# Automated Segmentation of the Eustachian Tube

## A Deep Learning Platform

**Project 3** – Ameen Amanian, Chanha Kim, Yuliang Xiao

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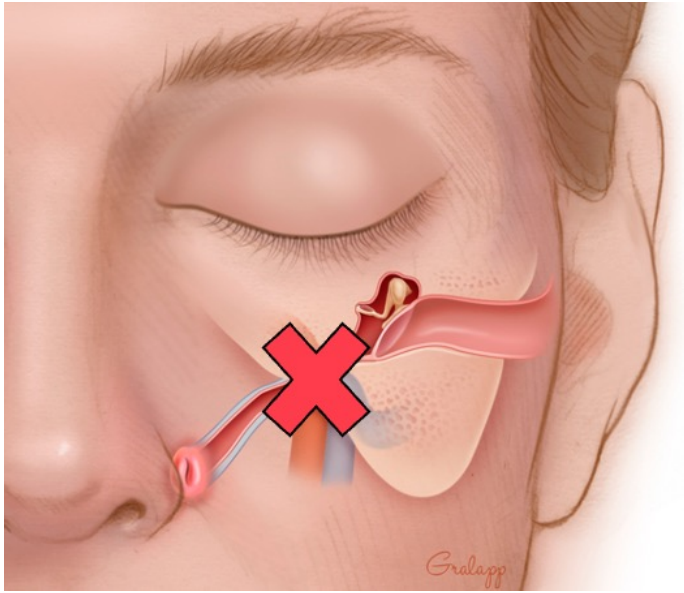
# What is eustachian tube dysfunction?

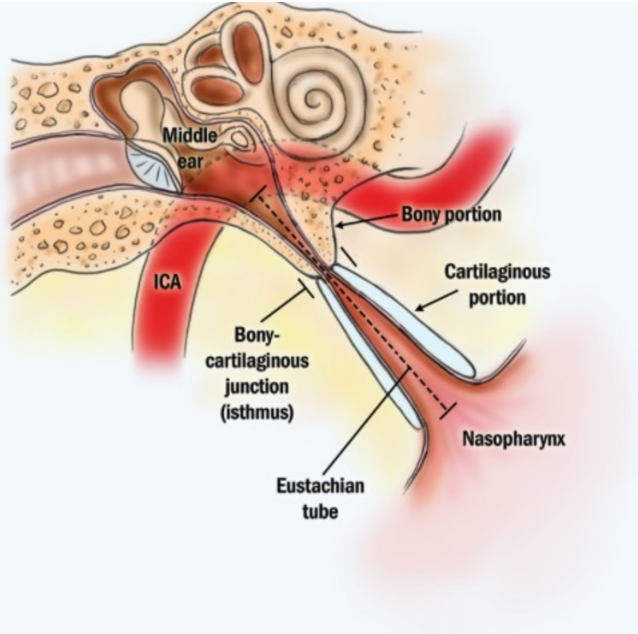
- **Impairment** in middle ear ventilation and pressure ventilation
- **Symptoms:** ear pain, pressure, cracking, difficulty hearing
- **Treatment** [1]
  - **Medical** – Nasal decongestants
  - **Surgical** – Eustachian tube dilation



[1] Froehlich et al, 2021

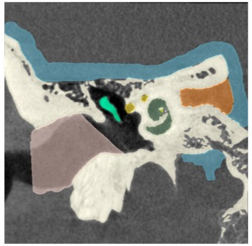
# Significance

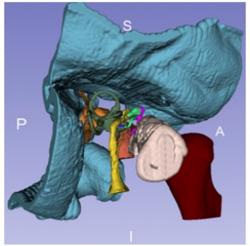
- Major impact on quality of life
- Eustachian tube dilation [2]
  - In-office procedure
  - Theoretical risk of critical near-by structures
- Lack of a registration-based image-guided system for this procedure

