3D Image Segmentation for Lung Cancer Using U-Net Architecture

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October 3, 2022

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Abstract -In this paper, we present a new method of medical image segmentation based on U-Net algorithm. The general idea is to create an optimal segmentation that allowed the medical staff to distinct the different parts of the tumor using the U-Net architecture which represent the more elegant architecture, called a fully convolution network. The main idea is to complete a contracting network by successive layers; pooling operations are replaced by over sampling operators. Therefore, these layers increase the resolution of the output. This technique is employed to merge different data sources in order to increase the quality of the information and to obtain an optimal segmented image.
Segmentation results from the proposed method are validated and the classification accuracy for the test data available is evaluated, and then a comparative study versus existing techniques is presented. The experimental results demonstrate the superiority of using Modified U-NET for image segmentation.

Keywords:
Segmentation, UNet architecture, Conventional Network, Classification.

I. Introduction

Image segmentation [1] is a fundamental problem of computer vision and image processing. In this framework, image segmentation has wide applications in many areas [2], and different techniques have been developed [3]. The purpose of image segmentation is the partition of the image into homogeneous regions with respect to particular application; further more to detect edges in digital images where the areas are with strong intensity contrasts and difference in intensity from one pixel to the next concrete major variation in the picture quality and image segmentation.

There are several image segmentation techniques available for biomedical image [4][5][6][7]. In this context, Ilhem et al. [4] have proposed an image segmentation technique by credibility labeling. The SD-Optical Coherence Tomography derived Macular Diseases has been automated identify by Combining 3D-Block-matching and Deep Learning Techniques.

Also, William et al. [5]have introduced a pap-smear analysis tool (PAT) for detection of lung cancer from Pap smear images. This work describes the development of a tool for automated diagnosis and classification of cervical cancer from pap-smear images. In their work, the authors have used a Trainable Weka Segmentation classifier and a sequential elimination approach was used for debris rejection to achieve the scene segmentation. Feature selection was achieved using simulated annealing integrated with a wrapper filter, while classification was achieved using a fuzzy C-means algorithm. The proposed system has the capability of analyzing a full pap-smear slide within 3 min as opposed to the 5–10 min per slide in the manual analysis.

In another study, Ben Chaabane et al. [6] have developed a segmentation algorithm based on evidence theory and fuzzy clustering, applied to breast cancer cells images. The fuzzy algorithm is used to estimate the mass functions where the evidence theory is used to combine the information sources coming from the same image.

With the same objective, Dago et al. [9] have proposed a segmentation method of tumors in PETscan medical imaging based on 3D random walk. This method presents an automatic segmentation method based on Random Walk (RM). Faced with some problems of the original algorithm such as the dependence on the choice of the hyper parameter, as well as the probability of the function exclusively of the gradient grayscale intensity that propose an approach to solve these problems, a new version of random path to segment tumors in medical imaging Emission Tomography (PET). The results obtained on a physical phantom and on patient data show that their method is better than the original algorithm.

However, the results of most existing segmentation techniques applied to 3D biomedical images cannot provide accuracy results. The segmentation of the tumors helps doctors to detect the tumors quickly and accurately. So, finding an optimal segmentation method is a crucial step of biomedical image processing process.

The objective of the present study is to analyze the performance of U-Net Algorithm, applied to 3D image segmentation for lung cancer. Hence, the main objective of this work is to develop segmentation in the medical imaging field and to obtain the hopeful result estimated by the doctor.

The U-Net architecture which is itself a specific type of fully convolution network (FCN) is a family of neural networks characterized by an encoder-decoder structure. These are designed for semantic segmentation also known as per-pixel classification. U-Net builds on the standard FCN architecture by introducing hop connections which means layer blocks in the shrinking phase can pass their output directly to blocks in the expanding phase, extracted high-level features from an image.

