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International Journal for Light and Electron Optics 00 (2016) 000–000

Computer Aided Diagnostic System for Ultrasound Liver Images: A Systematic Review

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Abstract

In this article an in-depth overview is presented on Computer aided diagnostic (CAD) system's usage for liver cancer. Besides, in a broader sense highlighting the technical aspects developed for medical ultrasound images is also discussed. CAD system is a process that provides adequate information that helps to analyze the Ultrasound images and helps to accurately detecting different types of liver cancer. However, the system performance is still not significantly improved. In this paper, firstly, we categorize the CAD system according to the four primary stages including data preprocessing, lesion segmentation, feature extraction, selection, and Classifier. In each stage, we review specific methods that are commonly used in most of the algorithms proposed for computerized tissue characterization and discuss their advantages and drawbacks. Then, recent proposed algorithms are presented in summarize form that have shown clinical value or specific possibility to the computerized analysis of setback for ultrasound liver images. These techniques or their combinations are the ones that are mostly used in the past few decades by the majority of work published in the Computer aided diagnosis domain.

Keywords: Ultrasound Image; Liver Cancer Diagnosis; Computer Aided Diagnositic System; Segmentation; Artificial Intelligence

1. Introduction

In therapeutic imaging and analytical radiology as a key subject matter of research Computer aided diagnostic (CAD) has emerged. CAD has applicability in numerous medical imaging modalities. Some of which are computerized tomography (CT), magnetic resonance imaging (MRI), ultrasound (US) imaging, and nuclear medicine [1], [2], [3], [4]. For US liver image diagnosis CAD strongly depend by the quality of data.

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The comparatively substandard of clinical US images reduces the success of early liver ailment finding and analysis. There are distinctive objectives [5] which make the system assignment complex, such as speckle, attenuation, signal dropout and shadows. It is due to the orientation dependence of acquisition that can outcome in losing boundaries. Additional complexities appear due to the highly variable shape of the liver, reduced contrast and intensity inhomogeneity within liver, weak boundaries to its nearest organs say heart and stomach, and intensity homogeneity to nearer organs. So, liver diagnosing from US device seems an exigent task that has called the attention of many researchers in recent times.

The data generated by the automated computer processes while diagnosis is helpful to the radiologist to realize the US liver images. So, the precision of image diagnosis is better, and the time required by regular methods in peruse an image is reduced [6]. Henceforth, utilizing CAD the analysis of diseases has become a vibrant area of research [7]. There is greater requirement of precisely analyzing the therapeutic images and lessening the time requisite for proper analysis of liver cancer.

The key objective of this review is emphasizing on the potentiality of intelligent computer systems to be utilized in clinical application to support pathologists to analyze and classify US liver cancerous tissue images. On the basis of methodical analysis of various liver conditions, CAD methods and organized summary of algorithm, we categorize the computerized system according to the four primary stages of analyzing liver US image. Here the using of general procedures including data preprocessing, lesion segmentation, feature extraction and selection, and depicting of cancer by means of a classifier [8] better summarizing the performance of each category leads to find the ideal solution for automatic computerized system performance and the four stages are given in Figure 1.

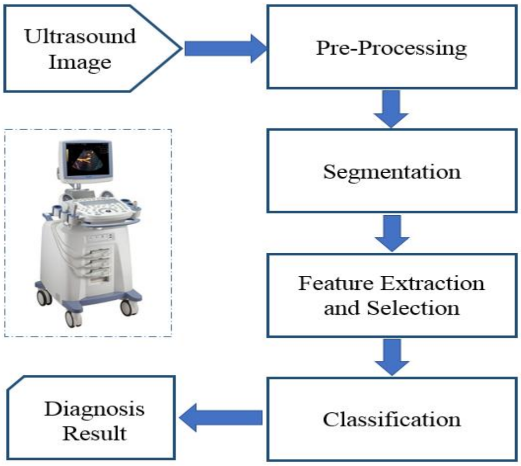

Fig. 1. Flow diagram of CAD for liver cancer.

1. Data preprocessing: The preprocessing task is to restrain the noise and to increase the image without eliminating the important features of Liver US images.
2. Image segmentation: Here image is divided into a number of small portions, and it forms the background the lesions detached. The edges of the lesions are outlined for feature withdrawal.
3. Feature extraction and selection: The stage identifies a feature set of liver cancer lesions that can precisely differentiate normal tissue or abnormal cancer tissue. The feature space could be vast and intricate, so withdrawal and choosing the finest features is decisive.

4. Classification: After the selected features, the apprehensive regions will be characterized into distinctive classifications, say normal tissue or cancerous tissue.

In following manner, this paper is arranged. Classification of liver cancer is presented in section 2. The literature review about the four stages of the CAD system in US liver diagnosis is discussed in section 3. Relevant research works are detailed in section 4. In section 5 concluding part is presented.

2. Classification of liver cancer

Globally liver cancer is much popular malignant disease, mainly in Southeast Asia and sub Saharan Africa. Worldwide, liver cancer has sixth position as the most familiar cancer with a half a million people affected each year. The number of people who develop liver cancer is increasing around the globe [9].

In human body liver is one of the indispensable organs. It's extremely hard to live without a sound liver because of its impacts on every other body parts. Mainly focal liver diseases and diffused liver diseases influence the liver. Diffused liver diseases, for example cirrhotic and fatty, harm the total surface of liver. Focal liver diseases which affect the small area of the liver surface, such as hepatocellular carcinoma (HCC), hemangioma (Hem), and cyst. Figure 2 presents three focal liver diseases in the US images. The hepatocellular carcinoma (HCC) and echo type in the liver based on US image representation, five types of primary carcinoma of liver tumour are there, they are correlative to low echo type, equal echo type, high echo type, mixed echo type and diffuse type correspondingly.

Complexity of the liver tumour in patients having chronic viral illnesses, can be classified from asymptomatic strong carriers to patients with liver cirrhosis [10], [11], [12]. In general, the US appearance of Cyst, Hem, and HCC visible similar. Brightness mode (B-mode) ultrasound [13] diagnosis is the foremost choice in well-liked analyses because of its effectiveness, non-invasiveness, and economy. All types of liver cancers are not correctly diagnosable in the US images, in case there is benign appearance of deadly tumours and observer's diagnostic level is not good, careless mistakes and visual fatigue. Hence, utilizing traditional method it is extremely difficult in decision making between them. A fully efficient automatic computer system is required to be developed for disease detection and diagnose with high performance.

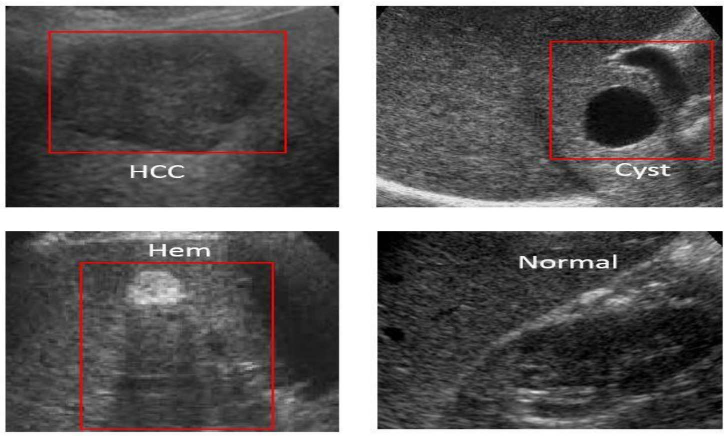

Fig. 2. Normal liver and focal liver US images.

3. Overview of the CAD system schemes

The most recent success in automatic diagnosing of liver US images is reviewed in this section. The four main steps in the CAD including data preprocessing, lesion segmentation, feature extraction and selection, and classifier of lesions are discussed in detail.

3.1. Data Preprocessing

Data preprocessing is aimed at filtering speckle noise, which impinge on the diagnostic value of the US image [14]. It makes image detail unclear and hazy drastically, demeans the image feature. Likewise, it decreased the pace and correctness of US image processing tasks say- division and classification. Hence, in US image processing tasks, speckle noise reduction is always an important prior requirement. Figure 3 depicts an example for speckle noise image and enhanced image.

