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Medical Image Segmentation for Liver Diseases: A Survey

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ABSTRACT
With the recent advances in the field of artificial intelligence and information technology, the improvement in the interpretation of the medical images has contributed significantly to the early diagnosis of different diseases. Medical images are difficult to process because they have various modalities. Therefore, the physicians cannot adequately detect and diagnosis the diseases in traditional ways. There should be Computer-aided detection/diagnosis (CAD) systems that help physicians to understand medical images. CAD systems are processes that give much information that help to understand the medical images and improve the accuracy of detection/diagnosis of various diseases. CAD systems consist of the segmentation of the lesion, extraction of features, and characterization of diseases by means of a classifier. There are many different CAD systems that have been proposed to diagnosis various diseases of various organs of the human body, such as liver and brain. This paper, introduces current different methods of segmentation based on medical images. In addition, this paper also concentrates on the work of different segmentation and classification techniques that have been proposed to diagnosis various liver diseases.

General Terms
Image processing, Computer Vision.

Keywords
Computer Aides Diagnosis (CAD) Systems, Medical Image Segmentation, Classification, Diagnosis of Liver Diseases.

1. INTRODUCTION
Recently, due to the advances in the field of artificial intelligence and information technology, improvement in the interpretation of the medical images has significantly contributed to the early diagnosis of different diseases [1]. Therefore, there should be CAD systems that help doctors to understand the medical image. One of the most important steps in CAD systems is the segmentation process that often refers to the delineation of specific structures [2].

The strategies of the segmentation process combine data knowledge with domain knowledge to obtain the result. Data knowledge is defined as the assumptions about homogeneity, continuity, and local smoothness of image features within segments. Domain knowledge introduces information about the objects to be delineated. We can define image segmentation process as, the partitioning of a digital image into distinct regions of similar pixels. The goal of segmentation is to convert the image to a form that contains a more meaningful information that can be easily analyzed. It is used to locate the various objects and boundaries in images. Therefore, segmentation of the medical image can be considered as a difficult problem because medical images commonly have reduced contrasts, missing boundaries, and different types of noise [3].

On the other hand, CAD systems are tools that enhance the detection/diagnosis of various diseases [4]. Diagnoses with the help of the computer are processes that give much information that help doctors to understand the medical images. As a result, the accuracy of medical diagnosis will be improved, and the time taken in reading an image by traditional methods will be decreased [5]. The main stages for diagnosing diseases using CAD systems are the segmentation of a lesion, extraction of features from a lesion, and describing of diseases by means of a classifier [6].

Therefore, the diagnosis of diseases using computers has become an active area of research [7]. There is a strong need to have efficient CAD system that accurately examines the medical images and reduce the required time for accurate diagnosing of diseases.

The liver is considered as one of the most important organs in the human's body. Without a healthy liver, we cannot survive because it affects nearly every organ in the human body. The main types of diseases that affect the liver are diffused liver diseases and focal liver diseases. The diffused liver diseases affect the entire liver surface, such as fatty and cirrhotic liver. On the other hand, if the diseases affect a small region of the liver surface, these diseases are called focal liver diseases. Examples of focal liver disease are Cyst, Hemangioma (Hem), and Hepatocellular Carcinoma (HCC). Figure 1 shows the ultrasound (US) images of the above three focal liver diseases of the liver.

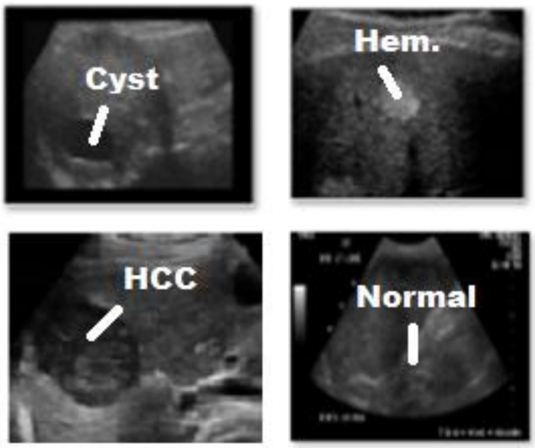

Figure 1: Focal liver diseases and normal liver.

