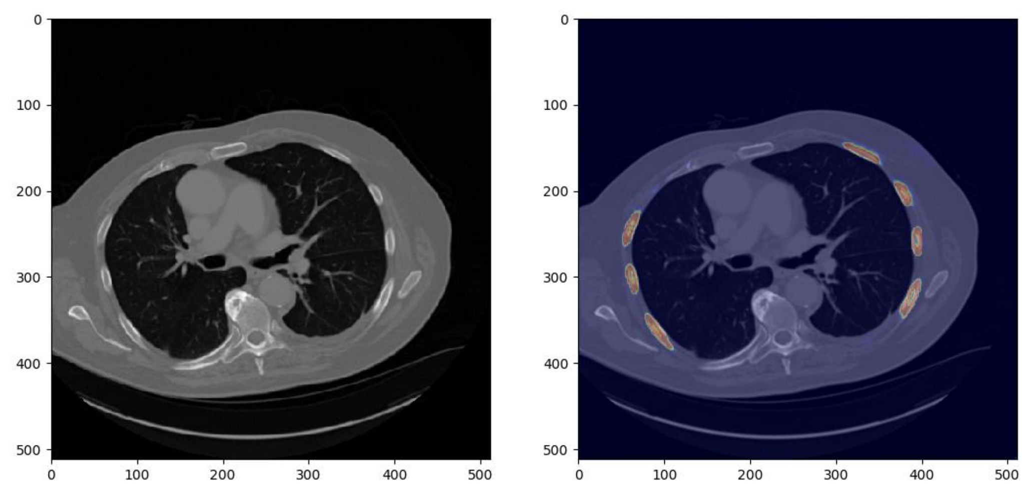

Figure 2: Segmentation of costa in a scan from a different patient than originally trained on.

References

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