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Modified U-NET on CT images for automatic segmentation of liver and its tumor

R.V. Manjunath *, Karibasappa Kwadiki

Department of Electronics & Communication Engineering, Dayananda Sagar Academy of Technology and Management, Bangalore 82, India

A R T I C L E   I N F O

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A B S T R A C T

Liver and tumor segmentation from abdominal CT images is a crucial phase in machine-assisted experimental involvements. FCNN has revealed extraordinary achievement in executing semantic segmentation by using convolutional layers for the whole planning and skip connections to combine diverse resolution features along with estimations in fruitful networks, such as UNet, ResUNet, etc. However here we recommend a system that select features automatically with convolutional layers, like modified Unet, and holds the spatial suggestion of each extracted feature. In the current study, an upgraded modified Unet procedure was applied on LITS 2D liver and tumor segmentation on CT images where it has achieved a dice similarity coefficient of 96.15% and 89.38% for liver and tumor, in addition, the algorithm was tested on a 3DIRCADb dataset where the system attains a DSC of 91.94% and 69.80% on CT images for segmentation of liver and its tumor effectively and the outcomes evidenced the efficiency of perfection.

1. Introduction

Hepatocellular carcinoma is the principal reason of Liver cancer death in the creation and it is the most common malignant tumors. Liver diseases treatment and prevention has become important emphasis of the creation. The detection of liver abrasions provides a vital source for medical and treatment planning, because in the prime liver cancer, the surface is categorized by bulky or minor irregular nodules and the surface is stiff, edges are uneven. [1]. The quick change of medical imaging knowledge provides new ways to detect prime liver cancer. Specialists can witness, investigate and detect the injury signs from the image. Though, existing medical imaging technology for liver testing depend severely on worker knowledge and skill and frequently has shortcomings of strong subjectivity, small reproduction, high labor intensity and low competence [2]. For detecting liver lesions there is a need to establish a vigorous, unbiassed, repeatable, effective and high-accuracy technique. In the arena of computer vision Semantic segmentation is an exciting research topic. The purpose of semantic segmentation is to allocate a label to each pixel in the image and divide the complete scene into numerous separate components to determine the diverse behaviours of the aim and resolve the high-level visual problems. A series of effective solutions proposed attracting more scholars by semantic segmentation due to the development of AI technology. However, the semantic segmentation model is still exciting due to the difficult background, multiscale contrast, boundary blurring for abdominal CT images, and precise segmentation of the target localization and segmentation. In recent years image semantic segmentation performance improved significantly due to the deep learning algorithms but these approaches constantly hurt from spatial irregularities. Chen et al. enhanced the spatial uniformity of the segmentation result by adding a completely associated restricted random field created on deep semantic pixel sorting [3]. Augmenting the performance of target location in the deep network a completely coupled conditional random field is added in the last layer and at different scales the response results are united by Deep lab method. For top level deep features and low level local feature information combination we can use this method widely [4]. In [5], Luc et al. projected a generative adversarial network technique to train the segmentation model. Owing to many scale faced entity image and low-level firmness of the feature map, semantic segmentation act is general in some precise and the overall average performance of the technique is decent, Positioning accuracy is lost while obtaining feature invariance that practices extreme pooling and down sampling approaches by a deep network [6].The architecture uses a encoder, decoder and a bridge system to precise semantic segmentation outcomes and condense spatial construction irregularity. To surge overview skill and exact training of the model, here we planned to use modified Unet

* Corresponding author.
E-mail address: manjunathrv@dsatm.edu.in (R.V. Manjunath).

