Automated Segmentation of the Eustachian Tube

A Deep Learning Platform

Project 3 – Ameen Amanian, Chanha Kim, Yuliang Xiao

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April 7, 2022

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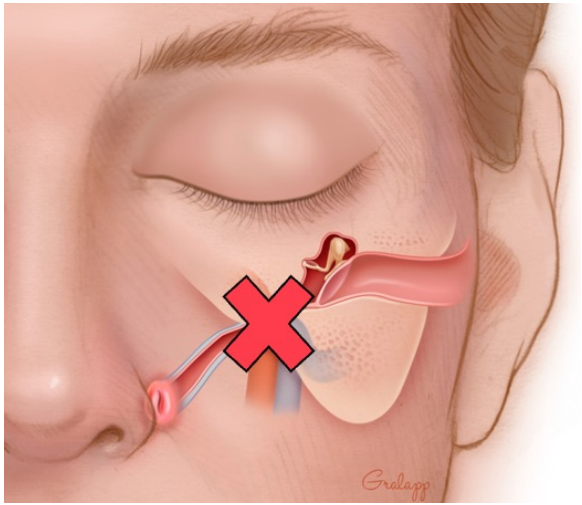
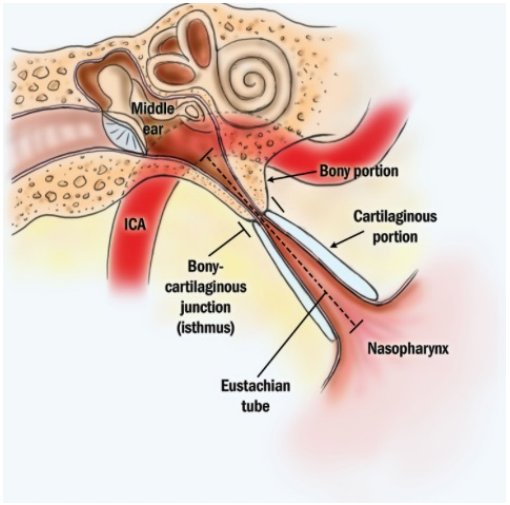
Background

Impairment in middle ear ventilation and pressure regulation [1]



Surgical treatment eustachian tube dilation [2]



[1] Froehlich et al, 2021; [2] NAENTA, 2018

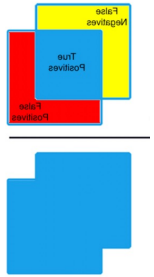
Goals and Significance

- Goals
  - Develop a deep learning framework for automated segmentation of the eustachian tube on CT images
- Significance
  - Allow clinicians to develop a better understanding of the eustachian tube anatomy
  - Improve the decision-making process for determining patients' surgical candidacy

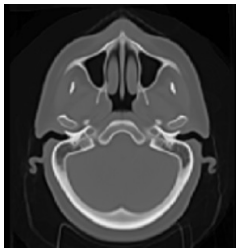
[2] NAENTA, 2018

Project Workflow

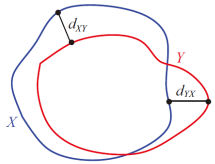
Ground Truth Dataset → Co-Registration of Training Set → Deep Learning Pipeline → Predicted Anatomical Segmentations



- CT head dataset
- ANTsPy registration algorithm
- nnUNet algorithm
- Validation via DSC, AHD, WHD



MIC
MEDICAL IMAGE COMPUTING



Dependencies

	Solution	Alternative	Status	Impact
Computation	GPU access at Homewood	Google Colab MARCC		Will not be able to train neural network
Imaging Dataset	Deidentified CT head	Public dataset		Will not be able to segment ROI
Imaging labels	Manual segmentations via 3D slicer	Public dataset with labels		Will not be able to train neural network

LABORATORY FOR
Computational
Sensing + Robotics

Deliverables

Minimum (March 31)

- CT registration script
- Dataset containing ground truth segmentations
- Preprocessed Dataset of CT Heads
- Trained nnU-Net pipeline
- Documentation
- Final Report

Expected (April 30)

- Validation script calculating metrics on the predicted segmentations (DSC, AHD, WHD)

New

- Heat map script demonstrating point to point difference between ground truth and predicted segmentations.

