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Autonomous Assistant for Medical Student

– ITSG report –

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Abstract

Nowadays one of the hardest tasks in the field of medicine is to interpret and analyse the MRI scans to understand them. The software assistant we are going to implement is trying to bring medicine and A.I. together. This will have a great impact on the learning curve for the students and will facilitate the already cumbersome process of reading the MRIs. In this paper, we will present an web application which will be able to compute a 3D volume and provide a visualization of heart chambers based on a MRI scan. The intelligent component is based on a DenseVnet fully convolutional neuronal network which will be trained on a set of MRIs which are already labeled by medical experts. We will use 3 classes: the heart, blood vessels and the rest of the MRI abdominal scan.

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Chapter 1

Introduction

Nowadays cardiac segmentation have a very high impact on various applications in the health and pathology domain. Magnetic resonance images(MRI), are used worldwide in the medical field, composed by various grey shades. Usually, students are facing challenges when they are trying to recognise the heart in a MRI scan. Without having a professional point of view it is quite impossible for the students to have a clear image regarding the heart positioning.

Researches shows that Convolutional Neuronal Networks are very efficient in solving tasks like classification,segmentation and object detection. The vastly anomalies among patients leads with a big challenge in patient segmentation, so a texture analysis should be done [3].

In this paper we will present our approach on helping medical students, based on a fully convolutional neural network. One of the biggest challenge will be to handle a small dataset. This will make us to find other solutions, like the augmentation. In chapter 2, we will present the a brief and plastic definition of the problem, and one of the biggest challenges of the era, designing a intelligent application that correspond with human ethics. In the 3'rd chapter is presented how others are trying to solve some similar problems. In chapters 4 and 5 is described the concept of the application and how it was developed and improved. The chapter 6 summarize all achievements and bring a new idea for future implementations.

Chapter 2

Scientific Problem

2.1 Problem definition

The MRI scans are gray-scale and very noisy, with a lot of organs, for the delimitation of the heart and the chambers, a specialized doctor is needed. When a medical student starts to learn about heart and its chambers, he needs a lot of research and a doctor to show him where exactly is everything. Therefore, we are trying to replace the specialized doctor by automating the whole process of segmentation.

The purpose of the application is to facilitate the activity of learning the heart, of the medical students. This application will be a web application, in this way this will be accessed by every student from any device. As main functionality, the student will be able to insert an MRI (in nifty format), and as a result the student will be able to see in a 3D view the delimitation of the heart.

2.2 Ethics

Nowadays intelligent machines, can do almost anything, from cooking, recognizing faces while authorizing on phone, to optimizing traffic and also making art. With them world become better and better, but with all of these benefits, some ethical values can be violated.

The primary concern of the population is that AI can take their working place. The McKinsey Global Institute report [2], until 2030 up to 14% of the workers will be affected an will lose their jobs due to automation and AI. At the same time there is the fear that these intelligent machines will do some very serious mistakes that can lead to disasters.

In this paper we only purpose a medical helper, for students and this will be scaled in a future for helping doctors, this will not implies the job loses, because the specialist should be there in order to detect anomalies, diseases and other parts that AI couldn't recognise. Due to the fact that, students are at the beginning of their experience with MRI's this assistant is a very appropriate and ethical compliant application.

"The ethics for humane technology framework provides lenses to understand human rights in the digital age, to understand the technological phenomena that threaten these rights and principles to build technology so as to create a beneficial future for humanity."[1]

Figure 2.1: Six lenses of human ethical problems

Chapter 3

Related work

3.1 3D FractalNet: Dense Volumetric Segmentation for Cardiovascular MRI Volumes - A State of the Art

The winners of HVSMR 2016 challenge, which describe deeply supervised fully convolutional architecture propose to segment 3D cardiac images.The main advantage is the input if the processed image can be arbitrary-sized. This network can put volumetric labels directly on a 3D input.