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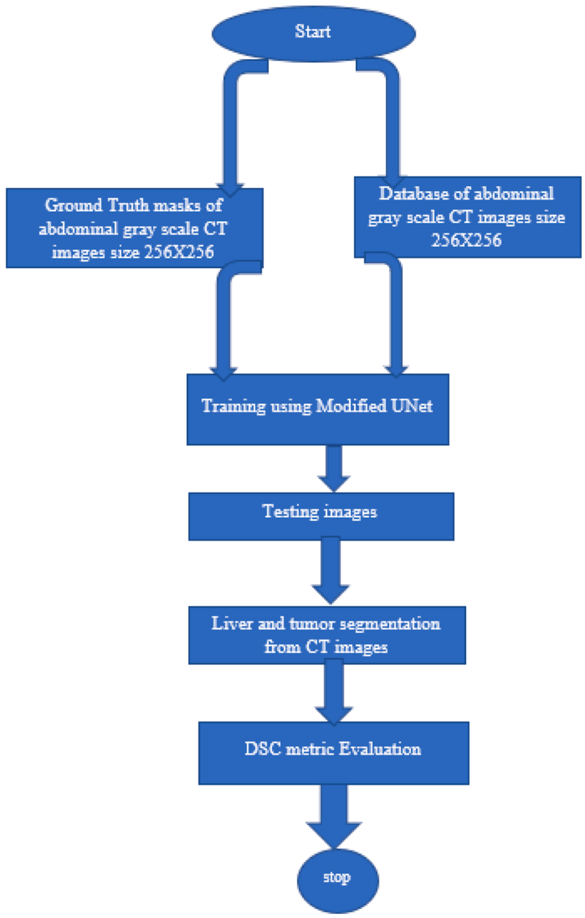

Fig. 1. Flowchart.

architecture. The results of the experiments revealed the performance of semantic segmentation algorithm projected here which surpasses many current segmentation algorithms, and also segmentation precision is upgraded by confirming the uniformity of semantic segmentation. Here remaining part of the paper is planned as shown. Section 2 outlines the correlated work. Section 3 demonstrates methodology. Section 4 results and debate. Lastly, Section 5 concludes the paper.

2. Related work

The segmentation process in the medical field has occupied the researchers to extract detailed information about any new findings for many years now. The use of Segmentation has no bounds starting from recognizing items from videos, face recognition, disease recognition, and fingerprint recognition. Jegou et al. [7] presented an idea in their paper as the use of skip layer in between up sampling and down sampling which has given good classification response in the FCN densenet architecture which results in efficient parameters, reuse of features and providing a deep supervised network. The unruly of liver tumor segmentation has remained everywhere for a long time with great attention established in the medical image computation community. In the medical image computing and computer-assisted intervention 3D Challenge [8] both manual and automatic approaches were acknowledged amid the automatic ones, the collective segmentation algorithm with Ada-Boost [9] was the best. The evolution of Deep neural networks (DNNs) is budding quickly in the computer vision arena since of its capability to increase vision from data. Christ et al. [8] in their investigation applied 2 cascaded Unet representations, one representation is exclusively for the segmentation of liver, and second one for the segmentation of the tumor inside a bounding box of the liver. The ultimate result was distinguished by a 3D restricted random field. The Liver tumor segmentation challenge conducted was led with an extensive quantity of involvement. The approaches used in both the top grading investigation was DNN. Han, the champion of the primary round, finished using 2 UNet alike representations with stretched and brief hop connections, where the primary model used for uneven segmentation of liver and secondary model was correlated to train the model to segment together liver and tumors at the same time. Kaijian Xia [10] developed a deep learning multi-scale adversarial network in combination with a weighted loss function for semantic segmentation and successfully ensured space consistency while increasing the segmentation efficiency. Omar Ibrahim alirr [11] used deep learning and a level set approach in heterogeneous CT scans from multiple scanners for liver and tumor automatic clinical analysis.

3. Methodology

Original .nii and Dicom formats are converted to two-dimensional jpeg and png image formats, later these image formats are resized to 256 × 256 and 128 × 128 dimensions. As shown in the flowchart below a database of abdominal grayscale CT images and their respective ground truth CT masks are kept in two distinct folders and a Modified Unet is applied for training the images on these two folders by setting various training options. Finally, segmentation is assessed by evaluating a dice similarity coefficient performance parameter after testing the model by a set of test images which are not been a part of the training database. The projected work is shown below in Fig. 1.

