Automated Segmentation of Temporal Bone CT Imaging for Robot-Assisted Microsurgery

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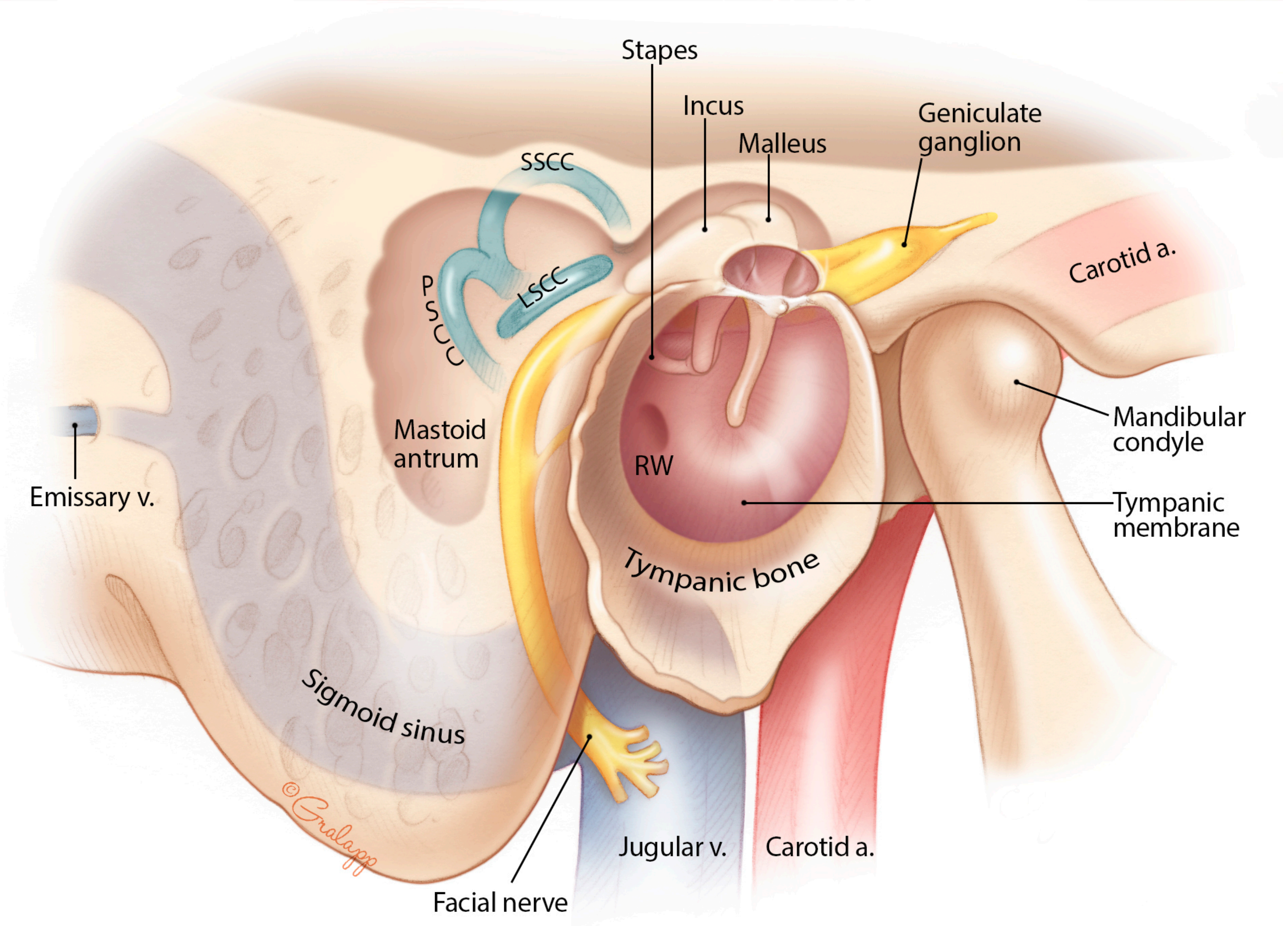
Mentors: Dr. Francis X. Creighton, Dr. Russell H. Taylor, Dr. Mathias Unberath, Max Zhaoshuo Li

