Skullstripping anatomical MRIs in AFNI using volumetric deep learning network: Preliminary results

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Introduction

- Deep learning-based segmentation techniques for brain MRI are becoming increasingly popular because of their self-learning capabilities and ability to generalize across extensive datasets.
- In this work we demonstrate a new 3D skullstripping tool in AFNI [1] using a volumetric, convolutional neural network (V-net) that can estimate detailed brain masks for raw-to-minimally processed human anatomical datasets.

Methods

- V-net is a volumetric neural network that is particularly suited to whole brain classification due to its in-built 3D convolutional kernel.

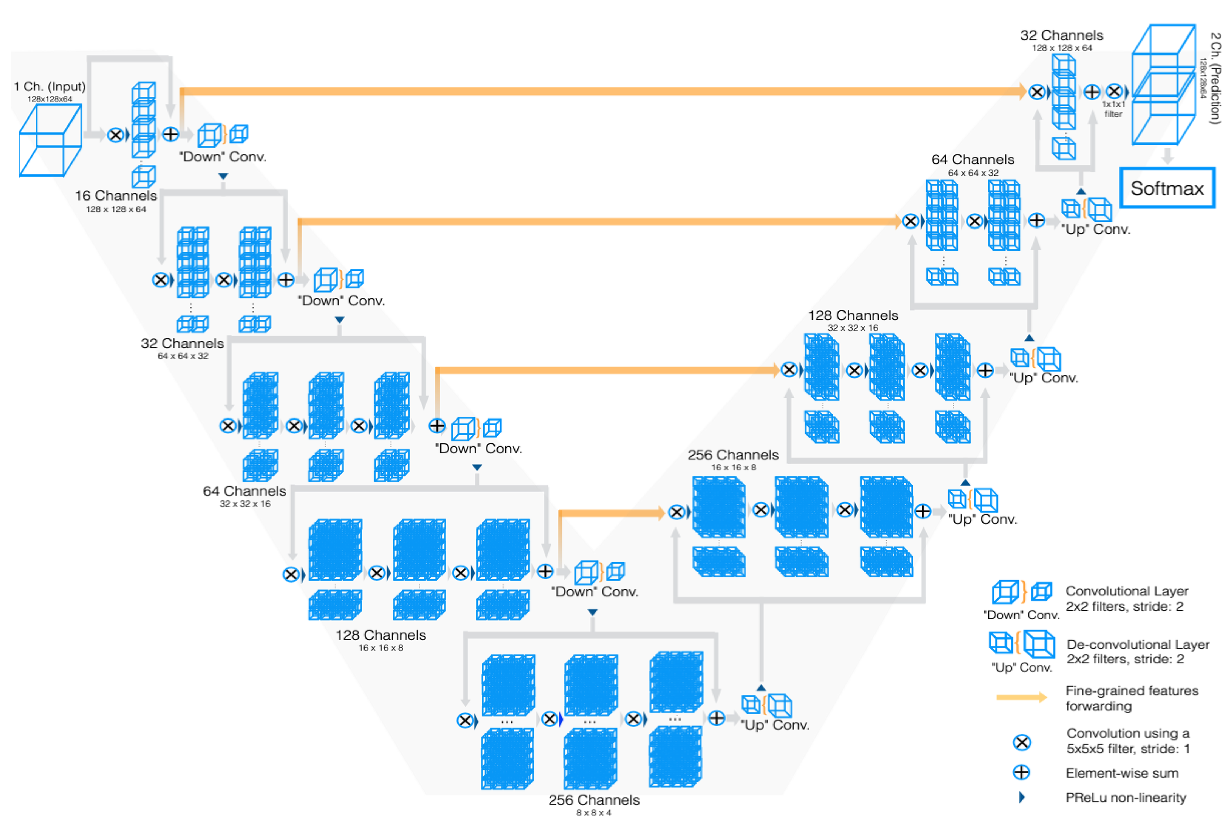


Fig. 1 Schematic representation of our network architecture

- The initial training and testing data used here were T1w volumes (1mm isotropic voxels) from across 8 sites on 3 continents with a large age range (8-70 yrs) and different 3T scanner types [2]. Initial training masks were created with FreeSurfer [3] and @SUMA_Make_Spec_FS.
- To increase robustness and generalizability of the V-net, we augmented the training data by using AFNI to derive volumes with the following characteristics: Gibbs ringing, gain inhomogeneity, zipper noise, strong shading and affine transforms.
- We have computed the performance metrics around the brain edge where algorithms vary the most, defining an "inner" and "outer" rim, using AFNI's 3dDepthMap.
- In both cases, the typical V-net results closely match the initial mask datasets. Visually checking example subjects, we can see example cases where differences are due to the V-net providing more accurate masks to the underlying anatomy than FreeSurfer (Fig. 4), particularly in cases with apparent noise, ringing or distortion.