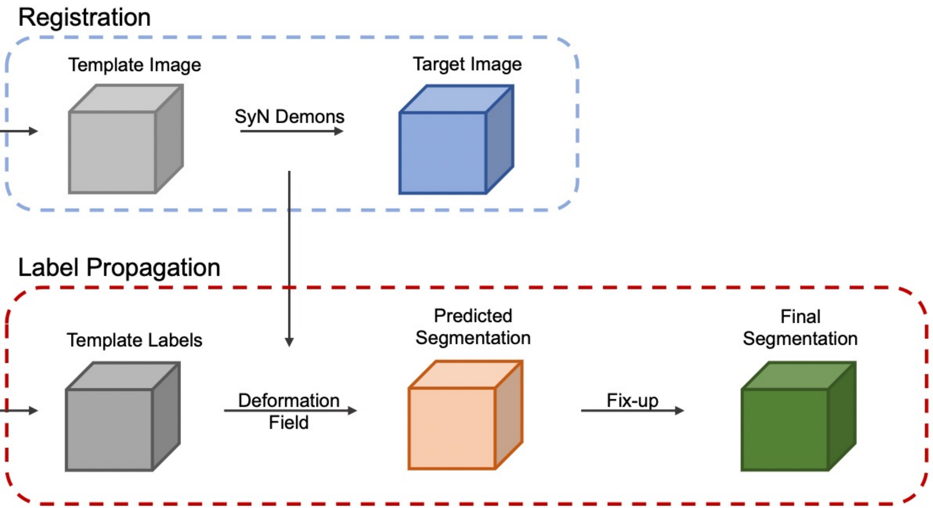



[2] NAENTA, 2018

# Current Solution [3-4]






Existing registration-segmentation pipeline has varying accuracy and is time consuming.

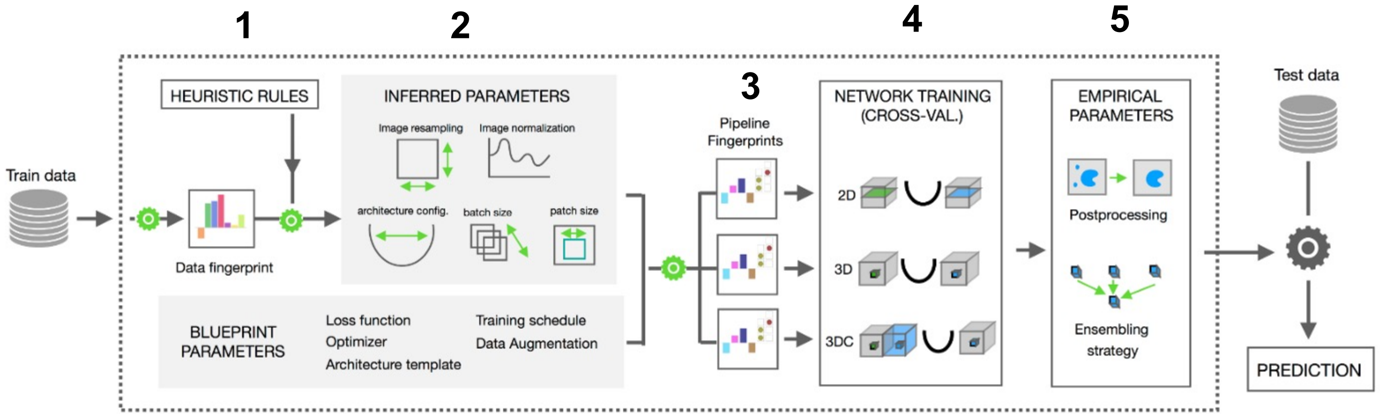
[3] Sinha et al, 2016; [4] Ding et al, 2021

*Can the eustachian tube be automatically segmented using <u>deep learning</u> to assist with surgical interventions?*

# Specific Aims

1. Utilize a supervised learning platform for automated segmentation of the ET.
2. Validate the predictions in comparison with the ground truth.
3. Explore unsupervised methods for image registration and segmentation.

# Technical Approach (nnU-Net Pipeline) [5]

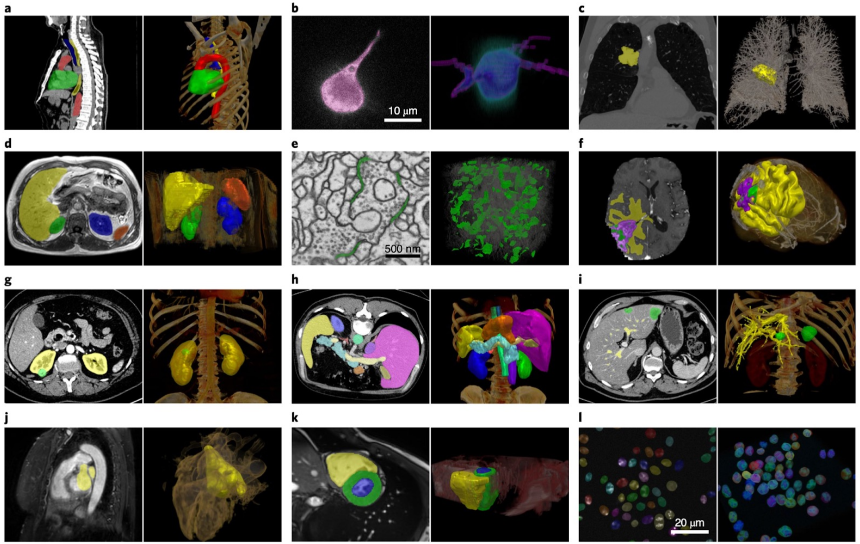



| Dataset | Workstation |
|---|---|
| 3D CT's (30 training, 10 testing)<br>Format: .nrrd or .nii.gz | Google Colab or MARCC<br>Awaiting Remote GPU Access |

