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Performance Analysis of Screening Liver Tumors Using Image Fusion and Neural Network Classifier

R.Rajagopal[1], P.Subbaiah[2]
[1]*Research Scholar, Department of ECE, St. Peter University, Avadi, Chennai, India*
Mail id: r.rajagopal1234@yahoo.com
[2]*Principal, Sri Sun flower college of Engineering and Technology, Lankapalli, India*

Abstract

Liver is the largest gland and internal organ in the human body. Liver tumor is the sixth most common cancer worldwide and the third most common cause of death from cancer. In this paper, we present computer aided automatic liver tumor detection from computed tomography (CT) images. The proposed systems consist of the pixel level fusion, Gabor transform, feature extractions and neural network classification. The liver images are enhanced using pixel level image fusion technique and the fused image is sharpened using median filter in order to enhance the tumor edges in the liver. The local binary pattern, Gray level co-occurrence matrix and grey level features are extracted from Gabor transformed liver image. These extracted features are trained and classified using feed forward neural network classifier. The proposed system achieved 98.2% of accuracy.

Keywords: Liver segmentation, Tumor segmentation, Computed Tomography, Texture analysis, Computer Aided Diagnosis, Neural networks.

Introduction

Liver cancer is one of the major death factors in the world [1]. Liver diseases are considered life threatening as they occur without pre-warning. Liver lesions are a wound or injury to body tissues. It is the area of tissue that caused damage because a wounding or disease. Liver lesions refer to those abnormal tissues that are found in the liver. In India, the international agency for research on cancer estimated indirectly that about 6,35,000 people died from cancer in 2008, representing about 8% of all estimated global cancer deaths and about 6% of all deaths in India. In 2010, more than 5,56,000 cancer deaths were estimated in India for people of all ages, and 71.1% occurred in people aged 30–69 years [2].

Medical image processing has become an essential component in many field biomedical applications such as tumor detection for automatic determination of liver tumors, volume of a heart chamber, screening of lung cancers and various other diseases. Hence, we use image processing for our automatic liver tumor detection methodology to identify tumors and assist radiologists to save time in the manual segmentation process and for further treatment planning.

From a liver CT scan, these lesions can be identified by a difference in pixel intensity from that of the normal liver tissues. Manual segmentation of this CT scans are tedious and prohibitively time-consuming for a clinical setting. Automatic segmentation on the other hand, is a very challenging task, due to various factors, such as liver stretch over 150 slices in a CT image, indefinite shape of the lesions and low intensity contrast between lesions and similar to those of nearby tissues.

Liver tumors can be benign or malignant. Benign tumors do not really cause harm to the health while malignant tumors can be fatal as it spreads to other parts of the body [3]. Computer Aided Diagnosis (CAD) which is based on computerized analysis of medical images, is used by radiologists as a ‘‘second opinion’’ in detecting tumors, assessing the extent of disease, and making diagnostic decisions. CAD for liver diseases consists of liver and suspected region (tumor) segmentation, texture feature analysis and disease classification.

Several approaches have been used for segmentation of liver from CT image datasets. Some of them are semi-automatic and some of them are fully automatic. Semi-automatic methods require user intervention to outline the region of interest before leaving to the computer for processing. In the task of liver tumor segmentation from CT images, anatomical variance combined with limited resolution and random noises in the image are some common problems that complicate the method. Therefore, to address the problems of manual segmentation and for an efficient computer aided diagnosis of liver diseases, an automatic liver and tumor segmentation algorithm from liver CT image is proposed. The proposed algorithm employs pre-processing, feature extraction, neural network for tumor detection and morphological operations for tumor segmentation.

The reminder of this paper is ordered as follows: Section 2 discusses the previous work on liver tumor detection and segmentation. Details of the proposed method are given in Section 3. Section 4 analyses the experimental results and discussion. Section 5 depicts the conclusion.

Related Works

In [4], Freiman et al. presented an automatic algorithm for the segmentation of liver tumors in computed tomography angiography (CTA) scans. Their method employed only a small number of seeds—at least one for the liver and for each type of tumor—inside and outside the tumors. The seeds were used to classify the image voxels with a support vector machine (SVM) classifier. The results showed that, an average aggregate score of 67 was obtained which was higher compared to that of other semi-automatic methods. The mean computation time for each tumor was 8:35 mins (SD=5:13 mins) on an PC with Intel Core2 Quad 2.4 GHz and 3GB RAM. The average symmetric surface distance of 1.76 mm (SD=0.61 mm) was obtained which was better than 2.0 mm obtained for other methods.

