Automatic Detection of Liver Lesions Using Hybrid Classification Techniques

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Abstract: - In this paper proposed a novel classifier method with Optimization technique for liver disease. LIBSVM is used for classification to classify the liver diseases. This paper concentration on five different types of diseases they are carcinoma, cirrhosis, fatty livers, hepatitis and cystic liver. Accurate classifications are done by using preprocessing and feature extraction. In preprocessing, speckle noise reduction and carried out by filtering technique afterwards segmentation process are taken in this paper. Feature extraction is done using gray level and co-occurrence matrix (GLCM). Several type of features are given as a input to the classification for liver diseases identification. This method outperforms the liver identification in terms of accuracy and execution time. Experimental shows the good performance than the existing method.

I. INTRODUCTION

Liver disease is roughly divided into focal, in which disease is concentrated in a small area and the remaining liver is normal, and diffused, which is distributed throughout the liver. Specialized radiologists determine whether liver tissue is normal or abnormal, but the accuracy of their diagnosis depends strongly on their experience, visual interpretation of images, and comparison with different pathologies. The similarity of diagnostic criteria for certain diseases, however, might confuse radiologists and cause them to make the incorrect judgments.

Chronic liver disease is a significant cause of morbidity and mortality in developed nations. It is commonly caused by viral hepatitis and alcohol abuse [20]

Image analysis and classification are important in computer-aided diagnosis widely used in characterizing medical images. The crucial step is in extracting appropriate features enabling accurate distinction. Feature extraction techniques include the gray level co-occurrence matrix (GLCM) [21], Gabor filters [22, 23 and 24], and wavelet transforms [25]. GLCM has been applied to texture feature extraction in medical image processing. In [26] used features from RF echoes prior to machine processing, image histograms, image gradients, co-occurrence matrices, and run-length matrices. In [27] proposed ultrasonic image analysis classifying liver symptoms as normal, hepatitis, or liver cirrhosis. They used the forward sequential search to find useful texture parameters from the co-occurrence matrix, statistical feature matrix, texture spectrum, and fractal dimension descriptors. In [28] used features from GLCM to distinguish between the normal liver and two types of liver tumor, hepatoma and hemangeoma.

A feature extraction module proposed in [29] calculates the average gray level and 48 texture characteristics derived from spatial ROI-based GLCM to characterize the normal liver, hepatic cysts, hemangioma, and hepatocellular carcinoma.

In this paper proposed a novel classification method with Optimization technique to identify the liver diseases. Five type of liver diseases are concentration and identified they are carcinoma, cirrhosis, fatty livers, hepatitis and cystic liver. Section II reveals about the related work for liver diseases identification. Section III discusses about the preprocessing, in which filtering technique and segmentation methods are described. Section IV tells about the classification of LIBSVM with Optimization technique. To prove the proposed method by experimental result and it is described in section V. Section VI describes about conclusion of proposed research.

II. LITERATURE SURVEY

There is a large literature demonstrating an association between chronic alcoholism and cognitive dysfunction [13, 14, 15 and 16]. Cognitive impairments observed in chronic alcoholics without liver disease are commonly thought to encompass executive functions including abstraction, planning, problem solving and working memory [14], while patients with the neurodegenerative Wernicke–Korsakoff's disease typically display impairments in the formation and retrieval of new memory [17, 18]. Despite the large number of neuro-scientific studies of alcoholism, there have been relatively few studies specifically investigating the contribution of liver disease to the spectrum of cognitive changes observed in alcoholics [19]. Several authors have hypothesised that the cerebral and hepatic consequences of alcoholism may combine to produce more severe cognitive dysfunction in ALD patients than in non-ALD patients [19].

There is a small literature directly assessing cognition in cholestatic liver disease, specifically primary biliary cirrhosis (PBC) and primary sclerosing cholangitis (PSC). A series of studies by Tarter et al. (44, 45) form the foundation of our understanding of cognition in these diseases. One study observed that a greater proportion of individuals with either PBC or PSC were impaired on tests of attention, concentration and psychomotor function relative to a control group of Crohn's disease patients (44). Another study compared 14 PBC patients to 10 PBC patients with co-existent Sjogren's syndrome and 10 normal controls (45).

