Detection and Categorization of Liver Diseases Using Level Set Based Back Propagation Neural Network Technique

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Abstract

To evaluate and analyze liver cancer accurately in a short time Computer-Aided Diagnosis (CAD) has been widely used, as manual detection of the cancer tissue is time consuming and complex task. In this work, the main objective is to detect the liver cancer automatically using CAD based method. We proposed a new approach called Level Set based Back Propagation Neural Network (LS-BPNN) for the detection and categorization of liver cancer automatically. The abdominal image taken from the Computed Tomography (CT) scan is used for the detection of affected liver. From this abdominal image, liver is segmented using Level Set method and tumor is segmented using Practical Swarm Optimization (PSO) method, then the features has been extracted. Next the features from the segmented liver were given to BPNN for classifying the liver cancer, it is generally classified as primary and secondary liver cancer. Primary liver cancer i.e. Hepatocellular carcinoma (HCC) or hepatoma, cholangiocarcinoma and angiosarcoma (hemangiosarcoma). Comparing with Feed Forward Neural Network (FFNN), our method achieved excellent accuracy. We have achieved excellent accuracy when compared with FFNN, BPNN classifier has 97.98% accuracy during the classification process where FFNN has 89% accuracy. The system we developed can be tested with enormous dataset and the radiologist using CT images the liver cancer is detected.

Keywords: CT scan, Liver cancer, Level Set method, PSO, BPNN, FFNN.

1. Introduction

In the world wide scenario, Liver cancer is one of the most common cancer, 18 million new cancer cases were estimated, determined as the second leading cause of death and 9.6 million deaths has been estimated in 2018 [1]. In 2018, it was reported as 841,080 new cases were diagnosed with liver cancer. Among those, 596,574 and 244,506 were found in men and women respectively [2]. The Computed Tomography (CT) image used to identify cancerous tissue accurately from the abdominal region. Tumor can be classified as benign or malignant, here we taken malignant tumour as primary and secondary. Malignant tumor indicates presents of abnormal cells grow in the tissue, primary liver cancer is where the liver tumor begins and secondary liver cancer is the cells break away from the other primary cancer and new tumor grown in the liver [3].
Image segmentation in medical imaging is an essential step. Various approaches for segmentation of livers have been proposed in literature review, some of the image segmentation methods are threshold method, watershed method, edge based method and region based segmentation [4].

Two different methods, Supervised and Unsupervised classification are used for detection of liver metastases. Comparing both classifications, textural analysis with supervised learning neural network and K-nearest neighbor (KPP), the first approach has most effective recognition rate equal to 80.667% [5]. Bingbing Xia et al. proposed the classification of Hepatocellular carcinoma (HCC) image predicated on the random forest and then the model is optimized by voting ranking. The experimental results has good performance by combined features with Voting Ranking Random Forest (VRRF) method [6]. Yun Soo Hung et al. proposed to analyze acute-on-chronic liver failure (ACLF) characteristics and outcome of patients with liver disease [7]. Yongchang Zheng proposed an approach for liver based on appearance and context features [8]. Aman Singh presents an EHC-ERF (Enhanced Hierarchical Clustering-Enhanced Random Decision Forest) techniques with intelligence-integrated model for liver classification. It has better accuracy, precision, true positive rate, root mean squared error and mean absolute error [9]. Alice Auxilia have taken the Indian liver ailment patient's dataset and using the machine learning techniques, the accuracy is predicted [10]. They proposed the hybrid method with WOA-SA (Whale Optimization Algorithm-Simulated Annealing) and Ensemble Classifier for Chronic Liver Disease Classification (CLD). The categorization are normal liver, cancerous liver, fatty liver, metastasis and cirrhosis [11]. The review was done for medical image analysis are done by neural networks and machine learning algorithms. The deep learning with big medical data will automatically analysis and also they cover various research applications of medical image segmentation, detection, registration, localization and classification [12]. In 2030, Liver cancer was the major public health threat causing diseases in the world. The estimated cancer cases referable to HBV and HCV (Hepatitis B & C Virus) in HCC, and data was calculated using GLOBOCAN 2012 [13]. Machine learning methodologies has been used to different dataset of various liver diseases, it diagnosis and analysis of disease accurately and predicts outcome result [14].