Anter et al. [5] proposed an automatic segmentation of liver lesions using hybrid segmentation techniques. Their system was based on two different datasets and experimental results showed that the proposed system was fast, robust and effective in detecting the presence of lesions in the liver, and compute the area of liver affected as tumors lesion, and provided classification accuracy of 93%, which could segment liver and extract lesions from abdominal CT in less than 0.15 s/slice.

Sharma and Kaur [6] made a review of all the existing CAD techniques for liver tumor segmentation. They compared the techniques based on computational time, sensitivity, specificity and accuracy. They analyzed various segmentation methodologies which were based on Region Based Segmentation, Thresholding Method, Level set approach, Model Based approach and Graph cut based methods.

Rajagopal and Subbiah [7] presented a new and accurate method for liver tumor segmentation from CT scans. Initially, the liver CT image was pre-processed, to remove noise. Then they employed SVM classifier, which is trained using the user fed image sets, to classify the tumor region from liver image. Sequentially, morphological operations and feature extractions were performed over the segmented binary image to further refine the rough segmentation result of SVM classification. Their experiment results provided an accuracy of 97.83% for dataset 1 and 95.23% for dataset 2.

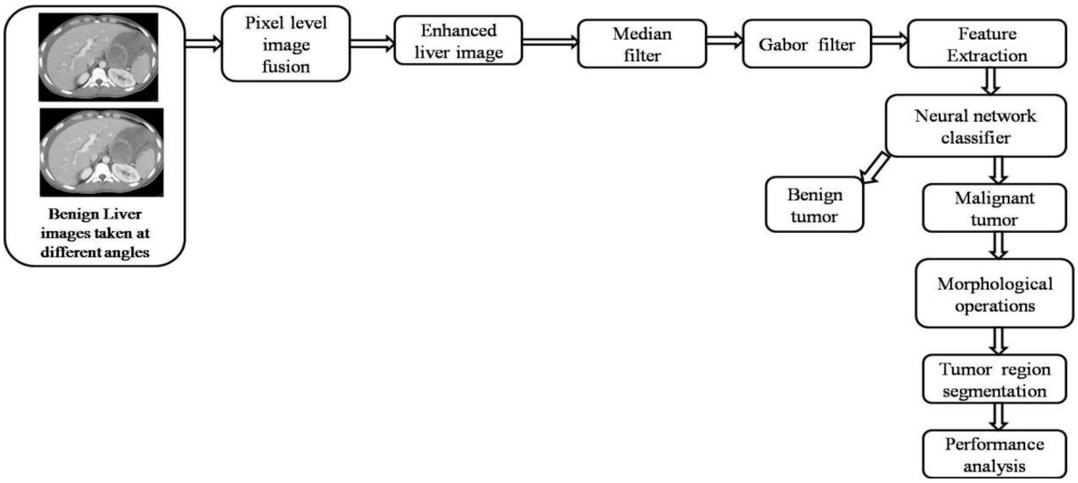
In [8], Kumar et al. proposed an automatic segmentation of liver and tumor from CT images based on computer-aided diagnosis. Their method used region growing, employed by pre- and post- processing functions for automatic segmentation of liver and Alternative Fuzzy C-Means (AFCM) algorithm for tumor segmentation. The mean and standard deviation of overlap for the 10 cases of liver segmentation was obtained as 0.9758 and 0.0050, and for tumor segmentation the values were obtained as 0.9174 and 0.0293, respectively.

Kumar and Moni [9] proposed a computer aided liver tumor detection method which employed feature extraction based on multi-resolution fast discrete Curvelet transform. The tumor region was extracted from the segmented liver using FCM clustering. They used artificial neural network classifier for exact classification of the tumor into benign and malignant, from the textural information obtained from the extracted tumor using Fast Discrete Curvelet Transform (FDCT) in the training mode. The segmentation results of the method provided 93.3% accuracy, 96% Specificity, 90% Sensitivity and 94.73% Precision.

