Liver Tumor Detection using Artificial Neural Networks for Medical Images

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Abstract

The purpose of this study is to compare the performance of Back-Propagation Neural Network and Support Vector Machine (SVM) for liver cancer classification. The performance of both models is compared and validated in terms of accuracy within the true positive rate and false positive rate. The total 583 cases is examined, 418 cases are classified accurately as true Positive rate and remaining as the false negative rate. The comparative results show that the BPNN classifier outperforms SVM classifier where BPNN gives an accuracy of 73.23%, and SVM gives classification accuracy of 63.11%. This result indicates that the classification capability of BPNN is better than SVM and may potentially fill in a critical gap in the use of current or future classification algorithms for liver cancer.

Keywords: Liver Tumor, Commuter Tomography, Artificial Neural Network, Back Propagation Neural Network, Support Vector Machine, Receiver Operating Characteristics

I. INTRODUCTION

In medical image analysis, image-guided surgery and organ visualization, segmentation plays a crucial role. The segmentation process is particularly arduous in abdominal computer tomography (CT) images because different organs overlap that lie within uniform intensity ranges and are often near to each other anatomically. Therefore, it is not possible to define accurately the boundaries of organs, their vessels and lesions using simple threshold based segmentation. On the other hand more complex algorithms involve and using many parameters of which adjustment is not a simple issue [1].

Numerous techniques have been proposed in the literature for extraction of organ contours in abdominal CT scans images. They can be roughly divided in two main groups: model driven and data driven approaches.

Model driven techniques uses pre-defined models to segment the meaningful objects or area of interest from the images being analyzed. In this kind of technique a model describe the organ to be segmented and is defined in terms of object characteristics such as position, texture and spatial relation to other objects, and the algorithm searches the images for instances that fit according to the given model.

Data driven techniques are try to emulates the human capacity to identifying objects by using some similarity information present on image data, automatically detecting and classifying objects and features in images. Many of them use traditional techniques such as region growing and thresholds, and combined with some prior knowledge about the object being analyzed.

Level set methods are model driven methods that based on partial differential equations to model deforming iso surfaces. These methods have been used successfully in medical image processing but usually required human intervention to set an initial solution and indicate explicitly when the model should stop expanding. However, semi-automatic level set based methods involve a time consuming trial and error procedure for optimum parameter tuning.

The parameters involved in traditional level sets implementation are related to the curves mean curvature, propagation rate and advection of the curve to certain characteristics of the image. Manually define to all these values on level set methods is a complex task, because their unclear relation with the final result and no guarantee that the optimal set of values will be found. Therefore, there is a demand for methods to define such parameters automatically.

Some works on liver segmentation approaching level set based methods are found in the literature. In a level set method, liver segmentation was proposed without edges, using the Chan-Vese methodology.

II. LIVER SEGMENTATION METHOD

The latest achievements in automatic liver segmentation are reviewed in this section. All the methods are discussed in one of the three categories including gray level based, structure based and texture based [2].

A. Image Pre-processing

An Ultrasound liver cancer tumour images has been taken for the pre-processing step typically used for reduce the noise and to prepare the ultrasound liver image for further processing such as segmentation and classification [3]. The generally used procedure to get a high-pass filter is firstly, apply a low-pass filter to the original image and then subtract that low-frequency image from the original image. And then result as an image only with high frequencies. Sometimes, there are desired to enhance the high frequencies without removing the low frequencies of an image, and called as the image with a high-frequency boost. After the removal of noise from the image histogram is applied to identify the maximum of the intensity value.

B. Gray Level Based Methods

Gray level is the most obvious feature of image. When extracting objects from image, the most natural way is to use the gray level to tell boundaries. The benefits of gray level based methods are: the feature is easy to extract without using special algorithm; they are stable and robust, can easily be used into similar cases; they often achieve high accuracy result. Their drawbacks are: most of them are semi-automatic methods and need user's operation; when the difference of gray level intensity between target and background is small, the methods will lose their effectiveness.

