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Diagnosis and Analysis of Automated Liver and Tumor Segmentation on CT

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***Abstract*—Theanalysis of the internal structures of human body such as liver, brain and kidney have wide range of different modalities for medical images are provided now a days. Computer Tomography(CT) is one of the most significant medical image modalities . The paper presents the automated computation of hepatic tumor from abdominal computed tomography images of diseased persons with images with inconsistent enhancement. The automated segmentation of livers is addressed first. Here we segment the tumor and classify about the images. Our technique improved significantly the segmentation of large tumors and segmentation Gaussian filter is used for denoising the liver image and Adaptive Thresholding algorithm is used for segmentation of liver. After segmentation we extract feature for the liver. Region Of Interest(ROI) helps to determine the value in feature extraction take place .It provides a significant impact on classification based performance. Due to the characteristics of liver tumor lesion inherent difficulties are appear in classification, For a better performance, A novel proposed system is introduced.ROI based feature selection and classification is performed. In order to obtain relevant features for Support Vector Machine(SVM)classifier is an important for better generalization performance. This classifier will classify the feature and predict the decision about the liver images. For liver tumor segmentation, here we will use fuzzy c means segmentation. Finally the segmented result will be displayed.The proposed system helps to improve the better classification performance , reason in which we can see significant reduction of features are used. The diagnosis of liver cancer from the computer tomography images is very difficult in nature. Early detection of liver tumor is very helpful to save the human life**

Keywords*—*Computed Tomography(CT),RegionOf Interest(ROI), Feature Extraction, segmentation, SVM classification

I. INTRODUCTION

Now a days medical image analysis is a challenging task. According to the the human psychological activities through medical imaging allows physicians and researchers to decide about disease information regard to the corresponding patient. This process help to diagnosis the liver tumor. One of the menacing disease in life is liver cancer, also it is oneofthedangerous internal malignancies disease in the world, and it leads to the death. Hence it is necessary to find out a clinical decision support system for detect and diagnose liver tumor. There are moreexsisting system for detection and also these systems are facing some challenging problem .So we need a system for finding the liver tumor in earlier stage that save a life .

According to the survival statistics of anAmerican cancer society in 2014,the studies have shown the patient have small liver tumor ,resectable(Removable tumor).It does not cause serious health problem or cirrhosis. Detection of early stage liver tumor can be helps to a liver transplant[2].Hepatocellular carcinoma (HCC) is a type of primary liver cancer, and it can be found at the time of diagnosis. Although secondary liver cancer,thislead to untreatable stage, and we take the treatment only for life expectation. Liver cancer is a disease, and then we can see an extra growth in the liver tissue. It causes the cell damage in the tissue and blemishes the cell. From the abnormal growth of the cell we detect the tumor is beginning or malignant stage.

Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) have been identified as accurate noninvasive image modalities in the diagnosis of the liver cancer. The radiologists can easily take an interpretation decision about medical image, by the human is limited due to nonsystematic search patters of human, the presence of structure noise in the image, and the presentation of complex planned adjustment or unpredictable due to the node failures. Of disease state requiring the integration of vast amount of image data and clinical information.

Computer-aided diagnosis (CAD), defined as a diagnosis by a radiologist who uses the output from a computerized analysis of medical images for detecting lesions, accessing extend of the disease, and making diagnostic decisions is used to improve the interpretation component of medical imaging. But CAD research for the liver cancer is insufficient because liver segmentation that plays an important role for CAD is difficult. This is mainly due to fact that there are other organs or tissues adjacent and close to the liver which make segmentation more difficult.so we want an efficient tumor burden analysis system for identify the liver tissues from the nervous one.

We propose a system that resolve all the earliest problem, introduce an efficient clinical decision support system. Introduce anautomated liver tumor segmentation technique after image preprocessing .The proposed methods include segmentation, andRegion Of Interest(ROI) based feature extraction and segmentation,Using Gray Level Co-occurrence Matrix(GLCM) and Support Vector Machine(SVM) classifier algorithm. , then we can analyze the abnormality and assisting the diagnostic tool robust for identify the variability in liver tumor lesions.