Clinical Motivation

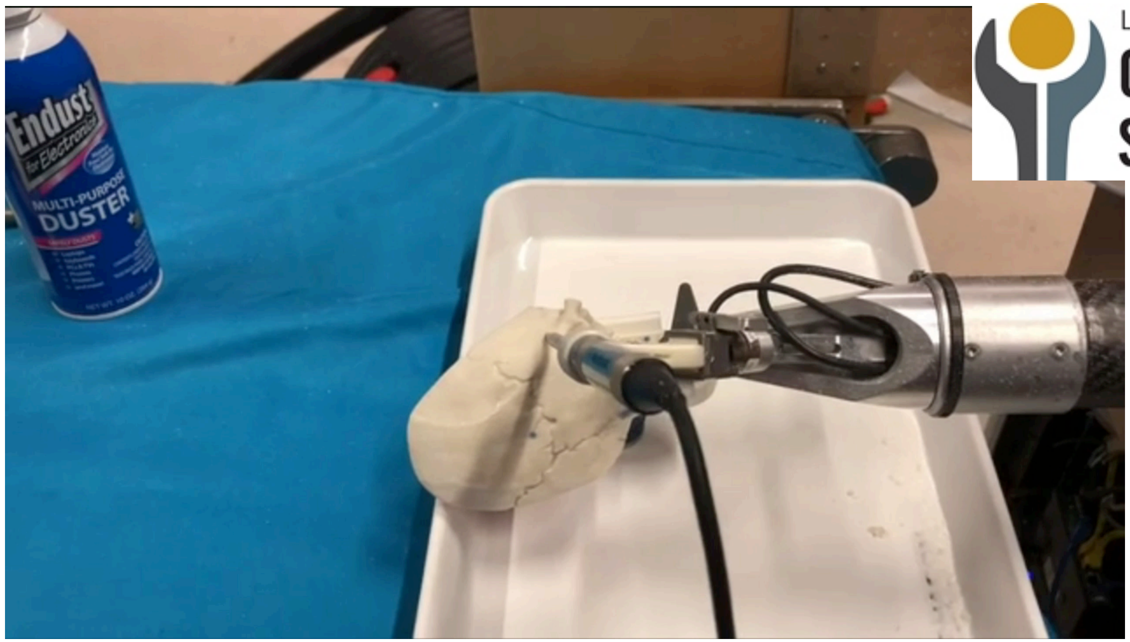
- Temporal bone anatomy is geometrically complex
- Surgical access requires drilling through mastoid bone
- Critical structures are often within millimeters of each other [1]
- Accidental damage can lead to: [2-4]
  - Changes in taste
  - Facial paralysis
  - CSF leakage
  - Closure of the sigmoid sinus



[1] Cousins, 2007; [2] Lloyd *et al*, 2007; [3] Fayad *et al*, 2003; [4] Zanoletti *et al*, 2014;

Clinical Motivation

- Possible solution: CT-registered robot-assisted surgery [5]
  - Reduces hand tremor
  - Reduces risk of intraoperative injury
  - Needs information about patient anatomy