Here, we presented a fully automated method for segmenting and classifying the abdominal CT liver images. In recent works, a wide range of problems are solved successfully by machine learning techniques. This paper deals with the detection of liver cancer using Back Propagation Neural Network. Here we develop a hybrid method based on Level set method for liver segmentation and PSO for tumor segmentation. From that segmented liver image, the features are extracted which has various informative data. Then the features are used for the classification process with BPNN. Finally the results shows the excellent accuracy classification when comparing with FFNN 89% accuracy, BPNN classifier has 97.98%.

2. Methodology

We Proposed a CAD model for abdominal CT Liver image segmentation and detection of liver cancer. Our approaches comprises four main stages: 1. Liver Segmentation 2. Tumor Segmentation 3. Feature Extraction from segmented tumor 4. Liver Cancer Classification.

We describe every phases in the following steps in detail which involves in all stages. In Image Processing, image quality is more important, the image noise is
need to degradation of image quality. Random variation of color or brightness in the images. The Gaussian filter is the popular technique for removing the noise in the image. In our approach, to reduce computation time the CT image is resize into 382x512 and the gaussian filter the image with a filter of 5x5. Next step is segmentation. The proposed workflow of the CAD system is shown in Figure.1 below.

**Figure 1. The Workflow of the Proposed CAD model**

**2.1 Liver Segmentation**

Image Segmentation as the name implies, deals with partitioning of an image. The subdivision of images is depends upon the problem being solved. The image segmentation algorithm has the intensity values properties of discontinuity and similarity. The discontinuity property is based on sudden changes in intensity values such as points, lines and edge. The similarity property is based on partitioning on the region that are similar corresponding to a set of predetermined criteria. Some of the approaches are Region growing, Thresholding, region splitting and region merging [15]. Different approaches for medical image segmentation: Level Set, Clustering Based, Thresholding, Region Based and Edge Based. For the analyzest of anatomical structures in medical imaging like blood vessels, muscles, tissues, bones, pathological region or abnormal cell (cancer) of entire image is divided into White Matter (WM) and Gray Matter (GM). The main objective of the image segmentation is to partition an image containing strong correlation with area of interest. In segmentation process, Level Set method to improve and solve topology problems [16]. The segmentation of liver tumor is done with LS method.

**LEVEL SET METHOD**

Level Set method was developed by Stanley Osher and J.A.Sethian [17, 18]. For medical image segmentation, it is one of the emerging image segmentation techniques. In this area, this method was very useful and influential. In image processing, Partial Differential Equations (PDE) are used. It is based on moving curves and surface with curvature-based velocities. Level Set method have their own importance in segmentation due to their accuracy. It has been widely used in
image segmentation, motion segmentation, object tracking etc. It is way to denote active contour.

LS method is to analyze and evaluate the consecutive motion of the interface in the process of velocity field $v$. It depends upon the position, time and geometry of surface, also some energy function [19]. For any given image $a_0$, to describe the contour with same size of image $a_0$, a LS function $\phi(x, y)$ is created. The contour is given as the zero LS of the function $\phi$ [20]:

$$C = \{(x, y) \mid \phi(x, y) = 0\}$$  \hspace{1cm} (1)

By Lipshitz continuous function $\phi$, the region of curves are explicitly given as

$$\begin{align*}
\phi(x, y) > 0 & \quad \text{inside the contour} \\
\phi(x, y) = 0 & \quad \text{contour} \\
\phi(x, y) < 0 & \quad \text{outside the contour}
\end{align*}$$  \hspace{1cm} (2)

