CT-based convolutional-neural-network segmentation of HCC regions with lung-cancer-based transfer learning

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INTRODUCTION

According to the guideline for modified response evaluation criteria in solid tumors assessment for hepatocellular carcinoma (HCC), the one of important factors in decision making of HCC treatment strategies is the longest viable tumor diameter, which should be correctly and automatically measured on contrast-enhanced arterial phase computed tomography (CT) images to reduce inter- and intra-observer variabilities. Convolutional-neural-network (CNN) with lung cancer CT image-based transfer learning may be promising for segmentation of HCC regions due to the larger number of lung cancer patients than that of HCC patients.

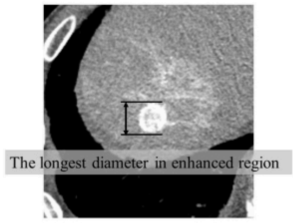


Fig.1 Measurement of longest viable tumor diameter in CT images according to mRECIST for HCC.

We investigate CT-based CNN segmentation of HCC regions with transfer learning based on lung cancer data.

MATERIALS AND METHODS

A deep learning architecture : a tensor-flow-based open-source CNNs (**NiftyNet**) for researches in medical imaging.

The CNN model pre-trained lung cancer CT images was retrained as an HCC-CNN segmentation model to segment HCC regions using CT images in training datasets.

We compare the proposed HCC-CNN segmentation model and the HCC-CNN segmentation model without pre-training for lung cancer.

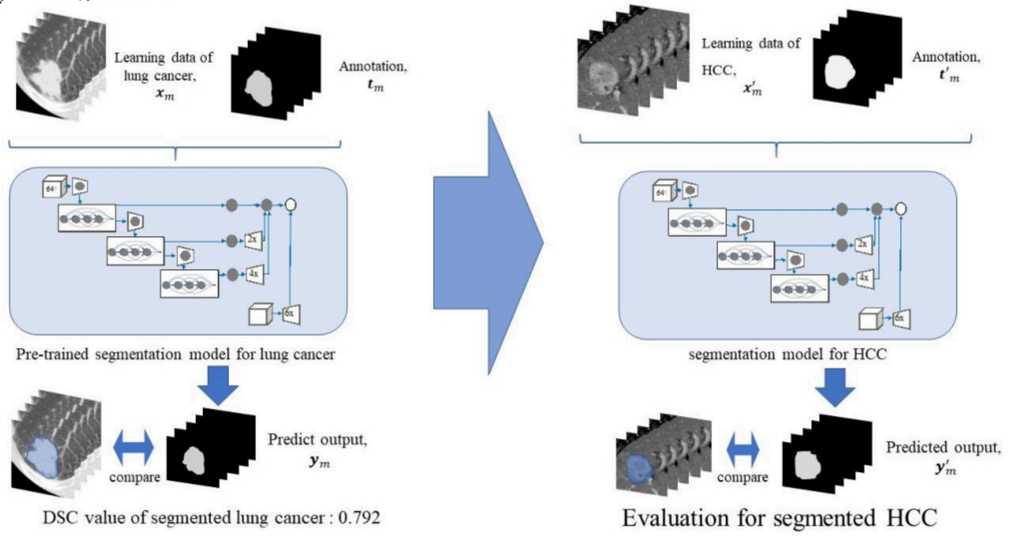


Fig.2 Overall scheme of transfer learning

An average Dice's similarity coefficient (DSC)* and Hausdorff distance (HD)** were employed for evaluation of the segmentation accuracy based on a 5-fold cross-validation test.

*DSC : Degree of region similarity between HCC regions annotated by a radiologist and the regions estimated with the proposed segmentation model.

**HD : Distance that measures how far two subsets of a metric space are from each other.

RESULTS

Figures 3 and 4 indicate the optimization of learning rate and dropout rate for the proposed HCC-CNN segmentation model and the HCC-CNN segmentation model without pre-training for lung cancer using Dice similarity coefficient (DSC) and Hausdorff distance (HD). The average DSC was 0.792 ± 0.06 (0.64 - 0.90) with the optimum learning and dropout rates. Similarity, the average HD was 2.42 ± 1.14 (0.75 – 6.36) mm with the optimum learning and dropout rates. The optimum learning and dropout rates were determined as 1×10^{-3} and 0.80 from Figures 3 and 4, respectively, because the highest DSC and the lowest HD were obtained at the hyperparameters.

Figures 5 (a) and (b) show DSCs and HDs between the proposed HCC-CNN segmented regions and the HCC-CNN without pre-training segmented regions. The average DSC of 0.792 ± 0.06 for the proposed HCC-CNN segmented regions was larger than that of 0.714 ± 0.10 for the HCC-CNN without pre-training segmented regions ($p < 0.05$, Welch's t test). The HD of 2.42 ± 1.14 mm for the proposed HCC-CNN segmented regions was smaller than that of 3.28 ± 2.20 mm for the HCC-CNN without pre-training segmented regions ($p < 0.05$, Welch's t test).

