به نام خدا

عنوان مقاله:بخش بندی کبد در تصاویر سی تی اسکن و ام ارای با استفاده از یادگیری عمیق

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This single-center retrospective study included 355 patients 238/117, mean age 60 years; training, *n* = 178; validation, *n* = 123; test, *n* = 54 who underwent acid enhanced abdominal MRI, including HBP and MRE, and pathological evaluation of the liver within 1 year of MRI.

Cropped liver HBP images from a custom-written fully automated liver segmentation were used as input for DL. A transfer learning approach based on the Image Net VGG16 model was used.

Different DL models were built for the prediction of fibrosis stages F1-4, F2-4, F3-4, and F4. ROC analysis was performed to evaluate the performance of DL in training, validation, and test sets and of MRE liver stiffness in the test set.

One of the most prevalent cancers in the world with a high mortality rate is liver cancer. The gold standard for  
diagnosing liver diseases such cirrhosis, liver cancer, and fulminant hepatic failure is a medical imaging modality  
like computed tomography (CT), magnetic resonance imaging (MRI), or positron emission tomography (PET) .  
Among them, CT scans, which have a good signal-to-noise ratio and excellent resolution, are currently the  
modality most frequently employed for diagnosing and treating liver lesions or tumors.

The accurate identification  
of liver cancer by doctors, together with knowledge of the shape, volume, and location of the lesion, can lead to  
more effective patient care.

Clinicians must manually segment liver lesions on a slice-by-slice basis, which takes  
time and is error-prone. As a result, the accurate and automatic segmentation of the liver and hepatic lesions is  
required for computer assisted diagnosis of liver illness and for creating a plan for liver transplant surgery.  
For volumetric or morphological analysis, segmentation is the technique of clearly defining an organ of interest  
on a multi-planar computed tomography (CT) or magnetic resonance imaging (MRI) image. Although many  
deep learning-based models have been created, segmenting liver lesions is still a popular field of research. Several  
survey papers on the segmentation of the liver have been published.

But to the best of our knowledge, there  
are not many survey publications on the segmentation of liver lesions.  
This study carries out a critical analysis of some of the published works related to liver lesion segmentation  
using deep learning models. The authors compared various deep learning models based on the models proposed,  
datasets, performance, and disadvantages of each model, and presented some major challenges encountered while  
segmenting liver lesions.

Finally, it was concluded that computer aided liver lesion segmentation is still an open  
research problem, especially facing small size lesions, for the available techniques have many limitations to be  
addressed.

Over the past decade, researchers have used different machine learning strategies to separate liver and tumors. Li et al. proposed an autonomous 3D liver segmentation approach that uses a total variation with the 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.

proposed a multi-atlas segmentation (MAS) based performance level estimation (SIMPLE) method for automatic segmentation of abdominal organs, including the

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.

Semi -automated method for fragmenting the hepatic low-intensity tumor using CT images that utilized abdominal arterial channels in the entrance stage. E t al. 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 organs. Deep neural networks are used extensively in present healthcare image segmentation frameworks.

Zhou 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. E t al. 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. 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. merged a 2D Dense Net network that combined the extracted intra-slice features and the 3D counterpart for hierarchically aggregating volumetric contexts for liver and lesion segmentation. The liver was segmented by Li et al.

Us 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. developed an edge system by incorporating spatial stream convolution into the U-Net network’s modules.

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. E t al. implemented probabilistic graphical model for segmentation for fundus images and obtained accuracy of 0.99. e t al. Fully Convolutional Network (FCN) to better segment the brain MRI having a varying size and shape ischemic lesion and obtained the DSC score of 0.75. e t al.

Res U-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 segmentation. Amin et al.

generative adversarial network (GAN). YOLOv3 detector and block localize the liver in the synthesized images. Moreover, DeeplabV3+ having Inceptionresnetv2 model as a base is implemented for better liver segmentation.

Jin et al. implemented a novel network called residual attention-aware U-Net (RA-U-Net) to segment 3D images of liver 3DIRCADb dataset. Moreover, et al. implemented U-Net to segment liver and liver tumor and obtained a DSC value of 0.96 and 0.74.

Sultan et al. applied a semantic pixel-wise classification network called Net 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.

We included patients who underwent baseline and 1-year follow-up MRI from a prospective cohort that underwent acid-enhanced MRI for hepatocellular carcinoma surveillance between November 2011 and August 2012 at a tertiary medical center.

Baseline liver condition was categorized as non-ACLD, compensated ACLD, and decompensated ACLD. The liver-to-spleen signal intensity ratio (LS-SIR) and -spleen volume ratio (LS-VR) were automatically measured on the HBP images using a deep learning algorithm, and their percentage changes at the 1-year (ΔLS-SIR and ΔLS-VR) were calculated.

The associations of the MRI indices with hepatic and a composite endpoint of liver-related death or transplantation were evaluated using a competing risk analysis with multivariable Fine and Gray regression models, including baseline parameters alone and both baseline and follow-up parameters.

Images can be blurry due to subjects’ involuntary movements and may also contain environmental and instrumental noises. Such noises and artifacts can affect performance while images through state-of.

