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A Web-Accessible Comprehensive (Weave) Platform for Vestibular Schwannoma Auto-Segmentation and Treatment Follow-up

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INTRODUCTION

- Vestibular schwannomas (VS) require long-term imaging surveillance to inform treatment type and monitor disease progress and treatment outcomes.
- Accurate and efficient delineation of VS is essential for clinical decision-making as volumetric assessment is more robust than linear measurements.
- Manual contouring and longitudinal tracking are time-intensive and variable and existing AI tools often lack longitudinal assessment and workflow integration.

KEY POINTS

- The WEAVE platform is a first-in-class, comprehensive, web-accessible platform for auto-segmentation and longitudinal monitoring of VS.
- WEAVE's user interface allows clinicians to visualize tumor volumes, edit contours as needed, and perform additional post-processing tasks. Users can choose to work with a single image for treatment planning or with a series of longitudinal images.
- The integrated segmentation models achieved mean Dice scores of ~0.9, approaching the typical range of human-to-human agreement.
- In longitudinal use, co-registration and standardized visualization within WEAVE enabled consistent volumetric trend analysis across time, supporting reliable assessment of tumor dynamics within the same clinical workspace.
- Future work will extend WEAVE's treatment-planning capabilities with dose prediction and automated plan generation.

REFERENCES

Prashad R, et al. (2026) *A WEb-Accessible comprehensiVE platform for automatic vestibular schwannoma segmentation and longitudinal volumetric tracking.* Neurooncol Adv.