By changing the values of $\phi$, the positive regions change to negative region and negative region change to positive region. According to the update value contour will change position as shown in Figure 2:

![Figure 2. Representation of the Level Set method and contour change](image)

For the equation 1, the evolution equation of the LS function $\phi$ is defined as nonlinear PDE:

$$\frac{\partial \phi}{\partial t} + F \mid \nabla \phi \mid = 0$$  \hspace{1cm} (3)

This equation is known as LS equation and velocity field $F$ is known as the speed function for image segmentation part and Velocity field depends on level set function $\phi$ and information of image data. The speed function $F$ which is related to the characteristics of the image like gray and gradient, evolving surface characteristics (e.g.: normal direction, curvature). The F depends on image information and the target edges has the zero which is the ideal value. The topological breaking and merging are done easily and well performed.

LS method provides computational and mathematical tool for racking of evolving interfaces with sharp corners, cusps. It extract clinically useful features from noise output of the images [21]. We applied the Level Set method to segment the whole liver from the abdominal CT image.

2.2 Tumor Segmentation

PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle Swarm Optimization (PSO) is a swarm intelligence technique which is used to solve an optimization problem in real life [22]. In 1995, PSO was presented by James Kennedy (American Sociologist and Psychologist) and Russell Eberhart (Electrical Engineer) [23,24]. This algorithm was biologically inspired by collective
and social behavior of bird (flocks) groups. Based on Social-Psychological principal, the particle swarm is a population–based stochastic algorithm for optimization. The particle swarm will not utilize selection (unlike evolutionary algorithm). They clustered together in the ideal region of search space is called as particle swarm [25]. This algorithm stimulates the search by movement and flocking of birds, every bird is called particle. A flocking of bird searching for food casually in an area. In that area, if it has a one portion of food, the location of food is unknown for the birds, but the birds will try to find food. In each iteration, the birds only know the distance of food where it is located. If we follow which bird is nearest to the food, then it is the best method to search the food [26].

For updating particles, the two best value is needed in PSO, pbest and gbest [27].

- In solution space, each particle is tracked by its coordinates. It is correlated with the best solution or fitness which is attained up to a point by the particle and the value is known as pbest (personal best).
- The PSO was traced and the best solution achieved by any particle still in the area of that particle and the value is referred as gbest (global best).

In PSO algorithm, the each particle of main operators were the velocity and the positions [28, 29]. For every iteration, particles position are estimated according to a fitness function .Next step is to update every particle, the velocity and the position according to equation given below:

\[
\begin{align*}
    v_n(t+1) &= w * v_n(t) + c_1 \cdot r_1 (P_{id} - x_n(t)) + c_2 \cdot r_2 (P_{gid} - x_n(t)) \\
    x_n(t+1) &= x_n(t) + v_n(t+1)
\end{align*}
\]  

The swarm is defined at the time ‘t’ and each particle ‘n’ moves in a multidirectional search space with position \(x_n(t)\) and velocity \(v_n(t)\). \(c_1\) and \(c_2\) are constant, \(r_1\) and \(r_2\) are two random number function in the range (0,1). \(w\) is the inertia weight. \(x_n(t)\) is the current position of the particle. \(P_{id}\) is the position of \(i^{th}\) particle i, \(P_{gid}\) is the global best position in all the particle [30-32]. We implement PSO clustering to find the tumor from the liver.

