Automatic liver segmentation in computed tomography scans using deep semantic segmentation

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Article Info

Article history:
Received Apr 30, 2022
Revised Aug 12, 2022
Accepted Sep 4, 2022

Keywords:
Computed tomography images
Convolution neural network
Deep learning
Liver
Segmentation

ABSTRACT

Division of the liver from figured computed tomography (CT) images is fundamental for the greater part of the PC supported clinical applications, for instance, the arranging period of a liver transfer, liver volume assessment, and radiotherapy. In this paper, a programmed liver location model from clinical CT filters utilizing profound semantic division convolutional neural organization will be introduced, this model will actually want to subsequently isolate the liver utilizing CT images. The proposed model presents simultaneously the liver ID and the probabilistic division utilizing a profound convolutional neural organization. The proposed approach was endorsed on 10 CT volumes taken from open data sets 3Dircadb1. The proposed model is totally programmed with no requirement for client mediation. Quantitative results show that proposed model is reliable and exact for hepatic volume assessment in a clinical course of action with testing exactness 98.8%.

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1. INTRODUCTION

Medical professionals may develop accurate illness evaluations and treatment strategies with the use of precise liver segmentation from computed tomography (CT) or magnetic resonance imaging (MRI) images. Automatic liver segmentation techniques are thus substantially necessary in the clinical. However, automated segmentation of the liver from various types of medical imaging continues to be difficult because of the low contrast of soft tissue, the variable look of the liver, and its indistinct borders. The challenge for automated segmentation algorithms will be exacerbated by the fact that for many scans, the voxel space next to the z-axis vector spans from 0.4 mm to 6.5 mm [1]. Additionally, a frequent injection technique used by radiologists to enhance CT or MRI images to better see malignancies up close. Further liver damage and other artefacts may result from this [2].

Human health and lives are seriously threatened by liver diseases. According to statistics, liver cancer is the second most prevalent cause of cancer-related death in males and the sixth most important cause in women. Indeed, in 2008, about 696,000 people worldwide lost their lives to liver cancer and almost 750,000 people had the disease officially diagnosed [3]. CT with contrast enhancement is now routinely used to diagnose liver disease and plan surgical procedures. A few computer-assisted medical operations, such as surgical treatment planning for a liver transplant from a living donor, radiation, and quantity measurement, all need the segmentation of the liver from a CT scan. The standard medical procedure for the liver delineation remains to be guidance delineation on each slice by specialists. Guide segmentation takes time,
subjective, and is not very repeatable. Expanding computerised methods is therefore essential to improve and ease prediction, treatment planning, and monitoring.

Due to the poor contrast between the liver and other surrounding organs, automatic liver segmentation from contrast-enhanced CT volume is a highly challenging process. Radiologists also frequently add an injection procedure to the CT image in order to clearly see the tumour. The liver area's imaging noise may rise as a result [4]. Automated segmentation techniques have extra difficulties since a lot of CT images have anisotropic dimensions with significant fluctuations along the Z axis (voxel spacing spans from 0.45 mm to 6.0 mm). Many segmentation techniques, including deformable models, region expansion, and strength thresholds, have been proposed to overcome these problems. However, these techniques rely on handcrafted characteristics and can only partially convey the features. Fully convolutional neural networks (FCNs) have recently achieved excellent results in a variety of cognitive difficulties [5], [6]. The literature may be generally separated into two groups since many researchers are advocating this collection of deep learning algorithms for issues with liver and tumour segmentation i) 2DFCN, including the UNet architecture [7], multi-channel FCN [8], and FCN built on VGG16 [9] and ii) 3D FCN [10], where 3D convolution with volume data input has been used in place of 2D convolution.

To address these issues of programmed liver segmentation from 3D studies, other research has been offered, including diagram cut procedures, deformable models, level-set, and chart book approaches. The majority of these tactics are appropriate for the physical highlight former footing class. However, as the precise liver component extraction process is difficult to demonstrate, these methodologies are not often used for low complexity real centre information. Recent research has shown that convolutional neural network (CNN)-based techniques are extremely strong to image appearance variability, which has prompted fresh interest in segmentation problems [11].

A planned liver tumour segmentation method in CT stomach area images was suggested by Lu et al. [12] using cascaded FCNs and thick 3D dependent irregular fields (CRFs). They first developed an FCN to fragment the liver as a contribution to the second FCN’s return on investment (ROI). Only damage from the projected stage 1 liver ROIs is segmented by the second FCN. The segmentation results were then improved using a thick 3D CRF that depicts both spatial rationality and appearance. The liver segmentation findings were produced by Peng et al. [13] using a deep image to-image to organise (DI2IN) procedure. Convolutional encoder-decoder technology was combined with staggered include connectivity, intense supervision, and convolutional encoding. The segmentation findings are then presented in a more elevated manner as a result of the preparation operations, which included the usage of an unfavourable method to separate the yield of DI2IN from the ground truth.

