From Pixel to Cancer: Cellular Automata in Computed Tomography

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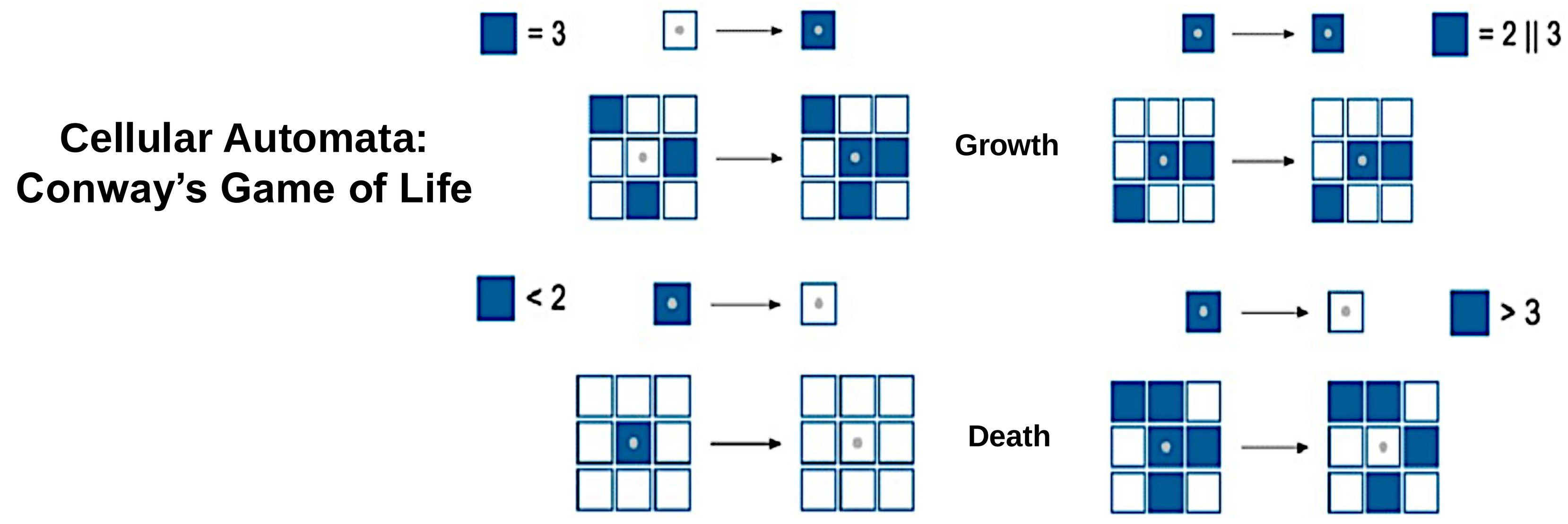
Introduction

AI in cancer detection faces challenges like data scarcity and annotation difficulties, especially for early-stage tumors. We propose a tumor synthesis method that generates synthetic tumors in CT images. Our approach uses three generic rules to simulate tumor growth, invasion, and death through **Cellular Automata**, allowing the creation of synthetic tumors at various stages.



Contributions

- **Requiring no manual annotation.**
- **Simulating tumor development.**
- **Synthesizing tumors across organs.**

Experiment and Setting

- **Visual Turing Test** involved three experts, each evaluating 150 CT images, with 50 images per organ. They were tasked with categorizing each CT image as either real or synthetic.
- **Tumor Segmentation Performance:** We benchmark Pixel2Cancer against the state-of-the-art modeling-based method (Hu et al., 2023) and the real-tumor method.
- **Ablation Studies:** We evaluated the impact of various tumor conditions on the performance of the model. We evaluated the effectiveness of generic rules on liver tumor segmentation.