They have started with a base case, and expanded it recursively until they have finished the 3DFractalNet architecture. This architecture is based on convolutional, max-pooling and deconvolutional 3D layers. Also they have introduced in learning process, auxiliary classifiers, which has different output dimensions, therefore the deconvolutional layers was added. As data-set they used HVSMR 2016 Challenge data-set, increasing with data augmentation from 20 cardiovascular magnetic resonance images to 80. The augmentation was performed by using rotation and axial flip of the images. They obtained quantitative and qualitative results [5].

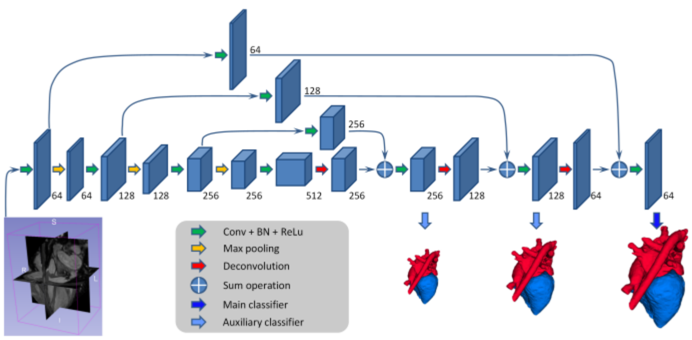

Figure 3.1: 3D FractalNet Proposed Architecture

3.2 Dilated Convolutional Neural Networks for Cardiovascular MR Segmentation in Congenital Heart Disease

An automatic method using dilated convolutional neural networks for segmentation of the myocardium and blood pool. For patients that have severe heart disease is required to have a surgery from childhood. The use of 3D models has been very helpful, mainly for the preoperative planning. A training on a CNN has been done, in which it was assigned a class label to every voxel. The CNN used dilated convolutions that allow large receptive fields with a few trainable parameters.

An experiment with a five-fold cross-validation has been performed, in which each fold contained two CMR scans. To segment the set for test, a single CNN has been trained using all the training images. The network parameters have been optimized with Adam using as a cost function the categorical cross-entropy. To compare the performance of a CNN with dilated convolutions and a CNN without dilated convolutions, segmentation's were performed using an identical CNN architecture containing 72,643 trainable parameters [4].

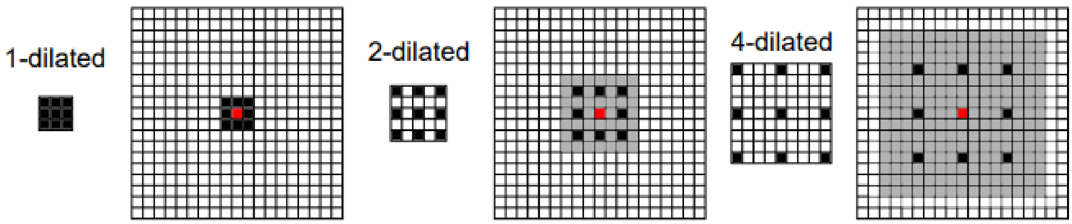

Figure 3.2: Convolutional Dilated Neural Network example

Chapter 4

Proposed approach

In order to resolve this problem, we will create a web application which will facilitate the learning process of the student by returning based on a full body MRI, a fully cropped heart. Also, to create this image we will train a Dense CNN figure 4.1 on the already labeled images from the HVSMR 2016 and create a model which will be used in the back-end. The web application will transfer the file to a