Maximum (July 31)

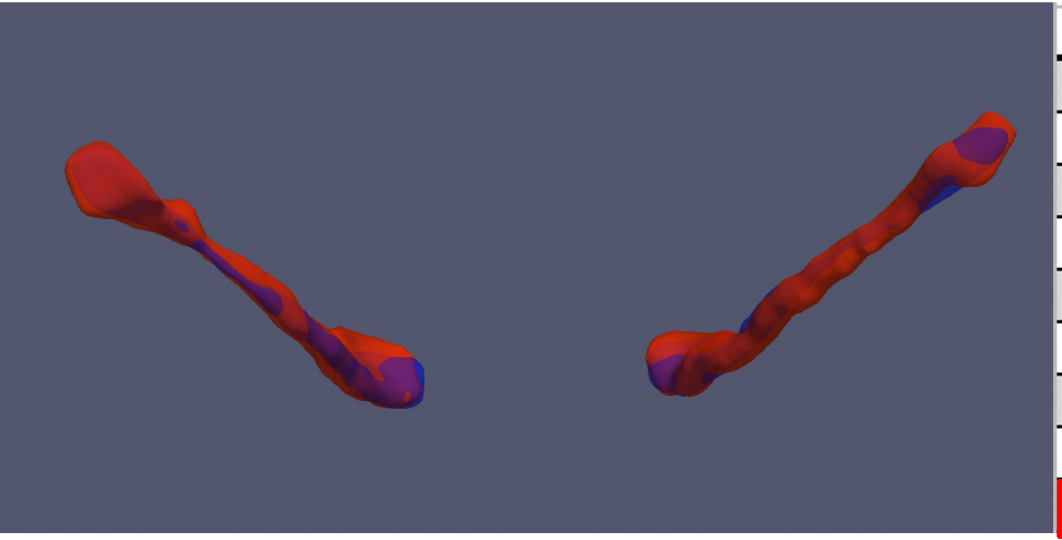
- Trained VoxelMorph or DeepReg imaging registration model
- Validation script comparing nnUNet model with VoxelMorph/DeepReg image registration models
- Conference Presentation and Manuscript Draft

nnUNet Configuration

- **Dataset:**
  - Training: 16 scans
  - Validation: 4 scans
  - Test: 14 scans
- **Configurations:**
  - 2D U-Net
  - 3D full resolution U-Net
  - 3D U-Net cascade
  - Optimal model selected based on dice score
- **Number of epochs:** 100
- **Loss function:** BCE + Dice

