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LIVER HEPATITIS DIAGNOSING BASED ON FUZZY INFERENCE SYSTEM

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Abstract

Hepatitis is considered a liver disease that is difficult to diagnose at an early stage. The number of infected people exceeds two billion, with one million deaths and more than four million infected people registered per year. Therefore, there is a great need for a system to diagnose this disease. Hepatitis is a critical inflammatory liver disease with different causes, including viral infection, alcohol, and the autoimmune system. Several systems were proposed to diagnose and classify this disease, using numerical, rigid, and low level methods such as color histogram, standard deviation, and entropy. In our research, we leveraged these to linguistic, flexible, and high level by applying Fuzzy Logic theory using a Fuzzy Inference System (FIS). In this paper, a model is implemented through many stages where 3D-Discrete Wavelet is applied to remove noise from liver biopsy images. Then the Normalized Mean Color Histogram (NMCH) is extracted as a visual feature, and a FIS is built for diagnosing the class of hepatitis using 45 fuzzy IF-THEN rules. The system is evaluated by calculating precision and accuracy, and the results were both very accurate and interesting. Diagnosis accuracy reaches 96%, with the corresponding approximated time ranging between 0.10 – 0.15 seconds.

Keywords: Fuzzy Inference System, Fuzzy Logic, 3D-Discrete Wavelet, Normalized Mean Color Histogram.

摘要 肝炎被认为是一种早期难以诊断的肝脏疾病。感染者人数超过 20 亿，每年有 100 万人死亡，400 多万感染者登记。因此，非常需要一种诊断这种疾病的系统。肝炎是一种严重的炎性肝病，其原因各不相同，包括病毒感染，酒精和自身免疫系统。提出了几种系统来诊断和分类这种疾病，使用数值，刚性和低水平的方法，如颜色直方图，标准偏差和熵。在我们的研究中，我们通过使用模糊推理系统（FIS）应用模糊逻辑理论，将它们用于语言，灵活和高水平。在本文中，模型通过许多阶段实施，其中应用 3D 离散小波来消除肝脏活组织检查图像中的噪声。然后提取归一化平均颜色直方图（NMCH）作为视觉特征，并使用 45 个模糊 IF-THEN 规则建立 FIS 以诊断肝炎类别。通过计算精度和准确度来评估系统，结果非常准确和有趣。诊断准确度达到 96%，相应的近似时间范围在 0.10-0.15 秒之间。

关键词: 肝炎，肝病，模糊推理系统，模糊逻辑，三维离散小波，归一化均值颜色直方图

I. INTRODUCTION

Hepatitis can be considered one of the most critical infections worldwide, with two billion infected people, and more than four million infections and one million deaths per year [1]. The hepatitis statistics make the need for implementing diagnosis models an urgent necessity. Liver hepatitis can be described by an inflammatory condition of the liver and it can be classified into two kinds, autoimmune and other hepatitis that caused by or a result of alcohol, medications, toxins, and drugs [2], [3].

Many models used for diagnosing medical infections such as data warehousing and OLAP models [4], [5], [6], [7], machine learning algorithms [8], and fuzzy inference systems [9] provided accurate predictions when diagnosing infections. Many techniques are used for liver diagnosis based on imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Technology, biopsy, and Ultrasounds [10]. The important aim of the models is to pre-diagnosis the infection and to find the most factors that cause it in order to prevent it. For liver hepatitis, a biopsy examination is required to determine and diagnose the disease in liver tissue [11]. Although obtaining material for the biopsy can maximize the diagnosis performance, the advantage of liver biopsy over traditional methods of imaging is that a liver biopsy provides very sensitive diagnosis and severity evaluation. [12].

FIS is an expert system based on IF-THEN rules where conclusions and premises are expressed linguistically [13]. FIS is also known as a fuzzy model, fuzzy rule-based system, fuzzy associative memory, or fuzzy controller when the system used as a controller. The basic components of FIS are the Rule base (which holds a number of IF-Then fuzzy rules), the Dataset (jointly with rule base refers to knowledge base, and which defines the membership function that is used by IF-Then rules_, the Decision-making unit (which performs the inference on the rules), Fuzzification unit (which converts the input variables into matching linguistic degrees), and Defuzzification unit (which transforms the results of fuzzy inference into a crisp output) [14]. FIS possesses a good ability to classify, learn, and construct. In this system, fuzzy rule extraction is performed on expert knowledge or numerical data and the rule base is adaptively constructed. In FIS, human intelligence can be tuned to fuzzy systems. The time required for the training structure is the main drawback of the system [15].