III. PREPROCESSING

A. Speckle Noise Reduction

The speckle noise model may be approximated as multiplicative and is given by

$$n_{i,j} = nf_{i,j} m_{i,j} + a_{i,j} \quad (1)$$

Where $n_{i,j}$ represent the noisy pixel and represent the noisy free pixel, $m_{i,j}$ signify the multiplicative noise and indicate the additive noise respectively i,j are indices of the spatial locations. Because the effect of additive noise is considerably smaller compared with that of multiplicative noise (1) may be written as

$$n_{i,j} = nf_{i,j} m_{i,j} \quad (2)$$

Logarithmic compression is applied to the envelope detected echo signal in order to fit within the display range [7]. Logarithmic compression affects the speckle noise statistics and it becomes very close to white Gaussian noise. The logarithmic compression transforms multiplicative form in (2) to additive noise form as

$$\log(n_{i,j}) = \log(nf_{i,j}) + \log(m_{i,j}) \quad (3)$$

$$X_{i,j} = y_{i,j} + n_{i,j} \quad (4)$$

The term $\log(n_{i,j})$ is the noisy image in the medical image after logarithmic compression is denoted as $X_{i,j}$ and the term $\log(nf_{i,j}), \log(m_{i,j})$ these are the noise free pixel and noisy component after logarithmic compression, as $y_{i,j}, n_{i,j}$ respectively.

De-speckling or speckle suppression is a pre-processing step for many ultrasound image processing problems. A wide variety of filters exist in the literature [1, 2, 3 and 4].This work analyzes the effect of applying select filters such as Box, Gaussian in linear filters, Min, Max, Midpoint, Median in Non Linear Order statistics filters,), Wiener Filter (Adaptive), Homomorphic Filter and Speckle Reduction Anisotropic Diffusion filters [5, 6 and 7] on liver ultrasound images for the removal of speckle noise.

B. Active Contour Segementation

Segmentation using active contours model (Snakes) was introduced in [8]. The idea behind active contours, or deformable models, for image segmentation is quite simple. The user specifies an initial guess for the contour, which is then moved by image driven forces to the boundaries of the desired objects. In such models, two types of forces are considered - the internal forces, defined within the curve, are designed to keep the model smooth during the deformation process, while the external forces, which are computed from the underlying image data, are defined to move the model toward an object boundary or other desired features within the image. One way of describing this curve is by using an explicit parametric form, which is the approach used in snakes. This causes difficulties when the curves have to undergo splitting or merging, during their evolution to the desired shape. To address this difficulty, the implicit active contour approach, instead of explicitly following the moving interface itself, takes the original interface and embeds it in higher dimensional scalar function, defined over the entire image. The use of level set method has provided more flexibility and convenience in the implementation of active contours

IV. FEATURE EXTRACTION

A. Feature Extraction using Gray Level Co-occurrence Matrix (GLCM)

Co-occurrence features [9] are a popular and effective texture descriptor using statistical approach. Given an image of n gray levels, s, characteristics of images are estimated from the second-order statistical features by considering the spatial relationship of pixels in the image. A GLCM element $P_\theta, d(i, j)$ is the joint probability of the gray level pairs I and j in a given direction θ seperated by distance of d units. For each region of interest (ROI) in this work, five features are determined for texture discrimination: Energy (ENR), Entropy (ENT), Sum Entropy (SEN), Difference Entropy (DEN) and Standard Deviation (STD). Each subdivided block is an independent ROI. Multi-distance and multi-direction can be used to extract a large number of features. Extract the GLCM features using one distance $d = \{1\}$ and four direction$\{\theta = \theta^0, 90^0, 180^0, 270^0\}$, which result in 20 that is $1 \times 4 \times 5$) features extracted for each block.

$$\mathrm{ENR} = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} P_d^2(i,j) \quad (5)$$

$$\mathrm{ENT} = -\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} P_d(i,j) \log_2 P_d(i,j) \quad (6)$$

$$\mathrm{SEN} = -\sum_{k=0}^{2n-2} P_{x+y}(k) \log_2 P_{x+y}(k) \quad (7)$$

$$\mathrm{DEN} = -\sum_{k=0}^{n-1} P_{x-y}(k) \log_2 P_{x-y}(k) \quad (8)$$

$$\mathrm{STD} = \sqrt{\frac{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (P_d(i,j) - \mu)^2}{n \times n}} \quad (9)$$