In most cases, the sonographic appearance of Cyst, Hem, and HCC overlap. Therefore, it is very difficult to make a distinction between them using traditional methods. An efficient CAD system should be developed to detect and diagnosis this disease with high performance.

The rest of this paper is organized as follows. Section 2 presents the different image segmentation techniques. In section, 3 the related work about different CAD systems used for detection and diagnosis of liver diseases are presented. Section 4 presents the challenge and future research. Finally, the conclusion of the paper is introduced in Section 5.

2. IMAGE SEGMENTATION TECHNIQUES

In this section, the various segmentation techniques of the medical images are introduced. Image segmentation approaches are mainly based on one of the two essential properties of intensity values that are discontinuity and similarity [8]. Segmentation techniques based on discontinuity scan the image searching for an obvious change in the level of intensity (such as edges). If there is one, they divide the image at this change. Whereas, segmentation techniques based on similarity scan the image and partition the image into multiple regions, which are similar according to a set of predefined criterias. Image segmentation techniques are usually designed and applied to certain organs of the body such as liver, brain, prostates, and breast. These methods can be used for various image modalities such as CT, MRI, and US. Therefore, image segmentation is still a challenging task for researchers to develop a general algorithm for image segmentation.

In this paper, we categorized the medical images segmentation techniques to four essential categories, which are thresholding techniques, region-based techniques, edge-based techniques, and clustering techniques as shown in Figure 2. In the sequent subsection, each segmentation type will be discussed in detail.

2.1 Thresholding Techniques

One of the most important used techniques for medical image segmentation is thresholding [9]. It segments the image in two regions, object/foreground and the rest of the image/background. In order to convert the gray image into a binary image, the value (T) of the threshold should be selected accurately. The obtained binary image contains the essential information about the place and the shape of the objects that we are interested.

The purpose of converting gray image to the binary image is to obtain easier data, and this leads to the simplification of the classification stage. Pixels whose original intensity is above the threshold value will be classified as white pixels (1) and are considered as a part of the object. Whereas, the pixels below this threshold value will be classified as black pixels (0) and belong to the background.

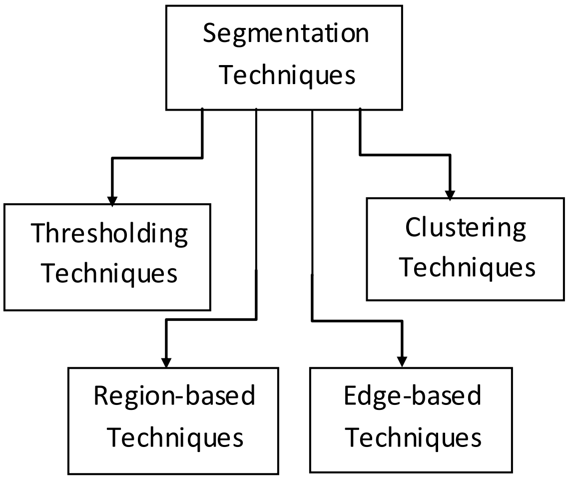

Figure 2: Image segmentation techniques.

The mainly two-thresholding techniques are global thresholding and local thresholding. In global thresholding, the value of the threshold T is constant. The problem of this type is that if the background of the image contains dissimilar illumination, the segmentation process may fail. In local thresholding, the threshold value T is not constant, so multiple thresholds can be used to overcome the problem of different illumination.

The value of thresholding value T can be automatically selected using various methods such as mean, histogram, Edge maximization technique (EMT) [10].

