



# Project 11: 3D Segmentation of Hard and Soft Tissue for Simulating X-ray Image Formation with Deep Learning

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# Fluoroscopy-guided Intervention

- Minimally-invasive procedures guided by continuous X-ray image (video) displayed on a monitor
- Applications in orthopedic surgery, liver biopsy, catheter insertion, enemas, angiography, urological surgery, pacemaker implantations, and more
- Rapidly growing discipline, prime for automation



# The Problem

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High-quality, expert-labeled  
ground truth medical image  
data is scarce



# The Solution: Digitally Reconstructed Radiographs (DRRs)



Computed Tomography  
(CT) Volume



Images:

<https://dissolve.com/video/Skull-neck-blood-vessels-rotating-rights-managed-stock-video-footage/002-D30-45-586> (skull)

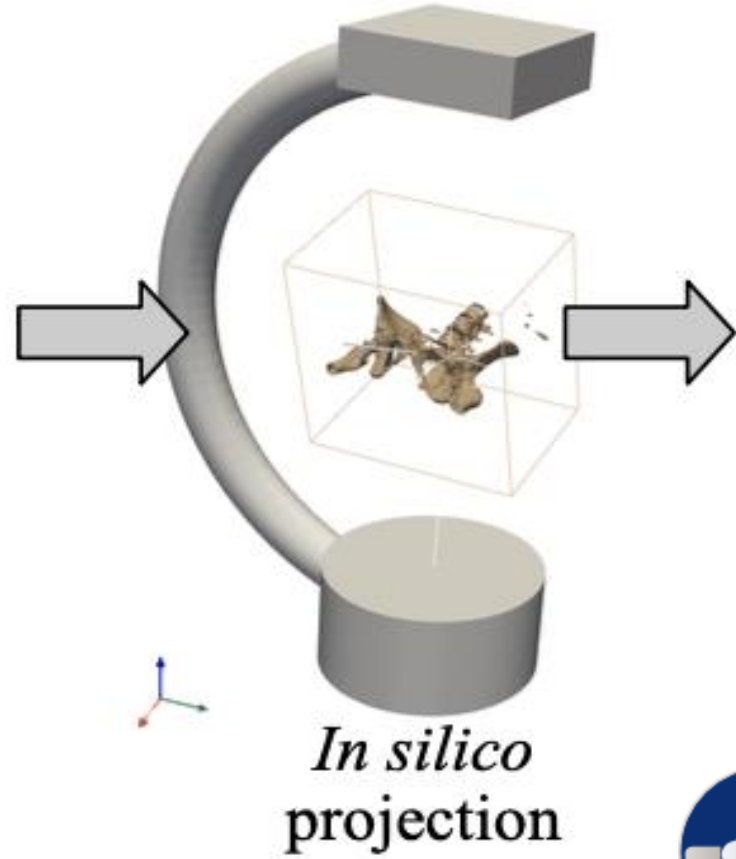
[https://www.researchgate.net/figure/Fig-1b-3D-CT-reconstruction-of-the-initial-situation-of-the-pelvis\\_fig2\\_305343551](https://www.researchgate.net/figure/Fig-1b-3D-CT-reconstruction-of-the-initial-situation-of-the-pelvis_fig2_305343551) (pelvis)

<https://github.com/arcadelab/deepdrr> (DeepDRR)