Validation

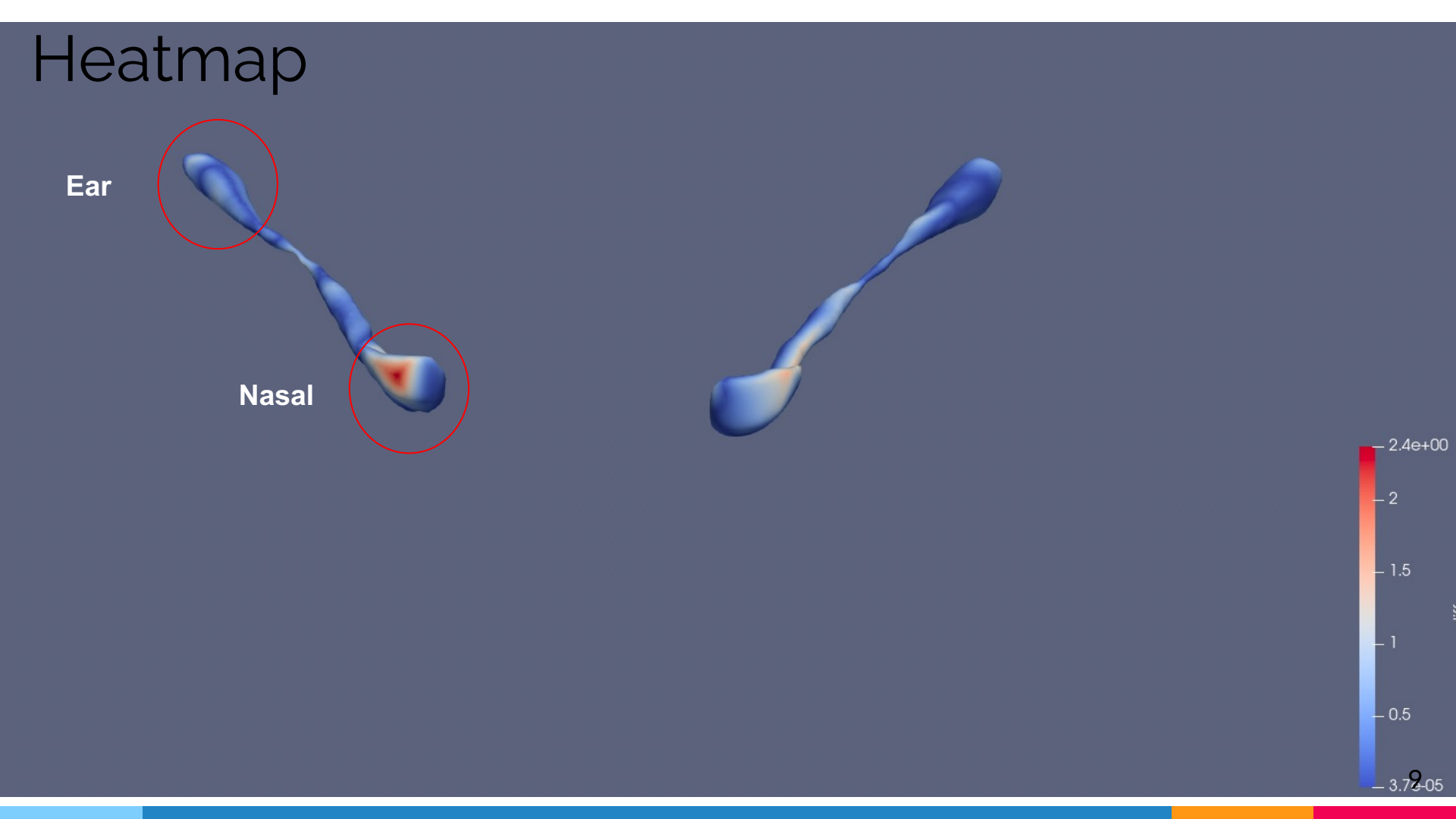
Test set – 8 CT's
DSC + AHD



File ID	Dice Score	Mean Hausdorff Distance
ETV2_169	0.6190561	0.277643829
ETV2_175	0.373139495	1.114886789
ETV2_170	0.62776558	0.399980875
ETV2_148	0.429834906	0.795101438
ETV2_168	0.376706827	0.952135432
ETV2_152	0.585750592	0.447091288
ETV2_140	0.577294127	0.513501167
ETV2_178	0.639607375	0.406772288
Average	0.528644375	0.613389138

