An Efficient and Automated Classification Scheme for Diagnosing Fatty Liver Disorder using Ultrasonic Images

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Abstract: **In the treatment of abdominal diseases like fatty liver disorder, ultrasonic images-based investigation is considered as the primary step of diagnosis. But, the noisy feature of ultrasonic images combined with the least contrasting features introduces maximum complexity during the process of automated classification. This paper contributes an Improved Active Contour Segmentation scheme for effective segmentation. Then Gray Level Co-occurrence Matrix (GLCM) and fractal features are extracted from the segmented ultrasonic images and the classification is achieved using an enhanced forest classification incorporated in the artificial neural networks (ANN) for accurate detection. The results of the proposed automated approach are investigated using classification accuracy, mean classification accuracy, true positive rate, false positive rate and true negative rate . The results of the proposed scheme also infers a classification accuracy rate of 98.73% and a mean classification accuracy rate of 97.65% compared to the baseline automated liver disorder classification techniques.**

Index Terms: **Fatty liver disorder, Improved isocontour Segmentation, Graph cuts, Taguchi Method, Fractal features**

I. Introduction

Computer-based automated diagnosis of diseases from biomedical images is considered as the potential field of research that integrates the benefits of Medical and Engineering domain [1]. The non-invasive, soft tissue visualization and economical characteristics of ultrasonic images has made them suitable for diagnosing the abdominal organs such as liver, spleen, pancreases and gall bladder [2]. In specific, liver diseases like heterogeneous liver and fatty liver can be effectively diagnosed by ultrasound images [3-4]. Heterogeneous liver belongs to the category of focal liver diseases that results in the swelling and inflammation of the organ due to pus formation caused by the infection of bacteria. Fatty liver disease relates to the category of diffused liver diseases that is caused due to the enormous deposit of triglycerides and other fat types in the liver cells. Inspite of the potential characteristics of ultrasonic images, the activity involved in classifying the normal cells from infected cells of the liver is influenced by minimum contrast, close appearances and hazy nature of images [5-7]. Inherently, the ultrasonic image of one liver disease may closely resemble the image of other liver disease or the similar ultrasonic images of the same liver disorder may exhibit different textures. This resembles of ultrasonic images result in a varying decision of the liver disorder made by the diagnosing radiologists [8]. Further, the diagnosis of this liver disease is influenced by the comfort and experience of the radiologist who are responsible for establishing the contrast and gain setting during the capture of ultrasonic images [9]. Furthermore, the patients' body condition, probe application and the absence of quality ultrasonic machine also impacts the quality and reassemblies of the images [10]. Hence, an automated classification scheme that is capable of handling texture and wavelet features in diagnosing liver diseases with improved accuracy becomes essential. In this paper, a novel texture and wavelet features-based automated liver disease diagnosis mechanism that uses improved active contour for segmentation, shift variant bi-orthogonal wavelet transform for filtering and an integrated random forest-based classification is proposed. The core objective of the proposed liver disease diagnosis scheme focusses on the enhancement of accuracy during classification such that diagnosis is achieved at a rapid rate with reliability.

The subsequent sections of this paper are ordered as follows. Section 2 highlights on the literature review conducted for elucidating the merits and limitations of the existing liver disease diagnosis schemes. Section 3 presents the outline of the proposed methodology and detailed explanation about each and every of the implemented automatic liver disease diagnosis scheme. Section 4 reveals the simulation results and analyses of the proposed liver disease diagnosis scheme in terms of Accuracy, Mean Accuracy and True Positive Rate. Section 5 presents the major contributions of the proposed scheme with possible scope of focus on the future enhancement.

