Background Reading Presentation

Project 3 – Ameen Amanian, Chanha Kim, Yuliang Xiao

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Project Overview

- Goal: To perform automated segmentation of the eustachian tube for CT-registration based surgical intervention.

- Public datasets
- JHU dataset

- ANTsPy registration algorithm

- nnUNet algorithm

- Validation via DSC and HD95

Paper #1

micromachines

MDPI

Article

Three-Dimensional Semantic Segmentation of Pituitary Adenomas Based on the Deep Learning Framework-nnU-Net: A Clinical Perspective

Xujun Shu [1,2,†], Yijie Zhou [3,†], Fangye Li [2], Tao Zhou [2], Xianghui Meng [2], Fuyu Wang [2], Zhizhong Zhang [2], Jian Pu [4,*] and Bainan Xu [2,*]

Clinical Problem

- Pituitary Adenomas (PAs) arise from the pituitary gland; comprise of 10-15% of primary brain tumors, and the third most common type of intracranial tumor
- Segmentations of Pituitary Adenomas are routine clinical tasks for treatment decisions, surgical planning, and radiation therapy
  - manual segmentations are time-consuming and laborious

Key Result

- PA volume was one of the most crucial factors that affected the performance of nnUNet models
  - **Small PAs** (<1,000mm^3) had dice coefficient similarity value of 0.47 while the **Medium PAs** (1000 ~ 10,000mm^3) and **Large PAs** (>10,000mm^3) had dice coefficient similarity value around 0.85
  - nnUNet had poor segmentation performance for **small PAs**
- Study concluded that it is appropriate to use nnUNet for medium to large size PAs while it suggests the manual segmentation for small PAs

Methods

- 243 PA MRI images total
- 35 of the images: test cases
- Two nnU-Net models
  - Model 1: 208 cases of all types of PA
  - Model 2: 109 cases of Primary non-functional PAs
- All images are manually segmented for “ground-truth”

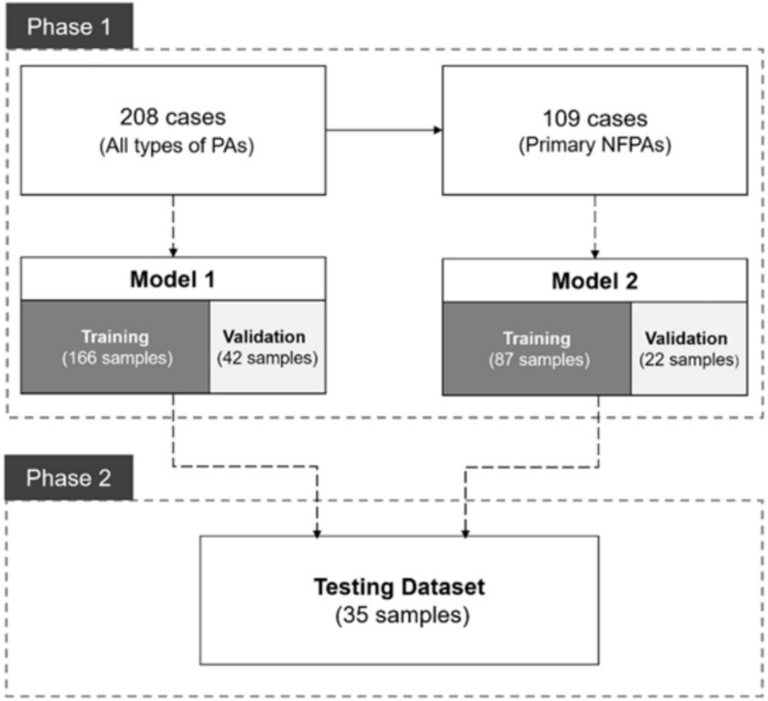


Figure 2. Schematic of the study design.