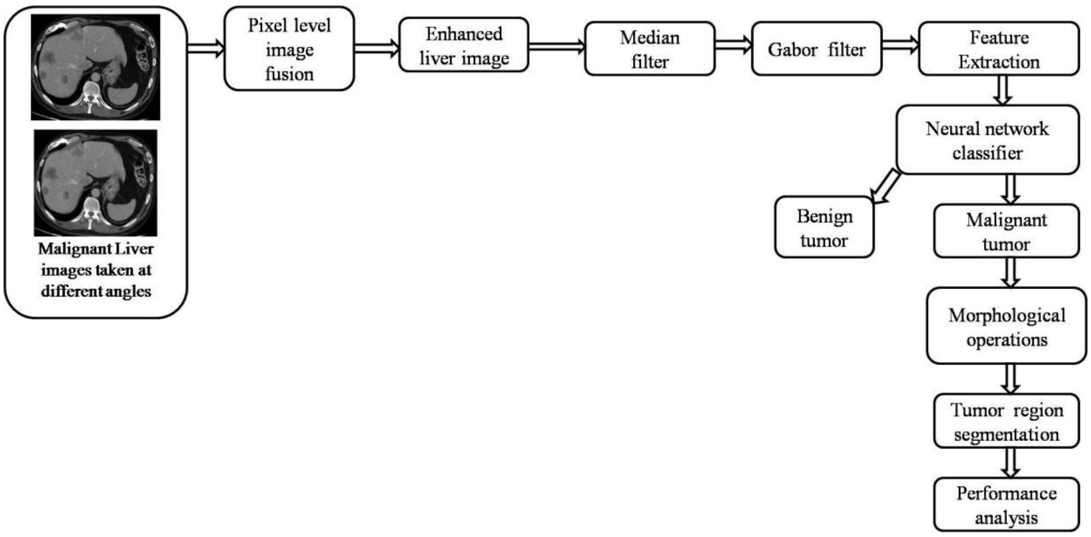
In all the above methods, though the methods are automatic, the accuracy in tumor detection is low due to processing of single liver image. Hence, we propose a neural network based liver tumor detection algorithm which detects the tumor region more accurately by applying image fusion technique and neural network algorithm.

Proposed Work

The proposed fully automatic technique and methods to segment liver structure and tumor region from liver CT is divided into two phases, namely liver region segmentation and tumor region extraction, after malignant tumor is detected. The liver tumor segmentation process from liver CT mage is shown in Fig. 1. Before the Pre-processing step, pixel level fusion of liver images is done, after which Gabor filter is applied to transform the image into frequency domain. The texture features are extracted from the image and the image is classified into tumor and non-tumor regions. If malignant tumor is obtained, we apply morphological operators for exact segmentation of the tumor region from other regions. The performance of the proposed method is analyzed in terms of accuracy and computation time and comparison with other methods are made. Fig. 1a and 1b illustrates the process flow for benign and malignant liver image tumor detection and segmentation process, respectively.



(a)



(b)

Figure 1: Proposed flow of liver tumor detection system for (a) Benign liver tumor image and (b) Malignant liver tumor image.

Pixel level image fusion

Pixel-level image fusion integrates the information from multiple images of one scene to get an informative image which is more suitable for human visual perception or further image processing. In our proposed system, we fuse two liver CT images of the same patient taken at different angles, in order to improve the image quality and also obtain the detailed information from the fused (enhanced) liver image.

A typical pixel level fusion system consists of six sub-systems: imaging, registration, preprocessing, fusion, post-processing and displaying. Various pixel level fusion algorithms have been proposed. We employ the simplest pixel level fusion method, namely the weighted averaging (WA) fusion. The simplest image fusion based on weighted averaging is by taking the average of the source image pixel by pixel, such as:

$$C(m,n) = \alpha A(x,y) + \beta B(x,y) \tag{1}$$

Where, α and β are the scalar weights. The WA method is simple and fast to implement. This method also reduces the noise present in the source image.

Median filtering

The liver CT images are prone to noise and are hard to interpret manually. Hence, they require a pre-processing procedure for image quality improvement and obtaining an accurate segmentation result. The pre-processing includes resizing the original image to a resolution of 128×128 pixels and then removal of background image. For further processing, the contrast of the image is enhanced to improve the visual quality of the liver region. The pre-processing phase employs median filtering for all the above described steps.

