Liver Tumor Segmentation and Classification: A Systematic Review

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***Abstract*— The major tissue in the abdomen of the human body is the liver, it has complex structure. Primary liver cancers can be classified as Hepatocellular carcinoma and Cholangiocarcinoma. In these two liver cancers, hepatocellular is a common type, this is the reason for most common liver cancer-causing death worldwide. Computed Tomography (CT) is the maximum considerably used imaging method for the identification and treatment of liver tumors. The tumor must be treated at the early stage, if not, it is going to cause several complications. The traditional methods used for detection of the tumor are time-consuming, give the error in detection, and these methods require experts to analyze the tumor. Hence automatic and integrated methods are required to use instead of traditional methods. Liver tumor segmentation from CT image is very important to analyze the liver function, pathological and anatomical study of the liver. It is also important for the diagnosis of disease. This paper discusses various methods for early detection of liver tumors and also discussed the merits and demerits of these methods.**

Keywords*— *CT Liver Image, Liver Tumor, Fuzzy c-means clustering, Support vector machine classifier, Convolution Neural Networks, CAD

I. INTRODUCTION

The liver is a hefty, weighty organ that present on the right side of the belly. Fig. 1. Shows the front view of the liver. Color of the liver is reddish-brown, weighs about 3 pounds. The liver has right and left lobes. The gallbladder, parts of pancreas and intestines present under the liver. All these organs and the liver are responsible for digest, absorb and process the food.

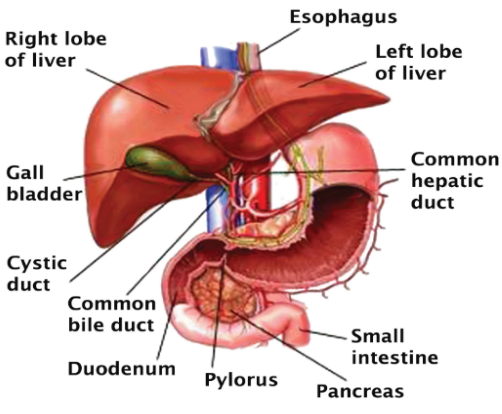

Fig. 1. The Liver [33]

The main function of the liver is to clean the blood coming from digestive tract, before supplying blood to rest the body. The liver also purifies chemicals and processes drugs. The liver also prepare proteins important for blood clotting and other functions.

Liver diseases are Hepatitis, Cirrhosis, hepatocellular carcinoma(Liver cancer), emochromatosis, Primary sclerosing cholangitis, Primary biliary cirrhosis, etc. These diseases occur due to infection, genetic diseases, and excessive alcohol. Some of the diseases occur due to unknown reason[22].

A CT scan of the abdomen is used to obtain clear pictures of the liver and other organs. Liver cancer is tenth most common cause of deaths in USA[11]. If cancers are detected and diagnosis early, then the survival rate increases[12]. CT is important modality for detection of liver cancer[13,14].

Standard treatment are used for diagnosis of liver cancer are: Surveillance, Surgery, Ablation therapy, Liver transplant, Embolization therapy, Immunotherapy, Targeted therapy, and Radiation therapy. The size of the tumor, shape of the tumor, and its location are mandatory for starting the treatment. The accurate segmentation of liver tumor is very difficult and very important for treatment, because its features such as shape, size and its location are differ among persons as shown in Fig. 2. Fig.2a, Fig. 2b, Fig. 2c, and Fig. 2d show CT liver images which has lesions

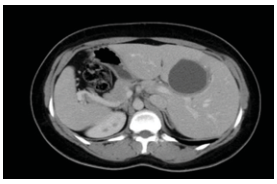

Fig. 2a. CT Liver Image 1

Fig. 2b. CT Liver Image 2

Fig. 2c. CT Liver Image 3

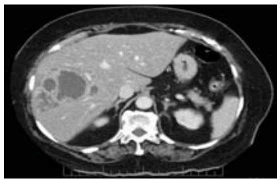

Fig. 2d. CT Liver Image 4

Fig. 2. CT Liver Images

Fig. 2. Shows CT images of Liver tumor, a, b, c, and d shows that tumor location, shape and size differ from person to person. Literature survey, general steps for Liver tumor segmentation and classification is provided in section II-VI, discussion of the paper is given in section VII, finally the paper is concluded in section VIII.