Model Performance

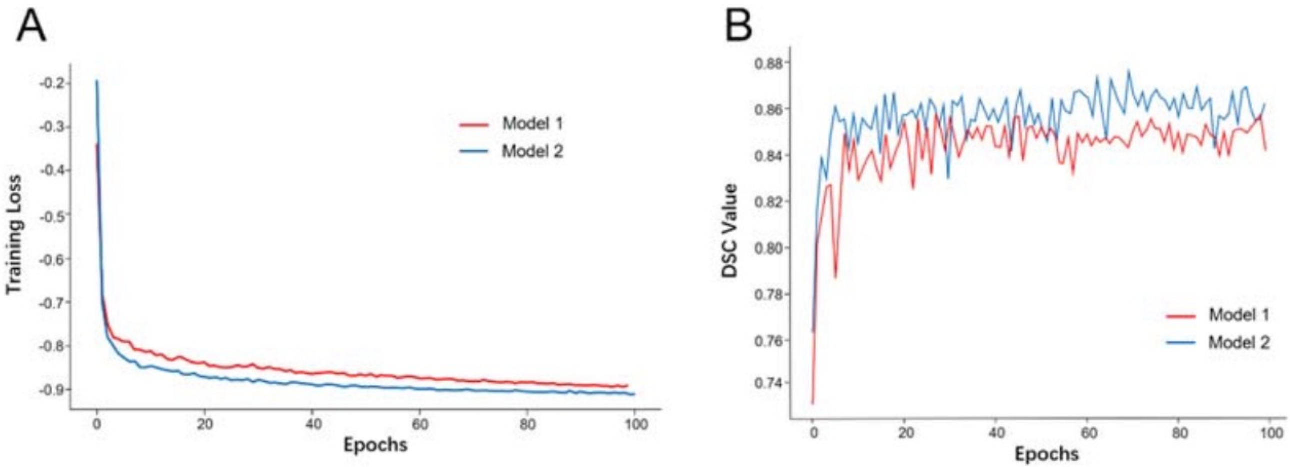


Figure 3. Loss curve of the training process for Models 1 and 2 (**A**). Evaluation metric curve of the training process for Models 1 and 2 (**B**).

Model Comparison

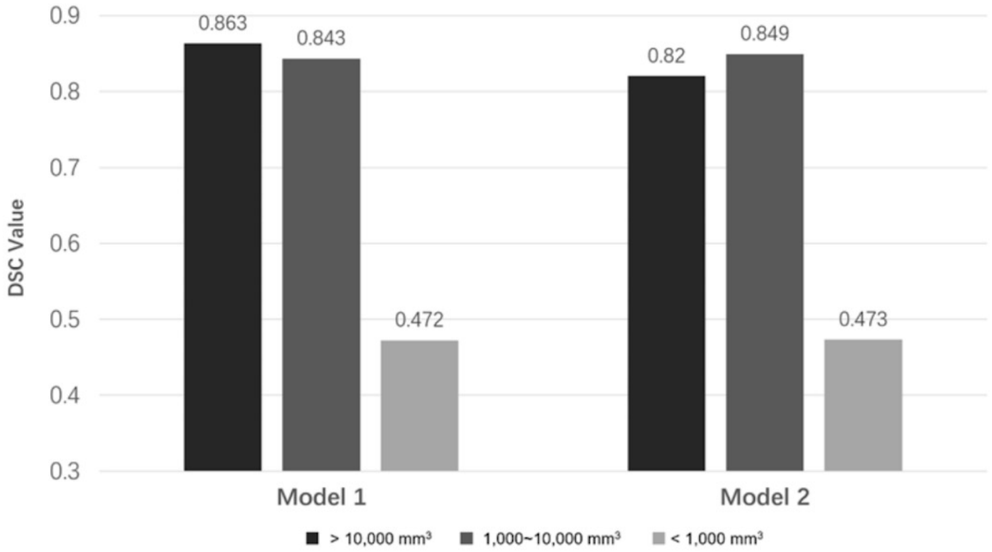


Figure 4. Performances of the models in different PA groups with different volumes in the testing dataset.