LABORATORY FOR Computational Sensing + Robotics

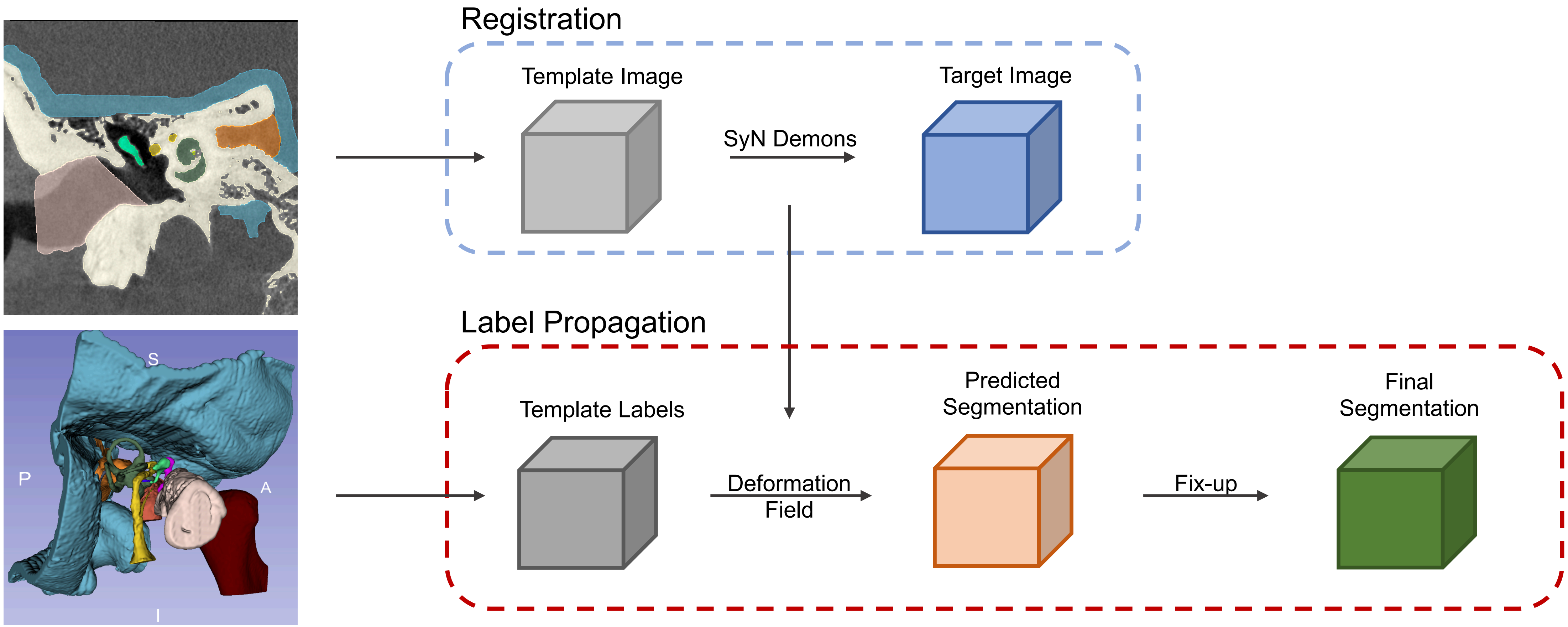
[5] Razavi *et al*, 2019

PROJECT VISION

Automated segmentation system of the temporal bone to prevent intraoperative injury of critical structures during robot-assisted microsurgery

Prior Work: Segmentation Propagation

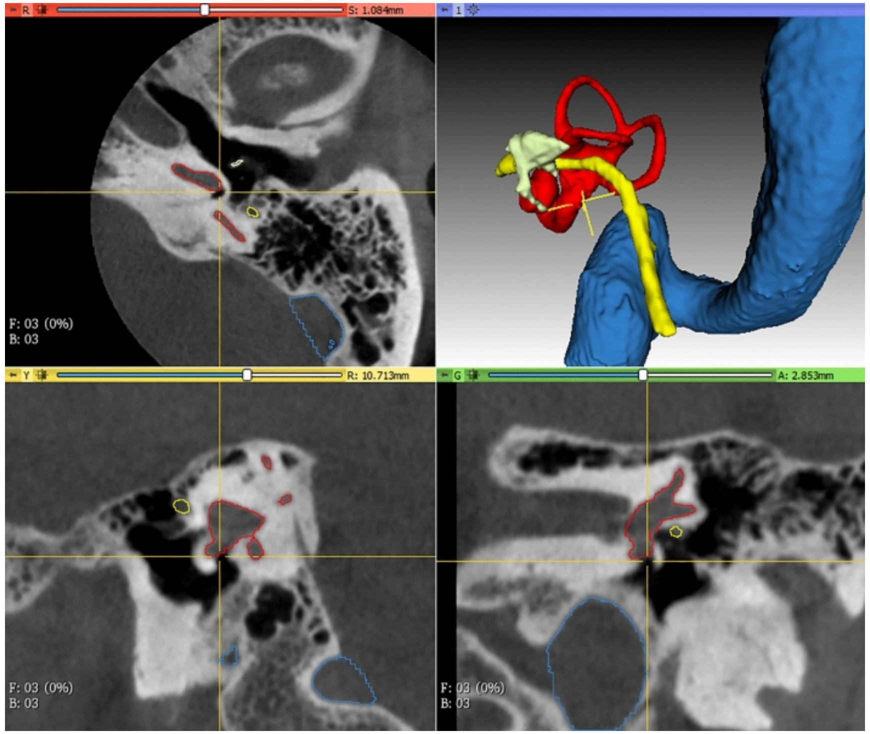
- Mapping template segmentations onto new CTs using registration techniques [6]



