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Automatic Liver Cancer Segmentation using active contour model and RF Classifier

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***Abstract:** In this paper, we presented the new method for liver cancer detection. Computed Tomography (CT) has becomes important tool for diagnosis of liver cancer. The proposed method used in this paper is Random Forest (RF) classifier algorithm for the detection of cancer in the liver. For the automatic segmentation, here we use active contour method to segment the liver and liver cancer to rectify the manual segmentation problem. It is fully automatic and the proposed classifier will successfully classifies whether it is malignant or benign liver cancer tumor. Manual identification is not accurate and also time consuming task. The new method proposed in this paper will segment the liver cancer from the CT image of liver automatically. It is highly accurate and less computation time. The experiment results show the accuracy of the proposed method. Random Forest classifier has 91% accuracy rate and less error rate and achieved excellent test result.*

***Key Words**— liver cancer, active contour segmentation, Computed Tomography (CT), Random Forest (RF).*

I. INTRODUCTION

In the modern medical field, computer are widely used in medical research [1]. Positron Emission Tomography (PET), Computed Tomography (CT), Ultrasound, Magnetic Resonance Imaging (MRI) are some of the imaging modalities used for diagnosis the liver cancer tumor.

Liver imaging is important, because it is a common site of metastatic spread, mostly from lungs, stomach, colon and pancreas and also in patients with hepatocellular carcinoma. Liver cancer is the one of the threats which is faced by the society. Early liver cancer detection will increase the survival here CT image is used.

II. RELATED WORK

In [2], proposed the Random Forests (RF) classifiers for training and improved the image segmentation for better accuracy. The Supervoxel-based RF classifier [3] makes the single-scale to multi-scale tree in context of liver tumor segmentation. It is simple and efficient to accurately find out the tissues. The semi-automatic approach of 3D segmentation learned from partial annotations, the random forest classifier is used to predict the annotation of the CT scan and graph-cut method used for final stage of segmentation [4].

The random tree [5] algorithm classify the liver diseases based on the analysis. The tree is generated using random decision tree. Liver cancer diagnosis for treatment either surgical or non-surgical. Based on the Random Forest [6], [7], multi-phase super voxel for the classification of liver tumor segmentation. The convolutional neural networks is fully automatic method which is used to solve the liver lesion segmentation problem based on random forest classifier [8].The detection of liver cancers are detected using various techniques and methods [9],[10].

In this work we segment the liver tumour using active contours segmentation method. Extract shape and texture features are identified. Using Random Forest classifier classify normal and abnormal liver images. The results show that RF classifier gives better classification accuracy.

III. PROPOSED METHOD

The automatic liver segmentation and classification is shown in Fig.1, block diagram for proposed system. It consist of four stages: preprocessing, segmentation, feature extraction and random classification.

First, the CT image of train and test images is preprocessed. Next the preprocessed image is segmented using active contour method and feature extraction. Random Forest classifier used for classifying normal and abnormal liver.

A. Pre Processing

It is an improvement of the image data, which is used to suppress unwanted distortions or enhances image features for further processing. Gamma correction

B. Active Contour

An active contour [11] or snake is a curve and made of energies, it is mould to the targeted object according to the shape. It is divided into two categories: Internal and External energy.

The Internal energy function for elasticity and curvature, while external energy function has properties of image like contrast and brightness. For the medical application, the active contour is designed for detecting