Results

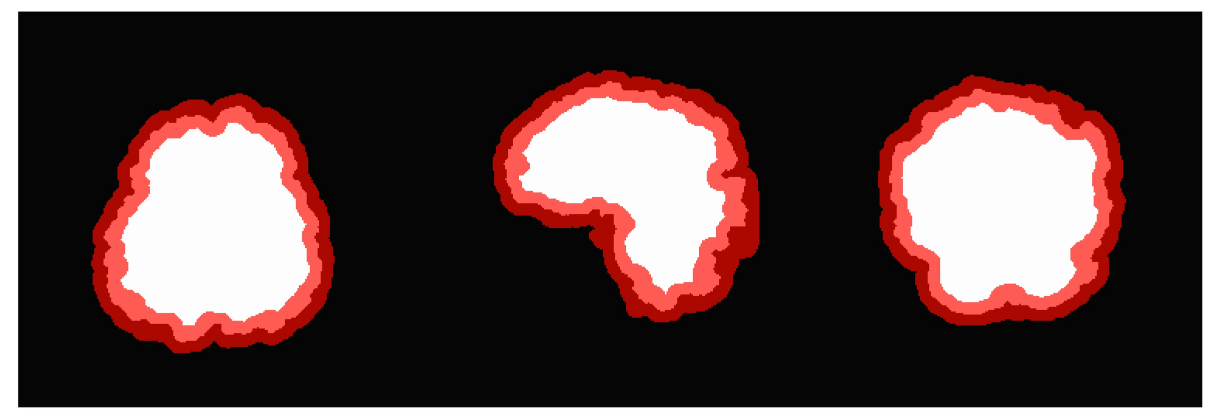
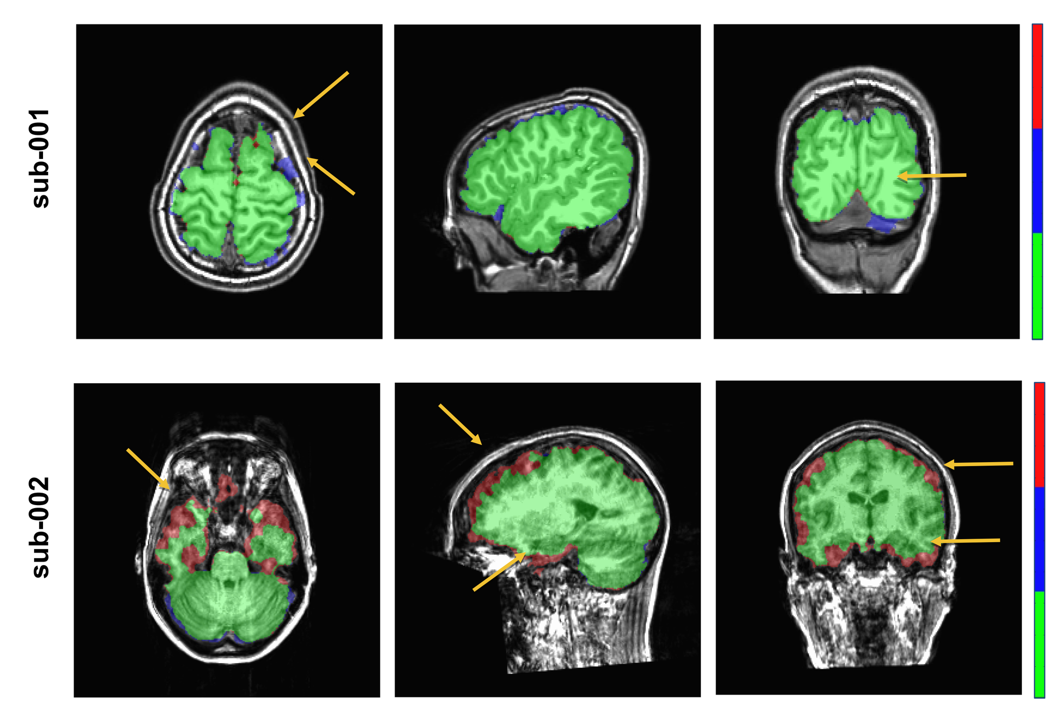


Fig. 2. A full "rim" region (red overlay) is shown around a ground truth brain mask (white underlay) for an example subject, in axial, sagittal and coronal views. The "inner rim" is where the two masks overlap, and the "outer rim" is the rim region surrounding the brain mask