II. LITERATURE SURVEY

The tumor boundary and neighboring noncancerous liver tissues are unclear. There are varies types of tumor appearance and density of tumor is also varies [9], because of these tumor segmentation in the liver become a difficult task. Hence, an automatic liver tumor segmentation techniques has become

978-1-7281-4994-3/20/$31.00 ©2020 IEEE

challenging for diagnosis and treatment of liver cancer, it also reduces the drawback of manual segmentation, it also can increase the success rate of liver tumor surgery.

Belgherbi, A et al. [23] has presented the two stages for segmentation. The morphological reconstruction is used to extract the liver from the first stage. The watershed transform is used to detect the hepatic lesions in second stage. Since there is low contrast between lesions and Liver intensity in CT liver image, segmentation of lesion is very difficult task. Hence to solve this problem, anatomical information and mathematical morphology tools is used for hepatic tumor segmentation.

Anter A.M. et al. [24] used NS and FCM for segmentation. The CT liver image is converted to NS domain, which is represented using T, I and F subsets, which gives percentage of truth, indeterminacy, and falsity. The indeterminacy is evaluated using entropy in NS. FCM is used to adapt threshold for NS. Connected component algorithm is used to segment CT liver image to obtain liver region.

Eugene Vorontsov et al. [25] has discussed a method using a fully convolutional network for automatic detection and segmentation. Manually segmented images are consider as ground truth images or labels to train the network. Deep learning with CNN for colorectal liver metastases (CLMs) segmentation has improved efficiency. The CT liver images with lesions are used to train and test the network.

T. Rajalakshmi et al. [26] has discussed Fast Greedy Snakes Algorithm (FGSA) to segment tumor region in the liver image. Then, the GLCM features are extracted from the segmented region, back propagation NN classifier is used to classify the tumor. A total of 60 images from database is used for training and testing. These methods of segmentation and classification gave great accuracy.

Xuechen Li et al. [27] discussed about FCM and level set to segment the liver. This method gives high accuracy and specificity. This method deals more effective with over segmentation comparing with standard level set method.in this experiment, the CT image is enhanced, then FCM is used to segment the liver region, then distance regularized level set is used for improvement, at last in post processing morphological operations are used.

Muthuswamy J [28] has used CAD for detection and classification of the tumor. In the preprocessing, median filter is used. Then liver is segmented using neutrosophic (NS) domain with FCM threshold, at last morphological operation is used to obtain liver contour in post processing. GLCM feature vectors are used to classify the tumor using SVM classifier.

Hepatocellular carcinoma (HCC) is one of liver cancer which causes the death of the people. The segmentation liver is very important for finding size of tumor, treatment and monitoring the treatment response. Automatic tumor segmentation and detection is required to avoid the manual segmentation, which requires more time to segment and it is also inaccurate. In Nadja Gruber et al. [29], two successive fully convolutional neural networks are used. one networks is used to segment the liver, whereas other network is used to segment the tumor. The networks are trained using dataset of LiTS.

Michal Heker et al. [30] proposed an automatic method for segmentation and classification of both liver and lesion. The author has used a dataset which contain 332 2-D CT images with cysts, hemangiomas, and metastases lesion. In this paper, a cascaded U-net is used to perform segmentation and classification simultaneously. Lesion segmentation model is trained using LiTS dataset. This method gives improved success rate and classification accuracy.

Manual detection of cancer tissue is difficult and it is also time consuming. In Amita Dasa U., et al. [31], CAD is used for detection of cancer tissues for treatment. In this CAD, a watershed Gaussian based deep learning (WGDL) technique is used for detection of liver tumor. The author has used 225 images to develop this method. Marker controlled watershed method is applied to segment the liver. The Gaussian mixture model (GMM) is used to segment the lesion. The texture features extracted from segmented lesion are given to deep neural network (DNN) classifier for automated classification of three types of liver cancer i.e. hemangioma (HEM), hepatocellular carcinoma (HCC) and metastatic carcinoma (MET). This method achieves higher classification accuracy, jaccard index using DNN classifier. This method has negligible validation loss during classification process.

In Huiyan Jiang et al. [32], an Attention Hybrid Connection Network architecture is designed. In this work, a network for liver localization, a network for liver segmentation, a network for tumor segmentation are proposed and all these networks are cascaded. The liver localization network is trained using joint dice loss function to achieve the accurate 3D liver bounding box. The tumor segmentation network is used for finding more potentially malignant tumor and reduce false positives by applying the focal binary cross entropy as a loss functions. This network is trained using the LiTS dataset. This cascade network gives accurate segmentation.