II. Literature Review

Traditionally, accurate classification between liver diseases is achieved based on the selection of potential features and Region of Interest (ROI) determination. But, the process of estimating the ROI region automatically from the ultrasound images leads to complexity since they do not possess continuous or definite boundaries in the diseased liver part used for analysis. Initially, an automated approach for liver disease detection is facilitated by utilizing the square ROI of 30X30 pixel dimension [11]. This method of liver disease diagnosis used 50 images that contained 30 fatty diseased liver images and the normal dis-infected liver images. It also used and integrated nearly seven textures during the fusion of the segmented images in order to ensure

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the significant classification rate of 96%. Then Alivar et al. [12] devoted a scheme that used ROI size of 64X64 pixels during segmentation. Then ROI images are carefully used for determining different quantifiable wavelet packet, Gray Level Co-occurrence Matrix and Gabor Transform for phenomenal feature extraction. These triple level methods of feature extraction are essential for achieving a significant classification rate. The Authors used a dataset of 45 ultrasonic image samples out of which 35 are dis-infected liver samples and the remaining are infected liver samples for identifying and improving the classification accuracy based on K-nearest technique.

Further, an integrated mechanism-based on the integration of discrete wavelet transform and contrast improvement was proposed in [13] for preventing speckle noise from the images. The data set used for speckle image removal consisted of 35 dis-infected liver images, 35 decompensated liver images and 30 compensated images. This classification process utilized the K-mean clustering scheme for classification as it proved to optimize the performance of the diagnosis based on estimated minimum Euclidean distance. The classification accuracy of this system is also verified to be 97.32 compared to the benchmarked approaches. Then, an optimal feature extraction scheme was contributed in [14] for diagnosing different level of liver disorders. This computer automated scheme used the concept of forward selection for accurate classification in the dataset that contained ultrasonic images that possessed two image parameters, three medical-oriented features and one laboratory-inspired features for extracting. In this scheme, total 97 number of samples related to dis-infected liver, carcinoma-based liver disease, chronic hepatitis and steatosis was used during classification. This classification of ultrasonic images proved a classification accuracy of 97.89% during its utilization of Support Vector Machine and K-mean clustering scheme.

Furthermore, an automated liver disease classification scheme was proposed by Minhas et al. [15] with integrated statistical features and wavelet packet transform for feature extraction. This automated detection scheme used support vector machine based multi-objective scheme for classification. The classification rate of this scheme was also confirmed to be greater than 97% since it used the ROI segmentation of 64x64 pixel dimensions. The tenfold strategy used during classification was also responsible for improving the classification accuracy over 97%. Finally, another automated liver disease automation scheme was proposed in [16] with improved classification rate of 98%. This method was formulated for handling data sets that possesses highly un-correlated ultrasonic images and that fail to possess standard boundaries.

From the thorough investigation of the aforementioned automated liver diagnostic approaches, the base induction for the formulation of the proposed work is determined.

III. The Proposed Work

This proposed scheme starts with the process of image acquisition, which is followed by improving active contour segmentation. Then shift-invariant bi-orthogonal wavelet transform is enforced on the segmented images for deriving diagonal, horizontal and vertical components based on which the component images are derived. Further, the Gray-Level Run-Length Matrix (GRLM) feature extraction is achieved from the derived component images and then the classification is performed using the method of random forests. The classification process using random forests is also improved through the incorporation of tenfold validation procedure. Further, the results obtained from the classification of the utilized GLRLM features and the benchmarked GLCM, intensity histogram and invariant moments are compared to validate the potential of the proposed diagnosis scheme.

A) Improved active contour-based segmentation

Initially, the image is divided into unique regions that contain pixels of similar attributes are segregated during the segmentation process. For achieving segmentation, improved active contour approach is used for separating the boundaries of the object from the utilized image based on the enforcement of constraints. The classical active contour method is improved by initially defining a false edge. When the basic process of active contour is facilitated then the reference point of each determined regions are checked. If the gradient value pertaining to the pixel of the segmented regions is very small then the false point is assigned to the reference point. The collection of these false points constitutes the false edges. Then the force is enforced on the false edges in the tangential direction which is upright until true edge is visible. Thus, this method can be used for the ultrasonic images since they do not possess a standard boundary and further, the existing boundary may also merge into the neighbourhood regions. Further, this improved active contour is also furthermore based on the contributed work of Chan and Vese [17] that focusses on reducing the energy level. Hence the proposed scheme is proving to be meritorious as it eliminates the limitations of the traditional segmentation schemes existing in the literature. In addition, the gradient is not used as the constraint for determining the boundaries of the regions and hence they are suitable for its application in the segmentation process of blurred and noisy images like the ultrasonic images.

