Diagnosis of Liver Images Lesions in Mr Images Using Improved Segmentation and Classification Task

M.Babu, G.Nanthakumar

ABSTRACT---Detection of liver abnormalities is a deep study that reflects the condition of liver during the time of liver disease. The diagnosis reveals the condition of liver in human body, however earlier detection of images during medical diagnosis is still a tough task with texture analysis and classification process. Hence, in this study we reveal the condition of liver as normal or abnormal based on the analysis done using the proposed method. The proposed system identifies the condition of liver through two stages: structural and statistical analysis and classification process. The former one is carried out with Gabor Gray Level - Local Binary Patterns (GGL-LBP) that provides the structural texture representation of a liver image. The latter one uses various machine learning classifiers to test the proposed method that includes Artificial Neural Network Fuzzy Inference System (ANFIS) is used for classification process. The set of images are used for training and testing the classifier using the structural features. The proposed classification method is evaluated using 225 test records and it is tested against conventional methods in terms of accuracy, sensitivity and specificity. The experimental validation shows that proposed method with ANFIS classifier acquires improved accuracy than other classifiers, namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naïve Bayes (NB), Decision Tree (DT) and Linear Discriminant Analysis (LDA).

Keywords:Liver Abnormalities, ANFIS Classifier, Normalized Gabor Filter, Co-occurrence Matrix, Local binary pattern

I. INTRODUCTION

In medical field, the cancer detection is considered difficult at its early stage. In most cases, the physicians and diagnostic fails to diagnose the presence of cancer from the abnormal image sequence or fames. Also, the abnormalities associated with MRI (Magnetic Resonance Imaging) of liver is not diagnosed properly due to poor diagnostic system. The difficulty in finding malignant lesions in liver MR images leads to high risk of paper being affected by that disease. Since, these poor image segmentation and classification fails to detect the malignant lesions in liver images at the time of diagnosis. This is true especially in case of ideal medical imaging cases for the detection of tumor cells, which lacks proper color space and specific lesion structure. Therefore, a better diagnostic system is required by the medical experts in place of existing diagnostic methods. This diagnostic system should be designed as a diagnostic process to resolve the above issues system using high level segmentation and classification process.

In literatures, there exist numerous techniques for the detection of tumors in liver MR images and few of which are color texture [9], texture descriptors [8], Gabor texture [3] and local binary patterns [7]. These descriptors is used for extracting the features in an image and these features are used for training the classifier. The texture descriptors [14] [17] [19] represents the structural representation of an image and this is used for further stages of classification and extraction to detect the liver image lesions. The textural features alone cannot detect the lesions present in the MR liver images [16] [21] [23]. However with proper segmentation and better extraction of texture features, the accuracy of classification can be improved to detect the lesions present in a MR image. Hence, the better structural features can be found by finding the frequencies spatial arrangement information, LBP information [4], and gray level co-occurrence matrix (GLCM) [2] information. These information helps in analyzing the abnormalities in a better manner than the extraction using textural descriptors.

The structural point of view, the image texture consists of texture elements that are arranged in accordance with a placement rule. The structural information is collected by extracting textural elements from a MR liver image. The structural representation of a MR liver image represents the presence of objects in an image. It then analyses and estimates the shape from these texture elements using placement rule. However, structural elements increases the complexity of feature representation. Hence, the use of statistical texture analysis provides more detailed texture description of liver MR images [25]. The analysis of liver MR images through structural geometry provides the basic structural and statistical texture information, which consists of gray level pixels associated with neighborhood pixels. Further, the spatial relationship between the neighborhood pixels in an image improves the corner, edges, texture and statistical information in an image. The human visual system recognizes the object thoroughly, which is used to find the structural arrangement, which is widely used for classification of image in several image applications [13].

Various studies has been surveyed that involves classification of high level features from MR liver images [5] [6] [15] [18] [20] [22] [24]. However, these diagnostic methods fails to recognize the low level textural structures from the image pixel groups. This carries out the local

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information required to classify the image and these structural information depends entirely on the image details, which is required for analyzing the image. The structural information fails in predicting the position or orientation of an object, but the use of statistical features helps in predicting the position or orientation of an object using rotational invariant feature extraction.

The structural co-occurrence method [12] identifies the texture of an image using its structural analysis. Here, GLCM is found using intensity of neighborhood pixel in terms of its direction and orientation features and this helps in computing the textural feature set based on the stored information. Further, the texture features extraction using filter array uses mean and standard deviation of filter responses to represent the structural features at various frequencies, scale and orientation [10]. Additionally, the GLCM computes the distributed intensities at a particular distance and its second order statistics compute the textural information [11]. Hence, in this paper, the extraction of features is carried out using a novel filter based Gabor Gray Level Local Binary Patterns (GGL-LBP).