III. General steps for Liver tumor segmentation

There are varieties of cancers in liver. The important step in treatment and evalution of cnacer are to identify whether tumor is present or not and identifying different stages of tumor.

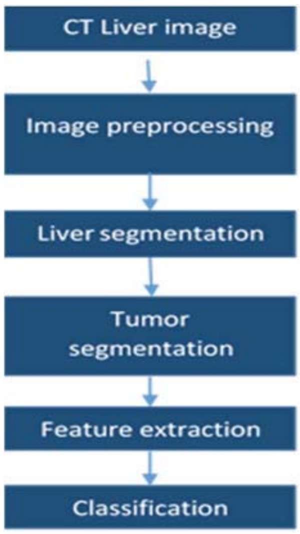

Fig. 3. Various steps used for the liver tumor segmentation and classification.

TABLE I. METHODS USED IN PREPROCESSING, SEGMENTATION AND CLASSIFICATION IN LITERATURE.

Paper	Preprocessing	Liver segmentation	Tumor segmentation	Image classifier	Data set
[23]	Histogram and thresholding	Morphological Reconstruction by dilatation	Watershed algorithm controlled with marker	-	radiological department of Tlemcen University Hospital and Beni-Saf Hospital (Algeria)
[24]	Median filter	NS and FCM	-	-	
[25]	-	fully convolutional network-1	fully convolutional network-2	-	LiTS
[26]	Weiner filter	Fast Greedy Snakes Algorithm	Fast Greedy Snakes Algorithm	neural network classifier	Different datasets
[27]	histogram operation	FCM with level set	FCM with level set	-	Different datasets
[28]	median filter	neutrosophic (NS) domain with FCM thresholding and morphological operation		support vector machine (SVM) classifier	
[29]	-	fully convolutional neural networks	fully convolutional neural networks	-	LiTS-challenge dataset
[30]	-	U-net architecture	U-net architecture	U-net architect ure	MICCAI 2017 Liver Tumor Segmentation (LiTS) Challenge
[31]	guided filter	Gradient magnitude, watershed transform, morphological operations	Gaussian mixture model	DNN using Tensor flow library	Clinical dataset
[32]		Attention Hybrid Connection Network architecture	Attention Hybrid Connection Network architecture		LiTS dataset, 3DIRCADb dataset, Clinical dataset

Liver tumor segmentation and classification can be done as shown in Fig. 3

A. *CT Liver Image*

CT liver image can be obtained from different dataset. The following are public data sets available to get CT Liver images: IRCAD, 3Dircadb, MICCAI Sliver07 datasets. The CT liver images can also obtained from cancer treatment hospitals.

B. *Image Preprocessing*

After getting CT liver images, CT liver image must preprocessed. The preprocessing is important to decrease the noise exist and improve the edges of the CT image to segment the liver and tumor efficiently. There are different spatial filters to enhance the CT liver image. They are wiener filter, bilateral filter, hybrid filter (combination of bilateral filter and wiener filter), guided filter, curvature filter, thresholding, histogram equalization, Kirsch filter, recursive Gaussian filtering and linear interpolation.

C. *Liver segmentation and Tumor segmentation*

It is very important operation for tumor detection and classification. these are different segmentation methods used in literature Morphological reconstruction by dilation, fuzzy c-mean clustering (FCM) using Neutrosophic sets (NS), fully convolution network, Fast greedy snakes algorithm, fuzzy c-mean clustering with level set, mean grey wolf optimization technique, watershed transform applied on gradient magnitude, confidence connected region growing algorithm, Gaussian mixture models, adaptive thresholding, PSOFFCM, Fast marching method, FCM algorithm based on the concave and convex points, random forest, label connected component and spatial regularization etc., [15,18,19].

D. *Feature extraction*

CT liver tumor image can be recognized by features such as texture, shape and size. Shape of the liver and gray-level information of liver region is not sufficient to classify the liver.

One of the important feature used in classification is texture.

Features such as statistical features (mean, standard deviation, skewness, and kurtosis), 2nd order statistical features(Gray-level co-occurrence matrix (GLCM)), and geometrical features(area, perimeter, circularity, equivalent diameter and roundness) are extracted from segmented region.