$$E_{snake}=E_{internal}+E_{external} \quad (1)$$

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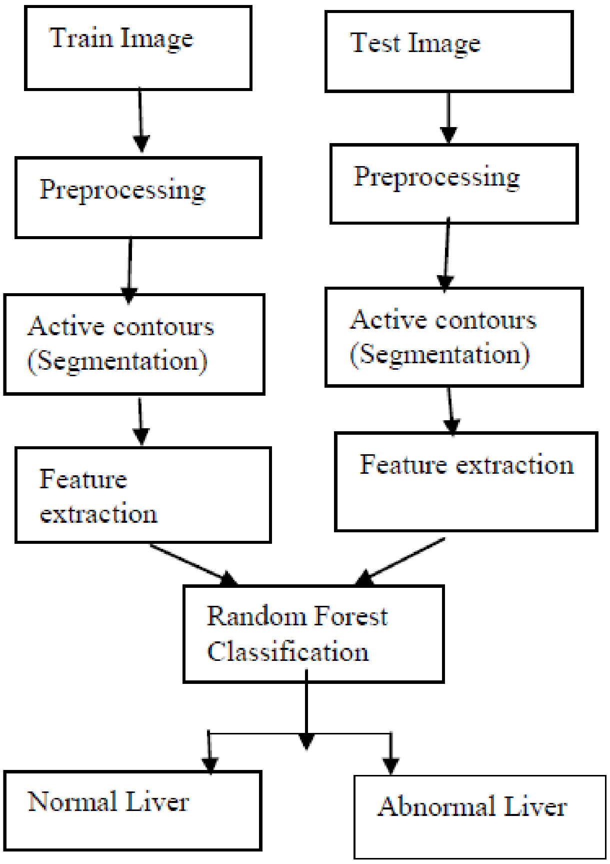


Fig.1: Block diagram for proposed methodology

Fig.2: Original abdominal CT Image

C. Random Forest Classification

Random forest is an ensemble classifier, which consists of many decision tress. In 1995, Tin Kam Ho of Bell Labs proposed term random decision forest. It combines the selection of features and Breiman's "Bagging" idea.

Each decision trees are individual learners and they are combined. CART (Classification And Regression Tree) is the type of decision tree. It is greedy, recursive partitioning, top-down binary, sets of disjoint rectangular regions are divided from feature space.

***RF Algorithm*:**

The following algorithm is used to construct each tree:

1. Let N and M be the number of training cases and the number of variables in the classifier.
2. To determine the decision at node of tree, the number *m* of input variables are used; *m* <M.
3. The training set for the tree is by choosing *n* times replacement from all N training cases. To estimate the error, rest of the cases are used, by predicting their classes.
4. Choose *m* variables for each node of tree randomly and calculate the best split using these *m* variables.
5. It is fully grown and not pruned.

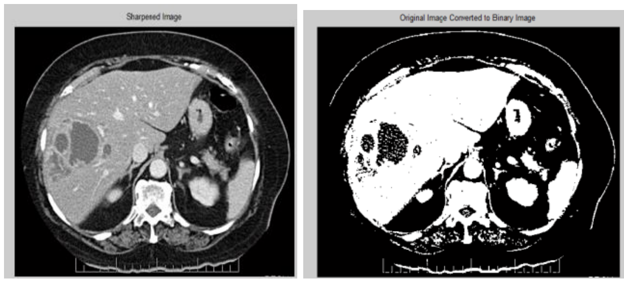
Estimating the test error:

- From the training samples, estimate test error.
- For each grown tree, 33-36% of samples are unselected in bootstrap. It is known as Out Of Bootstrap (OOB) samples.
- For the corresponding tree, OOB samples as the input, predictions are made when it has novel test samples.
- For all OOB samples, Classification and regression is computed.
- The estimate test error is accurate in practice.

IV. RESULT

The classification of the liver has been done using RF classifier [12]. The algorithm has segmented the liver using active contour method. The proposed algorithm using different abdominal CT images. The results shows the normal or abnormal liver. It is accurate and less computation time. The images are shown below in Fig.3. Contrast, correlation, energy, homogeneity also calculated for each image.

First, the CT image is taken and it is sharpened, then the original image is converted to binary image. The hole are closed and remove smallest organ in the abdominal CT image. Then getting largest organ from the image. The morphological operation takes place. Getting the segmented image of the liver from the abdominal CT image is shown in Fig.4. The OOB classification error is shown in Fig.5. Finally, it shows the result whether the given image is normal liver or abnormal liver.