### 2.3 Feature Extraction from segmented tumor

Feature Extraction is the method to analyze the preprocessed image to extract the prominent data’s from an image which contain more amount of data. In this stage only few useful information’s are extracted such as statistical, geometrical and texture features from each liver image by Gray Level Co-occurrence Matrix method (GLCM) [33]. GLCM is the statistical method that consider spatial relationship of pixel which is also known as the gray level spatial dependence matrix and it is second order statistical measurement which contain the information of pixels positions [34]. The commonly used pixel distance and angles are 0°, 45°, 90°, and 145°. Features obtained from the intensity histogram features are mean, energy, variance, entropy, skewness and kurtosis. GLCM features comprises of contrast, correlation, energy, homogeneity [35]. The geometrical features are also extracted namely area, major axis length, minor axis length, EquivDiameter, solidity and Perimeter and the following Table 1 shows GLCM features and Table 2 shows the equations of features corresponding to intensity histogram.
Table 1. Intensity Histogram Features

<table>
<thead>
<tr>
<th>S.No</th>
<th>Property</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>contrast</td>
<td>$\sum_{i,j}</td>
</tr>
<tr>
<td>2.</td>
<td>correlation</td>
<td>$\sum_{i,j} (i - \mu_i)(j - \mu_j) \frac{p(i,j)}{(\sigma_i \sigma_j)}$</td>
</tr>
<tr>
<td>3.</td>
<td>energy</td>
<td>$\sum_{i,j} p(i,j)^2$</td>
</tr>
<tr>
<td>4.</td>
<td>homogeneity</td>
<td>$\sum_{i,j} \frac{p(i,j)}{1 +</td>
</tr>
</tbody>
</table>

Table 2. Features of GLCM

<table>
<thead>
<tr>
<th>S.No</th>
<th>Property</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.</td>
<td>Mean</td>
<td>$\mu = \sum_{i=0}^{N-1} i p(i)$</td>
</tr>
<tr>
<td>6.</td>
<td>Energy</td>
<td>$E = \sum_{i=0}^{N-1} i p(i)^2$</td>
</tr>
<tr>
<td>7.</td>
<td>Variance</td>
<td>$\sigma^2 = \sum_{i=0}^{N-1} (i - \mu)^2 p(i)$</td>
</tr>
<tr>
<td>8.</td>
<td>Entropy</td>
<td>$H = \sum_{i=0}^{N-1} p(i) \log_2 p(i)$</td>
</tr>
<tr>
<td>9.</td>
<td>Skewness</td>
<td>$\mu_3 = \sigma^{-3} \sum_{i=0}^{N-1} (i - \mu)^3 p(i)$</td>
</tr>
<tr>
<td>10.</td>
<td>Kurtosis</td>
<td>$\mu_4 = \sigma^{-4} \sum_{i=0}^{N-1} (i - \mu)^4 p(i) - 3$</td>
</tr>
</tbody>
</table>

From the Image Processing Toolbox in Matlab, extraction step was done by regionprops and graycoprops functions for predicting the liver cancer probability. The features extracted from the images are namely mean, energy, variance, entropy, skewness and kurtosis, contrast, correlation, homogeneity, area, major axis length, minor axis length, EquivDiameter, solidity and Perimeter are obtained.

Some of the features like Area, Major Axis Length, Minor Axis Length, EquivDiameter, Solidity and Perimeter were calculated, where the definitions of features are derived from Matlab.
11. **Area**: Scalar value which defines the actual number of pixel in the region and computed as \(4 \times \text{Area}/\pi\).

12. **Major Axis Length**: In the ellipse, the major axis length (in pixels) that has the same normalized second central moments as the region.

13. **Minor Axis Length**: In the ellipse, the minor axis length (in pixels) that has the same normalized second central moments as the region.

14. **EquivDiameter**: In a circle, the region as the diameter with same area, calculated as \(\sqrt{4 \times \text{Area}/\pi}\).

15. **Solidity**: Scalar specifying the proportion of the pixels in the convex hull that are also in the region, computed as \(\text{Area}/\text{ConvexArea}\).

16. **Perimeter**: The distance around the boundary of the region of interest. It can be found out by the distance between adjoining pair of pixels around the border of the region.