3.1. Dataset

Developed semantic segmentation model performance is assessed by using training and testing images from the openly accessible datasets. The publicly available datasets are liver tumor segmentation and 3DIRCADb [11] contains 131 and 20 volumes of contrast-enhanced abdominal CT respectively with liver and tumors. Including data augmentation to ease training and testing total of 880 images are considered among which 760 images are for training and 120 images for testing.

3.2. Data grouping

The available data from the openly accessible datasets have been used for testing and training the developed model by converting the dataset into proper formats and by removing CT images with no liver and tumor in the mask, which also reduces the disparity between background and foreground of the image. The liver tumor segmentation dataset contains a mask for joint liver and tumor segmentation and also 3DIRCADb datasets contain a separate mask for the liver and its tumor.

3.3. Pre-processing

In the Liver tumor segmentation and 3DIRCADb dataset images having a size of 512 × 512 dimension initially & memory usage of these images is always challenging due to limited CPU. Subsequently, images from the dataset are resized to a size of 256 × 256 and 128 × 128 dimensions. Thus, a MATLAB software is used for the analysis and processing of CT images in the dataset.

3.4. Network planning

In this network a Modified Unet58 layers architecture is utilised for the segmentation of liver and its tumor.Signifying the traditional deep convolution network, we create a liver segmentation-Net network. It comprises of a retrenchment track (left) and an extension track(right). The retrenchment track (Encoder) is used to seizure the framework. To appreciate the specific position an extension track (Decoder) is used. The two tracks are proportionate to build a ‘U’ form, so it is termed U-Net. By

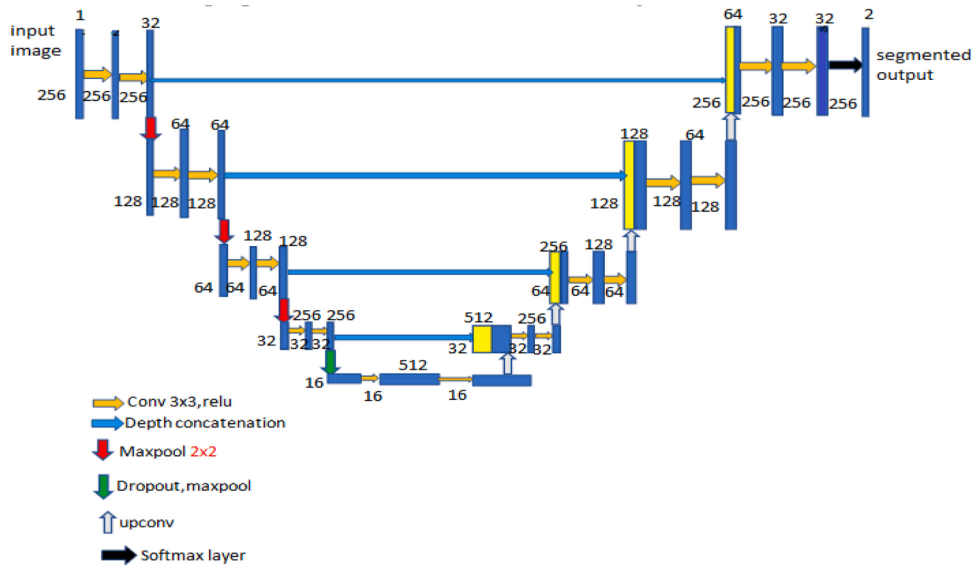

Fig. 2. Modified Unet58 architecture.

Table 1
DSC comparison on LiTS datasets(256 × 256).

Method	Liver(%)	Tumor(%)
Zhu Y et al. [14]	95.7	66.6
Kim J et al. [15]	93.4	64.5
Tang A et al. [16]	95.1	66.1
Kakkar P et al. [17]	95.5	69.7
Schenk A et al. [18]	96.00	67.6
Omar Ibrahim Alirr. [11]	95.6	70.00
Proposed method	96.15	89.38

Table 2
DSC comparison on 3Dircadb datasets(128 × 128).

