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Automatic Segmentation and Classification of Liver Tumor using Hybrid Neural Network

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Abstract*: Liver tumor is most common nowadays. Liver tumor segmentation is one of the most essential steps in treating it. We have chosen CT scan image for liver tumor diagnosis. Accurate tumor segmentation is done using computed tomography (CT) images. Since the manual identification is not that much accurate and time consuming, we go for active contour method. This automatic segmentation method is highly accurate and provides very less time for computation. The back propagation classifier method has a very good accuracy rate and a very less error rate and hence achieved the best result. The proposed method we used in this paper is back propagation classification algorithm for the detection of early and final stages of liver tumor. For the automatic segmentation, we use an active contour method to segment the liver and liver tumor to overcome the manual segmentation problem. This is an automatic method will help us to know whether the tumor is in benign or malignant stage.

***Keywords*: Liver tumor, Active Contour, Back propagation, Automatic segmentation, Computer tomography.**

I. INTRODUCTION

Liver tumor is the nodules that mainly starts in the liver and gradually spreads to other organs of the body. Liver tumor begins in the cells named hepatocytes. The most common types of benign liver tumors are hepatic adenoma, hepatocellular adenomas, focal nodular hyperplasia etc. The common symptoms are pain in the upper abdomen, abdominal swelling or bloating etc. Liver tumor segmentation from computed tomography (CT) images is performed for diagnosing and treating the liver tumor. Early detection of liver tumor will increase the survival rate and so it is very important. The subsequent quantitative analysis of liver tumor can help physician to evaluate effective therapy on tumors. Tumor volume is a precise representation of tumor size for deciding the stage of cancer and therapy evaluation. In the proposed classification method, the training samples are designated from user to distinguish tumors from a healthy carcinoma, a method based on deep neural network is presented to segment lesions from CT images and also it improves the efficiency. Firstly Active Contours assumes a significant job in the field of therapeutic picture segmentation. Liver tumor division in computed tomography pictures is a key issue in therapeutic picture handling. The objective is to correct partition of the tumor areas from the organs so as to picture and examine the doctors to foresee the kind and threat conditions.

Active form models, has been end up being an effective structure for picture division. Active contour is a curve based model and has two categories such as internal and external energy. Of these two, Internal energy is used for the functioning of elasticity and curvature while the external is used for contrast and brightness and when it comes to medical field it is used for detection. Secondly back propagation method is widely used for training the neural net. It is the method by which the neural net is finely tuned and based on the error rate obtained in the previous iteration. So therefore it helps to reduce the error rates and also increases the model generalization. Generalization mainly exists for other artificial neural networks. In deep learning it generally computes the gradient of the loss function rather than a naïve direct computation. It is referred to as the dynamic programming and done by stochastic gradient descent.

II. LITERATURE SURVEY

T.K.R.Agita et al., [1] proposed an automatic segmentation method and classification algorithm such as active contour method and random classifier algorithm. It removes the unwanted region in the images, decreases the computational time and provides result with a very good accuracy. R.Rajagopal et al., [2] presented an oval methodology for the detection and diagnosis of liver tumor based on hierarchical feature set and classifier. Since most of the previous methodologies have focused their work based on the shape and size of the abnormal lesions in the liver area, here they have developed various algorithms that can be categorized on the degree of automation–fully automatic and semi-automatic, and based on the segmentation algorithms such as region based, Contour based Segmentation Methods, Model Based approach, Level Based Approach, Graph cut methods etc. Ye-zhanZeng et al., [3] proposed a new automatic method for liver vessel segmentation by exploiting intensity and shape constraints of 3D vessels. This proposed method used two different methods namely 3D region growing facilitated by bi-Gaussian filter for thin vessel segmentation, and hybrid active contour model which is combined with K means clustering. D.Erhan, C.Szegedy et al., [4] proposed a saliency-inspired neural network model for detection, which predicts a set of class-agnostic bound in boxes along with a single score for each box, corresponding to its likelihood of containing any object of interest.