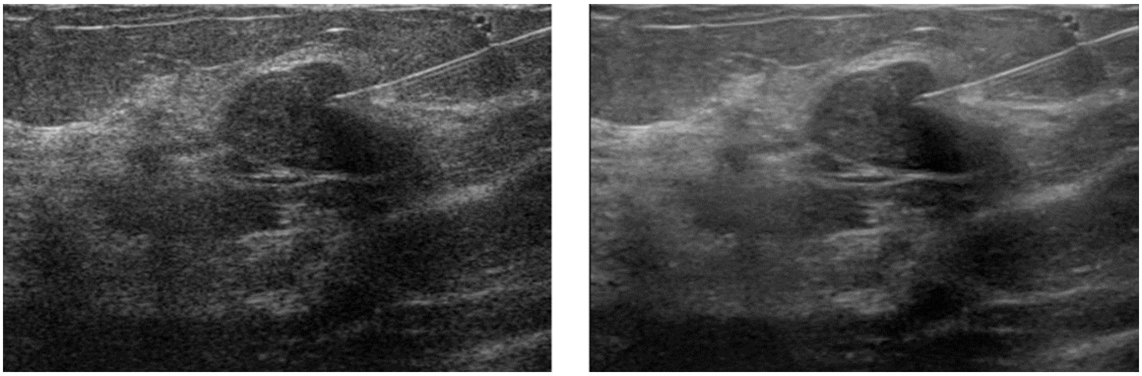

Fig. 3. (Left) Speckle noise image and (Right) Despeckled US image.

In this paper, we categorized the speckle reduction techniques into two major classifications, namely a) spatial filtering methods and b) multiscale methods. Those methods are effective in eliminating the speckle noise and conserving the analytical information in US images.

a. Spatial filtering process

The basis of spatial filter is proportion of local statistics. It is helpful to improve smoothing in uniform regions of the US images where speckle is completely visible. This method lessens smoothing substantially in surrounding areas of the image to conserve the helpful particulars of the image [15]. Lee and Kuan Spatial filters use local statistics to perform straight on the intensity of the image [16], [17], [18].

Various sorts of filters are utilized as a part of uses of speckle lessening in US imaging. The most usually utilized sorts of filters are:

- Mean filter [19] is easy to apply, also its a plain filter . However, speckles are not eliminated by it, but in the data averaged by it. It is an attractive technique for speckle noise diminishing as it can make loss of resolution and accuracy Image can be obscured by it. It has amazing quality for added substance Gaussian noise, though the speckled image comply a multiplicative form with non-Gaussian noise since the mean filter is not an ideal selection.
- Median filter [20] is very efficient against impulsive type noise and edge conserving characteristics. It generates least obscure images in comparison to mean filter. It requires listing of all near values into

numerical order to figure out the median and here it is the drawback. Moreover, it takes additional calculation time to list the intensity value of all set.

- Wiener filter [21], [22] replace images in the existence of noise and blur. Decreasing the quantity of noise presence in a signal by comparing with an assessment of the preferred noiseless signal is the aim of algorithm here. The approach of filter towards image smoothing is on the basis of calculation of local image variation. The smoothing becomes less when the local variation of the image is immense. The filter does more smoothing when the difference is small. This calculation over linear filtering over linear filtering. It conserves edges and other high recurrence information of the images, however takes more time for calculation than linear filtering.
- Enhanced Frost and Lee filter [23] is utilized to vary the capability in light of the limit value. The filter works out like a stern all pass filter when the local coefficient of variation is over a greater limit. On the other part as the local coefficient of variation goes under a poor limit then pure averaging is actuated. The stability amongst averaging and identity operation is processed when the coefficient of variation stands at middle of lower and higher thresholds.
- Gamma Map filter [24] is like preceding filter aside from that the local coefficient of variation takes place amid the two limits; the filtered pixel value depends on the Gamma estimation of the contrast proportions inside the proper filter window. It is utilized to reduce the loss of texture information. The filter needs suppositions about the dispersion of the genuine procedure and the degradation model.
- Frost filter [25] is an adaptive and exponentially weighted average making filter in light of the proportion of the local standard deviation to the local mean of the debase image. Within the $n \times n$ moving core it interchanges the region of interest with a weighted sum of the values. The weighting aspects lessen with difference from the region of interest. The weighting aspects increment in the mid region as difference inside the core grows.
- Lee filter [16], [17] relies upon the multiplicative speckle model. It can utilize local statistics to conserve borders and attributes adequately. It also uses the process like when the variance over an area is poor, then the smoothing will be done. When the difference is much similar to near borders, no smoothing will be done.
- Kaun filter [26] Irelies upon an image's Equivalent Number of Looks (ENL) to decide an unlike weighting function to do the noise reduction. The filter model is a local linear least square inaccurate filter relies on multiplicative model regarded as to be finer to Lee filter. It makes no estimation of the noise variance inside the filter window.
- Diffusion filter is for smoothing images on a nonstop area, nonlinear partial differential equation was implemented by Perona and Malik [27], which has since been extended and enhanced [28], [29]. Through many years, other denoising processes with extremely fascinating ability are developed for example: Bilateral filter along with derivatives [30]. In Speckle reducing anisotropic diffusion (SRAD) [31] dispersion of speckled images is edge-sensitive. Its preference is a rapid and a decent speckle lessening impact. In SRAD, the instantaneous coefficient of variation goes about as the border identifier. Here algorithm displays maximum gains at the borders and creates least gains in consistent areas. This way, it guarantees the mean-preserving conduct in the uniform areas, and conserves and improve the borders.

The noted diffusion methods can save or even improve important edges when taking out speckles. Even so, the techniques have one basic constraint in holding unobtrusive features of minute cyst and lesion in US images.

b. Multiscale process

For US imaging numerous speckle reduction algorithms are proposed in light of contourlet, curvelet and wavelet.

- Wavelet Transform: The key target of speckle diminishment is eliminating the speckle noise by not missing much data included in an image. To be successful this target Wavelet transform have set up since it gives an ideal representation for 1D (single dimensional) piecewise smooth signals, for example, an image's scan lines [32].The complex wavelet transform (CWT) just requires O(N) computational to enhance directional selectivity. Yet, in the past intricate wavelet change not broadly utilized, as it is hard to devise intricate wavelets with impeccable recreation properties and good filter attributes [33], [34]. Kingsbury proposed the technique known as dual-tree CWT in articles [35], [36], which can add faultless reform to the other appealing properties of difficult wavelets, incorporating limited redundancy, estimated shift invariance, six directional selectivity's, and proficient O(N) calculation. To build 2D complicated wavelets here Tensor-product 1D wavelets are utilized. The directional discerning dispensed by complicated wavelets (six directions) is vastly improved from what is acquired by the discrete wavelet transform (three directions), however is by now fewer. Such undesirable practices demonstrate that further potent representations are asked in upper dimensions.
- Contourlet Transform: a contourlet transform utilizing 2D transform process for image delineation and study executed by Do and Vetterli [37]. It was implemented in the detached space. likewise, the researchers justify its union in the uninterrupted space. It was implemented in a detached space multiple direction and a multiple resolution extension utilizing non-distinguishable filter banks. This brought about an adaptable multi-resolution, directional and local image extension using contour segmented region, and hence it is known as contourlet transform. As specified before by utilizing a filter bank that decouples the multiscale decomposition contourlet was completed and finished by Laplacian pyramid and then directional decompositions, which are completed utilizing a directional filter bank.
- The advantages of contourlet alter are as follows. 1) The rectangular grids are utilized to portray contourlet expansions, and thus offer an impeccable interpretation to the distinct world, where based on a rectangular grid the image pixel's sample is taken. The main disparity between the contourlet [37] and the curvelet framework [38] are to attain the rectangular grid attribute, the contourlet kernel roles have to be diverse courses and by just turning a lone function cannot be acquired. 2) As a consequence of rectangular grids, contourlet have 2D division on centric squares, besides centric circles for curvelets and polar coordinates to depict other systems. 3) Since usage of iterated filter banks for wavelets, contourlet transform utilizes quick bank calculations and adaptable tree structures. 4) This calculation gives a space multi-resolution action plan which gives lithe improvements of the spatial and angular resolution. The contourlet change characterizes a multiple scale and multiple directional delineation of an image. Likewise it is simply adaptable for identifying superior attributes in any placement at a variety of scale levels [39] ensuing in fine probable for efficient image examination.
- Curvelet Transform: A new algorithm is presented by Candes and Donoho in article [38] on the continuous 2D (two-dimensional) space R^2 utilizing curvelets. This calculation showed a fundamentally ideal estimation manner for 2D per piece plane functions that are curves. First generation curvelet transforms are deliniated in the uninterrupted domain [38] through multiscale filtering and after that on each bandpass image applied a block ridgelet transform [40]. The second generation curvelet transform [41] was produced utilizing no ridgelet transform but using frequency partitioning. However, for implementing both curvelet generation want a turning maneuver and ought to match with a 2D frequency division on the basis of on the polar coordinate. It gives the curvelet creation easily in the uninterrupted sphere, yet makes it critical sampling appears to be troublesome in discretized structures. The curvelet change is extremely proficient in representing curve-like edges. In any case, this transforms have two key disadvantages: 1) the discrete curvelet transform is superfluous. 2) They are not ideal beyond c^2 singularities for sparse approximation of curve features.

