International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-3 Issue-5, October 2013

Medical Image Analysis Using Unsupervised and Supervised Classification Techniques

V. Joseph Peter, M.Karnan

Abstract*—The evolution of digital computers as well as the development of modern theories for learning and information processing leads to the emergence of Computational Intelligence (CI) engineering. Liver surgery remains a difficult challenge in which preoperative data analysis and strategy definition may play a significant role in the success of the procedure. Extraction of liver fibrosis is done using image enhancement techniques using various filtering techniques, unsupervised clustering techniques such as modified k means and fuzzy c means and supervised techniques such as ANN, BPN and feed forward NN. It constructs a statistical model of liver fibrosis from these MRI scans using ANN, SVM, GA with k means, GA with Fuzzy and Feed forward back propagation neural network classifier. Our experimental study analyzed 250 MRI images. These results are better than the existing image-based methods which can only discriminate between healthy and high grade fibrosis subjects. With appropriate extensions, our method may be used for non-invasive classification and progression monitoring of liver fibrosis in human patients instead of more invasive approaches, such as biopsy or contrast-enhanced imaging. The proposed system is tested on more than 300 digitized MRI Image database to establish its competence.

Index Terms*—Computational Intelligence, enhancement techniques, clustering techniques, fuzzy c means, back propagation neural network.

I. INTRODUCTION

Medical image processing led to a major improvement of patient care by guiding the surgical gesture. From this initial data, new technologies of virtual reality and augmented reality can increase the potential of such images. The 3D modeling of the liver of patients from their MRI thus allows an improved surgical planning. Simulation allows the procedure to be simulated preoperatively and offers the opportunity to train the surgical gesture before carrying it out.

These three preoperative steps can be used intra-operatively, thanks to the development of augmented reality, which consists of superimposing the preoperative 3D modeling of the patient onto the real intra-operative view of the patient and his/her organs. Augmented reality provides surgeons with a transparent view of the patient. This facilitated the intra-operative identification of the vascular anatomy and the control of the segmental arteries and veins in liver surgery, thus preventing intra-operative bleeding.

It can also offer guidance due to the virtual improvement of their real surgical tools, which are tracked in real-time during the procedure. During the surgical procedure, augmented reality, therefore, offers surgeons a transparent view of their patient, which will lead to the automation of the most complex maneuvers.

The new ways of processing and analyzing liver images have dramatically changed the approach to liver surgery. Magnetic Resonance Imaging (MRI) is one of the best technologies currently being used for diagnosing liver fibrosis.

Magnetic Resonance Imaging (MRI) is an advanced medical imaging technique used to produce high-quality images of the parts contained in the human body. MRI imaging is often used when treating liver disease. From these high resolution images, one can derive detailed anatomical information to examine abnormalities. Liver fibrosis is diagnosed at advanced stages with the help of the MRI image.

Segmentation is an important process to extract information from complex medical images. Segmentation has wide application in medical field. The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted region such that each region of interest is spatially contiguous and the pixels within the regions are homogeneous with respect to a predefined criterion. In this thesis, Computer-Aided Diagnosis (CAD) system for Automatic detection of liver fibrosis through MRI system can provide the valuable outlook and accuracy of earlier liver fibrosis detection. The detection of segmentation is performed in two phases: unsupervised in the first phase and supervised classification in the second phase.

A novel automatic method for the classification and grading of liver fibrosis from MRI maps based on hepatic hemodynamic changes using supervised and unsupervised learning method. This method automatically creates a model for liver fibrosis grading based on training datasets. Our supervised and unsupervised learning methods evaluate hepatic hemodynamic from an anatomical MRI image.

Automated detection of image segmentation has been studied for the past two decades. Digitized MRI are used in various stages of Computer Aided Detection systems Obtaining real medical images for carrying out research is a highly difficult task due to privacy issues, legal issues and technical hurdles. Hence, the Hospital MRI Image database is used in this thesis to analyze the efficiency of the proposed intelligent system, since it is the real time project it demands the software to be run in a Hospital for research.