Method	Liver (%)	Tumor(%)
Yi Zhang. [19]	91.00	56.7
Proposed method	91.94	69.80

cumulating the amount of unseen layers, the performance of the neural network can be further endorsed. The architecture of the proposed network is shown below in Fig. 2.

4. Experiments and results

4.1. Evaluation metrics

To evaluate the segmentation performance, a ground truth mask is compared with the segmented output of the model which is a binary image. The segmentation of the liver and its tumor performance is evaluated with the metric Dice similarity coefficient.

4.1.1. Dice similarity coefficient

To calculate the amount of overlap between two binary image masks DSC is used. It is defined as the ratio of overlapped area of the two binary image masks to the total dimension of the two images. DSC value 1 means it indicates perfect segmentation, if it is 0 means it signifies no segmentation at all, hence the range between 0 and 1 signifies the performance of segmentation. To evaluate dice following equation is used [12,13].

$$Dice(A,B) = \frac{2|A \cap B|}{|A| \quad + \quad |B|} \tag{1}$$

A= Ground truth image, B= Segmented image

4.2. Testing and assessment

The established technique was trained on a desktop machine with 8GB RAM on an Intel(R) Core (TM)i5- 2400 CPU @ 3.10 GHz processor and established with a matrix laboratory 2020a tool. A ratio of 85%:15% is used to separate training and testing images from the database.

The Tables 1 and 2 below indicate the assessment of the Dsc metric for the two different datasets testing images and also the comparison of the proposed method with the existing methods. With a learning rate of 0.001 models were trained for 200 epochs where every epoch has taken 760 iterations, so a total of 152,000 iterations are taken for training by utilizing 58 layers. The details related to training progress for the LITS dataset is shown in Figs. 3 and 4. We observed as the size of the CT image is increased the eminence of segmentation also surges.

Results of liver segmentation

Segmentation of liver is assessed by the DSC metric and the results are tabulated in Tables 1 and 2 whereas liver segmented results are included in Fig. 5 where it has reached a DSC of 96.15% for LITS and 91.94% for 3dircadb.

Tumor segmentation results

Segmentation of tumor is assessed by the DSC metric and the results are tabulated in Tables 1 and 2 whereas tumor segmented results are included in Fig. 6 where it has reached a DSC of 89.38% for LITS and 69.80% for 3dircadb.

The original dataset of LITS and 3DIRCADb with sizes 512 × 512 is reduced to 256 × 256 and 128 × 128 for comparison of the results obtained from the proposed method with the existing methods. Secondly, the reason for scaling down the image is with a large image size the processor time is larger and also has the constraint of the available processor memory.

5. Conclusion

In this paper liver & tumor segmentation for LITS and 3Dircadb dataset is initiated using deep learning algorithms. The proposed Modified Unet outshines existing deep learning models in the segmentation of liver with a high DSC score of 96.15% and the segmentation of tumor with a DSC score of 89.38% for the LITS dataset of size 256 × 256