On US images most standard speckle filters perform fine, yet a few limits exist with them, which lead to image resolution degradation. In this way, while developing an efficient and strong denoising algorithm for data preprocessing stage in CAD one needs to consider various factors. In the design of despeckling methods, choices of despeckling filter and speckle model have important part. In above most usually favored models and filters were reviewed with its pros and cons.

3.2. Segmentation

Segmentation process is a mandatory step in CAD systems that frequently refers to the delineation of specific structures [42]. Segmentation's key objective is to convert the image to provide more significant data that can be effortlessly examined. It is used to distinguish the various boundaries and objects in images. Due to poor contrasts, different types of noise and missing the boundaries in medical images make segmentation Harder. Depending on anyone between the two vital traits of intensity values that are similarity and discontinuity Medical image Segmentation approaches are mostly based [43]. In subsection, the different segmentation procedures of the medical images are reviewed and it is composed into four basic classifications as appeared in figure 4.

- Region based method: On the basis of pixel alikeness in a region, these process is developed. It is used to approximate the region straight [44], [45]. This method classify the pixels with comparable attributes (like intensity) into regions. Classification of Region based methods have two methodologies such as- a) region expanding approach and b) region combining/dividing approach. In this approach, the procedure initiated by choosing a seed region (pixel). Adams and Bischof [46] proposed the first seeded region growing. The region develops by including the neighbor pixels having comparative established in advance standard with the seed, for example- texture, potency, difference, texture or gray level, etc. When no pixel is present for inclusion then the procedure stops. The issues with this approach are- the user has to choose the seed point and it will miss the efficacy when the region is inhomogeneous. Within the region, combining/splitting mode, the technique starts with the entire image as a seed. At that point, the seed is partitioned into various sub regions, most often into four sub regions. Thus, continuity of the process goes on till there are no regions of the partition by using each sub region as a seed. Lastly, based on same properties, for example intensity, variance or gray-level combine any adjacent regions.

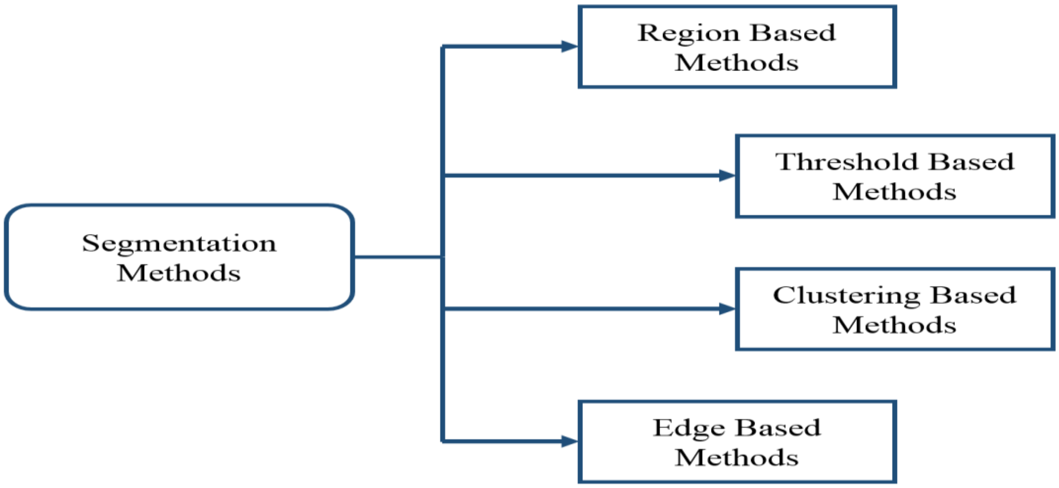

Fig. 4. Image segmentation methods.

- Edge based methods: Edge based methodology [44], [47] utilized for distinguishing the discontinuities in an intensity value for image segmentation. It is the sudden changes in potency level at the region borders of US images. The image border can be described as the perimeter isolated by different areas that vary in the level of potency [48]. Utilization of the borders are to identify the items' measurement and differentiate items from the background. Usage of edge detectors are needed to trace the distinctive points in the image where the potency actually changes. Border detection is a vital tool for the success of segmentation and interpreting the US image content, mainly when dealing with feature extraction and feature detection. There are two main techniques in order to detect an edge in US images such as searching and zero crossing techniques. Figuring the gradient magnitude by making use of first order derivative expressions takes place at first place in search-based technique. Subsequently, with the utilization of gradient direction local directional maxima of the gradient enormity is searched. In zero crossing technique, looking for a zero crossings in the second imitative of the image takes place. Finding zeros in the second imitative of image orders are detected, at this time the value of first imitative is high and zero is the value of second imitative. It is named Laplacian approach on the basis of edge detection.

  The edge based division method's disadvantage is, when there is presence of lots of edges in the image it does not work well.
- Threshold based methods: For image segmentation, Thresholding [49] is one of the imperative techniques used. It is helpful in a separate frontal region from the background region of the image. The gray level image can be changed to binary image by choosing a sufficient limit value T, All necessary data regarding the shape and position of the objects of interest (foreground) and the image's (background) other areas ought to be contained in the binary image. To acquire data easily gray image conversation to binary image is done, that result in the generalization of the categorization phase. Pixels having unique concentration less than the threshold rate is named "black pixels" (0) and belongs to the background. On the other hand, pixels over the threshold rate is called "white pixels" (1) and becomes object's part. There are two sorts of thresholding systems: a) global thresholding and b) local thresholding. There is fixed value of threshold T in global thresholding. Such threshold's difficulty is, if the background of the image holds unlike enlightenment, failure of segmentation procedure may occur. In local limiting, the threshold value T is not fixed, as such the problem of particular enlightenment can be sorted out by using numerous thresholds. Automatic threshold scheme utilizing different routines for example Mean, Edge maximization technique (EMT), Histogram dependent technique (HDT) is a system where [44] threshold value T for every image is automatically selected by the system exclusive of human intrusion.

Fig. 5. Examples of two types of thresholding system from left to right: Original cyst US image, local and global threshold segmented image.

The histogram-based techniques are dependent on achieving the estimated threshold value T. This threshold value T divides the two uniform backgrounds and area of the item in the image. The image having a uniform area of the item and background and separated by heterogeneous region between them, the HDT is appropriate for it.

In mean based framework, the threshold value T utilizes pixel's mean value and work fine in stringent cases of the images that have generally partly of the pixels connected with the objects and the rest half associated with the background.

The EMT segmentation system relies on finding the most border limit in the image to begin segmenting with the guide of border recognition process works. It is applied when the image holds excess of one uniform area or where there is an alteration in lighting between its background and item. As it occurs, the object sections may be united with the backdrop or a portion of the backdrop may be united with the item.

The inconvenience of thresholding method is barely two categories are created, and it cannot be tried on multichannel pictures. Thresholding does not judge the spatial distinctiveness of an image so it is irritable to noise. This distorts the histogram of the image, making the separation more troublesome. In general, thresholding procedures are reasonable for images that hold more and clear separation between the homogenous regions. It has resulted to enhance the effectiveness of the threshold technique.