The images ranging from 250 have been acquired from various hospitals in a random mode. The images are MRI images of dimension 256x256. The images are stored in MS Access database.

Manuscript published on 30 October 2013.
***Correspondence Author(s)**
Prof. V.Joseph Peter, Department of Computer Science, Kamaraj College, Tuticorin, Tamilnadu, India.
Dr.M.Karnan, Professor and Head, Dept. of CSE, Tamilnadu College of Engineering, Coimbatore, Tamilnadu, India.

The Data are then stored in a folder with a particular path name which can be later accessed in MATLAB through hyperlink. In the mat lab all the images will be converted into digital matrix. Images of a patient obtained by MRI scan is displayed as an array of pixels (a two dimensional unit based on the matrix size and the field of view) and stored in Mat lab 7.0. Here, grayscale or intensity images are displayed of default size 256 x 256.

II. IMAGE ENHANCEMENT

In Preprocessing and Enhancement, initially the labels are removed from the obtained MRI images. The tracking algorithm is proposed to remove film artifacts such as labels and X-ray marks from the MRI Image. The median filtering technique is applied to remove the high frequency components in the MRI image. The advantage of using the median filter is that it removes the noise without disturbing the edges and the performance evaluation is measured

III. DATA NORMALIZATION USING HISTOGRAM EQUALIZATION

Histogram modeling techniques provide a sophisticated method for modifying the dynamic range and contrast of an image by altering that image such that its intensity histogram has a desired shape. Unlike contrast stretching, histogram modeling operators may employ non-linear and non-monotonic transfer functions to map between pixel intensity values in the input and output images. Histogram equalization employs a monotonic, non-linear mapping which re-assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities. This technique is used in image comparison processes and in the correction of non-linear effects introduced by, say, a digitizer or display system. Mathematical Morphology is one of the most productive areas in medical image processing. The motivation comes from the collection of structural information about the MRI image domain. The content of mathematical morphology is completely based on set theory. By using set operations there are many useful operators defined in mathematical morphology. For instance erosion, dilation, opening and closing are the kinds of operations which are beneficial when dealing with the numerous medical image processing problems. Mathematical morphology can be used as the basis for developing image segmentation procedures with a wide range of applications and it also plays a major role in procedures for image description. In pattern recognition, the k -nearest neighbor algorithm (k-NN) is a method for classifying objects based on closest training examples in the feature space. The training examples are mapped into multidimensional feature space. The space is partitioned into regions by class labels of the training samples. The accuracy of the k-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the features scales are not consistent with their relevance. Much research effort has been placed into selecting or scaling features to improve classification.

IV. LEARNING METHODS

Learning methods can be classified into two types:

A. Supervised Learning:

In this, every input pattern that is used to train the network is associated with a target or the desired output pattern. A teacher is assumed to be present during the learning process when a comparison is made between the networks computed output and the correct expected output, to determine the error. Tasks that fall under this category are Pattern Recognition and Regression.

B. Unsupervised Learning:

In this learning method, the target output is not presented to the network. The system learns of its own by discovering and adapting to structural features in the input patterns as if there is no teacher to present the desired patterns. Tasks that fall under this category include Clustering, Compression and Filtering.

C. Supervised Learning Method

Supervised learning method for the automatic creation of a classification and grading model for mice liver fibrosis from MRI signal intensity time courses. Since fibrosis grades are hierarchical, this method uses the entire signal intensity time course of each image as input to a multistep classifier that discriminates them into fibrosis grades according to Batts and Ludwig. First, the classifier separates between maps of healthy and fibrotic liver (of all grades),

D. Semi Supervised Learning Method

To find fibrosis grades a binary support vector machine (SVM) is used. Since this method does not require a mechanical model and uses all the time-course information, it is potentially accurate and provides a quantitative evaluation of the entire liver. This may provide the radiologist an additional tool for better separation between fibrosis levels. But it is not suitable for classifying more number of grade levels implementation.

