A Lightweight ConvNet for 4D Multi-Structure Segmentation of Cardiac Cine-MRI

K.G. van Leeuwen[1, *], J.W. Benjamins[1], I. Everts[1], T. Hendrinks[1,2], W.H. Nijhof[2], F. van der Heijden[1], P. van der Harst[1,2]
[1] Siemens Healthineers, Den Haag
[2] University of Twente, Enschede
[3] University Medical Center Groningen, Cardiology
[4] GoDataDriven, Amsterdam
[*] kickyvanleeuwen@gmail.com

Abstract

Cardiac magnetic resonance imaging (MRI) is the gold standard for heart function assessment. We present a method for automatic segmentation of the left ventricular cavity (LVC), right ventricular cavity (RVC), and left ventricle myocardium (LVM) with a simplified, lightweight variation of the U-net trained in the cloud allowing for high throughput analysis. Dice indices on the test set were 0.95 for the LVC and 0.85 for both the LVM as RVC. A dashboard was created for visualization of the segmentation inferred cardiac function parameters. We demonstrate that this simple model trained on only a subset of the data yields satisfying segmentation results that can clinically aid cardiologists in diagnosis and treatment of heart failure patients as well as facilitate big data research on cardiac function.

1 Introduction

Heart failure is one of the most common diseases at time with a global prevalence of 2-4% rising to 6-10% when above 65 years of age [1]. The gold standard for the assessment of cardiac function for heart failure diagnosis, treatment planning and prognosis, is cine magnetic resonance imaging (MRI). The data is not yet exploited to its fullest as manual contouring of the heart segments is a time-consuming and tedious work with high intra- and inter-observer variability. An automated segmentation tool can aid clinically as well as in large scale studies to capitalize on the data at hand. In this study, we show that a simple and thus fast implementation of a 2D U-net[2] based network running on the cloud yields good results on the cardiac cine-MRI segmentation task for the left ventricle cavity (LVC), the right ventricle cavity (RVC), and the left ventricle myocardium (LVM). The convolutional neural network (CNN) is trained on only end diastolic (ED) and end systolic (ES) MR images, however is applied on all phases revealing the dynamics of the heart. Features derived from the segmented structures can be highly valuable in the context of computer aided diagnosis. A visualization tool has been developed as a first step to aid the cardiologist in the heart function assessment.

2 Method

2.1 Dataset

The dataset exists of 222 short-axis cine-MRIs (3 Tesla Achieva, Philips) of myocardial infarction patients from the University Medical Center Groningen[3]. Ground truth segmentation masks were

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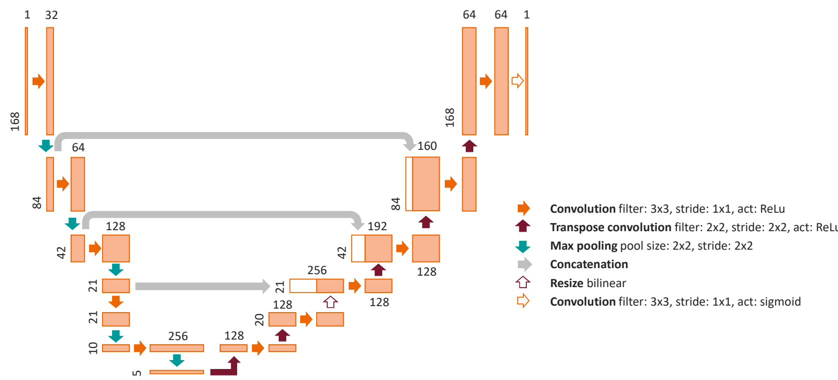

Figure 1: U-net inspired neural network architecture represented in 2D. The height of each block represents the X-, as well as the Y-dimension. The width represents the depth, or the number of filter.

created by medical experts only for the ED and ES phase for the right and left ventricle endocardium and the left epicardium. Not all subjects had masks for all structures and masks of left and right structures could be of a different phase. Patients were randomly assigned to the train or test set with chance 0.8 and 0.2 respectively.