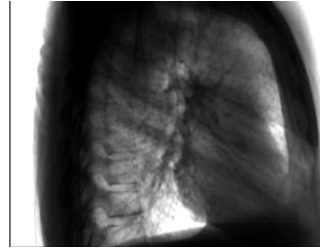
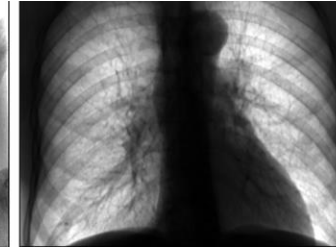
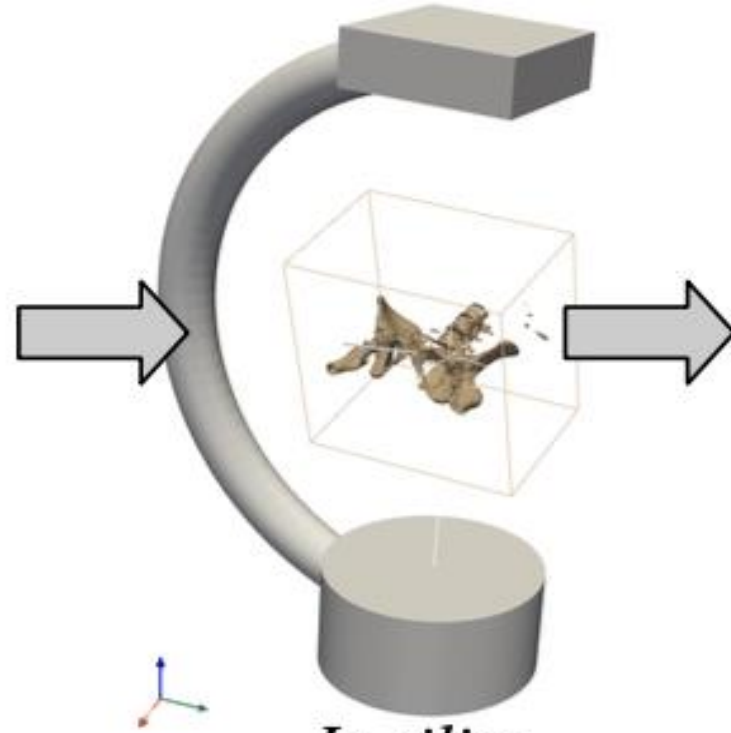
# The Solution: Digitally Reconstructed Radiographs (DRRs)



Computed Tomography  
(CT) Volume



# The Solution: Digitally Reconstructed Radiographs (DRRs)



Computed Tomography (CT) Volume

Digitally Reconstructed Radiographs (DRRs)

*In silico*  
projection



ARCADE



LABORATORY FOR  
Computational  
Sensing + Robotics

Images:

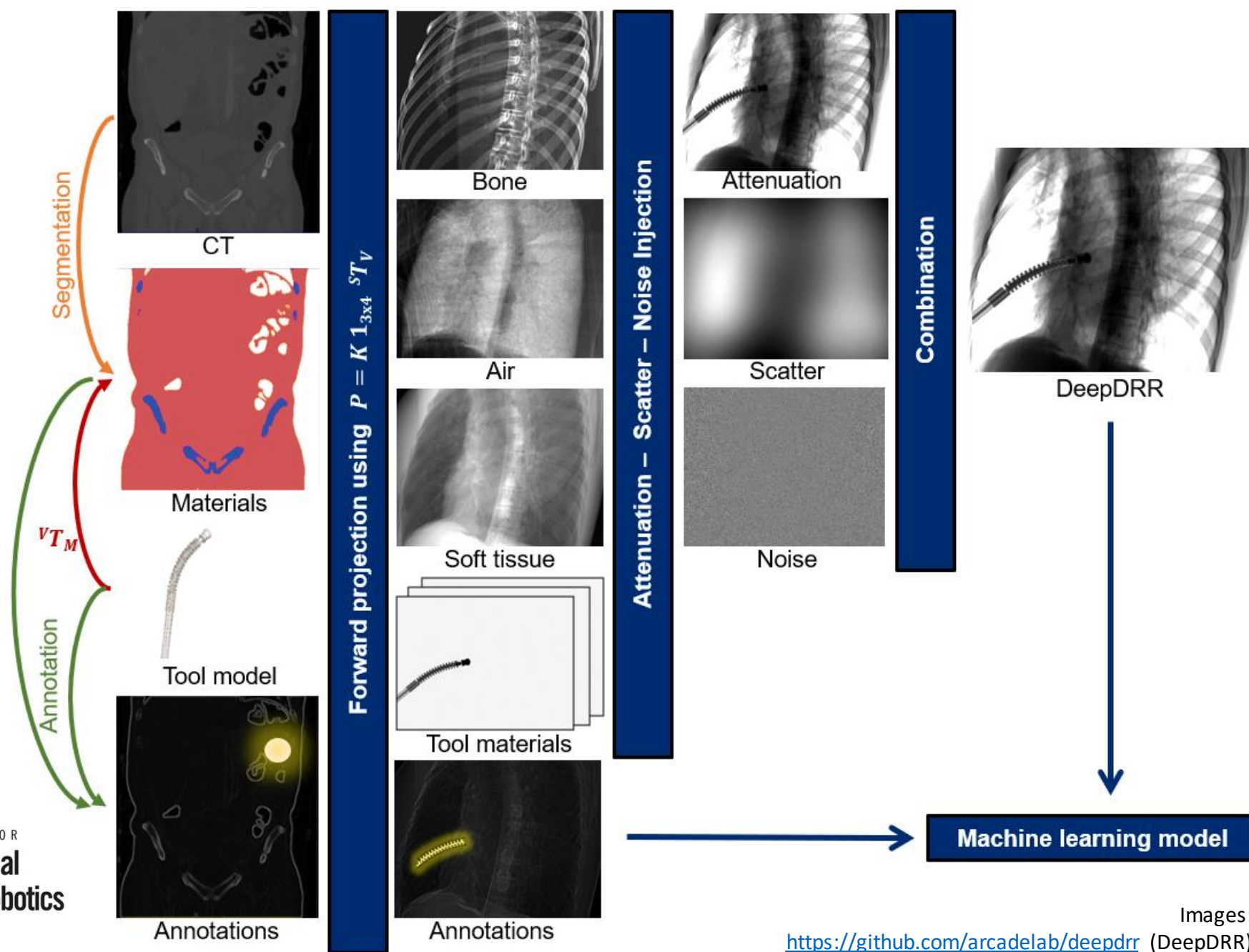
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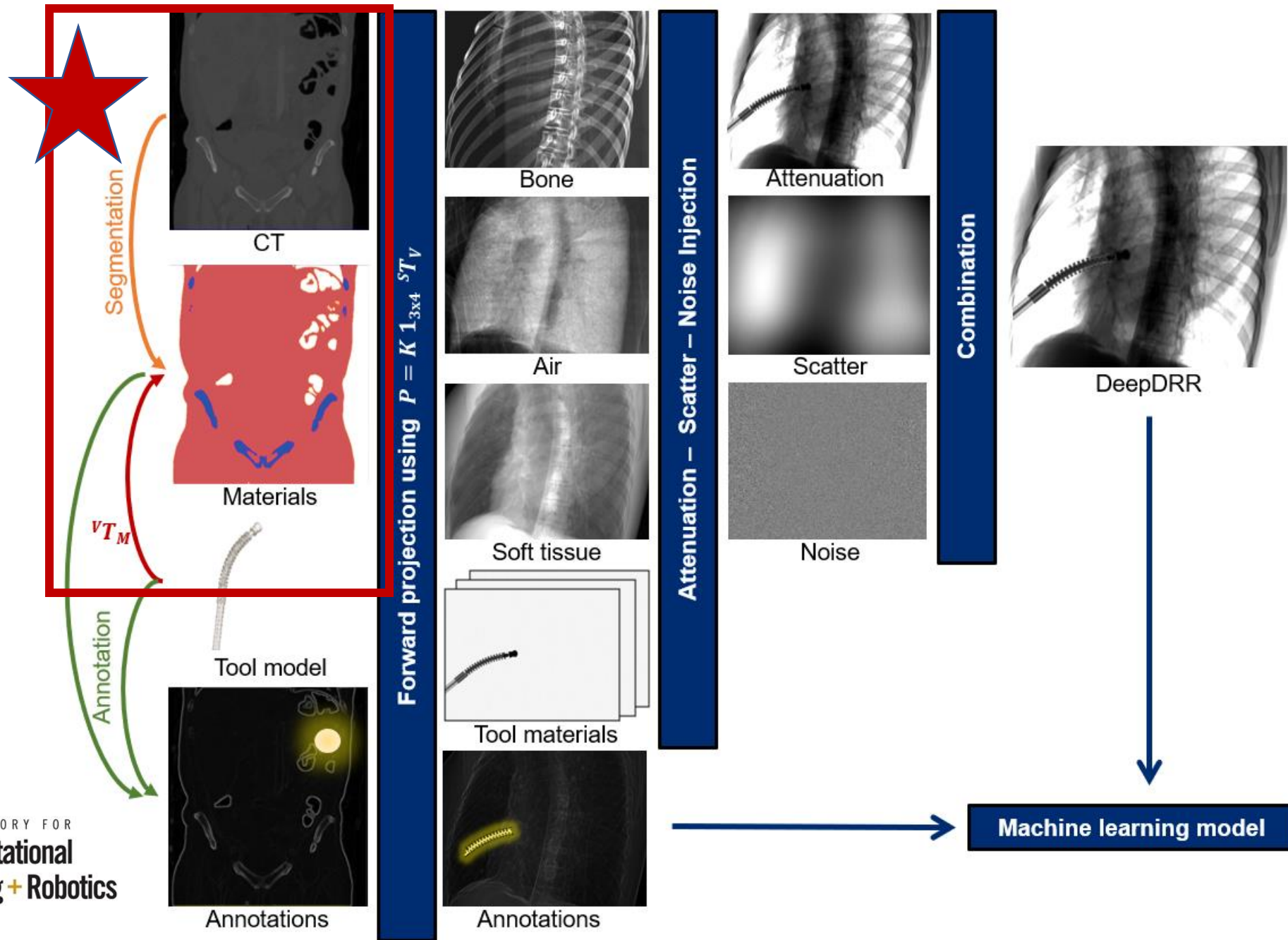
# DeepDRR