Median filter is a non-linear filtering technique which uses a window that moves over a signal and at each point, the median value of the data within the window is taken as the output. The impulse response of the median filter is zero and thus makes its use attractive to suppress impulsive noise. Median filters are robust and are well-suited for data smoothing when the noise characteristics are not known and also has the capability to preserve edges. This median filter belongs to the class of edge preserving smoothing filters which are non-linear filters. This means that for two images *A(x)* and *B(x)*:

$$median[A(x) + B(x) \neq median[A(x)] + median[B(x)] \tag{2}$$

These filters smoothes the data while keeping the small and sharp details. The median is just the middle value of all the values of the pixels in the neighborhood. The median filter considers each pixel in the image and its nearby neighbor pixels to decide whether it is representative of its surroundings or not. Instead of simply replacing the pixel value with the mean of neighboring pixel values, as in mean filter, it replaces it with the median of those values. The median is calculated by first arranging all the pixel values in ascending order and then the median (middle) pixel replaces the central pixel value in the 3×3 sub-image. Fig. 2 illustrates an example of median filtering process considering a 3×3 sub-image.

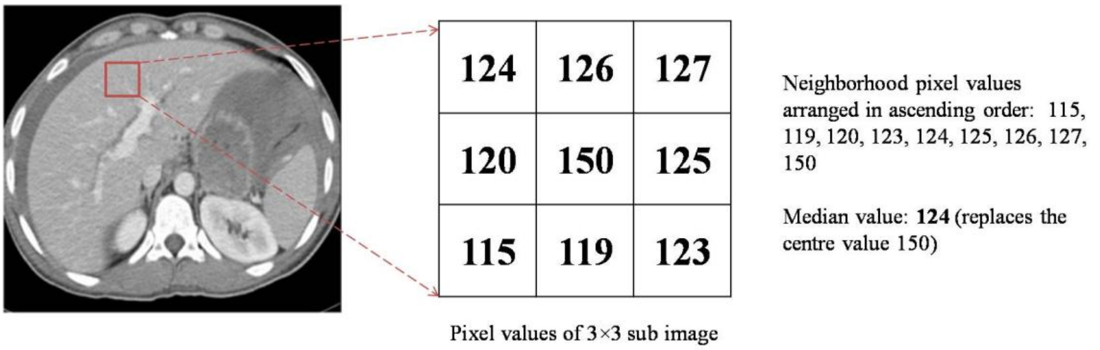


Figure 2: Computation of median value in a Median filter.

Gabor Transform

In image processing, a Gabor filter is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are identical to those of the human visual system. They are particularly appropriate for texture representation and differentiation. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. In Gabor filters, all filters can be generated from one mother wavelet by dilation and rotation and hence, they are self-similar.

Gabor filters can be designed for a number of dilations and rotations, thus directly related to Gabor wavelets. Gabor filters exhibit desirable characteristics of spatial locality and orientation selectively and is optimally localized in the space and frequency domains have been extensively and successfully used in face recognition. The Gabor kernels used are defined as follows:

$$\psi_{\mu,\upsilon} = \frac{k_{\mu,\upsilon}^2}{\sigma^2} \exp\left(-\frac{k_{\mu,\upsilon}^2 z^2}{2\sigma^2}\right) \times \left[\exp\left(ik_{\mu,\upsilon} z\right) - \exp\left(-\frac{\sigma^2}{2}\right)\right] \tag{3}$$

where, μ & υ are the orientation and scale of the Gabor kernels, respectively, z=(x,y), and $k_{\mu,\upsilon}$ is the wave vector. Finally, the noise removed liver CT image is transformed to frequency domain image after application of the Gabor filter.