[5] Isensee et al, 2021

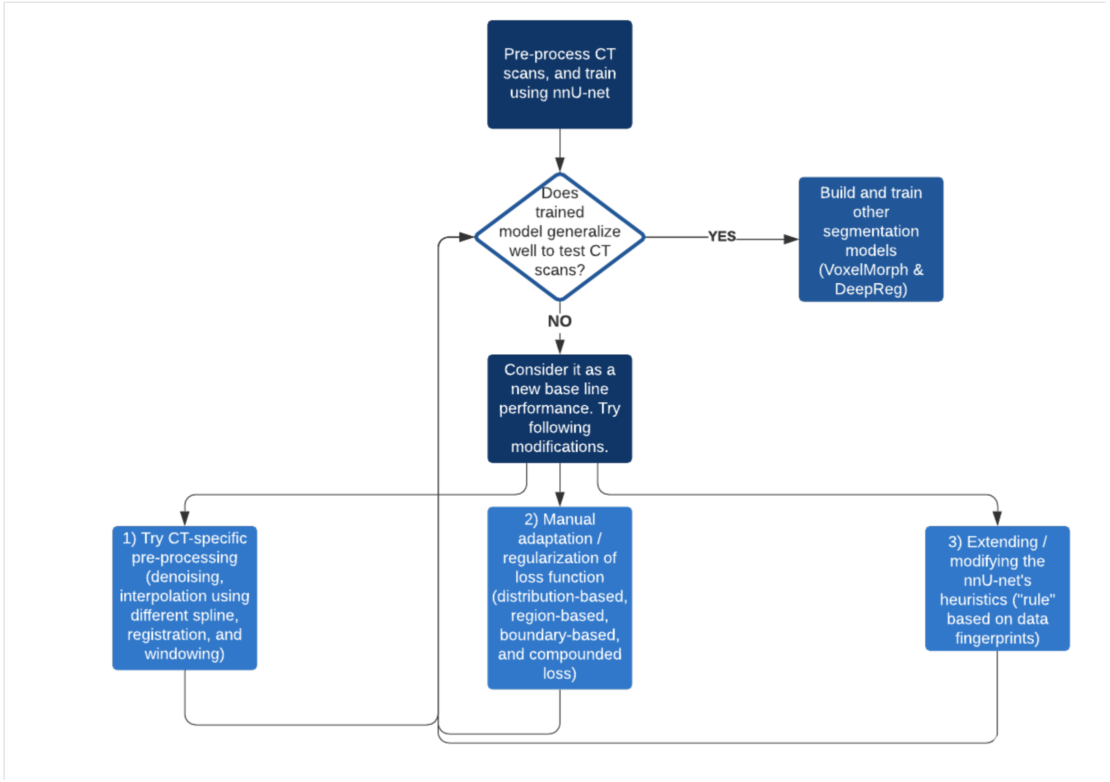
# Why nnU-Net?

- Handles a wide variety of target structures and image properties [5]
- Results surpass most existing approaches
- Self-configuring ability



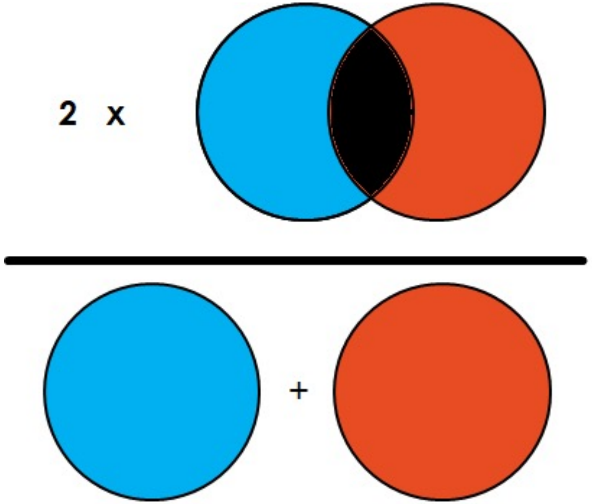

[5] Isensee et al, 2021

# Proposed Workflow



# Aim 2 – Model Validation [6]

- Goal: To determine performance of our semantic segmentation
- Approaches
  - Dice Similarity Coefficient
  - Hausdorff Distances




$$\frac{2 * |X \cap Y|}{|X| + |Y|}$$

[6] Zou et al, 2004

# Aim 3 – Unsupervised Learning

- VoxelMorph [7]
  - Learning-based registration method for atlas construction and image-to-image registration and segmentation.
  - Requiring no supervised information such as ground truth correspondences or anatomical landmarks during training.
- DeepReg [8]
  - Implements a framework for unsupervised learning, weakly-supervised learning and their combinations.
  - Clinical applications for paired images (intra-subject registration) and unpaired images (inter-subject registration).