This Chan and Vese-based scheme uses two terms $F_1(C)$ and $F_2(C)$ for fitting energy as depicted using Equation (1) and (2)

$$E_{Fit} = F_1(C) + F_2(C) \int_{in(c)} |O_I - l_1|^2 dydx + \int_{out(c)} |O_I - l_2|^2 dydx \quad (1)$$

With

$$\inf_C [F_1(C) + F_2(C)] \approx 0 \approx F_1(C) + F_2(C) \quad (2)$$

Where l_1 and l_2 refers to the mean outside and inside of O_I the image that contains regions related to the piecewise intensity constants with C as the evolutionary curve.

Then the fitting energy expressed in Equation (1) is minimized by incorporating two terms pertaining to the area and the length of the evolutionary curve as depicted in Equation (2). This segment also uses the level set method for solving the specific case of minimum partitioning issue that always evolve during the application of improved active contour scheme of Chan and Vese method

B) Shift Variant Bi-Orthogonal Wavelet Decomposition

The Shift Variant Bi-Orthogonal Wavelet Decomposition used in this automated approach aids in capturing the frequency and temporal data related to the utilized images' signal that comprises of multiple resolution scaling. This Shift Variant Bi-Orthogonal Wavelet Decomposition is used for investigating the signals of the image and prevents them from generating spurious information that are general in the image analysis. In this analysis, the signals of the image are investigated using varying number of least scales and translations. Initially, the segmented images are converted into four numbers of shift sets viz., $S_S = \{(0.0),(0,1),(1,0),(1,1)\}$ for the determination of image pairs. Then the individual image pairs results in four sub-images during the process of decomposition achieved using Equation (3) through the incorporation of filters f_1 and f_2.

$$I_{i-1,k} = \sum_k g_k I_{i,2l+k} f_{(i-1,k)} \quad (3)$$

The resulting sub-images correspond to three higher wavelet-co-efficient-based frequency sub-images and one approximation lower frequency sub-images. Further, the mixing operation of the lower frequency sub-images are performed based on shift sets using origin point such that aids in better approximation of the originally used image. This process of mixing and shifting is performed upto 'k' levels, such that better multiple scale representations of the original image are achieved. Then compute the co-efficients of approximation related to each of the resultant sub-images using Equation (4) and determine the wavelet co-efficient of the original image based on varying levels of intensity through Equation (5).

$$M_k^0(a,b) = \frac{(A_k^0(a,b) + B_k^0(a,b))}{2} \quad (4)$$

and

$$D_i^e(a,,b) = \sum_{a,b \subseteq k}^{n} w^e(a^1,b^1)[E_i^e(a+a^1,b+b^1]^2 \quad (5)$$

Then estimate the similarity of the original images using the derived multiple scale representations using the Equation (6)

$$M_{i,AB}^e(a,b) = 2\frac{\sum_{a,b\subseteq k} w^e(a^1,b^1)E_{i,A}^e(a+a^1,b+b^1)E_{i,B}^e(a+a^1,b+b^1)}{F_{i,A}^e(a,b)+F_{i,B}^e(a,b)} \quad (6)$$

Furthermore, estimate the weights of the co-efficient using Equation (7) and (8) and then perform the verification process of consistency using for achieving the weights that could be used for decision process during testing and training.

