Automatic tumor and multi-organ segmentation technique in CT based on Deep Learning for radiation therapy after breast-conserving surgery

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INTRODUCTION

For radiation therapy, segmentation of the target (breast tumor) and organs at risk (OARs) is a fundamental step. However, **manual delineation by physicians is labor-intensive, time-consuming and subjective** with inter- and intra-observer variability [1-3]. In recent years, Deep Learning (DL) technology has shown superior performance in computer vision field [4, 5]. In this study, we have developed an **automatic tumor and multi-organ segmentation technique in CT** based on DL for radiation therapy after breast-conserving surgery to reduce the variation and increase the contouring efficiency.

AIM

To develop a novel **tumor and multi-organ segmentation technique** in CT based on DL for radiation therapy after breast-conserving surgery

METHOD

(1) Dataset

CT images and RT structure files (RS) of **400 patients** who underwent radiation therapy after breast-conserving surgery were obtained as pairs under IRB approval. Each 3D segmentation map (target) was generated based on contours of **breast tumor** and three OARs which are **left lung, right lung, and heart**, acquired from RS reviewed by four radiation oncologists independently.

(2) Deep Learning model (Fig. 2)

A published 3D Convolutional Neural Network architecture (SCNAS-Net) optimized by Scalable Neural Architecture Search (SCNAS) [6] was implemented for this work.

(3) Evaluation

Dice coefficients (DICE) between output from the trained SCNAS-Net and target were calculated to evaluate the segmentation performance.

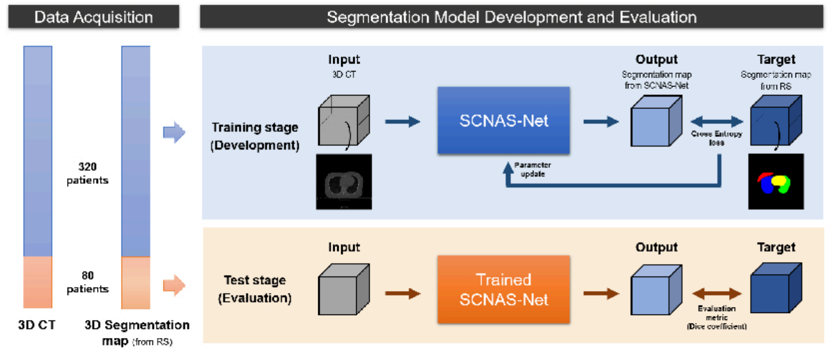

Figure 1. A schematic diagram of the novel segmentation model development and evaluation procedure

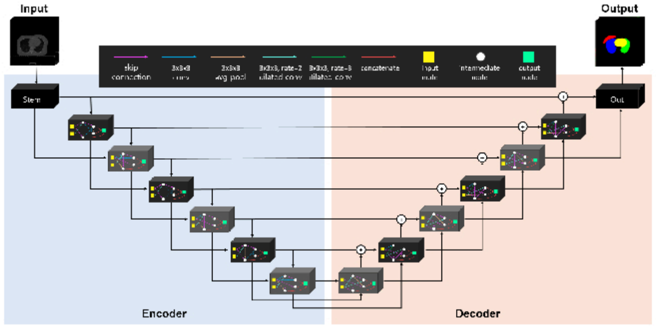

Figure 2. Overall architecture of SCNAS-Net

CONCLUSIONS

A novel **tumor and multi-organ segmentation technique in CT** was successfully developed. It could significantly reduce the time for the manual contouring of tumor and OARs, which is one of key steps in radiation therapy planning. This study indicates the potential for application of the proposed SCNAS-Net in real clinic as auto-segmentation system in the near future.

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RESULTS

- The trained SCNAS-Net showed **superior segmentation performance** for all regions. (Table 1)
- Especially for the breast tumor, despite **the difficulty of segmentation** due to the various shape, volume and location of the breast compared to other organs, DICE for breast tumor was significantly high.