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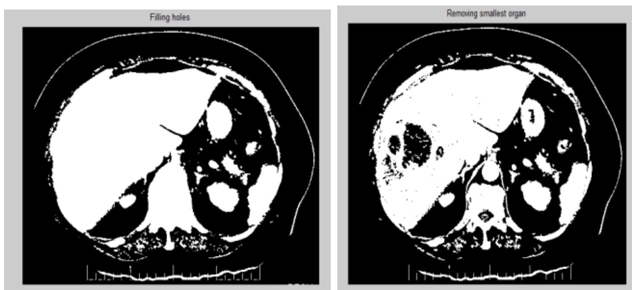

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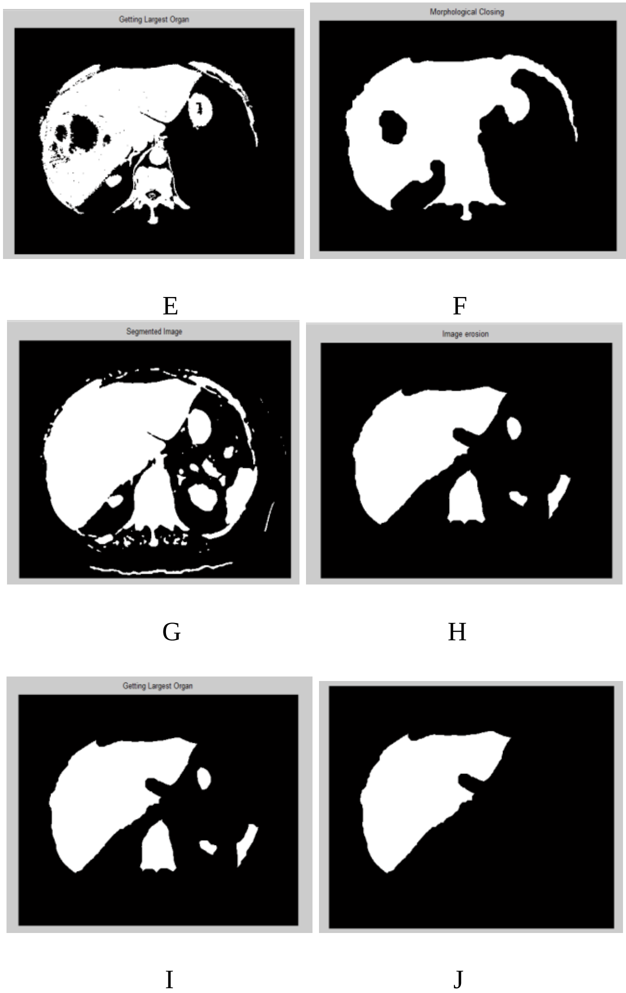

Fig.3: A.) Sharpened Image, B.) Orginal Image converted to Binary Image, C.) Filling Holes, D.) Removing smallest organ, E.) Getting largest organ, F.) Morphological closing, G.)Segmented Image, H.) Image Erosion, I.) Getting Lagest organ, J.) Segmented image.