$$\alpha_{i,A}^e = \sum_{a^1,b^1} w^e(a^1,b^1)\alpha_{i,A}^e(a+a^1,b+b^1) \quad (7)$$

$$\alpha_{i,B}^e(D_i^e(a,b)) = \frac{1}{2} + \frac{1}{2}\left(\frac{1-D_{i,AB}^e(a,b)}{1-F_M}\right) \quad (8)$$

and

$$E_{i,F}^e(a,b) = \alpha_{i,A}^e(a,b).E_{i,A}^e(a,b) + \alpha_{i,B}^e(a,b)E_{i,B}^e \quad (9)$$

Finally, determine the wavelet co-efficient of the decomposed image using Equation (9) that performs the mean operation using the shift sets.

C) Feature Extraction using GLRLM

In this scheme, nearly 11 features such as short-run emphasis, long-run emphasis, run percentage, run-length non-uniformity, gray-level non-uniformity, low gray level run emphasis, high gray level run emphasis, long run, low gray level run emphasis, long run high gray level run emphasis, short run low gray level run emphasis and short run high gray level run emphasis are extracted. Further, features related to Euclidean shape, color and to some extent texture contribute to the last level in this automated scheme of liver disease detection. The feature is extracted using GLRLM mainly for collecting potential values of the image pixels for classification by enforcing significant constraints in implementation. This GLRLM-based feature extraction scheme is confirmed to gather a better diversity of features even in the gray scale, hazy and appearance of ultrasonic images of liver. This automated approach possesses a better discrimination rate in classifying normal ultrasonic images of liver from diseased liver ultrasonic images in the spatial field. The proposed scheme is also compared with the classical detection techniques like invariant moments and intensity histogram techniques.

D)Enhanced Random Forest Learning-based classification scheme

In this automated fatty liver diagnosis system, the enhanced Random Forest Learning-based classification scheme is used for four important reasons viz., a) It is capable of resolving multiple-class dimensional problem of classification, b) It is significant in generating decision tree that enables individual voting process that transforms each input of classification into its most feasible probability classification label, c) It is fast and possess the potential of determining non linear data structures based on the the estimation of reliable ensemble parameter and d) it eliminates the degree of data over fitting even when the count of decision trees appended to the forests is increased. This proposed automated fatty liver diagnosis approach use the merits of three entities such as an improved instance filter, multi-perspective attribute estimator and forest classifier algorithm for effective and reliable classification. In this classification process, initially, three attributes quantification parameters pertaining to the uncertainty of correlation features, symmetric uncertainty and gain ration are used for better contextual selection that improves the degree of training for choosing the most related attributes for optimal classification. Then, an enhanced instance filter is mainly used for reliable balancing of multiple-class dimensional attribute classification since the data distribution need to be re-sampled when they are not uniformly distributed in order to enhance the efficiency of the classification process. In addition, the classical Random Forest Classification method is finally used over the transformed uniformly distributed data which is derived as the output of the incorporated instance filter phase. Hence, the classification accuracy of the proposed automated fatty liver diagnosis system is 98.72% compared to the classification schemes used for investigation.

IV. Result Analysis and Discussions

The performance of the proposed automated fatty liver disease diagnosis scheme is investigated using MATLAB R2013a based on evaluation parameters like classification accuracy and false positive rate.

The investigated result of the proposed automated diseased liver detection scheme is conducted using the data set that consists of 500 images classified under four categories collected from the scan centers of Chennai. The images are resized uniformly to the resolution of 512x512 such that the process of classification can be potentially improved. This proposed scheme was simulated using MATLAB R2013a with Weka for knowledge analysis. Nearly 500 iterations are carried out for separating the ROI from the images gathered for investigation and 100 iterations is used for segmenting out the smaller regions of ROI from the utilized original images. The GLRLM features are extracted with orientations viz., 0,45, 90 and 135 degrees such that 44 features are collected from 176 features involved in shift variant bi-orthogonal wavelet decomposition. The significance of the proposed approach is investigated using overall accuracy, mean accuracy and true positive rate.