In mean technique, the threshold value T equal to the average value of the pixels. It works well in the case where images have approximately half of the pixels belong to the objects, and the other half belong to the background.

In histogram technique, it depends on the success of the reducing the threshold value that separates the two homogenous regions of the object and background of an image. This method works well for images that contain homogenous regions of the objects and background, and the heterogeneous region between them.

EMT is used when the image contains multiple homogenous regions or when there is a difference in illumination between the object and background. In this case, portions of the object may be merged with the background or portions of the background may be merged with the object. This technique depends on searching for the maximum edge threshold in the image to start segmentation with the aid of edge detection techniques operators.

In general, thresholding segmentation techniques are suitable for images that contain largely homogenous regions, and there is a clear separation between them. It leads to increasing the efficiency of the used technique.

2.2 Region-based Techniques

These techniques are based on the similarity among the pixels within a region. They are used to determine the region directly [10], [11]. These techniques group the pixels with similar characteristics (such as intensity) into regions. Region-based techniques are mainly divided into two approaches that are region growing approach and region splitting/merging approach.

In the region growing approach, the process starts by selecting a seed region (pixel). The region grows by adding the neighbors' pixels that have the same predefined criteria with the seed, such as intensity or gray level. The process ends when there is no pixel to be added.

In region splitting/merging approach, the process begins with the whole image as a seed. Then the seed is split into a number of subregions, usually four subregions. Thus, the process is repeated using each subregion as a seed. The process ends when there are no regions of the partition. Then, merge any adjacent regions that have similar properties, such as intensity or gray-level.

2.3 Edge-based Techniques

One of the most common techniques for image segmentation that is used for detecting the discontinuities in intensity value is the edge-based technique [10], [12]. It is based on a sudden change in intensity level at the region's boundaries of images. The edge in an image can be defined as the border between two regions that differ in the level of intensity [13]. These edges are used to determine the size of objects and separate objects from the background. To locate the different points in the image where the intensity naturally change, edge detectors should be used.

The success of segmentation and interpreting the image contents depends on the success of edge detection. Edge detection is an essential tool in image processing and computer vision, especially when dealing with feature detection and feature extraction.

In order to detect an edge in the image, two main methods can be used. These methods are a search-based method and zero-crossing based method.

In search-based method, it first calculates the gradient magnitude using first order derivative expression. Therefore, it searches for local directional maxima of the gradient magnitude using the gradient direction.

In zero-crossing based method, it first searches for a zero crossings in the second derivative of the image. It can detect edges by locating the zeros in the second derivative of when the first derivative is at a maximum, the second derivative is zero. This method is also known as Laplacian based edge detection.

The problem of edge-based segmentation technique is that it does not work well when there are many edges in the image.

2.4 Clustering Techniques

A cluster is a collection of similar pixels that are dissimilar to the pixels in the other clusters [14]. Clustering techniques perform clustering either by partitioning or by grouping pixels. In partitioning type, it begins with the whole image and divide it into successively smaller clusters. Whereas, in the grouping type, it begins with each element as a unique cluster and merge these individual clusters to obtain larger clusters.

We can divide clustering techniques to supervised clustering and unsupervised clustering. Supervised clustering technique needs the interaction of humans to determine the clustering criteria, but in unsupervised clustering technique, the clustering criteria is determined by itself. Here we will focus on the most significant clustering algorithms that are, k-means, fuzzy c-means, and particle swarm optimization.

2.4.1 K-means Algorithm

It is an unsupervised clustering algorithm that follows a simple way to classify the input data points into certain number of clusters based on their distance from each other. As shown in Figure 3, the k-mean algorithm has the following steps [15]:

Step 1: Select k as a number of clusters.

Step 2: Select k as a number centroids and the centroids locations are chosen randomly.

Step 3: Assign each object to the nearest centroid.

Step 4: Recalculate the new k centroids for the clusters resulting from the previous step.