- Clustering based method: It is an unattended learning undertaking, where it perceives a limited set of classes known as clusters to categorize pixels [50]. Clustering performs by either grouping pixels or partitioning pixels. In the grouping type, it starts with every component as a distinct bunch and combines all the distinct clusters in forming bigger clusters. While, in partitioning type, it begins to split into successively smaller clusters from the entire image.

  The clustering techniques are divided to attended clustering and unattended clustering. In attended clustering to decide the clustering properties, Human interactions required. Whereas in unsupervised clustering technique, by own help the clustering properties are defined. There are two popular algorithms for unsupervised clustering that are, K-mean clustering and fuzzy clustering.

  1) K-mean clustering: It is an unattended clustering calculation. It categorizes the input data points into numerous categories based on natural space from one another. Here data vectors are organized into predefined number of clusters. At first, the centroids of the predefined clusters are initialized arbitrarily. The centroid and data vector dimensions are same. Every pixel is consigned to the cluster on the basis of nearness, estimated by the Euclidian distance measure. Following every one of the pixels are clustered, the average of every cluster is recalculated. Repetition of this procedure goes on until no noteworthy vary outcome for some fixed number of iterations or for each cluster mean [51].

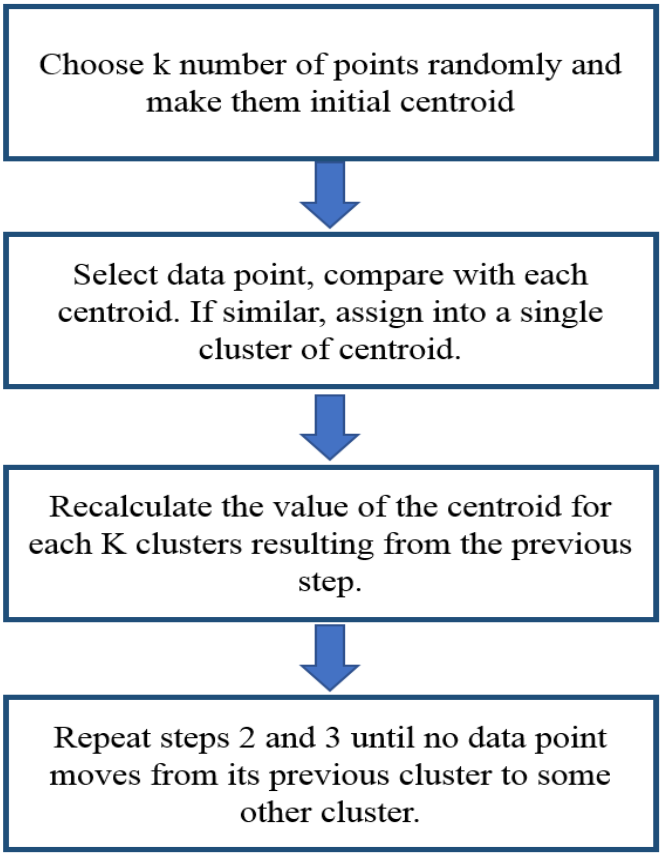

Fig. 6. K-mean clustering algorithm

2) Fuzzy clustering/Fuzzy c-means (FCM): it is an unsupervised clustering algorithm. Here a dataset is grouped into n clusters with all data point in the dataset staying with all bunches to an exact degree [52]. The Fuzzy clustering technique can be thought to be better than those of their harder counterparts, since they can represent the affiliation between the input pattern data and clusters more actually. Fuzzy c-means is a most prominent soft clustering technique; its viability to a great extent is limited spherical clusters. It has extra advantage as it is extra lithe than the corresponding stiff clustering algorithm.

3.3. Feature drawing out and choice

In the detection and classification of liver cancer feature drawing out and choice [53] are significant course of action. However, in computer-aided system only texture features are used as inputs. Texture feature extraction is the basic and traditional techniques. Different examination techniques are used to extract helpful attributes for US liver cancer image classifications. A few general utilization systems are:

- Laws Texture Energy Measure (TEM): In order to find various texture types of TEM [54] using convolution masks of 5x5. It works to produce 25 2D masks by convolving based on 5 basic 1D masks. Afterwards texture picture is filtered with produced masks by extracting helpful attributes.

- Gray Level Difference Statistics (GLDS): It is the Probability Density Function of pair pixels lying at a particular difference and holding a discrete potency value variation. Least variation of coarse texture and large variation of fine texture in Inter pixel gray level values.
- Spatial Gray level Dependence Matrices (SGLDM) [55]: It counts how often pixels with a potency i and j happen at a particular offset to calculate matrix. It makes use of spatial relationships amid gray levels of a picture furnishes to total texture properties of the picture
- Gray level Run length Statistics (GLRLM) [56]: Its rough texture consists of comparatively long runs than short runs. It utilizes fact that containing similar gray level along a particular course of the successive points in the image.
- Gray Level Histogram: Texture parameters are obtained by using the intensity distribution of the image.
- Fourier Power Spectrum (FPS): FPS used for normal wave like forms with a fixed interval. Fourier conversion gives the frequency of form and direction.
- Edge Frequency on the basis of Texture Features: It is opposite to the autocorrelation role and depending on difference concerned gradient little and big distance operator is detected using Micro-edges and macro-edges.
- Wavelet Features: It is derived from Region of Interest (ROI) or wavelet transform of the image. Foremost types are quincunx, Gabor and dyadic.
- First Order Parameters (FOP): It defines only diffuse variation and echogenicity characteristics and these are sovereign of spatial concern amid pixels.

Successive texture analysis methods depend on selecting appropriate features. Some important textural features include- contrast (CO), Short Run Emphasis (SRE), Local Homogeneity (LH), Energy (E), Gray Level Distribution (GLD), Variance (VAR), Homogeneity (H), Uniformity (U), Sum Entropy (SENT), Dissimilarity (D), Angular Second Moment (ASM), Run Length Distribution (RLD), Mean (M), Inverse Difference Moment (IDM) and Standard Deviation (SD).

3.4. Classification

After extraction of feature and selection process, we have to classify the images into lesion/non-lesion or normal/abnormal classes. Classifiers are divided into two types - statistical and neural network, which can be classified using unattended as well as attended procedure. An example for numerical unattained classifiers such as K means clustering [57] and for statistical attained classifier e.g. Support Vector Machine (SVM) [58], [59]. In the meantime for unattended neural grid like Self Organizing Map (SOM) [60] and for attended neural grid such as Multi-Layer Perceptron (MLP) [61], [62] are utilized to classify liver images. We summarize the different US liver detection and classification techniques are listed below

- Fuzzy neural network (FNN): Diverse stochastic associations are find out by it, which represent the attributes of a picture. The diverse sorts of stochastic are grouped (set of attributes) in which the elements of this set of attributes are blurry. It gives the scope to define various classes of stochastic attributes in the comparable type [63]. Accomplishment and correctness depend on the limit choice and unclear integral.
  The drawback of fuzzy neural network is exclusive of previous information output is not fine and accurate result depends on the route of decision.
- Support vector machine (SVM): SVM targets to reduce the superior bound of generalization fault by increasing the periphery amid the parting hyperplane and the data [64]. Fine division is gained by the hyper plane that has the biggest difference to the closest training data point of any class (operating margin), usually bigger the margin lowers the generalization mistake of the categorizer. SVM utilized Nonparametric with binary classifier approach. It can manage additional input data extremely proficiently. Accomplishment and accurateness depend on the hyperplane choice and core limit.

SVM reduces the calculating difficulty, easy to administer decision rule intricacy and fault occurrence. The drawbacks of SVM are low result transparency, training is time consuming and finding out of finest limits is not trouble-free in presence of nonlinearly separable training data.

