International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-6, August 2019

Liver Lesions Diagnosis Using Gwo-Anfis Framework

M.Babu, G.Nanthakumar

ABSTRACT--- In this paper, liver abnormality is detected using an improved classification model that consists of series of process. The study reveals the liver condition to be normal or abnormal using the proposed system. The study uses both structural and statistical analysis, where both these analysis is combined with the process of classification. Initially, the noises are removed using Impulse Noise Removal and then the Segmentation is carried out using Gray Wolf Optimisation (GWO) algorithm. After the segmentation, the features are extracted through Local Binary Patters (LBP) Operator and then Artificial Neural Network Fuzzy Inference System (ANFIS) classifies the liver regions as malignant or benign. Various images collected from laboratories are used in both training and testing stages. The results are validated in terms of two different texture feature extractors namely, GLCM and LBP. The result shows that the proposed classifier using GLCM classifier obtains improved classified patterns than the existing methods.

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

I. INTRODUCTION

The early detection of cancer in medicine is seen as difficult. The presence of cancer due to the abnormal image sequence or families is mostly not diagnosed by the doctors and diagnosis. In addition, Magnetic Resonance Imaging (MRI) related abnormalities of liver are not properly diagnosed due to a poor diagnostic system. Distress in liver MR-images causes the difficulties of finding malignant lesions, which lead to high paper risk. Since the malignant lesions in liver images are not detected in this poor segmentation and classification at the time of diagnosis. This is especially true for ideal cases of medical imaging for tumor cell detection, where the color space and the specific injury structure are lacking. Therefore, instead of existing diagnostic methods a better diagnostic system is required by medical experts. This diagnostic system should be designed to solve the above problems by means of high-level segmentation and classification.

Revised Manuscript Received on August 30, 2019.
* Correspondence Author
M.Babu*, Research Scholar, Sri Satya Sai University of Technology & Medical Sciences, Madhya Pradesh, India.
(E-mail: babukiot@gmail.com)
Dr.G.Nanthakumar, Associate Professor, AnjalaiAmmalMahalingam Engineering College, Thiruvarur, Tamilnadu, India.
(E-mail:gan_nand@yahoo.com)

The literature contains a number of techniques used to detect tumors, including color texture [1], texture descriptors [2], Gabor texture [3] and local binary pattern [4], in liver MR images. These descriptors are used to extract characteristics from a picture and these characteristics are used in the classifier training. The texture descriptors [5] depict the structural image representation, which is used to detect liver picture lesions for further classification and extraction stages [13]. The textural characteristics of the liver images MR alone can't detect lesions [5]. The precise classification can, however, be improved to detect lesions present in an MR image with proper segmentation and better extraction of the texture features. Therefore, information on frequency spatial arrangement, LBP information [6] and the gray level co-occurrence matrix (GLCM) [7] are the most appropriate structural features. This information helps to better analyze anomalies than removal with textural descriptors [14].

The texture of the image consists of texture elements arranged according to a placement rule. The structural perspective. The structural information is obtained from an image of the MR liver by extracting textural elements. The structural image of the MR liver is the presence of objects in the image [17]. The form of these texture elements is then analyzed and estimated using the positioning rule. However, the complexity of feature representation increases with structural elements. Thus, a more detailed texture description of the liver MR images is provided with a statistical texture analysis [9]. The analysis of MR images of liver using structural geometry provides basic information about structural and statistic texture consisting of gray pixels with neighborhood pixels. The spatial relationship of the pixels in an image improves the corner, edges, texture and image statistics. The human visual system thoroughly recognizes the object used for structural arrangements used in several image applications for classification [10].

Various studies involving the classification of high-level MR liver image characteristics have been studied. However the low level textural structures of the image pixel groups are not recognized in these diagnostic methods. This carries out the local information required to classify the image and these structural information depends entirely on the image details, which is required for analyzing the image [15] [16]. Structural data fail to predict an object's position or orientation but the application of statistical characteristics helps to predict its position or orientation by means of rotational invariant extraction. The structural co-occurrence method [11] uses its structural analysis to define the texture of an image.

GLCM is found here in terms of its orientation and directional features by the intensity of the neighborhood pixels and this helps in calculating the structural feature set based on the stored information. The texture extraction features using the filter array also use average filter responses and a standard deviation, to represent the structural characteristics at different frequencies, sizes and orientations.