Figure 1 and 2 portrays the input liver image before segmentation and liver image after Chen Vese segmentation

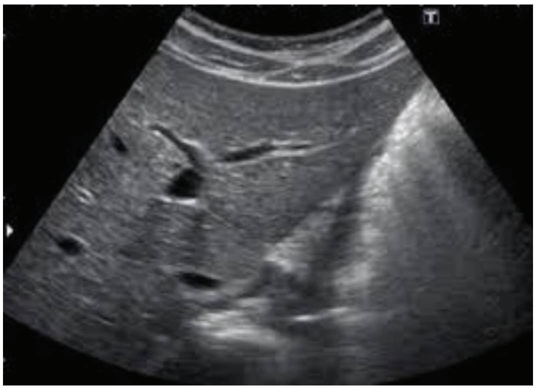

Figure 1. Input ultrasonic liver image used for detection

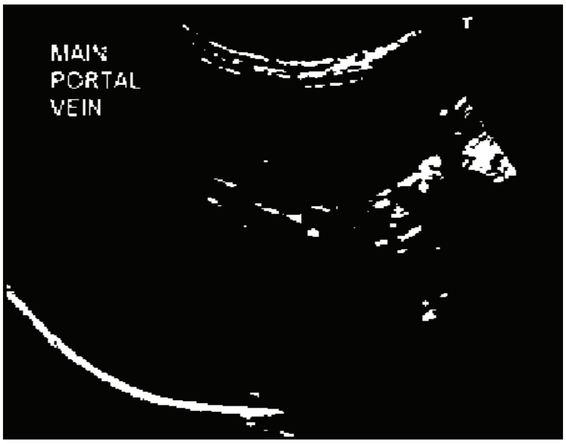

Figure 2. Chen Vese segmentation of liver image

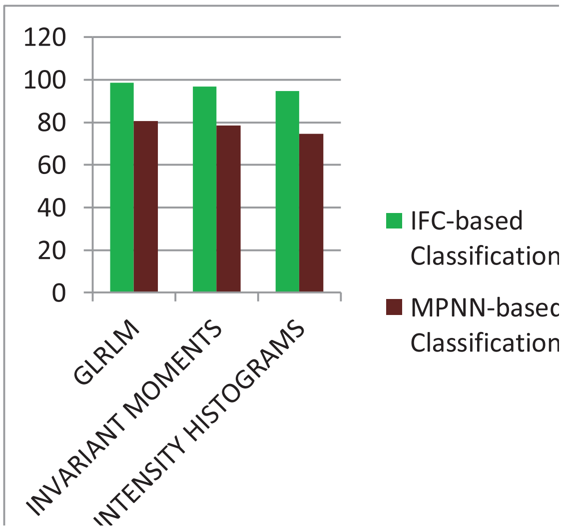

Figure 3. Classification accuracy percentage of IFC

Figures 3 presents the overall classification accuracy of the incorporated random forests and compared multilayer perceptron neural network. The overall accuracy of Improved Forest Classifiers(IFC) used in this automated detection technique seems to improve its classification accuracy by 19% predominant to the investigated MultiLayer Perceptron Neural Network (MPNN). Similarly, Figure 4 portrays the performance of the utilized IFC based on mean classification accuracy. The mean classification accuracy is also confirmed to be better by 23% superior to the comparable MPNN used for classification.