One of the most common problems in liver diagnosing systems is that the physicians are unable to get comprehensive and accurate information due to an imprecise dataset. Another problem is the low accuracy of diagnosing results which takes a long time. The proposed model is implemented based on the fuzzy inference system to identify and diagnose liver hepatitis. Model implementation passed through two phases, both offline and online. The offline phase entails the extraction process of visual features for all image datasets in order to implement later comparison. The online phase entails the extraction of the test image and passing these features into a Fuzzy Inference System for diagnosis. The dataset consists of 109 images, 88 images used as a training set, where 21 images are used as a test set. Many other techniques are used in feature extraction such as noise removal, visual feature extraction (converting color space from RGB to HIS, extracting mean color histogram, and mean color histogram normalization). FIS consists of three parts (Fuzzifier, Fuzzy Inference Engine, and Defuzzifier).

The most important concept related to diagnosing is the comparison of the extracted features with the trained features using a knowledge base of all features based on fuzzy inference rules.

The rest of the paper is organized as follow: section (2) presented the literature review and many of related works with some points of criticism. Section (3) presented the proposed model and explained the stages of model implementation and discussed the model evaluation. The final section, listed the concluded points and future works.

II. RELATED WORKS

Ekong, Onibere, and Imianvan [16] presented a model to diagnose liver disorders based on Cluster Means (C-Mean) or Fuzzy Cluster Means (FCM) by analyzing clinical symptoms and blood albumin. Model implementation based clusters includes many analytical decisions steps and methodologies to produces enhanced and valuable clusters. Many unusual and uncertainties data related to clinical data and Liver Functional Test (LFT) test are removed by the proposed model. However, the researchers did not present a performance comparison between their proposed model and other models.

M. Neshat, M. Yaghobi, M.B. Naghibi, and A. Esmaelzadeh [17] designed a system based on

fuzzy logic to diagnose, analyze, and learn of liver disorders. The data used to implement system was chosen form UCI database which included 345 records with 6 fields as input parameters. The liver disorder risk rate is used as system output parameter. The system is compared with other traditional systems of diagnosing and proved its speed, accuracy, and cheapness. Time diagnosing of liver and disorders improvement has been tested and proved its verification with 91%. However more enhancement can be added and more accurate results can be produced in diagnosing liver disorders.

Ibrahim, Olawale, and Funmilayo [18] proposed a model based on an adaptive neuro-fuzzy inference system to use a fuzzy inference system (FIS) and a neural network to learn about information related to hepatitis B based on a normalized dataset. To tune the membership functions (MFs) at the fuzzification stage, the square methods and neural network trigger the back propagation that is used. For the defuzzification stage, the center of area is used to measure the average weight of the intensity level and the fuzzy set of the disease in each record. MATHLAB language is used to implement the model based on a dataset consisting of 20 attributes with 155 records, which holds the most LFTs. Five attributes of LFTs were selected as the input parameters; the intensity level and linguistic values were used as the output parameters to identify the severity level of the infection. The system was evaluated, and the accuracy of the system was found to be 90.2%. However, the model can be further enhanced to obtain more accurate and fast results. The time factor was not included to measure the model performance.

Khaleel Sallam, Abiyev, and Bush [19] proposed an intelligent fuzzy neural system to detect liver disorders, based on neural networks and fuzzy logic. After conducting 10 cross-validation tests and using a dataset extracted from the UCI repository, the model was implemented. The researchers conducted two experiments with two accuracies, 72% and 97%, respectively. This demonstrated that their second experiment based on the proposed model obtained the optimal result. However, more new techniques and machine learning algorithms can be used on new image datasets to produce high accuracy results.