Pros and Cons

- **Pros:**
  - Paper attributed poor performance of nnU-Net model for small PAs to the use of DSC for performance metric. For small structures, DSC is more sensitive because it penalizes errors more in small segments than in large segments
  - Points out a need for new imaging technique with higher resolution
- **Cons:**
  - Biased Dataset: there were uneven distribution of datasets (medium-size PAs were majority)
  - Paper identified but didn’t modify nnU-Net DSC loss to resolve performance bottleneck

Take away and Next Steps

- Since we already saw that nnU-Net might have difficulties learning very small or thin structures, we will not use conventional DSC for our loss.

- We will look into new evaluation metric which emphasizes the small segments by assigning a higher weight to pixels in smaller segments.

- We do not need very large dataset to train a model with state-of-art performance as long as there is a good data distribution
  - saves time for labor-intensive manual segmentations

Paper #2

cancers

MDPI

Article

Fully Automatic Deep Learning Framework for Pancreatic Ductal Adenocarcinoma Detection on Computed Tomography

Natália Alves [1,*], Megan Schuurmans [1], Geke Litjens [2], Joeran S. Bosma [1], John Hermans [2] and Henkjan Huisman [1]

Summary

Clinical Problem

- Early detection of pancreatic ductal adenocarcinoma (PDAC) lesions are challenging as they are small and poorly defined on CT's
- PDAC has poor 5-year survival (10.8%)

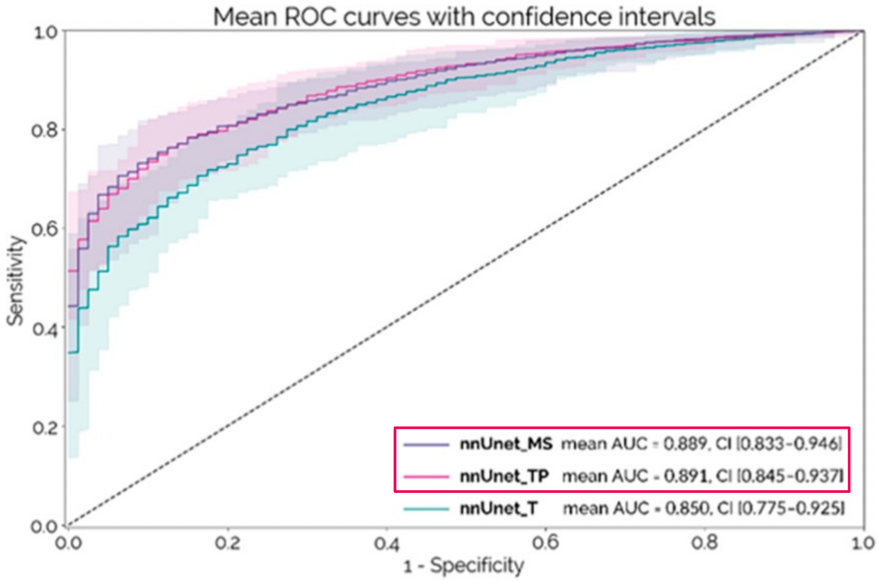
Research Question

- Can a deep learning pipeline improve detection and localization of PDAC lesions on CT images?
- Will integration of surrounding anatomy into the algorithm improve detection of PDAC?