Feature Extraction

GLCM Features

The grey level co-occurrence matrix (GLCM) is a feature to identify texture in an image, by modeling texture as a 2-Dimensional array grey level variation. This array is called Grey Level co-occurrence matrix. GLCM is a statistical method that considers the spatial relationship of pixels, hence it is also known as the grey-level spatial dependence matrix. GLCM features are calculated in four directions - 0°, 45°, 90° and 145°. Five properties of GLCM namely, contrast, correlation, energy and homogeneity are computed using,

$$\text{Contrast} = \sum\left(|i-j|^2 \times p(i,j)\right) \tag{4}$$

$$\text{Energy} = \sum p(i,j)^2 \tag{5}$$

$$\text{Homogeneity} = \frac{\sum p(i,j)}{1+|i-j|} \tag{6}$$

$$\text{Correlation} = \sum (i - \mu i)(j - \mu j)\frac{p(i,j)}{[\sigma i.\sigma j]} \tag{7}$$

The number of grey levels in an image determines the size of GLCM. The matrix element P(i,j│Δx,Δy) is the relative frequency with two pixels separated by pixel distance (Δx,Δy), which occurs within a given neighborhood, one with intensity i and other with intensity j.

A grey level co-occurrence matrix (GLCM) contains information about the positions of pixels having similar grey level values. A GLCM P[i,j] is defined by first specifying a displacement vector d = (dx,dy) and counting all pairs of pixels separated by d having grey levels i and j.

Local binary pattern features

The local binary pattern (LBP) operator is an efficient texture based image operator which transforms an image into an array or image of integer labels representing the small-scale appearance of the image. These labels are most commonly then used for further image analysis. The LBP operator has a computational simplicity; hence it is possible to analyze the liver CT images in real-time applications.

The LBP operator defines a two-Dimensional surface texture by 2 complementary measures, namely, grey scale contrast and local spatial patterns. The LBP operator creates labels for the pixels in the image by thresholding the 3×3 surrounding pixels with the centre value and stores the result as a binary number. In unsupervised pattern segmentation, LBP operator can be used in combination with a local contrast measure to produce higher performance.

A 3×3 mask window is placed over the image and a sub image is obtained. In the resulting 3×3 sub image, the value of the centre pixel is compared with its neighboring pixels. If the neighboring pixel has a value greater than the centre pixel, then the neighboring pixel value is replaced by 1, or else the neighboring pixel value is replaced by 0. Finally, all the neighboring pixels will be replaced by either 0 or 1, on merging which forms an eight digit binary number. The detailed operation is explained in Fig. 3.

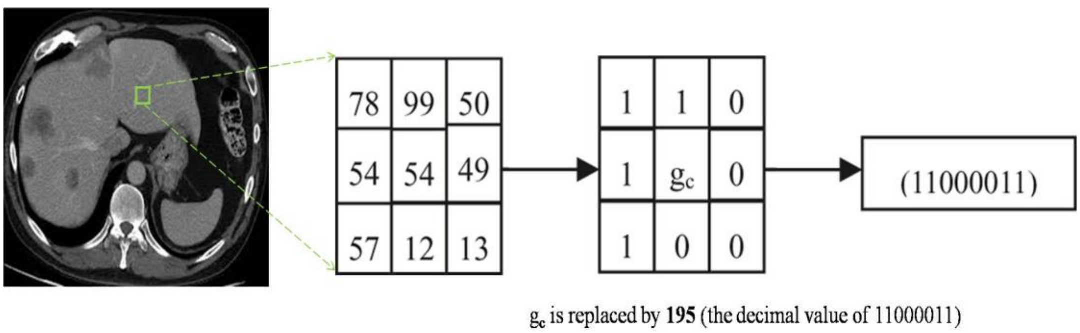


Figure 3: Computation flow of LBP feature

Grey level based features

These features are based on the differences between the grey-level intensity values in the candidate pixel and its surrounding pixels. Since liver tumor lesions are always darker than their surroundings, features based on the grey-level variations in the surroundings of the tumor region are an excellent option to segment the tumor region. A set of grey-level-based descriptors are derived from homogenized images I_H considering only a small pixel region centred on the described pixel (x,y). $S_{x,y}^{w}$ Stands for the set of coordinates in a *3×3* sized square window centered at the point (x, y). The Grey level based feature descriptors each represent a feature image and are represented as follows:

$$\left.\begin{array}{ll} \text{a)} & F_1(x,y) = I_H(x,y) - \min\{I_H(s,t)\} \\ \text{b)} & F_2(x,y) = \max\{I_H(s,t)\} - I_H(x,y) \\ \text{c)} & F_3(x,y) = I_H(x,y) - \text{mean}\{I_H(s,t)\} \\ \text{d)} & F_4(x,y) = \text{std}\{I_H(s,t)\} \\ \text{e)} & F_5(x,y) = I_H(x,y) \end{array}\right\} \quad (8)$$