Where

$$\mu = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} P_d(i,j)}{n \times n} \quad (10)$$

$$P_{x+y}(k) = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} P_d(i,j) \quad (11)$$

For $i + j = k$, here k=0,1,…,2n-2.

$$P_{x-y}(k) = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} P_d(i,j) \quad (12)$$

for $|i - j| = k$, k=0,1,…,n-1

GLCM features extraction (GFE) can be expressed as

$$\mathrm{GFE} = \mathrm{Img} \rightarrow \mathrm{Img} \times R^p \quad (13)$$

Where

$$\mathrm{GFE}(b_{IJ}) = F\left(\mathrm{GLCM}(b_{IJ})\right) = (b_{IJ}, f_p) \quad (14)$$

Where f_p is the feature vector and p is the number components (features extracted from b_{IJ})

The GLCM function is introduced in (14) can be defined as

$$\mathrm{GLCM}: \mathrm{Img} \rightarrow M_{n \times n}(N) \quad (15)$$

Where $M_{n\times n}(N)$ is the set of square matrices with the dimension n × n. The function in (15) takes a block b_{IJ} of the image Img and returns its GLCM, given a direction and a distance.

The F function introduced in equation (14) can be defined a

$$F: M_{n\times n}(R) \rightarrow Img \times R^p \qquad (16)$$

where the function of equation (16) takes a GLCM of a block b_{IJ} and returns $\left(b_{IJ}, f_p\right)$.

V. CLASSIFICATION:

The classification of abnormality and normality is improved here by using PSO with LSVM technique.

A. Particle swarm optimization

Particle swarm optimization (PSO) is a population-based optimization algorithm modeled after the simulation of social behavior of birds in a flock [11]. The algorithm of PSO is initialized with a group of random particles and then searches for optima by updating generations. Each particle is flown through the search space having its position adjusted based on its distance from its own personal best position and the distance from the best particle of the swarm. The performance of each particle, i.e. how close the particle is from the global optimum, is measured using a fitness function which depends on the optimization problem. Each particle i flies through an n-dimensional search space, R^n, and maintains the following:

x_i, the current position of ith particle (x-vector)

p_i, the personal best position of ith particle (p-vector), and

v_i, the current velocity of ith particle (v-vector).

The personal best position associated with a particle, i, is the best position that the particle has visited so far. If f denotes the fitness function, then the personal best of i at a time step t is updated as:

$$p_i(t+1) = \begin{cases} p_i(t) \text{ if } f(x_i(t+1)) \geq f(p_i(t)) \\ x_i(t+1) \text{ if } f(x_i(t+1)) < f(p_i(t)) \end{cases} \qquad (17)$$

If the position of the global best particle is denoted by gbest , then :

$$gbest \in \{ p_1(t), p_1(t), \dots\dots, p_m(t)\} = \min\left\{ f(p_1(t)), f(p_2(t)), \dots\dots f(p_m(t))\right\} \qquad (18)$$

The velocity updates are calculated as a linear combination of position and velocity vectors. Thus, the velocity of particle i is updated and the position of particle i is updated by the following equations.

$$v_i(t+1) = w.v_i(t) + c_1 r_1\left(p_i(t) - x_i(t)\right) + c_1 r_1\left(gbest - x_i(t)\right) \qquad (19)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (20)$$

In the formula, w is the inertia weight [10], c_1 and c_2 are the acceleration constants, r_1 and r_2 are random numbers in the range [0,1] and V_{i1} must be in the range $[-V_{max}, V_{max}]$, where V_{max} is the maximum velocity.

B. Library Support Vector Machine:

LIBSVM is a library for Support Vector Machines (SVMs). The goal is to easily apply SVM to their applications. LIBSVM has gained wide popularity in machine learning and many other areas. In this work, we present implementation of LIBSVM. Issues such as solving SVM optimization problems theoretical convergence multiclass classification probability estimates and parameter selection.