II. RELATED WORKS

In the recent years liver segmentation from computed tomography scans has gained a lot of importance in the field of medical image processing since it is the first and fundamental step of any automated technique for the automatic liver tumor diagnosis, liver volumemeasurement, and 2D-3D liver volume rendering. In this paperstudy about the semi-automatic and automatic liver segmentation techniques and we describe our automatized method. The study reveals that automatic liver segmentation is still a problem since various weaknesses and disadvantages of the proposed works must still be addressed. Our gray-level threshold based liver segmentation method has been developed to resolve all these problems; We believe that our technique improves those presented in the literature; nevertheless, a generally accepted performance measure are required to demonstrate it.

Disseminated cancer accounts for most deaths due to malignancy. Prepositionthis; research has focused on tumor development and progression at the primary stage. Recently, attention has shifted towards the field of tumor metastasis. Several new and exciting concepts that have emerged in the past few years may shed light on this complex area. The established canonical theory of tumor metastasis, as a process emerging from a stepwise accumulation of genetic events fuelled by somatic evolution in cancer, has been challenged. New declarations suggest that malignant cells can disseminate at a much earlier stage than previously recognized in tumor. These findings have direct relevance to clinical practice and shed new light on tumor biology. Gene-profiling studies support this explanation, suggesting that metastatic circulating tumor cells may be an innate property shared by the bulk of cells present early in a developing tumor mass. There is a growing recognition of the importance of host factors outside the primary stage in the development of metastatic disease. The role of the 'pre-metastatic niche' is being defined and with this comes a new understanding of the function of bone marrow-derived progenitor cells in directing the dissemination After the tumor cells come to rest at another site. Current research has highlighted the important roles played by non-neoplastic host cells within the tumor microenvironment in controlling metastasis. These new concepts have wide-ranging suggestion for our overall understanding of tumor metastasis and for the development of cancer therapeutics.

III. PROPOSED METHOD

The proposed system work on the liver CT images. Figure explain the different sequential steps in the proposedmethod.1))Preprocessing2)Liver segmentation 3)ROI and NON ROI selection 4)EnhancedGLCM based Texture feature extraction 5)Classification using SVM classifier 6)Liver tumor segmentation using Fuzzy C mean algorithm.

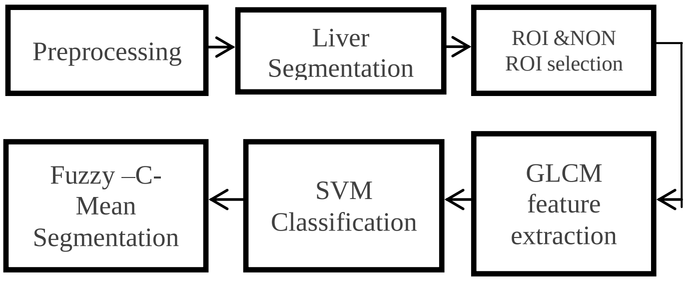


Fig1.Overview of a proposed system

A. *Image Preprocessing*

Medical images are widely used for disease analysis. Image preprocessing is the first step in analysis. image processing is used to enhance the CT image , smoothing and reduce the noise without destroy the important features of liver CT images for diagnosis. We use more effective and easier method for segmentation for qualities improvement and highlight certain features of the CT images. For image preprocessing the filtering technique are commonly used. The proposed work ,several steps are included in it 1)Denoising by Gaussian filter 2)Image resizing of CT image 3)Dynamic thresholding for global contrast calculation.

One of best nonlinear method for noise removal is Gaussian filter,It helps to remove the random noise or normal noise in the image before the filtering process image resizing is take place,This way we can reduce the computation and complexity. Gaussian filter is windowed filter of linear class, by its nature is weighted mean. Named after famous scientist Carl Gauss because weights in the filter calculated according to Gaussian distribution.We get the filtered image as an output apply Gaussian filtering process window based filtering, that decide the filtering requirements, by its weighted mean.