Hence, in this paper, liver abnormality is detected using an improved classification model that consists of series of process. The study reveals the liver condition to be normal or abnormal using the proposed system. The study uses both structural and statistical analysis, where both these analysis is combined with the process of classification. Initially, the noises are removed using Impulse Noise Removal and then the Segmentation is carried out using Gray Wolf Optimisation (GWO) algorithm. After the segmentation, the features are extracted through Local Binary Patters (LBP) Operator and then Artificial Neural Network Fuzzy Inference System (ANFIS) classifies the liver regions as malignant or benign. Various images collected from laboratories are used in both training and testing stages.

II. METHODS

The proposed liver lesions diagnostic method involves the following process: Initially, the proposed method uses windowing based method to remove the presence of impulse noise in MR liver images. The noise free images are segmented using GWO algorithm. The features are extracted using LBP and GLCM and sent as an input to train the classification system. Finally, the MR images are directly sent to the ANFIS classifier for detecting the liver lesions.

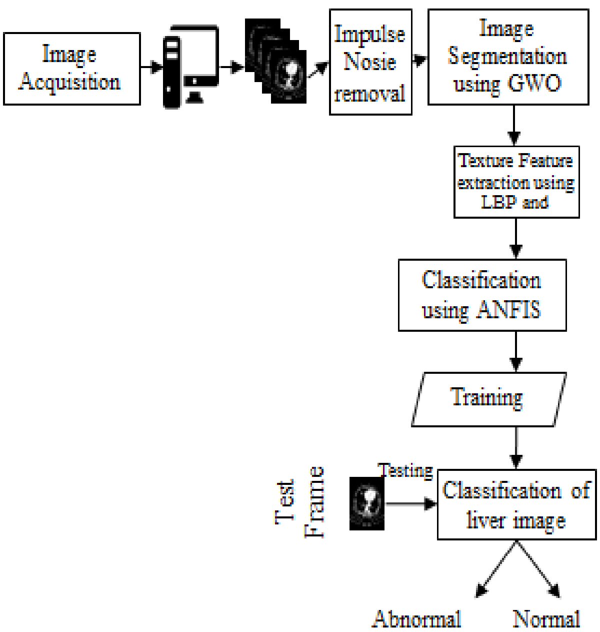

Figure 1. Diagnostic of liver lesions using proposed classification method

a. Pre-Processing using Impulse Noise Removal

In this paper, a median filter with effective decision making is used for removing the presence of impulse noises in MRI images. Initially, the decision on made on whether the pixel is clean or corrupted.

