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

Elloumi Nabila, Ben Chaabane Salim and Seddik Hassen

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ELLOUMI Nabila
RIFTSI Research Laboratory
ENICAR,University of carthage,tunisia
Nabila.elloumi@enit.utm.tn

Ben Chaabane Salim
RIFTSI Research Laboratory
ENSIT, University of Tunis,tunisia
s.chaabane@ut.edu.sa

SEDDIK Hassen
RIFTSI Research Laboratory
ENSIT, University of Tunis,tunisia
seddikhassne@gmail.com

Abstract **- Segmentation of pulmonary cancer is the big ambiguity of medical staff in their diagnostic, we will present our U-NET algorithm in this paper. 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. So, the resolution of the output is increased by these layers. To obtain the best result of the performance from the different data merged we choose the technique of 3D-UNET architecture.**

To elicit the optimal and best quality result of the segmented images, we choose this technique that allowed merging the different data source. The experimental results of the segmentation are approved by using U-NET for image segmentation.

Keywords-Segmentation, U-Net architecture, Conventional Network, Classification.

I. INTRODUCTION

Image segmentation [1] is a fundamental problem of computer vision and image treatment. In this contest, the segmentation of the images has the largest application in many fields [2] and many techniques have been developed [3]. The main idea of the segmented image for an homogeneous regions with the specific 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.

As well, William et al. [5] have introduced a pap-smear analysis tool (PAT) for detection of lung cancer from Pap smear images. This work accurate the classification and development tool of the automate to diagnostic the cervical cancer from the pap-smear images. In their work, the authors have used the technique of trainable segmentation weka and an approach of sequential elimination approach was used for debris rejection to achieve the scene segmentation. Achieving our simulation anneal the feature selection of the wrapper filter integrated, by using fuzzy C-means algorithm we introduce our classification. The system chosen analyze 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 point, Dago et al. [9] have proposed a segmentation method of tumors in PETscan medical imaging based on 3D random walk. The method we present is evaluated with an automatic segmentation method based on Random Walk (RM). The original algorithm present the problem of the hyper parameter, as well as the probability of the gradient grayscale intensity that propose and the solution of these problems, our new version of random path to segment tumors in medical imaging Emission Tomography (PET). The results combined on a physical patient phantom and the data shown that the used method is the best.

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 main idea of the present study is to check 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 neural networking 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. The design is taken from the semantic segmentation called pixel classification. The U-NET was created with the FCN architecture by introducing hop connections which means layer blocks in the shrinking that allowed output directly to blocks in the expanding phase, extracted high-level features from an image.

The paper is organized as follows: Section 1 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 medical images result is provided by a carcinology hospital Salah Azaiez of Tunisia.

Section 2 the proposed method will be introduced for biomedical image segmentation. The experimental results are discussed in section 3, and the conclusion is given in Section4.

II. PROPOSED METHOD

The medicine diagnosis uses the medical imaging that includes the different techniques for the treatment of the extended pathologies. This metamorphosis in medicine gives the access suddenly to the instruction (anatomical organs characteristics and the metabolism aspects).

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. The 3D CNN architecture is defined with our data to represent the sampled values and sub-sampled.

The method of the multiplanar reconstruction (MPR) is easier to define by building the volume on the stacked axial slices. The slices are cut simultaneity by the appropriate software especially for the DICOM images using the orthogonal planar 3D in the space. The technique of the 3D image segmentation for medical fields is processed by using the feature extraction by using the packs for recording and achieving those Dicom images for accurate the best diagnostic. Furthermore, this technique is based on threshold, edges and region. However, the segmentation of 3D medical imaging consists of processing the interest objects.

The main problems of the segmentation that are patch-based, with ignore the importance information of accuracy and reduce the inference.

To find solution of this problem, we propose our technique with our dataset based on 3D U-Net architecture. The U-Net namely as convolution neural network created for segmentation in biomedical image by using this CNN Model every pixel needs to be classified simultaneously. This fully convolution network is the main result of the extend architecture is gain the best accuracy and less training for result of segmentation. This model uses convolution and pooling layers similar to those in a classification.

In the present study, the method of 3D medical images is a very deep and wide field so we proposed our method; the decision of the result is applied to have in the last of the 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: A 2D operation takes the place by the best 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.For the step of training, our model of the U-Net modified given as input (256×256) slices of 2D CT images and the provided labels are (256×256) masks and the nodule pixels are 1, others are 0).
Step2: The trained model gives form images (256×256) in the output value of each pixel is between 0 and 1 indicating that the pixel belongs to the probability of a nodule).
The corresponding slice of the last U-Net layer is corresponding entries and prognostication on all patients see figure 3 and 4.