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METHODS AND MATERIALS

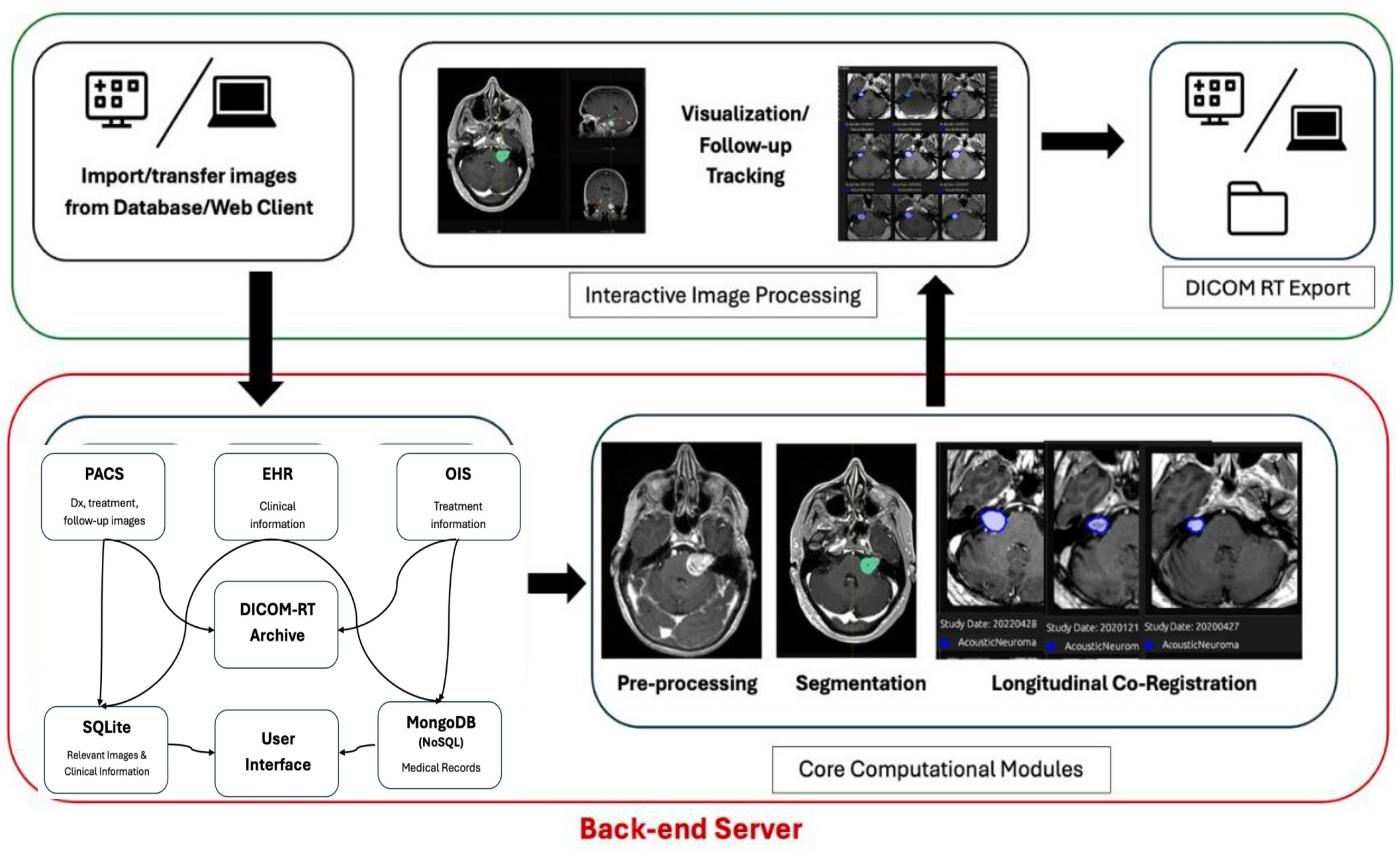

Figure 1. Overall workflow of WEAVE.

Platform Workflow

I. Image receiving: Via database transfer or user import from web client.
II. Database integration and auto-image processing: Backend server integrates scans into centralized database, pre-processes images, auto-segments VS, and co-registers new images with previous ones if there are any.
III. Visualization and interactive image processing: Processed image is displayed on web client and user can modify and post-process contours.
IV. DICOM-RT export: Refined contours can be exported.

Backbone nnU-Net Segmentation Model

Models + Applications

I. VS_CT-T1-T2: CT-based SRS treatment planning on CyberKnife and other general Linacs
II. VS_T1-T2: MRI-only SRS, longitudinal growth monitoring and post-treatment follow up
III. VS_T1: Scenarios where patients may have T1c images only, studying historical data

- Training
  - 93 patient cases - CT, T1 with contrast and T2 MRI
- Testing
  - Institutional: 20 patient cases - CT, T1 with contrast and T2 MRI
  - TCIA (The Cancer Image Archive): 242 patient cases - T1 with contrast and T2 MRI