The paper is organized as follows: the results of segmentation from the proposed method are validated and the classification accuracy and sensitivity for the test data available is evaluated. In addition, a comparative study versus existing techniques is presented, including Dago Pacome Onoma method of the automatic segmentation algorithm based on the random walk (RW) method [9] and Chen Li method of 3D U-Net [16]. The experimentation is carried out on a medical image provided by a carcinology hospital Salah Azaiez of Tunisia.

Section 2 introduces the proposed method for biomedical image segmentation. The experimental results are discussed in section 3, and the conclusion is given inSection4.

II. Proposed method

Medical imaging includes all the techniques used by medicine for the diagnosis also the treatment of a large number of pathologies. It is a revolutionized medicine by giving immediate and reliable access to information up to the invisible, such as anatomical characteristics, or even certain aspects of metabolism (functional imaging) of organs.

Medical imaging techniques do not provide a simple photograph of the tissue or organ studied but visual representation based on particular physical or chemical characteristics.

Current medical imaging processes particularly nuclear medicine carryout, directly in the context of reconstructions and acquisitions volumetric.

By analogy to the two-dimensional digital image where the process sampling revolves around the elementary components called pixels the volume sampling adds third dimension.

However, the representation of data sets on three dimensional represents Volume visualization so datasets are characterized by multidimensional arrays of scalar or vector data. These data are typically defined on lattice structures representing values sampled in 3-D space.

Multi-planar Reconstruction (MPR) is the simplest method of reconstruction. A volume is built by stacking the axial slices. The software then cuts slices through the volume in a different plane usually orthogonal.

Medical image segmentation is a technique of image processing which is used to extract image features, searching the medical image records for better and accurate medical diagnostics. Commonly used segmentation techniques based on threshold, edges and region.

However, the segmentation of 3D medical imaging consists of processing the interest objects.

However, most of the existing 3D medical image segmentation methods are patch-based, which ignore the global context information to accurate segmentation and also reduce the efficiency of inference.

To resolve this problem, we propose a 3D medical image segmentation method based on 3D U-Net architecture. U-Net is a convolutional neural network that was developed for biomedical image segmentation by using this CNN Model every pixel needs to be classified simultaneously. The network is based on the fully convolutional network and its architecture was modified and extended to work with fewer training images and more precise segmentations. The U-Net model uses convolution and pooling layers similar to those in a classification.

In the present study, the method of segmentation of 3D medical images is a very deep and wide field so we proposed 3D U-net; the rule is applied to obtain in the final the 3D segmentation.U-net architecture is an extension of 3D volume segmentation.

The Algorithm of the presented table of U-Net algorithm. Described by the proposed Method can be summarized as follows:

Step 1:2D operations replaced by corresponding 3D decompositions namely convolutions, 3D max pooling and 3D up-convolutions which are summarized in 3D axes.
Our architecture consists in selecting small boxes containing best candidates of cancerous nodules.
U-Net is a very useful CNN architecture for segmentation in biomedical imaging. The proposed version is the simplest of U-Net to limit memory expenditure see figure 1. During training, our modified U-Net takes as input (256 × 256) slices of 2D CT images and labels are provided (256 × 256 masks where nodule pixels are 1, others are 0).
Step2: The model is trained to give form images (256 × 256 Where each pixel in the output has a value between 0and 1 indicating the probability that the pixel belongs to a nodule).
By taking the corresponding slice of the last U-Net layer. U-Net corresponding entries and predictions on all patients see figure 3 and 4.

The architecture of the proposed method is presented in Figure 1.

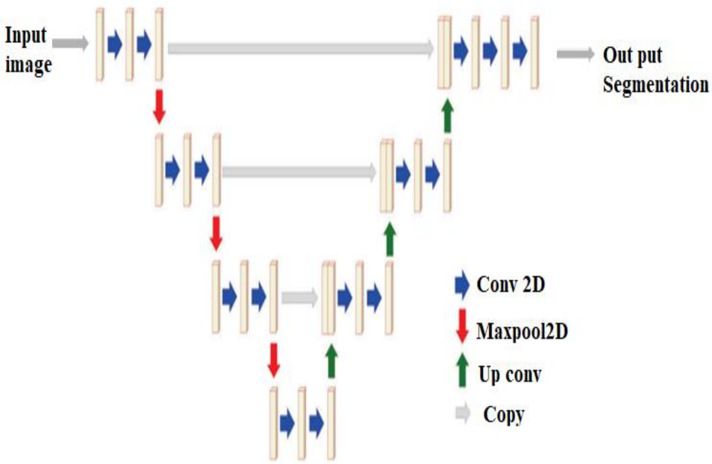

Figure1: Basic architecture of 3D-Unet.