To tackle the challenge of liver segmentation, Dou et al. [14] created a 3D profoundly controlled system (3D deeply supervised network (also known as DSN)). They provided a significant supervision component during the learning process to overcome probable enhancement obstacles, assisting the model in achieving a faster intermingling rate and exceptional separation capacity. They further improved the segmentation results by using a dependent irregular field model. All of the aforementioned tactics made use of FCNs using varied systems. However, they don't take into account 3D logical data and instead focus on individual 2D cuts. There are now two major groups of methods often used for programmed liver segmentation: methods that are hostile to learning-based strategies and methods that are learning-based. The earlier version includes diagram cutting [15] and area growing [16]. In order to suggest neighborhood-associated area development for programmed 3D liver segmentation, Ruskó et al. [17] connected the neighbourhood around the voxel. Level set approaches are appealing in liver segmentation because they have the ability to capture objects with complicated form and regulate shape regularity.

In order to cons-truct liver boundaries that have the same amount of variability as those obtained manually, particularly for some challenging clinical instances, Peng et al. [18] proposed a shape-power early level set model. The expansion of the illustrative chart cut provided, graph cut-based approaches are widely used in liver segmentation. In order to identify the liver, Linguraru et al. [19] used a non-exclusive affine invariant shape parameterization approach with a geodesic dynamic form, followed by graph-cut liver tumour segmentation. By using statistical shape models (SSMs), ASMs first construct an earlier state of the liver and then coordinate it with the objective image. A probabilistic active shape model was put out by Heimann et al. [20] that incorporated boundary, location, and shape data into a single level set equation. For the segmentation of the liver, Erdt et al. [21] presented a multitiered factual shape model. Recently, Wang et al. [22] used the insufficient shape arrangement (SSC) to create a robust form earlier for the liver in order to segment the liver, portal veins, hepatic veins, and malignancies precisely all at once.

2. METHOD

As shown in Figure 1, the proposed architecture consists of three phases the first phase is the
preprocessing phase based on data augmentation techniques, then dividing the dataset so that 80% is used for

Automatic liver segmentation in computed tomography scans using deep semantic … (Kadry Ali Ezzat)
training and 20% is used for testing. The second step is the deep CNN training phase, and the third phase is the testing of the trained model.

![Proposed architecture for semantic segmentation model](image)

**Figure 1. Proposed architecture for semantic segmentation model**

### 2.1. Preprocessing phase

The preprocessing phase is based on the augmentation process. To avoid and overcome overfitting, label-preserving transformations are applied to increase the images. The medical scanning process may face some kinds of transformation during the process, so data augmentation is used to help the model become more resilient and invariant. The rotation approach at various angles was used as the augmentation strategy in this study. In (1) and (2) are used to compute the image transformation using the rotation approach.

\[
a_2 = \cos(\phi) \times (a_1 - a_0) + \sin(\phi) \times (b_1 - b_0)
\]

\[
b_2 = -\sin(\phi) \times (a_1 - a_0) + \cos(\phi) \times (b_1 - b_0)
\]

Where the coordinates of a point \((a_1, b_1)\) in the augmented image become \((a_2, b_2)\) when rotated by an angle around \((a_0, b_0)\). The dataset now contains 9 times more images than it did before the chosen augmentation procedure was used. 8000 photos are included in the dataset, which is utilised for both training and testing. The suggested model will become more resilient for any form of rotation as a result, which will significantly increase the accuracy of CNN testing. Examples of various rotation angles for the images in the dataset are shown in Figure 2.

![Rotated images for a sample image in the dataset applying 30, 60… 270 angles](image)

**Figure 2. Rotated images for a sample image in the dataset applying 30, 60… 270 angles**

### 2.2. Semantic segmentation model

Deep CNN provide the foundation of the suggested semantic segmentation paradigm. It has ten convolutional layers, thirteen ReLU layers, four max-pooling layers, four de-convolution layers, one soft-max layer, and lastly a layer for pixel categorization. The model’s input layer is a 128*128-pixel medical image, followed by the layers stated above. The first and second convolutional layers each have 64 filters, the third
and fourth convolutional layers have 128 filters, the fifth and sixth layers have 256 filters, the seventh and eighth layers have 512 filters, and the ninth and tenth layers have 1,024 filters. All convolutional layers have windows that are 3 by 3 pixels in size. ReLU layer comes after each convolutional layer. Additionally, there is a max pool layer between every two convolutional layers that cuts the image size in half. The deconvolutional component consists of four deconvolutional layers, the first of which has 1,024 filters, the second of which has 512 filters, the third of which has 256 filters, and the fourth of which has 128 filters. The ReLU layer comes after each deconvolutional layer. The soft-max layer and the pixel categorization layer are the final two layers to be shown in the model. A visual depiction of the suggested model is shown in Figure 3.

