Cascaded Convolutional Neural Network for Automatic Myocardial Infarction Segmentation from Delayed-Enhancement Cardiac MRI

Yichi Zhang

School of Biological Science and Medical Engineering, Beihang University

Abstract. Automatic segmentation of myocardial contours and relevant areas like infraction and no-reflow is an important step for quantitative evaluation of myocardial infarction. In this work, we propose a cascaded convolutional neural network for automatic myocardial infarction segmentation from delayed-enhancement cardiac MRI. We use a 2D U-Net to focus on the intra-slice information to perform a preliminary segmentation, and then a 3D U-Net to utilize the volumetric spatial information for a subtle segmentation. We evaluate our method on 2020 MICCAI EMIDEC challenge dataset and achieve average Dice score of 0.8786, 0.7124 and 0.7851 for myocardium, infarction and no-reflow respectively, which demonstrate the accuracy and effectiveness of our proposed method.

Keywords: Magnetic Resonance Imaging · Myocardial Infarction · Segmentation · Convolutional Neural Networks

1 Introduction

Myocardial infarction (MI) is a myocardial ischemic necrosis caused by coronary artery complications that cannot provide enough blood and has become one of the leading causes of death and disability worldwide [1]. The viability of the cardiac segment is an important parameter to assess the cardiac status after MI, such as whether the segment is functional after the revascularization. Delayed enhancement-MRI (DE-MRI) that performed several minutes after the injection is a method to evaluate the extent of MI and assess viable tissues after the injury.

Automated segmentation of the different relevant areas from DE-MRI, such as myocardial contours, the infarcted area and the permanent microvascular obstruction area (no-reflow area) could provide useful information like absolute value (mm3) or percentage of the myocardium for quantitative evaluation of MI. Recently, deep learning-based methods have achieved state-of-the-art results for various image segmentation tasks and shown great potential in medical image analysis and clinical applications. In this paper, we propose a cascaded convolutional neural network for automatic myocardial infarction segmentation from delayed-enhancement cardiac MRI. The training and validation processes of our network are based on MICCAI 2020 EMIDEC Challenge dataset[1][2].

2 Methods

2.1 Network Architecture

As the most well-known network structure for medical image segmentation, U-Net [3] is a classical encoder-decoder segmentation network and achieve state-of-the-arts results on many segmentation challenges [4,5]. The encoder is similar with the typical classification network and uses convolution-pooling module to extract more high-level semantic feature layer by layer. Then the decoder recovers the localization for every voxel and utilizes the extracted feature information for the classification of each pixel. To incorporate multi-scale features and employ the position information, skip connections are constructed between the encoder and decoder in the same stage.

For segmentation of 3D biomedical images, 3D U-Net [6] are proposed to extract volumetric spatial information using 3D convolutions instead of just focusing on intra-slice information. However, for some volumes with highly anisotropic voxel spacings, 3D networks may not always outperform 2D networks when inter-slice correlation information is not rich [7]. For example, Case_N042 is a 3D MRI volume with image shape of 166*270*7 and voxel spacing of 1.667*1.667*10 on x, y and z axis, respectively. Which means, x and y axis preserve much higher resolution and richer information than the z axis. Under this circumstance, using pure 3D network that treat the three axes equally may not be the best choice.

To issue this problem, we propose a cascaded convolutional neural network for automatic myocardial infarction segmentation from delayed-enhancement cardiac MRI. As illustrated in Fig.1, our network can be mainly divided into two stages: firstly, after the preprocessing of input data, we use a 2D U-Net for a preliminary segmentation focusing on intra-slice information. After that, a 3D U-Net is used to utilize the volumetric spatial information and make a subtle segmentation based on the original input volume and 2D segmentation results. In the end, after the postprocessing like removing the scattered voxels, we get the final segmentation results.

[1] http://emidec.com/

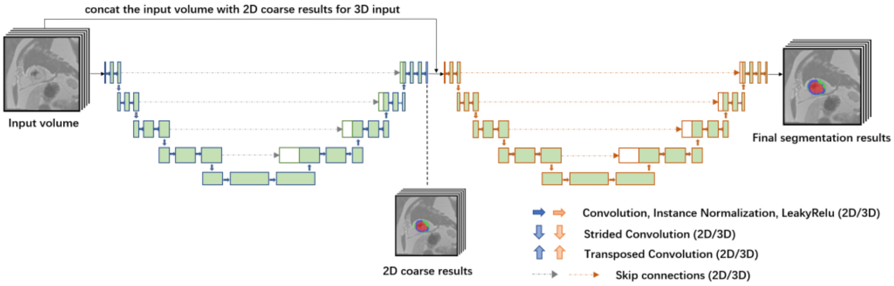

Fig. 1. The overall architecture of our cascaded convolutional neural network. The blocks and arrows viewed in blue and red denote corresponding structure for 2D and 3D network.

