LIVER TUMOR SEGMENTATION USING 3D FULLY CONVOLUTIONAL NEURAL NETWORK

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Abstract – Liver cancer is one of the most common cancers. Liver tumor segmentation is one of the most important steps in treating liver cancer. Accurate tumor segmentation on Computed Tomography (CT) images is a challenging task due to the variation of the tumor's shape, size, and location. To this end, this paper proposes a liver tumor segmentation method on CT volumes using Multi-Scale Candidate Generation method (MCG). In this paper, we use the3D U-Net for liver segmentation before liver tumor segmentation. Although the image after liver segmentation reduces a large number of non-interested regions, the tumor region of interest is still too small to be segmented in liver regions. To solve this problem, we decided to cut each segmented liver image into tumor candidates and then classify the tumor candidates to obtain the segmentation results. Propose A Multi-Scale Candidate Generation method (MCG) for dividing liver regions into tumor candidates. The method includes multi-scale superpixel method and multiple neighborhood information.

Key Words: MCG, Computed Tomography (CT).

INTRODUCTION:

Cancer is one among the foremost common causes of death in the present time; liver cancer ranking among the three most dangerous diseases. Segmentation of liver tumors would facilitate oncologists to confirm changes in tumor size. This data can then be used to evaluate the patient's response to treatment and, if necessary, to adapt the medical aid. Medical image classification is one of the prime factors in numerous applications in an exceedingly medical image retrieval system. [1]. Liver tumors or hepatic tumors are tumors or growths that develop on or inside the liver. The hepato- or hepatic is the Greek word for liver and there are several distinct types of tumours that can develop in the liver. These growths can be benign or malignant (cancerous). There are many types of liver tumors: Malignant and Benign. [2 These benign epithelial liver tumors develop in the liver and an uncommon occurrence, found mainly in women using estrogens as contraceptives or in cases of steroid abuse. In most cases, these tumors are detected and diagnosed at right hepatic lobe. The size of adenomas ranges from 1 to 30 cm. Symptoms associated with hepatic adenomas are all associated with large lesions which can cause intense abdominal pain. The prognosis for these tumors has still not been mastered and there has been an increase with occurrences of this specific type of adenoma over the last few decades. Some correlations have been made such as malignant transformation, spontaneous hemorrhage, and rupture. [3]. Viral hepatitis: Hepatitis viruses are viruses that infect the liver. Two common types viral hepatitis are hepatitis B and hepatitis C. Viral hepatitis is the largest risk factor for this type of cancer worldwide. Hepatitis C has become much more common than hepatitis B because there is no vaccine to prevent hepatitis C. Viral hepatitis can be spread from person to person due to the exposure to another person's blood or bodily fluids. [4]. Hepatologists are the doctors with the most experience in screening primary liver cancer. Screening options include testing the blood for a substance called Alpha-Fetoprotein (AFP), which may be produced by cancer cells, or having imaging tests like an ultrasound, CT or CAT scan, or (MRI). More information about these tests can be found in the diagnosis part of treatment. [5]. Diagnosis is the procedure of recognizing an infection by its indication, signs and after effects of different analytic strategies. The diagnosis conclusion that comes through the procedure in the matter of whether a tumor is malignant or benign is called diagnosis.[6] The various disease-directed treatment options can be grouped according to whether they may cure the cancer or may improve survival, but most likely not eliminate the cancer. The common treatments are aimed at managing side effects and symptoms. The goals of each treatment are discussed clearly with the doctor while receiving the treatment. [7]. When a tumor is found at an early stage and the patient‟s liver is working well, the treatment would aim at trying to eliminate the cancer. The care plan may also include treatment for symptoms and side effects, an important part of cancer care. When liver cancer is found at a later stage or the patient‟s liver is not working well, the patient and doctor should talk about the goals of each treatment recommendation.[8] Blood tests: Along with physical examination, the doctor would most likely do a blood test to look for a substance called AFP. AFP is found in elevated levels in the blood of about 50% to 70% of people who have HCC. The doctor would also test the patient‟s blood to see if he or she has hepatitis B or C. Other blood tests can show how well the liver is working.