The architecture of the suggested process is presented in Figure 1.

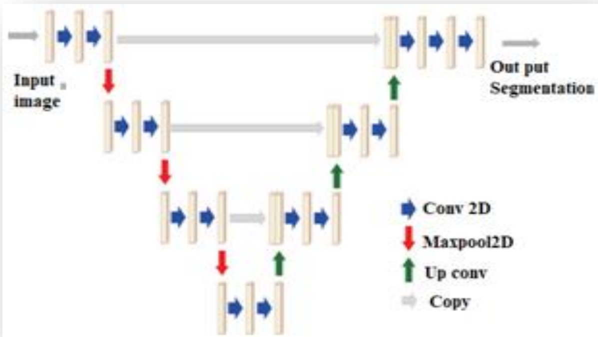

Fig. 1.Basic architecture of 3D-Unet.

III. EXPERIMENTAL RESULTS AND DISCUSSION

In disposition to estimate the proficiency of the precision and sensitivity of the suggested process, the segmentation performance of the datasets are proceeding. The results of the segmentation are compared with methods that exist as demonstrated. These processes are uploaded out with the MATLAB software10.

The format RGB (red, green and blue) is used to store the original 3D images. Each pixel takes 8bits of the primitive color and the range intensity between 0 and 255. The user initializes the labeling of the DICOM images taken after for our segmentation.

Several results of biomedical images are given in this section. Samples of the images data is shown in Figure2.

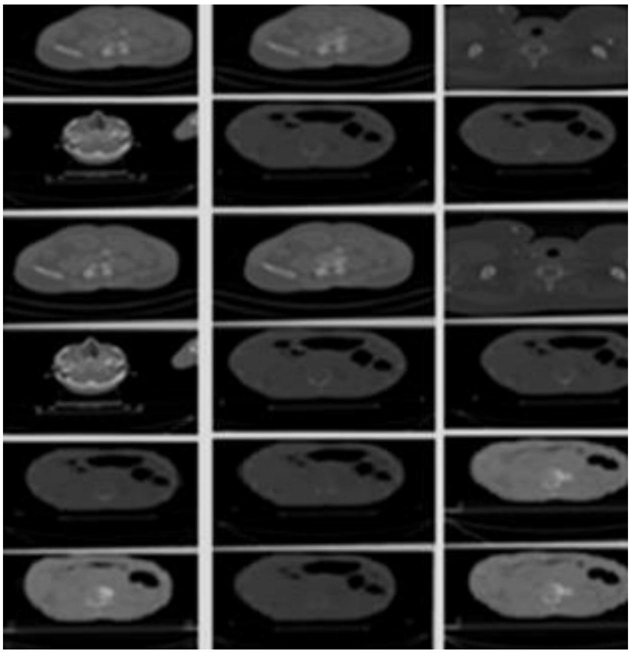

Fig. 2. Dataset used in the experiment. Twelve were selected for a comparison study. The patterns are numbered from 1 through 18, starting at the upper left-hand corner.

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

The patients for this case will be operated for the biopsy analyze and to approved the diagnostic of the medical staff. The result of this step takes importance for the examination.

In this research we introduce the U-Net architecture as deep neural networks suggested to determinate the problems of segmentation in medical field, 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 offer the skill of the unsupervised layer of multi level structure that automatically selected to other illustrations. The CNN architecture of encoder-decoder mainly avoids the hardness of the bias that canaries when the neural network is training (without pre-initialization).

The pre-training U-Net gives 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. The training composed using 2356 images include the data augmentation each net work was trained from the scratch. Each image has the form (512, 512, N), where N is the number of forms. The mask of everyone has the shape (512,512, 1).

To establish the masks of images found in the dataset, we divide the dataset into sub-images then make the masks using the version modified of the k-means algorithm. The dimension of the images are modified to(128×128) as considering the quality of the image degradation while processing all package of images with the initial sizes is impossible due to the narrow of GPU memory. The performance of the loss functions for the first net works showed better during training. The Adam optimizer was selected for the segmentation of images.

The U-Net architecture presented as a family of neural networks that characterize the structure of the encoder-decoder and mainly types of fully convolution neuronal network (FCN).The semantic segmentation is designed with the pixel classification and build on the FCN architecture by importing the connections that include the layer blocks directly to output blocks in the diversity stage.

