CT Guided Diagnosis: Cascaded U-Net for 3D Segmentation of Liver and Tumor

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Abstract. Volumetric estimation of the liver tumor is the first step to identifying the liver's critical disorder. The liver and its tumor ratio prerequisite measures to select the therapeutic procedure. 3D printing and virtual reality platform require a segmented liver entity mask to evaluate the pre and post-treatment analysis. A cascaded U-Net model is proposed for automatic segmentation of liver and tumor in CT images. LiTS CT data set utilized for this study. The images were pre-processed using the windowing technique for contrast enhancement. Two U-Net models were modified for liver and tumor segmentation, respectively and connected in a cascaded manner. U-Net decoder end was modified in comparison to the original U-Net. The probability map of the first U-Net fed to the second U-Net and the input image to segment out the liver tumor. Eight subject volumetric CT datasets were utilized to test the cascaded U-Net performance and achieved average Dice coefficient for liver and tumor 0.95 and 0.69, respectively. Liver tumor diagnosis and treatment accuracy depend upon the precision of segmentation algorithms. Designed model segmented liver almost accurately and tumor segmented with limited accuracy. A further modification is required for the tumor segmentation cause of the occurrence of false negative.

1. Introduction

The liver is situated below the thorax and above the pelvic region. The liver is the largest internal organ in humans and performs ample body functions [1]. Liver cancer is one of the life threatening diseases among other kinds of abnormality. Liver primary cancer is initiated at the liver site and liver secondary cancer recived by other organs, also known as metastasis. The liver is the first suspect organ to confirm the metastasis stage of cancer. Liver cancer incidence increases and its is the fifth most cause of mortality worldwide [2], [3].

Liver and tumor segmentation from CT image is the first step for liver cancer diagnosis and therapeutic procedures. Liver and tumor segmentation is performed manually by medical experts for precise radiation therapy procedures, which is time-consuming and tedious. Liver tumor morphology, contrast, and location variability make segmentation challenging (Figure 1). This article's main objective is to devise a model for automatic segmentation of liver and tumor from abdominal CT
images. These models reduced medical experts' workload and are treated as the second opinion for the segmentation results.

![Liver and Tumor Segmentation Images](image)

**Figure 1.** Heterogeneity in liver and tumor; shape, size, intensity profile (a) Raw Image, (b) Ground Truth [Gray: Liver; White: Tumour], (c) 3D Display [Red: Liver; Green: Tumour], (d) 3D Tumour [Green Tumour]

Many methods have been proposed for the segmentation of the liver and tumor. The segmentation technique is classified into two types first, semiautomatic segmentation and fully automatic segmentation methods [4]. Semiautomatic segmentation is mainly used in medical practice because results can be modified at any stage and need user interaction. Still, the fully automatic segmentation method not in practice because of less accuracy, and results are varied with respect to the source of data. Data drift still a challenging problem to get precise segmentation, mainly in medical image applications.

Various automatic segmentation technique studies like atlas-based, deformable model approach, but these techniques depend upon parameter optimization, which is rigid with respect to data and patient-specific [5], [6]. Fully automatic liver and tumor volume estimation is highly demanded and developed algorithm will be appreciated by medical experts if it will be error-free, more precise, and consistent. The research attempts to address the challenge of liver and tumor segmentation using graph cut[7],[8] statistical shape model[9], deformable model, level set technique, and machine learning [10], still limited by the generalizing capability of these approaches remains accepted for the healthy liver segmentation.

In the last decade, deep learning-based techniques have shown promising results for semantic segmentation of medical images. However, deep learning-based models have further classified a fully convolution network (FCN) most preferable model because of input and output as an image. FCN models overcome the limitation of machine learning techniques such as handcrafted feature extraction.
and selection of appropriate classification [11], [12]. In this article, the FCN model U-Net architecture is modified and connected in cascaded order for automatic segmentation of liver and tumor.

