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Contribution of artificial deep learning for image segmentation in medical imaging

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Abstract: An important task in image analysis is image segmentation. Once this key task done, there are huge of applications which can be done. Of course, the more accurate the segmentation, the better the quality of the applications. Deep learning algorithms can improve image segmentation. Their improvement offers new perspectives for the development and implementation of imaging biomarkers in clinical routine.

Keywords: Deep learning; image segmentation; medical imaging

1. Introduction

For a few years now, we have been experiencing a new digital revolution, which is the integration of artificial intelligence in our daily lives. The use of artificial intelligence methods is not novel, but the improvement of performances allowed by the use of deep learning leads to the creation of new powerful tools, including in medical imaging.

An important task in image analysis is image segmentation. Segmentation consists of identifying and delimiting structures on the image. It allows measuring organs and lesions as well as performing specific analyses on the segmented structures. Manual segmentation is a tedious task when the structures to be segmented are large or complex in shape. Moreover, like any process involving humans, manual segmentation suffers from inter-observer variability. Therefore, automating the segmentation process using deep learning methods could save time, increase the accuracy of quantitative measurements, and help creating new biomarkers.

2. Deep learning for image segmentation

There are several possible approaches for image segmentation. Before the advent of deep-learning, the main approaches were categorized as thresholding-based, regions-based, shaped-based, and machine learning-based methods [1]. Since a few years, many papers have shown the superiority of deep learning over these methods for the majority of segmentation tasks. In some cases, performances of deep learning are comparable to that of clinical experts.

Convolutional neural network (CNN) is a particular type of deep learning network which is adapted to image analysis. There are several available CNN architectures that are either suited for classification tasks like the AlexNet [2] or suited for segmentation tasks like the encoder-decoder architecture. The encoder-decoder architecture combines several layers of convolutions as well as scale reduction between each layer during the convolution part and progressive restoration of the initial scale of the image during the deconvolution part. This helps the network to consider the globality and the details of the image. A particularly popular encoder-decoder architecture for medical image segmentation is the U-Net architecture that has been used for many purposes [3].

3. Saving time and increasing accuracy

Quantitative measurement is a key element in medicine both for diagnosis and follow-up. In medical imaging, structure recognition is a prerequisite for most quantitative measurements. To measure a lesion, one must first be able to identify it and delineate its contours. To date, most imaging measurements are manual or based on visual assessment.

In clinical practice, manual measurements are usually performed in 2D, which is less accurate than 3D volumetric measurements, and are known to suffer from inter-observer variability. The use of segmentation methods allows for more reliable automated measurements based on volumetric analysis. Artificial intelligence-based computer aided detection software has been used for years to estimate the volume of lung nodules, allowing their evolution to be studied with more precision than a simple comparison of diameters. The comparison of volumes rather than diameters is recommended in Europe [4]. The use of deep learning methods improves the quality of segmentations and thus the accuracy of measurements for decision making [5].

Cardiac MRI is another example of an examination for which quantitative measurements are of great importance. The quantitative study of cardiac volumes requires that the contours of the cardiac chambers have been correctly delineated. Advances in automated segmentation tools through the development of deep learning allow for much more accurate segmentations [6]. This improvement help reducing the time radiologists spend manually editing segmentations, which is very time consuming. This allows an increase in productivity and quality.

Pulmonary nodule segmentation and cardiac chamber contouring are two applications where automated segmentation methods are used in daily practice and where deep learning is replacing previous approaches. Deep learning could also be used to automate quantification tasks that typically rely on semi-quantitative visual assessment. Indeed, the use of deep learning methods allows for the accurate segmentation of complex shaped organs or lesions that could not be segmented by previously used methods. Deep learning algorithms have been proposed for quantification of the extent of interstitial lung disease. They allow an automated quantification as precise as a manual segmentation where the radiologist would have manually annotated all the CT slices [7]. This automated assessment is therefore much more accurate than a semi-quantitative visual assessment. Segmentation of lung disease was particularly emphasized during the first wave of the COVID-19 pandemic, during which several deep learning-based quantification tools were developed to help radiologists to estimate the extent of lung involvement [8,9]. Automated accurate lung disease segmentation takes only seconds using deep learning, compared to 6-10 hours when performed manually, slice by slice.

Radiotherapy is another medical specialty where image segmentation is of particular importance. Radiation treatment planning requires a complete segmentation of the lesion but also of the surrounding organs. Theses segmentations are used to plan the geometric and dosimetric aspects of the therapy. The automation of segmentation by deep learning methods is already used in clinical routine and has resulted in considerable time savings [10].