Many interesting methods and algorithms have been presented; generally, interactive methods achieved higher average scores than automatic approaches and featured a better consistency in the segmentation quality. The three common rated automatic approaches are all based on statistical shape models with some form of additional deformation and these interactive methods are based on:

- graph-cuts and Interactive refinement
- Region-growing and interactive refinement
- Two-dimensional level sets with transversal contour initialization.

III. RELATED WORK

Yufei Chen et al. [4], described a liver segmentation method based on region growing approach. They first, introduced the basic theory of region growing approach. Secondly, by using anisotropic filter and Gaussian function a pre-processing method was employed to form same liver likelihood images for segmentation further. Thirdly, proposed an improved slice-to-slice region growing method with combination of both centroid detection and intensity distribution analysis. Finally, the superior liver region was extracted by applying the morphologic operation.

H. Badakhshannoory et al. [5], proposed method relies on two types of information: liver's shape and its intensity characteristics. Here the liver shape information was retained by measuring the shape similarities between consecutive slices of the liver's CT scans by using deformable registration scheme. The liver intensity was utilized by a multi-layer image segmentation algorithm that emphasizes on the true boundaries of the liver. The average results for volumetric overlap error and relative volume difference is 11.12% and 2.21% respectively.

S. Rathore et al. [6], represented a combination of repeated patterns with regular/irregular frequency in the texture form. Here, they attempted to summarize the efficiency of textural analysis techniques which introduced for Computed Tomography (CT), Ultrasound and some other imaging modalities like Magnetic Resonance Imaging (MRI), in well-known performance metrics term.

S. Priyadarsini et al. [7], performed an extensive comparative analyses to illustrate the advantages and disadvantages of various available techniques in liver segmentation from CT images. To highlight the position of various automated techniques which could indirectly aid in developed novel techniques was the main objective for solving the health care problem of the medical sector.

Wenhan Wang et al. [8], described a High-Speed liver segmentation method applied on abdominal CT image. Firstly, based on the morphological feature of the liver region under various window-level settings, they apply the region-growing algorithm to remove other tissues and hence the discrete points of the liver region could be acquired. Secondly, they recovered the liver region from the original image by calculating the coordinates of the discrete points. Compared with other liver segmentation methods, their method had lower time complexity, which could satisfied the demands of real-time processing.

A.M Anter et al. [9], based on two different datasets and experimental results showed that the proposed system robust, fastest and effectively detected the presence of lesions in the liver, count the distinctly identifiable lesions and computed the area of liver affected as tumours lesion. And provided good quality result, that segment liver and extracted lesions from abdominal CT less than 0.15s/slice.

A.M. Anter et al. [10], presented algorithm tested using two different datasets to obtain the experimental results. The approach was promising which could segment liver from abdominal CT in less than 0.6s/slice and the overall accuracy obtained of the approach was 93%.

Changyang Li et al. [11], proposed a level set model incorporating likelihood energy with the edge energy in liver CT scans. The Chan-Vese model was not successful in segmenting hepatic tumours and their model outperformed the geodesic level set model. The results on 18 clinical datasets showed that algorithm had a Jaccard distance error of 14.4 3.1 mm.

Guotai Wang et al. [12], to address segmentation problem, incorporated the Sparse Shape Composition (SSC) in the computer assisted liver surgery planning system. The basic modules of the system consist of: (1) Segmentation module, (2) Approximation of liver segments, (3) Visualization module. The results of clinical experiment showed the system had a good performance in providing accurate and robust liver surgery planning.

D. Selvathi et al. [13], evaluation of potential role of the adaptive hybrid segmentation algorithm, Contour let transform and the Extreme Learning Machine in the differential diagnosis of liver tumours in CT images were proposed. The segmentation results were compared with expert results and analyzed. The classifier differentiated the tumour with relatively high accuracy and provided a second opinion to the radiologist.

