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Deep-Learning-based Detection and Segmentation of Vestibular Schwannoma: A Multi-Center and Multi-Vendor MRI Study

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PURPOSE

Accurate measurement of vestibular schwannoma (VS) is important for evaluation of VS progression and treatment planning. In clinical practice, linear measurements are manually performed from MRI. Manual measurement is time-consuming, subjective, and restricted to 2D planes. In this study, we aim to develop a deep learning convolutional neural network (CNN) model to automatically detect and segment VS in 3D from Gadolinium (Gd)-enhanced MRI.

METHOD AND MATERIALS

In total 124 patients with unilateral hearing loss referred to MRI exam were enrolled, including 84 VS-positive and 40 VS-negative cases. MRI data were acquired from 37 centers, by 12 different MRI scanners from 3 vendors. Typical image resolution was 0.35×0.35×1 mm, and field of view ranged from 130×130×24 mm to 270×270×188 mm. In 84 positive cases, VS was manually delineated by two observers, supervised by a senior radiologist. The 124 subjects were randomly divided into three non-overlapping sets: training set (N=72), validation set (N=18), and test set (N=34). We trained a 3D no-new-Unet CNN for both VS detection and segmentation. Training was performed on a NVIDIA Tesla V100 graphics processing unit with 16GB memory.

RESULTS

Applied to the test set, the CNN correctly detected VS in 24 subjects and excluded VS in 10 (sensitivity 100%, specificity 100%). We evaluated the Dice index, Hausdorff distance, and surface to surface (S2S) distance in two scenarios, namely, CNN vs. observer 1, and observer 1 vs. observer 2. No significant differences were found: Dice 0.91±0.06 vs 0.92±0.05 ($p=0.5$ by paired Wilcoxon test), Hausdorff 1.3±1.5mm vs. 1.2±1.0 mm ($p=0.6$), S2S 0.4±0.3 mm vs. 0.4±0.2 mm ($p=0.9$). The annotation time was 6.0±3.3 min for the observer and 2.5±2.8 min for the CNN model.

CONCLUSION

In a multi-center and multi-vendor setting, a CNN model can accurately detect and delineate VS in 3D from Gd-enhanced MRI, to faciliate diagnosis and measurement of VS in clinical practice.

CLINICAL RELEVANCE/APPLICATION

Our study demonstrated the capability of a CNN model to fully automatically detect and delineate VS from Gd-enhanced MRI. The CNN model showed high sensitivity and specificity for VS detection, and sub-millimeter accuracy for VS segmentation, comparable to human observers. Simultaneous

detection and segmentation implies that the model can be used for screening, diagnosis, follow-up, and quantitative assessment of VS.

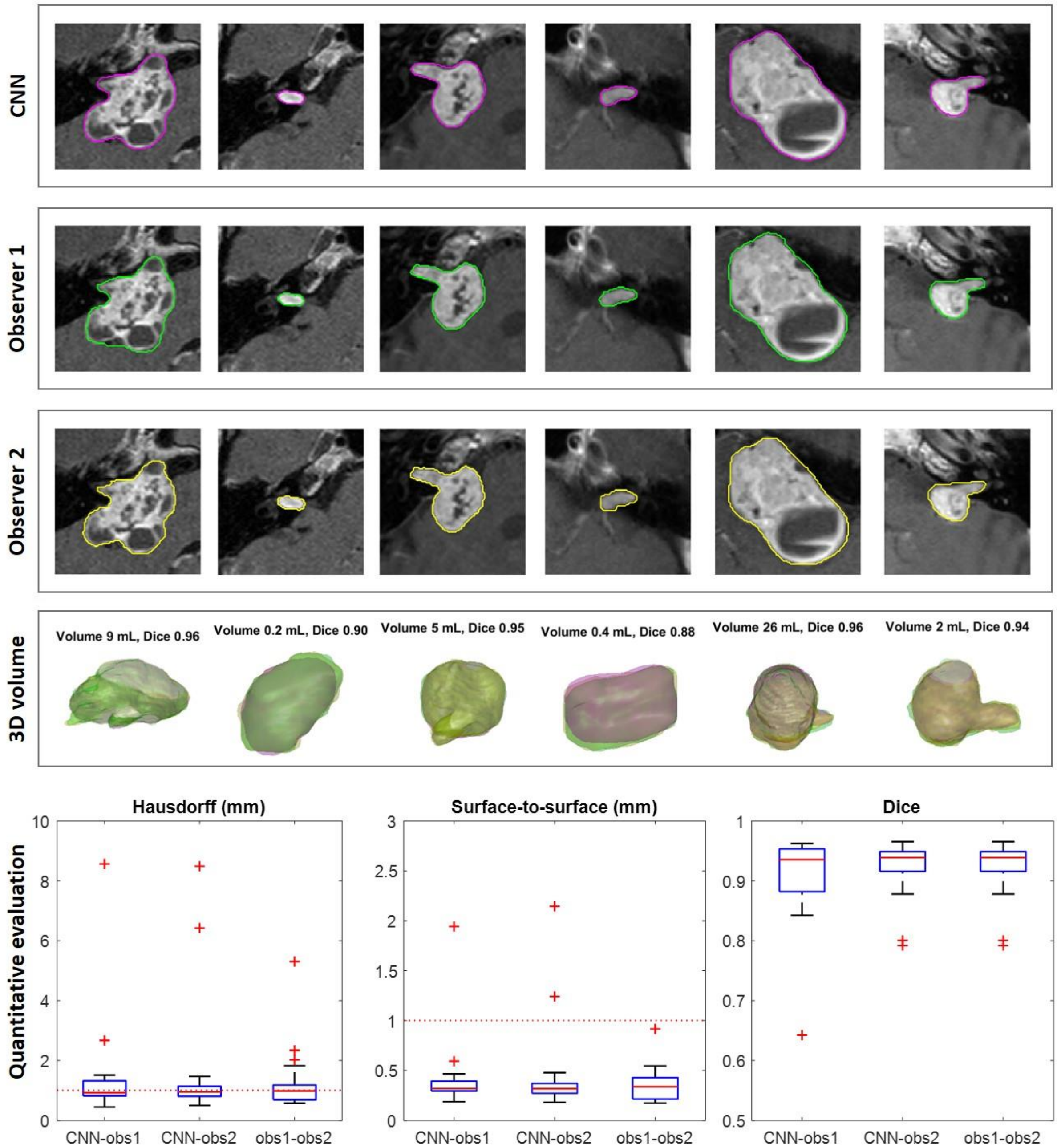

Figure 1. Six examples of VS segmentation by our developed CNN (first row), observer 1 (second row), and observer 2 (third row). All examples are from the independent test set. Images were cropped with the same field of view: 50×50mm. 3D VS reconstructions are also shown (fourth row). Color: purple: CNN, green: observer 1, yellow: observer 2. The last row shows the boxplot of the three quantitative measures for VS segmentation accuracy: Hausdorff distance, surface-to-surface distance, and Dice indices. We compared CNN with the two observers, as well as between observers. The outlier is a peripheral cyst, not present in the training set.