B. *Liver segmentation*

Image segmentation is an important role in medical image diagnosis. Through segmentation process we assign a label to each pixel in the liver CT image.After the image segmentation we get a different representation of image then it will became easier to analyze. In medical image processing field the liver segmentation using computer tomography data has gained a lot of importance.In our proposed work we use the adaptive threshold segmentation. It will segment the image based on threshold value. First we have to select a gray-level T between those two dominant levels, which will serve as a threshold to distinguish the two classes (objects and background). Where the value marked as T is a natural choice for a threshold. Using this threshold, a new binary image can then be produced, in which objects are painted completely black, and the remaining pixels are white. Denote the original image f(x, y), then the threshold product is achieved by scanning the original image, pixel by pixel, and testing each pixel against the selected threshold: if $f(x, y) > T$, then the pixel is classified as being a background pixel, otherwise the pixel is classified as an object pixel. This can be summarized in the following definition, where b(x, y) denotes the threshold binary image. In the general case, a threshold is produced for each pixel in the original image; this threshold is then used to test the pixel against, and produce the desired result (in our case, a binary image).According to this, the general definition of a threshold can be written in the following manner:

$$T= T [x, y, p(x, y), f(x, y)] \quad (1)$$

Where f(x, y) is the gray level of point (x, y) in the original image and p(x, y) is some local property of this point (we shall explain this shortly). When T depends only on the gray-level at that point, then it degenerates into a simple global threshold (like the ones described in the previous section). Special attention needs to be given to the factor p(x, y). This was described as a property of the point. Actually, this is one of the more important components in the calculation of the threshold for a certain point. In order to take into consideration the influence of noise or illumination, the calculation of this property is usually based on an environment of the point at hand. An example of a property may be the average gray-level in a predefined environment, the center of which is the point at hand. The key feature of this segmentation technique is to select the threshold value. Several methods are used now a days, but we does not want .From each CT images we derive the thresholds ,this segmentation image is suitable for better result.

C. *ROI and NON ROI selection*

Now a days medical imaging technology such as computer aided diagnosis method is used for diagnosis of the disease and medical operation .The available tool provide biomedical image having noise and fuzz.Diagnosis and analysis of the biomedical image become a challenging task.One of the neuro psychological concept is Region Of Interest in which the regions that people concern in the small scenes. The build software the function fast and precise the researchers try of copy and modify the neuro –psychological concept. In analysis tool we can a limitation in the speed ROI method helps to optimize the processing .Only relevant data is consider in account for the processing that efficiently increase the speed.

In proposed work we use ROI and non ROI selection .Based on the ROI the texture feature analysis is take place.ROI based GLCM feature extraction is better compared with previous methods. The generation of ROI s and non ROIs can used as the preprocessing method for any other segmentation technique. This ROI generation can make the next step image feature extraction faster.

D. *Feature extraction*

Dimensionality take place in feature extraction.in this the input image is too large and we can see the redundancy behavior in it.so we want to reduce it into a set of feature, for this the ROI based feature extraction using GLCM algorithm become very helpful. It is used to get statistical information about the image such as entropy, energy, correlation, sum of the energy etc. for the feature extraction [6].

A gray level co-occurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values. A co-occurrence matrix is a two-dimensional array, P, in which both the rows and the columns represent a set of possible image values. A GLCM Pd[i,j] is defined by first specifying a displacement vector d=(dx,dy) and counting all pairs of pixels separated by d having gray levels i and j.

In our proposed system from the liver CTimage we extract texture features using the gray level co-occurrence matrix (GLCM).four direction(0º, 45º, 90º and 135º degrees) are chooses for calculating the co-occurrencematrix. In four angles, we have to extract the 12 different statistical features. Haralick texture descriptors each of which extracted from each co-occurrence matrices .The texture feature is Contrast, Correlation, Cluster prominence, Cluster shade, Dissimilarity, Energy, Entropy, Homogeneity, Maximum probability, Sum of squares ,Auto correlation&Inverse different Moment.

E. *Classification using SVM*

Machine Learning is a field of study that gives computers the ability to learn without being explicitly programmed. Given a training set, we feed it into a learning algorithm.The learning algorithm then outputs a function, which for historical reasons is called the hypothesis.The parameters that define the hypothesis are what are “learned” by using the training set. After the feature set has been computed for each pixel, it will be used by a classifier to decide whether each pixel represents a tumor pixel or a normal pixel .In classification method we are used the Support Vector Machine Classifier. SVM classifier is a binary classifier. It is a machine learning algorithm.it will predict about the features. It is like normal or abnormal.in our proposed system we based on the SVM. Along with normal liver we want to discriminate different diseases of liver. Through supervised learning method we discriminate different disease in liver lesion. Using GLCM feature extraction we extract seven haralick texture features theuse svm for separating the classes using hyper plane. The classification stage has two components, a training phase and a testing phase. In the training phase, pixel features and their corresponding manual labels represent the input, and the output is a model that uses the features to predict the corresponding label. This training phase needs to be done only once, since the model can then be used to classify new data. The input to the testing phase is a learned model and pixel features without corresponding classes, and the output of the testing phase is the predicted classes for the pixels based on their features.