Treatment is called a multidisciplinary team. Cancer care teams also include a variety of other healthcare professionals, including physician assistants, oncology nurses, social workers, pharmacists, counsellors, dieticians and others. Treatment options and recommendations depend on several factors[9].

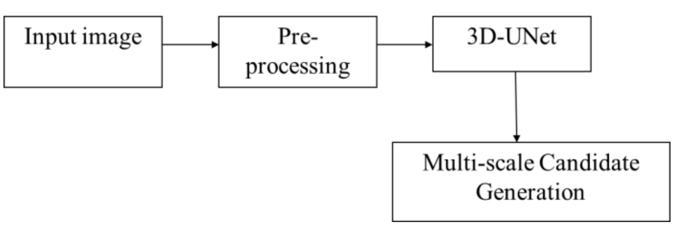

Fig:1 Process flow chart

2.METHODOLOGIES

In this paper, they propose a method for liver tumor segmentation. First, 3D U-Net is used to segment liver regions. Then, liver regions are segmented to tumor candidates by multi-scale candidate generation. Tumor candidates are consequently classified and fused for the purpose of segmentation. This method can increase the proportion of liver tumor information compared with the liver information in candidate regions. This paper proposes a method combining the multi-scale superpixel segmentation method and multiple neighborhood information to generate liver tumor candidates for segmentation, which can involve more complete tumor information for candidate regions. This increases the network's classification sensitivity to liver tumor details and reduces computational complexity caused by redundant information while increasing the amount of effective information.

A. IMAGE ACQUISITION

Experiment dataset is the LiTS dataset, involving patients' contrast enhanced abdominal CT scans which include tumor patients and normal patients. The number of slices per patient varies greatly. The dataset contains 58638 slices in total which is collected from six clinical sites by different scanners and protocols, with very different in-plane resolution from 0.55mm to 1.0mm and section spacing from 0.45mm to 6.0mm. The dataset covers dramatic changes in population, contrast, scan range, pathology and field of vision (FOV). Most CT scans are pathological, including tumors of different sizes, metastases and cysts. It is worth noting that the 3DIRCADb dataset is a subset of the LiTS dataset. In order to evaluate our model fairly, we use DIRCADb dataset as the testing data and the remaining data in LiTS dataset is considered as the training data.

B. PRE-PROCESSING

To facilitate experimental training, we clip the pixels outside the range (-150, 250) of the original images to the minimum/ maximum value to improve the contrast between the liver and surrounding organs and tissues, therefore, excluding organs that are not of interest. After that, the image is normalized. Since smaller proportion of the number of slices containing tumors in the dataset, in order to enhance the classification effect of the network, the dataset needs to be expanded. The data expansion is in addition to a series of geometric transformations, such as random cropping, flipping, shifting, scaling and tilting, and also using Elastic Distortions, which enables the network to learn deformation invariance, to expand the training data, to prevent over_fitting, and further enhance the ability of generalization. The main aim of pre-processing is to improve the quality of the input image by reducing the noise. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

C. Median filter

Median filter is the most commonly used filter. It is a non linear method of filtering. The size of the kernel can be of nxn size which is made to convolve or slide over a mxm corrupted image. While performing this operation the median value of nxn kernel on the image is obtained and then the value of a particular pixel is replaced with the median value of the nxn kernel.

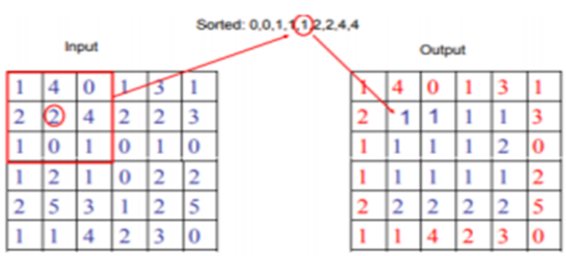

Fig: 2 Sorting in median filter

D. 3D-UNET

3D U-Net is used to segment liver regions. The first stage is the process of dividing the image into tumor candidates. First, the 3D U-Net is used to find the mask of the liver on CT image, which is used to reduce the background regions.