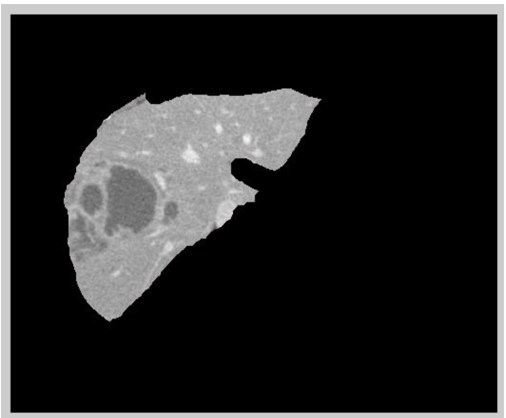

Fig.4: Segmented liver image

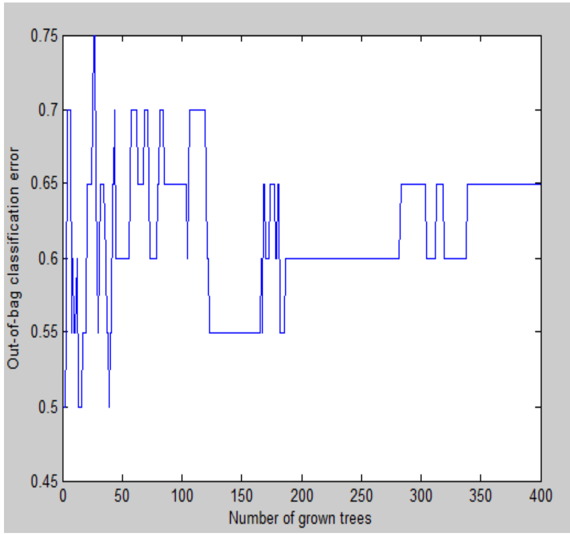

Fig.5: Out Of Bag Classification Error

The Performance of the classification test is given by the statistical measure of specificity and sensitivity. The sensitivity measures the actual positives and the specificity measures the negatives which are properly identified. The Area Under the Curve (AUC) - Receiver Operating Curve (ROC) used for the performance measurement for classification problem. The ROC curve of the RF classifier is shown in Fig.6. The ROC curve data is given in Table 1.

Sensitivity = TP/ (TP+FN)

Specificity = TN/ (TN+FP)

Accuracy = (TP+TN) / (TP+TN+FN+FP)

- TP = True Positive, liver tumor correctly identified as tumor.
- FP = False Positive, normal liver incorrectly identified as liver tumor.
- TN = True Negative, normal liver correctly identified as normal liver.
- FN = False Negative, liver tumor incorrectly identified as normal liver.

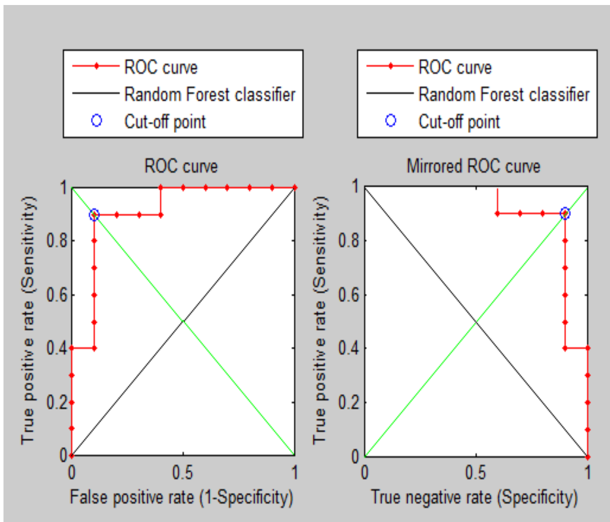

Fig.6: ROC Curve of the RF classifier

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Cut off point	Sensitivity	Specificity
1.0000	0.0000	1.0000
2.0000	0.1000	1.0000
3.0000	0.2000	1.0000
4.0000	0.3000	1.0000
5.0000	0.4000	1.0000
6.0000	0.4000	0.9000
7.0000	0.5000	0.9000
8.0000	0.6000	0.9000
9.0000	0.7000	0.9000
10.0000	0.8000	0.9000
11.0000	0.9000	0.9000
12.0000	0.9000	0.8000
13.0000	0.9000	0.7000
14.0000	0.9000	0.6000
15.0000	1.0000	0.6000
16.0000	1.0000	0.5000
17.0000	1.0000	0.4000
18.0000	1.0000	0.3000
19.0000	1.0000	0.2000
20.0000	1.0000	0.1000

Table 1: ROC CURVE DATA

From the above data's, the Area Under the Curve (AUC), Standard Error (SE) rate and Confidence Interval (CI) are shown in Table 2. ROC curve analysis shows that the test taken by the RF classifier. The 95% CI was 0.77225 and the standardized AUC, P-value is 5.8337 and the area is statistically greater than 0.5.Here AUC has 0.91 which means the test result was excellent with less error rate of 0.7028.

AUC	0.91000
SE	0.07028
95 % CI	0.77225
COMMENT	Excellent test

Table 2: ROC Curve Analysis

V. CONCLUSION

In this paper, we proposed an automatic segmentation and classification algorithm for liver cancer. This proposed method remove unwanted region and decreases the computational time. From the abdominal CT image, the liver region is segmented using active contour method. The classification of liver cancer is classified using Random Forest classifier. The proposed method performs well in both segmentation and classification. It achieved 91% accuracy rate and has excellent test result. In future, the performance analysis of this RF classifier is obtain by comparing with other classification techniques.

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