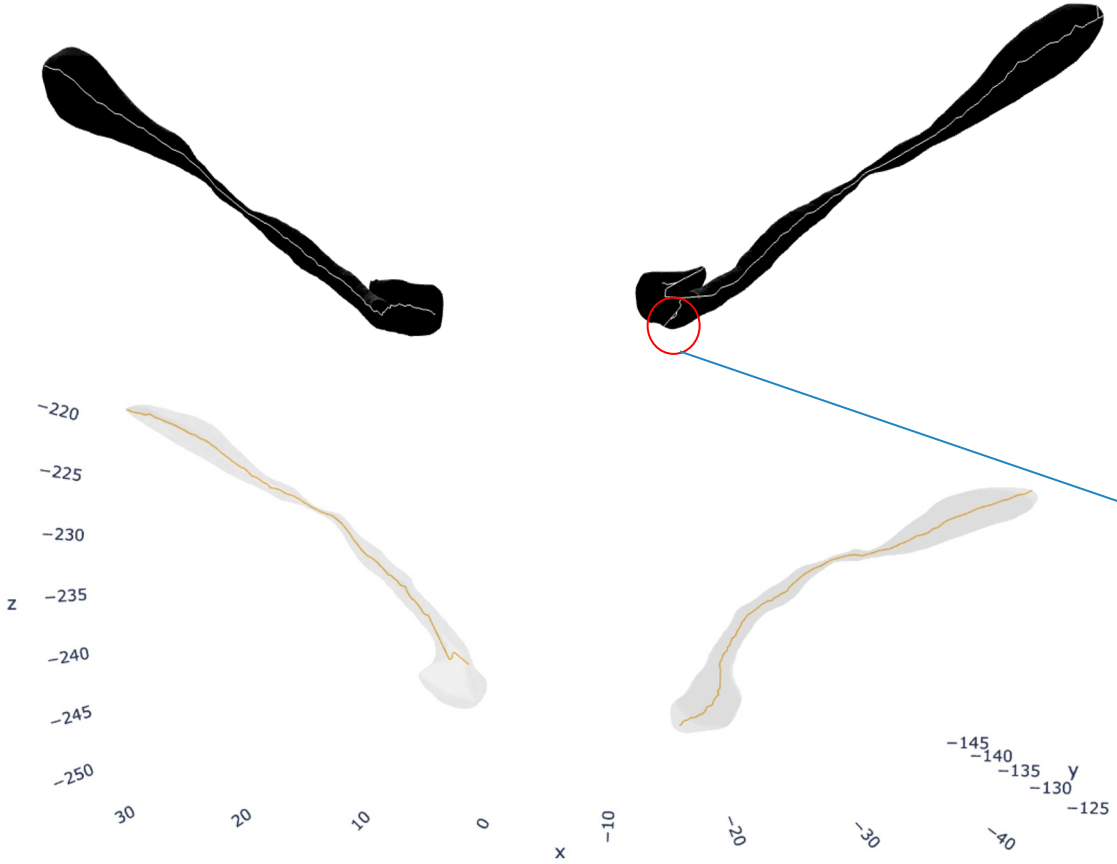
Red - Ground truth
Blue - Prediction

Heatmap



Weighted Hausdorff Distance

1) skeletonize



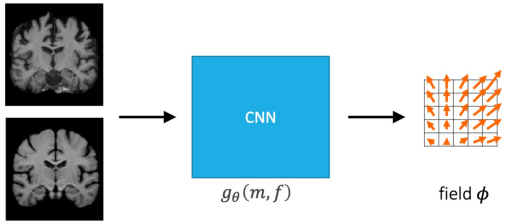
2) Prune the skeleton

3) Get new mapping and apply probability map

Could a registration platform result in better predictions?

- **nnU-Net:** supervised method to learn the boundaries of Eustachian Tube from a CT scan directly

- **VoxelMorph:** unsupervised registration method to learn pixel-to-pixel mapping (deformation field) between CT scans



- Supervised (have example triplets $\{m, f, \phi\}$)
- Unsupervised (only have images $\{m, f\}$)

Proposed semi-supervised registration-based segmentation pipeline using VoxelMorph

Preprocess Data

- Intensity Normalization (0 - 1 pixel values)
- Affine Alignment
- Cropping & Same dimensions
- Conversion from Nifty to Npy format

Template Creation

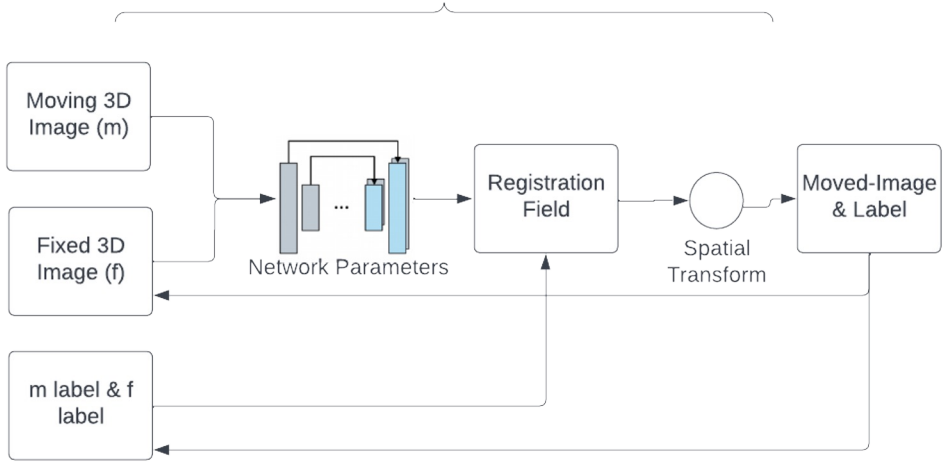
- Optional Atlas creation to perform scan-to-atlas training

