Pediatric Automatic Defacing to Protect Patient Privacy

Children's Hospital of Philadelphia
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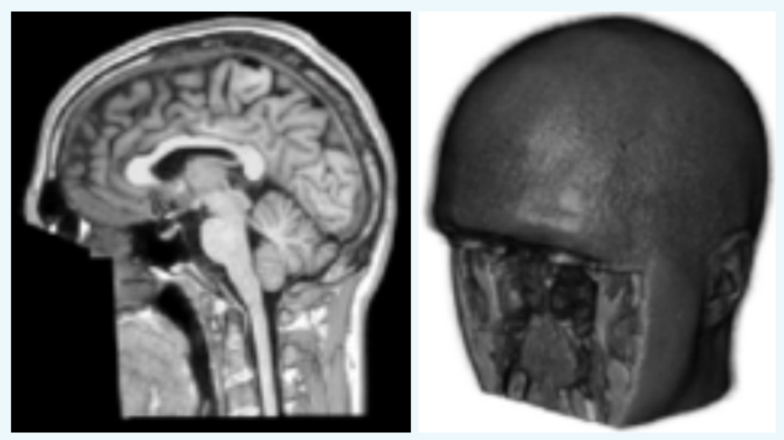
PURM Penn Undergraduate Research Mentoring Program

Background

- Defacing: a technique that removes identifiable facial features from MRI scans without affecting the brain
- Defacing Application: protects patients' privacy by preventing facial reconstruction



Objective

Develop a pediatric specific defacing technique using a convolutional neural network in order to publicly share imaging data and protect patient privacy

Significance

- Commonly used defacing methods, such as MiDeface, are created for adult subjects with T1- weighted images
- Deep learning will create a more generalizable defacing model than the mathematical algorithms currently available
- Model will better adapt to rapid development of brain structures that occurs in pediatric scans and account for different MRI types

Data

- Data was collected from the Children's Brain Tumor Network
  - Unprocessed and treatment naive scans
  - Large-scale and multi-institutional
- Age Range: 4 months - 21 years; Average Age: 9 years
- Tumor Types: Medulloblastoma and Glioma

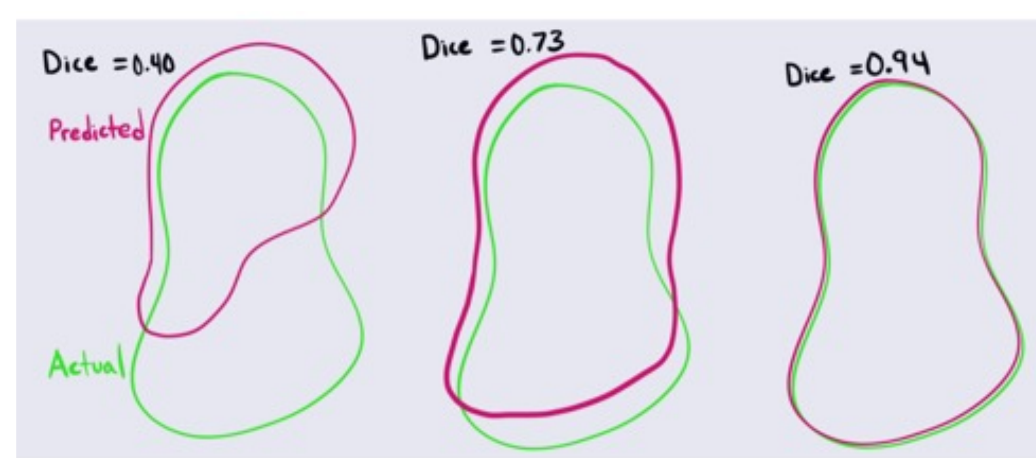
Children's Brain Tumor Network
Until every child is cured

Methods

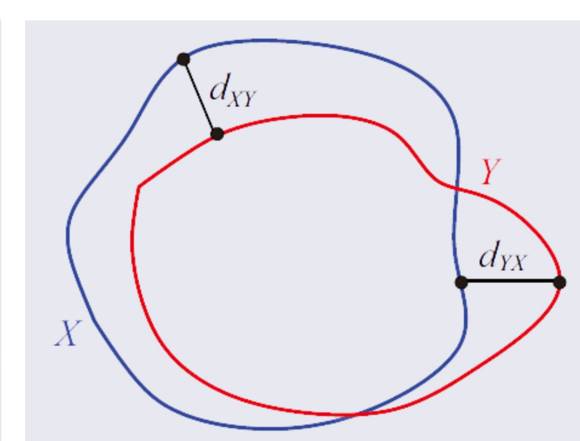
- Used MiDeface to generate initial facemasks for 186 pediatric subjects in Flywheel
  - Every subject had a T1, T1ce, T2, and Flair scan
- Used editing software to correct 386 scans that were inaccurately defaced by MiDeface
  - Filled in facial features needing further defacing and restored impacted brain voxels
- Accurate facemasks were divided into training and testing data to develop the defacing model using nnU-Net: a deep learning model used for imaging data
- Performance metrics including dice similarity score, sensitivity, and Hausdorff95 were calculated