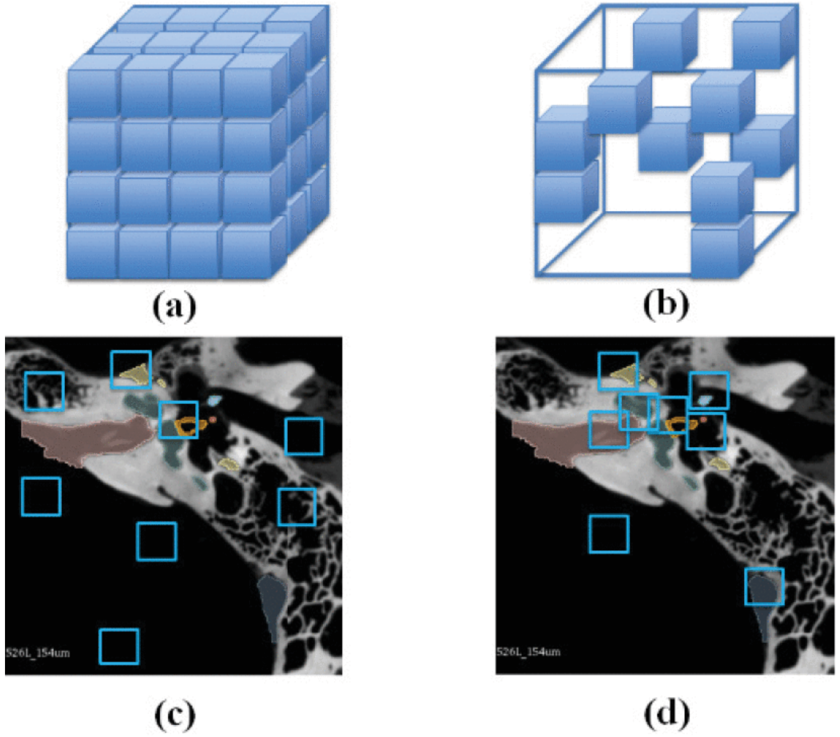
[6] Sinha *et al*, 2016

Prior Work: Deep Learning Semantic Segmentation

- Comparison of ResNet, UNet, and AH-Net [7]



- Patch-based segmentation (PWD-3DNet) [8]



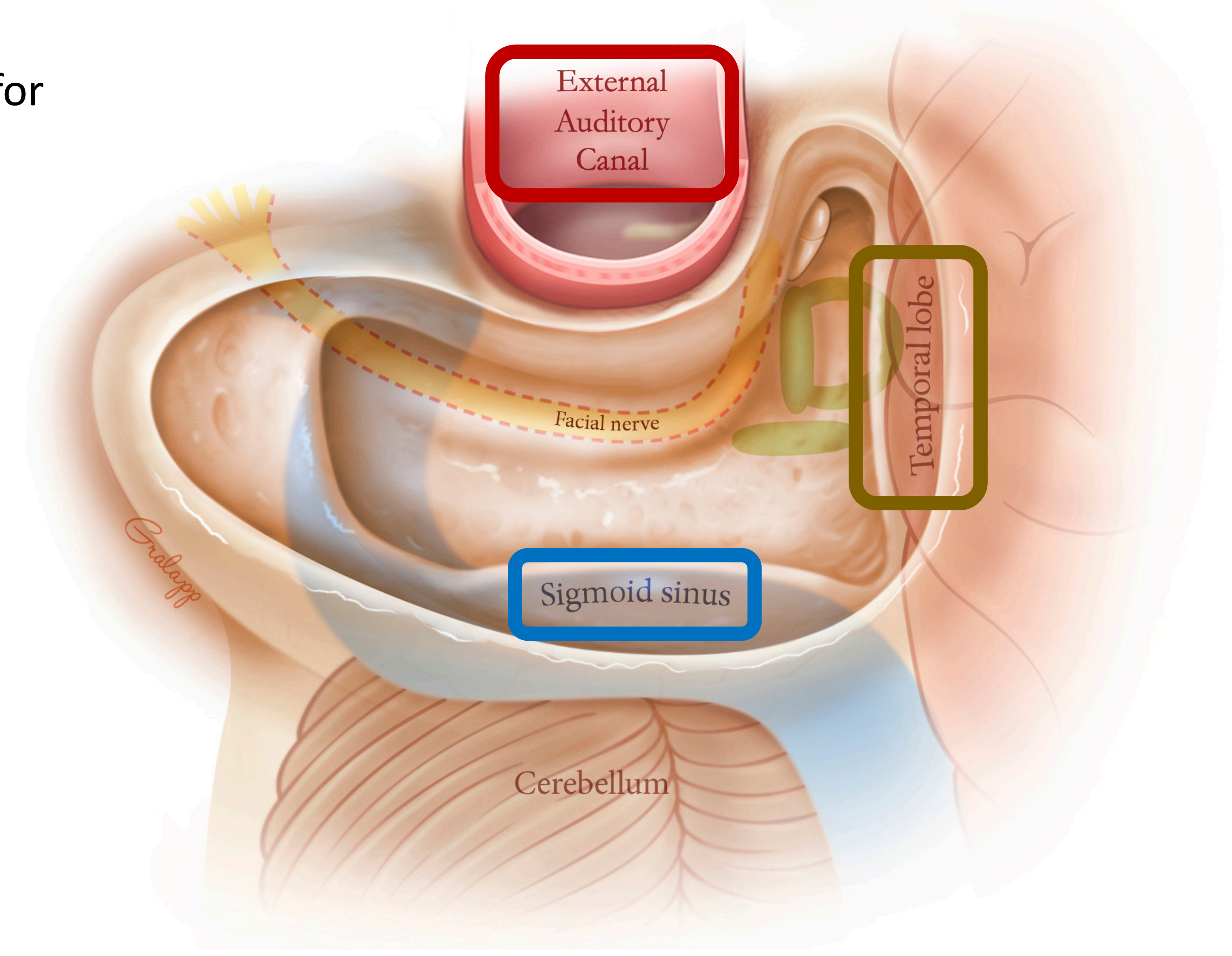
[7] Neves *et al*, 2021; [8] Nikan *et al*, 2021