Figure 6 illustrates segmentation results for 3 cases with HCC regions annotated by a radiologist (white line) and the regions estimated by the proposed approach (green line).

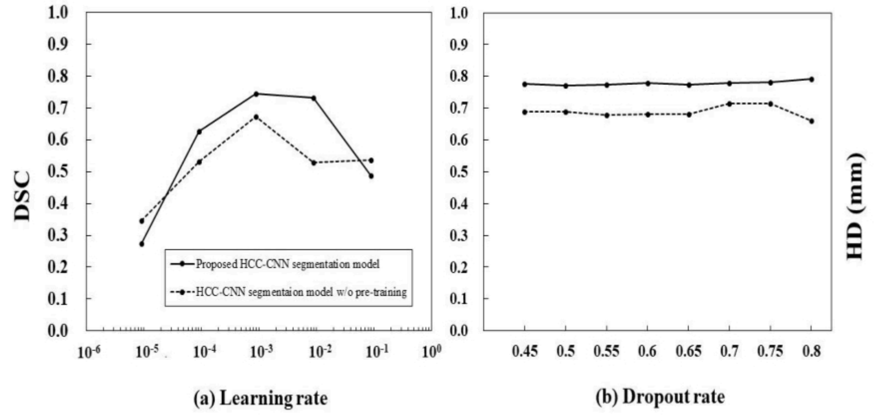


Fig.3 Illustrations of optimization of (a) learning rate and (b) dropout rate using DSC

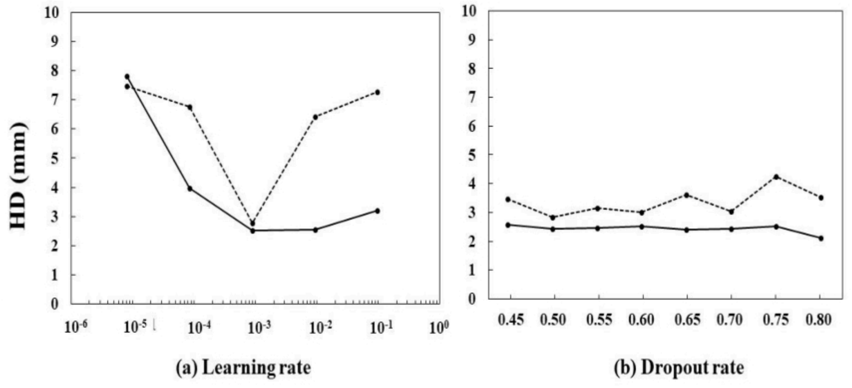
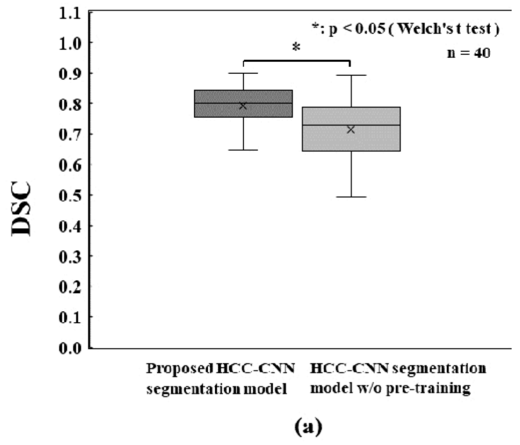


Fig.4 Illustrations of optimization of (a) learning rate and (b) dropout rate using HD



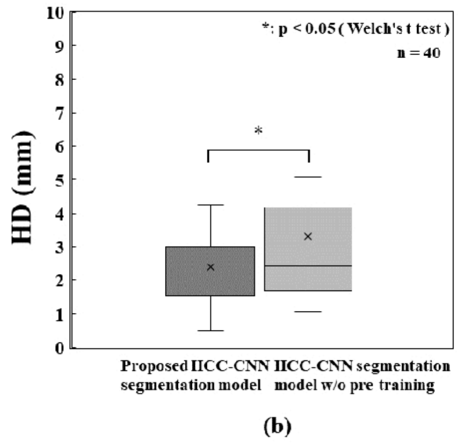


Fig.5 DSCs (a) and HDs (b) between the proposed segmentation model and the model without pre-training. Upper horizontal line of box, 75th percentile lower horizontal line of box, 25th percentile horizontal bar within box, median cross mark, mean upper horizontal bar outside box, maximum lower horizontal bar outside box, minimum.

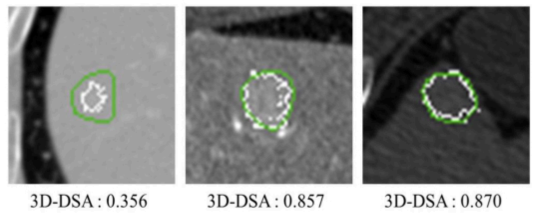


Fig.6 Segmentation results for 3 cases. White line shows HCC regions annotated by a radiologist and green line shows the regions estimated by the proposed method. 3D-DSCs are shown in these CT images.

CONCLUSIONS

The proposed approach with lung-cancer-based transfer learning showed the potential to automatically delineate the HCC regions on CT images.

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