III. EXPERIMENTAL RESULTS AND DISCUSSION

In order to evaluate the efficiency of the accuracy and sensitivity of the proposed method, the segmentation results of the datasets are reported. The segmentation results are compared with existing methods, as described earlier. These methods are carried out on the MATLAB software10.

The images originally are stored in RGB format. Each of the primitive color (red, green and blue) takes 8 bits and has the intensity range from 0 to 255. The labeling of the original image is generated by the user based on the image used for segmentation.

Several segmentation results of biomedical images are given in this section.

Samples of used images data base is showninFigure2.

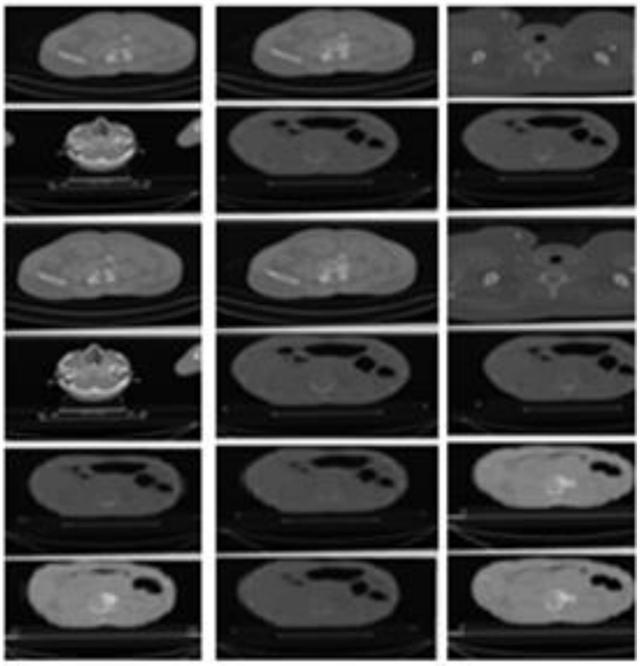

Figure 2. Dataset used in the experiment. Twelve were selected for a comparison study. The patterns are numbered from 1 through 12, starting at the upper left-hand corner.

Forty patients included respectively. All patients are injected with 18F-FET at the time of diagnosis before any biopsy or treatment (tumor resection, chemotherapy, radiotherapy).

Patients who required rapid surgery due to mass effect or intra_cerebral hemorrhage, as well as patients with a history of brain biopsy or neurosurgery were excluded. All patients performed these imaging examinations as routine care and gave written informed consent prior to inclusion.

In this research we present the deep neural networks with U-Netarchitectureandareproposedtoeffectivelysolveimagesegm entation problems it is a deep learning models which is one of the most recognized models in segmentation medical images in the form of convolution net works.

This unsupervised learning offers a layer-by-layer multi level structure, automatically selecting more and more representations from the layers. The CNN encoder-decoder architecture mainly avoids the gradient problem that canaries when training a standard neural network (with out pre- initialization). U-net pre-training increases the performance of optimizing the model.

Our model chosen for the segmentation of images of the lungs in MRI, pet scan and radiotherapy (accelerator) is in 3D, with tumor annotations for segmentation. Each net work was trained using 2346 images with data augmentation from scratch. Each image has the form (512, 512, N), where N is the number of forms. Each mask has the shape (512,512, 1).