Goals & Significance

- Evaluate state-of-the-art deep learning models for semantic segmentation of the temporal bone
- Build the largest comprehensively annotated temporal bone CT database for future use in research and industry

If successful, this project will provide:

- Robust virtual safety barriers for robot-assisted temporal bone surgery
- Patient-specific segmentations to reinforce anatomical knowledge in junior otologists
- Most complete dataset for training future deep learning networks



General Setup

- Dataset:
  - 23 manually segmented high resolution head CTs (voxel size ~ 0.1 mm) of left and right ears
  - 512 x 512 x 512 3D image files (DICOM / NRRD)
- Rigs:
  - Temporary Setup – Used for training before laboratory rig arrives
  - Big Rig – Used for training after arrival.

	Temporary Setup	Big Rig
	Cloud: MARCC	**Baltimore Local Setup**
GPU	NVIDIA K80, V100	GeForce RTX 3090
VRAM	24 GB DDR5 / 32 GB DDR5	24 GB DDR6
OS	Ubuntu / CentOS	Ubuntu / Windows
RAM	16 to 64 GB	32 GB

Technical Approach [1/2]

- Data Generation
  - Blur data to simulate different CT protocols (optimized for soft-tissue vs. bony structures).
  - Re-sample data to simulate lower-resolution data.

- nnUnet (Isensee F et al)
  - New benchmarking pipeline developed to standardized medical imaging.
  - 33 top leaderboard results for 53 different datasets with this method.
  - 2D and 3D approach available.

Technical Approach [2/2]

- AH-Net (Liu S. et al, Neves, C.A., Tran, E.D., Kessler, I.M. *et al*)
  - Due to network architecture, it can leverage models trained on 2D images and extrapolate the learned weights to apply to image volumes.
  - This model outperformed common architectures (UNet, 3D ResNet) for a similar application (segmentation of micro CTs on ears).
- PWD-3DNet (S. Nikan *et al*.)
  - Uses 3D patches to reduce computational load + balanced patch sampling method.
  - High dice score and low hausdorff distance.

Key Deliverables

	Deliverable
Minimum	Fully functioning model for CT segmentation.
	Internal validation with ground truth segmentations.
Expected	Comparison of Different Models for CT Segmentation (including code).
	Accuracy and performance reports for CT segmentation models.
Maximum	Manuscript preparation.
	Building a high quality segmented temporal bone CT dataset using our segmentation models.
	External validation with Western University’s dataset.