E. Unsupervised Learning Method

Clustering is a method of unsupervised learning. Types of clustering Data clustering algorithms can be Hierarchical. Hierarchical algorithms find successive clusters using previously established clusters. These algorithms can be either bottom-up or top-down. Bottom up algorithm begin with each element as a separate cluster and merge them into successively larger clusters. Top up algorithms begin with the whole set and proceed to divide it into successively smaller clusters. Partition algorithms typically determine all clusters at once, but can also be used as Top up algorithm in the hierarchical clustering. Density-based clustering algorithms are devised to discover arbitrary-shaped clusters. In this approach, a cluster is regarded as a region in which the density of data objects exceeds a threshold.

Segmentation is the second stage where Optimization forms an important part of our day to day life. Many scientific, social, economic and engineering problems have parameter that can be adjusted to produce a more desirable outcome. Over the years numerous techniques has been developed to solve such optimization. This thesis investigates supervised and unsupervised techniques with the most effective optimization method, known as hybrid Ant Colony Optimization (ACO) to the field of medical Image Processing.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-3 Issue-5, October 2013

The application of the proposed clustering algorithm to the problem of tumor detection and segmentation of MRI image is investigated. New CAD System is developed for verification and comparison of liver fibrosis detection algorithm. ACO automatically determines the optimal intensity value of given image. Finally, the clustering algorithm automatically calculates the adaptive threshold for the liver fibrosis segmentation.

V. FEATURE EXTRACTION

The texture of liver fibrosis images refers to the appearance, structure and arrangement of the parts of an object within the image. A feature value is a real number, which encodes some discriminatory information about a property of an object. It may not always be obvious what type of information or feature, is useful for a particular detection task. Additionally, there are potentially many ways to describe a particular object characteristic such as texture. It may not be obvious which method of computation extracts the most useful discriminatory information.

The performance of the classifiers, i.e. the ability to assign the unknown object to the correct class, is directly dependent on the features selected that represent the object description. Texture is one of the important characteristics used in identifying an object. The texture coarseness or fineness of an image can be interpreted as the distribution of the elements in the matrix. This section presents texture-analysis methods such as SRDM and SGLDM. The segmented liver fibrosis images from segmentation approach are considered inputs for feature extraction methods.

A. Surrounding Region Dependency Matrix

The SRDM is based on a second-order histogram in two surrounding regions. The liver fibrosis image is transformed into a Surrounding Region-Dependency Matrix and the features are extracted for this matrix. Let us consider two rectangular windows centered on a current pixel (x, y). R_1 and R_2 are the outermost and outer surrounding region of size 7×7 and 5×5, respectively. The number of pixels greater than the selected threshold value (q) is counted in each region. Let us assume m and n to be the total number of pixels from the outermost region (R1) and the outer region (R2). The element in the corresponding surrounding region dependency matrix M (m, n) is incremented by 1. This procedure is repeated for all the image pixels and the matrix gets updated.

B. Spatial Gray Level Dependency Matrix

In this method, a co-occurrence matrix is generated to extract the texture features from the segmented liver fibrosis image. The co-occurrence matrix is a technique that allows for the extraction of statistical information from the image regarding the distribution of pairs of pixels. It is computed by defining a direction and a distance (d) and pairs of pixels separated by this distance, computed across the defined direction (θ), are analyzed. A count is then made of the number of pairs of pixels that possess a given distribution of gray level values. Each entry of the matrix thus corresponds to one such gray level distribution.

