Universite de Bourgogne

Medical Sensors

Semester Project

Deep Learning-based Method for Fully Automatic Segmentation of Left Ventricular Endocardium and Epicardium for MRI Images

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1 Introduction

1.1 Overview

MRI cardiac segmentation is one of the challenging tasks in medical imaging despite the significant evolution of techniques and network architectures in the last ten years.

Segmentation of the heart on cardiac MR images consists of delineating the outer wall, also called epicardium and the inner wall, called endocardium. Difficulties exist in Segmentation of Endocardioum that mostly originate from gray level inhomogeneities and in Epicardium due to poor contrast between myocardium and surrounding tissues.[2]

In this project, we have implemented a paper titled **"Deep Learning–based Method for Fully Automatic Quantification of Left Ventricle Function from Cine MR Images: A Multivendor, Multicenter Study"**. This paper was published by Qian Tao, PhD and Rob J. van der Geest, PhD in 9th Oct, 2018.

1.2 Objectives

The main objective of the project is to segment the left ventricular endocardium and epicardium.It is required to get endocardial border of the left ventricle, epicardial border of the left ventricle and finally create a graphical user interface and an executable software.

2 Implementation of the Method

The whole method consists of three steps: *Pre Processing , U-NET Model Training and Post Processing*

The following picture describes the complete overview of the model:

2.1 Pre-Processing

The pre-processing consists of three basic steps:

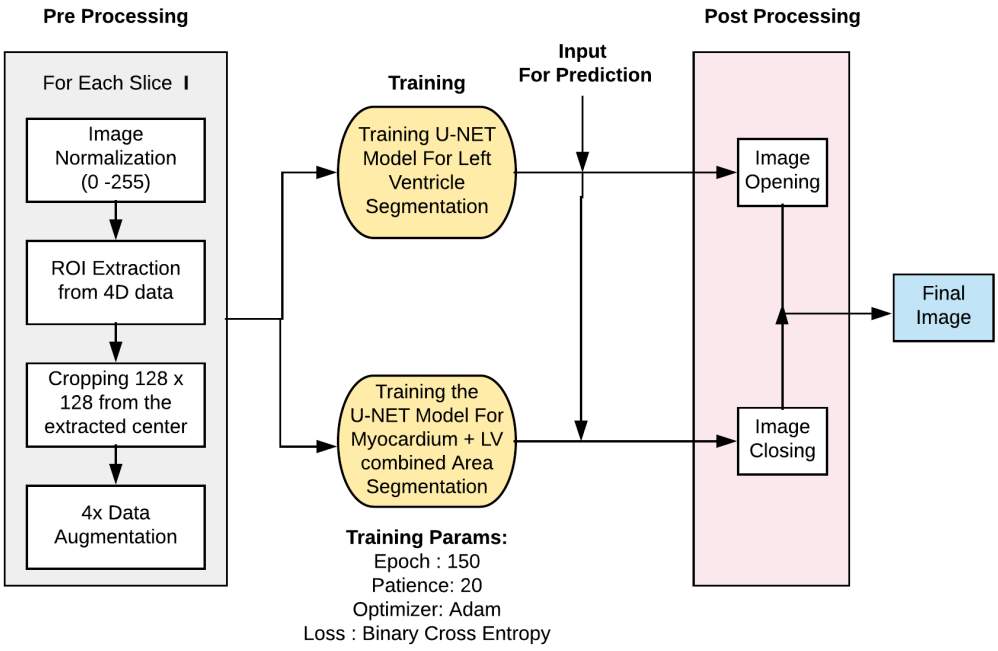

Figure 1: Overview of the Whole Process

2.1.1 Normalization

Since all the images are not of the same intensity range, the images were normalized to be within the intensity range of 0-255.

2.1.2 Detection of Region of Interest

The Region of Interest of Size 128 x 128 Pixels was selected by measuring the *Standard Deviation* on the *middle slice* with respect to time. Since, Heart is the only organ moving near the middle of the image, after applying a threshold on the measured standard deviation, the center of the heart was calculated. 128 x 128 region was cropped with the extracted point at its center.[4]

2.1.3 Data Augmentation

Since the data provided to us was for only 100 patients, we divided the data into training (*90*) and testing (*10*) sets. Since, deep learning model is data hungry and it's efficiency is directly proportional, we performed **x4** augmentation by rotation. This new data was used for the training of the model.

