

# Chapter 41

## M2UNet++: A Modified Multi-Scale UNet++ Architecture for Automatic Liver Segmentation From Computed Tomography Images

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### ABSTRACT

*Liver segmentation is instrumental for decision making in the medical realm for the diagnosis and treatment planning of hepatic diseases. However, the manual segmentation of the hundreds of CT images is tedious for medical experts. Thus, it hampers the segmentation accuracy and is reliant on opinion of the operator. This chapter presents the deep learning-based modified multi-scale UNet++ (M2UNet++) approach for automatic liver segmentation. The multi-scale features were modified channel-wise using adaptive feature recalibration to improve the representation of the high-level semantic information of the skip pathways and improved the segmentation performance with fewer computational overheads. The experimental results proved the model's efficacy on the publicly available 3DIRCADb dataset, which offers significant complexity and variations. The model's dice coefficient value is 97.28% that is 7.64%, and 2.24% improved from the UNet and UNet++ model. The quantitative result analysis shows that the M2UNet++ model outperforms the state-of-the-art methods proposed for liver segmentation.*

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## INTRODUCTION

Healthcare is one of the high-priority sectors where people presume the utmost care and services. In the healthcare sector, due to technological advancement, disease diagnosis and clinical procedures have become technology-driven. In diagnostic radiology, medical imaging is the fundamental tool for the analysis and interpretation of diseases using medical images. Medical imaging is the non-invasive technique to visualize the body organs and tissues' internal anatomy, which allows the medical expert to diagnose the disease, decide the treatment planning, and post-treatment assessment (Razzak et al., 2018). The radiological images are acquired using acquisition devices that produce digital images of internal body parts and tissues in different imaging modalities. The commonly exploited image modalities are X-ray, Ultrasound, Computed Tomography (CT), Magnetic Resonance Imaging (MRI) by medical experts. Recently, medical data became more prominent due to advanced medical image acquisition devices capturing high-resolution radio images with many slices per scan to represent the internal structure in 3D that increases volume and storage requirements of the medial images (Hesamian et al., 2019). However, the analysis and interpretation of the large volume of medical images are challenging for the medical experts to reach the correct decision in less time. In making the process automated through computer vision algorithms, many researchers developed interactive and automatic methods for analyzing and interpreting medical images that enable the medical experts to reach the correct decision faster.

## BACKGROUND

The liver is one of the highly critical and largest human body organs. It accomplishes the major functionality of detoxification and supplying fluids to the body parts. Automatic liver segmentation has been decisive in medical explication and therapy framing for hepatic complications such as liver transplantation, hepatectomy, treatment of the liver tumor for the targeted therapies (radioembolization), post-treatment assessment, and also beneficial for the progress of the computer-aided diagnosis (CAD) framework for hepatic disease diagnosis (Bilic et al., 2019) (Moghbel et al., 2018). In clinical routine, the radiologist or physician delineate the liver manually slice by slice manner. However, the liver's manual outline is time-consuming and tedious because the availability of the abundant medical data volume that leads the segmentation depends on the expert because of its inconsistency, human limitations, and intricacy of the data. Because of these reasons, investigators in the domain focusing on the separation of the liver automatically. For hepatic diseases, CT images are widely used for clinical diagnosis due to their sturdiness, broad accessibility, speedy capturing procedure, and superior resolution (Gotra et al., 2017) (Domingues et al., 2020). In literature, to foster the medical field's demand, several frameworks are proposed for the automatic liver segmentation from CT volume without human intervention that becomes the second opinion for the medical experts to make the correct decision in less time. However, it remains challenging due to liver size variation, fuzzy liver boundaries, and Intensity similarity between the liver and adjacent organs. The liver is a delicate tissue, and its structure is extremely reliant on its adjacent organs. Typically, liver images are obtained by injecting a contrast agent to improve the liver area in CT images while capturing. However, acquiring CT images is a noisy process without contrast enhancement. The contrast enhancement further introduces noise in the CT scan images, and its injection phase decides the amount of noise in the acquired CT images (Moghbel et al., 2018). Because of the above complications, it remains a challenging task.

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