Thus, the location of the k centroids is changed every time. If the points need to be moved to different clusters, steps 2, 3, and 4 should be repeated hat until there is no more need for the points to be moved to another cluster.

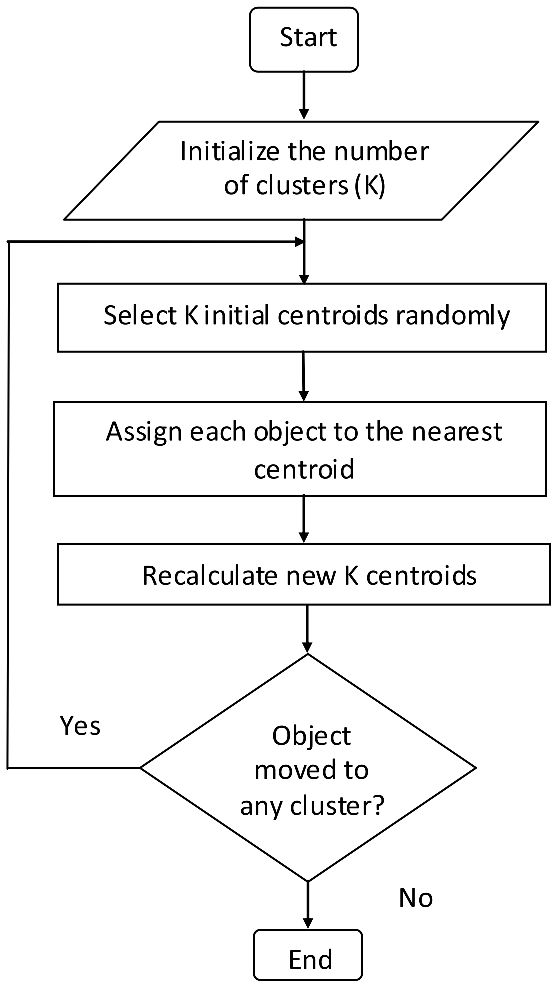

Figure 3: The flowchart of K-means algorithm.

2.4.2 Fuzzy C-Means Algorithm (FCM)

It is an unsupervised algorithm for the analysis of data and construction of models [16]. Unlike k-means clustering algorithm, in which each data point should be moved to only on cluster. FCM clustering algorithm group the points of the given dataset to all clusters with each data point relates to every cluster with a membership degree between 0 and 1. To understand that, consider an example where, a data point lies close to the center of an individual cluster (cluster 1) and far away from the center of another cluster (cluster 2). Thus, the data point will have a high degree of membership to cluster 1 and a low degree of membership to cluster 2. Thus, FCM clustering algorithm partitions an n- vectors Vi, i = 1,2,3,….,n into C fuzzy clusters. Then, it searches for the center of each cluster in such a way to minimize the cost function of the difference measure. The FCM algorithm consists of the following steps:

Step 1: It determines the centers of the clusters and fill the membership matrix with random values between 0 and 1. Therefore, for every data point, the summation of membership must equal to one.

Step 2: It determines the centers of fuzzy clusters.

Step 3: It computes the cost function.

Step 4: It computes a new membership matrix and repeat the steps until an optimum result is obtained.

Thus after each iteration, the membership and cluster centers are updated until reaching the optimum solution.

2.4.3 Particle Swarm Optimization Algorithm (PSO)

PSO algorithm was inspired by the animal swarming behavior when moving from place to another for immigration or for searching food as a group [17]. In addition, it is based on the social behavior of human when reaching for the optimal solution to a given problem that cannot be solved by traditional methods. A particle swarm is made up of a collection of particles. Each particle will move in the space to reach the better and best position that will be considered as the optimal solution. In order to determine the better and best positions for the particles, PSO should use fitness evaluation function. This function takes the position of the particle and assigns it a fitness value. Thus, to reach the best position, the fitness function should be optimized. In general, the fitness function is pre-defined and depend on the problem. Initially each particle maintains:

1- Its current position in the search space.