- Artificial neural network (ANN): It is the combination of arithmetic techniques inspired by the characteristics of biological nervous system and the tasks of versatile biological learning models. Its plain formations are neurons that can be interrelated in distinctive arrangements. It utilizes a nonparametric method. Accomplishment and accuracy depends on the grid formation and the quantity of inputs. There are many types of ANN classifier, but only few algorithm proven efficiency in neural network learning like multi-layer back propagation [65], [66]. The advantages of ANN is a data driven self-adaptive process, competently controls noisy inputs, calculation rate is good and its major problem is taking more time for training data and complexity in selecting the type grid architecture.
- Probabilistic neural network (PNN): There are input, output and hidden (summation) layer in Feed Forward Neural Network. Pattern layer formed by the input data set with the product of the weights tracked by the summing up layer that gets results related to the given class. The output layer contains the classification results. The main advantage of PNN classifier is its maximum training speed [67]. The scale factor of the exponential activation functions used to control the smoothing parameter (σ) of this classifier.
- Decision tree: In medical image study it is used as a attended categorizer. This process is comprised of 3 parts- Dividing the nodes, locate the terminal nodes and sharing of class labels to terminal nodes. A node in a tree represents a test for a exact attribute, and each part of that node represents the likely result of the test [68]. A pathway in the tree, from the root of the tree to an end leaf, details the categorization, with the ending leaf representing an object class. The Decision tree is based on the hierarchical statute based method and utilizes the nonparametric process. It is simple and computational efficiency is good, but becomes a difficult computation when diverse values are undecided or when variety of results are correlated.
- K-nearest neighbor (K-NN): It is a process to analyze image feature on basis of closest training illustrations in the feature space. It utilizes a separate calculate to make guess the class of the new test sample. This technique is one of the least complex of all machine learning calculation: a feature is arranged by a maximum vote of its neighbors, with the item being allocated to the class most ordinary amongst its k adjacent neighbors when k is small and the item is merely assigned to the class of its adjacent neighbor when K=1 [69].
- Bayesian neural network (BNN): It used in many areas of medicine. In US features prophetic of malignancy have been widely analyzed and the reactivity and specificity of these attributes for malignancy are easily obtainable [70]. The scheme of BNN is to cast the work of training a grid as a difficult of inference, which is sorted out utilizing Bayes theory [71]. A Bayesian neural network is extra optimized and strong in comparison to traditional neural grids, particularly when the training data set is not big.

3.5. Performance estimation

Quantitative measurement of system correctness is measured in term of true positive (TP), true negative (TN), false positive (FP), false negative (FN) with relation to positive predictive value (PPV), negative predictive value (NPV), sensitivity, specificity and accurateness [72]. It is given by:

$$PPV = \frac{(TP)}{(TP+FP)} \quad (1)$$

$$NPV = \frac{(TN)}{(TN+FN)} \quad (2)$$

$$Sensitivity = \frac{(TP)}{(TP + FN)} \quad (3)$$

$$Specificity = \frac{(TN)}{(TN + FP)} \quad (4)$$

$$Accuracy = \frac{(TP + TN)}{(TP + FN) + FP + FN)} \quad (5)$$

- *TP* represents number of diseased lesions that is rightly classify as diseased.
- *TN* represents number of non-diseased lesions that is properly classify as non-diseased.
- *FP* represents number of non-diseased lesions that is incorrectly categorized as diseased.
- *FN* represents number of diseased lesions that is incorrectly categorized as non-diseased.
- The accuracy used to diagnose diseased and benign cases, the sensitivity calculated for the classification model to categorize diseased cases and the specificity used to evaluate benign cases.
- *PPV* represents percentage of predictive positives that is always positive.
- *NPV* represents percentage of predictive negatives that is always negative.

Some authors have evaluated their proposed system just by manual inspection performed by radiologist Specialists while others have exploited area under receiver operating characteristic (ROC) curve analysis. ROC applied to demonstrate the competence of the trade-off between the *TP* and the *FP* [73].

4. Related work

In recent years, the liver cancer analysis using CAD system has turned into a dynamic area of research. There are different approaches that are proposed for liver ailment analysis on the basis of medical picture analysis. In this section, we elaborate various techniques.

In article [62], a CAD system is proposed by Mittal et al. by which doctors can be guided in diagnosis of focal liver ailment from 2D mode US images. The suggested technique has been utilized for detecting and analysis of four types of focal liver ailment and compared them with normal liver. At the first image noise are reduced, then they divided the areas of interest to 800 segmented areas. Next, on the basis of the texture 208 features are extracted from each segmented region. Finally, they proposed use of Artificial Neural Networks (ANN) in reducing the training errors with two phases to diagnose the ailment. The general precision achieved by the CAD system was86.4%.

Authors on paper [63] proposed an algorithm using Fuzzy Neural Network (FNN) to automatically characterize diffused liver diseases. For classification utilizing RUNL, GLDS, FOP, SGLDM and FDTA 12 texture features were taken out. Then again, the features were reduced to six utilizing multiple feature combinations. After that to produce blurry sets and create class edges in a statistical way voronoi diagram of training patterns was built which was utilized by FNN. The Authors showed 82.67% classification accuracy for verification using 150 liver images.

Design made from M-mode motion curve of liver and B-mode US liver picture on the basis of feature extraction by Guohui et.al. [74]. They took out 25 features utilizing M-mode movement curve through GLDS, FOP, RUNL, and a couple of additional extraordinary attributes. After taking out attribute, they used Fisher linear decision rule for choosing 20 helpful features depending on the minimum classification error. Experiment's outcome divulged that features gained utilizing movement curve were further reasonable for discerning ordinary or cirrhosis, liver in expressions of reactivity and specificity.

For US liver images categorization, Cao et al. suggested different process [75]. For taking out feature SGLDM and FDTA on 64x64 pixels sub-image were utilized by them. In this way the joint feature vector was gained, which was utilized to differentiate 273 sound and 99 fibrosis liver pictures. Fisher linear classifier and

SVM (leave-one-out calculation) were utilized. It was found effective in expression of categorization rate. Yet it is proved that the joint feature vector is a bit better.

The author's of paper [76], used an algorithm to recognize diffused liver ailment utilizing Gabor wavelet and categorized ultrasonic liver picture into usual, hepatitis and cirrhosis categories. Familiar three advantages of Gabor wavelets were used by them, which is invariance to swing of picture contents, maximum joint space frequency resolution, and littler feature vector. Attributes were extricated and pictures were categorized into various classes utilizing Gabor wavelet change, dyadic wavelet change, statistical moments and attributes.

Researchers under lead of Balasubramanian suggested a method [77] for automatically categorized benign, malignant, cyst and regular liver pictures utilizing texture attributes via TEM, SGLDM, RUNL, and Gabor wavelets. By manual selection and on the basis of Principle Component Analysis (PCA) on the basis of idea attributes, eight attributes were selected. K-means clustering calculation used by PCA based features whereas physically chosen attributes were categorized by BPN. Finally, it is proved that categorization outcome of BPN were improved than K-means. Poonguzhali et.al., [78] authors classified same liver diseases. The attribute taking out from the ROI of US pictures through Autocorrelation, TEM, Edge Frequency method and SGLDM. Optimal attribute sets selected from extracted features using PCA. For K-means categorization afterwards optimal features were utilized.

Jeon et al. presented a technique to classify focal liver lesion based on multiple ROI, to obtain more reliable and better classification performance [79]. This technique can be utilized to classify focal liver ailment, for example Hem, Cyst, and Malignancies. From the complete US image the ROI features are extricated at first. Lastly, the categorization of cysts and hemangiomas, categorization of cysts and malignancies, and categorization of hemangiomas and malignancies are classified using the SVM classifier. The preprocessing stage is complicated since it affects the subsequent stages and improves the quality of the images. Their method has shown the overall accuracy of 80%.

Ribeiro et.al., [80] implemented an algorithm using three dissimilar classifiers to classify the different chronic liver ailment. The classifiers utilized are SVM, KNN, and decision tree. The outcome showed that the SVM gained superior performance than the KNN and decision tree classifier. The classification's precision was 73.20%utilizing SVM with a radial basis kernel. Yet, the general accurateness of this process is not high. In another paper [81], the authors given a partly automatic method to categorizing unceasing liver ailment from US liver pictures. For this approach the data, which is collected from laboratories and clinic, are generated by utilized SVM classifier with a polynomial core of the fourth degree. The data achieved 91.67% of sensitivity better than previous approaches. In the coming works, they will extend their method of merging more textural features.

A few more compact summaries of different author's algorithms and accuracy of their proposed technique up to recent years presented in table 1.

