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Automated Segmentation of Multimodal MRI/MRA Images for Cerebral AVM SRS Treatment Planning - A Deep Learning Approach

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Objectives: Stereotactic radiosurgery (SRS) is a standard treatment for unresectable arteriovenous malformations (AVMs). Accurate AVM nidus delineation is critical for treatment planning. Unlike tumors, however, the AVM nidus can be difficult to delineate as it requires interpretation across several imaging sequences. Our objective was to use deep learning artificial intelligence to automatically segment cerebral vascular structures from multi-modal magnetic resonance images (MRI), combining information across three high-resolution MRI modalities to produce high-resolution vascular maps for SRS planning.

Methods: Subjects: 21 patients with cerebral AVMs were included. Spetzler-Martin Grade ranged from I-V. Ruptured, intact, and partially embolized lesions were included. 15 cases were used for training and 6 for validation. Imaging: Patients underwent brain MRI/MRA, including 3D time-of-flight (TOF), contrast enhanced 3D fast-spoiled gradient echo (FSPGR), and 3D T2 sequences. TOF, T2, and FSPGR images were reconstructed with resolutions of 0.45/1mm, 0.5/0.9mm, and 0.49/1mm (axial-plane/slice), respectively. FSPGR and T2 volumes were registered to TOF volumes and re-sampled to the TOF resolution. Labeling: Voxel scale structure labels were generated using a combination of automated and manual labeling. Briefly, samples of structures of interest (arteries, veins, embolized vessels, brain parenchyma, CSF) were manually labeled, as was the extracerebral volume. Images and labels were imported into MATLAB and a support vector machine-based algorithm was used to generate labels for the remainder of the image volume. The resulting label volumes were then meticulously edited slice-by-slice to correct clearly mislabeled voxels. These labels were used to train a neural network to predict voxel scale labels from the multimodal image volumes. The training set contained 2733 unique image slices. Augmentation by L/R reflection of nidus-containing slices yielded an additional 789 slices. Neural Network Implementation: A 2D U-Net convolutional neural network was implemented in Python using Keras. There were 9 input channels, (3 contrast x 3 slices [1 above/center/1 below]). A weighted categorical cross entropy loss function accounted for class imbalance. Predictions were made at the native resolution of the TOF images. Testing: Performance was evaluated using the Dice Similarity Coefficient (DSC) to compare labeled and predicted classifications on a per voxel basis.

Results: DSCs on the training set were good across all categories, with values of 0.82, 0.89, 0.98, 0.91, 0.88, and, 0.99 for arteries, veins, brain, CSF, embolized vessels, and extracerebral tissue, respectively. DSCs on the validation set remained good for arteries, veins, brain, CSF, and extracerebral tissue, with values of 0.72, 0.84, 0.96, 0.90, and 0.97, respectively. Validation DSC for embolized vessels was 0.20.

Conclusions: Automated, deep learning-based vascular segmentation of multi-modal MRI/MRA shows promise for assisting AVM SRS target delineation. Overall, we found good agreement between labeled and predicted vascular maps across an anatomically highly diverse dataset. While classification performance for embolized vessels was low compared with other categories, we hypothesize that this is due to the rarity of these structures in the training dataset and that performance can be improved with the incorporation of additional training examples.