Support vector machine (SVM) based classifier or the linear discrimination analysis method can be applied. Aim of classification is to group items that have similar feature values into groups. Classifier achieves this by making a classification decision based on the value of the linear combination of the features.

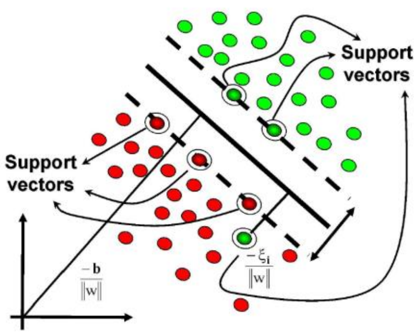


Fig 2: SVM classification

F. *Liver tumor segmentation*

Liver tumor segmentation becomes a challenging task now days. Pixel intensity of CT liver image inhomogeneity in nature and so many open problems are there. For getting an efficient result in tumor segmentation, method having high accuracy and invariant inhomogeneity is required. We can high performance in different modality images through this method. A proposed Fuzzy C-Mean (FCM) method is a simple statistical feature comparison of pixel attributes that distinctively characterize the object these pixels constitute. The features employed by the proposed method encompass mean and standard deviation of gray scale measurements of pixel blocks. The values obtained from feature measurement are subject to two basic observations:

1. Image pixel colors are lighter than those of background in gray scale level, and
2. Pixels that differ slightly in mean value or standard deviation are considered belonging to the same object.

Using conventional statistical mean described by the following relation.

$$\bar{p} = \frac{1}{q}\sum_{i=1}^{q} p_i \qquad (2)$$

and the standard deviation

$$s = \sqrt{\frac{1}{q-1}\sum_{i=1}^{q}(p_i - \bar{p})^2} \qquad (3)$$

Where$q$ denotes the number of pixels in each block. These statistics were utilized as the feature values of object pixel colors. However, it was found that gray scale feature values offered better discernable results than the RGB counterpart. As such, a colorto- gray scale conversion scheme was devised according to the following straightforward mapping

IV. RESULTS & DISSCUSSION

To analyze the performance of the proposed system to detect the tumors, the images obtained using the proposed methodology is compared with its corresponding ground truth images. A number of different measures are commonlyused to evaluate the performance of the method. These measures including classification accuracy (AC) and Mathews Correlation Coefficient (MCC) are calculated from confusion matrix. The confusion matrix describes actual and predicted classes of the method.

Actual	Predicted	
	Positive	Negative
Positive	TP(True Positive)	FP(False Positive)
Negative	FN(False Negative)	TN(True Negative)

Table 1: Confusion Matrix

MCC is used to measure the quality of binary classification. The MCC can be calculated from the confusion matrix using the formula. It returns a value from -1(inverse prediction) to +1(perfect prediction)