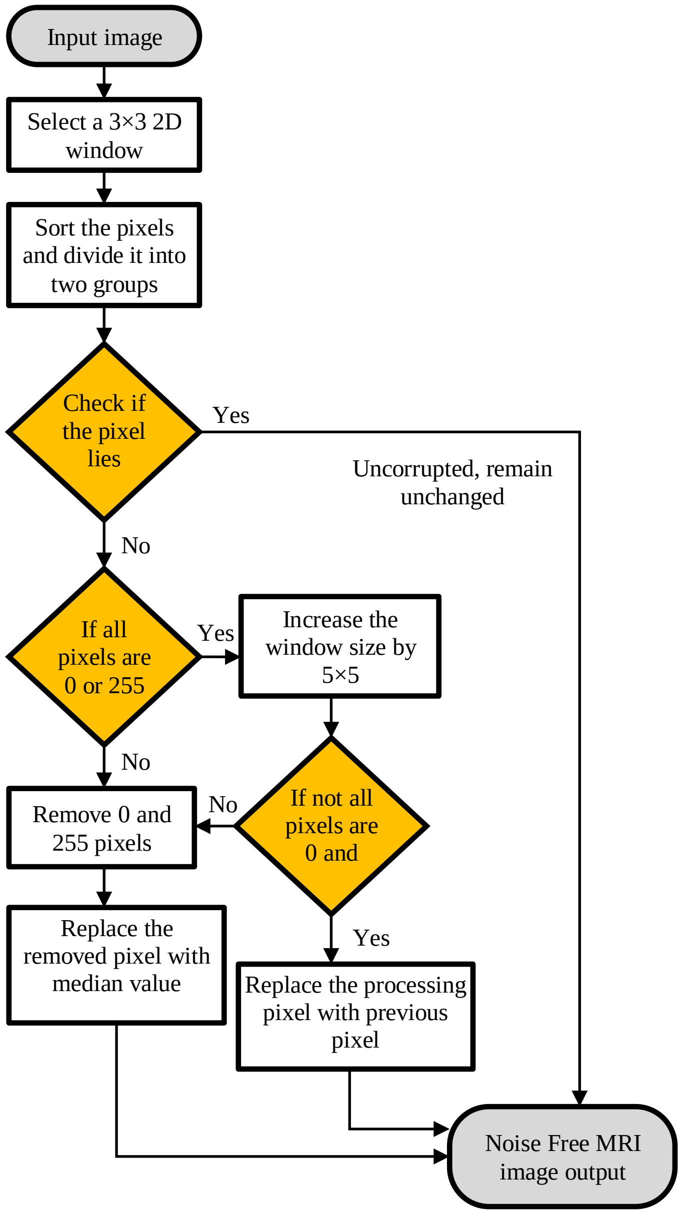

Figure 2: Flowchart of impulse noise removal

The flowchart of impulse noise removal is given in Figure 2. Consider $P(i,j)$ as the pixel values present at a current location (i,j). If the processed pixel satisfies the criteria $0 < P(i,j) < 255$, the pixel is treated to be uncorrupted and the value of it is unaltered. If the processed pixel takes the values 0 and 255, the pixel is treated to be corrupted and it is then processed. During the processing of corrupted pixels, the window size is increased to 5x5 after the initial stage window processing of size 3x3. The size of the window is increased to accommodate the processing of all corrupted pixels in the given processing scheme. A median value is generated from these corrupted pixels is a corrupted one and increasing the size of window tends to obtain median value. The improved median value(s) is/are replaced over the corrupted pixel(s) in the present window. However, if all the pixels in a window is found to be corrupted, then the present corrupted pixel is replaced with past pixel value. Once the processing over the first window is completed, move the present window to the subsequent pixel processing element.

Algorithm 1: Window based Impulse Noise Removal

Input: A corrupted MRI image with impulse noise.
Output: MRI image free from Impulse noise.
Assume $P(i,j)$ is the current processing pixel
Step 1: Select a 2D window of size 3x3.

Step 2: Sort the current processing pixels in the current window and cluster them into two individual groups. The first group is represented as $N(i,j)$ and the second group is represented by $N(i,j)$, which involves the pixel values 0 and 255, and excluding the values 0 and 255, respectively.

Step 3: If the criteria $0 < P(i,j) < 255$ is satisfied, the processing pixel is considered as uncorrupted and it is remained unchanged.

Step 4: If all the pixel values are not 0 and 255, then delete 0 and 255 and then replace the processing pixel with median value

Step 5: If the criteria $P(i,j) \in$ 0 and 255 is satisfied in the processing and neighborhood pixels, the window size is increased to 5x5,

Step 5.1: If all the pixel values available in the current window are not 0 and 255, then Goto Step 4

Step 5.2: If all the pixel values available in the current window are 0 and 255, then replace the present pixel with past pixel value.

Step 6: Once all the pixels are processed, move the present window to the subsequent pixel processing element.

Step 7: Repeat the process until all the pixels are processed in the element.

b. 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.

i. GWO

The GWO impersonators the social behavior of grey wolves and its hunting behavior. In addition to its former behavior, pack hunting is yet another appealing action of them. The process of GWO involves encircling the prey, hunting the prey and attacking the prey. The CGWO algorithm is further developed by introducing chaos in GWO algorithm [12]. The chaos is considered as a deterministic method with random wolves' behavior. This behavior is considered similar to dynamical non-linear system, which is non-converging, non-period and bounded. In general, chaotic system describes the behavior of randomness in wolves. The chaos behavior is initialized in optimization process using chaotic maps. This helps in exploring the search space with more dynamicity.

The initial value in chaotic maps is chosen between 0 and 1. However, it should be carefully selected, say 0.7 to avoid significant impacts on the fluctuation pattern of certain chaotic maps. The convergence rate in GWO is affected by chaotic maps in a positive manner and the chaotic maps induces chaos in acceptable region (predictable over a shorter initial time) and stochastic (for a longer time period).

