Segmentation of Liver Tumor in Computed Tomography Scan

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Segmentation of images is a common task within medical image analysis and a necessary component of medical image segmentation. The segmentation of the liver and liver tumors is an important but challenging stage in screening and diagnosing liver diseases. Many automated techniques have been developed for liver and tumor segmentation; however, segmentation of the liver is still challenging due to the fuzzy & complex background of the liver position with other organs. As a result, creating a considerable automated liver and tumour division from computed tomography (CT) scans is critical for identifying liver cancer.

Keywords: liver segmentation ; ResU-Net ; medical imaging ; tumor detection

1. Introduction

Malignant liver neoplasm is one of the most common types of human cancer and is responsible for the high death rate due to its late diagnosis. Liver disease had the sixth-highest occurrence of all cancers, and the fourth-highest mortality rate in the world, with around 841,000 new cases at a rate of 93 cases per million people and about 782,000 deaths at a rate of 85 cases per million people in 2020 [1]. As tumors can be detected in medical images, the focus of recent research has been shifted towards the segmentation of liver and tumor. It is evident from the fact that the number of studies based on segmentation of liver and tumor has doubled recently [2]. Although the windowed Hounsfield unit values may provide a range of values for the marking of different regions in medical images, identifying voxels that portray liver and lesion regions is challenging due to the low contrast between the liver and the neighbouring organs [3]. Owing to the different sizes, form, and locations of lesions, liver tumor segmentation becomes more complex and challenging in different patients [4]. Furthermore, the margins of some lesions are imprecise, such as hazy, making it hard to detect using edge-based segmentation algorithms. It warrants the need for an algorithm using artificial intelligence that may help medical physicians segment organs and malignancies. In addition, computed tomography (CT) has become one of the most commonly used imaging technologies for identifying and detecting liver tumors because of its excellent spatial precision and speedy laser power. In typical clinical operations, segmentation can be done manually by operators with sufficient competence, but it is time-consuming, and results from different operators are sometimes inconsistent. As a result, developing an automatic segmentation method is extremely difficult, because of the variable forms of tumours, the vast range of tumor intensities, and the uncertainty of tumor and adjacent normal hepatic tissues borders. Over the last few years, semantic segmentation of CT images has become a hot topic of study. Deep learning has significantly enhanced artificial intelligence performance in recent years. In medical imaging, deep learning methods, especially fully convolutional neural network, have surpassed their competitors significantly. Herein, ResU-Net architecture for liver and liver tumor segmentation in CT Scan images has been implemented. The training and testing of the ResU-Net are conducted with selected image pre-processing techniques, Housnfiled windowing unit, histogram equalization and data augmentation methods.

2. Strategies to Separate Liver and Tumors

Over the past decade, researchers have used different machine learning strategies to separate liver and tumors. Li et al. [5] proposed an autonomous 3D liver segmentation approach that uses a total variation with the L1 norm (TV-L1) to detect an initial liver border, followed by a level set method that uses both local and global energy functions. A texture analysis method based on the grey level co-occurrence matrix (GLCM) is used for refined segmentation. Xu et al. [6] proposed a multi-atlas segmentation (MAS) based performance level estimation (SIMPLE) method for automatic segmentation of abdominal organs, including the liver. Song et al. [7] developed an adaptive FMM-based fully automatic liver segmentation algorithm. Self-adaptive parameter adjustment is used in the proposed adaptive FMM. In FMM, the arrival time is adjusted based on the intensity statistics of the potential liver region, which can be used to estimate the size of the liver region on the corresponding computed tomography (CT) slices. Maklad et al. [8] developed a semi-automated method for fragmenting the hepatic low-intensity tumor using CT images that utilized abdominal arterial channels in the entrance stage. Peng et al. [9] proposed a finite difference energy technique that incorporates brightness, region attractiveness, or surface smoothing.

Automatic and robust liver segmentation from CT volumes is challenging due to the low-intensity contrast between the liver and neighbouring organs. Deep neural networks are used extensively in present healthcare image segmentation frameworks [10][11].Tianfei Zhou et al. [12] introduced quality-aware memory network for interactive segmentation of 3D medical images. The memory-augmented network can quickly encode and retrieve segments from the past for segmentation of new slices. Elshaer et al. [13] used two trained deep CNN models to reduce the computational time of a large number of slices. After obtaining the liver segmentation with the first model, the second model was used to avoid the impact of image resampling by removing small missing lesions. Chen Li et al. [14] employed a convolutional neural network (CNN) that used image patches. Each pixel is considered as a patch of the image, with the pixel of interest at its center. It divides the patches into normal or tumor liver tissues. The patch is considered positive if it contains at least 50 percent or more tumor tissue. Hu et al. [15] merged a 2D DenseNet network that combined the extracted intra-slice features and the 3D counterpart for hierarchically aggregating volumetric contexts for liver and lesion segmentation. The liver tumour was segmented by Li et al. [16] using a cascading architecture in which soft and harsh focus techniques and long or short skip linkages were integrated. False positives were reduced by using a joint dice loss function. Jiang et al. [17] developed an edge system by incorporating spatial stream convolution into the U-Net network's modules. Furthermore, current liver segment techniques are designed for segmenting diagnostic CT pictures and may not even be suitable for segmenting interventional CT images. In addition, CT scans frequently show low gentle brightness, roughness, and other abnormalities. Current tumor segmentation approaches have had mixed results in resolving these challenging problems. As a result, U-Net was used by Chen et al. [18] in conjunction with a recurrent neural block [19] to resolve the limitation of the state-of-the-art models and schemes. The U-Net will use the recurrent neural network to gain relevant data about the hepatic area, aiding in improved liver and hepatic segmentation methods. Hao Xiong et al. [20] implemented probabilistic graphical model for segmentation for fundus images and obtained accuracy of 0.99. Karthik et al. [21] implemented a Fully Convolutional Network (FCN) to better segment the brain MRI having a varying size and shape ischemic lesion and obtained the dice similarity coefficient (DSC) score of 0.75. Manjunath et al. [22] implemented modified ResU-Net to segment livers and their tumors. The modified system obtained 96.35% DSC and 89.28% accuracy 99.71% and 99.72% for liver and tumour segmentation. Javaria Amin et al. [23] generated synthetic images utilizing a generative adversarial network (GAN). YOLOv3 detector and Resnet block localize the liver in the synthesized images. Moreover, DeeplabV3+ having Inceptionresnetv2 model as a base is implemented for better liver segmentation. Qiangguo Jin et al. [24] implemented a novel network called residual attention-aware U-Net (RA-U-Net) to segment 3D images of liver 3DIRCADb dataset. Moreover, Yodit Abebe Ayalew et al. [25] implemented U-Net to segment liver and liver tumor and obtained a DSC value of 0.96 and 0.74. Sultan Almotairi et al. [26] applied a semantic pixel-wise classification network called SegNet for tumor classification of the liver. The implemented network obtained an accuracy of 99.9% for liver tumor. The liver is an essential organ in the abdominal area, and overlapping the tumor region on the liver may cause trouble automatically segmenting the liver. Some surrounding tissues may also cause boundary problems for the automated liver segmentation task. The residual block in the segmentation model would provide efficient backpropagation gradient capability to train the deep learning model well and produce efficient segmentation results.

However, due to the heterogeneity and variation in shapes of the liver and its potential tumors, segmenting CT images remains challenging, and many efforts have been made to address it.

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