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The model naturally, handled a variable number of instances for each class and allows for cross-class generalization at the highest levels of the network. Lei Bi, Jinman Kim et al., [5] presented a traditional segmentation approach which depends upon hand-crafted features and the priori knowledge of the user. The deep learning methods based on fully convolution networks like FCNS have been successful in many segmentation problems primarily because they hold a large labelled dataset to hierarchically learn the features that correlate to the shallow visual appearance as well as the deep semantics of the areas to be segmented and we overcome these limitations using deep residual networks like ResNet to segment liver lesion. P.F.Christ, F.Ettlinger et al., [6] presented a Cascaded FCNs and dense 3D CRFs that are trained on CT volumes and are suitable for automatic localization and combined volumetric segmentation of the liver and its lesions. They provide the trained models under open-source license allowing fine tuning for other medical applications in CT data and the application of further cascaded FCNs on lesions ROIs to classify malignancy of the lesions as well as advanced techniques such as data augmentation using adversarial networks could enhance the accuracy of the segmentation later. Hans Meine, Bram Van Ginneken et al., [7] proposed an Accurate automatic liver tumor segmentation that have a big impact on liver therapy planning procedures and follow-up reporting, automation, standardization and incorporation of full volumetric information. They proposed an automatic method for liver tumor segmentation using computed tomography (CT) images based on a two dimensional convolution deep neural network with a shape-based post processing. Their proposed method achieved segmentation quality for detected lesions that was compared to a human expert and is able to detect 77% of potentially measurable tumor lesion. X.Han, [8] used a LiTS (Liver Tumor Segmentation Challenge) that provided a common test for comparing different automatic liver lesion segmentation method. This challenge is done by developing a deep convolution neural network (DCNN) and this model works in 2.5dimensional in which it takes a stack of adjacent slices as input and produces the segmentation map corresponding to the middle slice. It makes use of both long range concatenation connections of U-Net and short-range residual connections from ResNet and has 32 layers. This DCNN model was trained using the 130 LiTS training datasets and achieved an average Dice score of 0.67 when evaluated on the 70 test CT scans. Hame.Y, [9] presented the segmentation in two stages. In the first stage a rough segmentation of tumors is obtained by simple threshold and morphological operations and the second stage cleared the rough segmentation result. It used fuzzy clustering and a geometric deformable model (GDM) that is fitted on the clustering result. The method was rated with data provided by Liver Tumor Segmentation Challenge 08 (LTS08), to which the method also participated. The data included 10 images from which 20 tumors that were segmented and the method showed promising result. Kaiming He, XianguZhang et al., [10] presented a residual learning framework to ease the training of networks that are deeper than those used previously since deeper neural networks are more difficult to train and reformulated the layers as learning residual functions with respect to the layer inputs, instead of learning unreferenced functions. They provided complete results based on proof showing that these residual networks are easier to develop, and can gain accuracy from considerably increased depth. Deep residual nets are foundations of their submissions to the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation. OldrichKodym and Michael Spanel, [11] used a manual segmentation of three-dimensional data obtained through CT scanning which is a very time demanding task for clinical experts and therefore the automation of this processes required. Semiautomatic approaches demanding a certain level of expert interaction are being designed since the results of fully automatic approaches often lack the required precision in cases of non-standard treatment, which is often the case when computer planning is important. It presented a semi-automatic method of 3D segmentation applicable to arbitrary tissue that takes several manually annotated slices as an input. The final segmentation is obtained using the graph-cut method.

III. PROPOSED METHOD

Process of medical image is very useful in the area of research such as various disease detection and analysis which will help the medical profession to provide the easy way for diagnosis of diseases accurately. The learning of medical images is very difficult task in which this operation is skilled based on the device we are using and it is also based on the patient's current situation. Because of various imperfection in the image learning, various noise may influence the image. These issues can be reduced by eliminating the external entities such as noise, and other factor which could affects the image during the time of acquisition. Hence, it is very important to preprocess the given images to eliminate the noise and other external entities. Preprocessing is the very important task in the image processing so that image could not contain any impurities i.e., noise in the extracted images, and it will be considered as better image for the upcoming process such as segmentation, feature extraction, and so no. The segmentation of the tumor will provide accurate result only if the segmentation is done properly. The correct detection will allow us to precise feature extraction and also gives accurate classification. Thus the tumor segmentation can be done perfectly only if the preprocessing of the image is done correctly. "Fig.1" shows the sequential process of liver tumor segmentation using hybrid neural network.