2- Its velocity (direction at which particle will travel).

3- Its best position.

4- Its fitness that calculated by the objective function.

In addition, there is the global best position that is maintained by the swarm.

The process of the PSO has the following steps:

Step 1: It initializes a population of particles with velocities and random positions in the search space.

Step 2: the fitness value for each particle is evaluated.

Step 3: It makes the necessary updates for the best position for every particle and the global best position for the swarm.

Step 4: It makes the necessary updates for the position and velocity of each particle in the swarm.

Repeat steps 2, 3 and 4 until the object function is satisfied.

3. RELATED WORK

There are many different techniques have been proposed for segmentation of liver tumor and diagnosis of liver diseases based on medical image analysis. For example, Mittal et al. [18] presented a CAD system for helping doctors to diagnosis focal liver diseases from B- mode US images. The proposed system have been used to detect and diagnosis four focal liver diseases. These diseases are Cyst, Hem, HCC, and Metastases (Meta). They also compared these diseases with the healthy liver. The CAD systems had the following steps: Step 1, the images are improved. Step 2, they segmented the regions of interest to 800 segmented regions. Step 3, from each segmented region, 208 features based on the texture are extracted. Lastly, they used Artificial Neural Networks (ANN) with two steps to diagnosis the diseases. The overall accuracy of their CAD system was 86.4%. In their proposed system, they used a traditional method such as NNs to reduce the training errors. They did not compare their system with other classifiers such as SVM.

Jeon et al. [19] proposed an approach; so-called multiple-ROI based focal liver lesion classification, to obtain better and more stable classification performance. The proposed system can be used to differentiate focal liver diseases, such as Cyst, Hem, and Malignancies. Their system consists of extraction of regions containing a liver lesion from the whole US image. Then, the features are extracted from the ROI. Finally, they used SVM classifier for three classification cases that are, classification of cysts and hemangiomas, classification of cysts and malignancies, and classification of hemangiomas and malignancies. The performance of this approach has shown the overall accuracy of 80%. In their proposed system, they did not make any enhancement for the used images. The preprocessing stage is critical because it improves the quality of the images and affects the subsequent stages including a definition of ROIs.

Andreia et al. [20] proposed a semi-automatic classification technique to examine steatosis liver tissues using B-scan US images. Many features have been extracted. They classified the diseases using three various classifiers, ANN, K-Nearest Neighbors (KNN), and SVM. The system can be used to differentiate between steatosis liver and a healthy liver. The three classifiers were trained using the ten cross-validation approach. The obtained results showed that the performance of the SVM classification is higher than the ANN and the KNN. The performance of the proposed approach has shown the overall accuracy of 79.77%, 76.92, and 74.05, respectively. In their proposed system, they used all the displacements and orientations that may lead to redundant features.

Sakr et al. [21] proposed an automated classification system used for diagnosing of various focal liver lesions using Multi-SVM. The system was used to diagnosis three focal liver diseases, which are Cyst, Hem, and HCC, relative to the healthy liver. First, the images were enhanced using a bilateral filter; then the segmentation process was done using Fuzzy c-means (FCM) and level set technique. The features are extracted using local texture descriptors and histogram-based features. Finally, they used a Multi-SVM classifier. They compared their approach with the KNN approach. The results showed that the classification using Multi-SVM achieved an overall accuracy of 96.11%. Whereas, KNN-classifier achieved an overall accuracy of 93.3%. In their proposed system, they used classical FCM for segmentation. They may use another segmentation technique or combine two techniques to obtain better segmentation accuracy.

Aldeek et al. [22] proposed a Bayesian model for a semi-automatic approach for liver segmentation from CT images. They trained and validate their model using 44 clinical volumes for patients with different types of liver diseases. Their results showed an overall accuracy of 87%. In their future work, they will prepare for a complete clinical study on the statistical importance of the inter-observer variability and reliability of liver segmentation from CT images.