Measures	GLCM
AC(%)	98
MCC(-1 to +1)	0.92

Table 2: Evaluation results

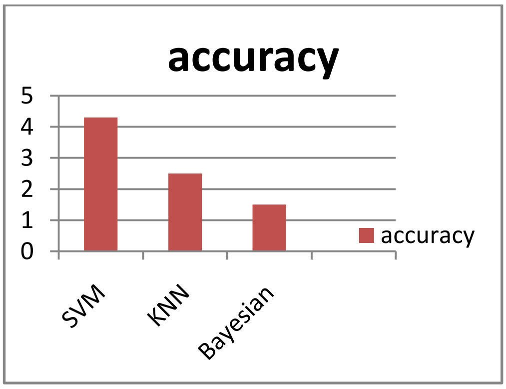


Fig 3: Accuracy of classifiers

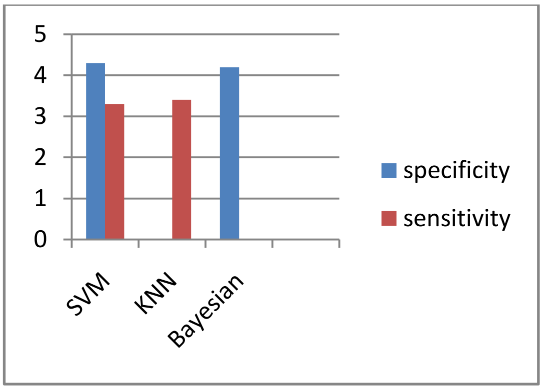


Fig 4: performance graph of sensitivity and specificity ofclassifiers(Statistical Classification

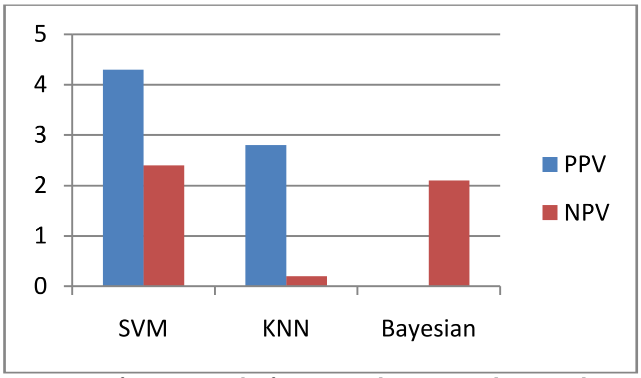
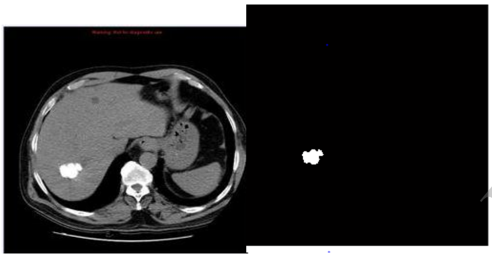
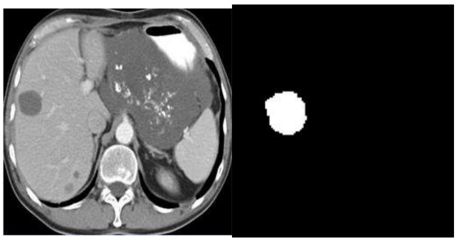


Fig 5: Performance graph of positive andnegative predicative value

According to the figure SVM shows the best classification accuracy. A set of support vectors can uniquely define the maximum margin hyper plane for the learningproblem.SVM is extremely powerful nonlinear classifiers.Here we concluded that SVM gives the better classification accuracy than KNN and Bayesian. Our resulting SVM performance accuracy is about 84.62% was obtain. SVM is best classifier method. The utilization of new and more efficient classifiers could improve the accuracy performance.The below figure shows the result of FCM tumor segmentation .fig (a) and fig (b) input images and fig(c) & fig (d) shows output liver tumor segmented image.



(a) (b)



(c) (d)

V. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In this paper, a new approach for the segmentation and classification of liver tumor is proposed. It helps the physician and radiologist for liver tumor detection and diagnosis for tumor surgery. After the pre-processing Here segment the tumor and classifies about the images ROI based gray level co-occurence features are extracted from liver images with benign and liver images with malignant and normal liver images. These extracted features are trained using SVM classifier in training mode. The same features are extracted from test liver image and classified withtrained patterns using SVM classifier in classification mode. The technique is improved significantly and the segmentation of large tumor .Reduce the number of false tumor detection Tumor burden computes the percentage of total tumor in the liver. An automated computation of hepatic tumor burden from CT images, the system achieved a good performance than manually and automatically measured tumor burdens.This proposed computer aided automation system for liver tumor segmentation and classification achieves 99.4% of sensitivity, 99.6% of specificity, 97.03% of positive predictive value and 99.5% of overall accuracy.Future we want to improve the system using colorization. Here we segment the liver tumor by the use of FCM method. In future we may try to segment the tumor by other segmentation algorithm. In future we have to analyze about the tumor by the size, area, shape and etc…

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