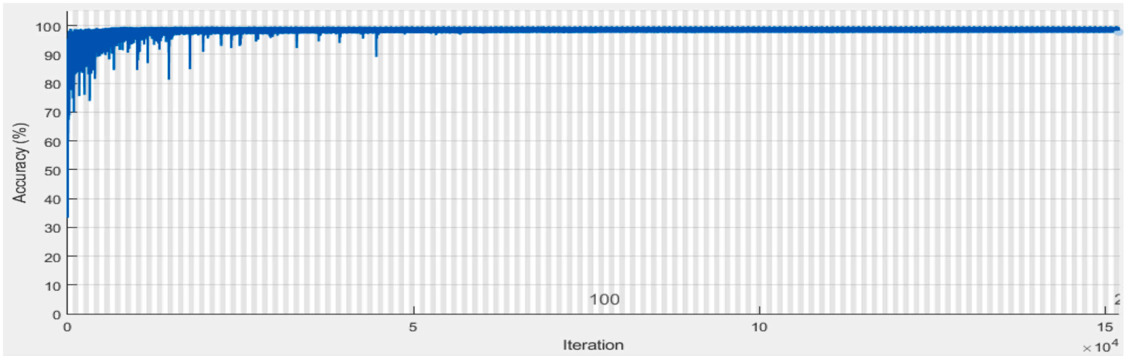

Fig. 3. Accuracy vs Iterations.

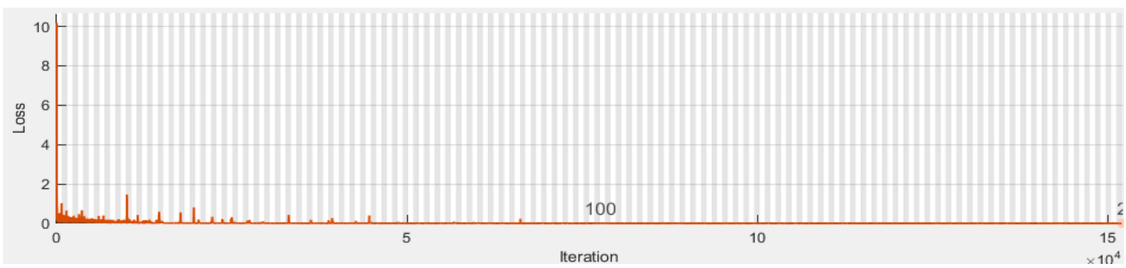

Fig. 4. Loss vs Iterations.