RESULTS

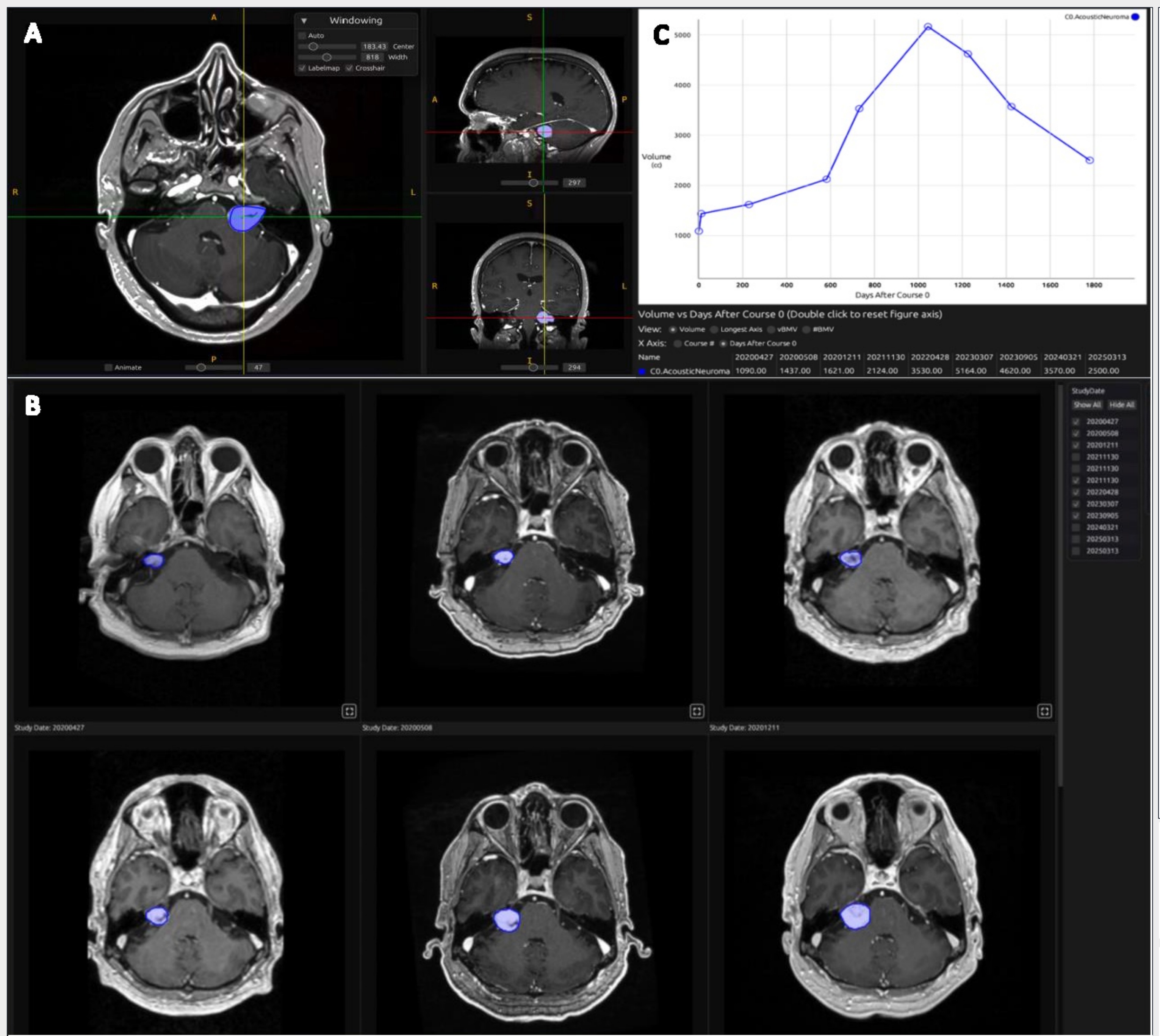

Figure 2 (A) Single image viewer; (B) Longitudinal tracking interface; (C) volume change over time generated by the platform's tracking capabilities.