Neural Network classifier

The neural network (NN) classifier is defined as an information-processing system inspired by the structure of the human brain. Inspired by the biological neuron in the brain, ANNs consist of a number of interconnected neurons. A neuron is an information-processing unit that receives several signals from its input links, each of which has a weight assigned to it. These weights correspond to synaptic efficiency in biological neurons. Weights are the basic means of the long term memory in NNs [8].

Generally, the initial weights of the network are set to random numbers and subsequently the weights are calculated from a set of training liver CT images. The transfer function transforms the activation level of a neuron into an output signal. The behavior of the NN depends on both the weights and the activation function specified for the neuron. Significantly, each layer has its own transfer function. We use supervised learning, which is a training process for an artificial neural network by giving a data set consisting of input vectors and desired output associated with each input vector.

Back-propagation algorithm is one of the most popular training methods used in artificial neural network. Back-propagation networks consist of at least three layers of units: an input layer, at least one hidden layer and an output layer. The output from the input layer is connected as an input into the hidden layer. Similarly, the output from the hidden layer is connected as an input into the output layer to produce the final output of the ANN. Fig. 4 shows a back-propagation Neural Network.

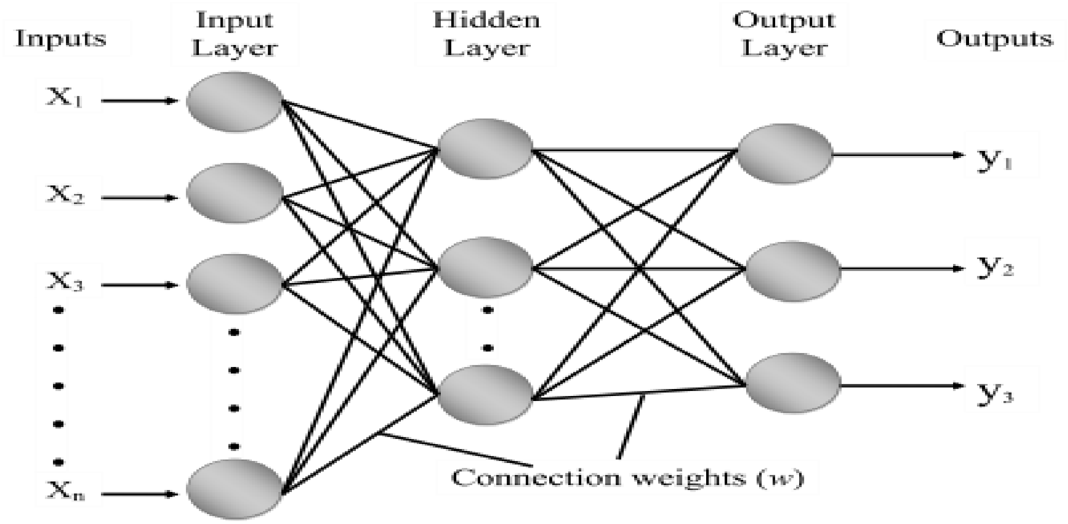


Figure 4: Back propagation neural network.

In general, the interval activity of the neuron can be estimated using,

$$AF_k = \sum_{p=1}^{n} w_{kp} x_p \quad (9)$$

Where, AF_k is the activation function, such that the output of the neuron (y_k) depends on the activation function. The activation function acts as a squashing function, such that the output of a neuron in a neural network is between certain values (usually 0 and 1, or -1 and 1). Generally, there are three types of activation functions (AF), denoted by $\delta(\,)$.

$$\delta(AF) = \begin{cases} 1, if\ AF \geq 0 \\ 0, if\ AF < 0 \end{cases} \quad (10)$$

Secondly, the Piecewise-Linear function uses the values of 0 or 1, but also takes values between that depend on the amplification factor.

$$\delta(AF) = \begin{cases} 1\ AF \geq \frac{1}{2} \\ AF\ -\frac{1}{2} > AF > \frac{1}{2} \\ 0\ AF \leq -\frac{1}{2} \end{cases} \quad (11)$$