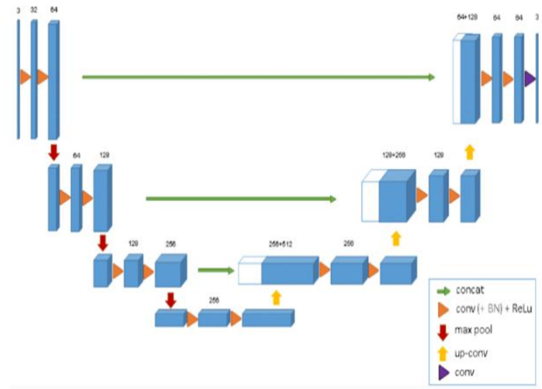

Fig: 3 3D U-Net Architecture

Like the standard u-net, it has an analysis and a synthesis path each with four resolution steps. In the analysis path, each layer contains two 3 × 3 × 3 convolutions each followed by a rectified linear unit (ReLu), and then a 2 × 2 × 2 max pooling with strides of two in each dimension. In the synthesis path, each layer consists of an upconvolution of 2 × 2 × 2 by strides of two in each dimension, followed by two 3 × 3 × 3 convolutions each followed by a ReLu. Shortcut connections from layers of equal resolution in the analysis path provide the essential high-resolution features to the synthesis path. In the last layer a 1×1×1 convolution reduces the number of output channels to the number of labels which is 3 in our case.

E.MULTISCALE CANDIDATE GENERATION

This paper proposes a method combining the multi-scale superpixel segmentation method and multiple neighborhood information to generate liver tumor candidates for segmentation, which can involve more complete tumor information for candidate regions. This increases the network's classification sensitivity to liver tumor details and reduces computational complexity caused by redundant information while increasing the amount of effective information. The superpixel method, linear spectral clustering (LSC), which maps images to high-dimensional spaces to find relationships between pixels, putting the same type of pixels into the same candidates. LSC can generate good candidates with prior knowledge which benefits tumor segmentation. Therefore, LSC is used to generate tumor candidates. The traditional superpixel classification method is to directly classify superpixels as classification units and class them by extracting superpixel features. However, it has been experimentally found that the single-scale segmentation results heavily depend on the superpixel segmentation results. If the segmentation result of a single-scale superpixel segmentation method cannot segment the tumor boundary accurately, it will also affect the final segmentation result.

F_n (I_k)=LSC(I_k,n)

where *LSC(.)* stands for linear spectral clustering operation. Parameter *n* represents the number of superpixels we segment I_k by LSC in one scale. $F_n(I_k)$ is the superpixel mask of I_k and l_{th} superpixel region in $F_n(I_k)$ is $B_{(k,l)}$.

F. MULTIPLE NEIGHBORHOOD INFORMATION

Although using the multi-scale superpixel segmentation method can generate good tumor candidates, these tumor candidates, which contain only single slice image information and ignore background information, are not sufficient for effective segmentation. Therefore, a novel approach (MCG) which includes both context information and multi-scale information is developed to increase multiple neighborhood information in superpixel results of each scale. Let function J represent the transformation from the liver region volume data to the input of the proposed network and J^(-1)stand for the transformation from the output of the proposed network to the segmentation results:

$$X_{in} = J\left(I_k, F_n(I_k)\right), \qquad X_{in} \in R^{mXiXLXLXs}$$

$$Y = J^{-1}\left(X_{out}, F_n(I_k)\right), \qquad Y \in R^{mX512X512}$$

Where m is the number of slices, J^{-1} is the inverse operation of J, *Xin* is the input of the 3D FCN and *Xout* is the output of the 3D FCN.