The liver fibrosis image is an eight-bit image; for such an image, the allowed gray level values range from 0 to 255. The size of this matrix will then be 256×256. A set of 20 co-occurrence matrices are computed for five different distances in the horizontal, vertical and two diagonal directions: The distances are 1, 3, 5, 7 and 9 and the four angles 0^o, 45^o, 90^o and 135^o are defined for calculating the matrix for each of the five distances. Since the co-occurrence matrix analyzes the gray level distribution of pairs of pixels, it is also known as the second-order histogram. The entropy, average, standard deviation, variance covariance Haralick features are extracted from all the texture analysis methods, from these features set; feature selection algorithms are used to select the reduced features. The Haralick features are discussed as follows:

C. The Haralick Features

A smooth region in a texture image consists of pixels having more or less equal gray levels. Thus, peaks along the diagonal of the distribution matrices represent smooth regions, while off-diagonal peaks may correspond to regions having a specific texture. They also correspond to edge regions, provided that the edges are sharp enough. The texture analysis matrix itself does not directly provide a single feature that may be used for texture discrimination. Instead, the matrix can be used as a representation scheme for the texture image and the features are computed. The features based on the distribution matrices should therefore capture some characteristics of textures such as homogeneity, coarseness, periodicity and others. Haralick et al. have suggested 14 texture features, which can be put into four groups

Features that express visual texture characteristics: Angular Second Moment (ASM), Contrast (CON), Correlation (COR). Features that are based on statistics: Variance (VAR), Inverse Difference Moment (IDM), Sum Average (SA), Sum Variance (SV) and Difference Variance (DV). Features that are based on information theory: Entropy (ENT), Sum Entropy (SENT) and Difference Entropy (DENT). Features that are based on information measures of correlation: Information Measures of Correlation (IMC1, IMC2) and Maximal Correlation Coefficient (MCC).

The liver fibrosis textural features are extracted from the segmented image. The textural analysis method such as Spatial Gray Level Dependency Matrix, Surrounding Region Dependency Matrix, is used to extract the fourteen Haralick features from the segmented image.

VI. FEATURE SELECTION

A. Genetic Algorithm

In this work, textural matrices such as SRDM, SGLDM, are created for each liver fibrosis image. For each defined distance and direction the Haralick features are extracted for all the 250-liver fibrosis images. The features are grouped into four categories as discussed single feature value for all the images is considered the initial population string for Genetic Algorithm. An optimum value is computed for each individual feature set. In a group, the optimum value from each individual set is compared; the feature set, which selects the optimum among other features in the same group, is selected for classification. Like this, for every group an optimum feature is selected. Finally, the algorithm selects the four optimum features from the set of fourteen features. Only the selected features are used for classification.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

From the population of the individual feature set, the fitness value is calculated for each feature using the fitness function $(1/1+P_i)$,where P_i is the feature value. Then the probability of each feature value is calculated. And the cumulative probability is compared for each feature value. Then a random number between zero and one is generated for each feature value. If the cumulative probability value for a feature is higher than the random number, then the feature selection count is incremented by one.

This procedure is repeated for the number of times equal to the population size. Next, the population is reproduced with the feature values whose selection count is greater than zero. Each feature is copied into the reproduced population corresponding to the number of times it has been selected. For example, if a selection count for a feature is two, then that feature will be copied two times in the reproduced population. After reproduction the single point crossover operation is performed on population strings depending upon the crossover probability (P_c). The P_c ranges from zero and one. In the single point crossover operation, initially the pair of population strings is randomly selected for matting. And a random bit position is selected for each pair.

The bits available after the random bit position are exchanged between the population strings in the pair. Thus the matting is performed to create another population set with different values. Next, the mutation operator is applied to the matted population strings depending upon the mutation probability (P_m), where P_m is a small number ranging from zero and one. In mutation, a random bit position is selected from the population. If the bit value is one in that position it is flipped to zero; else it is changed to one. The population now contains a new set of strings for the next population. The next iteration is performed with the new population of strings. This procedure is repeated 30-200 times . Finally the maximum value from the recent population is returned as optimum value of the feature set. The features selected from this algorithm are ASM, VAR, ENT and IMC2.

B. Ant Colony Optimization

In the proposed algorithm, the individual feature set is considered the solution space for the ACO search. Each feature value is labeled with a number corresponding to its fitness value, calculated using the fitness function $(1/1+P_i)$, where P_i is the feature value. A solution matrix is created with the feature values, fitness values and their corresponding labels. Initially, the number of ants (NA) start their search from a randomly selected feature value, with an initial pheromone of T_o. A random number q is generated and is compared with q_o, if $q \le q_o$. Then the corresponding feature value is assigned the maximum label from the label set. Otherwise, a random label is assigned for that feature value. This step is repeated for each ant and for each feature value in the feature set. Once all the ants are created their solution, the pheromones of the ants are locally updated.

