

Deep Learning Segmentation of Small and Irregular Meningiomas Using nnU-Net Ensembling and Tversky Focal Loss: An Exploratory Approach

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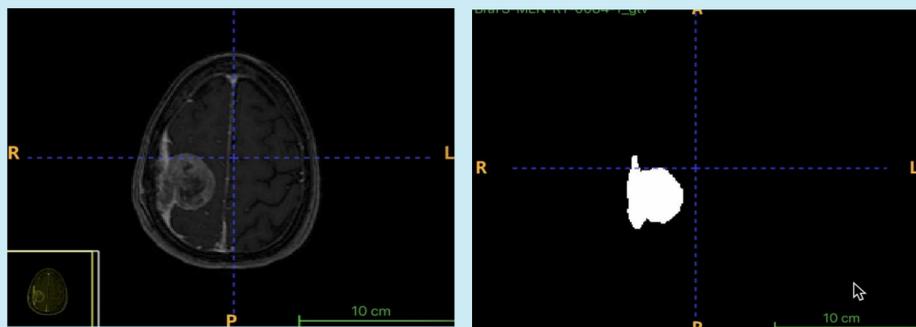


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Introduction, Background & Purpose

Segmentation consists in the identification of areas of interest on medical images. The task carries significant importance in volumetry, pre-operative planning, and post-operative follow-ups. A type of convolutional neural network (CNN), the nnU-Net, performs relatively well in contouring meningioma with regular shapes and volumes $\geq 20\text{mL}$.

However, nnU-Net's performance falls sharply when segmenting meningioma with volumes $\leq 10\text{ mL}$ and/or with irregular, complex contours. The purpose of this study was to build a CNN based on the architecture of nnU-Net, capable of adequately segmenting complex meningioma, without losing performance on the larger, more regularly-shaped ones.



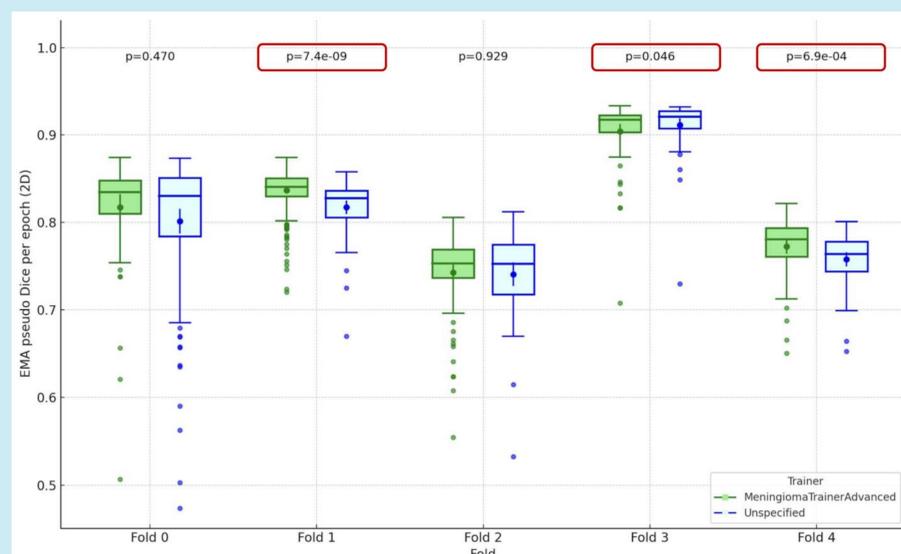
Meningioma segmentation performed by a neuroradiologist

(Source : BraTS)

The goal is to recreate these segmentations as accurately as possible.

Results

Our modified model demonstrates a narrowing of DICE interquartile ranges with significantly uplifted lower quartiles, indicating enhanced performance on lesions with more complex shapes and localizations.



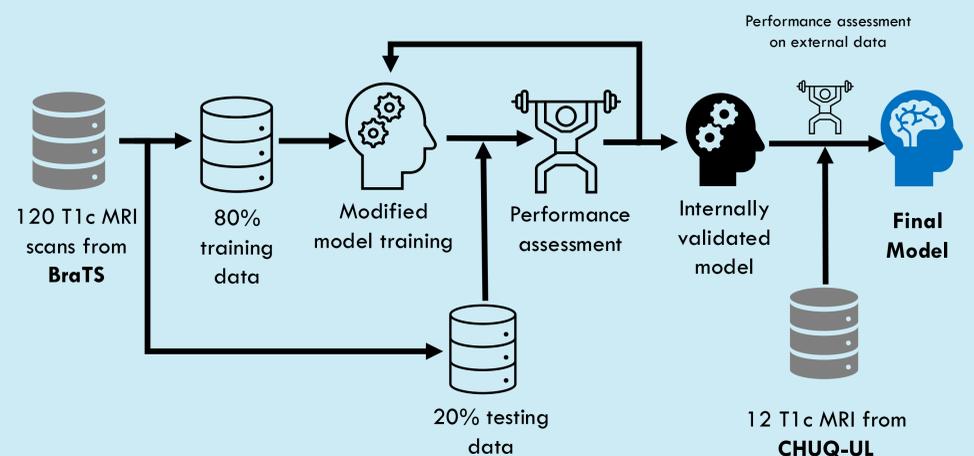
DICE Score distribution across 5 training and testing folds. Our Tversky-modified ensemble model (in green) shows consistent lower quartile uplift compared to the baseline nnU-Net model (in blue).

(Source: Khalili, M., Côté, M., Champagne, P.O)

Materials & Methods

A total of 120 T1c MRIs displaying meningioma of various shapes and localizations were retrospectively gathered from the multicentric BraTS database with their respective segmentations, performed by neuroradiologists.

Baseline 2D and 3D nnU-Net models were trained and benchmarked against our modified ensemble model, built by overlaying 2D and 3D and modified by implementing a Tversky focal loss function. This modification ensures heavier penalization of false positives, encouraging the model to recognize meningioma voxels, and iteratively learn from cases with poorer performance. A five-fold cross-validation method was employed to ensure robustness. Model performance was quantified with the DICE similarity coefficient, measuring the similarity between the automated segmentation and the radiologist's. Additional external validation was performed by testing the model on 12 unseen T1c MRI scans from CHU de Québec-Université Laval.



Model training and validation workflow (Source: Khalili, M., Côté, M., Champagne, P.O)

Conclusions

Our Tversky-modified nnU-Net ensemble segmentation model yields incremental yet clinically meaningful improvements in the segmentation of small and irregular meningioma. While the overall magnitude of DICE score gains was limited, the noticeable improvements on more complex cases signal potential for loss-function engineering to address clinically challenging segmentation tasks.

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