[7] Balakrishnan et al, 2019; [8] Fu et al, 2020

# Dependencies

| | Solution | Alternative | Status |
|---|---|---|---|
| **Computation** | Remote GPU access at Homewood | Google Colab<br>MARCC | Currently using Colab |
| **Imaging Dataset** | Deidentified CT head | Public dataset | Obtained access to JHU CT dataset |
| **Imaging labels** | Manual segmentations via 3D slicer | Public dataset with labels | Creating manual segmentations |

Google Cloud

LABORATORY FOR Computational Sensing + Robotics

# Deliverables

**Minimum**

- Preprocessed dataset of CT head
- Trained nnUNet model
- Compare the model prediction result to the ground truth (Compute the dice score)
- Documentation & Final Report

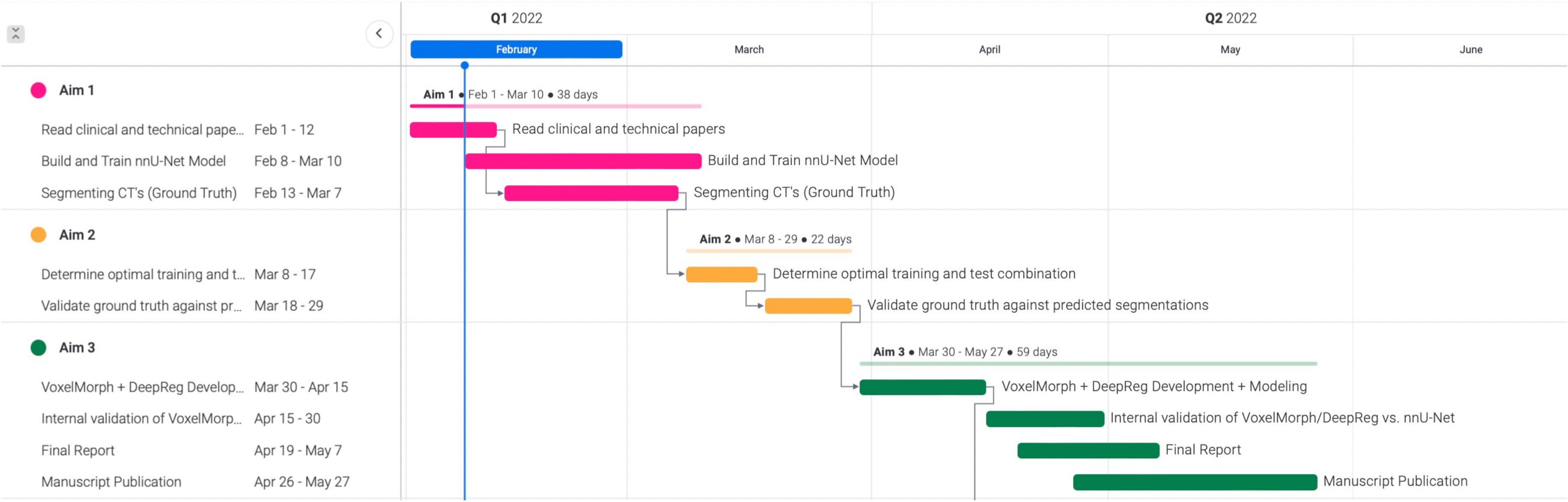
**Expected**

- Documentation & Final ReportBuild and train VoxelMorph imaging registration model
- Build and train DeepReg imaging registration model
- Compare the model prediction results to the nnUnet model (Supervised Learning vs. Unsupervised Learning)