The performance of the liver tumor segmentation was calculated by sensitivity, specificity, accuracy.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \quad (6)
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \quad (7)
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)
\]

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

### 2.4 Liver Cancer Classification

#### 2.4.1 FEED FORWARD NEURAL NETWORKS:

An Artificial Neural Network (ANN) is a mathematical model of biological nervous systems in the human brain. ANNs comprises group of interconnected neurons and a neuron is an information processing unit. It changes its structure in learning phase. Neural Network works like adaptive system [36, 37]. It is used to find out clusters and patterns in data. It is designed through learning process for particular application such as pattern categorization and data classification.

Feed Forward Neural Networks (FFNN) is simpler and it was the first type of artificial neural network. The connection between nodes do not form a cycle or loops. The information travels only in forward direction in the networks so it is called as feed forward. The signal flow in one direction from the input layers, to the hidden layer and finally to the output layer. FFNN is one of the supervised learning method [38, 39].
### a. Single layer perceptron:

The perceptron is the simplest type and it has no hidden units, it has only an input node and output node. It has binary outputs which as the value of 0 and 1.

### b. Multi-layer perceptron:

The artificial neural network with many perceptron’s is called Multi-layer perceptron (MLP). Unlike single layer perceptron, it has hidden layers. It consist of an input layer and some hidden layers, and an output layer. A fully connected MLP on three inputs with one hidden layer, each with three perceptron’s is shown below in Figure 3.

![Figure 3. A fully connected Multi-layer perceptron](image)

### 2.4.2 BACK PROPAGATION NEURAL NETWORKS:

Back Propagation (BP) algorithm is the one of the popular ANN’s algorithm, and the short form for Back Propagation is “Backward Propagation of errors”. It is a type of supervised feed forward neural network. It has four stages in BP algorithm. After the weight are choosing randomly the BP algorithm will compute the corrections in the network. It is broken down to following four stages: Feed forward computation, Back-Propagation to the output layer, Back-Propagation to the hidden layer, weight updation \[40-42\]. In Figure 4. Neural network with three layer is shown.

![Figure 4. Neural Network with three layers](image)

**Step 1:** In the NN training finding the weights which minimize predication error. First weight is generated randomly, then update the weights.

**Step 2:** Then given inputs are multiplied by weights, then forward to next layer.
Step 3: Next to calculate the difference between actual output and prediction.

\[ \text{Error} = \frac{1}{2} \left( \text{Prediction} - \text{actual} \right)^2 \]  \hspace{1cm} (9)

The Error is always positive because of the square, Error = 0, if prediction = actual.

Step 4: In the training, reducing error or difference between prediction and actual output is the main goal.

Actual output is always constant. Therefore we have to reduce the error in predication value (i.e.) to change predication value. We have to change weight values.

\[
\begin{align*}
\text{Prediction} &= \text{out} \\
\text{Prediction} &= (h_1)w_5 + (h_2)w_6 \\
\text{Prediction} &= (i_1w_1 + i_2w_2)w_5 + (i_1w_3 + i_2w_4)w_6
\end{align*}
\]

Step 5: By using gradient decent, the weight are updated. It evaluates the gradient of the error function with respect to the neural network weight. It proceeds backwards through the network.

Step 6: To update new weight, take the old weight (current weight) and subtract the particular derivation of error function with respect to weight. By the selected number, multiply the derivative of the error the new updated weight will minimize the error function. It is called learning rate (\(a\)).

\[
*W_6 = W_6 - a \left( \frac{\partial \text{Error}}{\partial w_6} \right) \]  \hspace{1cm} (10)

By applying the chain rule, for the derivative of the error function

\[
\left( \frac{\partial \text{Error}}{\partial w_6} \right) = \Delta h_2 \]  \hspace{1cm} (11)

The updated weight \(W_6\)

\[
*W_6 = W_6 - a \Delta h_2 \]  \hspace{1cm} (12)

Similarly, for \(W_5\) the updated weight

\[
*W_5 = W_5 - a \Delta h_1 \]  \hspace{1cm} (13)