Then the fitness values of all the ants are locally improved by replacing with the maximum fitness value. The maximum fitness value is searched from the set of fitness values of the features having optimum label. The optimum fitness value is selected from the set of fitness values from the set of solutions created by all the ants. This value is known as the local minimum (Lmin). If this value is greater than the global minimum (Gmin), then Gmin is assigned to the Lmin. The ant that generates the Gmin is globally updated. At the final iteration, the Gmin has the label of the optimum feature. This entire procedure can be repeated a number of times for obtaining the further enhanced value. As in the ACO algorithm, the optimum feature is selected from each group and only those selected features are further used in the classification. As a result the ASM, IDM, ENT and IMC2 are the selected features from this algorithm.

C. Experiments And Results

Table.1 shows the list of features selected by the feature selection algorithms such as Genetic Algorithm and Ant Colony Optimization. The combined features such as ASM, VAR, IDM, ENT and IMC2 are given as input to the BPN classifier.

Table 1 Selected features from feature selection algorithms

Algorithms	Selected Features
GA	ASM, VAR, ENT, IMC2
ACO	ASM, IDM, ENT, IMC2

Textural features are extracted for classification of fibrosis. The feature set may contain irrelevant or redundant information. These features are eliminated to improve the accuracy and to reduce the time complexity of the classifier. In this chapter, metaheuristic algorithms are used to select the features from the feature set. The reduced feature sets from each selection algorithms are combined to form the reduced feature set, which is used for classification.

VII. SUPERVISED CLASSIFICATION

Classification of objects is an important area of research and of practical applications in a variety of fields, including pattern recognition, artificial intelligence and vision analysis. Classifier design can be performed with labeled or unlabeled data. Neural Networks (NN) can learn various tasks from training examples: classify phenomena and model nonlinear relationships.

However, the primary features that are of concern in the design of the networks are problem specific. Despite the availability of some guidelines, it would be helpful to have a computational procedure in this aspect, especially for the optimum design of an NN. The gradient descent algorithms have encountered difficulties in learning the topology of the networks whose weights they optimize.

Artificial Neural Networks (ANN) is the network of interconnected simple units that are based on a simplified model of the brain. ANN is a useful learning tool because it enables one to compute results quickly interpolating data well. There are two main types of ANN, feed forward networks and recurrent networks. Three main perceptron learning algorithms are covered: mistake bound perceptron algorithm, perceptron training rule and the Delta rule. The Delta rule uses gradient descent, which makes it easy to compute what changes are needed to optimize the network. The Back Propagation learning algorithm is widely used for multi-layer feed forward network. Bayesian learning is based on statistics and knowledge of prior statistics to classify or predict. The Bayes theorem is central to Bayesian learning.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

A. Artificial Neural Networks

The classifier employed in this thesis is a three layer Back Propagation Neural network. The Back Propagation Neural network optimizes the net for correct responses to the training input data set. More than one hidden layer may be beneficial for some applications, but one hidden layer is sufficient if enough hidden neurons are used.

B. Back Propagation Algorithm

The Back Propagation algorithm can be implemented in two different modes: online mode and batch mode. In the online mode the error function is calculated after the presentation of each input liver fibrosis image features and the error signal is propagated back through the network, modifying the weights before the presentation of the next image features. This error function is usually the Mean Square Error (MSE) of the difference between the desired and the actual responses of the network over all the output units.

Then the new weights remain fixed and a new liver fibrosis image features are presented to the network and this process continues until all the image features have been presented to the network. The presentation of all the image features is usually called one epoch or a single iteration. In practice many epochs are needed before the error becomes acceptably small. In the batch mode the error signal is calculated for each input liver fibrosis image features and the weights are modified every time the input image features is been presented. Then the error function is calculated as the sum of the individual MSE for each image features and the weights are accordingly modified (all in a single step for all the images) before the next iteration.