4. Development and use of new biomarkers

Improved segmentation methods may be a key to the development and use of new biomarkers. Skeletal muscle surface area is an example of a biomarker that can be measured manually but is not used in clinical routine due to lack of automation. However, its measurement is a simple way to look for sarcopenia, which is defined as insufficient muscle mass and is a marker of general status. It has been shown that sarcopenia is linked to outcome in patients treated by chemotherapy, immunotherapy or surgery [11–13]. The assessment of skeletal muscle surface area could allow optimizing patient care by introducing nutritional interventions, adapting the concentration of chemotherapy or selecting the most suitable therapy for patient's general status. Skeletal muscle area is usually measured by outlining the psoas, paravertebral, and parietal muscles on an axial CT section passing through the middle of the 3rd lumbar vertebra. Several deep learning models have been developed to segment these muscles with the same accuracy as radiologists. Therefore, dedicated software can be expected to make this biomarker routinely usable in clinical practice (**Figure 1**).

In neuroradiology, hippocampus segmentation is of key importance for diagnosis, and therapeutic decision of neuropsychiatric disorders, including Alzheimer's disease [14]. Hippocampus can be segmented both on magnetic resonance or computed tomography images. However, manual segmentation of the hippocampus is tedious and therefore not often performed in clinical routine. Again, automated segmentation tools using deep learning [15] can lead to the wider adoption of this biomarker in clinical routine.

Finally, the segmentations can be used to develop more complex imaging biomarkers using, for example, a radiomics approach. Radiomics consists in combining imaging features of varying complexity to create models that correlate with clinical outcomes [16]. This is done by extracting and analyzing imaging features such as histogram characteristics, shape and texture. Feature extraction requires a prior segmentation step to extract features from the regions of interest. The use of automated segmentations allows for better reproducibility of the imaging features and the possibility of clinical use of these models.

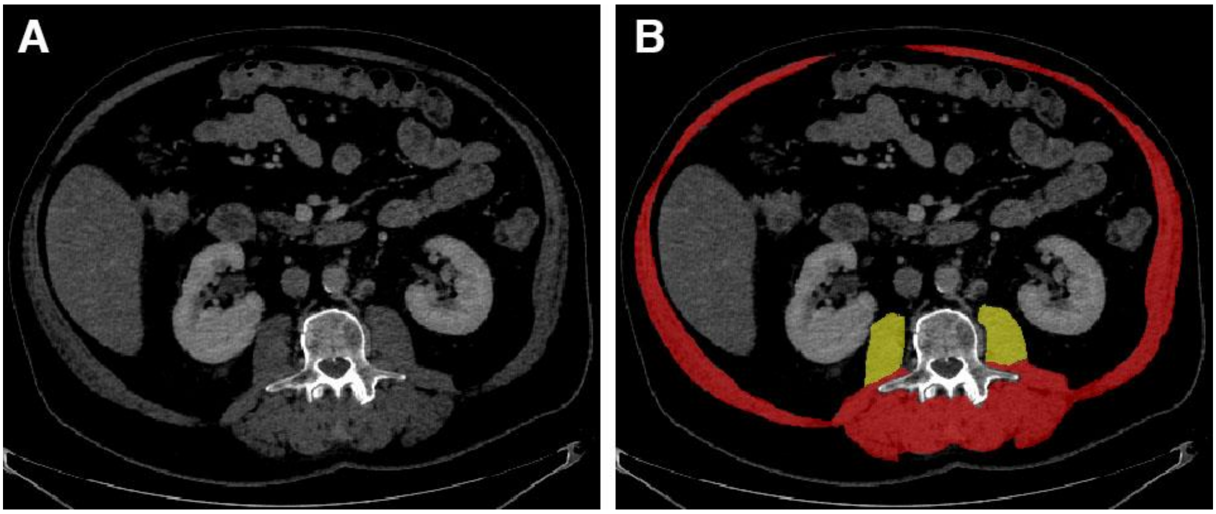

Figure 1. Deep learning method for automated segmentation of abdominal muscles in L3. The parietal (red contours) and psoas (yellow contours) muscles visible on a CT slice passing through the L3 vertebra (A) can be automatically segmented using a deep learning method (B) in order to identify patients with sarcopenia

One of the main advantages of segmentation tools over other AI-based tools is that their results are verifiable. Indeed, the machine is asked to automate a task that the radiologist is able to do and therefore to verify. The use of deep learning for image segmentation is not intended to produce segmentations that a radiologist would not be able to produce, but to make them accessible to clinical practice. Thus, there is no ethical problem of responsibility as it is encountered in computer-aided diagnostic tools that are asked to make predictions. Explainability is becoming a major concern in AI.

5. Conclusion

The improvement of image segmentation methods through the use of deep learning offers new perspectives for the development and implementation of imaging biomarkers in clinical routine. These tools are not intended to bring new skills to radiologists but to allow them to extract quantitative data that they could not have extracted for lack of time. They are intended for all radiologists and should both save radiologists time and increase the contribution of imaging to patient care. Despite the advances of recent years, progress in artificial intelligence is still to be expected, particularly in the generalizability and robustness of algorithms. That is, their ability to maintain satisfactory performance even in unusual cases such as artifacted images.

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