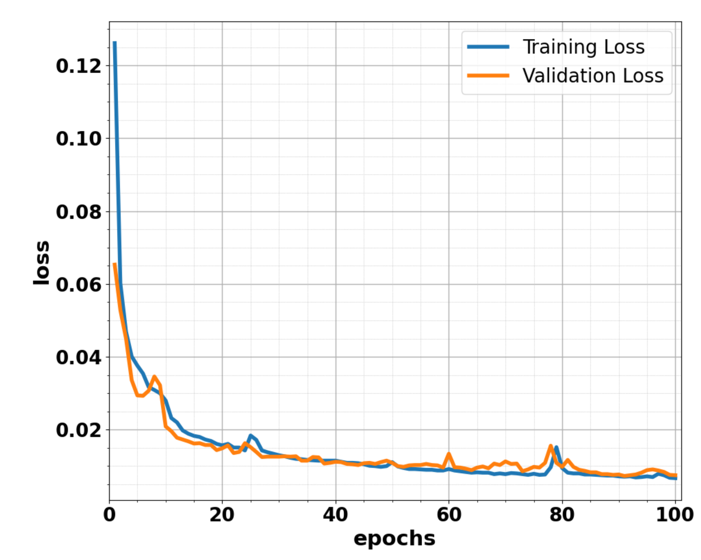


Fig. 3. Plot shows the average loss value across groups in training and validation phases over many epochs.

Fig. 4. Example cases of the similarities and differences between the Freesurfer and V-net predicted masks for a given T1w anatomical input (shown as underlay in axial, sagittal and coronal views). Green regions show where the two masks overlap/agree, while blue shows FreeSurfer-only regions and red shows V-net only ones. While general agreement is high, results differ in several places around finer features around the boundary, particularly for sub-002 whose dataset contains notable ringing.

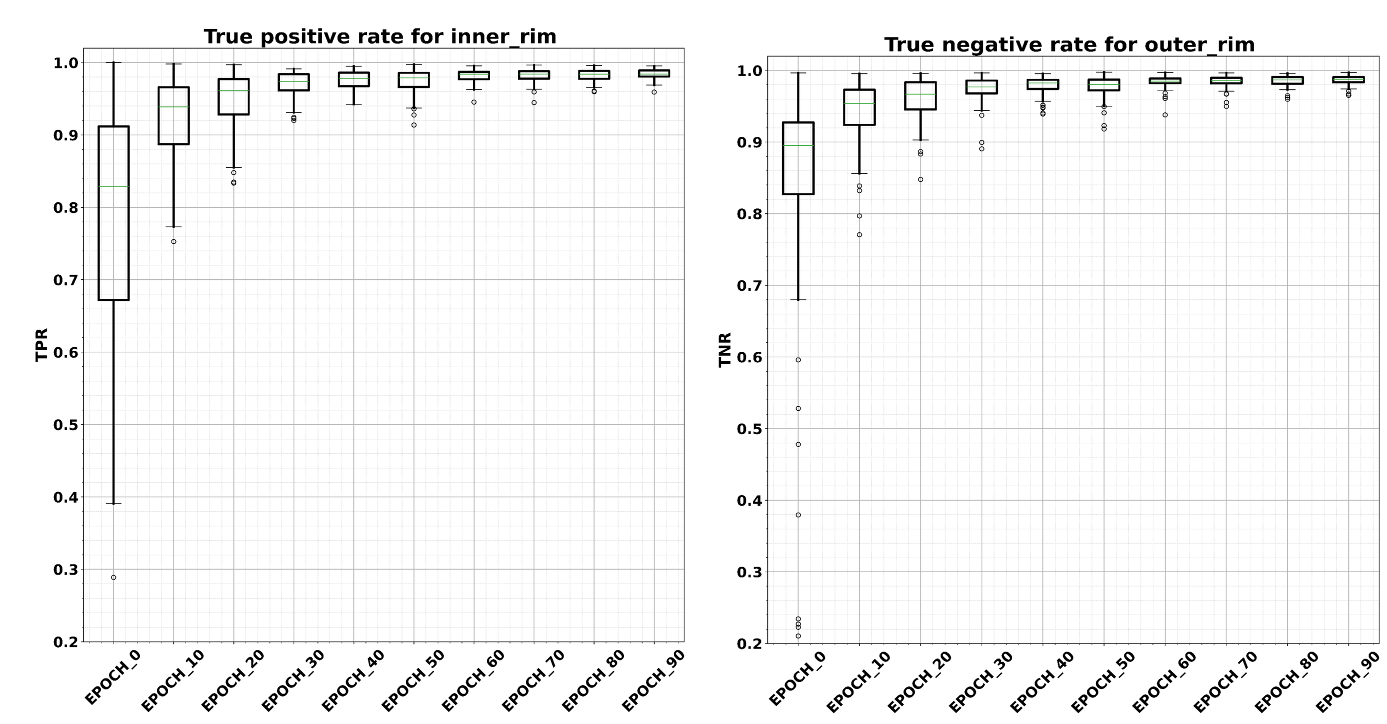


Fig.5. The plot shows boxplots of the true negative rate (increasing TNR means increasing agreement) for the outer rim region for the training group across epochs.

Conclusion

- In future work we plan to expand the training dataset size with datasets from multiple other sites around the world, and expand the application to multiclass (e.g., tissue) classification [4].
- This network be used within AFNI as a new tool to facilitate anatomical and FMRI data processing (updating 3dSkullStrip).

Acknowledgment & References

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