The single layer perceptron provides a powerful solution to the problems, which are linearly separable. Multi-layer perceptrons are considered to be difficult for training. Error Back Propagation algorithm is an effective solution to train multi-layer perceptrons based on error correction learning. In the forward pass outputs are computed and in the backward pass weights are updated or corrected based on the errors. The development of the Back Propagation algorithm is a landmark in neural networks in that it provides a computationally efficient method for the training of multi-layer perceptrons.

VIII. CLASSIFIER

Initially the reduced feature set selected from the feature selection algorithms are normalized between zero and one. That is each value in the feature set is divided by the maximum value from the set. These normalized values are assigned to the input neurons. The number of hidden neurons is greater then or equal to the number of input neurons. And there is only one output neuron. Initial weights are assigned randomly (-0.5 to 0.5). The output from the each hidden neuron is calculated using the sigmoid function

$S_1 = 1 / (1 + e^{-\lambda x})$, where $\lambda = 1$ and $x = \Sigma_i w_{ih} k_i$

where w_{ih} is the weight assigned between input and hidden layer and k is the input value. The output from the output layer is calculated using the sigmoid function

$S_2 = 1 / (1 + e^{-\lambda x})$, where $\lambda=1$, and $x = \Sigma_i w_{ho} S_i$

where w_{ho} is the weight assigned between hidden and output layer and S_i is the output value from hidden neurons. S_2 is subtracted from the desired output. Using this error (e) value, the updation of weight is performed as:

$delta = e * S_2 * (1 – S_2)$

The weights assigned between input and hidden layer and hidden and output layer are updated as:

$W_{ho} = W_{ho} + (n * delta * S_1)$

$W_{ih} = W_{ih} + (n * delta * k_i)$

where n is the learning rate, k is the input values. Again calculate the output from hidden and output neurons. Then check the error (e) value and update the weights. This procedure is repeated till the target output is equal to the desired output. The network is trained to produce the output value 0.9 for abnormal images, and 0.1 for normal images.

A three-layer Back Propagation Neural network is used for classification. The values of the features available in the reduced feature set, constructed from the feature selection algorithms are normalized and given as input to the classifier. For each testing image, the output is calculated using sigmoid function. The error is calculated between the actual output and the target output. Based on this error value the weights are propagated to reduce the error value. Thus the classifier was trained to produce the output value 0.9 for abnormal images, and 0.1 for normal images. [1-20]

IX. PERFORMANCE ANALYSIS

Receiver Operating Characteristic curve (ROC) analysis is based on statistical decision theory, developed in the context of electronic signal detection, and has been applied extensively to diagnostic systems in clinical medicine. The ROC curve is a plot of the classifier's true positive detection rate versus its false positive rate. The False Positive (FP) rate is the probability of incorrectly classifying a non-target object (e.g. normal tissue region) as a target object (e.g. tumor region). Similarly, the True Positive (TP) detection rate is the probability of correctly classifying a target object as being a target object.

The TP and FP rates are specified in the interval from 0.0 to 1.0, in the liver fibrosis image. The TP rate is referred to as sensitivity and 1.0 minus FP rate is called specificity. The input to the BPN classifier has parameters such as threshold and hidden neurons for SRDM, the distance, theta and hidden neurons for SGLDM. The BPN network is tested by using a Jack Knife method. The results are analyzed by using ROC analysis. ROC analysis is employed to evaluate the performance of the texture analysis methods in classifying the benign and malignant. The area under the ROC curve, Az value is used as a measure of the classification performance.The experiments and results show that supervised techniques performs better than other existing algorithms. It was observed that proposed ANN outperforms the existing methods.

