more standard in practice, the responsibility of the radiation oncologist has evolved to identifying and tracking all brain metastases, treated and untreated. We sought to develop and validate a neural network for automated segmentation of intracranial metastases and organs at risk on SRS treatment planning brain MRIs that could also facilitate tracking of previously treated lesions.

Materials/Methods: The sample consisted of 401 brain SRS cases from 265 patients with a total of 2375 intracranial metastases at a single institution. One hundred cases with 423 metastases from 86 patients were randomly selected to be the test set. We utilized the nnU-Net, a state-of-the-art self-configuring 3D convolutional neural network. Multichannel input consisted of 3D T1 thin slice post-contrast brain MRIs with contours of intracranial metastases as well as non-target organs at risk, including the globes, lens, brainstem, optic nerves and optic chiasm. Masks from prior treatment targets (previously treated lesions) were included as additional multichannel input. Manually contoured gross tumor volumes were the gold standard. Patch size was $64 \times 192 \times 160$. The network trained for 1000 epochs with a combination of dice and cross entropy loss on a RTX 3090.

Results: The median Dice score for segmenting metastases in the test set was 0.79 (interquartile range: 0.59-0.86). Overall sensitivity was 84.1% with a positive predictive value of 74.4% (1.2 false positives per case). The median missed metastasis size was 0.05 cm^3 compared to 0.15 cm^3 for detected metastases. There were strong correlations between manually contoured and predicted metastasis volumes ($R = 0.87$) and between the number of manually contoured and predicted metastases ($R = 0.91$). Median Dice scores for segmenting the brainstem, globes, lens, optic chiasm and optic nerves were 0.92, 0.89, 0.64, 0.70 and 0.68 respectively. The model successfully labeled previously treated targets for longitudinal tracking, with zero false positives in previous targets.

Conclusion: This 3D convolutional neural network performs automated segmentation for brain SRS quite well, though can be improved for detection of small metastases. Future applications to tracking lesions over time and integration into SRS workflow should be explored.

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1120

A Multi-Centric Evaluation of AI-Driven Synthetic CT Generation Form Low Field Magnetic Resonance Imaging

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Purpose/Objective(s): Magnetic Resonance is an essential modality in the context of radiotherapy primarily for providing additional information with respect to tumor functional information leading to better target delineation (brain, prostate, etc.) and secondary in the context of emergence of magnetic resonance guided radiotherapy. However, in both cases computed tomography acquisition remains necessary for dosimetric purposes hampering the workflow, introducing additional cost and dose simulation/optimization discrepancies (due to the registration issues between MR & CT) while being associated with additional patient toxicity. This study aims to investigate in a retrospective manner the relevance deep learning synthetic CT generation as an alternative for simulation and planning for pelvic tumors treated with low field (0.35T) MRgRT.

Materials/Methods: In the context of this study, a cycle generative adversarial neural network (GAN) deep learning architecture was trained to determine a bijective transformation between a low field (0.35T) MR and the associated computed tomography scan acquisition. The training set involved 350 pairs of weakly aligned data of pelvis cases. A retrospective cohort involving 20 test cases coming from eight different institutions (US: 2, EU: 5, AS: 1) involving different CT vendors was considered for testing.

Results: Reconstruction performance was assessed using the OARs used for treatment. The observed average scaled (between maximum and minimum HU values of the CT) difference between the reconstructed and the CT used for planning was 35.08 with significant discrepancies across organs. Femoral heads were the most reliably reconstructed (4.51 & 4.77) while rectum and sigmoid were the less precise ones (53.13 & 51.48). In terms of qualitative evaluation, the presence of fiducial markers heavily penalizes the reconstruction due to the implicit propagation of errors associated with the "convolution" nature of deep learning. The presence of air bubbles visible on the CT (sigmoid and rectum) is also an issue since these elements are marginally perceptible in the MR and therefore can hardly be predicted from generator. Detailed reconstruction results per organ are appended.

Conclusion: This retrospective multi-centric study is a first step toward assessing the potential of a fully low field MR-based treatment planning workflow that eliminates the need of CT acquisition. Integration of the synthetic CT in the simulation/optimization and assessment of the induced dosimetric errors are necessary steps to determine the clinical relevance of our preliminary findings.

Abstract 1120 − Table 1

Organ/Reconstruction Error	mean (de scaled diff min (%))	means (observed CT)	mean (synthetic CT)
anal canal	63,08	39,56	58,44
bladder	20,62	16,94	32,06
left femoral head	4,51	263,35	278,65
penile bulb	47,62	38,67	50,58
prostate	36,80	37,57	56,14
rectum	53,13	-0,33	29,44
right femoral head	4,77	256,10	280,10
seminal vesicle	31,47	27,53	47,53
sigmoid	51,48	-14,28	-1,53
Total	**33,20**	**85,30**	**104,08**

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