Table 1. Summary of various researches on CAD for liver diagnosis

Authors/Year	Number of samples	Features	Classifier	Performance
Fayazul et al ., /2012 [82]	88	Wavelet packet transform	SVM	~95%
Acharya et al., /2012 [83]	100	Wavelet and Higher order spectra feature	DT	93.3%
Jitender et al., /2012 [84]	56	Wavelet packet transform	SVM	88.8%
Jitender et al., /2013 [85]	31	Wavelet packet transform and Gabor Wavelet transform	SVM	98.3%
Jitender et al., /2013 [86]	108	FOS, GLCM, GLRLM, FPS, GWT, TEM	BPNN	87.7%

Jitender et al., /2013 [87]	108	FOS, GLCM, GLRLM, FPS, TEM, Gabor	SVM	87.2%
Nivedita et al., /2014 [88]	42	GLCM	SOM and MLP	81.5%
Jitender et al., /2014 [89]	108	FOS, GLCM, GLRLM, FPS, TEM, Gabor	Neural network ensemble	88.7-95%
Rivas et al., /2015 [90]	7	GLCM	Binary logistic regression	95.45%
Wu et al., /2015 [91]	288	Mean, SD, Kurtosis, Skew	SVM and Random forest	72.81%
Hwang et al., /2015 [92]	115	FOS, GLCM, TEM, Ecogenecity	Baysian regularity learning	96%
Acharya et al., /2016 [93]	100	GIST descriptor	PNN	98%

5. Conclusion

This study proposed in a new way of categorizing and summarizing the different stages of the computerized system scheme applied to ultrasound (US) with focus on liver cancer diagnosis. The up to date review of existing approaches in the literature has been reviewed. To the best of our knowledge, there has been no unique consensus on computer aided diagnosis (CAD) system. Many different algorithms mentioned in the state of art used to find and design optimal solution for automatic liver cancer diagnosis scheme. In our opinion, there should be a trade-off, strengths and weaknesses associated with the choice of the algorithm used for image analysis. In the future, researchers must pay attention to data pre-processing stage meanwhile minimizing motion artifacts, image noise and tolerable classification time using optimized neural network. It might be possible that integrating multiple effective techniques, potentially improve the general correctness, exactness and techniques concerned to speed of segmentation, also lessening the quantity of manual interactions of user. Moreover, greater part of the work in the literature concentrated on detection and classification of B-Mode US imaging. Our research in the future will be directed by introducing a novel CAD algorithm for 3D high resolution ultrasound imaging device that accurately characterize and detect liver lesions by including more features and classification techniques such as duct extension, Microlobulation and compressive sensing (CS) framework. In the upcoming years, CAD system will be a useful device for discovery sooner and treatment of liver lesions by radiologist and diagnostic examinations in everyday clinical work.

Acknowledgment

This work done by the support of the National Research Foundation of Korea (NRF) grant provided by the Korean government (NRF-2015R1A2A1A05001826).

References

[1] K. Doi, "Overview on research and development of computer-aided diagnostic schemes," *Semin. Ultrasound, CT MRI*, vol. 25, no. 5, pp. 404–410, 2004.

[2] M. L. Giger, "Computerized analysis of images in the detection and diagnosis of breast cancer," *Semin. Ultrasound, CT MRI*, vol. 25, no. 5, pp. 411–418, 2004.

[3] H. Yoshida and A. H. Dachman, "Computer-aided diagnosis for CT colonography.," *Semin. Ultrasound. CT. MR*, vol. 25, no. 5, pp. 419–31, 2004.

[4] Q. Li, F. Li, K. Suzuki, J. Shiraishi, H. Abe, R. Engelmann, Y. Nie, H. MacMahon, and K. Doi, "Computer-aided diagnosis in thoracic CT.," *Semin. Ultrasound. CT. MR*, vol. 26, no. 5, pp. 357–363, 2005.

[5] F. W. Kremkau and K. J. Taylor, “Artifacts in ultrasound imaging.,” *J. Ultrasound Med.*, vol. 5, no. 4, pp. 227–237, 1986.

[6] S. Marwaha, H. Monga, S. M. Student, and H. Cse, “Automatic Diagnosis Systems Using Image Processing- A systematic Study,” *IRACST -International J. Comput. Sci. Inf. Technol. Secur.*, vol. 2, no. 2, pp. 2249–9555, 2012.

[7] G. Litjens, O. Debats, J. Barentsz, N. Karssemeijer, and H. Huisman, “Computer-aided detection of prostate cancer in MRI.,” *IEEE Trans. Med. Imaging*, vol. 33, no. 5, pp. 1083–1092, 2014.

[8] Gunasundari S, “A Study of Textural Analysis Methods for the Diagnosis of Liver Diseases from Abdominal Computed Tomography,” *Int. J. Comput. Appl.*, vol. 74, no. 11, pp. 0975–8887, 2013.

[9] A. Jemal, F. Bray, and J. Ferlay, “Global Cancer Statistics,” vol. 61, no. 2, 2011.

[10] H. Yoshida, D. D. Casalino, B. Keserci, A. Coskun, O. Ozturk, and A. Savranlar, “Wavelet-packet-based texture analysis for differentiation between benign and malignant liver tumours in ultrasound images.,” *Phys. Med. Biol.*, vol. 48, no. 22, pp. 3735–53, Nov. 2003.

[11] M. E. Mayerhoefer, M. Breitenseher, G. Amann, and M. Dominkus, “Are signal intensity and homogeneity useful parameters for distinguishing between benign and malignant soft tissue masses on MR images? Objective evaluation by means of texture analysis.,” *Magn. Reson. Imaging*, vol. 26, no. 9, pp. 1316–22, 2008.

[12] G. Xian, “An identification method of malignant and benign liver tumors from ultrasonography based on GLCM texture features and fuzzy SVM,” *Expert Syst. Appl.*, vol. 37, no. 10, pp. 6737–6741, 2010.

[13] R. S. C. Cobbold, *Foundations of Biomedical Ultrasound*. Oxford University Press, 2007.

[14] S. Tang and S.-P. Chen, “An Effective Data Preprocessing Mechanism of Ultrasound Image Recognition,” *Bioinforma. Biomed. Eng. 2008. ICBBE 2008. 2nd Int. Conf.*, pp. 2708–2711, 2008.

[15] Sk. Narayanan, “A View on Despeckling in Ultrasound Imaging,” *Int. J. Signal Process. Image Process. Pattern Recognit.*, vol. 2, no. 3, 2009.

[16] J.-S. Lee, “Digital Image Enhancement and Noise Filtering by Use of Local Statistics,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-2, no. 2, pp. 165–168, 1980.

[17] J.-S. Lee, “Refined filtering of image noise using local statistics,” *Comput. Graph. Image Process.*, vol. 15, no. 4, pp. 380–389, 1981.

[18] D. Kuan, A. Sawchuk, T. Strand, and P. Chavel, “Adaptive restoration of images with speckle,” *IEEE Trans. Acoust.*, vol. 35, no. 3, pp. 373–383, Mar. 1987.

[19] R. C. Gonzalez and R. E. Woods, “Digital Image Processing,” *Addison-Wesley Publ. Co.*, 2002.

[20] W. N. M. and P. L. A. T. Loupas, “An Adaptive Weighted Median Filter for Speckle Suppression in Medical Ultrasound Images,” *IEEE Trans. Circuits Syst.*, vol. 36, no. January, pp. 129–135, 1989.

[21] R. C. G. and R.E.Woods, “Digital Image Processing,” *3rd ed. Pearson Educ.*, 2008.

[22] A. K. Jain, *Fundamentals of digital image processing*. Prentice-Hall, Inc., 1989.

[23] A. Lopes, R. Touzi, and E. Nezry, “Adaptive Speckle Filters and Scene Heterogeneity,” *IEEE Trans. Geosci. Remote Sens.*, vol. 28, no. 6, pp. 992–1000, 1990.

[24] a. Lopes, E. Nezry, R. Touzi, and H. Laur, “Maximum A Posteriori Speckle Filtering And First Order Texture Models In Sar Images,” *10th Annu. Int. Symp. Geosci. Remote Sens.*, pp. 8–11, 1990.