- Combines machine learning models for material decomposition and scatter estimation in 3D and 2D, respectively, with analytic models for projection, attenuation, and noise injection to render quality DRRs
- Developed in-house
- Segmentation pipeline is currently limited to bone, soft tissue, and air



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# Project Goals

## Build

Build algorithms that automatically segment tissues of varying X-ray absorption rates from CT data.

## Evaluate

Compare the performance of (3) different 3D segmentation model architectures on at least 2 different tissue types (cardiac, lung, liver, etc...)

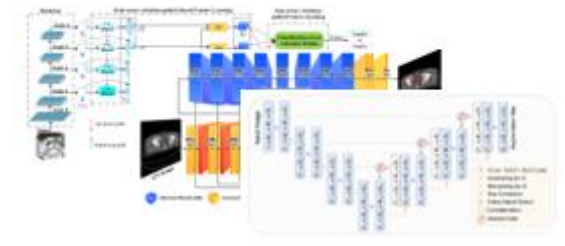
## Integrate

Integrate our 3D segmentation pipeline with the current DeepDRR simulation system and improve DRR quality.

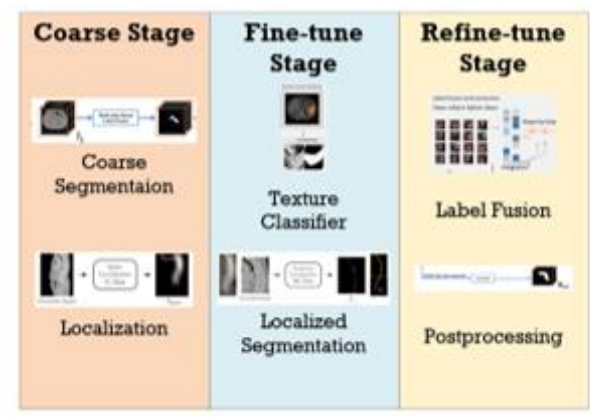
We started with a literature review...  **ARCADE**

**Categories  
of  
Researches**

**An End-to-End  
Network**



**An Coarse-to-  
fine framework**



# An End-to-End Network



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A network that does "everything"

Click to add text  
Pros:

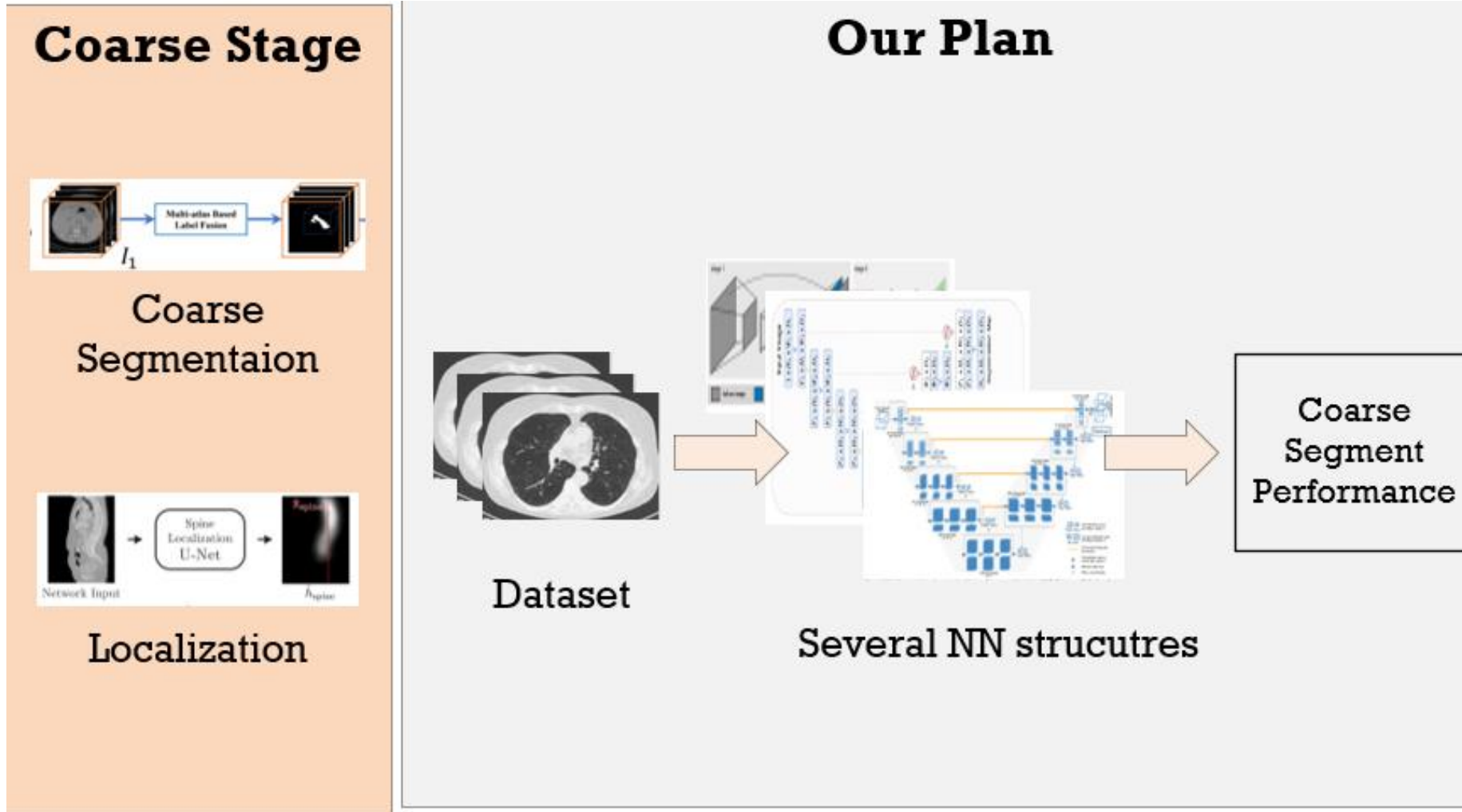
Straightforward

Cons:

Difficult to enhance the performance

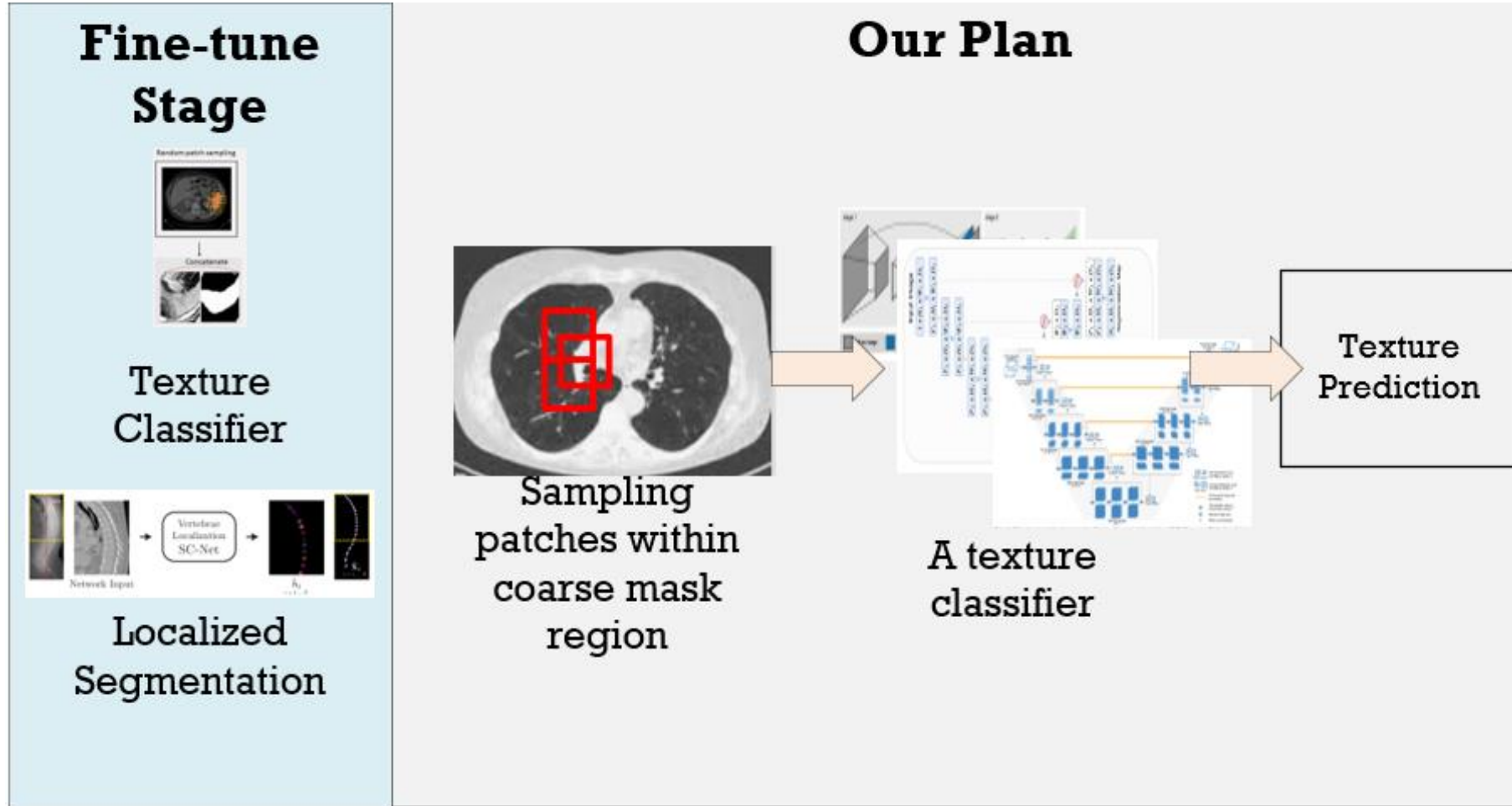
About 4/15 paper in our review use this strategy.

# Coarse Segmentation Stage



- Take a light-weight Network with good performance!