2.2 Implementation Details

All the training procedure of our network are performed on NVIDIA Tesla V100 GPUs using the Pytorch framework based on the nnU-Net implementation [5]. During training, we use Adam optimizer with initial learning rate 0.01. Instead of patch-based methods, we use the whole short-axis slice and whole volume for the input of the 2D and 3D networks. To enhance the attention of foreground voxels, we use the combination of cross-entropy (CE) loss and dice loss [8] as the loss function for training of our network. The final loss function can be summarized as follows:

$$L = L_{CE} + L_{Dice} \tag{1}$$

$$L_{Dice} = 1 - \frac{2 * \sum y_{true} * y_{pred} + \varepsilon}{\sum y_{true}{}^2 + y_{pred}{}^2 + \varepsilon} \tag{2}$$

2.3 Dataset and Evaluation Metrics

The EMIDEC Challenge dataset consists of delayed-enhancement cardiac MRI with a training set of 100 patients including 67 pathological cases and 33 normal cases and a testing set of another 50 patients including 33 pathological cases and 17 normal cases. For training cases, manual annotations are provided with 0 for background, 1 for cavity, 2 for normal myocardium, 3 for myocardial infarction and 4 for no-reflow.

For evaluation of segmentation results, clinical metrics include the average errors for the volume of the myocardium of the left ventricle, the volume and the percentage of MI and no-reflow and geometrical metrics include the average Dice coefficient for the different areas and Hausdorff distance for the myocardium are considered.

3 Experiments and Results

There are totally 100 scans with published labels to train our network while the other 50 scans remained for final evaluation. We make random 5-fold cross-validation by randomly shuffling the sequence of cases and splitting the training dataset into 5 fixed folds with 20 MR scans in each fold, using 4 folds for training and the other one for testing. In this way, we can make a more comprehensive evaluation of our method.

Table 1 and Table 2 represents the cross-validation results of our 2D coarse segmentation output and final segmentation output. The evaluation of clinical and geometrical metrics is based on the official code[2]. From the result we could see that the application of 3D U-Net could make use of the volumetric spatial information and improvement the segmentation result.

For our final segmentation results, the network performs well on myocardium segmentation, with an average dice score of 0.8715. However, for more challenging segmentation of pathological areas, the average dice score is only 0.7208 and 0.7101 for infarction and no-reflow. Also, the performance variance is very small, which indicates the robustness of our method. Fig.2 illustrate two samples of our segmentation results and corresponding ground truth in the validation set of our own split. We could see that for our segmentation results are closely approximate the ground truth.

Table 1. Quantitative 5-fold cross-validation results of 2D coarse segmentation output

Targets	Metrics	fold 0	fold 1	fold 2	fold 3	fold 4
Myocardium	Dice(%)	83.98	85.29	85.94	85.83	85.59
	VolDif(mm^3)	10906.43	6384.88	6012.93	5423.57	11629.66
	HSD(mm)	17.01	13.77	13.68	12.60	12.65
Infarction	Dice(%)	44.39	53.12	48.10	50.55	66.34
	VolDif(mm^3)	9883.17	4821.30	3449.09	4986.66	6621.52
	Ratio(%)	7.10	4.39	2.96	4.68	5.00
NoReflow	Dice(%)	65.26	63.84	70.61	60.24	66.67
	VolDif(mm^3)	2703.34	775.07	480.32	703.7	443.86
	Ratio(%)	1.68	0.68	0.37	0.67	0.32

[2] https://github.com/EMIDEC-Challenge/Evaluation-metrics

Table 2. Quantitative 5-fold cross-validation results of our final segmentation output.

Targets	Metrics	fold 0	fold 1	fold 2	fold 3	fold 4
Myocardium	Dice(%)	86.66	86.46	87.87	87.61	87.13
	VolDif(mm^3)	8680.23	5405.52	6087.88	4880.5	7317.76
	HSD(mm)	15.88	14.12	12.96	13.43	13.79
Infarction	Dice(%)	61.44	72.08	81.51	68.48	76.87
	VolDif(mm^3)	6536.55	3233.94	3514.97	4091.74	3520.3
	Ratio(%)	4.67	2.91	2.85	3.96	2.64
NoReflow	Dice(%)	68.47	68.33	79.67	65.12	73.48
	VolDif(mm^3)	2158.34	712.36	451.84	620.93	649.98
	Ratio(%)	1.37	0.65	0.35	0.61	0.46