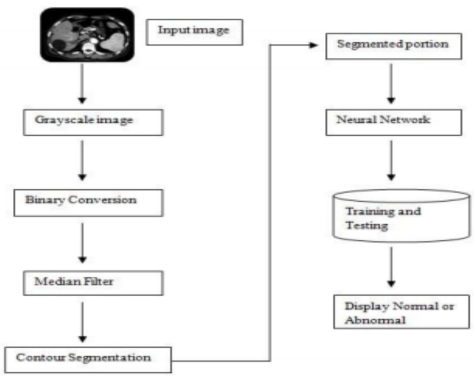

Fig. 1. Sequential process

A. Preprocessing

The primary objective of preprocessing is to enhance the visualization of the images. Preprocessing mostly aims to eliminate the clamor, stabilizing the intensity of the images and remove the artifacts.
Image data can be improved before providing it to the computational process using image processing technique. The input medical images we have chosen are CT images which are preprocessed to remove the noise and other external factors. Preprocessing is done using a filter that is noises in the images can be removed using a filter called median filter. Generally CT images must be preprocessed before carrying it to further process. The function that acts as the preprocessing is contrast enhancement, noise reduction and segmentation. The image data are divided into multiple segments before visualization. Preprocessing can be done in two phases. At the first phase, the noises and other artifacts can be removed by means of median filter, and in the second term, erosion is applied to the constructing element by decreasing the size by one for each time. By using this type of preprocessing it provides various benefits such as it avoids over segmentation and it keeps the structure of tumor as the same. Some of the common factors that affects the performance of the common factors that affects the performance of these technique they are distribution of data, operating environment and operating parameters. Fig.2 shows the CT scan of Liver organ which we have taken as input image.

Fig. 2. CT scan of liver organ (input image)

B. Filtering

The medical image is chosen for preprocessing, the noises and other external entities can be removed by using various filters such as median, alpha-trimmed mean, Gaussian, Gabor, High-pass, Laplace and Bilateral filter. For our proposed system preprocessing can be done using a filter called median filter. The reason and working principles of this filter is discussed below: • Median Filter The median filter, used to remove noise from an image, it is non-linear filtering technique. This noise removal is done in the pre-processing step which will provide better image for the upcoming processing. It is clearly known that median filtering is widely used in the digital image processing in which it preserves edges while removing noise. Median filter work by running through the signal entry by entry, and then it will replace each entry with the median of neighbor entries. We are using 2D images, whereas for 2D image the patterns of neighbors should include all entries. As linear Gaussian filtering, median filtering is also a kind of smoothing technique. All smoothing technique will affect the edges whereas effectively remove the noise in the smooth region. Edges are very important for visualization of image. Median filter is better than Gaussian filter in which the median filter removes the noise, and at the same time it will also preserve the edges of an image. Due to this reason, in digital image processing median filtering is used to remove the noises in the images. Fig.3 shows the Binary image of the CT scan whose pixel value is 0 and 1. Where 0 represents black color and 1 represent the white color of the image. Fig.4 is the Filter image of the CT scan. It filters out the impurities in the image.

