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Dose Predictions for Head and Neck Cancers Using Hybrid Structure Sets Containing Manual and Automated Contours

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Purpose/Objective(s): The purpose of this study was to create a deep learning dose prediction model for head and neck (H&N) cancer treatments using computed tomography (CT) images, planning target volumes (PTV), and hybrid organ at risk (OAR) contour sets containing manually defined structures from historical treatments and artificial intelligence (AI) generated structures. The aim of this work was to enhance dose prediction models by including AI generated contours.

Materials/Methods: 140 H&N patients were selected for model training and testing. All patients had a PTV treated to 6996 cGy and possibly contained one or more of six lower-dose PTVs ranging from 6600 cGy to 5400 cGy. 9 OARs were selected as important critical structures for dose planning and included the total parotids, total submandibular glands, brainstem, cerebellum, mandible, spinal cord, esophagus, oral cavity, and body. In instances where one or more of the OARs was not contoured for the treated plan, an automated contour was inserted in the vacancy. A U-Net architecture was developed for training the dose prediction model and contained 17 input channels including CT images, 7 PTVs, and 9 OARs. Dose was normalized using a maximum dose point such that the objective dose for training the model was between zero and one. The model used five convolution layers with 32, 64, 128, 256, and 512 filters, respectively. After each convolution, 2×2 max pooling was performed to down sample the input matrix. 117 patient data sets were used for training and 23 patients were used for testing. Due to computational memory constraints, the model was trained using individual shuffled slices and in batches of 32 slices. Mean square error (MSE) was used as the loss function and a linear activation function was used for generating the predicted dose.

Results: The predicted mean dose to PTV_{6996} was $1.9 \pm 2.7\%$ lower than the actual mean dose. The mean percent differences between the predicted and actual $D_{95\%}$ and $D_{2\%}$ values for PTV6996 were $-8.1 \pm 5.1\%$ and 1.5 ± 2.9 %, respectively. The maximum predicted dose to the spinal cord was $11.0 \pm 10.8\%$ lower than the actual dose. The percent difference and deviation for the mean dose to the total parotids was 15.0 $\pm$17.7% lower than the actual dose. The mean predicted dose to the external body contour was $5.8 \pm 10.1\%$ lower than the actual dose.

Conclusion: The model was able to predict a dose distribution that agreed with treatment planning principles for H&N cancers, with target volumes receiving high dose and OARs receiving lower doses. The current model is a work in progress. More work is needed to validate and refine the prediction accuracy, which predicted lower doses to structures than the delivered dose. After refinement, the model will be used to assess the effects of AI generated contours on the predicted dose.

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Automatic Dose Prescription for Radiotherapy of Brain Metastases Using Two-Path Three-Dimensional CNN

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Purpose/Objective(s): AI modeling physicians' clinical decision making (CDM) can improve the efficiency and accuracy of the clinical practice and provide a valuable tool for initial consultations to patients seeking secondary opinions. We propose to develop an AI model that mimics physician decision process based on physician-specific or institution-specific clinical practice. We will use dose prescription as an example to demonstrate the feasibility of such models in this study.

Materials/Methods: This study included 148 patients with brain metastases treated by hypo-fractionated radiotherapy from 2017 to 2021. CT images and contours of the target volume and organ at risk (OAR) were extracted from the treatment planning system. A 3D convolutional neural network (CNN) architecture was built using two encoding paths with the same kernel and filters to capture the different image and contour features. Specifically, one path was built to capture the tumor feature, including the size and location of the tumor, and another path was built to capture the relative spatial relationship between the tumor and OARs. The model combines information from the two paths to make a final prediction of dose prescription. The actual prescription in the patient record was used as the ground truth for modeling training. The model performance was assessed by 8-fold cross-validation, in which each fold consisted of randomly selected 100 training, 20 validation, and 20 testing subjects.

Results: Of the 148 patients, 90 were treated by a single fraction (1×21, 1×22, 1×24 Gy) and 58 were treated by multiple fractions (3×9 Gy, 5×6 Gy) by 10 physicians based on the record. 138 (93%) cases were predicted correctly, and 10 (7%) cases were predicted incorrectly by the model. For the 10 failed cases, 8 were caused by the practice variations among different physicians, which was not accounted for by the model trained using data from a group of physicians.

Conclusion: This study demonstrated the feasibility of an AI model to predict dose prescription in CDM modeling. In the future, clinical parameters, such as patient performance score, tumor type, re-treatment, adjuvant therapy, will be included in the model to improve its performance further. The physician-specific model will also be explored to model individual physician's practice. Such physician-specific or institution-specific CDM models can serve as vital tools to address healthcare disparities by providing initial consultations to patients in underdeveloped areas or developing countries. It can also become a valuable QA tool for physicians to cross-check intra- and inter-institution practices.

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Decoding Brain Fog in Head and Neck Cancer Survivors Using Artificial Intelligence

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Purpose/Objective(s): Brain fogging, which is characterized by memory decline, word-finding difficulty, and decreased multi-tasking ability, is common in head and neck cancer survivors. The precise causes of brain fog are poorly understood, as MRIs are essentially normal in these patients. The purpose of this study was to use artificial intelligence (AI) to detect micro-architectural and biological changes in the brain that are invisible to human eyes.

Materials/Methods: DVH of temporal lobes and whole brain were obtained in 566 and 60 patients, respectively, who underwent IMRT or proton radiation with concurrent chemotherapy for nasopharyngeal carcinoma. EORTC QLQ-C30 was obtained from 92 patients who enrolled in two prospective clinical studies. Automated cortical region segmentation using an open-source software for processing and analyzing brain MRI images was performed in 33 patients with a minimum follow-up of 4 years. Architectural and biological MRI changes in gray matter, white matter, and subcortical brain regions were determined in 34 brain regions. Graph theory-based brain connectome was evaluated to assess the connectivity between different regions of the brain. Radiomics which employs high-