M. Jayanthi et al. [14], proposed an approach for segmentation of liver and tumour from CT Images and basically used for computer aided diagnosis. Method used in region growing with optimized threshold algorithm. Liver segmentation using region growing method that starts from a seed point automatically detected and efficiently closed around the vessels and tumours.

IV. METHODOLOGY

Liver image segmentation is the process of partitioning a liver image into multiple segments (sets of pixels, also known as super pixels). The goal of Liver segmentation is to simplify and changes the representation of an image into something, which is more meaningful and easier to analyse by the experts to detect tumor portion. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, Liver segmentation is the process of assigning a label to every pixel in an image and same label to the pixels that share certain characteristics.

The classes divide feature space into different groups according to the tissue, or anatomical region. As the process will be supervised, the classifiers require training data set that are manually segmented and then used as a reference for automatically segmenting new data. The Final classifier will be evaluated with test set total error in cancer segmentation of the liver will be calculated as shown in flow chart fig.1.

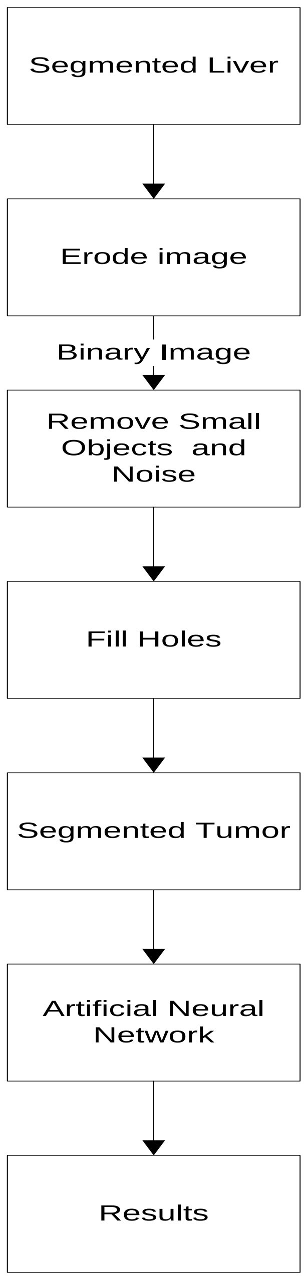

Fig. 1: ANN based classification for Liver Tumor Detection

Final Training with Neural Networks involved in developing the ANN based classification models namely; input variable selection, preprocessing, model implementation. Matlab R2012b Neural Network Toolbox is used to develop ANN classification model. The first step in developing the classification models is input variable selection. The next step is data pre-processing and partitioning. Data pre-processing contained two phases which are data normalization and data conversion. Data is normalized between the range of 1 and 2 using a linear transformation so that the classifier can have a common range to work with. Then, all of the data are converted into numeric value. As an example, benign and malignant tumours can be represented as {1, 2} before it can be supplied into the classifiers. 1 symbolizes benign tumours while 2 represent malignant tumours. Next, the data is divided into two partitions namely; training set and testing set.

V. RESULT ANALYSIS

An approach for segmentation of liver and tumour from CT Images is mainly used for computer aided diagnosis of liver is required. The method is use contour detection with optimized threshold algorithm. The liver is segmented using region growing method that starts from a seed point automatically detected and efficiently close around the vessels and tumours. The Entire process is a supervised learning process, the classifiers require training data set that are manually segmented and then used as a reference for automatically segmenting new data. The Final classifier is evaluated with test set total error in tumor segmentation of the liver is be calculated. Algorithm should be based on segmentation of abnormal regions within the liver. The classification of the regions can be done on the basis of shape categorization and many other features using methods such artificial neural networks.