We have to update for \(W_1, W_2, W_3, W_4\). When moving backward, the updated formulas are

\[
\begin{align*}
*W_6 &= W_6 - a (h_2 \cdot \Delta) \hspace{1cm} (14) \\
*W_5 &= W_5 - a (h_1 \cdot \Delta) \hspace{1cm} (15)
\end{align*}
\]
\[ *W_4 = W_4 - a(i_2, \Delta W_6) \]
\[ *W_3 = W_3 - a(i_1, \Delta W_6) \]
\[ *W_2 = W_2 - a(i_2, \Delta W_5) \]
\[ *W_1 = W_1 - a(i_1, \Delta W_5) \]

Rewrite the update formulas in matrices
\[
\begin{bmatrix}
W_5' \\
W_6'
\end{bmatrix} = \begin{bmatrix}
W_5 \\
W_6
\end{bmatrix} - a \begin{bmatrix}
h_1 \\
h_2
\end{bmatrix} = \begin{bmatrix}
W_5 \\
W_6
\end{bmatrix} - \begin{bmatrix}
ah_1 \\
ah_2
\end{bmatrix}
\]
\[
\begin{bmatrix}
W_1' & W_3' \\
W_2' & W_4'
\end{bmatrix} = \begin{bmatrix}
W_1 & W_3 \\
W_2 & W_4
\end{bmatrix} - a \begin{bmatrix}
i_1 \\
i_2
\end{bmatrix} = \begin{bmatrix}
W_1 & W_3 \\
W_2 & W_4
\end{bmatrix} - \begin{bmatrix}
i_1 \\
i_2
\end{bmatrix}
\]

Find the new weight using derived formula. Learning rate is a hyperparameter, manually guess its value. Using the new weight, repeat the forward passed. Comparing with the previous prediction. Now the prediction is closer to actual output. Repeat the steps of forward and backward until the error is equal or close to zero.

### 3. Experimental Results and Discussions

The proposed approach for detection of liver cancer was tested with 40 scanned abdominal CT images having cancer tumor, 20 samples of primary cancer and 20 samples of secondary cancer. The liver tumor structure and size are varies in the dataset where the images differ from one image to other images. The experimental analysis is done with MATLAB R2014a 64bit using an Intel(R) Core i3 processor with 4GB RAM in a personal computer. The results are shown from the dataset.

Our CAD method has two processes, segmentation of the liver and detection of the tumor. In the first process, Gaussian filtering used to remove the smallest organ. From abdominal CT images, the liver is segmented by the Level Set method. In the second process, the segmented liver is given to PSO. This PSO clustering is used to segment the tumor from the segmented liver. Here two image samples of liver cancer are used, Figure 5(a) (sample1 and sample2) shows the original input CT image. The Gaussian filter that used to separate the small region and smallest organ from the CT abdominal image shows in Figure 5(b), (c) and the results of LS method that used to segment liver from CT abdominal images shows in Figure 4(d), (e). Then the segmented liver was clustering using PSO shows in Figure 5(f), (g), (h), (i) and the result of liver tumor segmentation shows in Figure 5(j). Then features are extracted using GLCM, 16 features are taken from the CT liver image. Here 300 epochs are used for the trained model and 0.01 was set as the learning rate. The classification of liver cancer was classified using the BPNN classifier. Finally, the result shows the given input image of sample1 is primary liver cancer and sample2 is secondary liver cancer. Hence we have compared the performance of BPNN with FFNN.
The ROC graph depicts the overall accuracy and classification rate. ROC analysis allows analyzing both the sensitivity and specificity together at various cut-point [43]. The graph was plotted to measure the sensitivity in the y-axis that is True Positive Rate (TPR) and specificity in the x-axis that is False Positive Rate (FPR). The ROC curve is a plot of test with TRP (sensitivity) and FPR [1–Specificity]. The Area under the Curve (AUC) is a framework which denotes the intrinsic accuracy of the diagnosed analysis. The AUC range for classification accuracy for a diagnostic test $0.9 < \text{AUC} < 1.0$ (excellent test) shown in Table 3. For the diagnostic tests, the ROC curve is the best method to find possible optimal cut-point. The ROC graph of both BPNN and FFNN shows an excellent classification accuracy. If the epochs are increased, the training accuracy increases and loss decreases. The model attained excellent accuracy of 97.98% at 300 epochs. The ROC curve of FFNN and BPNN is shown in Figure 6.