A. Simulation Results And Graphs

The simulation process is carried on a computer having Dual Core processor with speed 1.73 GHz and 2 GB of RAM. The MATLAB version used is R2010a.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

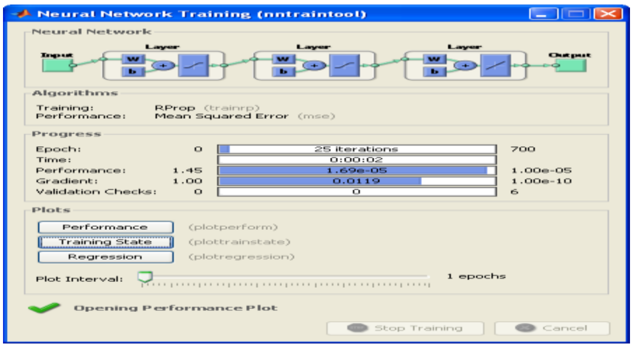

Figure 1 Neural Networks Training with extracted features

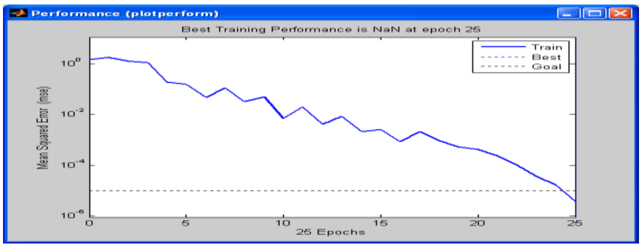

Figure 2 MSE graph Obtained Graph Epoch vs. MSE figure, Obtained Regression graph

And also we can get the message as Normal and Fibrosis grade as 2, 4, etc., in the Neural Network classification stage

Figure 4 Obtained result for given input image

X. CONCLUSION

We have presented a new method for Liver fibrosis grading based Disease analysis using supervised and unsupervised techniques. In this thesis, novel approaches to liver fibrosis image segmentation and classification based on the combination of Markov Random Field, Genetic Algorithm with modified k means and fuzzy c means, and Back Propagation Neural network were proposed.

The liver fibrosis textural features were extracted from the segmented image and they were classified using BPN. The textural analysis method SRDM is compared with the other conventional texture analysis methods such as SGLDM. The feature set was selected using the feature selection algorithms such as Genetic Algorithm and Ant Colony Optimization. The selected textural features were given as input to a three-layer Back Propagation Neural network classifier, to classify into abnormal or normal. The BPN classifier was trained using Jack Knife method. From the viewpoint of classification accuracy and computational complexity, the SRDM was superior to the other conventional methods. The results from the classifier were analyzed using ROC analysis. Under the Az curve the performance of the classifier was evaluated. The overall performance and the results show that the GA with fuzzy c means algorithm performs better than the other existing methods comparatively.