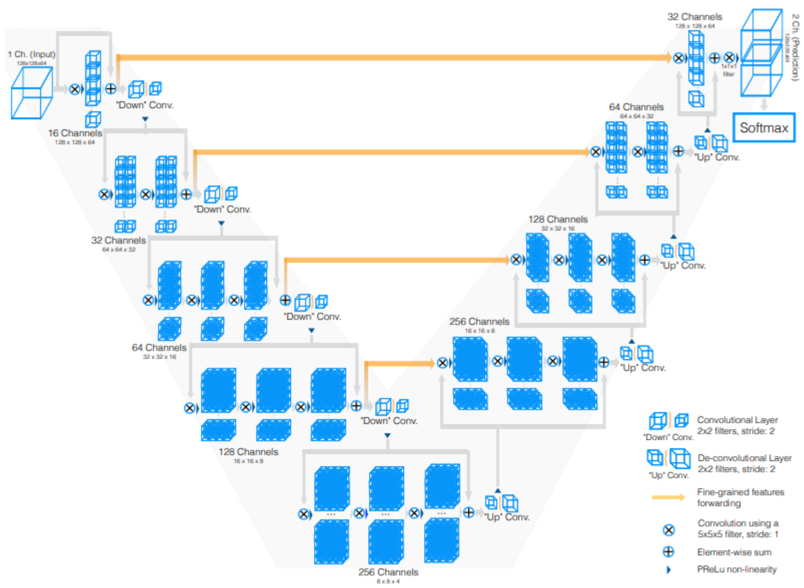

Figure 4.1: VNet Architecture

web API which will run the trained model and create the 3D image of the heart. Due to the fact that the application will provide a 3D file, it can be visualized in any tools that student is used to, thus the application provides a vast technological flexibility.

Chapter 5

Application

5.1 Architecture

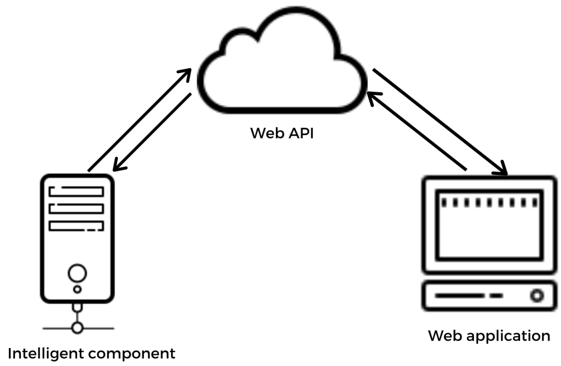

Figure 5.1: System Architecture

The application will be composed of two main parts: the intelligent component and the web application. The complete system architecture can be seen in figure 5.1. The intelligent component will be based on a NiftyNet DenseVnet. The architecture of the network is composed of two parts. The first half of the convolutions represents the compression path and the right part is the decompression path until the pixel reaches the original size.

Due to the fact that in anatomy our interest point is relatively small, and that's why this architecture has a dice loss layer. The pixels are passing trough a soft-max layer, a probabilistic algorithm, which define the pixel as background or foreground.

For the efficiency of the algorithm, GPU processing power was used, performing parallel computations with CUDA. Each convolution process a 5x5x5 voxels volumes image, due to the compression the resolution decrease.