Dependencies

- Label/Annotation Finalization (2/12)

- Workstation arrival (2/27) - soft dependency
  - Contingency, continue to use gcloud/MARCC
  - Already have access to MARCC

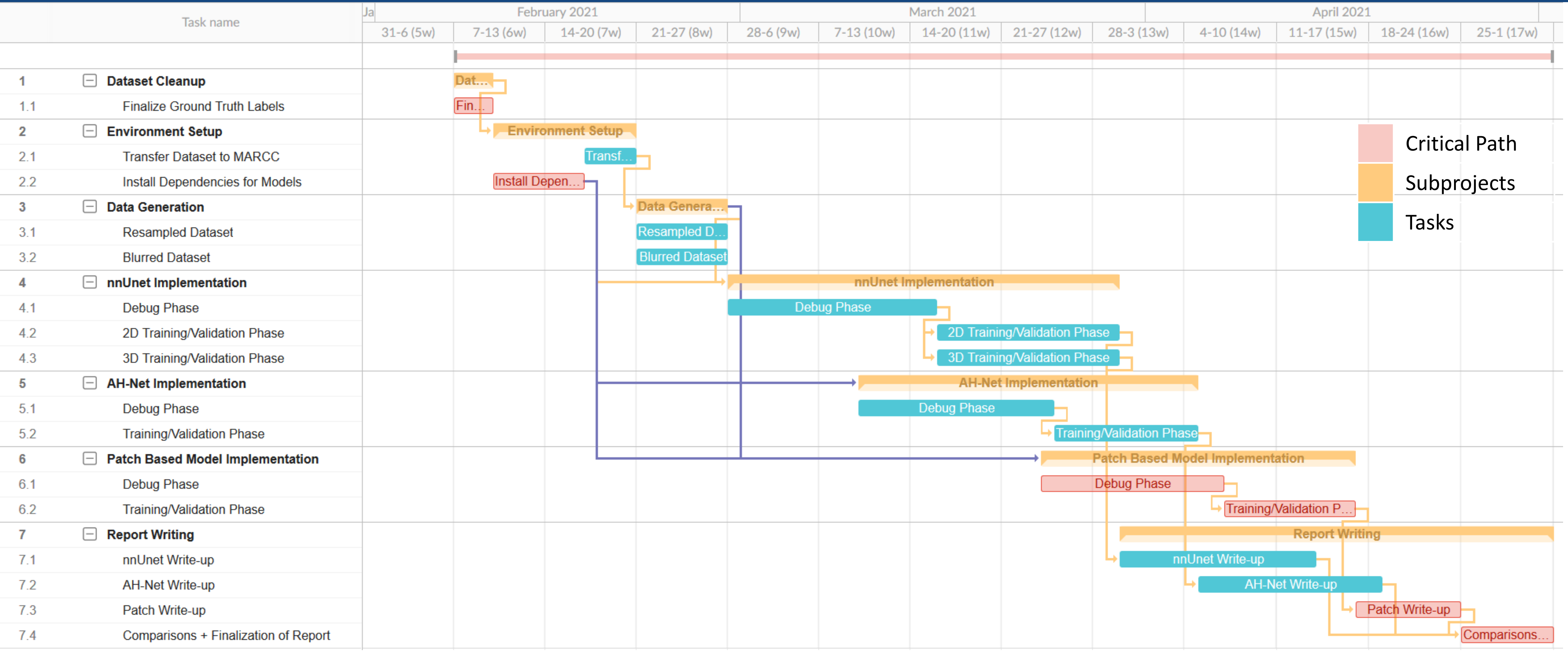
MARCC
Maryland Advanced Research Computing Center

Google Cloud

Timeline/Milestones

Milestones	Start	End
Finalize Ground Truth Labels	2/9	2/12
Setup Environment • Transferring dataset to MARCC • Installing dependencies for nnUNet and other DL models	2/13	2/19
Finish Data Generation	2/17	2/23
nnUnet Implementation • Debug Phase • 2D Ensemble Training + Validation Phase • 3D Training + Validation Phase	2/24	3/25
AH-Net Implementation • Debug Phase • 3D Training + Validation Phase	3/8	4/2
Patch-Based Network Implementation • Debug Phase • 3D Training + Validation Phase	3/27	4/19
Final Technical Report + Code	3/26	5/4