Likewise, the liver size varies with the body shape, gender and age, also the malevolent tissue often has low contrast with the normal tissue, thus making malignant tissue detection difficult. Hence, for adequate structural analysis; for instance, after artifact removal, and registration, the accurate localization and lesion detection are per formed .

Consequently, preprocessing images reduces the false negative rate. Afterwards, distinct and meaningful features are required to differentiate between normal and malignant tissues After extraction and selection, these features are utilized to perform classifications between desired outcomes. Various algorithms have been reported to perform such diagnosis in the best possible ways. The overall schematic of the CAD system is shown in Fig.

The classified outcomes are employed to identify the ailment regions for further treatment such as radiation therapy cryosurgery, etc.

Comprehensive scoring systems for evaluating the liver function, such as the Child-Pugh (CP) score and the model for end-stage liver disease (MELD) score, have been developed. The CP Grading System is used for uniformly describing and classifying liver cirrhosis into different stages according to symptom severity.

The ranking into the three CP groups (A-C) is based on a point scale the CP score is calculated based on three objective serum albumin, serum bilirubin, and international normalized ratio (INR] and two subjective (ascites and encephalopathy) parameters.

The subjective parameters vary with the use of diuretics in the treatment of ascites and the treatment of encephalopathy with lactulose .Therefore, in recent years, it has become common practice to use the MELD score to describe the severity of liver diseases as no subjective parameters are considered.

The MELD score is especially used in the allocation of organs for liver transplantation; it helps identify and prioritize the care of patients in acutely life-threatening situations due to liver disease and/or whose treatment is of utmost urgency.

The MELD score is calculated using the following objective parameters: serum bilirubin, serum creatinine, and INR, from 6 to 40 points; the higher the score is, the lower the patient's probability of surviving the next 3 months without a liver .

The CP score and MELD score assess global liver function and are useful in determining whether patients with HCC and cirrhosis are candidates for resection or transplantation, but they are unable to determine the safe extent or removal .While they can roughly estimate the risks of performing a hepatectomy, they are not appropriate as a diagnostic tool in the preoperative environment.

liver fibrosis features excessive protein accumulation in the liver interstitial space resulting from repeated tissue injury due to chronic liver disease. Liver fibrosis eventually proceeds to cirrhosis and associated complications.

So, early diagnosis and staging of liver fibrosis are of vital importance for clinical treatment. Liver biopsy remains the gold standard for the diagnosing and staging of fibrosis, but it is suboptimal due to various limitations.

Recently, efforts have been made to migrate toward noninvasive techniques for assessing liver fibrosis. CT is relatively easy to perform, relatively standardized for different scanners, and does not require additional hardware in liver fibrosis staging.

MRI is frequently performed to characterize indeterminate liver lesions. Because it does not use ionizing radiation and features high image contrast, its role has increased in the staging of liver fibrosis

. More recently, several studies on liver fibrosis staging using deep learning algorithms in CT or MRI have been proposed and have shown meaningful results. In this review, we summarize the basic concept, diagnostic performance, and advantages and limitations of Computed tomography (CT) is used as a routine medical imaging modality for the of anatomical structures, for example, the liver, because of its high spatial and temporal resolutions .However, the increasing use of medical CT has raised concerns about the potential radiation risk.

As a result, lowering the CT radiation dose as reasonably achievable (the ALARA principle) while maintaining imaging quality is the most encouraged practice in the CT field A direct way to reduce the radiation dose is to lower the ampere-seconds but insufficient photons will unavoidably generate larger quantum noise, thus reducing the signal-to-noise ratio (SNR) of reconstructed CT images which will significantly degrade image quality

The liver is the only organ in the human body that can be regenerated after partial resection. Therefore, fully understanding of liver anatomy is a prerequisite for liver tumor resection and liver transplantation.

Each technique to noninvasively stage liver fibrosis.Despite the fact that is considered to be the gold standard for detecting diffuse liver diseases, it is an invasive method with numerous side effects. Diffuse liver diagnosis using may be influenced by Physician subjectivity.

Therefore, an accurate of liver diseases remains a notable demand. In this study, to categorize the liver status, a novel deep, comprised of pre-trained (CNNs) is proposed.

Several networks, namely Res, ResNet18, ResNet34, ResNet50, and Alex Net which concatenated with fully connected networks (FCNs) are used. Extracted deep features using can provide sufficient classification information.

An FCN can then put images into different states of the disease, namely normal liver, liver hepatitis, and. Two-class (normal/cirrhosis, normal/hepatitis, and cirrhosis/hepatitis) and three-class (normal/cirrhosis/hepatitis) classifiers were trained to distinguish these liver images.

Since two-class classifiers showed better performance compared to the three-class classifiers, a hybrid classifier is proposed so as to integrate the weighted probabilities of the classes obtained by means of each. Then, a majority is employed to select the class with a higher score.

The experimental results show an accuracy of 86.4% using ResNet50 with a hybrid classifier for liver images which were classified into three classes. In the distinction between normal and cirrhosis liver as well as normal and hepatitis liver, the results demonstrate the sensitivity and specificity of the first group to be 90.9% and 86.4% and the latter group shows the sensitivity of 90.9%, and specificity of 81.8%