The sigmoid function ranges between 0 and 1, but also uses the -1 to 1 range. An example of the sigmoid function is the hyperbolic tangent function given by,

$$\delta(AF) = \tanh\left(\frac{AF}{2}\right) = \frac{1-\exp(-AF)}{1+\exp(-AF)} \quad (12)$$

The fundamental learning rule of supervised NN is that, if two units m and n are active simultaneously, their interconnection must be strengthened. If m receives input from n, the weight $W_{mn}$is given by,

$$\Delta W_{mn} = \tau y_m y_n \quad (13)$$

where τ is a positive constant of proportionality representing the learning rate. Another rule uses not the actual activation of unit n but the difference between the actual and desired activation d_n (given by user) for adjusting the weights:

$$\Delta W_{mn} = \tau y_m(d_n - y_n) \quad (14)$$

Morphological operation based tumor segmentation

The purpose of the morphological operators are to separate the tumor part from the liver image and noted for further tumor diagnosis. The morphological operations are applied on the grey scale liver image to segment the abnormal regions. Erosion and dilation are the two elementary operations in Mathematical Morphology. An aggregation of these two characterizes the rest of the operations. The symbols $\oplus, \ominus, \circ$, and $\bullet$ denote the four fundamental binary morphological operations: dilation, erosion, opening, and closing, respectively. A function f (x, y) denotes the image, and the function h(x, y), or h denotes the structuring element. The four operations are defined as follows:

Dilation:

$$(f \oplus h)\,(x,y) \;=\; \sup_{(r,a)\in H} \{x - r, y - s) + h(r,s)\} \quad (15)$$

Erosion:

$$(f \ominus h)\,(x,y) \;=\; \inf_{(r,a)\in H} \{x + r, y + s) - h(r,s)\} \quad (16)$$

Opening:

$$f \circ h = (f \ominus h) \oplus h \quad (17)$$

Closing:

$$f \bullet h = (f \oplus h) \ominus h \quad (18)$$

Where, *sup*{} and *inf*{} denote the supremum and infirmum operation. Erosion and Dilation are merged to form a powerful operator called Opening, by which objects that are adjacent are spaced and objects that are adjoined are detached and the holes within the objects are enlarged. Now only the tumor portion of the image is visible. This portion has the highest intensity than other regions of the image.

Results and Discussion

To analyze the performance of the proposed algorithm to detect and segment the liver tumor, the images obtained using the proposed methodology is compared with their corresponding ground truth images. The performance of the proposed technique is analyzed with the following parameters:

- Sensitivity [Se = TP / (TP +FN)]
- Specificity [Sp = TN / (TN +FP)]
- Accuracy [Acc = (TP + TN) / (TP+FN+TN+FP)]

All the above parameters help in defining the performance of our proposed technique. Se and Sp define the ratio of well-classified tumor and non-tumor pixels, respectively. Lastly, Acc is the ratio of total well-detected and classified liver tumor pixels. TP is true positive which represents the number of correctly identified tumor region piexls.TN is true negative which represents the number of wrongly identified tumor region pixels. FP is the false positive which represents the number of correctly identified non-tumor region pixels. FN is false negative which represents the number of wrongly identified non-tumor region pixels.

The Local Binary Pattern features, GLCM features, and grey level based features are extracted for a set of liver images for training. Then, the feed forward neural network (NN) classifier is used to classify the test liver image features with these trained features in the classification mode. In the classification mode, the NN classifier segments the tumor regions into benign and malignant. Figure 5 illustrates the result of each intermediate steps for the detection and segmentation of liver tumors.