[25] V. S. Frost, J. A. Stiles, K. S. Shanmugan, and J. C. Holtzman, “A model for radar images and its application to adaptive digital filtering of multiplicative noise.,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 4, no. 2, pp. 157–66, 1982.

[26] D. T. Kuan, a a Sawchuk, T. C. Strand, and P. Chavel, “Adaptive noise smoothing filter for images with signal-dependent noise.,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 7, no. 2, pp. 165–177, 1985.

[27] P. Perona and J. Malik, “Scale-space and edge detection using anisotropic diffusion,” *IEEE Trans.*

Pattern Anal. Mach. Intell., vol. 12, no. 7, pp. 629–639, 1990.

[28] R. de Luis-García, R. Deriche, M. Rousson, and C. Alberola-López, "Tensor Processing for Texture and Colour Segmentation," in *Image Analysis*, 2005, pp. 1117–1127.

[29] T. D, "Anisotropic diffusion PDE's for image regularization and visualization," in *Handbook of Mathematical Methods in Imaging, 1st Edition,Springer*, 2010.

[30] C. Tomasi and R. Manduchi, "Bilateral Filtering for Gray and Color Images," *Int. Conf. Comput. Vis.*, pp. 839–846, 1998.

[31] S. T. Acton, "Deconvolutional speckle reducing anisotropic diffusion," *Proc. - Int. Conf. Image Process. ICIP*, vol. 1, no. 11, pp. 5–8, 2005.

[32] S. Mallat, "A Wavelet Tour of Signal Processing," *2nd ed. Acad. Press*, 1999.

[33] X. Q. Gao, T. Q. Nguyen, and G. Strang, "A study of two-channel complex-valued filterbanks and wavelets with orthogonality and symmetry properties," *IEEE Trans. Signal Process.*, vol. 50, no. 4, pp. 824–833, 2002.

[34] J. Neumann and G. Steidl, "Dual-Tree complex wavelet transform in the frequency domain and an application to signal classification," *Int. J. Wavelets, Multiresolution Inf. Process.*, vol. 03, no. 01, pp. 43–65, 2005.

[35] N. Kingsbury, "Complex Wavelets for Shift Invariant Analysis and Filtering of Signals," *Appl. Comput. Harmon. Anal.*, vol. 10, pp. 234–253, 2001.

[36] N. Kingsbury, "Image processing with complex wavelets," *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, vol. 357, no. 1760, pp. 2543–2560, 1999.

[37] M. N. Do and M. Vetterli, "Contourlets: a directional multiresolution image representation," in *Proceedings. International Conference on Image Processing*, 2002, vol. 1, pp. I–357–I–360.

[38] Emmanuel J. Cand`es and David L. Donoho, *Curvelets – A Surprisingly Effective Nonadaptive Representation For Objects with Edges*, Saint-Malo. Vanderbilt University Press, 2000.

[39] A. M. Eskicioglu and P. S. Fisher, "Image quality measures and their performance," *IEEE Trans. Commun.*, vol. 43, no. 12, pp. 2959–2965, 1995.

[40] E. J. Can and D. L. Donoho, "Ridgelets: a key to higher-dimensional intermittency?," *Phil. Trans. R. Soc. Lond.A*, vol. 14, pp. 423–438, 1999.

[41] E. J. Candès and D. L. Donoho, "New tight frames of curvelets and optimal representations of objects with piecewise C 2 singularities," *Commun. Pure Appl. Math.*, vol. 57, no. 2, pp. 219–266, 2004.

[42] K. D. Toennies, "Guide to Medical Image Analysis Methods and Algorithms," *Adv. Comput. Vis. Pattern Recognit.*, no. 2191–6586, pp. 1–19, 2012.

[43] T.Sheela and M.S.Abirami, "Analysis of Image Segmentation Techniques for Medical Images," in *Proceedings of International Conference on Emerging Research in Computing, Information, Communication and Applications*, 2014.

[44] E. P. Thakur and E. N. Madaan, "A survey of image segmentation techniques," *Int. J. Res. Comput. Appl. Robot. www.ijrcar.com*, vol. 24, pp. 158–165, 2014.

[45] M.Suganthi and P.Elayaraja, "A survey of image segmentaion techniques," *Int. J. Adv. Res. Comput. Commun. Eng.*, vol. 3, no. 11, 2014.

[46] R. Adams and L. Bischof, "Seeded region growing," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 16, no. 6, pp. 641–647, Jun. 1994.

[47] R. M. S. and K. S. Selvanayaki, "A Survey on Image Segmentation Techniques for Edge Detection," in *International Conference on Innovation in Communication, Information and Computing (ICICIC)*, 2013.

[48] A. A. M. Rajiv Kumar, "A Comparative Study of Image Segmentation Using Edge-Based Approach," *Int. J. Math. Comput.*, vol. 7, no. 3, 2013.

[49] S. Saleh Al-Amri, N. V Kalyankar, and K. S. D, “Image Segmentation by Using Thershod Techniques,” *J. Comput.*, vol. 2, no. 5, pp. 2151–9617, 2010.
[50] V. D. Santanu Bhowmik, “A Survey on Clustering Based Image Segmentation,” *Int. J. Adv. Res. Comput. Eng. Technol.*, vol. 1, no. 5, pp. 2278–1323, 2012.
[51] O. Oke, T. Adedeji, O. Alade, and E. Adewusi, “Fuzzy kc-means Clustering Algorithm for Medical Image Segmentation,” *J. Inf. Eng. Appl.*, vol. 2, no. 6, pp. 21–33, 2012.
[52] R. R. and K. Tejaswini, “A Survey of Image Segmentation Algorithms Based On Fuzzy Clustering,” *Int. J. Comput. Sci. Mob. Comput.*, vol. 2, pp. 200–206, 2013.
[53] I. Levner, V. Bulitko, and G. Lin, “Feature Extraction for Classification of Proteomic Mass Spectra: A Comparative Study,” in *Feature Extraction*, Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 607–624.
[54] K. I. Laws, “Texture energy measures,” in *Image understanding workshop*, 1979, pp. 47–51.
[55] R. M. Haralick, K. Shanmugam, and I. Dinstein, “Textural Features for Image Classification,” *IEEE Trans. Syst. Man. Cybern.*, vol. 3, no. 6, pp. 610–621, 1973.
[56] M.M.Galloway, “Texture classification using gray level run lengths,” *Comput. Graph. Image Process.*, vol. 4, pp. 172– 179, 1975.
[57] D. Gaitini, Y. Baruch, E. Ghersin, E. Veitsman, H. Kerner, B. Shalem, G. Yaniv, C. Sarfaty, and H. Azhari, “Feasibility study of ultrasonic fatty liver biopsy: Texture vs. attenuation and backscatter,” *Ultrasound Med. Biol.*, vol. 30, no. 10, pp. 1321–1327, Oct. 2004.
[58] W.-C. Yeh, S.-W. Huang, and P.-C. Li, “Liver fibrosis grade classification with B-mode ultrasound.,” *Ultrasound Med. Biol.*, vol. 29, no. 9, pp. 1229–35, Sep. 2003.
[59] Z. Jiang, K. Yamauchi, K. Yoshioka, K. Aoki, S. Kuroyanagi, A. Iwata, J. Yang, K. Wang, Z. Jiang, K. Yamauchi, J. Yang, ·. K. Wang, K. Yoshioka, K. Aoki, S. Kuroyanagi, and A. Iwata, “Support Vector Machine-Based Feature Selection for Classification of Liver Fibrosis Grade in Chronic Hepatitis C,” *J Med Syst*, vol. 30, pp. 389–394, 2006.
[60] M. S. Gebbinck, J. T. Verhoeven, J. M. Thijssen, and T. E. Schouten, “Application of neural networks for the classification of diffuse liver disease by quantitative echography.,” *Ultrason. Imaging*, vol. 15, no. 3, pp. 205–17, 1993.
[61] N. H. K.Ogawa,k. Kubota, “Computer-aided Diagnostic System for Diffuse Liver Diseases with Ultrasonography by Neural Networks,” *IEEE Trans. Nucl. Sci.*, vol. 45, no. 6, pp. 3069–3074, 1998.
[62] D. Mittal, V. Kumar, S. C. Saxena, N. Khandelwal, and N. Kalra, “Neural network based focal liver lesion diagnosis using ultrasound images,” *Comput. Med. Imaging Graph.*, vol. 35, no. 4, pp. 315–323, 2011.
[63] S. Pavlopoulos, E. Kyriacou, D. Koutsouris, K. Blekas, A. Stafylopatis, and P. Zoumpoulis, “Fuzzy neural network-based texture analysis of ultrasonic images,” *IEEE Eng. Med. Biol. Mag.*, vol. 19, no. 1, pp. 39–47, 2000.
[64] S.-T. J. Christianini N, “An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods,” *United Kingdom: Cambridge University Press*, 2000.
[65] Y. Hirose, K. Yamashita, and S. Hijiya, “Back-propagation algorithm which varies the number of hidden units,” *Neural Networks*, vol. 4, no. 1, pp. 61–66, 1991.
[66] G. E. H. and R. J. W. David E.Eumelhart, “Learning representation by back-propagation errors,” *Lett. to Nat.*, vol. 323, pp. 533–536, 1986.
[67] P.D.Wasserman, *Advanced Methods in Neural Computing*. Van Nostrand Reinhold, 1993.
[68] F. van der Heijden, R. P. W. Duin, D. de Ridder, and D. M. J. Tax, *Classification, Parameter Estimation and State Estimation: An Engineering Approach Using MATLAB*. Chichester, UK: John Wiley & Sons, Ltd, 2004.