2. Materials and methods

2.1 Data sets

The Liver Tumor Segmentation (LiTS) Benchmark was utilized for this experiment. This data contains 201 volumetric abdominal CT of hyper and hypo contrast levels. This data is carrying ground truth for the liver and its tumor of 131 subjects. Image resolution ranges from 0.56 mm to 1.00 mm in axial and 0.45 mm to 6.0 mm in the Z-direction. The number of Z direction slices ranges from 42 to 1026 [13].

2.2 Methodology

The first input image is preprocess using window clipping [-100, 400], then fed to the model. The presented model was based on Cascaded U-Net, which was found to be optimal for segmentation. This model contains two U-Nets in a 'cascaded' order; one U-Net's output serves as the input for the second U-Net. The first U-Net input is the raw input data, and it produces a result as a probability map belongs to liver pixels. The probability map received from the first U-Net and original image serves as the second U-Net input. The second U-net's essential purpose is segmenting liver and tumor from a given input (Figure 2).

![Figure 2 Block diagram of the proposed methodology](image)

2.3 Network Architecture

The U-net architecture is synonymous with encoder-decoder architecture. The proposed architecture differs from the U-net architecture proposed by Ronneberger et al. [14]. We modified the decoder portion of architecture with unique upsampling feature sequences. In the original U-net, up-convolution was done with half a number of features in the previous layer, whereas in the proposed architecture, the numbers of features are kept the same as in the last layer. Due to this, the loss of information during up-convolution is prevented. The difference can be visualized in Figure 3. After up-convolution, features are concatenated with features from the corresponding layer in the encoder.

![Figure 3. Proposed modified U-Net for automatic liver and tumor segmentation](image)
Modified U-Net architectures are trained using a stochastic gradient descent optimizer. Categorical cross-entropy as loss function trained with learning rate 0.001 for the 40 epochs.

3. Results
Volumetric CT of 130 subjects data from LiTS Challenge data was used for this study. Training model results tested on eight subjects' data sets. The results quantify evaluated using DICE evaluation and methodology achieved average DICE 0.95 and 0.65 for liver and tumor. Qualitative results are demonstrated in Figure 4, which shows that liver and tumor segmented accurately (liver in yellow color and tumor is in red). We have considered the image slice where the liver shape has a concave boundary and multiple tumor regions in the same image. At the liver's concave boundary region, mostly algorithms fail to segment liver accurately; however, cascaded modified U-Net can segment the liver with the concave boundary. This method produces some false-negative results for the tumor segmentation (marked by the indigo square box) within the center tumor shown in Figure 4 (c).

![Figure 4. Test results of Cascaded Modified U-Net (a) Original Image (b) Ground Truth Image (c) Predicted Image](image)

The result of Cascaded modified U-Net compares with the exiting model with respect to DICE coefficient (Table 1). H-Dense U-Net performance is better among the existing model for segmentation of liver and tumor. The proposed model achieved an average Dice of 0.95 and 0.69 for liver and tumor segmentation. Cascaded modified U-Net needs to investigate for the segmentation of liver tumor because only 0.69 dice were achieved.

| Method              | Liver Dice | Tumor Dice |
|---------------------|------------|------------|
| ResNet [15]         | 0.95       | 0.49       |
| H-DenseUNet [16]    | 0.98       | 0.94       |
| nnU-Net [17]        | 0.95       | 0.73       |
| DeepX [18]          | 0.96       | 0.82       |
| Cascaded ResNet [15]| 0.95       | 0.50       |
| Proposed            | **0.95**   | **0.69**   |

4. Conclusion
In this method, cascaded modified U-Net has proposed to segment liver and tumor from CT image automatically. The cascaded model can segment the liver precisely with the dice coefficient of 0.96. Proposed U-Net architecture has class in balancing problem, so two U-Net models connected in a cascaded manner. Further investigation is required for automatic segmentation of liver tumor cause of
limited accuracy achieved. The ratio of tumor class to non-tumor class is less within the image, so class in balancing problem affects tumor segmentation results’ accuracy. Accurate segmentation of liver tumors is a high need in clinical practice. In the future, architecture may changes with different connectivity for better results.

5. References

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