Method

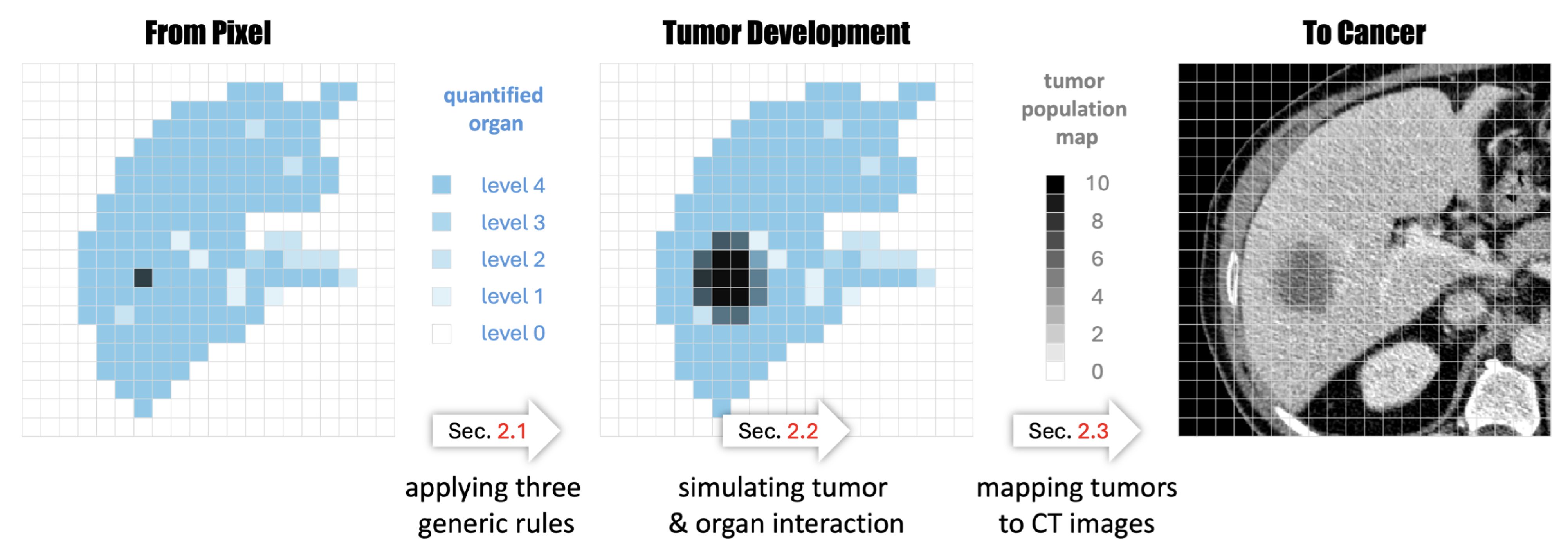


Figure 1— Pipeline

We begin by quantifying the organ from CT intensity and selecting a starting pixel. Next, we apply three rules—growth, interaction, and death—to simulate tumor development and record the results in a tumor population map. Finally, tumors are generated in CT scans using a mapping function based on the population map and CT intensity.