[69] Y. M. Kadah, A. A. Farag, J. M. Zurada, A. M. Badawi, and A. B. M. Youssef, “Classification algorithms for quantitative tissue characterization of diffuse liver disease from ultrasound images,” *IEEE Trans. Med. Imaging*, vol. 15, no. 4, pp. 466–478, 1996.

[70] Y. I. Liu, A. Kamaya, T. S. Desser, and D. L. Rubin, “A Bayesian classifier for differentiating benign versus malignant thyroid nodules using sonographic features.,” in *AMIA symposium proceeding*, 2008, pp. 419–23.

[71] H. B. P. P.C.Bhat, “Bayesian Neural Networks,” in *Proceedings of PHYSTAT 05*, 2006, pp. 151–155.

[72] W. Zhu, N. Zeng, and N. Wang, “Sensitivity , Specificity , Accuracy , Associated Confidence Interval and ROC Analysis with Practical SAS ® Implementations K & L consulting services , Inc , Fort Washington , PA Octagon Research Solutions , Wayne,” *NESUG Heal. Care Life Sci.*, pp. 1–9, 2010.

[73] J. R. Beck and E. K. Shultz, “The use of relative operating characteristic (ROC) curves in test performance evaluation.,” *Arch. Pathol. Lab. Med.*, vol. 110, no. 1, pp. 13–20, 1986.

[74] G. Zhou, Y. Wang, W. Wang, Y. Sun, and Y. Chen, “Decision of Cirrhosis Using Liver’s Ultrasonic Images.,” in *Proceedings of the 2005 IEEE Engineering in Medicine and Biology*, 2005, vol. 4, pp. 3351–4.

[75] G. Cao, P. Shi, and B. Hu, “Liver fibrosis identification based on ultrasound images.,” in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society.*, 2005, vol. 6, pp. 6317–20.

[76] A. Ahmadian, A. Mostafa, M. Abolhassani, and Y. Salimpour, “A texture classification method for diffused liver diseases using Gabor wavelets.,” in *IEEE Engineering in Medicine and Biology Society.*, 2005, vol. 2, pp. 1567–70.

[77] D. Balasubramanian, P. Srinivasan, and R. Gurupatham, “Automatic classification of focal lesions in ultrasound liver images using principal component analysis and neural networks.,” in *IEEE Engineering in Medicine and Biology Society*, 2007, pp. 2134–7.

[78] S. Poonguzhali, B. Deepalakshmi, and G. Ravindran, “Optimal Feature Selection and Automatic Classification of Abnormal Masses in Ultrasound Liver Images,” in *2007 International Conference on Signal Processing, Communications and Networking*, 2007, pp. 503–506.

[79] J. H. Jeon, J. Y. Choi, S. Lee, and Y. M. Ro, “Multiple ROI selection based focal liver lesion classification in ultrasound images,” *Expert Syst. Appl.*, vol. 40, no. 2, pp. 450–457, 2013.

[80] R. Ribeiro, R. Marinho, J. Velosa, F. Ramalho, and J. M. Sanches, “Chronic liver disease staging classification based on ultrasound, clinical and laboratorial data,” in *IEEE International Symposium on Biomedical Imaging: From Nano to Macro*, 2011, pp. 707–710.

[81] R. Ribeiro, R. T. Marinho, J. Velosa, F. Ramalho, J. M. Sanches, and J. S. Suri, “The usefulness of ultrasound in the classification of chronic liver disease.,” in *IEEE Engineering in Medicine and Biology Society*, 2011, pp. 5132–5.

[82] F. U. A. A. Minhas, D. Sabih, and M. Hussain, “Automated classification of liver disorders using ultrasound images,” *J. Med. Syst.*, vol. 36, no. 5, pp. 3163–3172, 2012.

[83] J. S. S. U. Rajendra Acharya, S. Vinitha Sree, Ricardo Ribeiro, Ganapathy Krishnamurthi, Rui Tato Marinho, João Sanches, “Data mining framework for fatty liver disease classification in ultrasound: A hybrid feature extraction paradigm,” *Med. Phys.*, vol. 39, 2012.

[84] J. Virmani, V. Kumar, N. Kalra, and N. Khandelwal, “SVM-based characterization of liver ultrasound images using wavelet packet texture descriptors,” *J. Digit. Imaging*, vol. 26, no. 3, pp. 530–543, 2012.

[85] N. K. Jitendra Virmani, Vinod Kumar Naveen Kalra, “Prediction of liver cirrhosis based on multiresolution texture descriptors from B-mode ultrasound,” *Int. J. Converg. Comput.*, vol. 1, pp. 1–19, 2013.

[86] J. Virmani, V. Kumar, N. Kalra, and N. Khandelwal, “A comparative study of computer-aided

classification systems for focal hepatic lesions from B-mode ultrasound.," *J. Med. Eng. Technol.*, vol. 37, no. 4, pp. 292–306, 2013.

[87] N. K. Jitendra Virmani, Vinod Kumar, Naveen Kalra, "PCA -SVM based CA D System for Focal Liver Lesions using B-Mode Ultrasound Images," *Def. Sci. J.*, vol. 63, pp. 478–486, 2013.

[88] M. Roy, "Classification of Ultrasonography Images of Human Fatty and Normal Livers using GLCM Textural Features," vol. 4, 2014.

[89] V. J., K. V., K. N., and K. N., "Neural network ensemble based CAD system for focal liver lesions from B-mode ultrasound," *J. Digit. Imaging*, vol. 27, no. 4, pp. 520–537, 2014.

[90] V. Morocho, P. Vanegas, and R. Medina, "Hepatic Steatosis Detection Using the Co-occurrence Matrix in Tomography and Ultrasound Images," in *2015 20th Symposium on Signal Processing, Images and Computer Vision (STSIVA)*, 2015, pp. 1–7.

[91] J. Y. Wu, M. Beland, J. Konrad, A. Tuomi, D. Glidden, D. Grand, and D. Merck, "Quantitative ultrasound texture analysis for clinical decision making support," in *Medical Imaging 2015: Ultrasonic Imaging and Tomography*, 2015, vol. 9419, p. 94190W.

[92] Y. N. Hwang, J. H. Lee, G. Y. Kim, Y. Y. Jiang, and S. M. Kim, "Classification of focal liver lesions on ultrasound images by extracting hybrid textural features and using an artificial neural network," in *Bio-Medical Materials and Engineering*, 2015, vol. 26, pp. S1599–S1611.

[93] U. R. Acharya, H. Fujita, S. Bhat, U. Raghavendra, A. Gudigar, F. Molinari, A. Vijayananthan, and K. Hoong Ng, "Decision support system for fatty liver disease using GIST descriptors extracted from ultrasound images," *Inf. Fusion*, vol. 29, pp. 32–39, 2016.