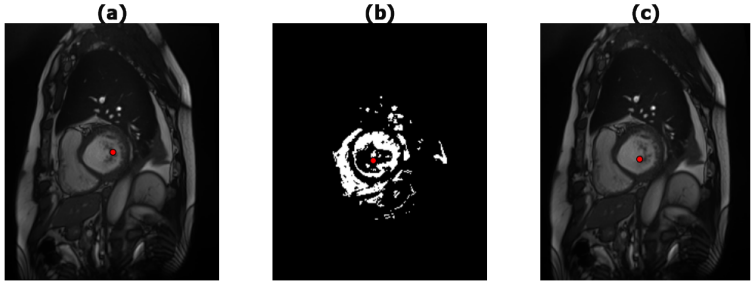

Figure 2: (a) Image Center Before Applying Standard Deviation Centering , (b) Standard Deviation Threshold (c) Image Center After Applying Standard Deviation Centering

2.2 Training the Model

The network architecture that we have used to train the dataset is called **U-Net**. The **U-Net** is convolutional network architecture for fast and precise segmentation of biomedical images. We used U-Net because it achieves better performance and accuracy than regular CNN in the segmentation of biomedical images and works very effectively even with fewer training samples.

To train the model, we have used Keras on top of Tensorflow. We compile the model using Adams optimizer with a learning rate of 1E-5 and binarycrossentropy cost function. The metrics used to measure the performance of the model is accuracy. The U-Net architecture that we have used is depicted in figure 3.

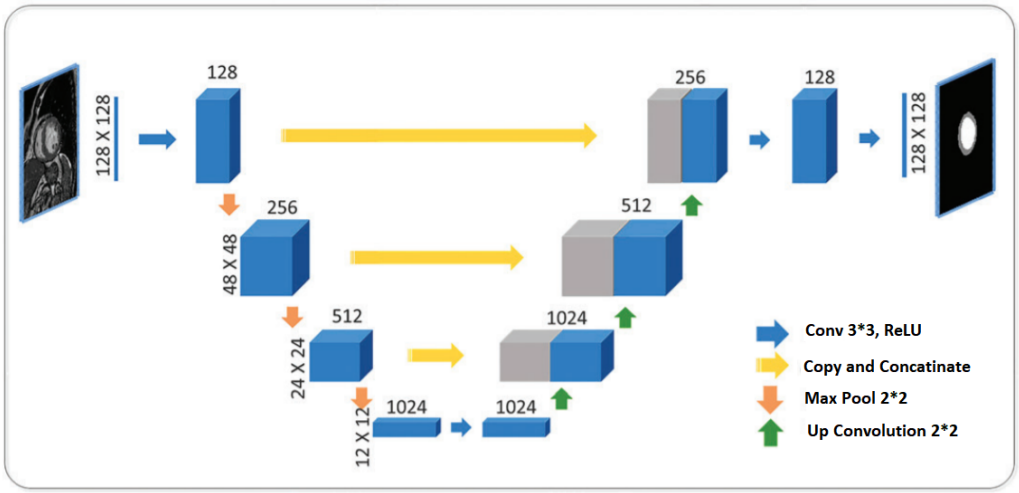

Figure 3: U-Net Architecture-Image taken from[1]

U-Net architecture is separated in **3 parts**. The first one is the **contracting path** which contains 3x3 Convolution Layer, ReLU activation function and 2x2 Max Pooling. The second one is **bottleneck** which is built from simply 2 convolutional layers. The third part has **expanding path** which has deconvolution layer with stride 2 and Concatenation with the corresponding cropped feature map from the contracting path and 3x3 Convolution layer.[3] In our architecture, we have used ReLU activation function for all the layers except the last layer which uses sigmoid activation function.

To train the model, we divided the 100 patients MR images into two groups. For training, we used only the MRI images of the first 90 patients and the rest(10) is used for testing. After augmenting the training data, we have separately trained the U-Net model for left ventricle and myocarduim. The two trained models have the same architecture but they have different weights.