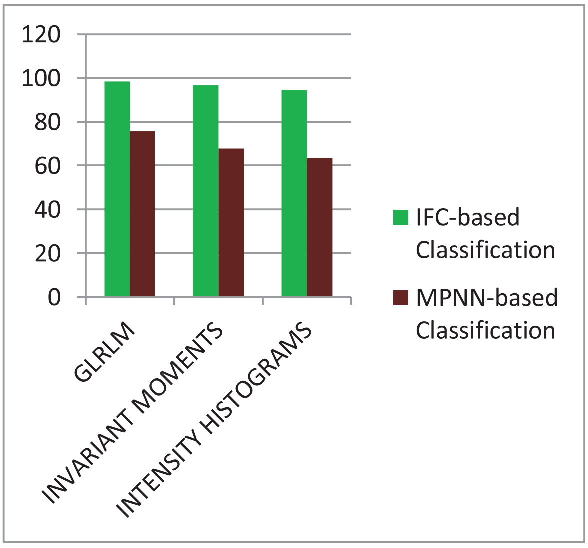

Figure 4. Mean Classification accuracy of IFC

Likewise, Figures 5 presents the true positive rate of random forests and compared MPNN. The true positive rate of IFC used in this automated detection technique is conformed to infer an excellent classification accuracy of 22% better to the compared multi-layer perceptron neural network.

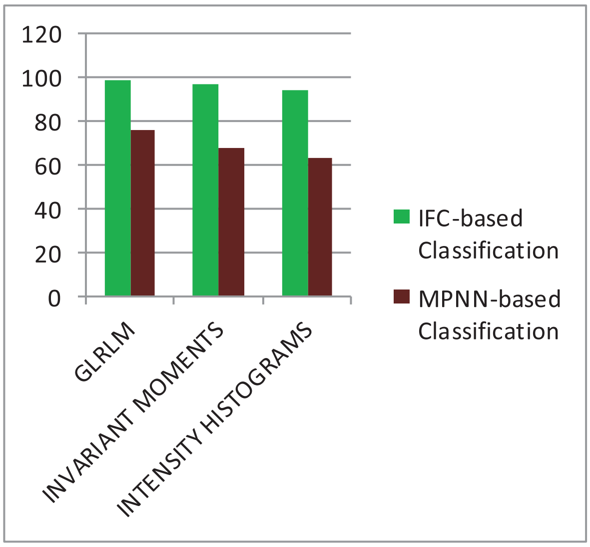

Figure 5. True positive rate of IFC

This improvement in true positive rate of this proposed automated scheme is due to eleven different GLRLM features extracted and the hybrid classification module used during deployment.

Furthermore, the performance of the proposed automated liver disease diagnosis system is investigated based on the significance of the system with instance filter, system without instance filter, system to Chen Vese Method and system without Chen Vese Method is presented in Table 1 .

TABLE 1.
PERFORMANCE OF AUTOMATED LIVER DETECTION SCHEME.

Schemes of comparison	Decrease in False Positive Rate	Increase in True Negative Rate
Proposed Forest classifier based detection with instance filter	18.13%	27.25%
Proposed Forest classifier based detection without instance filter	14.12%	20.43%
Segmentation with Chen Vese method [17]	21.12%	29.21%
Segmentation without Chen Vese method [18]	13.21%	20.65%

Table 1 clearly portrays that the proposed scheme is highly potent due to the incorporated Chen Vese method of segmentation and Enhanced Forest Classification Technique in its detection methodology. The proposed IFC method with the Chen Vese method of segmentation is proven to decrease the false positive rate by 8 % and increase the true negative rate by 8.64% superior to the benchmarked liver detection schemes used for investigation.

V. CONCLUSIONS

The exhibited novel texture and wavelet features-based automated liver disease diagnosis mechanism improves the accuracy, mean accuracy and true positive rate by 19%, 23% and 22% compared to the benchmarked approaches considered for investigation. The utilization of shift variant bio-orthogonal wavelet transforms is confirmed to increase the contrast during the diagnosis of liver disorders. The results of the proposed liver disease detection scheme confirmed better classification accuracy of 98.56% better to the baseline liver disease automated techniques used for comparison. The true positive rate of the proposed scheme is also inferred to be better by 22% predominate to the comparative techniques under the evaluation using the features extracted using GLRLM, invariant moments and intensity histograms. In addition, the proposed IFC method with the Chen Vese method of segmentation is proven to decrease the false positive rate by 8 % and increase the true negative rate by 8.64%

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