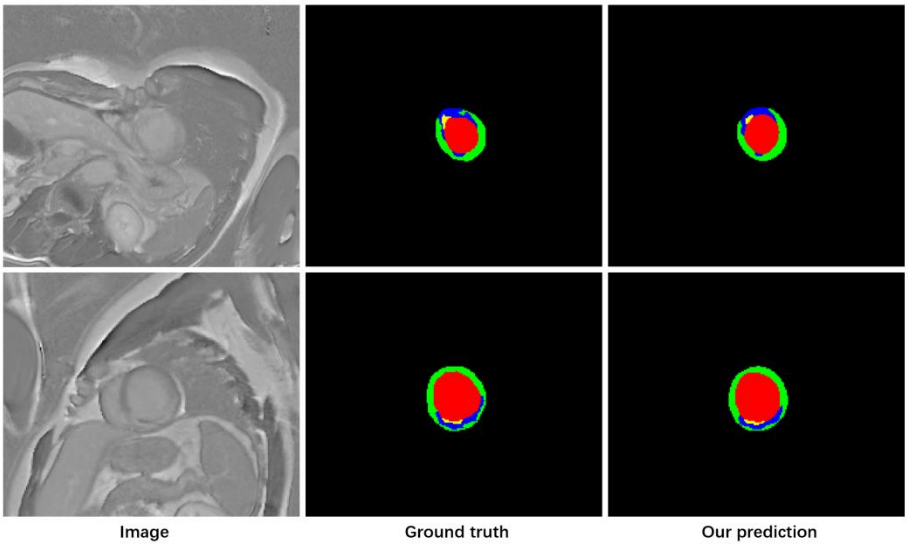

Fig. 2. Two samples of our segmentation results. The columns from left to right are the image, ground truth and prediction (cavity in red, myocardium in green, infarction in blue, no-reflow in yellow).

In the inference stage, we obtain the final prediction of testing set by ensembling the segmentation results of each fold using majority voting. The evaluation results of our method on the testing set of EMIDEC dataset is presented in Table 3. The average dice score is very similar to our cross-validation results (even higher on some metrics), which indicates that our method is stable for myocardial infarction segmentation task.

Table 3. The Evaluation results of our method on EMIDEC test set.

Myocardium			Infarction			NoReflow		
Dice(%)	VolDif(mm^3)	HSD(mm)	Dice(%)	VolDif(mm^3)	ratio(%)	Dice(%)	VolDif(mm^3)	ratio(%)
87.86	9258.24	13.01	71.24	3117.88	2.38	78.51	634.69	0.38

4 Conclusion

In this paper, we propose a cascaded convolutional neural network for automatic myocardial infarction segmentation from delayed-enhancement cardiac MRI. The network consists of a 2D U-Net to focus on the intra-slice information to perform a preliminary segmentation and a 3D U-Net to utilize the volumetric spatial information to make a subtle segmentation. Our method is trained and validated on MICCAI 2020 EMIDEC challenge dataset. For the testing stage, our ensembled model has achieved average Dice score of 0.8786, 0.7124 and 0.7851 for myocardium, infarction and no-reflow respectively, which demonstrate the effectiveness of our method.

References

1. Thygesen, Kristian, Joseph S. Alpert, and Harvey D. White. "Universal Definition of Myocardial Infarction." Circulation 116.22: 2173-2195 (2007).
2. Lalande, Alian, et al. "Emidec: A Database Usable for the Automatic Evaluation of Myocardial Infarction from Delayed-Enhancement Cardiac MRI. " Data, 5, 89（2020）.
3. Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-Net: Convolutional Networks for Biomedical Image Segmentation." International Conference on Medical Image Computing and Computer Assisted Intervention. 234-241(2015).
4. Heller, Nicholas, et al. "The state of the art in kidney and kidney tumor segmentation in contrast-enhanced CT imaging: Results of the KiTS19 Challenge." arXiv: Image and Video Processing (2019).
5. Isensee, Fabian, et al. "nnU-Net: Breaking the Spell on Successful Medical Image Segmentation." arXiv: Computer Vision and Pattern Recognition (2019).
6. Cicek, Ozgun, et al. "3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation." International Conference on Medical Image Computing and Computer Assisted Intervention. 424-432(2016).
7. Abulnaga, S. Mazdak, and Jonathan Rubin. "Ischemic Stroke Lesion Segmentation in CT Perfusion Scans using Pyramid Pooling and Focal Loss." arXiv: Computer Vision and Pattern Recognition (2018).
8. Milletari, Fausto, Nassir Navab, and Seyedahmad Ahmadi. "V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation." International Conference on 3d Vision 565-571 (2016).