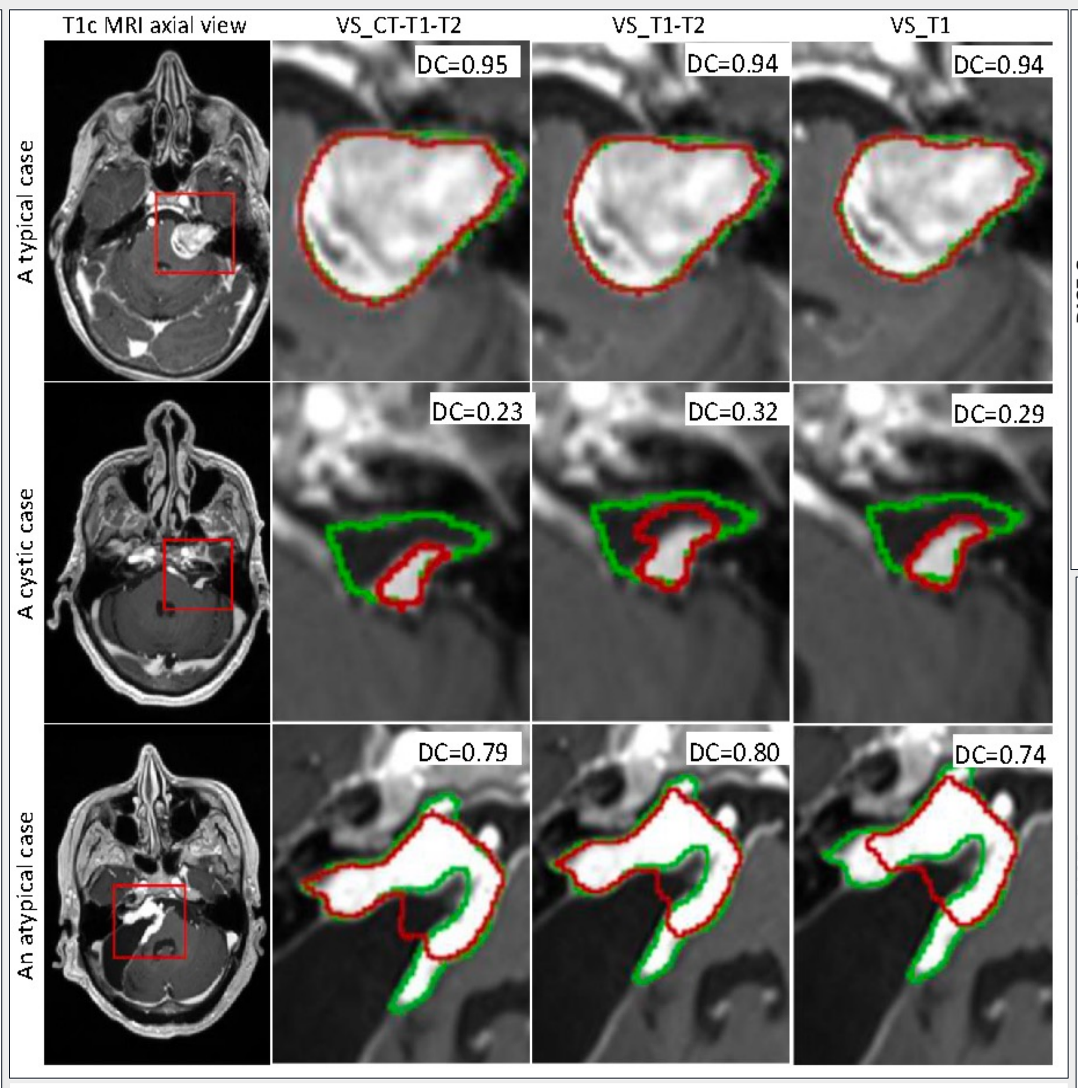

Figure 3 Illustration of auto-segmentation results across models. Row I: a typical case; Row II: a cystic case; Row III: an atypical case. Green: ground truth contours, Red: AI contours.