2.2 Training

Myocardium masks were generated by extracting the LV endocardium mask from the LV epicardium mask. Images were scaled to equal mm/pixel ratio, contrast enhanced, and symmetrically cropped. Random elastic deformation increased the number of training samples. A U-net based network[2] was implemented in Keras with Tensorflow backend (Figure 1). This lighter version was created by using single instead of double convolutional layers reducing the number of parameters from 3.7 million to less than 2 million, increasing training and prediction speed. The network was trained with the Adam optimizer, binary cross-entropy loss function, with dropout and batch normalization layers. A model was created for each cardiac structure. The segmentations of the different structures were combined by committing each pixel to the structure with the maximum pixel value. For each structure, only the largest connecting volume was kept and holes in the predicted masks were filled. Computations were performed on the Compute Instance of the Google Cloud Platform.

2.3 Evaluation

The dice index was the main performance metric representing the similarity between ground truth mask and predicted mask. In total seven patients (five train, two test set) were excluded from evaluation, because of MRI orientation variations. Volumes were calculated by adding frustum volumes of the stacked areas. A dashboard was created for easy interpretation of the results.

3 Results

The dice index on the test set of 44 patients was 0.945 for the LVC, 0.850 for the LVM, and 0.851 for the RVC as can be seen in Table 1. Note that these numbers were based on only two frames per patient as only ground truth labels were present for the ED and ES phase. Train and test set performance were similar suggesting the models were not overfit. At the ED phase, better performance was achieved compared to the ES phase for the LVC and RVC. For the LVM the opposite is demonstrated. Figure 2 shows the prototype visualization tool made for the cardiac MRI analysis representing the volume changes of the different structures over the cycle in the top figure. Segmentation results are shown in the bottom figures and change according to the phase clicked on in the top graph. The table presents the most important clinical parameters.

Table 1: Dice index for the train and test set of the segmentation of the left ventricular cavity (LVC), left ventricular mass (LVM), and right ventricular cavity (RVC) at end diastolic, end systolic phase and both

	LVC		LVM		RVC	
	Train	Test	Train	Test	Train	Test
End diastolic	0.960	0.956	0.848	0.841	0.873	0.859
End systolic	0.926	0.921	0.866	0.858	0.842	0.835
Both	0.949	0.945	0.857	0.850	0.863	0.851

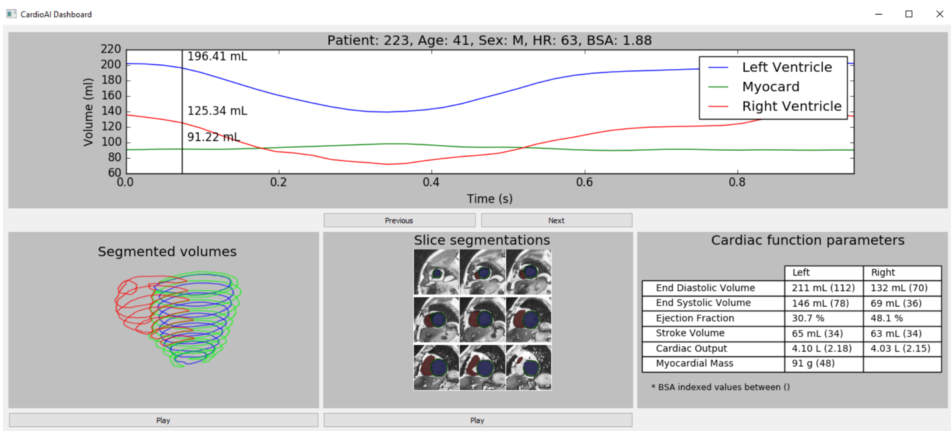

Figure 2: Interactive dashboard for visualization of segmentation results and inferred parameters

4 Discussion

We show a method and visualization tool for automatic segmentation of 4D cardiac cine MRI with a lightweight CNN. The mean dice index for all structures is 0.88 and comparable to recent research performed with U-net based 3D CNNs (0.89[4] and 0.86[5]) and recurrent networks (0.89[6]). Currently we are working on retraining the models in the ML Engine of Google Cloud and developing a web application for the visualization. An automatic segmentation methodology as presented here does not only enable more efficient heart function assessment in a clinical context. It also reveals information about the cardiac dynamics as all phases and slices of the cardiac MRI can be used instead of only the ES and ED phase as is the norm now. This could allow for striking big data research concerning the growing population of heart failure patients.

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