A typical use of LIBSVM involves two steps: first, training a data set to obtain a model and second, using the model to predict information of a testing data set. For SVC and SVR, LIBSVM can also output probability estimates.

This is same as SVM technique; where in training SVM an m by 1 vector of training labels (type must be double) is taken.

Then parameters for gamma in LIBSVM are taken from PSO algorithm. And the Cost parameter is set as the parameter C of C-SVC is taken.

1. Kernels:

Kernel methods in general have gained increased due to the grown of popularity of the Support Vector Machines. Support Vector Machines are linear classifiers and regressors that, through the Kernel trick, operate in reproducing Kernel Hilbert spaces and are thus able to perform non-linear classification and regression in their input space.

Here Radial Bias Function Kernel is used and it is expressed as

$$RBF = \exp\left(\frac{1}{2\sigma^2 \|x - x_i\|^2}\right) \qquad (21)$$

And detailed description is given in [12]. This is given as kernel in LIBSVM technique. By this the classification of abnormal and normal MRI brain images is performed and their affected disease is identified.

VI. EXPERIMENTAL RESULT

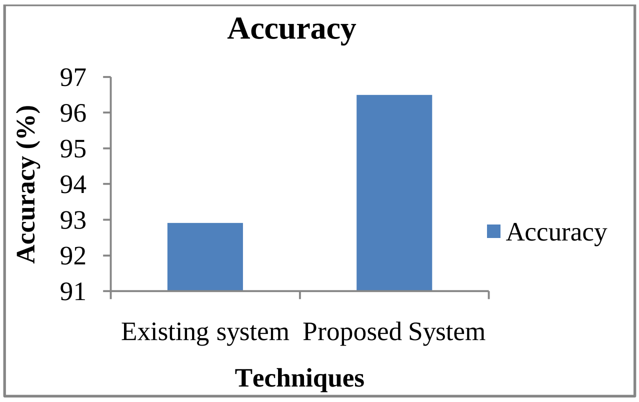
To evaluate the proposed work which is implemented here is analyzed and results produced from this algorithm are shown here. To prove its efficiency here it is compared the proposed LIBSVM with optimization technique with segmentation and existing system of SVM technique without segmentation [29]. The images are collected from freely available open source and this technique is implemented in MATLAB software of R2012a version environment. The performance of this work is measured using accuracy of correctly classified and execution time taken for this work to complete the process.

Table I : Comparison of Accuracy

Technique	Accuracy
Existing SVM without segmentation	92.91
Proposed LIBSVM with Optimization technique with segmentation	96.5

The above table I provide the comparison of accuracy between existing system and proposed system. From the table observes that the proposed system provides better accuracy than the existing classification system.

Figure 1: Comparison of Accuracy

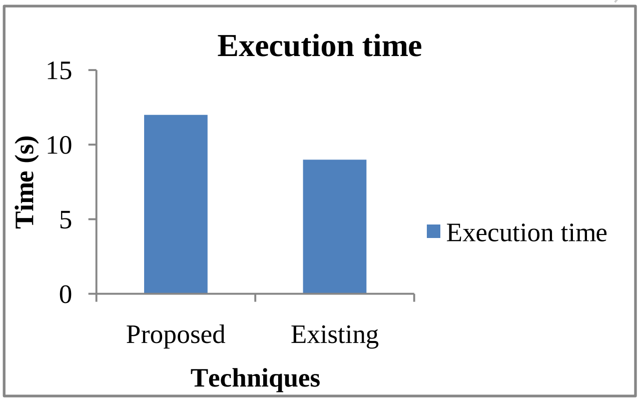


The figure 1 illustrates the comparison of accuracy between proposed LIBSVM with segmentation and existing SVM without segmentation.

Table II: Comparison of Execution time

Technique	Execution time
Proposed	12s
Existing	9s

The above table II provides the comparison of execution time between existing system and proposed system. From the table observes that the proposed system provides less execution time than the existing classification system.



The figure 2 illustrates the comparison of execution time between proposed LIBSVM with segmentation and existing SVM without segmentation. From the figure 2 analyzed that the proposed system gives less execution time than the existing system.

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