III. The Proposed Method

We have proposed a fuzzy logic-based liver hepatitis diagnosis method in two phases, as shown in Fig. 1:

Offline Phase: In this phase, the visual features of each image in the image dataset are extracted and saved for later use. The total number of liver biopsy images in our dataset is 109: 88 images for training and 21 images for testing. Our image dataset is mainly divided into two major groups, as follows:

1. Non-infectious hepatitis, which has two classes: alcoholic and autoimmune.
2. Viral hepatitis, which has five classes: A, B, C, D, and E.

Online Phase: In this phase, our system is provided with a query image (liver biopsy image) for a patient. Then, the system extracts the visual features from the image and passes it into the proposed FIS to diagnose the hepatitis class of the patient's liver biopsy image.

Our proposed method is explained in detail in the following steps:

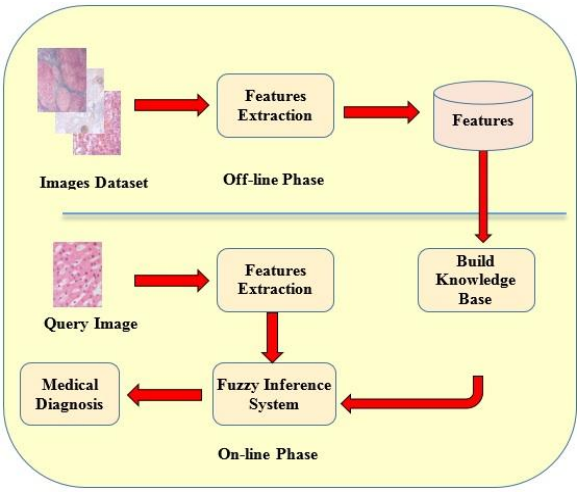

Figure 1. Liver hepatitis diagnosis system.

A. Noise Removal:

Before applying the visual feature extraction algorithm, the query image is analyzed using 3D-Discreat Wavelet to remove the noise and increase the stability of the extracted visual features. A wavelet transform image contains a few large-magnitude wavelet coefficients. Wavelet coefficients, which are small in value, are typically noisy, and the coefficients can be "shrunk" or removed without affecting the signal or image quality [20].

B. Visual Feature Extraction:

This algorithm extracts the visual features (normalized mean color histogram [NMCH]) from the query image in the following steps:

1) Convert the Color Space from RGB to HSI:

The visual features must be presented to the proposed FIS in a linguistic form, not in a

numerical form. The problem is that the RGB color space is not well-suited for describing colors in terms that are practical for human interpretation [21]; consequently, the visual features cannot be described in a linguistic form.

The problem is solved by converting the query image from an RGB color space to a HSI color space, because it is an ideal tool for developing image processing algorithms based on color descriptions that are natural and intuitive to humans [22]. Given an image in the RGB color format, the H, S, and I components of each RGB pixel are obtained using the following equations [21]:

$$H = \begin{cases} \theta if B \le G \\ 360 - \theta if B > G \end{cases} \quad (1)$$

$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}}\right\} \quad (2)$$

$$S = 1 - \frac{3}{(R+G+B)}[min(R,G,B)] \quad (3)$$

$$I = \frac{1}{3}(R+G+B) \quad (4)$$

2) Extracting the Mean Color Histogram:

After converting the image color space, the image is split into three layers, then the color histogram is extracted from each layer, separately. The hue layer has valuable color information; therefore, it is divided into 12 bins. The saturation layer is only divided into three bins. The intensity layer is divided into four bins. The three, color histograms are concatenated into one, 19-bin color histogram, as shown in Fig. 2. Finally, we calculated the mean of all the color histograms for each liver hepatitis class to be used for creating the FIS knowledge base.