Kumar et al. [23] presented an automatic segmentation approach for liver and tumor segmentation from abdominal CT images. The proposed algorithm used thresholding based on analysis of intensity distribution and morphological erosion to simplify the image. It decreases the computation time and is affected by removing the regions of other structures and tissues. The liver is segmented using region growing method. It starts from a seed point automatically detected and efficiently close around the vessels and tumors. The tumor segmentation from the segmented liver is done using an alternative FCM clustering. The results are compared to manually segmented results. The results show high overlap between the ROIs produced by the two methods.

Wang et al. [24] proposed a CAD system to diagnosis liver diseases from CT images. The CT liver images are examined by experienced doctors to locate the ROIs. They extracted the texture features of each ROI by using first-order statistics (FOS), spatial gray level dependence matrix (SGLDM), gray level run-length matrix (GLRLM), and gray level difference matrix (GLDM). They used a SVM to classify diseases. They used one-against-all (OAA) and one-against-one (OAO) methods to construct multi-SVMs. The classifier classified liver tissues into the hem, primary hepatic carcinoma, and a healthy liver. The result showed that the multi-SVM using the OAO method gives a total accuracy of 97.78% that is better than the OAA method. However, they did not compare their CAD system with other systems that use different classifiers.

Anuja and Anuba [25] proposed a complete liver image classification system for CT images. They used the Detect before extract technique (DBE) to automatically extract the liver boundary. Then, they used the MPNN classifier to diagnosis liver diseases. Their system consists of an automatic liver contour extraction process, an image enhancement algorithm, and a hemangioma classification network that used for the classification of the CT liver image. They located the edge of the liver CT images using the local entropy method. Then, they used the morphological method to detect the object regions. From the contour modification algorithm and local entropy method, they obtained the liver image and found the cancer location of the liver. Thus, they proved that the local entropy is an effective method of CT liver image segmentation and can help the diagnosis of liver cancer. They did not compare their proposed system that used local entropy algorithm with other segmentation algorithms to indicate the performance and accuracy of their algorithm.

Virmani et al. [26] introduced a CAD system based on PCA-SVM for diagnosing focal liver disease. They extracted texture features from the areas inside and outside of the infected regions. The used feature set was consisting of 208 texture features (104 texture features and 104 texture ratios features). They used principal component analysis (PCA) to determine the optimal number of principal components used for training SVM. The experimental result of their system achieved an overall accuracy of 96%, 90%, 87.5% and 82.2% and 85% of Cyst, Hem, HCC, Met, and NOR cases, respectively. In their proposed system, they did not make any preprocessing for enhancing the used images. The features were extracted directly from ROIs, which may not provide accurate performance.

Ribeiro et al. [27] dealt with the identification and diagnosis of different stages of chronic liver diseases. They used texture-based features and US image intensity along with the collected data from clinics and laboratories in the staging process. They used three different classifiers to classify the various diseases. The used classifiers are KNN, decision tree, and SVM. The results proved that the SVM achieved higher performance than the other two classifiers. The accuracy of the classification by using SVM with a radial basis kernel was 73.20%. However, the accuracy of their system is low. They may use multi-classifier to improve the accuracy.

Ribeiro and Sanched [28] proposed an automatic classification approach for diagnosing the liver steatosis (fatty liver) from US images. Since physician's diagnosis depends on some characteristics using traditional methods (visual inspection of US images), the features are selected to obtain the similar characteristics utilized by the doctors. They used Bayes classifier that was trained with the data classified manually by expert clinicians and used as ground truth. They achieved an overall accuracy of 95% and 100% of sensitivity. However, to develop a more robust technique, the number of patients should be increased. In their future work, they will test some other classifiers like SVM and ANN.