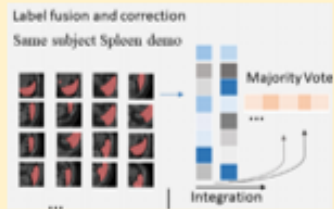
# Fine Segmentation Stage



- Take a model sensitive to texture changes

# Refine Segmentation Stage

## Refine-tune Stage



Label Fusion



Postprocessing

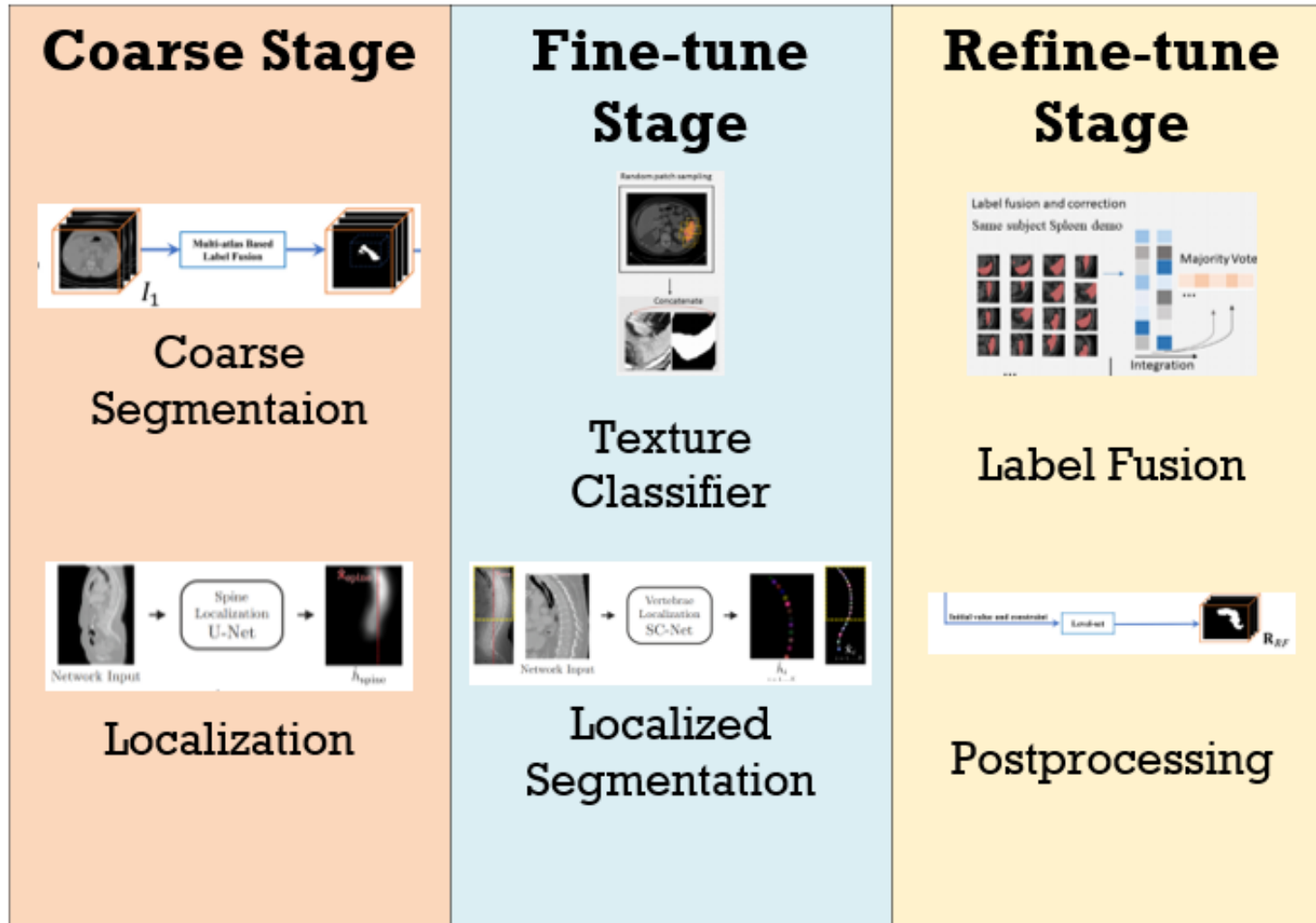
## Our Plan

Simplest one: Majority Voting Fusion

Optional: Postprocessing with classical methods

- Check performance on X-Ray Simulation

# A Coarse-to-Fine framework

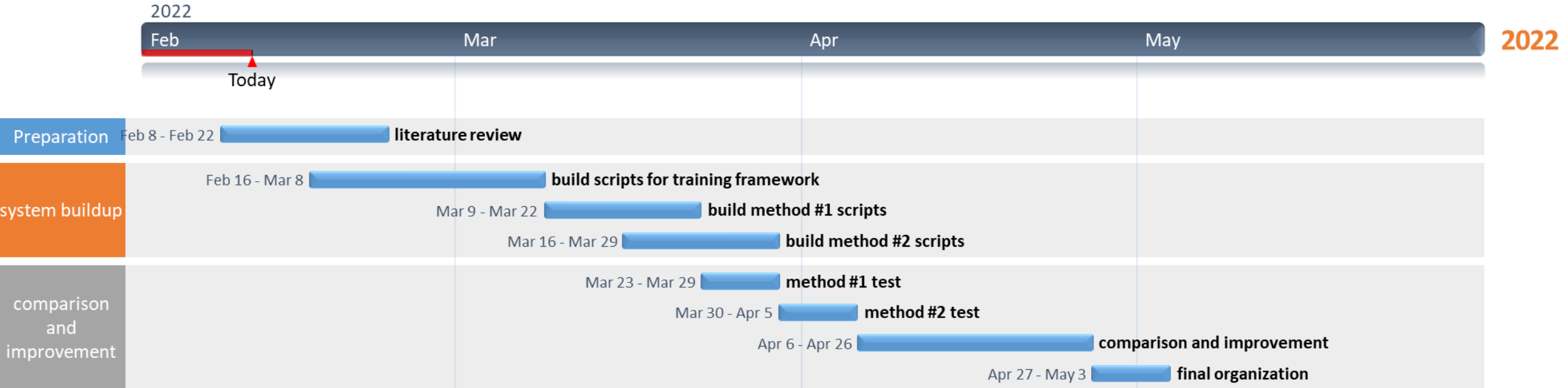


- A step-by-step process
- Easy to check progression in each time point
- Combining various methods

# Project deliverables

- Minimum:
  - Scripts of a validated segmentation pipeline for bone, soft tissue, and air in full-body CT.
  - Comparison report of existing models on different type of tissues.
- Expected: Minimum +
  - Scripts and results for segmenting lung, cardiac, liver in full-body CT.
  - Integrated scripts into the DeepDRR simulation.
- Maximum: Expected +
  - Validation scripts and results on full and partial CT with possible data corruptions, fractures, wounds, etc.
  - Analysis report of the DRR performance using the improved segmentation pipeline.

# Project timeline



# Milestones

Milestones	Expected Date
Comparison report of existing models	Feb 22
Scripts for training framework	March 8
Scripts for bone, soft tissue and air segmentation	March 22
Scripts for lung, cardiac and/or liver segmentation	April 6
Report for segmentation results	April 12
Integration to deepDRR system	April 12

# Dependencies

Dependencies	Needed by	Remedies
Access to the workstation for training models in Dr. Unberath's lab	Feb 28th	Run the training process on PC; pay for commercial servers.
Full body CT dataset (already have one dataset with limited cases)	Feb 28th	Use partial CT dataset for bones, soft tissue or other tissues.
Pretrained model for specific tasks(optional)	March 15th	Drop the optional task