3. RESULT AND DISCUSSION

INPUT IMAGE

The input image is the CT liver image.

Fig: 4 Input image

PRE-PROCESSING

The aim of pre-processing is to remove noise or unwanted distortions from CT images. In the proposed method median filter is used for pre-processing step for producing better output.

Fig: 4. Pre-processing

LIVER REGION DETECTION

In the proposed method 3D-UNet is proposed for liver region detection.

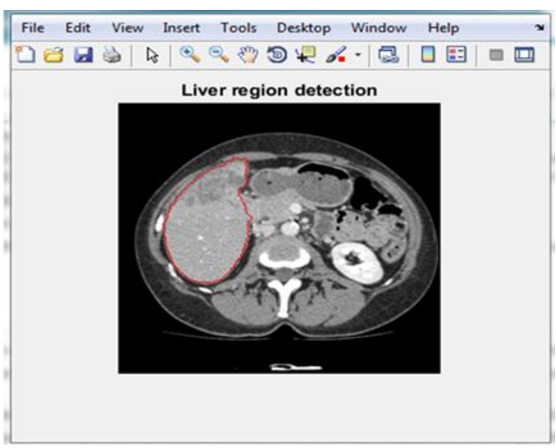

Fig: 5 Liver Region Detection

MULTISCALE SUPERPIXEL SEGMENTATION

The superpixel method, which maps images to high-dimensional spaces to find relationships between pixels, putting the same type of pixels into the same candidates.

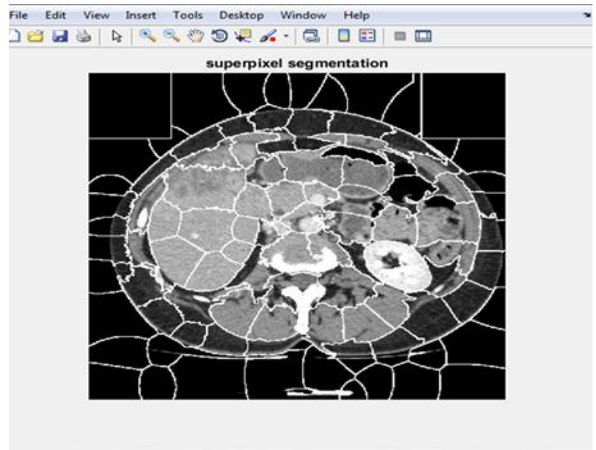

Fig: 6 Superpixel segmentation

FINAL SEGMENTED IMAGE

The multi-scale candidate generation method produces the final segmented output.

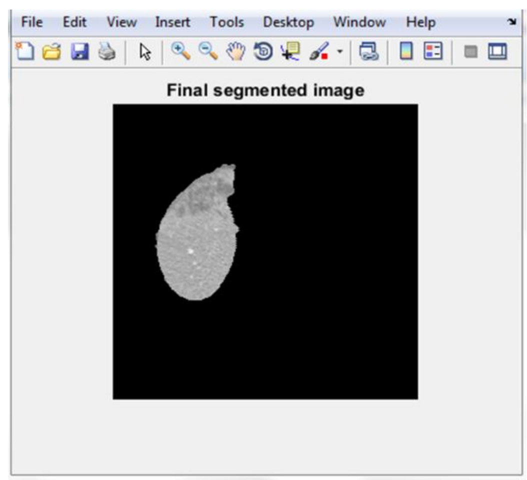

Fig: 7 Final segmented output

4. CONCLUSION

Liver lesions are considered as an injury to the body tissues. Lesions are the areas of tissue that has been damaged because of a wounding or disease. Liver lesions refer to those abnormal wounded tissues that are present within the liver. These lesions can be identified in CT scan by analyzing the difference of pixel intensities with other regions of liver. In the proposed method having three modules. They are pre-processing used to remove noise from the image, 3D-UNet for segmenting liver region. The next step is segmenting tumor candidates within liver regions.

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