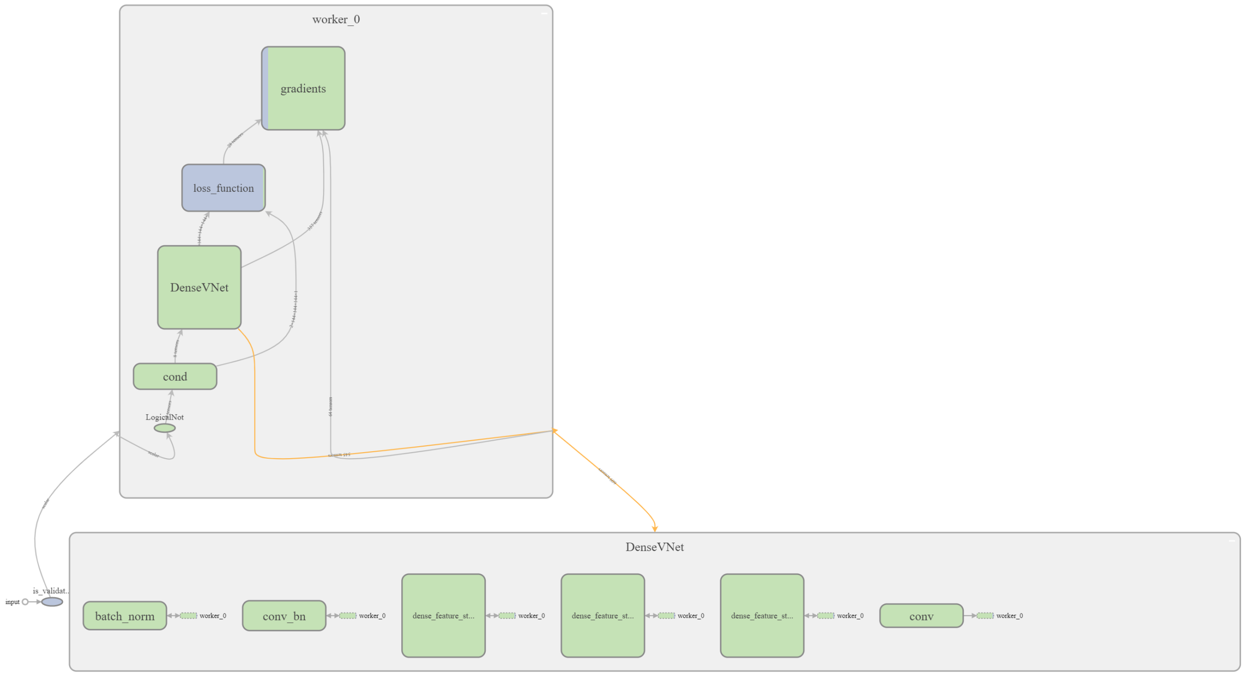

Figure 5.2: Neuronal Network Implementation Design

Main technologies used to create and train the model were:

- NiftyNet - Deep learning library for medical imaging `https://niftynet.io/`
- Mango - Visualisation for medical images `http://ric.uthscsa.edu/mango/`
- Anaconda - Python distribution for package management `https://www.anaconda.com/`

5.2 Data

For the dataset on which to train our neuronal network, we are using the HVSMR 2016 axial full-volume, axial cropped and short-axis cropped training data. The total amount of data is 20 MRI scans for learning and 10 for testing.

In order to maximise the results we had an augmentation step. The pre-processing was performed in three different ways: adding random angles for each axis, flipping the image axes and random scaling volumes. We will use as training data set 80% amount of data and 20% for validation.

5.3 Methodology

The neuronal network was trained using a Dice loss, a batch size of 2 samples, a re-sizable window sampling and a learning rate of 0.001. Every tenth iteration we saved the model with the best results.

After less then 100 iterations, we managed to recognize the heart, but it is impossible to separate it visually from the other components of the body. Figure 5.3 present the 3D result of this model.