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Sensing + Robotics

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Weekly meeting on Thursday with mentor

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Additional meetings as necessary

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Project group slack channel

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Git repository for code management

Project  
management

# Reading List

- Unberath, M., Zaech, J. N., Lee, S. C., Bier, B., Fotouhi, J., Armand, M., & Navab, N. (2018, September). Deepdrr—a catalyst for machine learning in fluoroscopy-guided procedures. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 98-106). Springer, Cham.
- Liu, P., Han, H., Du, Y., Zhu, H., Li, Y., Gu, F., ... & Zhou, S. K. (2021). Deep learning to segment pelvic bones: large-scale CT datasets and baseline models. *International Journal of Computer Assisted Radiology and Surgery*, 16(5), 749-756.
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- 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>
- Tang Y, Gao R, Lee H H, et al. High-resolution 3D abdominal segmentation with random patch network fusion[J]. *Medical Image Analysis*, 2021, 69: 101894.
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- Schlemper J, Oktay O, Schaap M, et al. Attention gated networks: Learning to leverage salient regions in medical images[J]. *Medical image analysis*, 2019, 53: 197-207.

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- Nadeem S A, Hoffman E A, Sieren J C, et al. A CT-based automated algorithm for airway segmentation using freeze-and-grow propagation and deep learning[J]. IEEE transactions on medical imaging, 2020, 40(1): 405-418.
- Milletari F, Navab N, Ahmadi S A. V-net: Fully convolutional neural networks for volumetric medical image segmentation[C]//2016 fourth international conference on 3D vision (3DV). IEEE, 2016: 565-571.