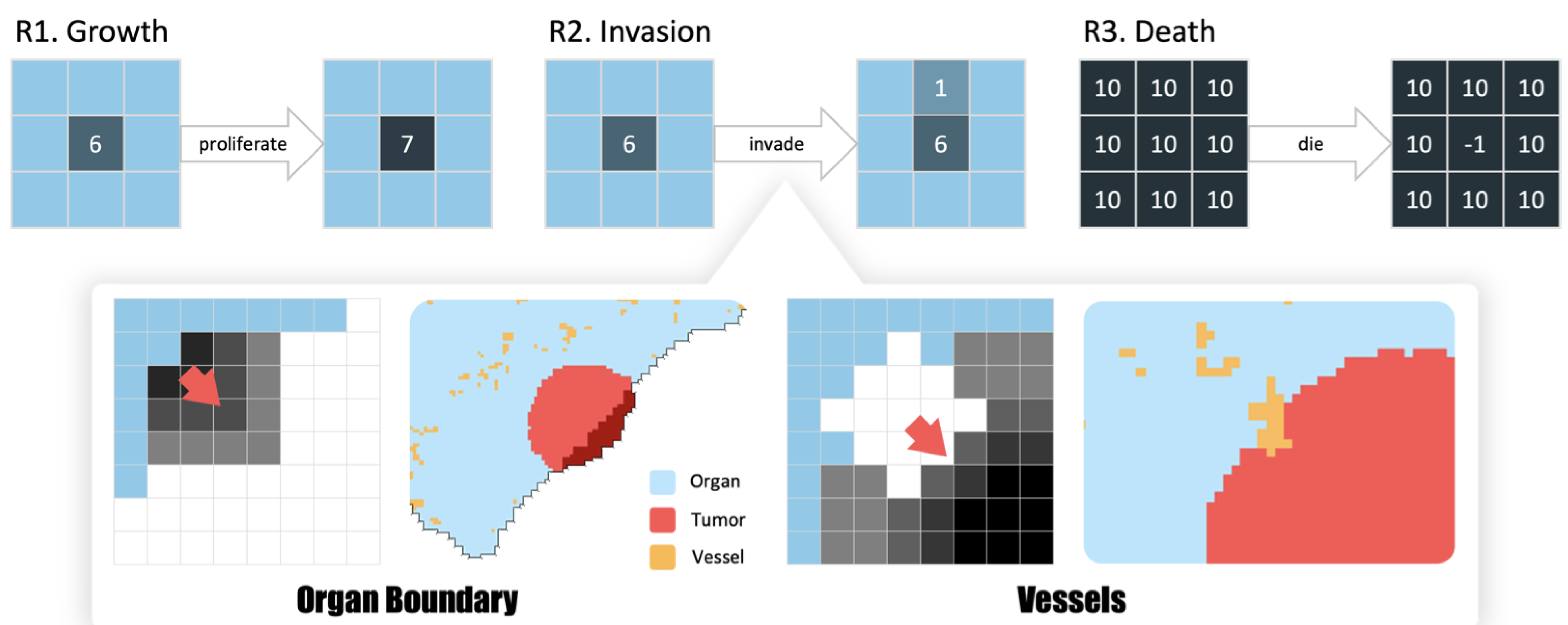


Figure 2—Rules of Simulation

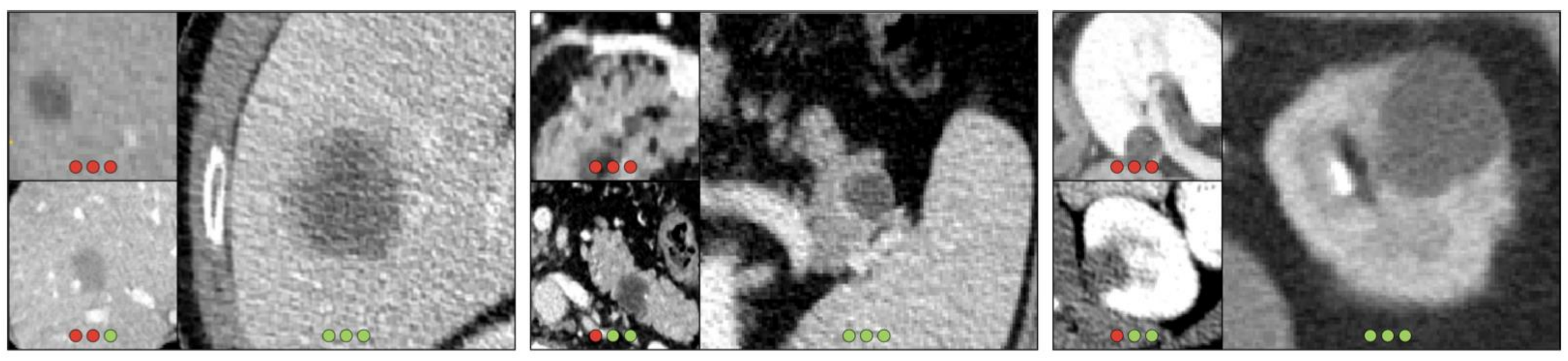
R1.Growth: Tumor cells proliferate themselves (self-state +1) with probability.
R2.Invasion: Tumor cells can invade neighboring cells (neighbor-state +1). we simulate interactions among tumors, organ tissues, vessels, and boundaries. At the bottom line, we present cases where tumors are compressed by organ boundaries and vessels.
R3.Death: Tumor cells surrounded by a full population of neighboring cells (state = 10) will undergo cell death (self-state ← -1).

Results

Visual Turing Test

	metric	liver	pancreas	kidneys
R1 *3-year experience*	sensitivity (%)	100	95.0	95.5
	specificity (%)	27.3	22.7	26.7
	accuracy (%)	60.9	57.1	67.6
R2 *7-year experience*	sensitivity (%)	94.7	87.5	90.0
	specificity (%)	47.8	47.4	56.3
	accuracy (%)	69.1	65.7	75.0
R3 *10-year experience*	sensitivity (%)	100	100	100
	specificity (%)	45.4	55.6	57.9
	accuracy (%)	68.4	72.4	75.8