Semi-supervised Learning-based registration

- Train a VoxelMorph model in a semi-supervised fashion with ground-truth segmentations

Evaluation

- Transform a template segmentation by applying the trained model, and compare the result with nnUNet



Next steps / Potential Impact

- Modify nnU-Net configurations to obtain the most optimal results for ROI predictions.
- Finalize the evaluation methods to validate ET predictions
- Develop unsupervised registration-based segmentation pipeline
- The best performing method has utility to be assessed within the clinical setting for treating patients with eustachian tube dysfunction

Documentation

Github (Source + Version Control)

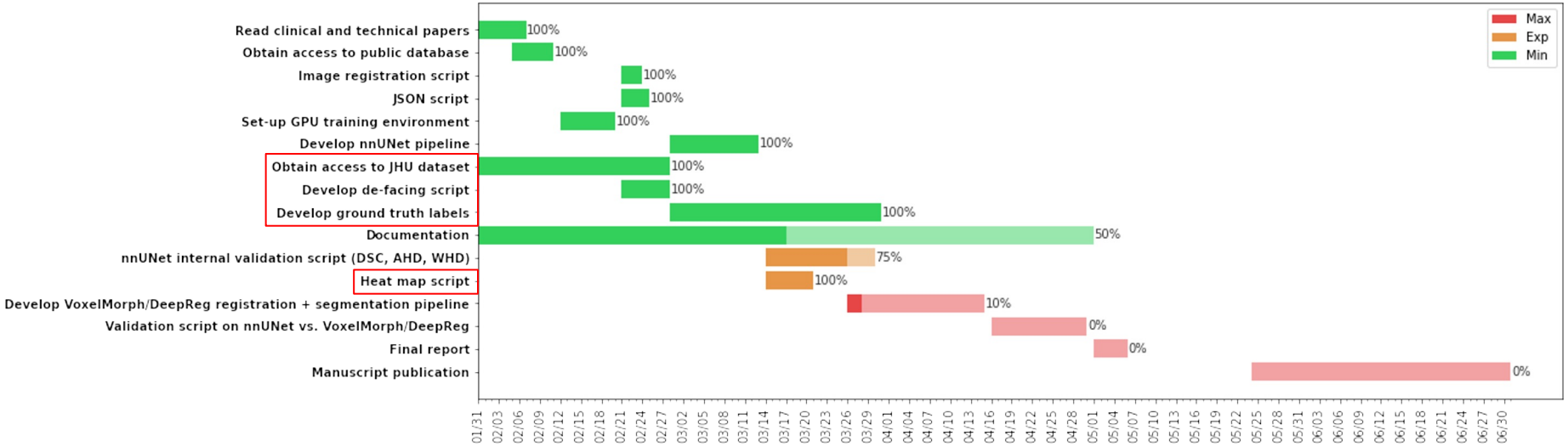
- nnU-Net pipeline
- Co-registration scripts
- Validation scripts
- Specifications documented in Readme file

Dataset (OneDrive)

Microsoft Teams + Course Wiki

- Specification documentation pertaining to each section of the workflow (e.g. Validation)
- Weekly presentations

Gantt Chart


Read clinical and technical papers
Obtain access to public database
Image registration script
JSON script
Set-up GPU training environment
Develop nnUNet pipeline
Obtain access to JHU dataset
Develop de-facing script
Develop ground truth labels
Documentation
nnUNet internal validation script (DSC, AHD, WHD)
Heat map script
Develop VoxelMorph/DeepReg registration + segmentation pipeline
Validation script on nnUNet vs. VoxelMorph/DeepReg
Final report
Manuscript publication
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Thanks!

Any questions?