



# Cascaded Dilated Deep Residual Network for Volumetric Liver Segmentation From CT Image

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## ABSTRACT

Volumetric liver segmentation is a prerequisite for liver transplantation and radiation therapy planning. In this paper, dilated deep residual network (DDRN) has been proposed for automatic segmentation of liver from CT images. The combination of three parallel DDRN is cascaded with fourth DDRN in order to get final result. The volumetric CT data of 40 subjects belongs to “Combined Healthy Abdominal Organ Segmentation” (CHAOS) challenge 2019 is utilized to evaluate the proposed method. Input image converted into three images using windowing ranges and fed to three DDRN. The output of three DDRN along with original image fed to the fourth DDRN as an input. The output of cascaded network is compared with the three parallel DDRN individually. Obtained results were quantitatively evaluated with various evaluation parameters. The results were submitted to online evaluation system, and achieved average dice coefficient is  $0.93 \pm 0.02$ ; average symmetric surface distance (ASSD) is  $4.89 \pm 0.91$ . In conclusion, obtained results are prominent and consistent.

## KEYWORDS

Computed Tomography, Convolutional Neural Network, Dilated Deep Residual Network, Dilation, Dilation Convolution Filter, Semantic Segmentation, Windowing

## INTRODUCTION

The liver is the largest internal organ in human body, which is situated right side of the abdominal region. This organ performs the second-largest number of functions, such as detoxification of chemicals, drug metabolism and bile secretion (Glenisson et al., 2014; Thapa & Walia, 2007). According to WHO, about 46% of global diseases, 59% of the mortality is because of chronic liver diseases (WHO, 2012). Liver diseases are major medical problems and mortality reached 216,865 or 2.44% of the total deaths in India (Asrani, Devvarbhavi, Eaton, & Kamath, 2019).

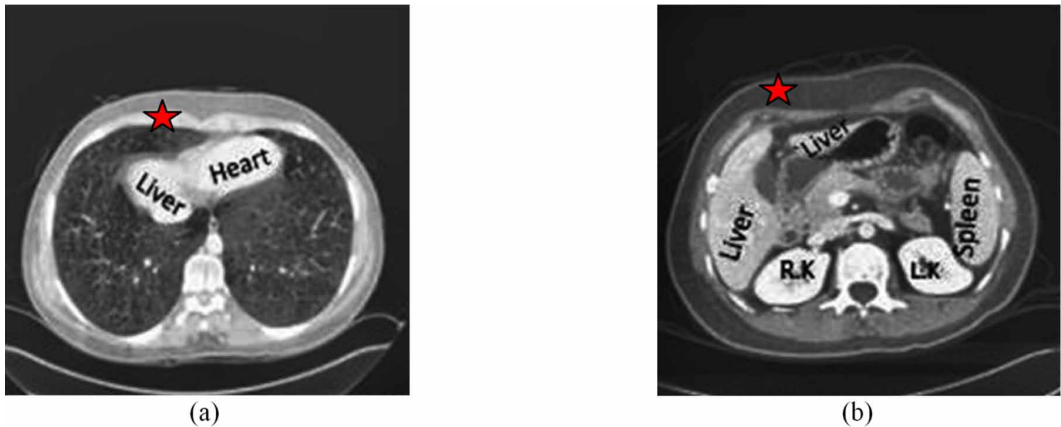
The most commonly Computed Tomography (CT), Ultrasonography (US), Magnetic resonance imaging (MRI) are used for early prognosis and analysis of anatomical abnormality. CT has often

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avored modality for the identification of different cancers because it provides high contrast, high-resolution and image acquisition is faster compared to other medical imaging modalities (Beutel, Kundel, & Van Metter, 2000). Liver segmentation helps the oncologist to measure the volume of the liver from 3D medical images in radiation dose planning. Liver volume estimation is the most difficult and challenging task among researchers. Since liver and its neighboring organs have approximately similar gray level intensity so it is difficult to delineate the liver boundary precisely (Figure 1 (a)) and liver divided into two parts (Figure 1 (b)).

**Figure 1. Example of liver segmentation challenges (Axial View of 3D CT Scan) (a) Liver and heart intensity homogeneity highlighted by star (b) Liver divided into two parts highlighted by star**



Windowing is one of the contrast enhancement methods which perform gray level slicing to each pixel in an image. A medical expert has to set the window settings to observe pathology within an image. Each window shows a different appearance in terms of varying contrast. Windowing is a subjective matter which changes from person to person. Therefore same idea is used while training the network architecture for different windows and its aggregation. Literature shows a single-window used for training the deep learning model, which has limited learning capability. Different windowing represents an image at various gray-level quantization and dilation convolution enhance learning capability at various spatial resolution of an input image. The proposed method is an amalgam of dilation convolution and windowing method along with a unique network connection.

Convolutional neural network (CNN) is a combination of various building blocks such as convolutional layer, pooling layer and fully connected layer (Li, Jia, & Hu, 2015). The CNN becomes dominant in semantic segmentation for medical image analysis. Residual network (Res-Net) is one of variants of CNN. It helps to increase the depth of network along with learnable parameters without increasing the computational complexity. Dilation convolution extract features correspond to adjacent neighbor pixels and interval neighbor pixels as per the dilation rate.

In this paper, we are proposing a Cascaded DDRN for the automatic segmentation of liver. Three similar DDRN are connected in parallel and trained separately for different windows. The outputs of three DDRN combined with original image and feeds through the fourth cascaded DDRN. All DDRN have same architecture and learnable parameters. The proposed method achieved better performance while comparing it with evaluation parameters. This novel cascading technique is able to remove false-positive results from predicted maps and achieved substantial Average Symmetric Surface Distance (ASSD), Hausdorff Distance 95 (HD 95) evaluation values.

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