Editorial for "3D Breast Cancer Segmentation in DCE-MRI Using Deep Learning With Weak Annotation"

Magnetic resonance imaging (MRI) shows higher diagnostic performance in the detection of breast tumors, compared with other imaging modalities.[1] Breast MRI protocols include dynamic contrast-enhanced (DCE) images with high spatial and temporal resolution and are central in diagnosis, staging, and follow-up of breast cancer.[2] DCE features provide physiological and anatomical lesion characteristics. To extract these data, manual lesion segmentation is currently performed, which is a critical time-consuming step, introducing bias and variability and impacting the reproducibility of the extracted features. To overcome these limitations, artificial intelligence algorithms have been explored, especially deep learning (DL) methods, for automatic lesion segmentation. This has been an active area of research, pivotal in the analysis of quantitative medical images. Most lesion segmentation methods have been based on semi-automatic or supervised learning approaches, presenting an important limitation: slice-by-slice 2D segmentations are typically performed, leading to suboptimal 3D masks upon concatenation. Recently, DL methods based on vision transformers have gained popularity in breast lesion segmentation, improving results over traditional machine learning.[3] Although fully convolutional neural networks (CNNs) show powerful learning capabilities, their performance in learning long-range dependencies is limited, presenting decreased capacity in the segmentation of structures including different shapes and scales.

UNETR is an architecture that replaces the CNN-based encoder with a transformer, which can capture low-level details in 3D segmentation. UNETR directly connects the encoder to the decoder via skip connections and can directly use volumetric data. Compared with CNN or transformer-based segmentation methods, UNETR can better capture dependencies at diverse spatial scales, both local and long-range enabling improved segmentation.[4]

In this retrospective study, Kim et al developed a model based on weak annotations, for detection and 3D segmentation of breast cancer in a sample of 736 women, using different input combinations in a three-time point (3TP) approach, from DCE-MRI images, acquired in two 3 T scanners from different manufacturers.[5] The sample was divided into training ($N = 544$) and test sets ($N = 192$). To reduce the workload required to obtain ground truth segmentations, tumors were first segmented using weak annotations by two radiologists in consensus drawing bounding rectangles encompassing the lesion on two projection images. The rectangles were used to generate a 3D bounding box applied to the image obtained by subtracting the pre-contrast from the post-contrast image. An automatic thresholding method was used for automatic lesion segmentation; the mask was then refined to better define the lesion boundaries and exclude noisy or confounding regions (false positives). For training the segmentation network, images acquired at three different temporal acquisition points (pre-contrast, early, and delayed post-contrast) were used to construct three inputs: input 1 (pre-contrast, early phase), input 2 (pre-contrast, early, and delayed phase), and input 3 (pre-contrast and delayed phase). A different UNETR model was trained for each input, and segmentation performances were compared, qualitatively and quantitatively, based on MRI features and immunohistochemical (IHC) classification.

The best DL model presented a reliable performance for automated 3D segmentation of breast cancer with a median dice similarity coefficient (DSC) of 0.75 for the whole breast and 0.89 for the index lesion. The performance of the UNETR model was in accordance with the DSC values reported by other researchers employing alternative segmentation algorithms.[6–8]

Regarding the qualitative analysis of the segmentation results, the segmentation was successfully done in 83% of the cases derived from inputs 1 and 2, and from these, 95% were considered as acceptable detection. The authors also evaluated the performance of the segmentation according to baseline characteristics and found significant differences for the whole breast and main lesion. For main lesion, significant differences were observed according to lesion size and IHC type. Regarding visual analysis, significant differences were found between lesion type (mass vs. non-mass enhancement) and background parenchymal enhancement (BPE) level. In their study, there were nine cases of failed segmentation, which corresponded to tumors with small volumes, from which five cases were not segmented and four cases corresponded to abundant BPE, meaning false-positive results.[5]

Further developments of 3D UNETR architecture could be done to improve small lesion detection, to distinguish between mass and non-mass lesions, especially the boundaries of non-masses, and to distinguish between BPE and tumors. Attending to the implementation of DL algorithms in the clinical practice, this type of algorithm is expected to improve the detection of small lesions and the prediction of response to treatment, thereby reducing the number of performed biopsies and, potentially, enabling the use of an abbreviated MRI protocol, which would reduce MRI exam durations, improving patient comfort, and reducing costs.

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Luísa Nogueira, MSc, PhD and
Nuno Adubeiro, MSc, PhD
Department of Radiology, School of Health of Porto/Polytechnic Institute of Porto (ESS/IPP), Porto, Portugal
EPIUnit, Institute of Public Health, University of Porto, Porto, Portugal
Departement of Public Health, Laboratory for Integrative and Translational Research in Population Health (ITR), Porto, Portugal

Rita G. Nunes, PhD
Institute for Systems and Robotics – Lisboa and Department of Bioengineering, Instituto Superior Técnico, Universidade de Lisboa, Lisbon, Portugal

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