The main contribution of the paper is given below:

- Then an optimization process using Chaotic grey wolf optimization algorithm (CGWO) is used to carry out the segmentation process.
- The classification process is carried out using Adaptive Neuro Fuzzy Inference System (ANFIS) to classify the normal and malignant liver images.
- Finally, the authors compare the proposed classification method with other existing algorithms to prove the efficacy of the proposed method.

The outline of the paper is given below: Section 2 gives the detailed discussion of the proposed classification method. Section 3 provides the performance measures used to evaluate the proposed method. Section 4 evaluates the proposed method and provide discussions over it. Finally, section 5 concludes the entire work with future direction.

II. METHODS

The proposed liver lesions diagnostic method involves the following process:

(i) The noise free images are segmented using CGWO algorithm. The segmentation process helps in finding the presence of liver lesions in MR images.

(ii) The features are then extracted using GGL-LBP and the extracted features are sent as an input for ANFIS classification system for its training purpose.

(iii) Finally, the MR images are directly sent to the classifier to detect the liver lesions using trained data.

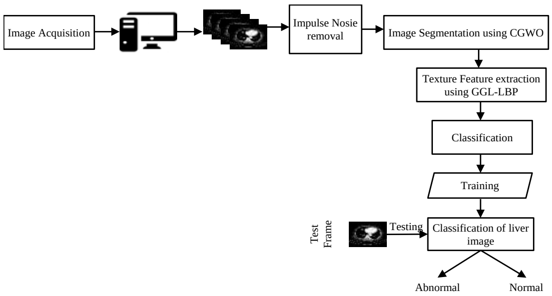

Figure 1. Diagnostic of liver lesions using proposed classification method

a. Segmentation using CGWO

The segmentation process is carried out using Chaotic grey wolf optimization algorithm (CGWO). This section initially provides the details of GWO and then it discusses the image segmentation using CGWO algorithm.The CGWO algorithm is shown in following steps:

Algorithm 1: CGWO Process

Step 1: Initialize the grey wolves population randomly where (G_i = 1, 2,…, n)

Step 2: Initialize the generation counter t

Step 3: Initialize the chaotic map value in a random manner.

Step 4: Initialize the vector or parameters a, A and C

Step 5: The first, second and third best hunt agent is defined by G_α, G_β and G_δ.

Step 6: For i = 1

a. Repeat

b. For i = 1: G_i (size of grey wolf pack)

 i. Introduce chaos between the hunt agents

 ii. Update the current hunt agent location

 iii. Update chaotic sequence of chaotic map (x_i +1)

 iv. Update the grey wolf position

c. End for

d. Calculate the fitness value of entire current hunt agents

e. Update G_α, G_β and G_δ%Replace the worst fit grey wolf with the best fit grey wolf

f. Update a, A and C

g. i = i +1

h. Repeat until i reaches the maximum value

i. Output G_α, G_β and G_δ(first three optimal ROI pixel around liver lesions)

Step 7: End

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b. Feature Extraction

The extraction of textural features from a MR liver image is obtained using following process, which is given below:

III. LBP 2D GABOR FILTER

The Gabor filter is represented in spatial domain using a Gaussian function $G(x,y)$ having x and y coordinates. The Fourier transform of $G(x,y)$ is given by $G_f(u,v)$ with frequency components u and v, which is described as in Eq.(1).

$$G(x,y,\sigma,\Omega)=\left(\frac{1}{2\pi\sigma_x\sigma_y}\right)exp\left[-0.5\left\{\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right\}+2\pi i\Omega x\right] \quad \textbf{(1)}$$

where, σ_x is considered as the standard deviation of co-ordinate x, σ_y is the standard deviation of co-ordinate y and Ω is the center frequency of high response filter's.

The Gabor filter is obtained from the convolution of complex sinusoidal and Gaussian function in Fourier domain. The standard deviation σ_x and σ_y controls the Gaussian window spread along its spatial axis x and y. The main advantage of Gabor filter with LBP is that it can perform the image analysis of spatial frequency in multi-resolution domain with directivity selection and bandpass nature as its fundamental characteristics. The orientation selection and phase selection properties is modeled as human visual perception system using Gabor filters [27]. Thus the Fourier transform for the proposed Gabor filter with LBP and frequency components is described as in Eq (2).

$$G_f(x,y,\sigma,\Omega)=exp\left[-0.5\left\{\frac{(u-\Omega)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right\}\right] \quad \textbf{(2)}$$

where,

$$\sigma_u=\frac{1}{2\pi\sigma_x} \textbf{ and } \sigma_v=\frac{1}{2\pi\sigma_y}$$

c. ANFIS classifier

The extracted feature includes image texture through 2D Gabor filter with LBP and textural features through GLCM that differentiates normal liver and malignant liver images. The structural texture information that consists of texture elements and its shape are grouped into a feature vector of N number of features for both normal liver and malignant liver images. The grouped feature vector is sent as an input to the classifier to differentiate the normal and malignant liver image. In this paper, ANFIS classifier is used to obtain high level of classification accuracy. The ANFIS classifier classifies the malignant features from both low and high intensity MRI images with five intermediate hidden layers and a single I/O layer. The neurons present in each input layer represents the total number of features from the grouped feature vector. Also, number of neurons found in each hidden layer is 10 and after several iterations, the neurons are fixed to obtain higher classification accuracy. Finally, a single neuron present inside the output layer yields binary low (if the classified image is not-malignant) and binary high (if the classified image is malignant) on feature vector.

