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Session Item

Radiomics, modelling and statistical methods

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Impact of deep learning segmentation methods on the robustness of MR glioblastoma radiomics

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Abstract

Abstract Title: Impact of deep learning segmentation methods on the robustness of MR glioblastoma radiomics

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Purpose or Objective

Radiomics is a method that extracts a large number of quantitative features from medical images. This virtual profile builds a tumor phenotype and might help in patient stratification. Delineation of the lesion's volume of interests (VOI) is an essential step that is often performed manually. Deep learning (DL) segmentation methods have shown high accuracy in performing this time-consuming task prone to inter-observer variability (IOV). We studied the robustness of MR radiomics against six DL segmentation methods in glioblastoma patients.

Material and Methods

In total, 30 glioblastoma patients from three centers were included. Four MR sequences (T1, T1ce, T2, T2 FLAIR) were collected retrospectively for each patient. Six DL segmentation methods delineated four VOIs: necrosis and central non-enhancing tumor (CNEH), peripheral non-enhancing components (often referred to as edema, PNEH), contrast enhancing tumor (CET) and the combination thereof (Combined). Images were resized to 2 mm^3 voxels using trilinear interpolation and normalized using histogram matching to a reference patient. IOV among DL segmentation methods was assessed with Dice and Hausdorff distance. Intensity (n=17), texture (n=137), and wavelets (n=1232) based radiomic features were calculated using an in-house developed software implementation (Z-Rad, Python v3.7). Features were considered robust when the intra-class correlation coefficient > 0.9.

Results

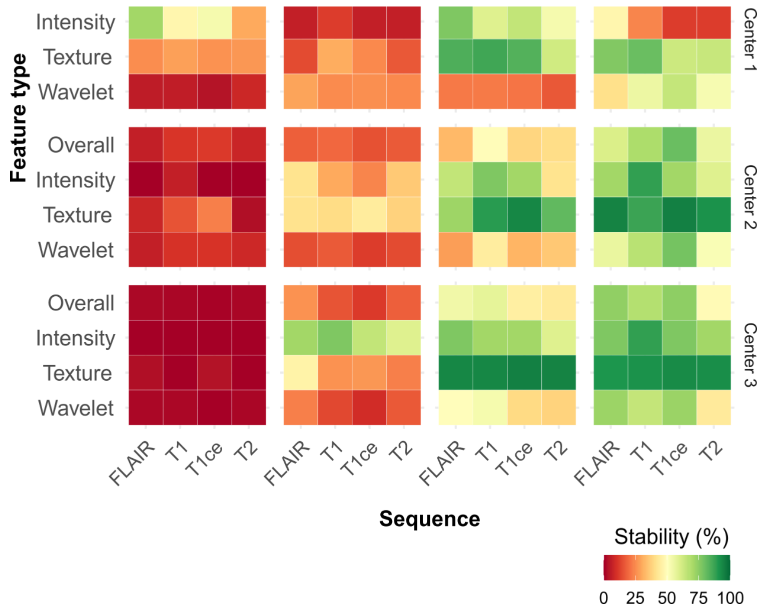

Figure 1: Heatmap of the robustness evaluation. Green represents high and red low robustness for given combination of center, sequence, feature type and VOI.

Good agreement was found between segmentation methods in PNEH and CET region and slightly worse agreement in CNEH for both Dice (0.86 [range: 0.82-0.90], 0.83 [0.79-0.85], 0.75 [0.70-0.82]) and Hausdorff distance (14.46 mm [3.88-23.90], 16.74 mm [9.06-25.66], 21.03 mm [11.75-29.03]), respectively. DL segmentation methods had a stronger influence on the robustness of radiomic features for small VOIs. Lowest robustness was observed for CNEH (only 1.6% of features) which was also the smallest VOI and largest robustness for CET (40.1%). Feature robustness improved when VOIs were combined (64.6%). Regardless of VOIs and sequences, texture features had the highest robustness (mean 53.4%). Lower robustness results were found in intensity (44.0%) and wavelet features (29.0%). DL segmentation methods affect features similarly across MR sequences (mean robustness rates 29.4-31.5%). Robustness of radiomics varies with centers, but to a lesser degree compared to VOI (robustness rates 37.0-46.3% vs. 1.6-64.62%, Figure 1).

Conclusion

The impact of DL segmentation methods on radiomic features depends on the volume of the VOI (large more robust than small) as well as on the feature type (texture more robust than intensity) and to a lesser degree on the MR sequence. The IOV varies between centers but considerably less compared to the studied VOI volume.