E. Classification

Based on the feature extraction, tumors are classified into different types classifiers.

IV. Methods used for Liver Image Preprocessing

This section discusses different type of filters used for preprocessing.

A. Median filter

In this, center pixel value of rectangular window is replaced by median of the pixel values in the rectangular window as shown in Eq. (1).

$$\hat{f}(x,y) = \underset{(s,t)\in S_{xy}}{\text{median}}\{g(s,t)\} \quad (1)$$

S_{xy}, subimage, represent a $m \times n$ rectangular window, center of the rectangular window is at (x,y). $g(x,y)$ is input image.in the area defined by S_{xy}. $\hat{f}(x,y)$ is median filtered image.

B. Bilateral filter (BF)

The BF is used to smooth images without altering the edges. The bilateral filter is expressed as in Eq. (2)

$$BF[I]_p = \frac{1}{W_p}\sum_{q\in S} G_{\sigma_s}(\|p-q\|)G_{\sigma_r}(I_p - I_q) \quad (2)$$

W_p is called normalization factor and is given as in Eq. (3):

$$W_p = \sum_{q\in S} G_{\sigma_s}(\|p-q\|)G_{\sigma_r}(I_p - I_q) \quad (3)$$

$G_\sigma(x)$ represents the 2D Gaussian kernel as in Eq. (4)

$$G_\sigma(x) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2}{2\sigma^2}\right) \quad (4)$$

C. Wiener filter

It is also called the minimum mean square error filter used for images corrupted by additive noise and blurring. This is used in frequency domain.

$X(u,v)$ is frequency domain representation of degraded image $x(n,m)$. The frequency domain representation of original image can be obtain by multiplying $X(u,v)$ with the Wiener filter $G(u,v)$ as in Eq. (5):

$$\hat{S}(u,v) = G(u,v)X(u,v) \quad (5)$$

The inverse DFT is applied to $\hat{S}(u,v)$ to obtain the original image.

D. Guided filter

It is linear translation-variant filter. Here I, p and q are guidance, input and output images respectively. Guidance and input images are known in advance depending on the application. The output of the filter at ith pixel is presented as a scaled average as in Eq. (6):

$$q_i = jW_{ij}(I)p_j \quad (6)$$

Here i and j represent pixel locations. The $W_{ij}(I)$ depends on I and independent of input image. The output q of filter varies linearly with p.

The filter kernel weights is represented as in Eq. (7):

$$W_{ij}(I) = \frac{1}{|w|^2}\sum_{k:(i,j)\in w_k}\left(1 + \frac{(I_i-\mu_k)(I_j-\mu_k)}{\sigma_k^2+\epsilon}\right) \quad (7)$$

Here, $|w|$ is the total number of pixels in w_k, μ_k is mean and σ_k^2 is variance of guided image in w_k.

E. Recursive Gaussian filtering

It is best low pass filter. Deriche (1992) represent recursive Gaussian filters as in Eq. (8):

$$H(Z) = H^+(Z) + H^-(Z) \quad (8)$$

Van Vliet, Young and Verbeek (1998) represent recursive Gaussian filters as in Eq. (9):

$$H(Z) = H^-(Z) \times H^+(Z) \quad (9)$$

$H^-(Z)$ is anti-causal systems

$H^+(Z)$ is causal system

F. The Kirsch operator

It is a non-linear operator, used for edge detection. This operator is a kernel and this kernel is interchnaged in increments of 45° over 8 directions: N, SW, NW, SE, W, E, S, and NE. the maximum magnitude across all directions gives edge magnitude as in Eq. (10):

$$h_{n,m} = \max_{z=1,2,\ldots,8}\sum_{i=-1}^{1}\sum_{j=-1}^{1} g_{ij}^{(z)} \cdot f_{n+i,m+j} \quad (10)$$

Where z computes the compass direction kernels $\boldsymbol{g}$ as in Eq. (11):

$$\left.\begin{aligned} g^{(1)} &= \begin{bmatrix} +5 & +5 & +5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \\ g^{(2)} &= \begin{bmatrix} +5 & +5 & -3 \\ +5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \\ g^{(3)} &= \begin{bmatrix} +5 & -3 & -3 \\ +5 & 0 & -3 \\ +5 & -3 & -3 \end{bmatrix} \\ g^{(4)} &= \begin{bmatrix} -3 & -3 & -3 \\ +5 & 0 & -3 \\ +5 & +5 & -3 \end{bmatrix} \end{aligned}\right\} \quad (11)$$

and so on.