Initially, the grey wolves are initialized stochastically and then GWO is mapped by the chaotic map along with the initialization of a variable and a chaotic number. The parameters or vector a, A and C involved in exploration - exploitation are initialized as in GWO. The fitness value in the search space is estimated and sorted based on fitness value. The wolves after sorting is ranked as first, second and third wolves. This is updated at regular intervals. The optimal position of a wolf is found and then the parameters are updated after every iteration to find the optimal value. After final iteration, final fitness value is considered as most optimal solution in segmenting an image [12].

c. Feature Extraction using LBP Operator

The textural features are extracted from MR liver image using a LBP operator. Initially, original pixel and its neighborhood pixel values of image is determined to find the LBP (T) features of liver image, which is expressed as given below:

$$T = t(g_c, g_0, g_1, \ldots, g_{p-1}) \tag{1}$$

where, $g_0, g_1, \ldots, g_{p-1}$ - gray value of a pixel, which is centered around an optimal ROI pixel around liver lesion and g_c - gray value of pixels at ROI.

The difference between the gray levels of any two neighborhood pixel value is identified by the LBP operator that considers center symmetry. This calculation reduces the dimensions of pixel and it reduces the computational complexity, where it centers around 16 dimensions rather than with 256 dimension in LBP. The collection of binary sequence takes place after the gray level values are estimated. This is estimated w.r.t a decimal number and it reduces the time for estimation and the storage space. The GGL-LBP encoding rules is expressed as follows:

$$GGL-LBP_{P,R}(x,y) = \sum_{s}\left(g_i - g_{i+\frac{N}{2}}\right)2^i \tag{2}$$

where, P - total pixel lying within the circumference of a circle and R - radius of the circle

d. ANFIS classifier

The extracted feature includes a 2D Gabor filter with LBP texture and GLCM textural properties, which distinguishes normal liver and malignant liver images. For normal liver and malicious liver images, the structural texture information consisting of texture elements and their form are grouped into the N-vector of numbers of features. The grouped vector is sent as an input to the classifier for the normal and malignant liver image to be distinguished. ANFIS Classifier for high classification accuracy is used in this paper. The ANFIS classifier classifies both low-and high-intensity MRI images with five intermediate hidden layers and a single I / O layer for malignant features. The neurons in each input layer are the total number of characteristics of the grouped vector feature. Furthermore, the number of neurons found in every hidden layer is ten and the neurons are fixed after multiple iterations for greater precision. Finally, one neuron in the output layer produces binary low and binary high levels in the feature vector (when the classified image is not malignant).

III. 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:

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

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

$$FPR = 1 - TNR \quad (5)$$

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

where,
TP - True Positive,
TN - True Negative,
FP - False Positive and
FN - False Negative

a. Datasets

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.

Table 1. Different Classifier performance Proposed Framework with GLCM texture Feature extraction

Classifier	Accuracy	Sensitivity	Specificity
Proposed ANFIS	0.995977	0.777159	0.998507
SVM	0.994671	0.750413	0.997849
KNN	0.994555	0.722689	0.997681
NB	0.993748	0.871676	0.994879
DT	0.993461	0.70885	0.996917
LDA	0.986264	0.90771	0.986985

Table 2. Different Classifier performance using Proposed Framework with LBP texture Feature extraction

Classifier	Accuracy	Sensitivity	Specificity
Proposed ANFIS	0.965951	0.716806	0.977293
SVM	0.966107	0.725076	0.976826
KNN	0.964219	0.698569	0.97635
NB	0.963646	0.695057	0.975927
DT	0.96293	0.686166	0.975825
LDA	0.96138	0.67885	0.974218

The Table 1 and 2 shows the performance comparison in terms of accuracy, sensitivity and specificity between the proposed framework and other classifiers with GLCM and LBP Feature extractor. The results between ANFIS and SVM classifier are found to be similar. However, the proposed method outperforms other classifiers in terms of its accuracy, sensitivity and specificity. Similarity, the results of classification is higher for GLCM classifier in Table 1 than LBP in Table 2.