The training of the model: training was done for 150 epochs with validation split of 0.1 and batch size of 32. The training was faster because we used a GPU, GeForce GTX 1050 Ti with 4 GB memory. It took around 5 hours to train each model for 1678 training images(image size 128*128) plus the (1678*4) augmented images. Then we merged the predicted results of each model into one to create the final output.

2.3 Post Processing

We trained two models separately. One for *Left Ventricle Segmentation* and the second for *myocardium + left ventricle* combined area segmentation.In order to get the final result of both endocardium and epicardium segmentation, the post-processing can be divided into three basic steps:

2.3.1 Image Opening for Left Ventricle Endocardium Segmentation

The output of the trained model has some small circular areas that have been wrongly predicted to be the part of left ventricle.

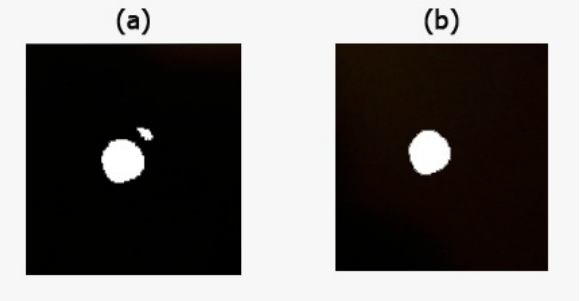

Figure 4: (a) Predicted Image (b) Post processed Image

2.3.2 Image Closing for Myocardium and Left Ventricle Segmentation

Due to the presence of different tissues that surround the epicardium with similar intensity,some of the areas are excluded from being the part of myocardium. Hence Image Closing is performed.

2.3.3 Combination of the Two Methods

The above two outputs are combined. The inverse of the first output image is multiplied with the second image.Then, this new image and the first image are added to get the final output.

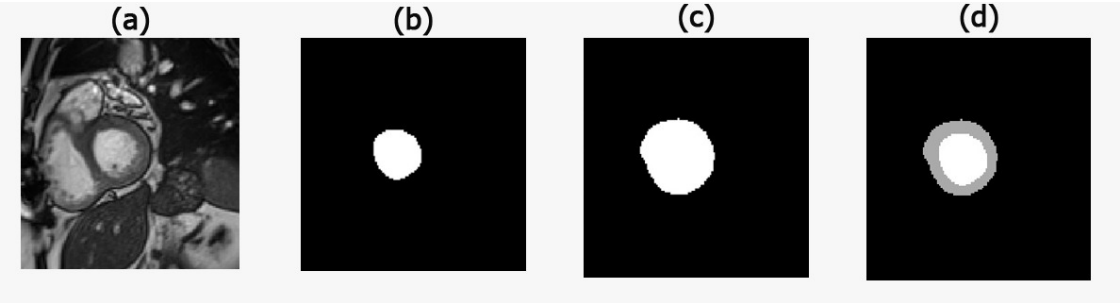

Figure 5: (a) Test image, (b) Left ventricle predicted(model1) (c) Left ventricle and Myocarduim predicted combined(model2) (d) final output of model 1 and model 2

3 GUI of the Application Developed

After we implemented the system, we developed a graphical user interface(GUI) and an executable file that can be installed on a computer. The GUI looks like this:

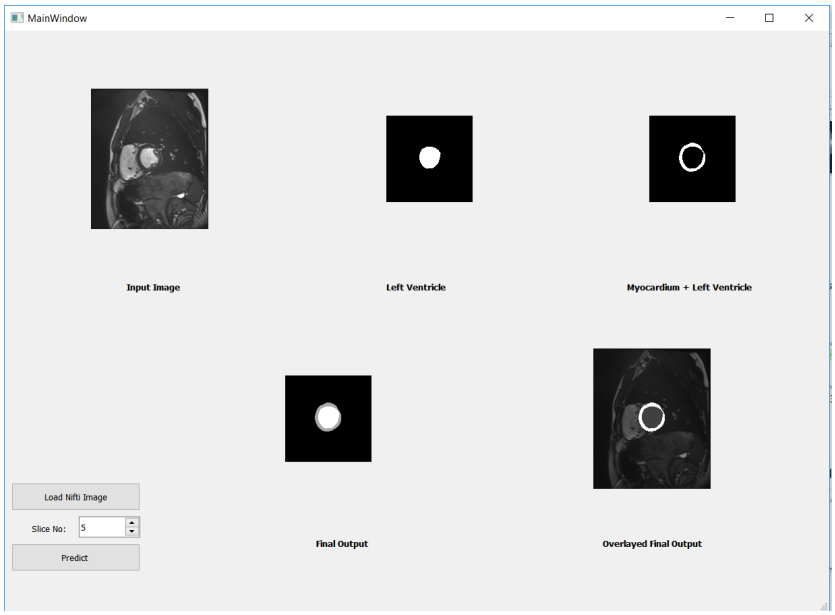

Figure 6: Graphical User Interface

As you can see from figure 2, The GUI has a button named "Load Nifti Image", which help us to select and load the nifti image. Then, we can choose the slice number by incrementing and decrementing the value of spin box. Finally, we press the "Predict" button, in order to predict the left ventricle and myocardium contours. In the displayed images, the first one is the input image that we have selected, the next image shows the predicted left ventricle. The third one displays the predicted myocadruim. The last two images show, the final predicted image overlayed on the original image.

4 Results and Future Improvements:

4.1 Results

10 Patients data was separated before the training of the model.These image were used as the testing set to study how good is the output of the trained model. The dice coefficients for Left Ventricle and Myocardium Segmentation in the cases of diasytole and systole were calculated as follows:

	LV Diastole	LV Systole	Myo Diastole	Myo Systole
Dice Coefficient	0.8843	0.8018	0.6846	0.7429

Table 1: Results of Our Implementation on the Testing Data

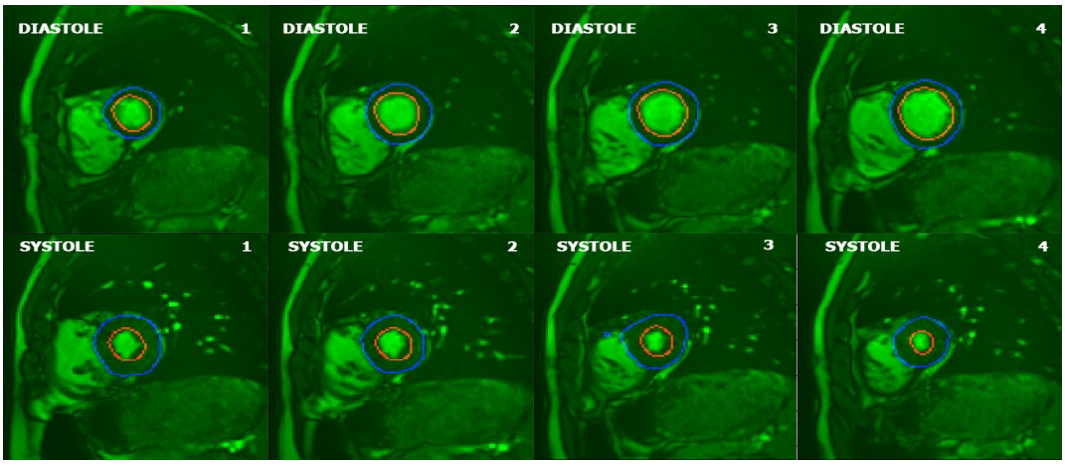

Figure 7: Results of our Trained Model on Testing Images

4.2 Future Improvements

Due to the limitation of the GPU processing power at disposal as well as the time constraint, we were able to perform only 4x augmentation and the model was trained for only 150 epochs. However, better results can achieved if the data augmentation is increased to 10 x and the epochs are increased to more than 150.

References

[1] Qian Tao(PHD) and Rob J. van der Geest(PHD), Deep Learning–based Method for Fully Automatic Quantification of Left Ventricle Function from Cine MR Images
https://doi.org/10.1148/radiol.2018180513

[2] Caroline Petitjean, Jean-Nicolas Dacher. A review of segmentation methods in short axis cardiac MR images.. Medical Image Analysis, Elsevier, 2010, epub ahead of print.
<10.1016/j.media.2010.12.004>. <hal-00551034>

[3] U-net: Convolutional Networks for Biomedical Image Segmentation:
https://arxiv.org/abs/1505.04597

[4] Marwa M. A. Hadhoud, Left Ventricle Segmentation in Cardiac MRI Images
http://article.sapub.org/10.5923.j.ajbe.20120203.07.html