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. We way out 3D images of lung cancer small cell (CPC) of the different stage which is related to the consumption of tobacco and represents 25% of lung cancers the other classification is the non-small cell lung cancer (NSCLC) that deposed 75% of lung cancers. The result represent the unqualified quality of MRI of seventeen patients was excluded the massive metastatic disease excluded six patients.

The development of the 3D U-Net algorithm present the total of 493 patients engaged for all mpMRI data was anonymized preliminary to the insertion of scientific information account (age, weight, and stage) of the matriculate patient. 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 implementation of the 3DU-Net Algorithm assimilated to the Chen Li [16] method that represents the outgrowth applied to biomedical image segmentation of the experimental CT. The outcomes of the segmentation are shown in Figure3.

Regarding the accuracy and sensitivity, in Table1schedule the correct segmentation rate of the dataset used in the different experiment methods.

It can be seen from Table 1 that the accuracy (AC%)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(Sens%) 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 I
The Performance of the experiment comparison of the segmentation results and our proposed method from the dataset shown in Figure2.

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

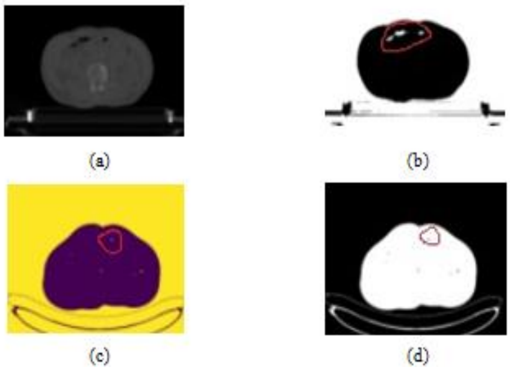

Fig. 3. Segmentation 3D of lungs seen from the side of pet scan Images, (a) original image, (b) segmented image by using U-net, (c) ROI (c) segmentation U-net.

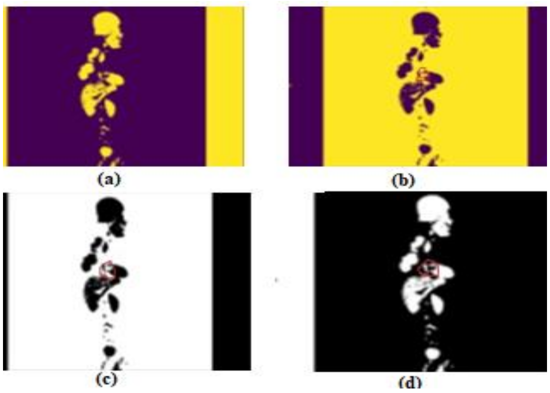

Fig. 4. Segmentation 3D of lungs seen from the side of pet scan images, (a) original image, (b) segmented image by using U-net, (c) ROI (d) segmentation U-net.

Actually, the probationary outgrowth of the 3D U-Net architecture point out that the suggested process used is more faithful than the classical process in terms of quality of segmentation as marked by the sensitiveness of the segmentation, see Table 1.Furthermore,the implementation of the segmentation sensitivity on our data is more significant than the other suggested method. We conclude that the insertion of 3D U-Net can support network to gain the best execution on the model of 3D volume segmentation confront to the other methods.

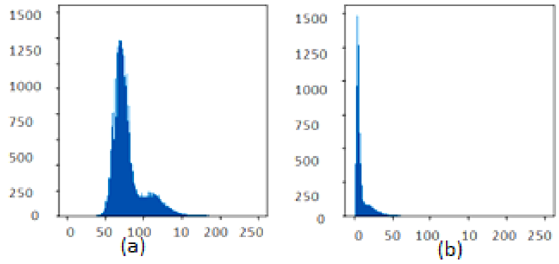

Fig. 5. Redistribution of the histogram by intensities shifts (a) 3D medical images in PETscan, (b) 3D medical images in MRI.

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 presented in (1):

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

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 the 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

This item, we introduce an up-to-date process of frame based on segmentation based on U-Net Algorithm. The proposed method consists to establish a new template in the medical field with the deep learning architecture that can improve the vision in the radiotherapy medicine especially to diagnostic the tumor segment.

The results obtained demonstrate that these techniques can accurately the image into homogeneous regions.

The result shows the potential of our testing. That opens the stage to develop the biomedical images.

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