IV. CONCLUSIONS

Hence, in this paper, liver lesion diagnostic model is proposed for improved detection of liver lesions. The study reveals the liver condition to be normal or abnormal using the proposed system. The study uses both structural and statistical analysis, where both these analysis is combined with the process of classification. Initially, the noises are removed using Impulse Noise Removal and then the Segmentation is carried out using GWO algorithm. After the segmentation, the features are extracted through LBP Operator and then ANFIS classifies the liver regions as malignant or benign. Various images collected from laboratories are used in both training and testing stages. The simulation condition reveals that the proposed method obtains improved accuracy, sensitivity, and specificity than other existing classification models. This shows the efficacy of the proposed method than the other existing models against liver lesion classification.

REFERENCES

1. Riaz, F., Hassan, A., Nisar, R., Dinis-Ribeiro, M., & Coimbra, M. T. (2017). Content-adaptive region-based color texture descriptors for medical images. IEEE journal of biomedical and health informatics, 21(1), 162-171.
2. Gotlieb, C. C., & Kreyszig, H. E. (1990). Texture descriptors based on co-occurrence matrices. Computer Vision, Graphics, and Image Processing, 51(1), 70-86.
3. Riaz, F., Silva, F. B., Ribeiro, M. D., & Coimbra, M. T. (2012). Invariant gabor texture descriptors for classification of gastroenterology images. IEEE Transactions on Biomedical Engineering, 59(10), 2893-2904.
4. Nanni, L., Lumini, A., & Brahnam, S. (2012). Survey on LBP based texture descriptors for image classification. Expert Systems with Applications, 39(3), 3634-3641.
5. Guo, Z., Zhang, L., & Zhang, D. (2010). Rotation invariant texture classification using LBP variance (LBPV) with global matching. Pattern recognition, 43(3), 706-719.
6. Yang, X., Do Yang, J., Hwang, H. P., Yu, H. C., Ahn, S., Kim, B. W., & You, H. (2018). Segmentation of liver and vessels from CT images and classification of liver segments for preoperative liver surgical planning in living donor liver transplantation. Computer methods and programs in biomedicine, 158, 41-52.
7. Liu, L., Lao, S., Fieguth, P. W., Guo, Y., Wang, X., & Pietikäinen, M. (2016). Median robust extended local binary pattern for texture classification. IEEE Transactions on Image Processing, 25(3), 1368-1381.
8. Lloyd, K., Rosin, P. L., Marshall, D., & Moore, S. C. (2017). Detecting violent and abnormal crowd activity using temporal analysis of grey level co-occurrence matrix (GLCM)-based texture measures. Machine Vision and Applications, 28(3-4), 361-371.
9. Kohli, M., & Arora, S. (2018). Chaotic grey wolf optimization algorithm for constrained optimization problems. Journal of Computational Design and Engineering, 5(4), 458-472.
10. Sampat, M. P., Wang, Z., Gupta, S., Bovik, A. C., & Markey, M. K. (2009). Complex wavelet structural similarity: A new image similarity index. IEEE transactions on image processing, 18(11), 2385-2401.

11. Sweeney, S. M. (2014). AACR Cancer Progress Report 2014. American Association for Cancer Research, 126, 1078-0432.
12. Zalama, E., Gómez‐García‐Bermejo, J., Medina, R., & Llamas, J. (2014). Road crack detection using visual features extracted by Gabor filters. Computer‐Aided Civil and Infrastructure Engineering, 29(5), 342-358.
13. Vivekanandan, P., et al. (2013). An efficient SVM based tumor classification with symmetry non-negative matrix factorization using gene expression data. In 2013 International Conference on Information Communication and Embedded Systems (Icices) (pp. 761-768). IEEE.
14. Sivaram, M., et al. "Advanced Expert System Using Particle Swarm Optimization Based Adaptive Network Based Fuzzy Inference System to Diagnose the Physical Constitution of Human Body." International Conference on Emerging Technologies in Computer Engineering. Springer, Singapore, 2019.
15. Raja R., et al., Analysis on Improving the Response Time with PIDSARSA-RAL in ClowdFlows Mining Platform. EAI Endorsed Trans. Energy Web 5.20 (2018): e2.
16. Dhas, C. S. G., et al., (2018). High-performance link-based cluster ensemble approach for categorical data clustering. The Journal of Supercomputing, 1-24.
17. Babu M., Nanthakumar G. (2019). Diagnosis of Liver Images Lesions in Mr Images Using Improved Segmentation and Classification Task. International Journal of Recent Technology and Engineering, 8(4), 748-752.