Key Result

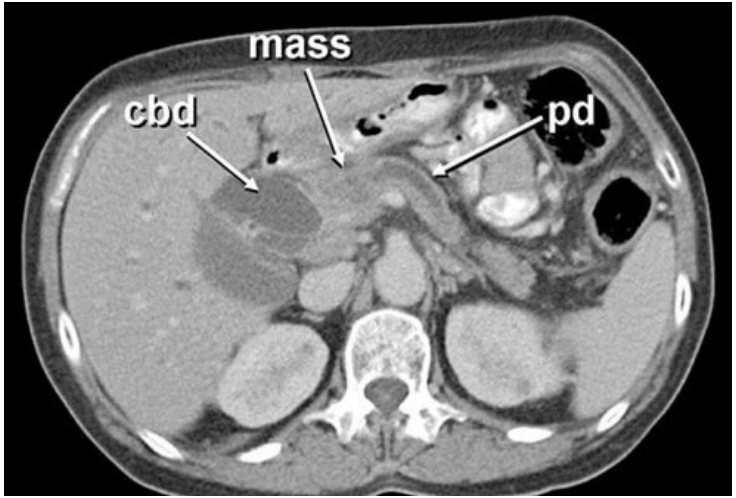
Three algorithms

- nnUNet_T
- **nnUNet_TP**
- **nnUNet_MS**



Background and Significance

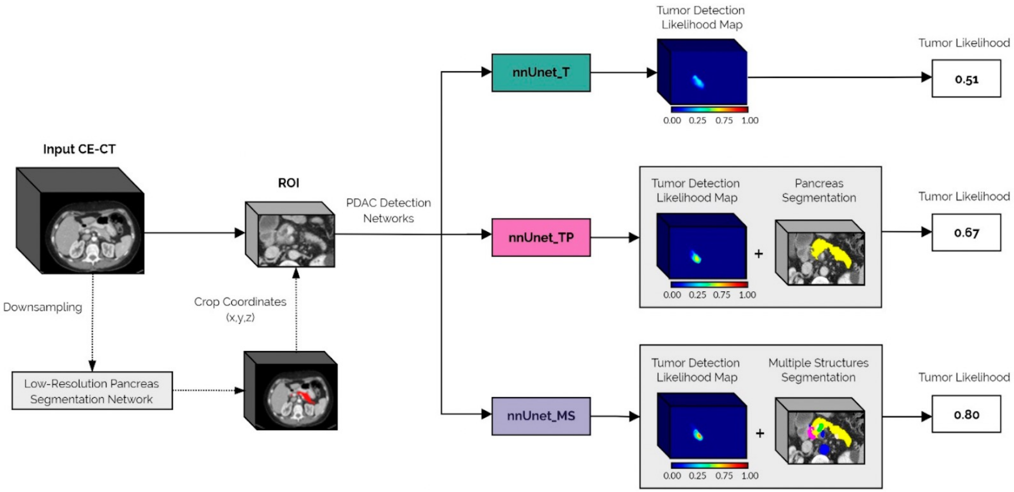
- Early detection is challenging as patients are usually asymptomatic in the early phase and population-wide preventive screening is not possible.
- Patients diagnosed in early stages (tumor < 2cm in size) present a much higher survival rate.
- Early diagnosis of PDAC may lead to improved patient outcomes.