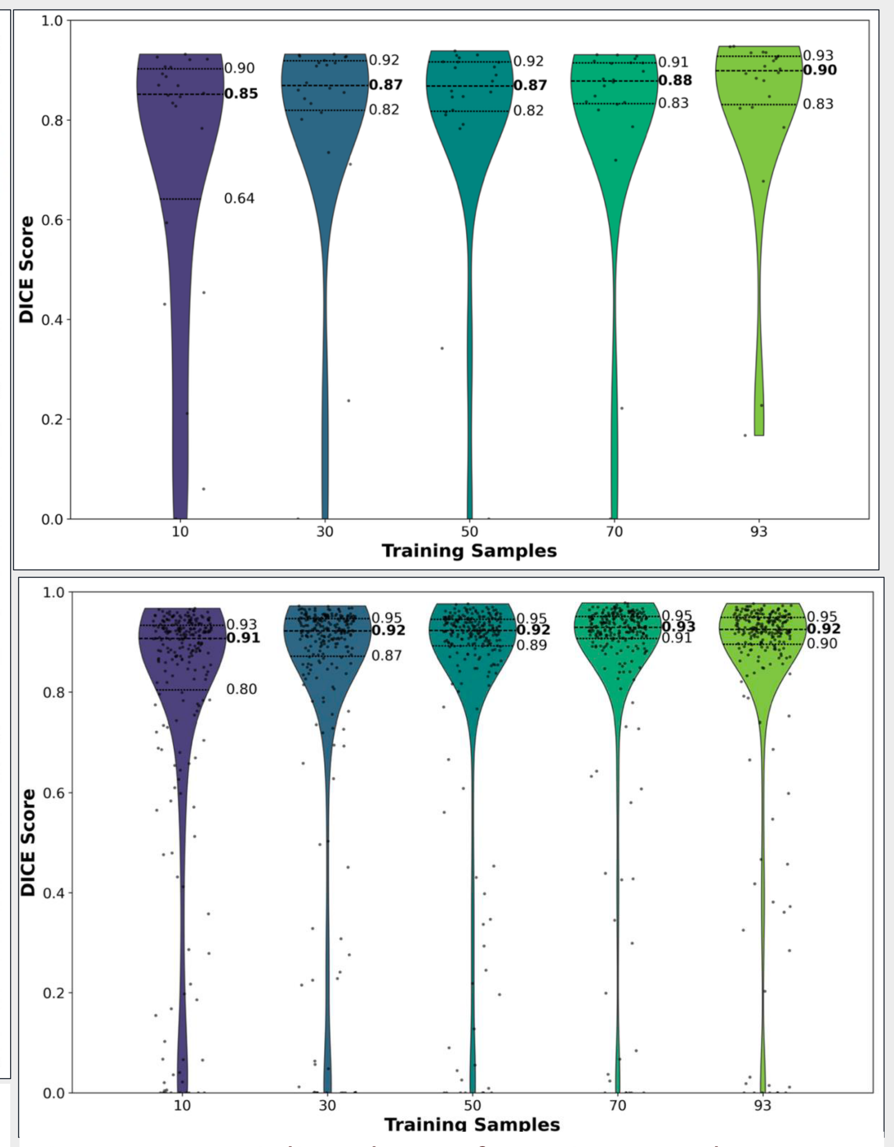

Figure 4. Violin plots of testing results across sample sizes (institutional dataset top, TCIA bottom)