REFERENCES

1. Bell BP, Manos MM, Zaman A, Terrault N, Thomas A, Navarro VJ, et al. The epidemiology of newly diagnosed chronic liver disease in gastroenterology practices in the United States: results from populationbased surveillance. Am J Gastroenterol 2008;103:2727-2736.
2. Friedman SL. Mechanisms of hepatic fibrogenesis. Gastroenterology 2008;134:1655-1669.
3. Talwalkar JA, Yin M, Fidler JL, Sanderson SO, Kamath PS, Ehman RL. Magnetic resonance imaging of hepatic fibrosis: emerging clinical applications. HEPATOLOGY 2008;47:332-342.
4. Standish RA, Cholongitas E, Dhillon A, Burroughs AK, Dhillon AP. An appraisal of the histopathological assessment of liver fibrosis. Gut 2006;55:569-578.
5. Castera L, Pinzani M. Biopsy and non-invasive methods for the diagnosis of liver fibrosis: does it take two to tango? Gut 2010;59:861-866.
6. Garrido MC, Hubscher SG. Accuracy of staging in primary biliary cirrhosis. J Clin Pathol 1996;49:556-559.
7. Regev A, Berho M, Jeffers LJ, Milikowski C, Molina EG, Pyrsopoulos NT, et al. Sampling error and intraobserver variation in liver biopsy in patients with chronic HCV infection. Am J Gastroenterol 2002;97: 2614-2618.
8. Bedossa P, Darge`re D, Paradis V. Sampling variability of liver fibrosis in chronic hepatitis C. HEPATOLOGY 2003;38:1449-1457.
9. Rockey DC, Bissell DM. Noninvasive measures of liver fibrosis. HEPATOLOGY 2006;43:S113-S120.
10. Poynard T, Morra R, Halfon P, Castera L, Ratziu V, Imbert-Bismut F, et al. Meta-analyses of FibroTest diagnostic value in chronic liver disease. BMC Gastroenterol 2007;7:40.
11. Castera L, Forns X, Alberti A. Non-invasive evaluation of liver fibrosis using transient elastography. J Hepatol 2008;48:835-847.
12. Talwalkar JA, Kurtz DM, Schoenleber SJ, West CP, Montori VM. Ultrasound-based transient elastography for the detection of hepatic fibrosis: systematic review and meta-analysis. Clin Gastroenterol Hepatol 2007;5:1214-1220.
13. Friedrich-Rust M, Ong MF, Martens S, Sarrazin C, Bojunga J, Zeuzem S, et al. Performance of transient elastography for the staging of liver fibrosis: a meta-analysis. Gastroenterology 2008;134:960-974.
14. Caste´ra L, Le Bail B, Roudot-Thoraval F, Bernard PH, Foucher J, Merrouche W, et al. Early detection in routine clinical practice of cirrhosis and oesophageal varices in chronic hepatitis C: comparison of transient elastography (FibroScan) with standard laboratory tests and non-invasive scores. J Hepatol 2009;50:59-68.
15. Muthupillai R, Lomas,DJ, Rossman PJ, Greenleaf JF, Manduca A, Ehman RL. Magnetic resonance elastography by direct visualization of propagating acoustic strain waves. Science 1995;269:1854-1857.
16. Yin M, Talwalkar JA, Glaser KJ, Manduca A, Grimm RC, Rossman PJ, et al. Assessment of hepatic fibrosis with magnetic resonance elastography. Clin Gastroenterol Hepatol 2007;5:1207-1213.
17. Huwart L, Sempoux C, Vicaut E, Salameh N, Annet L, Danse E, et al. Magnetic resonance elastography for the noninvasive staging of liver fibrosis. Gastroenterology 2008;135:32-40.
18. Talwalkar JA. Elastography for detecting hepatic fibrosis: options and considerations. Gastroenterology 2008;135:299-302.
19. Caste´ra L, Foucher J, Bernard PH, Carvalho F, Allaix D, Merrouche W, et al. Pitfalls of liver stiffness measurement: a 5-year prospective study of 13,369 examinations. HEPATOLOGY 2010;51:828-835.
20. Hines CD, Bley TA, Lindstrom MJ, Reeder SB. Repeatability of magnetic resonance elastography for quantification of hepatic stiffness. J Magn Reson Imaging 2010;31:725-731.

AUTHOR PROFILE

Prof. V.Joseph Peter, received the Master of Computer Science and Applications Degree from, Manonmaniam Sundaranar University, Tamil Nadu, India, in 2000. Currently he is working as Professor Department of Computer Science, Kamaraj College, tuticorine, Tamil Nadu, India. His area of interests includes medical image processing, artificial intelligence, neural network, genetic algorithm, pattern recognition and fuzzy logic.

Dr.M.KARNAN. received the Master of Computer Science and Engineering Degree from Government College of Engineering, Manonmaniam Sundaranar University, Tamil Nadu, India, in 2000. He obtained his Ph.D degree from Gandhigram Rural Institute-Deemed University, Gandhigram, Tamilnadu, India in 2006.Currently he is working as Professor and Head, Department of Computer Science & Engineering, Tamilnadu College of Engineering, Coimbatore, Tamil Nadu, India. He published more than 150 papers. His area of interests includes medical image processing, artificial intelligence, neural network, genetic algorithm, pattern recognition and fuzzy logic.