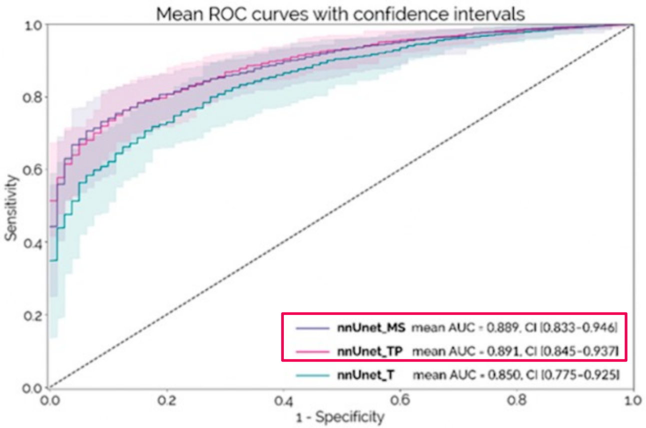
Technical Approach

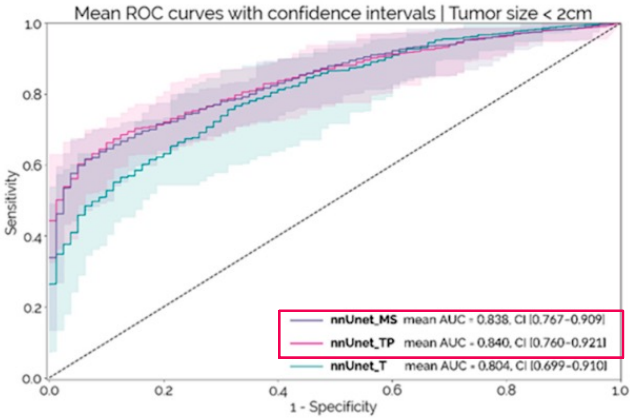
Experiment

- Use nnU-Net architecture to build three models (nnUnet_T, nnUnet_TP, nnUnet_MS)
- Downsample datasets and train the low-resolution pancreas segmentation network
- Make three models do inferences on ROI (extracted by low-resolution pancreas network) to get tumor likelihood



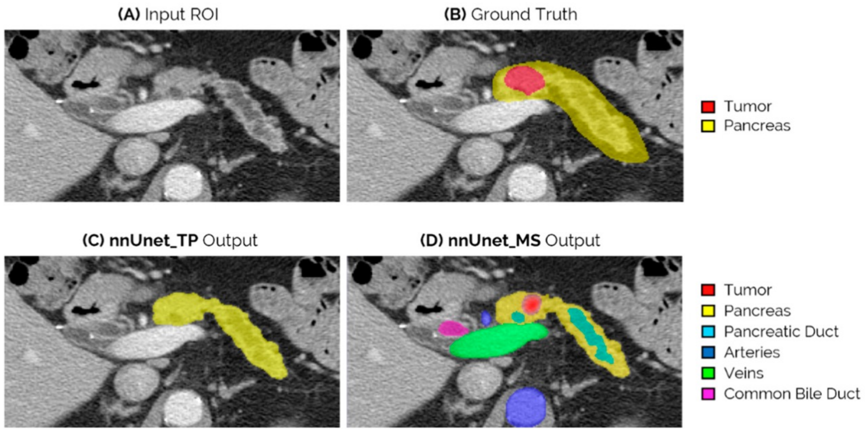
Results


Mean ROC curves with confidence intervals
Sensitivity
1 - Specificity
nnUnet_MS mean AUC = 0.889, CI [0.833-0.946]
nnUnet_TP mean AUC = 0.891, CI [0.845-0.937]
nnUnet_T mean AUC = 0.850, CI [0.775-0.925]


Mean ROC curves with confidence intervals | Tumor size < 2cm
Sensitivity
1 - Specificity
nnUnet_MS mean AUC = 0.838, CI [0.767-0.909]
nnUnet_TP mean AUC = 0.840, CI [0.760-0.921]
nnUnet_T mean AUC = 0.804, CI [0.699-0.910]

Enhanced performance with inclusion of surrounding structures

- **nnUNet_TP** could NOT detect the tumor while **nnUNet_MS** correctly identified the lesion



Pros and Cons

Pros

- Validation of the model on an external dataset
- Inclusion of surrounding structures in addition to the pancreas and tumor
- Extract ROI easily from test dataset when inference

Cons

- Inclusion of tumors in the pancreatic head only (as opposed to other locations) which may not be as generalizable.
- Manual labeling of ROI is time-consuming.

Take Away and Next Steps

- Assess the performance of several models (ET only vs. ET + surrounding structures)
- Modify the default loss function (this study found the Cross Entropy loss function to be better than the default soft DICE + BCE.
- Ensembling strategies (3D U-Net Cascade) may improve the generalizability of the model and account for variations present in CT images.

Thanks!

Any questions?

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