**Maximum**

- Conference presentation
- Manuscript publication

# Gantt Chart



Q1 2022
Q2 2022
February
March
April
May
June
Aim 1
Read clinical and technical pape... Feb 1 - 12
Build and Train nnU-Net Model Feb 8 - Mar 10
Segmenting CT's (Ground Truth) Feb 13 - Mar 7
Aim 2
Determine optimal training and t... Mar 8 - 17
Validate ground truth against pr... Mar 18 - 29
Aim 3
VoxelMorph + DeepReg Develop... Mar 30 - Apr 15
Internal validation of VoxelMorp... Apr 15 - 30
Final Report Apr 19 - May 7
Manuscript Publication Apr 26 - May 27
Aim 1 • Feb 1 - Mar 10 • 38 days
Read clinical and technical papers
Build and Train nnU-Net Model
Segmenting CT's (Ground Truth)
Aim 2 • Mar 8 - 29 • 22 days
Determine optimal training and test combination
Validate ground truth against predicted segmentations
Aim 3 • Mar 30 - May 27 • 59 days
VoxelMorph + DeepReg Development + Modeling
Internal validation of VoxelMorph/DeepReg vs. nnU-Net
Final Report
Manuscript Publication

# Key Milestones

- February 25: Read papers and preprocessing the CT scans
- March 10: Build and train the nnUnet model on the Google Colab
- March 25: Finish model prediction on test data and compare the results to the ground truth

  **Minimum Deliverable Achieved**
- April 15: Build and train the Voxel Morph, DeepReg model
- April 30: Finish model prediction on test data and compare both results to the nnUnet model

  **Expected Deliverable Achieved**
- May 15: Final Report / conference publication

  **Maximum Deliverable Achieved**

# Management Plan

- Mentors
  - Team meetings – Mondays + Fridays
  - Mentor meetings – Wednesdays
- File management: GitHub (Source + Version control)
- Documentation: Google Drive + CIS Course Wiki

# Reading List


1. Magro I, Pastel D, Hilton J, Miller M, Saunders J, Noonan K. Developmental Anatomy of the Eustachian Tube: Implications for Balloon Dilation. *Otolaryngol Head Neck Surg*. 2021;165(6):862-867. doi:10.1177/0194599821994817.

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4. Isensee, F., Jaeger, P.F., Kohl, S.A.A. et al. nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nat Methods 18, 203–211 (2021). https://doi.org/10.1038/s41592-020-01008-z.

5. Balakrishnan G, Zhao A, Sabuncu MR, Guttag J, Dalca AV. VoxelMorph: A Learning Framework for Deformable Medical Image Registration. IEEE Trans Med Imaging. 2019 Feb 4. doi: 10.1109/TMI.2019.2897538. Epub ahead of print.

6. Fu Y, Brown NM, Saeed SU, et al., (2020). DeepReg: a deep learning toolkit for medical image registration. Journal of Open Source Software, 5(55), 2705. https: 1 //doi.org/10.21105/joss.02705.

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# References

1. Froehlich MH, Le PT, Nguyen SA, McRackan TR, Rizk HG, Meyer TA. Eustachian Tube Balloon Dilation: A Systematic Review and Meta-analysis of Treatment Outcomes. *Otolaryngol Head Neck Surg.* 2020;163(5):870-882. doi:10.1177/0194599820924322.

2. North Atlanta ENT & Allergy. (2018). *Eustachian Tube Balloon Dilation*. https://naenta.com/ent-services/sinus/eustachian-tube-balloon-dilation/.

3. Sinha A, Leonard S, Reiter A et al. Automated segmentation and statistical shape modeling of the paranasal sinuses to estimate natural variations. *Proc SPIE Int Soc Opt Eng*. 2016; 9784:97840D. doi: 10.1117/12.2217337.

4. Ding AS, Lu A, Li Z, et al. Automated Registration-Based Temporal Bone Computed Tomography Segmentation for Applications in Neurotologic Surgery. *Otolaryngol Head Neck Surg*. 2021; Online Ahead of Print. doi: 10.1177/01945998211044982.

5. Isensee F., Jaeger PF, Kohl SAA. et al. nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. *Nat Methods*. 2021;18, 203–211. doi.org/10.1038/s41592-020-01008-z.

6. Zou KH, Warfield SK, Bharatha A, et al. Statistical validation of image segmentation quality based on a spatial overlap index. *Acad Radiol*. 2004;11(2):178-189. doi:10.1016/s1076-6332(03) 00671-8

7. Balakrishnan G, Zhao A, Sabuncu MR, Guttag J, Dalca AV. VoxelMorph: A Learning Framework for Deformable Medical Image Registration. *IEEE Trans Med Imaging*. 2019; Epub ahead of print. doi: 10.1109/TMI.2019.2897538.

8. Fu Y, Brown NM, Saeed SU, et al. DeepReg: a deep learning toolkit for medical image registration. *Journal of Open Source Software.* 2020; 5(55), 2705. doi.org/10.21105/joss.02705.

# Thanks!

**Any questions?**

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