Performance Metrics Definitions

Dice Similarity Score



Hausdorff95



Results

Statistics

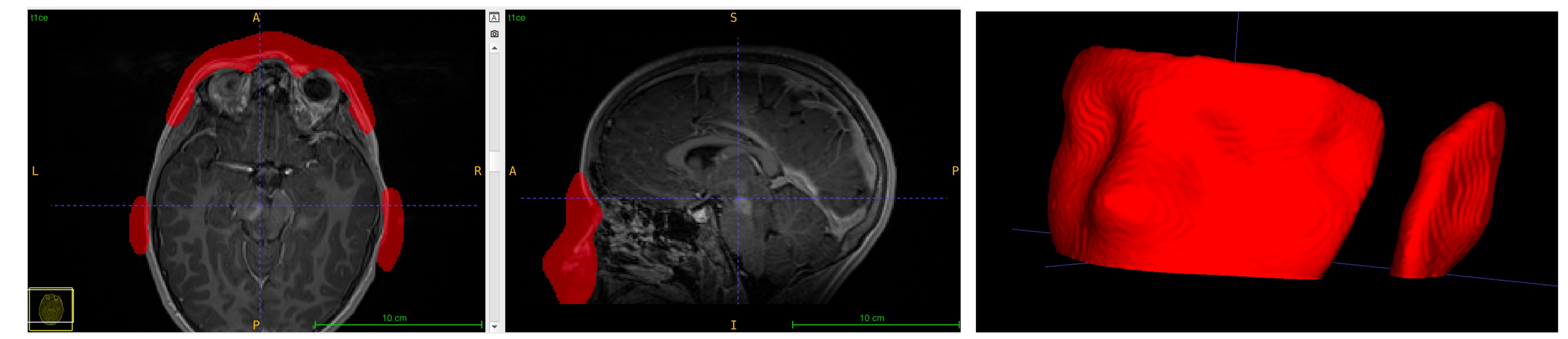
Summary Statistics			
	Mean	Median	Standard Deviation
Dice	0.779	0.801	0.074
Sensitivity	0.796	0.827	0.108
Hausdorff 95	7.072	5.385	5.598

Results - Continued

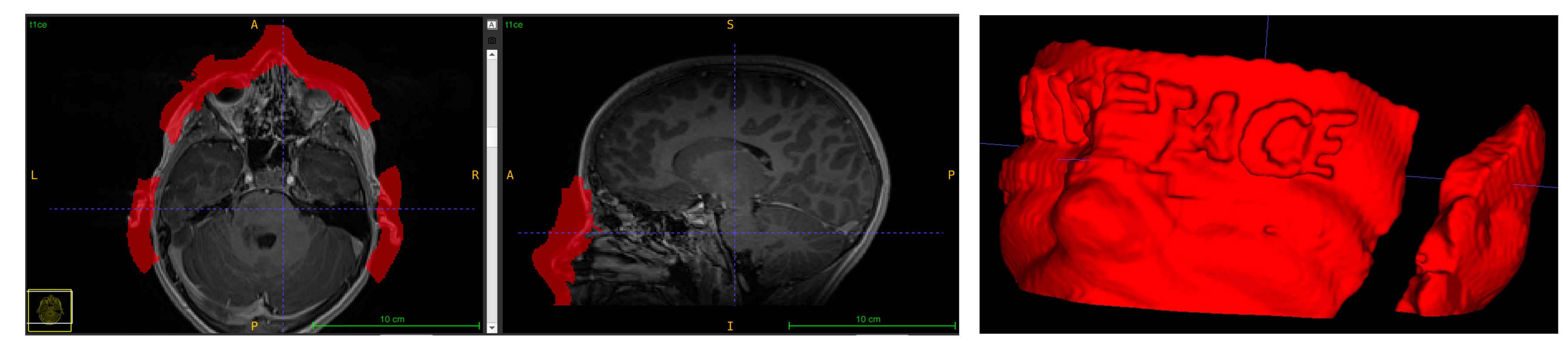
Facemask Comparison

Example Subject (Dice Score = 0.869)

Model Generated Facemask :



Manually Generated Facemask :



Conclusions

- Visually the model is performing very well and generates accurate facemasks according to median dice similarity score
- Low outlier dice scores were a result of manual edits made to facemasks rather than an indication of an inaccurate model

Next Steps

- Find new method of evaluating model performance
- Modify training data to improve model performance
- Assess facemask's effect on current 3D rendering software
- Deploy software as a gear on the flywheel data management platform

References

1. This research was conducted using data and/or samples made available by The Children's Brain Tumor Network
2. Isensee, F. *et al.* nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. *Nat Methods* 18, 203–211 (2021).