Table 1. Evaluation of the segmentation performance of the trained SCNAS-Net

	Breast Tumor	Left Lung	Right Lung	Heart
DICE	0.8327	0.9771	0.981	0.9351

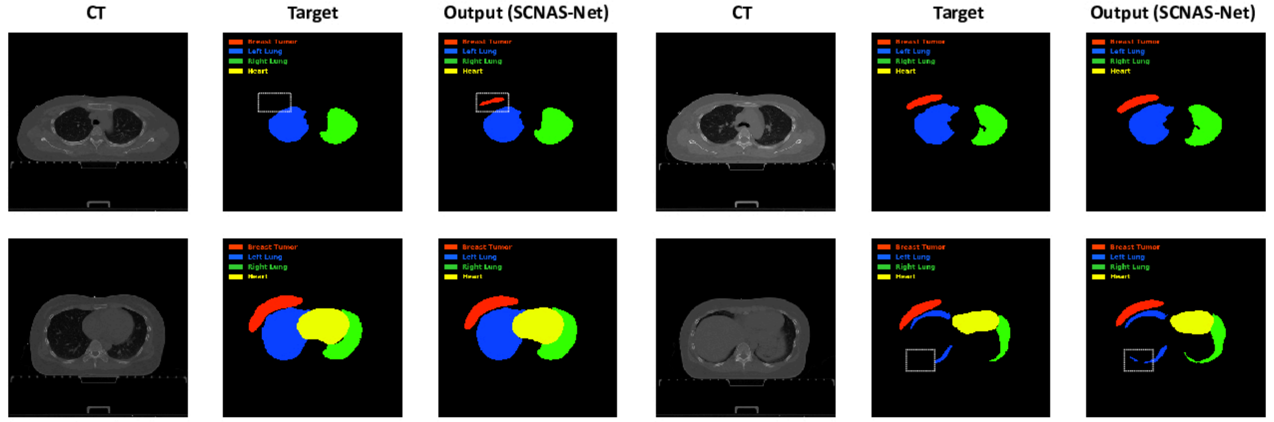

Figure 3. Segmentation results obtained from the trained SCNAS-Net (Patient #1)

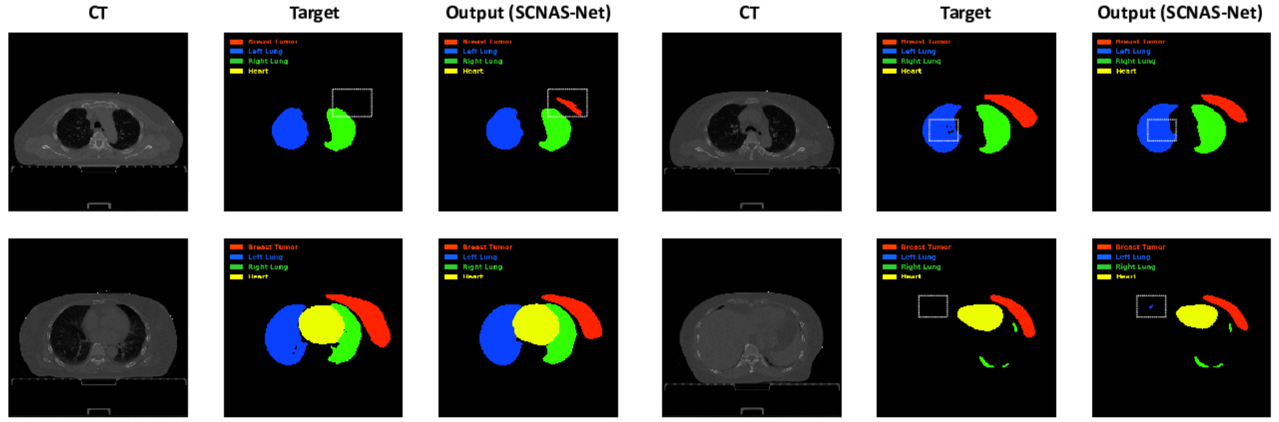

Figure 4. Segmentation results obtained from the trained SCNAS-Net (Patient #2)

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