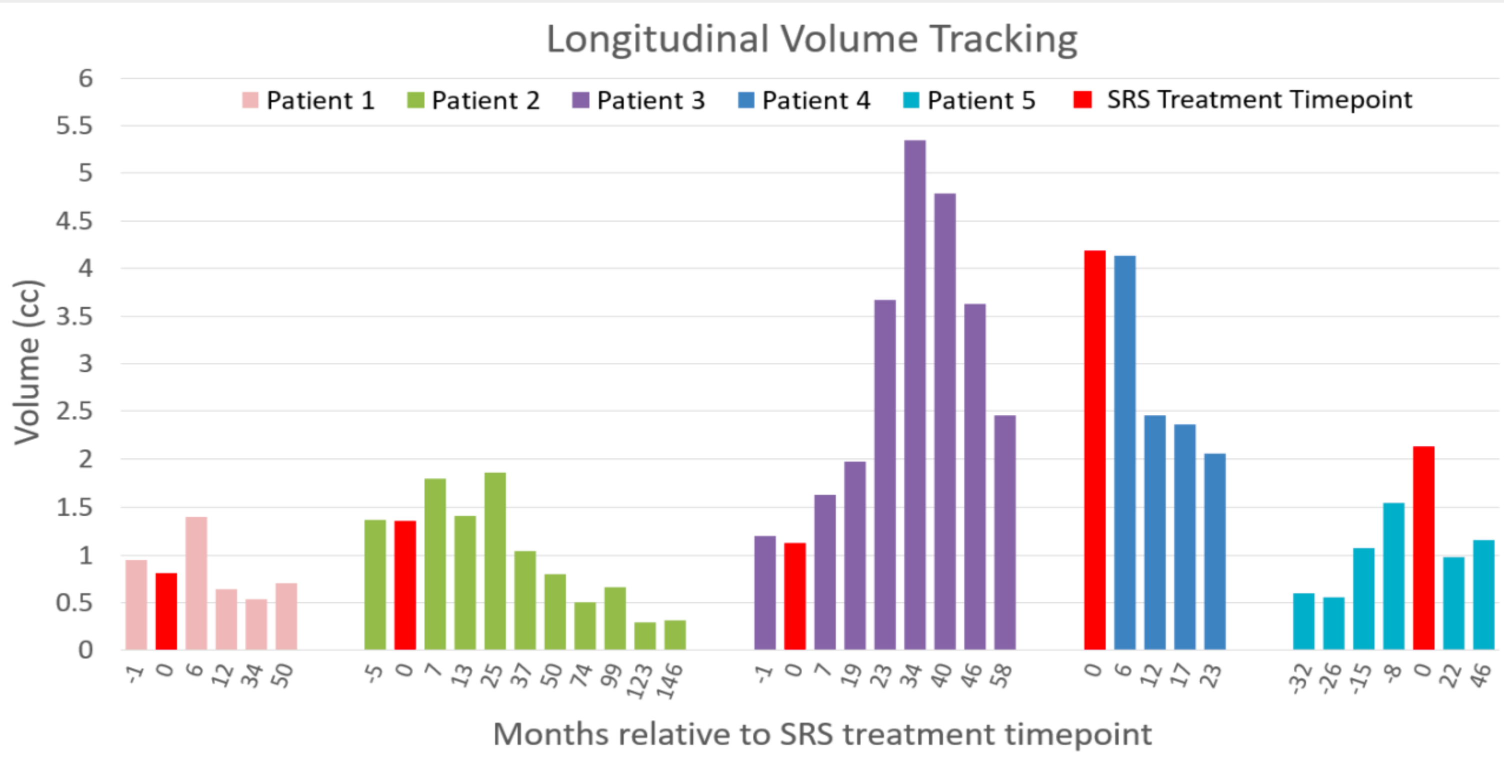

Figure 5 Tracking volume changes of tumor volumes over time in months with SRS treatment time point (red bar) as month 0.

- The developed platform combines automated tumor delineation with longitudinal volumetric analysis through a centralized workflow connecting imaging data and clinical databases (**Figure 1**).
- The user interface supports both single-image and longitudinal visualization, enabling users to assess tumors in three orthogonal planes and track volumetric changes across co-registered scans (**Figure 2**).
- In most cases, automated contours required minimal to no manual editing, although performance was reduced for cystic and irregularly shaped tumors (**Figure 3**).
- Quantitative evaluation demonstrated strong segmentation performance across all models. Mean Dice scores were slightly higher on the smaller institutional testing dataset (0.89) than on the larger TCIA testing dataset (0.86). Although the VS_CT-T1-T2 model achieved the highest overall performance, differences between models were not statistically significant. Similarly, the VS_T1 and VS_T1-T2 models showed comparable median Dice scores on the TCIA dataset. Performance improved with increasing training sample size and remained consistently high on the TCIA dataset (median Dice ≈ 0.92). On the institutional dataset, median Dice scores approached 0.90 as training sample size increased, while the 50- and 70-case models exhibited nearly identical interquartile ranges, suggesting stable and generalizable performance beyond 50 training cases (**Figure 4**).
- Longitudinal volume tracking revealed growth patterns consistent with expected post-SRS treatment response, characterized by transient tumor enlargement followed by stabilization or shrinkage, indicating tumor control (**Figure 5**).