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An Optimized Training Module for Deep Learning-based Auto-Segmentation

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INTRODUCTION

Deep Learning (DL) algorithms have shown enormous potential for efficient and robust segmentation in radiation therapy (RT). Deep learning-based auto-segmentation (DLAS) that can substantially improve efficiency and consistency of segmentation often require large datasets, a unique training process for each tumor site and/or image modality. Thus rendering the whole process labor intensive as multiple iterations may be required to achieve optimal accuracy of individual models [1].

AIM

The presented study provides a significant leap and proposed an innovative unified training platform (*AccuLearning, Manteia)* for DLAS models for targets and organs of interest for multiple anatomical sites and modalities.

- Test and evaluate a pre-optimized *AccuLearning tool*, designed to train, modify and customize segmentation models independent of tumor site and image modality, with limited training data and user input.
- Facilitate Magnetic Resonance (MR)-guided radiotherapy [2] workflow, by evaluating segmentation accuracy of 3 MR image models trained with 2 unique scanners and 3 image sequences.

METHOD

AccuLearning tool was designed to facilitate both CT and MR images, with Z-score optimization and adaptive removal of outliers employed to achieve uniform intensity distribution for MRIs. This allowed training of MRIs independent of scanner and sequences. The training could be conducted with either U-Net or V-Net and optimized DL parameters.

- The training module trained 3 models for abdomen, using, 22 T1 and T2-weighted DIXON and HASTE from a 3T MR simulator, and 12 T1-weighted motion averaged FFE from a 1.5T MR-Linac system. The training contours were created by team of researchers using RTOG guidelines [3].
- To prove validity of the recommended optimized parameters, multiple iterations were trained by varying the DL parameters shown in Table 1 on an Intel® Xeon® CPU E5-280.

Table 1: Optimizable DL network and training parameters

	Recommended	Editing Range
Neural Network	2D U-Net	U-Net, V-Net
Batch Size	16	4,8,12,16
Sampling	Label Balanced	Uniform
Activation Function	ReLu	
Learning Rate	0.0003	
Loss Function	Dice	
Maximum Iterations	2000	Up to 20,000
Sampling Window Size	CT (320×320×1), MR (192×192×0)	< input image size

RESULTS

AccuLearning tool utilized minimum user input and trained each model in 30 minutes, with 11 organs-at risk auto-segmented in 20 seconds. Multiple iterations were trained and optimal results were observed using parameters shown in Table 1.

- For evaluation, DLAS accuracy was subjected to TG 132 tolerance metrics [4]. The tabulated metrics (DSC and MDA) of (A_Aorta, Bowel_Large, Bowel_Small, Duodenum, Kidney_L, Kidney_R, Liver, Pancreas, SpinalCord, Spleen and Stomach shown in Figure 1 and visual representation of segmented anatomy (Figure 2) showcase robust and comparable segmentation capabilities for the three models, thus confirming the strength of a scanner independent MRI training and the module's ability to perform in presence of multi-parametric MR images.
- *AccuLearning* module for DLAS repeatably delivered acceptable models for majority of OARs without a labor- and data-intensive process. Thus, the module framework eliminated the need of large cohort of training data for DLAS, an otherwise handicap for deep-learning based training and execution.

Figure 1: Accuracy metrics, DSC and MDA tabulated for 11 organs-at-risk for the 3 models.