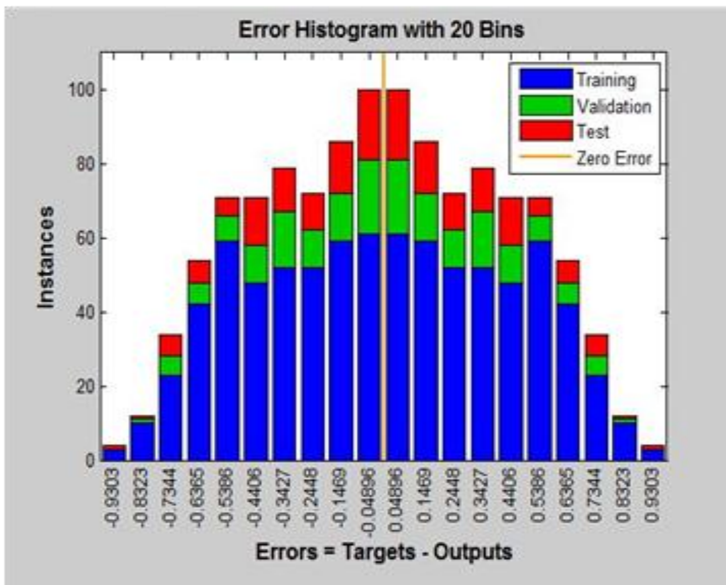

Fig. 2: Error Bins of Liver Segmentation with Zero Error

As in fig.2 error histogram with 20 bins of liver segmentation shows the best result at the zero error.

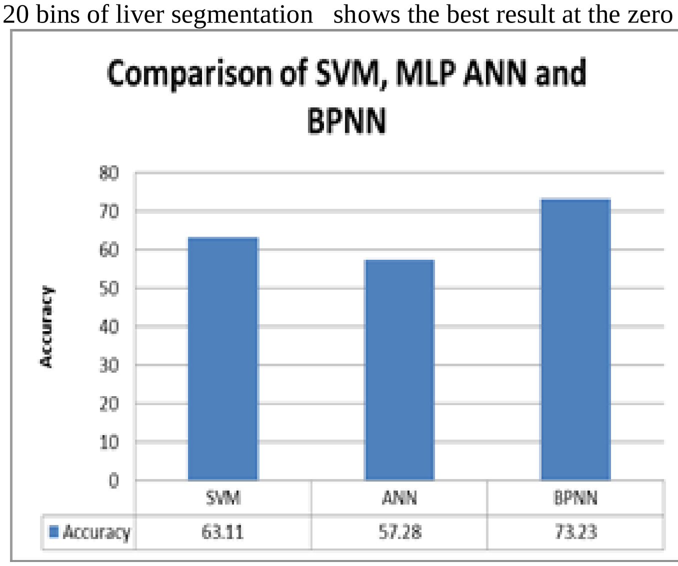

Fig. 3: performance of the classifiers

Fig.3 above depicts the comparison between Support vector machines, Multilayer Perception and Back-Propagation Neural Network (BPNN). It is evident from results that the BPNN produces better results as compared to SVM and other algorithms. Accuracy is used to approximate how effective the classifier is by showing the percentage of the true value of the class label. In this case, the accuracy of BPNN (73.23) is better SVM (63.11%) and ANN (57.28%). Thus, it means that BPNN classifier could correctly classified more data than other classifier [15].

VI. COCLUSION & FUTURE SCOPE

In this research the performance of ANN been examined in classifying the liver tumor. An approach is required for segmentation of liver and tumour detection from CT Images for computer aided diagnosis. The Final classifier is evaluated with test set total error in tumor segmentation of the liver is be calculated. Algorithm should be based on segmentation of abnormal regions within the liver. The classification of the regions can be done on the basis of shape categorization and many other features using methods such artificial neural networks.

Experimental results show that BPNN gives good results for liver Tumor classification in terms of accuracy about 73-76%. This work indicates that BPNN can be effectively used to help the medical experts to diagnose liver tumors in liver segment.

Training artificial neural networks based upon data generated form contour and thresholding processes is very challenging task we want accomplish this work in upcoming future. Even though by now some progress has been achieved, there are still remaining challenges and directions for future research. Different ANN transfer functions and different SVM kernel functions can be used in future research to improve the classifier performance.

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