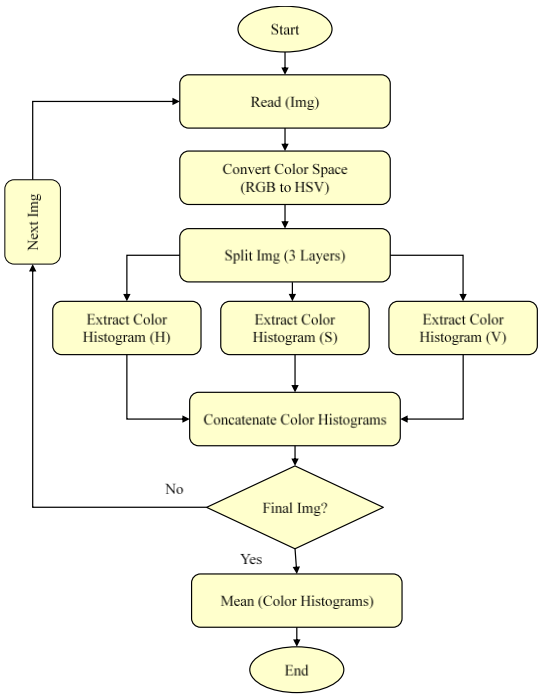

Figure 2. Normalized Mean Color Histogram (NMCH) extraction algorithm.

*3) **Mean Color Histogram Normalization:***

The extracted visual features were spread unregularly, ranging between 0–1. Consequently, these features are not suitable input for the proposed FIS. To tackle this issue, these features should be normalized. We normalized these features in a wide enough range, between 0–10, so they can be easily managed by the proposed FIS using the following equation:

$$Y = \frac{(X-a)(B-A)}{b-a} + A \quad (5)$$

where X, a, and b are the original value and its range, respectively. Y, A, and B are the new value and its range, respectively.

C. The proposed FIS:

An FIS is a method for mapping an input space to an output space using fuzzy logic. It is composed of three components, as shown in Fig. 3 [23]:

a. The fuzzifier contains the MFs used to transform a real-valued variable into a fuzzy set. An MF is a curve that defines how each point in the input space is mapped to a degree of membership ranging between 0 and 1 [24].

b. The fuzzy inference engine contains a knowledge base (fuzzy IF-THEN rules), which is considered to be the heart of the FIS. The fuzzy inference engine evaluates the input information according to the IF-THEN rules created by the user during the programming and design stages of the FIS [25].

c. The defuzzifier transforms a fuzzy set into a real-valued variable.

We have built our proposed FIS in the following steps:

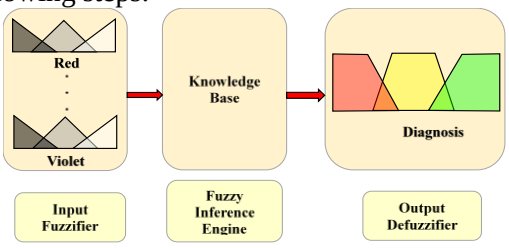

Figure 3. The proposed FIS.

A) Fuzzy Input and Output Variables:

The input to the FIS is the Normalized Mean Color Histogram NMCH. As we explained previously, the NMCH contains 19 bins: 12 bins for Hue layer, 3 bins for Saturation layer, and 4 bins for Intensity layer. Therefore, the FIS consists of 19 input variables, as follows:

- For Hue Layer, there are 12 linguistic variables: Red, Red-Orange, Orange, Yellow-Orange, Yellow, Yellow-Green, Green, Blue-Green, Blue, Blue-Violet, and Violet.
- For Saturation layer, there are 3 linguistic variables: Low-Saturation, Medium-Saturation, and High-Saturation.
- For Intensity layer, there are 4 linguistic variables: Low-Intensity, Medium-Intensity, Medium-High-Intensity, and High-Intensity.

The purpose of building our FIS is to diagnose the hepatitis class of the query image. So, the FIS consists of only one output variable which is called Diagnosis.

B) Fuzzy Membership Functions:

The FIS uses its membership functions to convert the numerical input variables into linguistic variables in order to be ready for fuzzy IF-THEN rules processing and output calculation. We have selected only two types of membership functions (triangular and trapezoidal), because they are the simplest membership functions, which are formed using straight lines that minimize the computational cost of the degree of membership.

$$y = triangle\,(x; a, b, c) = \begin{cases} 0, & x \le a. \\ (x-a)/(b-a), & a \le l \le b. \\ (c-x)/(c-b), & b \le x \le c. \\ 0, & c \le x. \end{cases} \quad \dots (6)$$

The parameters $\{a, b, c\}$ (with $a < b < c$) determine the x coordinates of the three corners of the underlying triangular MF, as shown in Fig. (4).