Gantt Chart



Task name
Ja
February 2021
March 2021
April 2021
31-6 (5w)
7-13 (6w)
14-20 (7w)
21-27 (8w)
28-6 (9w)
7-13 (10w)
14-20 (11w)
21-27 (12w)
28-3 (13w)
4-10 (14w)
11-17 (15w)
18-24 (16w)
25-1 (17w)
1 Dataset Cleanup
1.1 Finalize Ground Truth Labels
2 Environment Setup
2.1 Transfer Dataset to MARCC
2.2 Install Dependencies for Models
3 Data Generation
3.1 Resampled Dataset
3.2 Blurred Dataset
4 nnUnet Implementation
4.1 Debug Phase
4.2 2D Training/Validation Phase
4.3 3D Training/Validation Phase
5 AH-Net Implementation
5.1 Debug Phase
5.2 Training/Validation Phase
6 Patch Based Model Implementation
6.1 Debug Phase
6.2 Training/Validation Phase
7 Report Writing
7.1 nnUnet Write-up
7.2 AH-Net Write-up
7.3 Patch Write-up
7.4 Comparisons + Finalization of Report
Dat...
Fin...
Environment Setup
Transf...
Install Depen...
Data Genera...
Resampled D...
Blurred Dataset
nnUnet Implementation
Debug Phase
2D Training/Validation Phase
3D Training/Validation Phase
AH-Net Implementation
Debug Phase
Training/Validation Phase
Patch Based Model Implementation
Debug Phase
Training/Validation P...
Report Writing
nnUnet Write-up
AH-Net Write-up
Patch Write-up
Comparisons...
Critical Path
Subprojects
Tasks

Roles and Responsibility

- The Team:
  - **Andy Ding** and **Jessica Soong**: Shared responsibilities for all tasks.

- Mentors:
  - **Dr. Russell Taylor**: Technical Lead
  - **Dr. Francis X. Creighton**: Clinical Lead
  - **Dr. Mathias Unberath** *(TBD)*: Deep Learning Lead
  - **Maxwell Zhaoshuo Li**: Technical Consultant

ciis JOHNS HOPKINS MEDICINE ARCADE

Management Plan

- **Meetings:**
  - Weekly meetings with the LCSR (Wednesdays)
  - Weekly meetings with Dr. Unberath (Fridays)
  - Biweekly meetings with Max Li (TBD)

- **Communications:**
  - Slack channel with the LCSR (Technical Leads/Consultants)

- **File Sharing**:
  - Data/Reports: Hopkins OneDrive, CIS II website
  - Code: Private repository on Github

Reading List

- S. Nikan *et al.*, "PWD-3DNet: A Deep Learning-Based Fully-Automated Segmentation of Multiple Structures on Temporal Bone CT Scans," in *IEEE Transactions on Image Processing*, vol. 30, pp. 739-753, 2021, doi: 10.1109/TIP.2020.3038363.
- Neves, C.A., Tran, E.D., Kessler, I.M. *et al.* Fully automated preoperative segmentation of temporal bone structures from clinical CT scans. *Sci Rep* **11,** 116 (2021). https://doi.org/10.1038/s41598-020-80619-0
- li, Xiaoguang & Gong, Zhaopeng & Yin, Hongxia & Zhang, Hui & Wang, Zhenchang & Zhuo, li. (2020). A 3D deep supervised densely network for small organs of human temporal bone segmentation in CT images. Neural Networks. 124. 10.1016/j.neunet.2020.01.005.
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- Liu S. et al. (2018) 3D Anisotropic Hybrid Network: Transferring Convolutional Features from 2D Images to 3D Anisotropic Volumes. In: Frangi A., Schnabel J., Davatzikos C., Alberola-López C., Fichtinger G. (eds) Medical Image Computing and Computer Assisted Intervention – MICCAI 2018. MICCAI 2018. Lecture Notes in Computer Science, vol 11071. Springer, Cham. https://doi.org/10.1007/978-3-030-00934-2_94

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7. Neves CA, Tran ED, Kessler IM, Blevins NH. Fully automated preoperative segmentation of temporal bone structures from clinical CT scans. *Scientific Reports*. 2021;11(1). doi:10.1038/s41598-020-80619-0.
8. Nikan S, Van Osch K, Bartling M, et al.. PWD-3DNet: A Deep Learning-Based Fully-Automated Segmentation of Multiple Structures on Temporal Bone CT Scans. *IEEE Transactions on Image Processing*. 2021;30:739-753. doi:10.1109/tip.2020.3038363.
9. Isensee F, Jaeger PF, Kohl SAA, Petersen J, Maier-Hein KH. nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. *Nature Methods*. 2021;18(2):203-211. doi:10.1038/s41592-020-01008-z.