Ribeiro et al. [29] presented a semi-automatic approach to classifying chronic liver disease from US liver images and data collected from clinics and laboratories. They used a set of features from US, laboratory, and clinical. They used SVM classifier with a polynomial kernel of the fourth degree, achieving a sensitivity of 91.67%. In their future work, they will expand their approach to merging more textural features. In addition, they will examine other classifiers techniques.

Ribeiro et al. [30] presented a semi-automatic method to the segment the liver contours from the medical image. They used a classifier to diagnosis the diffused liver diseases. The collected data from clinics and laboratories are used to extracting features from the liver contour in the staging process to train supervised classifiers. When they used the KNN classifier with leave-one-out cross-validation method, they achieved an overall accuracy of 80.68%. In their future work, they intend to include other features to increase diagnostic accuracy. In addition, they intend to perform more analysis to use a combination of classifiers to improve the classification accuracy.

Kumar and Moni [31] presented the design and implementation of a CAD system consisting of liver and tumor segmentation, feature extraction, and classification modules. They proposed a new feature extraction method based on multiresolution fast discrete curvelet transform (FDCT) for liver diseases diagnosis with the aid of the computer. They segmented the liver from CT images. Then, they used FCM clustering algorithm to extract the tumor from the segmented liver. After that, the texture features are selected from the extracted tumor. Finally, they used ANN classifier to diagnosis the liver tumor into hemangioma and hepatoma. The obtained results showed that the overall accuracy achieved using FDCT was 93.3% that was higher than the wavelet-based technique that was 88.88%.

Freiman et al. [32] presented an automatic segmentation method to segment the tumors in the liver from CTA scan. It first classifies the liver voxels into the tumor and healthy tissue classes with an SVM classification engine from which a new set of high- quality seeds is generated. Then, it defines the energy function that describe the propagation of these seeds over the 3D images. Their principal methodology consists of a set of linear equations that are optimized with the conjugate gradients method. The obtained result is a continuous segmentation chart. To obtain binary segmentation, the segmentation map should be thresholded. The advantage of this method is that, it requires less user interaction compared to other methods. In addition, it achieves accurate results for a wide variety of tumor types with smooth and fast user interaction. However, they did not make any enhancement for the used images. In addition, they did not compare their proposed system with other systems to indicate the performance and accuracy of their proposed system.

Rajagopal and Subbaiah [33] presented a fully automatic liver tumor segmentation algorithm from CT images. In the pre-processing step, they improved the contrast of the image to remove the noise using a median filter. Then, they converted the image into binary, and they separated the tumor part of the image that has the highest intensity than other regions of the image. After that, they extracted the local binary pattern features for a set of images. Finally, they used SVM classifier. Their experimental results showed that the average overall accuracy achieved 95%. However, they did not compare their proposed system with other systems to indicate its performance and accuracy.

4. CHALLENGES AND FUTURE RESEARCH

As shown from the related work presented in the previous section, various CAD systems were presented to detect and diagnosis various liver disease. In these CAD system, there are many approaches and methods used for medical image segmentation. However, it is still a big challenge to develop a universe approach suitable for all types of medical images and all types of applications. Future research in the segmentation of medical images should be done towards the improvement of the accuracy, precision and computational speed of segmentation methods, as well as reducing the amount of manual interaction of user.

5. CONCLUSION

CAD systems are critical for physicians to understand the medical images and to improve the accuracy of detection/diagnosis of various diseases. Segmentation is the most important step for CAD systems, and the efficiency of diseases diagnosis depends on the effectiveness of segmentation. Although, there are many techniques that are used for medical image segmentation, it is still a challenging issue to develop a universally accepted approach that can be applied to all types of images and applications. In addition, the selection of an appropriate technique for a particular kind of image is a difficult problem. Therefore, image segmentation remains a challenging issue in the fields of image processing and computer vision. In our future work, we will introduce a novel segmentation algorithm that accurately segment the various liver diseases based on medical image analysis.

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