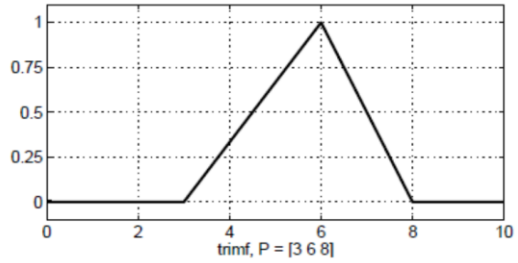

Figure 4. Triangular membership functions.

$$y = triangle\,(x; a, b, c) = \begin{cases} 0, & x \le a. \\ (x-a)/(b-a), & a \le x \le b. \\ 1, & b \le x \le c. \\ (d-x)/(d-c), & c \le x. \\ 0, & d \le x. \end{cases} \quad \dots (7)$$

The parameters $\{a, b, c, d\}$ (with $a < b \le c < d$) determine the x coordinates of the four corners of the underlying trapezoidal MF, as shown in Fig. (5).

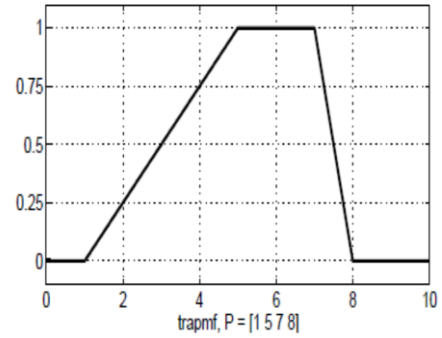

Figure 5. Trapezoidal membership function.

We have constructed 11 triangular input membership functions having the following labels, as depicted in Fig. (6): Nil, Very-Low, Low-Very-Low, Low, Medium-Low, Medium, Medium-High, High, High-Very-High, Very-High, and Full. The FIS consists of 7 trapezoidal output membership functions, as depicted in Fig. (7): Class-A, Class-B, Class-C, Class-D, Class-E, Autoimmune, and Alcoholic.

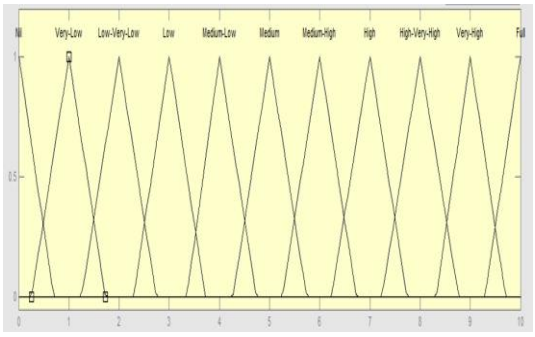

Figure 6. Fuzzy input membership functions.

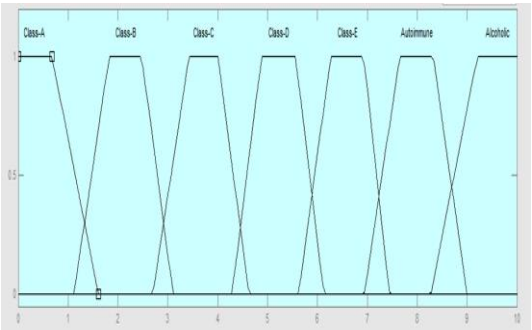

Figure 7. Fuzzy output membership functions.

C) Knowledge Base:

The brain of the FIS is the knowledge base. We have written 45 fuzzy IF-THEN rules by examining the Normalized Mean Color Histogram (NMCH) previously extracted from image dataset of known hepatitis classes in offline phase.

