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EDITORIAL

"Fuzzy" radiomics: the way forward for nuclear medicine imaging applications?

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Since the early development of statistical measurements dedicated to quantifying tracer heterogeneity [1], to the first investigations of using textural features [2, 3] for the same goal, and the exponential rise of radiomics applied to nuclear medicine (NM) imaging [4, 5], partial volume effects (PVE) have been one of the many issues affecting the use of radiomics in positron emission tomography (PET) and single-photon emission computed tomography (SPECT) applications [6]. Despite improvements in spatial resolution and overall image quality over the last two decades, nuclear medicine devices still suffer from a relatively worse spatial resolution compared to computed tomography (CT) or magnetic resonance imaging (MRI), and it remains a limiting factor of an accurate quantification of the signal in reconstructed images of small objects of interest, either organs or tumors. Even the characterization of large tumors is affected by PVE, since transitions between different levels of uptake in case of heterogeneous tracer distribution within the volume of interest can exhibit fuzzy values.

In the vast majority of studies investigating radiomics in NM imaging, objects of interest have been delineated (either manually or semi-automatically) in 2D or 3D in the images, and a binary mask has been considered for the calculation of features characterizing the object [5]. This means that voxels in the images are considered to be either part of lesions or not. As a result, the sensitivity of the typical features to changes in the binary mask can vary (some features are more robust than others), but the characterization of the object does not take into account the PVE occurring at the borders of the mask in the original uptake signal.

In their work focusing on real clinical radiomic datasets, Grahovac et al. [7] investigated an alternative, called "fuzzy radiomics," previously introduced and evaluated in the context of phantom images [8]. The approach consists in weighting voxels contributions to the calculation of features instead of including lesion voxels with a binary yes/no decision. Except for these weights from the fuzzy mask, feature calculation is exactly the same as for the conventional one, based on the image biomarker standardization initiative (IBSI) [9]. This can potentially bring a few advantages over the conventional method: It can model and account for the actual PVE of any given scanner as long as the PSF is known, it enables encoding different delineations as a weighted mask, it can incorporate the object's surroundings (i.e., tumor habitat) with specific weights, and finally, it can directly use masks derived from automated algorithms that are most often inherently probabilistic in nature, before being binarized for a final output.

Grahovac et al. thus evaluated the potential benefit of this approach according to two measurements: First, the level of redundancy amongst features and, second, the performance of machine learning (ML) models built using the features (conventional vs. fuzzy). In order to avoid modeling biases, 4 different random forests and one multi-Gaussian classifiers were trained, and a majority voting of the 5 results models was used as the final prediction to compare fuzzy and conventional models.

Interestingly, they conducted the evaluation in 3 different clinical settings with their own tracer, tumor target, and clinical endpoints: 11C-methionine (MET) PET in glioma (3-year survival), [18F]FDG PET/CT in lung (2-year survival), and [68 Ga]Ga-PSMA-11 PET/MRI in prostate (low- vs. high-risk classification).

Their findings suggest that relying on fuzzy radiomic features instead of conventional ones not only improves the redundancy (clusters of features with a Spearman rank correlation value below 0.9 increased by about 20%), but also leads to better predictive performance of the ML models. The improvements were small (a few points of area under the ROC curve) but consistent across the 3 cohorts.

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Although recently published guidelines on radiomics for NM highlighted the potential benefit of considering alternative delineations (e.g., larger volumes encompassing the tumor surroundings) [10], future validations and comparisons should now be conducted in order to confirm whether fuzzy radiomics instead of conventional calculations should be relied upon in NM imaging, at least when smaller lesions are concerned.

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