Figure 3. Graphical representation for the semantic segmentation model

3. RESULTS AND DISCUSSION

Using a piece of software, the suggested paradigm was put into practise (MATLAB). The solution was used using NVIDIA Titan Xp GPUs, which have 3,840 NVIDIA CUDA cores and 12 GB of GDDR5X standard memory. On a machine with an intel Core i9 running at 2 GHz and 32 GB of RAM, all trials were conducted. The dataset includes 8,106 photos following the augmentation procedure, as was indicated in the part before. After the augmentation procedure, the dataset was split into two halves, the first section is for instruction, and the second section is for testing. Divided by two, it is 80% and 20%. based on the random data splitting approach, 80% for the training phase and 20% for the testing phase. While 1,622 photos were utilised in total during the testing phase, 6,484 images were used in total during the training phase. The suggested model's total testing accuracy, measured across the testing pictures, is 98.80%. The result of the suggested model for four distinct patients is shown in Figure 4. Where Figure 4(a) show the original image, Figure 4(b) show the ground truth of segmented liver, Figure 4(c) show the output segmented image of the proposed model over the original image, and Figure 4(d) show the difference image between the result segmented image and the ground truth image. It displays the initial image, the initial manual segmented image (the ground truth image), the resulted segmented image using the proposed model, and the difference between the resulted image and the ground truth image, which contains red pixels that reflect the incorrect segmented pixel images and is caused by a summation error for all testing images that is 1.20% error in all segmented output images. A selection of rotated medical photos were taken from the testing dataset to see how well the proposed model could find and segment the liver in each situation of rotation. This was done to assess the proposed model's robustness and resilience. Figure 5 shows test results for four patients with variously rotated angles and varying liver size, structure, and texture. Where Figure 5(a) show the original image, Figure 5(b) show the ground truth of segmented liver, Figure 5(c) show the output segmented image of the proposed model over the original image, and Figure 5(d) show the difference image between the result segmented image and the ground truth image. The outcome was rather intriguing, with an average mistake rate of 1.2% and the ability of the suggested model to properly identify the liver regardless of its position, size, or colour in the picture. Table 1 compares the testing accuracy of its results to those of comparable works.
Figure 2. Samples images for 4 different patients (a) the original image, (b) the ground truth of segmented liver, (c) the output segmented image of the proposed model over the original image, and (d) the difference image between the result segmented image and the ground truth image.

Figure 5. Samples of rotated images for 4 different patients (a) the original image, (b) the ground truth of segmented liver, (c) the output segmented image of the proposed model over the original image, and (d) the difference image between the result segmented image and the ground truth image.

Table 1. Comparison of this study against the related works according to the testing accuracy

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Year</th>
<th>Method</th>
<th>Network size</th>
<th>dataset</th>
<th>Compute resource</th>
<th>Training time</th>
<th>Testing acc (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chlebus et al. [23]</td>
<td>2017</td>
<td>Fully CNN in two dimensions with object-based post processing.</td>
<td>4 convolutional layers</td>
<td>179 liver CT volumes</td>
<td>GeForce GTX 1080</td>
<td>8 hours</td>
<td>96.00</td>
</tr>
<tr>
<td>Nanda et al. [24]</td>
<td>2019</td>
<td>Cascaded CNN and genetically optimized classifier</td>
<td>13 convolutional layers</td>
<td>131 CT scan images</td>
<td>Nvidia GTX 750 Ti</td>
<td>Not mentioned</td>
<td>95.57</td>
</tr>
<tr>
<td>Liu et al. [25]</td>
<td>2018</td>
<td>CNN and SVM</td>
<td>12 convolutional layers</td>
<td>5500 liver images</td>
<td>NVIDIA GeForce GTX 960</td>
<td>38sec/slice</td>
<td>97.43</td>
</tr>
<tr>
<td>Presented model</td>
<td>2022</td>
<td>Deep semantic segmentation CNN</td>
<td>10 convolutional layers</td>
<td>8106 liver images</td>
<td>NVIDIA Titan Xp</td>
<td>4 hours</td>
<td>98.80</td>
</tr>
</tbody>
</table>
4. CONCLUSION

In this study, the automated segmentation of the liver in abdominal CT images is performed using a deep semantic segmentation CNN. For the creation of CT images of the liver, a generative deep semantic CNN model was trained. To create an initial segmentation, a liver probability map was acquired in the meanwhile. The key benefit of the suggested solution is that there is no user input necessary for startup. As a result, amateurs can use the suggested approach. The suggested model is also one of the early attempts to separate the liver using deep semantic segmentation and CNN. On the medical image computing and computer-assisted intervention (MICCAI)-Sliver07 and 3Dircadb1 public datasets, the suggested model was assessed. Our model's segmentation accuracy was higher when compared to cutting-edge automated liver segmentation techniques. The suggested model has 98.8% testing accuracy and has practical application for liver segmentation based on the good correlation between our segmentation and manual reference. Future study will involve applying our approach to medical image segmentation problems including kidney and spleen segmentation.

REFERENCES


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