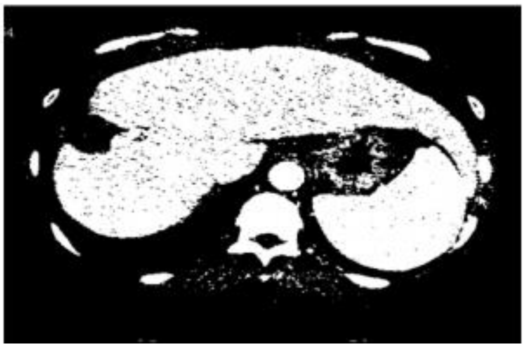

Fig. 3. Binary image

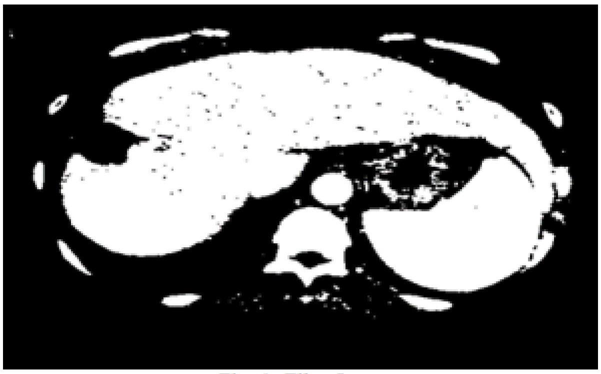

Fig. 4. Filter image

IV. SEGMENTATION

Image segmentation implicates that the whole image is separated into a particular regions that are represented by a masks, the segmented region is masked with white and other region with black. Based on this method we can process the required region which contains nodules based on the intensity. Segmentation is used to simplify our further processing. It will represent a given image into meaningful and an analyzable region. Image segmentation process segments the given input images into various part based on the features and intensities. Segmentation process takes places after preprocessing step, there are various types of segmentation techniques we have chosen active contour technique for our proposed system. This technique will limit the search to those regions containing nodules, instead of searching the whole image area for abnormality. Fig.5 shows the boundary region of the liver based on the intensity values.

A. Active Contour

Active contour technique is one type of segmentation technique it is based on the use of energy force and condition for the collection of the required region for the further processing and analysis of image.

Active contour technique is used for the separation of foreground from the background and then segmented region that contains nodule will undergoes further analysis. Medical image processing uses the active contour model very effectively, that it separates the important region from the foreground. Contour is used to define the boundaries in the processing medical image. The separated region from image is displayed as a collection of points in the contour that undergoes interpolation process. This process will describe the curve in the image using curvature. This technique has some external and internal force applied into it, which will describe curvature of the models with various contour algorithms. Active contour is based on two features of an image they are edge based and region based. Edge based contour algorithm is used to obtain an edges of an images. Region based contour algorithm is used to obtain a required region based on the intensity value of an image for the upcoming process. We are using region based contour algorithm for our proposed system which will takes up only the required region i.e., affected part for the classification process. Fig.6 shows the segmented portion of the liver. Fig. 6. Segmented.

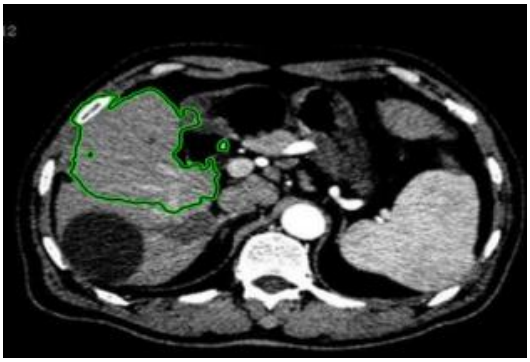

Fig. 5. Boundary region

Fig. 6. Segmented region

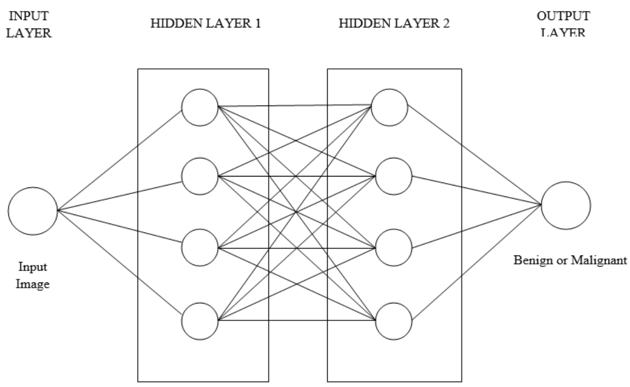

Fig. 7. Architecture of neural network

V. CLASSIFICATION USING BACKPROPAGATION ALGORITHM

Classification process is used to classify segmented image based on the visualization of the image content. Back propagation neural network consists of three layers of units they are input unit, hidden unit and output unit. All three layers are interconnected to each other layer of units. This network is simple because own representation of the input unit can be independently constructed by the hidden unit. Therefore input unit and hidden unit are connected and they contain weights which determine that hidden unit is active. The representation of the hidden unit is depends on the modification of these weights. We are using back propagation algorithm to classify a given image which comes under supervised learning. Back propagation algorithm can be applied to the segmented image to predict the stages of liver tumor. This algorithm is used to establish the deep neural network concept for training the image and testing the image with the help of weight estimating classifier. The result image will compared with the dataset images and it will display whether it is normal or abnormal. Input layer takes the input image and then the features are extracted by hidden layer 1. Hidden layer 2. Output layer provides the output whether it is Benign or Malignant. The Fig. 7. Shows the architecture diagram.