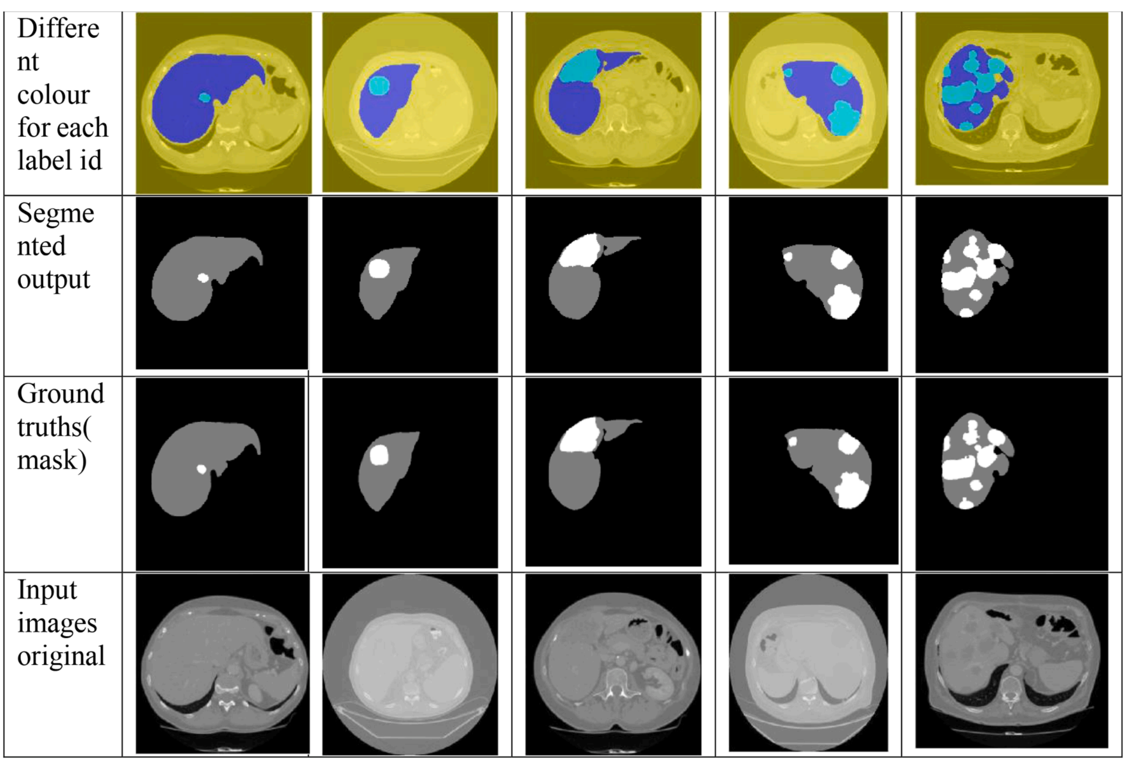

Fig. 5. liver segmentation.

respectively. In addition, a high DSC score of 91.94% for segmentation of liver and 69.80% for segmentation of tumor for a 3Dircadb dataset of size 128 × 128 is obtained. In the future, real-time images from hospitals and their different sizes can be trained and tested to identify the model efficiency, and also different CNN models can be tested to identify the smallest tumors. Further, volumetric analysis of the ct images along with additional parameters in addition to DSC can be evaluated to assess the segmentation. Finally, Automatic segmentation can also be applied to different organs dataset.

Declaration of Competing Interest

I hereby declare that I have no known competing financial interests or personal relationships that could have appeared to influence the work

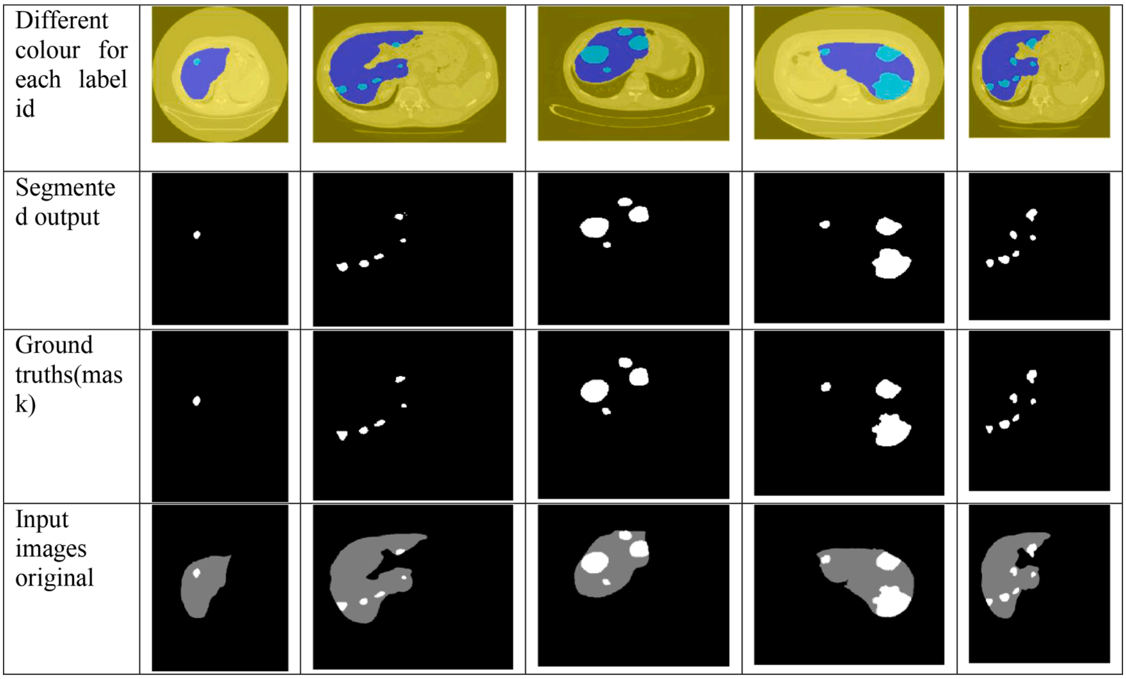

Fig. 6. Tumor segmentation.

reported in this paper.

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