Each NMCH has 19-bins which are entered into FIS, then the degree of membership is evaluated for each membership function in a range between 0 and 1. If the degree of membership is greater than 0, this means that the corresponding membership function is triggered. All triggered membership function are written in "IF-part" of the rules with "AND" operator connecting between them. The hepatitis class of each NMCH is previously known, therefore the output membership function corresponding to that class is written in "THEN-part" of the rules, as illustrated in Fig (8). Some examples are listed below:

- IF (Red is Nil) AND (Red-Orange is Nil) AND (Orange is Nil) AND (Yellow-Orang is Nil) AND … AND (High-Intensity is Full) THEN (Diagnosis is Class-A).
- IF (Red is Nil) AND (Red-Orange is Nil) AND (Orange is Nil) AND (Yellow-Orang is Nil) AND … AND (High-Intensity is High) THEN (Diagnosis is Class-B).
- IF (Red is Nil) AND (Red-Orange is Nil) AND (Orange is Nil) AND (Yellow-Orang is Nil) AND … AND (High-Intensity is Nil) THEN (Diagnosis is Alcoholic).

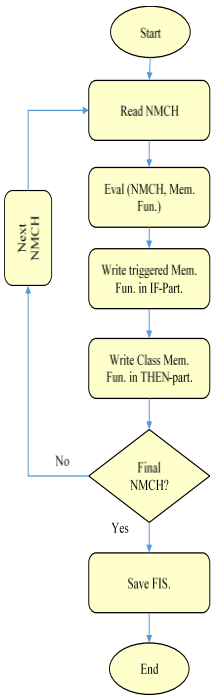

Figure 8. Writing fuzzy IF-THEN rules algorithm.

D) Result Evaluation

In this very important phase, we have calculated the True Positive, False Positive, True Negative, and False Negative of our diagnosis system using Confusion Matrix, as depicted in Table (1).

Table 1.
Confusion matrix with precision for each class

	Class A	**Class B**	**Class C**	**Class D**	**Class E**	**Alcoholic**	**Autoimmune**
Class A	14	1	0	0	0	0	0
Class B	0	11	0	0	0	0	0
Class C	0	0	28	0	0	0	0
Class D	0	0	0	21	0	0	0
Class E	0	0	0	3	3	0	0
Alcoholic	0	0	0	0	0	7	0

Autoimmune	0	0	0	0	0	0	21

The Precision of the diagnosis system for each class, and the Accuracy of the diagnosis system for all classes are calculated from confusion matrix, as illustrated in the following two equations and Table (2).

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positve} \quad \dots (8)$$

$$Accuracy = \frac{\sum_{i=1}^{n} True\ Positive_i}{\sum_{i=1}^{n} (True\ Positive_i + False\ Positive_i)} \quad \dots (9),$$

where *n* and *i* represent the total number and the current number of liver hepatitis classes in the images dataset respectively.

Table 2.
Precision calculations

	Class A	**Class B**	**Class C**	**Class D**	**Class E**	**Alcoholic**	**Autoimmune**
Precision	0.93	1	1	1	0.5	1	1

The accuracy of our proposed system is (0.96). Also, we have made many experiments using Matlab 2016a on Windows 10 system. The corresponding approximated time ranges between: 0.10 – 0.15 second.

IV. CONCLUSION

The diagnosed hepatitis classes include viral hepatitis which holds five classes (A, B, C, D, and E) and non-infectious hepatitis which hold (Alcoholic, and Autoimmune). The proposed model is implemented based on a fuzzy logic technique. This technique is inherent in the nature of hepatitis biopsy images, and human thinking process. As a result, our method has improved the classical methods in the meaning (leverage from low level to high-level measures), processing (moving from statistical calculation to linguistic inference). Many inferred rules are derived for FIS and these rules have been inferred from the Normalized Mean Color Histogram (NMCH). Some NMCH needs only one fuzzy IF-THEN rule because each value of NMCH triggers only one membership function (membership grade = 1). Other NMCH needs up to 8 fuzzy IF-THEN rules because some values of NMCH triggers two membership functions (membership grade ≈ 0.5 for each). Training and testing dataset consist basically of arbitrary images collected from different websites. Finally, the diagnosis accuracy measured throughout approximate test time 0.10-0.15 second with accuracy reaches to 96% which can be considered as promising diagnosing results. The main advantage of the proposed method is the highly accurate results based on non-standard images with a very short time of processing. The high accuracy and short time are the most factors that made this model as proper for the physicians to diagnosing liver hepatitis.

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