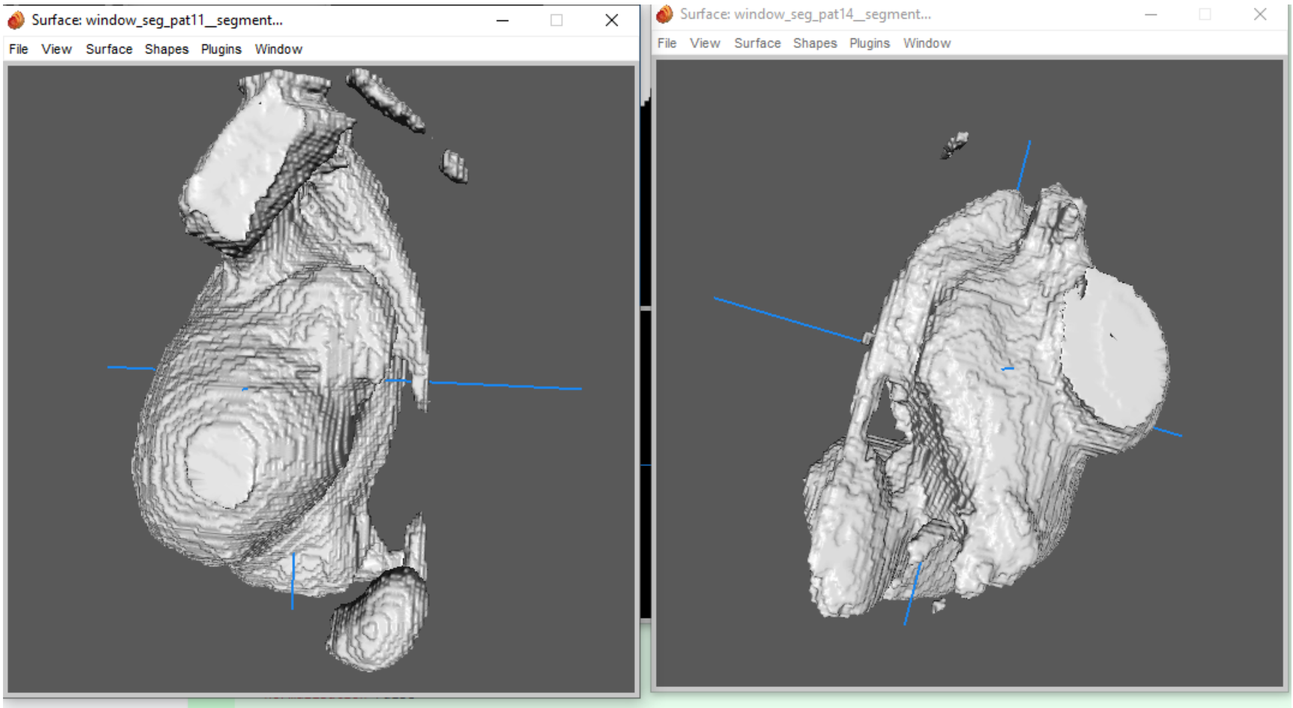

Figure 5.3: 3D heart image after less than 100 iterations

We created an MVC Web Application in .NET Framework on which the user is able to upload and download 3D images. We also simulated the user behaviour by trying to open the resulted image in several tools to see if the image is compatible with them.

5.4 Analysis and Improvements

After observing initial result, we increased the number of iteration of training. Furthermore, we set the interpolation order during the inference to trilinear. Figure 5.4 present the 3D result of the resulted model.

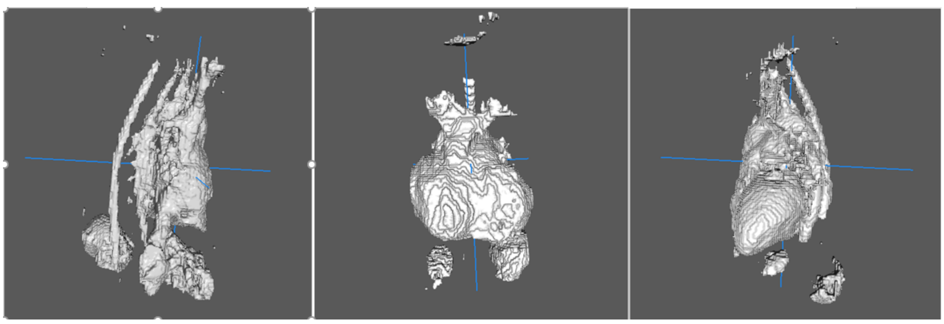

Figure 5.4: 3D heart image after 380 iterations

Also, we discovered that the UI component is getting stuck when the files are uploaded or downloaded,thus we made the whole process asynchronous so the user can roam freely the application while the files are processed.