VI. RESULT

The classification of the liver has been done using back propagation classifier. Active contour segmentation algorithm has been used to segment the liver. Different abdominal CT images are used to segment the liver tumor. The result is accurate shows us whether the liver tumor is in benign or malignant stages and it provides very less computation time. Fig.8 shows us the 118 training dataset images stored in the database which is trained and then compared with our input image. First the CT images are taken as the input images which is converted to the grey scale image. Then the grey scale image is converted to binary image in which the pixel value is taken as either 0 or 1. Now the binary image is filtered using the median filter technique. And then the filtered image is taken to the segmentation process, based on the intensity values the boundary region is found and segmented using active contour region based segmentation method. The segmented image will be classified using the back propagation classification algorithm and the results would be obtained by comparing with the training datasets that will classify whether the tumor is benign or malignant. Fig.8 shows the benign stage liver tumor which noncancerous and are common. Fig.9 shows the malignant stage liver tumor which is cancerous and spread to nearby lymph nodes and other organs.

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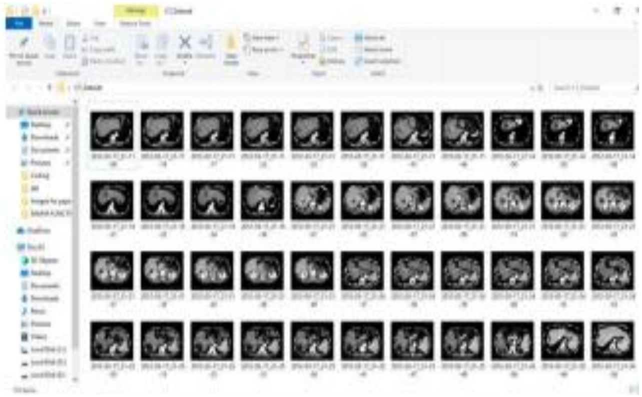

Fig. 8. Training dataset

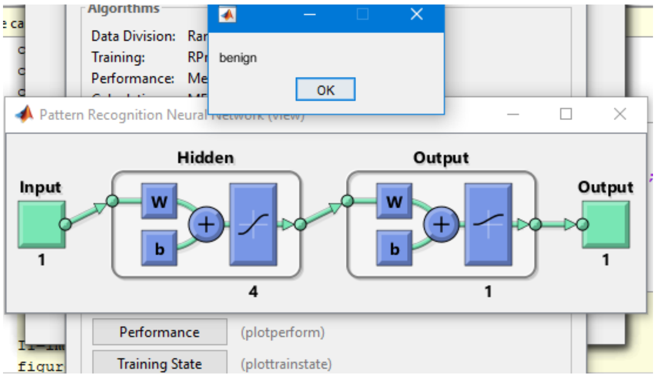

Fig. 9. Benign stage

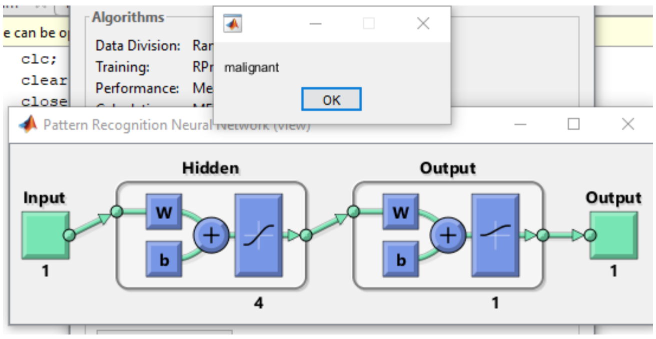

Fig. 10. Malignant stage

VII. CONCLUSION

In this paper, for the segmentation and classification of liver tumor we have used two methods namely active contour and back propagation in which active contour is an automatic segmentation method. The purpose of these proposed methods is to remove the unwanted region and to reduce the computational time. From the abdominal part of CT images, using the active contour method, the liver region is segmented and then it is classified using back propagation method. The segmented part of the input images is compared with our data sets and then classification is performed using back propagation algorithm and thus the result is obtained. In future, the performance of back propagation classifier can be obtained by comparing with the other classification techniques.

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