In order to establish the images and masks found in each dataset, we split the dataset into sub-images and produced the masks using a modified version of the k-means classification algorithm. Since processing all images with these sizes is difficult due to limited GPU memory, the images are therefore scaled to a dimension of (128×128) considering the image quality degradation. The loss functions for the first two net work shave showed better performance during training. The segmentation of tumor images thus Adam was selected as an optimizer.

The U-Net architecture which is itself a specific type of fully convolutional network (FCN); a family of neural networks characterized by an encoder-decoder structure. These are designed for semantic segmentation also known as per-pixel classification-Net builds on the standard FCN architecture by introducing hop connections which means layer blocks in the shrinking phase compass their output directly to blocks in the expanding phase.

Extract high-level features from an image. Our data is taken from the Salah Azaiez institute of cancerology of different radio diagnostic service, nuclear medicine, and radiotherapy of the local system of archiving and communication of images (PACS) for the development of algorithms. For the choice we took 3D images of the different types of lung cancer small cell lung cancer (CPC) which is closely linked to tobacco consumption and represents15%oflung cancers and non-small cell lung cancer (NSCLC) which represents more than 80% of lung cancers. Fifteen patients were excluded due to unqualified MRI quality, 6 patients were excluded for obvious and massive metastatic disease.

A total of 493 patients were ultimately recruited for the development of the 3D U-Net algorithm, all mpMRI data was anonymized prior to inclusion and clinical information, such as age and stage of each enrolled patient was recorded. Advanced techniques for medical image formats including DICOM have shown excellent performance on anatomy detection in medical imaging.

Thus, the segmentation of medical images for areas of interest and their boundaries has shown good results.

The performance of the 3DU-Net Algorithm is compared to the Chen Li [16] method that shows the results of the CT experimental volume segmentation that has recently been applied to biomedical image segmentation. The segmentation results are shown in Figure3.

Regarding the accuracy and sensitivity, in Table1 lists the correct segmentation rate of the different methods for the data set used in the experiment.

It can be seen from Table 1 that the accuracy represent 80%, 92.56% and 99% of pixels by the Dago Pacome Onoma[9] and the method of Chen Li [16] and the proposed method, respectively furthermore the sensitivity represented in the same table 1 respectively 95.98% of the Chen Li [16] and 99% of our method .

However, the regions are correctly segmented in Figure3 (d), and Figure4 (d) applied to our DICOM dataset and the accuracy and sensitivity was more satisfied.

Table 1: The Performance of the experiment comparison of the segmentation results and our proposed method from the dataset shown in Figure2.

Methods	Model	AC	Sensitivity
Our Proposed Method	3DUnet	99%	98%
Chen Li [16]	3DUnet	92.56%	95.98%
The Dago Pacome Onoma Method[9]	random walk (RW)	80%	-

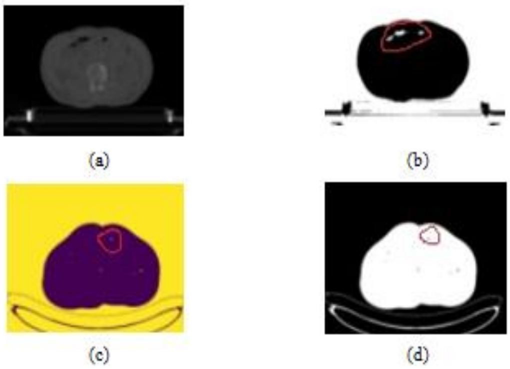

Figure 3. Segmentation 3D of lungs seen from the side of pet scan Images, (a) original image, (b) segmented image by using U-net, (c) ROI (c) segmentation U-net.