5.5 Results

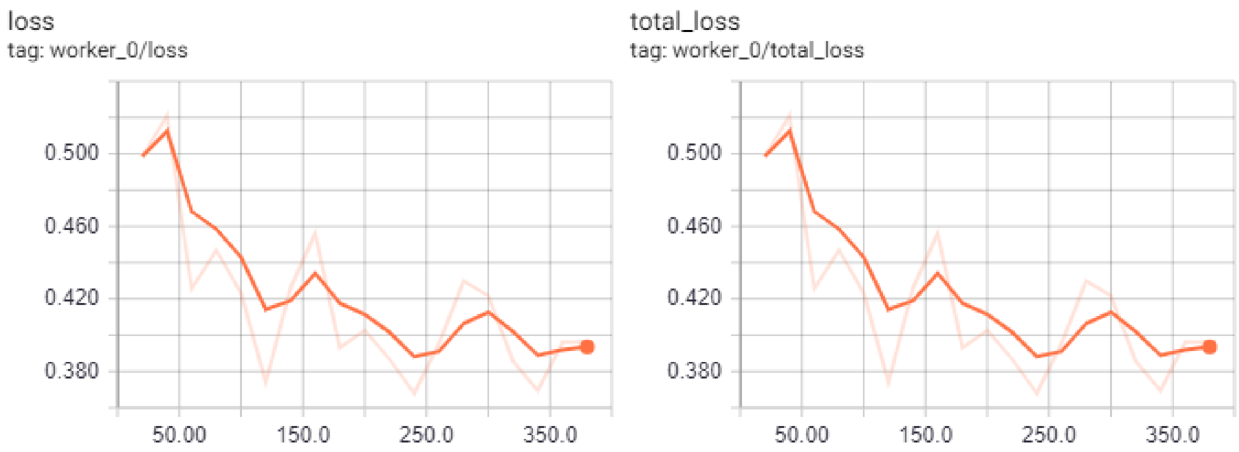

Figure 5.5: Loss graph for 383 iterations

As we can see in Figure 5.4 the heart is starting to be recognizable among the other organs. We can see an improvement from the previous result and we also are able to analyse the structure of the heart. Also, the web application is no longer stuck during the file processing. On the other hand, in Figure 5.5 we can see that the loss function is stabilising around the 0.40 value, meaning that the model will not be as accurate as we desired.

Blod Vessel Class	Dice Loss	Jaccard
part 0	0.328467	0.196507
part 1	0.040482	0.020659
part 2	0.285799	0.166724
part 3	0.185206	0.102053
part 4	0.125614	0.067016
part 5	0.06335	0.032711
part 6	0.2312	0.124678
part 7	0.33787	0.203275
part 8	0.394185	0.245473
part 9	0.459523	0.298299
Avg	0.24517	0.14574

Blod Vessel Class	Dice Loss	Jaccard
part 0	0.381853	0.333384
part 1	0.272917	0.245053
part 2	0.463317	0.345053
part 3	0.307553	0.301985
part 4	0.430805	0.220145
part 5	0.479631	0.34218
part 6	0.2312	0.147372
part 7	0.33787	0.283279
part 8	0.394185	0.256358
part 9	0.459523	0.329129
Avg	0.375885	0.280394

Figure 5.6: Evaluation result before and after re-center

In order to evaluate the results we needed to re-sample the resulted volumes to make them have the same dimensions as the labels we trained on. By performing the evaluation we discovered that after the re-sampling process we had to re-center the hearts in the middle of the volume. In the Figure 5.6

we can see the Dice and the Jaccard coefficient for each volume, before and after this process.

5.6 Discussion

We can observe from the beginning that the model cannot achieve a high grade of accuracy due to the small amount of data available in the field. This proves to be an even grater challenge when the difference between volumes are considerable and the model is not able to differentiate between the background and the main point of interest.

Another topic of discussion can be the augmentation process which proves to be the main reason in the increased accuracy, nevertheless from our point of view that data is produced in an artificial way, thus making the results of the research debatable.

Furthermore, after analysing the evaluation table we can see that some volumes were much more closer to the original label volumes than the others. This result might be caused by the fact that several labels might look similar, and by the lack of data the more unique ones are much harder to be cropped by the neuronal network.

Chapter 6

Conclusion and future work

We presented in this article a web application, that can help medical students during the study process. The application has a volatile behaviour which let the student to chose the desired visualization tool for the 3D volumes. The challenge created by the small amount of data, was partially solved by the augmentation process, but may prove that the results cannot be as valuable as we desired. In this report we also evaluate the volume results and analyse the possible causes of the loss stagnation at a relative high value and consider that it might be caused by the lack of data.

For future work, we plan to improve the neuronal network model and increase the speed of execution by simplifying the unnecessary layers and also we would like to improve the UI component by making it more responsive to the end user. As first improvements we want to make the application available on phone in order to increase the accessibility.As a future perspective we want to evolve this application and make it available for the doctors also.

We would like also to add the possibility to visualise the heart online using a default tool, but still we would like to keep the possibility to download the volume in order to be later analysed and visualised by the medical student.

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