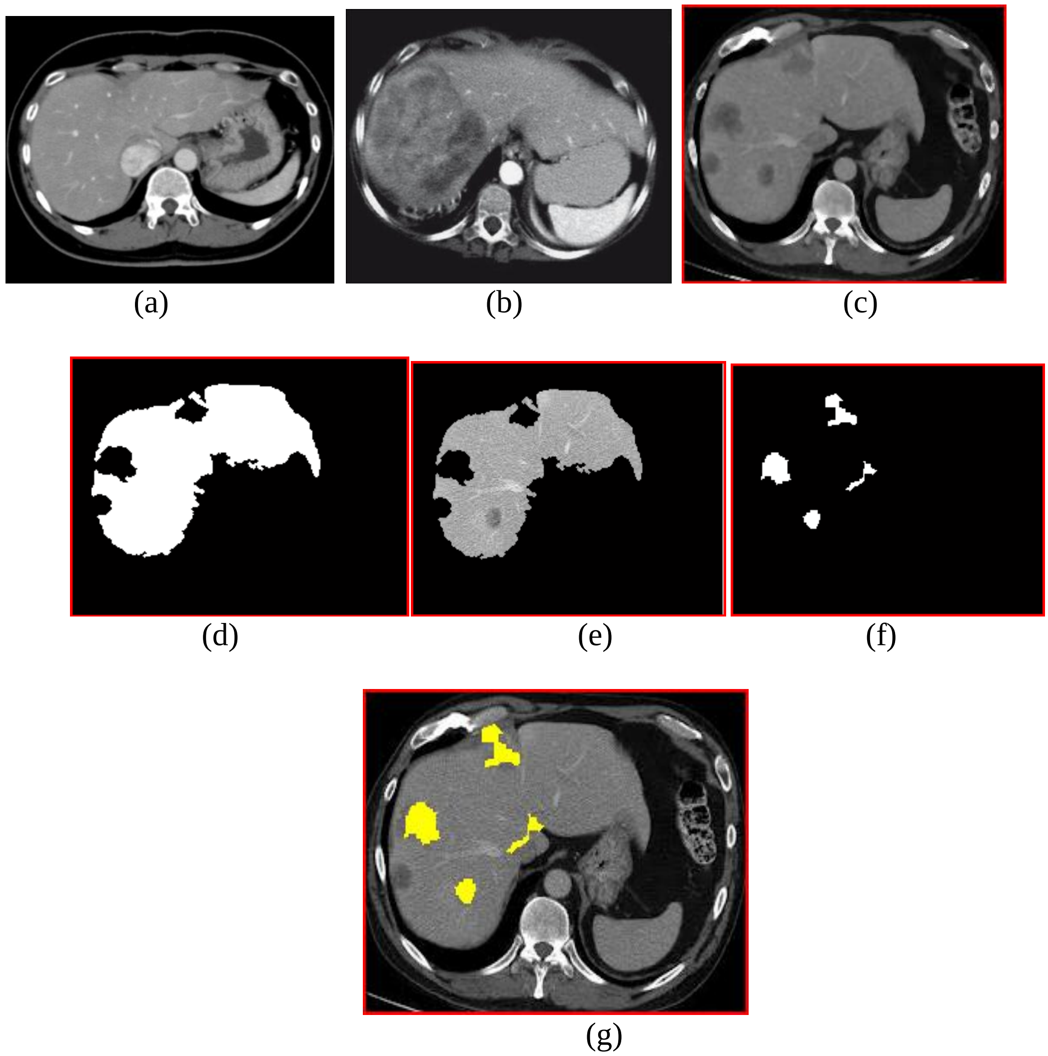


Figure 5: Results of proposed methodology (a).Malignant Liver Image (b).Fused Image (c). Median filtered Image (d). Thresholded Image (e). Gabor transformed Image (f). Detected tumor regions (g). Result of tumor segmentation

Table 1 illustrates the performance evaluation of the proposed tumor detection algorithm in terms of the performance evaluation parameters. The average accuracy achieved is 98.2% for malignant tumor region in accordance with ground truth images.

Table 1: Performance evaluation of proposed algorithm.

Methodology	Year	Accuracy (%)
Proposed work	2015	98.2
Anter et al.,[5]	2013	93.0
Kumar et al.,[8]	2011	93.3
Rajagopal et al.,[7]	2014	95.23

Conclusion

We have proposed a pixel level fusion technique based automatic detection and segmentation of liver tumors from liver CT images. The tumor segmentation method proposed in this paper includes a novel method for tumor classification which helps the medical experts for further diagnosis of liver tumors in to mild, moderate and severe depends on the severity level f the liver tumors. The main advantage of our method is that it yields accurate results for different types of liver tumors with ease and without manual interaction. The proposed system achieved 97.2% of accuracy.

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