V. Methods used for Liver and tumor segmentation

There are various methods for segmentation of liver. Morphological Reconstruction by dilatation, fuzzy c-mean clustering (FCM) using Neutrosophic sets (NS), fully convolutional network-1, Fast Greedy Snakes Algorithm, Fuzzy C means clustering (FCM), Mean Grey Wolf Optimization technique (mGWO), NS domain with FCM thresholding and morphological operation, fully convolutional neural networks, U-net architecture, watershed transform applied on magnitude of gradient and morphological Operations, Fast marching method, adaptive threshold using local mean intensity value on NS image, watershed algorithm, Extract largest connected component, NS, PSOFFCM, morphological operators and Connected Component Labeling algorithm as given in **Table. I**.

Automatic segmentation of tumor in liver is essential and difficult process in CT liver image[17, 18], due to factors such as low contrast, blurred image, irregular liver shape and size, similar intensity with other abdomen organs[21, 22].

Methods used for liver segmentation is also used for Tumor segmentation.

VI. METHODS USED FOR TUMOR CLASSIFICATIONS

SVM classifier, DNN classifier are used for classification.

VII. DISCUSSION

The initial treatment approaches consisting of interventional therapy, surgical resection, and locoregional ablation. These approaches need the complete tumor data like shape, size, and location before therapy for introducing a fine treatment. Many techniques on the basis of machine learning techniques were introduced for segmenting liver tumor from CT images that consisting of classical deep learning and machine learning techniques. By using traditional deep learning techniques, the image-level segmentation has resulted in unsatisfactory sensitivity to segment liver tumor. Moreover, the drawbacks with the existing algorithms for segmentation are it is computationally computing more time, over segmentation; it may not define the shade of original image, and provides extreme segmentation for natural images.

Even though there are multiple classifiers for diagnosing liver tumor, still there are some defects with the existing models so that a new model needs to be implemented for accurate segmentation and classification. Among them, CNN [1] has better performance, and it is one of the triumphant classifier for image recognition. But more capacity computers are required. FFCM with PSO [2] is accurate and consumes less amount of time, and it is less sensitive to noise. Although, there are few defects like it should be validated on real time datasets, and more theoretical analysis need to be performed. FFCM [3] is utilized for statistical data analysis, and it is a clustering approach. Still, it requires CT images in more number for validating the performance. Logistic regression [4] is employed to categorize the tumors, and it has high performance. Yet, it needs to implement more methods for attaining tumor alignment automatically. Fuzzy pixel classification algorithm [5] is used to compute the probability whether a particular pixel belong to particular image class. However, it needs to improve the accuracy when considered large number of data. Decision Tree [6] has an improved performance, and it is an operative model for automatic liver cancer recognition. However, it requires more training time. 3D FRN [7] consists of many shortcut connections while performing back propagation, and it increases the speed. But, it needs to develop accurate segmentation methods. HMRF-EM [8] the computational time without influencing the accuracy, and it enhances the classification quality acquired by EM. But, it consumes more time for huge images. PD-NETs [9] are heterogeneous, and used in many applications and it shows and early improvement in detecting the disease. Still, the performance needs to be improved. FCN [10] has attained high accuracy and they substitute the fully connected layer of traditional CNN with convolutional layer and interchanged convolutional layer restores the feature map as the actual image size. However, it is very complex and it is little bit slowly. Thus, the defects mentioned above are helpful for guiding the researches to develop a new model in an efficient manner for diagnosing lung tumor disease.

VIII. CONCLUSION

In the Region growing method to segment the liver, if the pixels satisfy predefine condition then the pixels in the image is grouped into regions. Before grouping the pixels into regions, the seed point is selected in the region where the segmentation has to be performed. Hence the problem related with the region growing is to select the initial seed point to get more accurate segmentation of images. Here, the performance of segmentation will be improved by the modified region growing algorithm, in which the seed point will be selected by FCM clustering.

The liver tumor classification model is improved with the aid of optimal feature selection and optimized classification models to minimize the detection error, computational complexity and to enhance the classification accuracy. The performance of classification will be improved by optimizing the weight or number of hidden neurons of RNN and CNN

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