IV. PERFORMANCE MEASURES& RESULTS

The performance of proposed liver lesion diagnostic automation model is compared with existing classifier in terms of several performance metrics that includes: True Positive Rate (TPR) or sensitivity (Eq.(17)), True Negative Rate (TNR) or specificity (Eq.(18)) and Accuracy (Eq.(20)). The values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are used to compute the accuracy, which is given in Eq.(20).

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

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

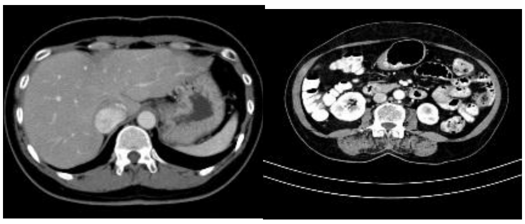
$$FPR=1-TNR \quad \textbf{(5)}$$

$$Accuracy=\frac{TP+TN}{P+N} \quad \textbf{(6)}$$

d. Datasets

The datasets are collected from a hospital from 220 patients, who are reported with liver lesions. The comparison between normal liver image (Figure 3(a)) and the one with liver lesions (Figure 3(b)) using different MR Scanning is given in following figure. The collected dataset is used for the purpose of experimenting the proposed and other classifiers. The use of MRI scanning helps in finding the liver lesions using proposed diagnostic model. The proposed diagnostics model provides the details of tumor i.e. benign and malignant.

The collected datasets are divided into two different classes i.e. normal and abnormal. The former one uses 120 different images of healthy liver and the latter one uses 120 images of the one affected with liver lesions. The MR images are collected at phase in and phase out stage of MRI scanning. The entire set of 120 images of abnormal classes are used for training and then a new set of images are used for testing the system.



(a) Normal Liver Image(b) Abnormal Liver image
Figure 3. Collection of liver image through MRI scanning for the purpose of training and testing the proposed model.

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The collected image dataset is used in such a way that collected set (120 images) is used for training and fresh set (100 images) is used for testing. This partitioning is done to make the system to work well with future data and generalization of the proposed diagnosis model is improved using k-cross validation on the selection of training and testing data. Here, 10-cross-validation is carried out on ANFIS classifier to obtain a concrete results during training phase.

Once the features are extracted from the input images after impulse noise removal and filtering, the image is sent to ANFIS classifier to classify it as normal or abnormal class. The results are presented in Table 4 that shows the performance of different classifiers used to classify the given features after a single iteration of training process in a 10-fold cross validation. The proposed method with ANFIS classifier is compared with other classifiers namely, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naïve Bayes (NB), Decision Tree (DT) and Linear Discriminant Analysis (LDA). The result shows that proposed GGL-LBP based ANFIS classification method obtains improved classification that other methods. The accuracy level between different classifiers using the proposed method and variations between these methods are minimal.

	Accuracy	Sensitivity	Specificity
ANFIS	0.996901	0.927023	0.998183
SVM	0.996542	0.926827	0.998183
KNN	0.996146	0.93642	0.997293
NB	0.996133	0.935083	0.997306
DT	0.99543	0.944444	0.996367
LDA	0.995378	0.943764	0.996327

Table 4(a). Different Classifier performance using Proposed Framework with GGL-LBP Feature extraction

The Table 4(a) shows the performance comparison in terms of accuracy, sensitivity and specificity between the proposed Framework with various classifiers with GGL-LBP Feature extractor. The results between ANFIS and SVM classifier are similar. However, the proposed method outperforms other classifiers in terms of its accuracy, sensitivity and specificity.

V. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we present an liver lesion diagnostic model that consists of four different stages: (i) impulse noise removal, (ii) segmentation, (iii) feature extraction and (iv) classification. Each stage is processed using different techniques that involves, (i) window based technique, (ii) CGWO, (iii) GGL-LBP and (iv) ANFIS classifier. The removal of impulse noise is very evident from the results. The noise free MR image is segmented well by the proposed optimization model and this sets the beginning for feature extraction. The structural and statistical feature representation of MR images are extracted out by the proposed feature extraction method and after training of images using classifier, the proposed model extracts the lesions from the test images. The evaluation shows that proposed model classifies the well the lesions that other classifiers. From this it is evident that proposed model is suitable for classification of liver images than other methods. Further, the technique can be improved by analyzing the color based features for improved diagnosis in other medical fields like gynecology, entomology etc.

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