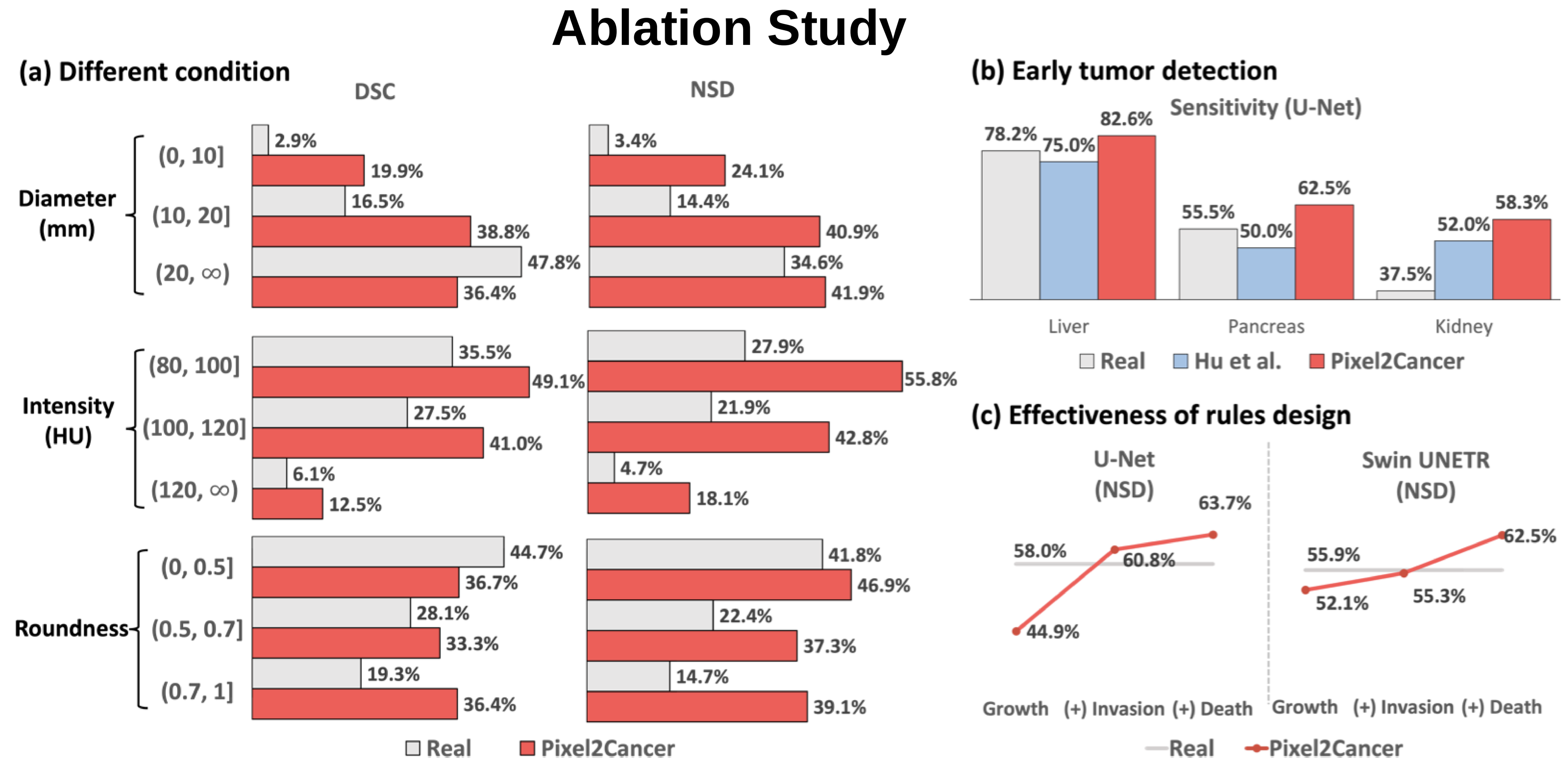
positives: real tumors ($N = 25$); negatives: synthetic tumors ($N = 25$).



synthetic liver tumors — synthetic pancreatic tumors — synthetic kidney tumors

Can you identify which one is the synthetic tumor?

Ablation Study



Performance of Tumor Segmentation

organ	tumor	U-Net DSC/NSD (%) ↑	U-Net SD/HD (mm) ↓	Swin UNETR DSC/NSD (%) ↑	Swin UNETR SD/HD (mm) ↓	nnU-Net DSC/NSD (%) ↑	nnU-Net SD/HD (mm) ↓
liver	real tumors	56.7/58.0	23.2/61.4	53.5/55.9	21.3/57.8	56.2/55.3	24.6/58.3
	Hu et al.	54.5/57.6	23.8/58.8	52.3/56.5	22.9/56.9	53.7/56.1	22.5/57.2
	Pixel2Cancer	58.9/63.7	17.9/52.4	56.7/62.5	18.7/51.3	57.9/63.2	18.9/52.7
pancreas	real tumors	57.8/56.5	13.1/47.7	56.7/52.8	24.6/53.9	56.8/52.1	14.5/44.6
	Hu et al.	54.1/52.2	15.7/49.3	53.6/54.9	22.5/47.4	54.6/52.4	17.1/48.0
	Pixel2Cancer	60.9/57.1	12.4/43.5	59.3/59.5	20.4/40.7	59.8/56.9	13.3/41.4
kidney	real tumors	71.3/62.8	27.2/64.3	70.7/61.2	19.8/57.1	65.2/58.1	25.6/59.3
	Hu et al.	63.2/55.4	35.1/69.0	61.7/52.3	26.2/61.6	55.5/49.9	27.9/62.7
	Pixel2Cancer	73.2/65.0	13.6/40.9	73.9/63.5	15.9/45.7	67.6/60.1	14.8/42.2

DSC - dice similarity coefficient; NSD - normalized surface dice.
SD - surface distance; HD - Hausdorff distance.

Paper

Code

Awesome Synthetic Tumors