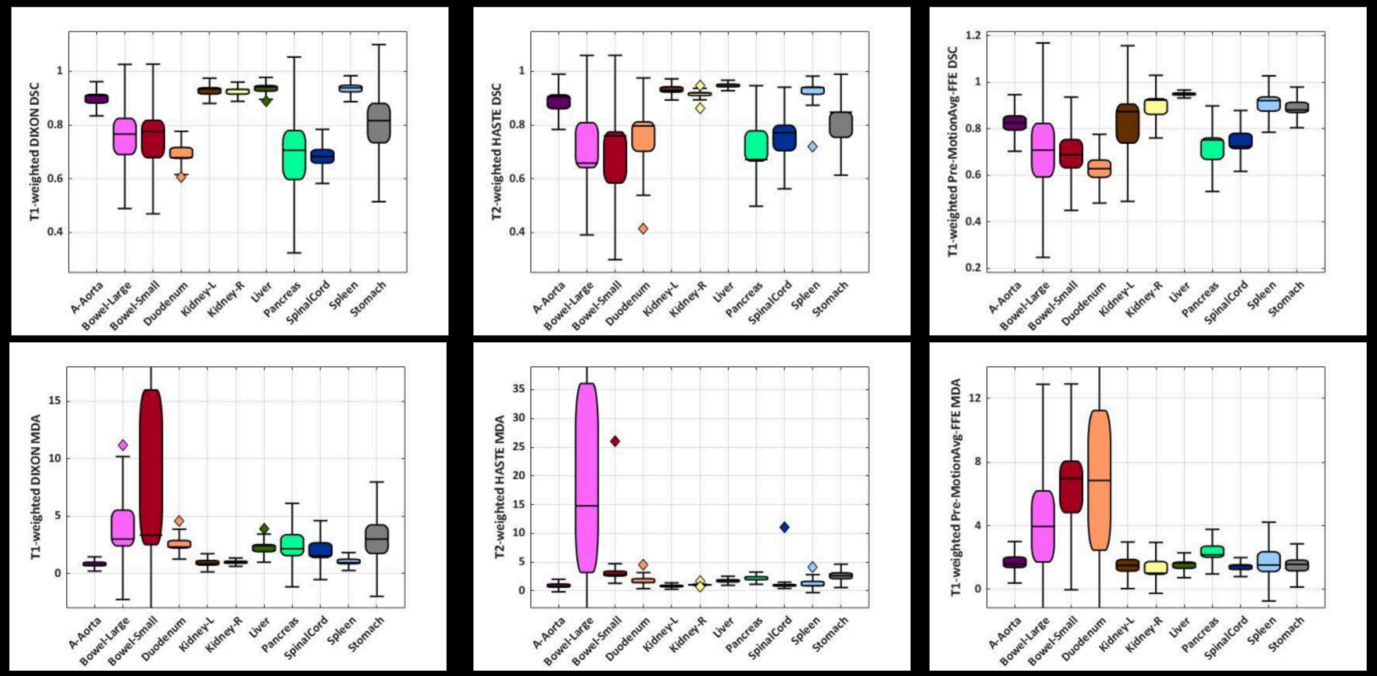
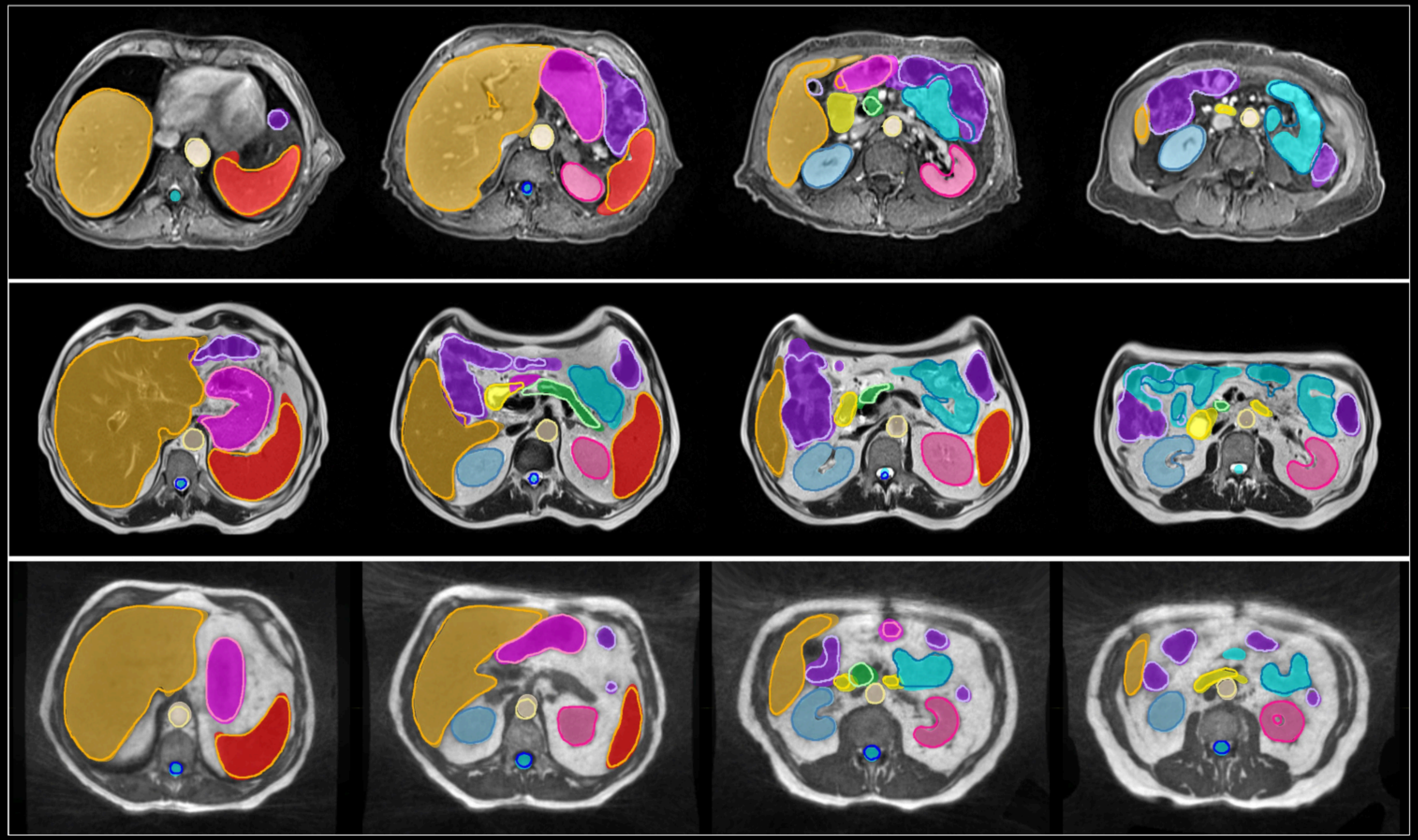


Figure 2: Slice-by-slice comparison of ground truth contours (filled) with auto-segmented contours (thick lines). 11 organs-at-risk are shown for the 3 models; top) T1-weighted fat-suppressed, water-only DIXON , middle) T2-weighted HASTE, bottom) T1-weighted, pre-treatment, motion-averaged FFE.



CONCLUSIONS

The present study capitalized on the growing need for fast and robust segmentation, by providing an anatomical site and modality independent DL auto-segmentation model training solution, applicable for multi-purpose clinical radiation therapy workflows.

- A user-friendly, pre-optimized solution for auto-segmentation of OARs is proposed for a variety of RT images.
- The module was able to incorporate intensity variations and bias field effect, intrinsic to MR, and deliver robust structures across all multi-parametric images.
- While, interestingly reasonable segmentation performance was observed for organs strongly subjective to inter/intra-patient motion (Bowel_Large/Small) and partial volume effect, however, there is clearly room for improvement as seen by a broad range of DSC and MDA values.

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