Automated Vestibular Schwannoma Detection Using YOLO-Based Models

Sahika Betul Yayli, MD, Postdoctorate Research Fellow, Radiology, Mayo Clinic
Parv Mehta, MD; Daniel Blezek, PhD; Matthew Carlson; Neetu Soni, MD; Milan Sonka, PhD; Bradley Erickson, MD, PhD, CIIP, FSIIM; Girish Bathla, MD

Introduction

Accurate localization of vestibular schwannomas prior to segmentation is critical for improving automated analysis. YOLO-based object detection models may offer robust, rapid tumor localization, streamlining subsequent segmentation tasks.

Hypothesis

We hypothesize that YOLO-based object detection models can reliably identify regions of interest encompassing vestibular schwannomas, ensuring complete tumor inclusion within a single 3D-bounding box.

Methods

T1-weighted contrast-enhanced MRI slices were preprocessed into 2D slices with normalized intensities, and bounding box annotations were generated from ground truth masks. YOLOv8 and YOLOv10 models, including lightweight (s) and medium (m) variants, were trained and evaluated on internal and external datasets for precision, recall, F1-score, and complete tumor containment. Complete tumor containment was assessed by calculating the percentage of tumor volume encapsulated within a 7 cm^3 bounding box, derived by taking the 3D center of the detected bounding boxes on 2D slices.

Results

Both YOLOv8 and YOLOv10 achieved high detection accuracy, with F1-scores exceeding 0.93 and 100% complete tumor containment. YOLOv10m demonstrated slightly superior performance, with an Intersection-over-Union above 0.85 on both internal and external datasets. This reliable ROI determination enables consistent cropping for subsequent segmentation models, ensuring stable and improved segmentation results.

Conclusion

YOLO-based models are effective tools for vestibular schwannoma detection, guaranteeing that the entire tumor is contained within the predicted region. This automated localization step improves data preprocessing quality and forms a robust foundation for downstream segmentation tasks.

Figure(s)

	Model	Total Average IoU	Precision	Recall	F1-Score	Complete Containment Rate
Internal Test Set Results (n = 77)	YOLOv8s	0.8400	0.9365	0.9257	0.9311	100%
	YOLOv8m	0.8457	0.9408	0.9244	0.9326	100%
	YOLOv10s	0.8491	0.9521	0.9159	0.9336	100%
	YOLOv10m	0.8538	0.9554	0.9124	0.9334	100%
External Test Set Results (n = 240)	YOLOv10m	0.8705	0.9673	0.9991	0.9829	100%

Table 1. Performance metrics of selected YOLO models for tumor detection

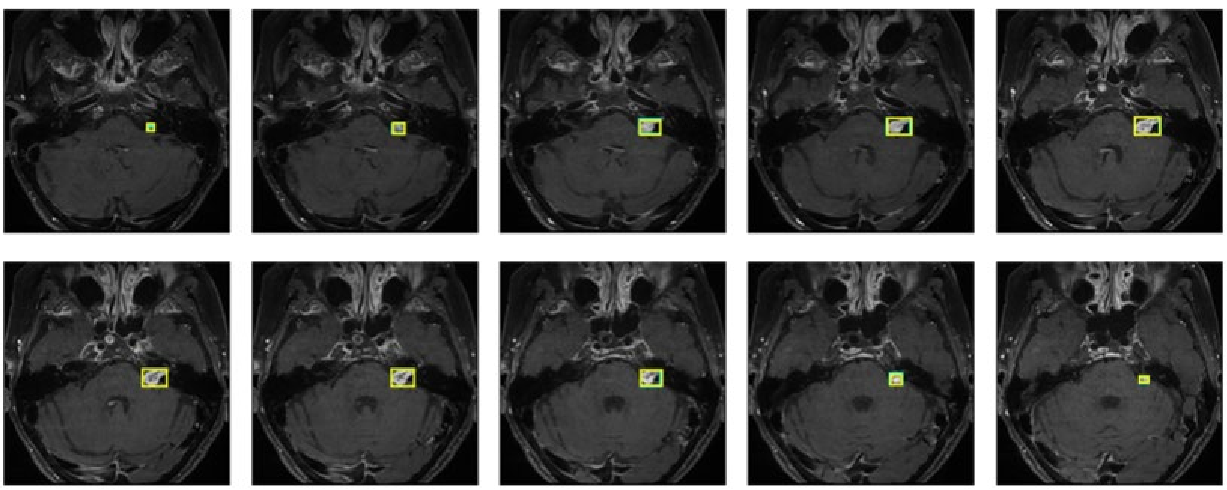

Figure 1. Illustrates the detection of a tumor on a sample data using the YOLOv10m model. Each image represent a slice of the same volume. The yellow rectangle represents the predicted bounding box, while the blue rectangle indicates the ground truth bounding box. It is evident that the model made detections that closely overlap with the actual bounding box in all slices, even those with small tumor volumes.

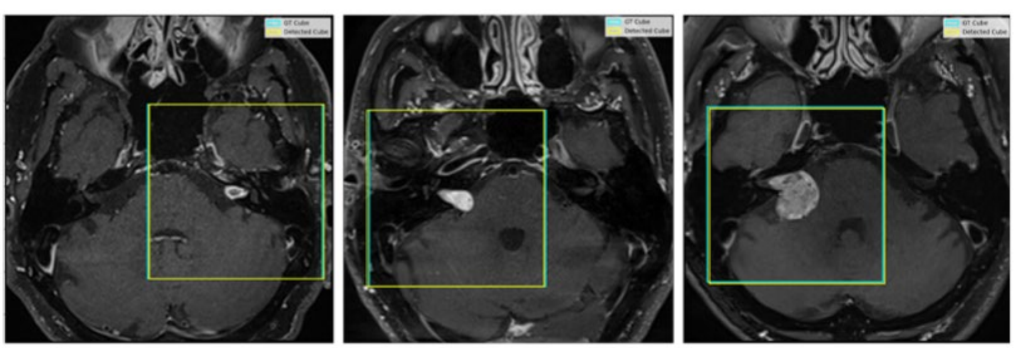

Figure 2. The predicted and actual cubic areas are drawn on three different MRI images. The images include slices passing through the center of the tumor. The blue square shows the cube centered on the center calculated from the masks in the

mask files of the MRIs, and the yellow square shows the boundaries of the cube centered by calculating the bounding boxes detected by the YOLO model.

Keywords

Artificial Intelligence/Machine Learning