**Table 3. AUC Range for Accuracy classification**

<table>
<thead>
<tr>
<th>AUC Range</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0.9 &lt; \text{AUC} &lt; 1.0$</td>
<td>Excellent Test</td>
</tr>
<tr>
<td>$0.8 &lt; \text{AUC} &lt; 0.9$</td>
<td>Good Test</td>
</tr>
<tr>
<td>$0.7 &lt; \text{AUC} &lt; 0.8$</td>
<td>Fair Test</td>
</tr>
<tr>
<td>$0.6 &lt; \text{AUC} &lt; 0.7$</td>
<td>Poor Test</td>
</tr>
</tbody>
</table>

The MSE measure the networks performance according to the mean of squared error. The perfect test shows point in the upper left corner with 100% sensitivity and 100% specificity. Result of training data shows an accuracy of 97.98% in BPNN and 89% in FFNN. The Standard Error (S.E) and 95% Confidence Interval (C.I) are shown in Table 4. Our approach is in comparison with the some others article results shown in Table 5. From that table, its shows that we achieved the excellent result for detecting the liver cancer automatically.

**Table 4. ROC Curve Analysis of FFNN and BPNN**

<table>
<thead>
<tr>
<th></th>
<th>FFNN</th>
<th>BPNN</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AUC</strong></td>
<td>89%</td>
<td>97.98%</td>
</tr>
<tr>
<td><strong>S.E</strong></td>
<td>0.05381</td>
<td>0.02217</td>
</tr>
<tr>
<td><strong>95% C.I</strong></td>
<td>0.78454</td>
<td>0.93635</td>
</tr>
<tr>
<td><strong>Classification comment</strong></td>
<td>Good Test</td>
<td>Excellent Test</td>
</tr>
</tbody>
</table>
Figure 5. (a) Input image (b) Removing smallest organ (c) Remove all small regions (Except Large area) (d) Level Set Input (e) Segmented Liver using LS method (f) PSO clustering (g) cluster 1 (h) cluster 2 (i) cluster 3 (j) Segmented liver tumor

Figure 6. ROC curve of (i) Feed Forward Neural Network (ii) Back Propagation Neural Network

Table 5 Summary of the work comparison with other approaches

<table>
<thead>
<tr>
<th>Authors</th>
<th>Year</th>
<th>Classifier</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wen Li</td>
<td>2015</td>
<td>CNN</td>
<td>80.06</td>
</tr>
<tr>
<td>Kumar</td>
<td>2010</td>
<td>FFNN</td>
<td>94.3</td>
</tr>
<tr>
<td>Sethi</td>
<td>2015</td>
<td>SVM,ANN,Genetic Algorithm</td>
<td>95.1</td>
</tr>
</tbody>
</table>
4. Conclusion

In this paper, a new automatic approach for the detection of liver cancer in abdominal CT images is proposed. This approach has Level Set method and PSO clustering for liver segmentation to detect the cancer tumor. Extract the features (shape and texture) from tumor, then it is used in the next stage using classification process. The BPNN classifier has main advantage of automatic detection of finding tumor with 97.98% accuracy. Experimental results shows that our method has excellent accuracy compared with FFNN and other approaches from literature. This proposed method is to detect primary and secondary liver cancer from abdominal CT images and it will be effective and helpful in clinical diagnosis for early detection of the patient at low cost. In this work, less CT images are used. So the future scope of the work can be enhanced using huge dataset with 3D images and also include other diseases in abdominal images.

**References**