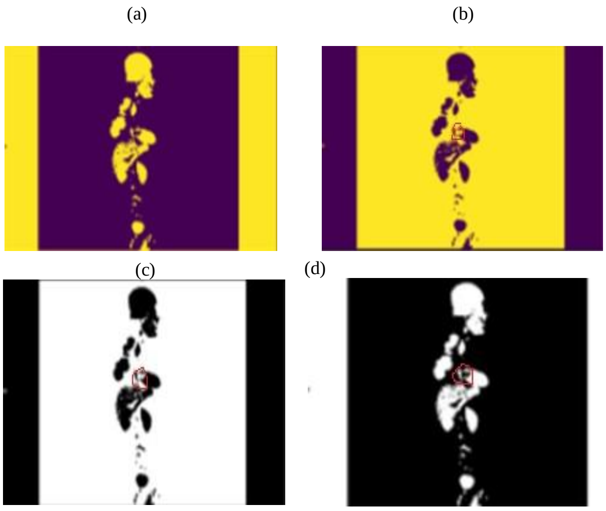

Figure 4. Segmentation 3D of lungs seen from the side of pet scan images, (a) original image, (b) segmented image by using U-net, (c) ROI (c) segmentation U-net.

In fact, the experimental results indicate that the proposed method, which uses the 3D U-Net architecture, is more accurate than the traditional methods in terms of segmentation quality as denoted by the segmentation sensitivity, see Table 1. In addition, the performance of the segmentation sensitivity on our data is more important than the other proposed method. We conclude that the introduction of 3Dunet can help network to

Obtain a better performance on our model of 3D volume segmentation compared to the other methods.

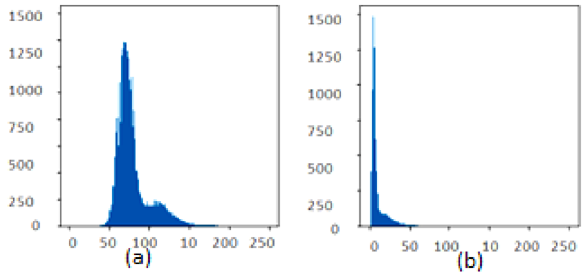

Figure 5. Redistribution of the histogram by intensities shift
(a) 3D medical images in PETscan, (b) 3D medical images in MRI.

In this article, we analyze the algorithm of the distribution of pixel intensity in the basic histogram and its implementation. By comparing the result of the two images presented in section 3. For each result, the first two images presented in the original images that the contrast performed are clearly observed. The other two images show the distribution of the pixel intensity comparing with the original images. After verification of the experimental results, the entropy is used as a criterion of homogeneity of the gray level images which are generated from several 3D images of size (512 × 512) pixels. The goal is to segment the area of interest defined by the doctor to enable him to refine his diagnosis. The segmentation must therefore be precise around the area of interest and mustn't be disturbed by the noise (respiration, movement of the patient) of the image.

We consider the histogram as a density of probability (probability of occurrence of a gray level compared to all the pixels) which allows it certain robustness to changes in average luminosity.

The evolution of the histogram shows that our chosen hypothesis could be valid because the final histograms of the object and the background are close to Gaussian. We have also compared the histograms obtained during the iterations by minimizing the entropy and by minimizing the variance-dependent criterion, where the variance of the Gaussians are estimated at each iteration of the histogram, the pixel intensities are distributed over the entire intensity range.

The histogram distribution represented by the probability *p*, of the intensity with the mean μ and the variance σ^2:

$$p = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{(X-\mu)^2}{2\sigma^2}\right)} \tag{1}$$

The histograms increase linearly as expected, causing the original image's pixel intensities to be stretched into a wider range. According to the results presented in Figure 5, we can show that the results of 3D segmentation in PET scan and MRI that the performance of our technique applied to the PET scan in medical imaging thus the performance result of the histogram shows that the 3D imaging area of the intensity of the pixel is more important on the results of the PET scan compared to the MRI.

IV. CONCLUSION

In this paper, we have presented a new method of image segmentation based on U-Net Algorithm. The proposed method consists to create a model for segmentation in the medical field with the deep learning architecture that can improve the vision in the nuclear medicine especially to diagnostic the tumor segment. The results obtained demonstrate that this technique can accurately segment the image into homogeneous regions. Extensive testing results have shown great potential on the proposed method. It can be useful for color biomedical image.

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