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Automated Intelligent Diagnostic Liver Disorders Based on Adaptive Neuro Fuzzy Inference System and Fuzzy C-Means Techniques

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Abstract: Liver disorders are most common in the world in recent times. In this study, an automated intelligent diagnostic approach has been proposed to indicate the liver disease by various sorts and separating facts of the disease using Adaptive Neuro Fuzzy Inference System (ANFIS) and Fuzzy C-Means (FCM) techniques. The data required to study has been chosen by more complex Neuro Fuzzy Model before its inspection on the clinical data. In order to ensure the adeptness of the physician, diagnosing the liver disease and prescribing the absence of sensational ways is very energetic assignment. To make the process more meaningful and scientific a data of about 583 patients, who were undergoing treatment of the doctors in various hospitals, is collected. Since the study includes the detailed information of the patient, so pre-processing was done. The Neuro Fuzzy techniques have been applied over the patient data. The results of these valuation show that Neuro Fuzzy technique can be applied successfully for advising the anesthetic for liver disease patient.

Keywords: AI, ANFIS, FCM, Machine learning, Neuro fuzzy.

I. Introduction

Being a vital organ of the human physique, Liver forms an essential part in the physiological system such as regulation of most chemical levels in the blood, production of bile and certain proteins for blood plasma, clearance of bilirubin, detoxification of blood, etc. But Liver disorders in particular hepatitis, liver tumours, and cirrhosis are progressively increasing over the years and have been emerging as the fifth casual agent resulting in death throughout the world according to National statistics in the UK [1]. Liver disorders are known as the second foremost fatality reason in the midst of gastrointestinal morbidity in the United States [2]. According to the CDC and American Liver Foundation, almost 31,000 people die from cirrhosis and 4000 people die from hepatitis in the US annually [3]. In fact liver disorders claimed 259,749 deaths in India in 2017 [4]. World Health Organization too started Global Burden of Disease (GBD) Project to assess persistent mortality and morbidity rate fluctuating with location, gender and other factors [5].

This alarms an urgent need for the effective timely diagnosis and treatment to mitigate the mortality rate worldwide. Liver disorders can be diagnosed with blood tests, imaging test and tissue analysis. But expected results have not been achieved so far. Soft computing techniques have been promising out as medical expert systems for assisting medical practitioners for accurate diagnosis of the diseases. This paper presents a soft computing technique based on Neuro-Fuzzy System (NFS) for effective diagnosis of liver disorder.

II. Aims and Objective

The main objective of this paper is to present an intelligent diagnostic liver disorder system based on simplified ANFIS and hybrid ANFIS with FCM technique. This paper also aims to evaluate the performance between these two systems.

III. Literature Review

Being a soft computing technique, Neuro-Fuzzy System (NFS) has been emerging an important research domain in medical diagnosis to be used by researchers for various typical disease diagnoses since few years as it can handle the issues, such as nonlinearity, multidimensionality, and vagueness in data. A survey has been done on NFS techniques proposed by various researchers to diagnose various medical diseases.

Mohd Fauzi bin Othman et al. [6] introduced a fuzzy-neural diagnostic system for detection and analysis of medical complications. The main objective of their study was to find out the suitability and performance of FCM classification technique (as compared to the conventional Sub-clustering algorithm) as a classifier in neuro fuzzy model ANFIS for diagnosing diabetes. This system achieved the accuracy of 72.66% as compared to conventional approach that had shown accuracy of 71.09%. *A. Q. Ansari and Neeraj Kumar Gupta* [7] presented an adaptive neuro fuzzy inference system integrated with back propagation learning algorithm for automatic diagnosis of Asthma. *Subhagata Chattopadhyay* [8] also proposed neuro-fuzzy system based on Mamdani's fuzzy logic controller integrated with feed forward back propagation algorithm for the diagnosis of depression. This model predicted accuracy of 95.50% with 100% precision. *R. Sampath and A. Saradha* [9] presented a fuzzy neural diagnostic classifier based on Runge Kutta method to diagnose Alzheimer's disease from MRI images. The proposed approach consists of the steps: pre-processing the MRI images using histogram based thresholding approach, normalization of preprocessed image to MNI standard using SPM2, parcellation of brain scan into 8 ROI using spatial FCM algorithm, feature extraction and classification of features by ANFIS and Runge Kutta learning algorithm. *Geetha C. and Pugazhenthi D.* [10] proposed Fuzzy Neural Network (FNN) diagnostic classifier integrated with Discrete Wavelet Transform (DWT) for automated multiclass diagnosis of Dementia i.e. Alzheimer, Mild Cognitive Impairment (MCI) and Huntington from MRI images. The features derived from MRI images by DWT technique was utilized for the purpose of training a FNN in order to classify the features into three classes like Alzheimer's, Mild Alzheimer's and Huntington's disease. Then proposed DWT with FNN classifier was compared with DCT (Discrete Cosine Transform) with Artificial Neural Network (ANN) and Support Vector Machine (SVM). The proposed system provided better accuracy than ANN.

IV. Methodology

This study presents a Liver disorder diagnostic approach based on *simplified ANFIS* and *ANFIS with FCM*. The dataset for the study has been taken from Kaggle [11] and consists of 583 instances. Each patient record has various clinical parameters as shown in Table I. The data acquired is pre-processed with generalized methods and also normalized with different statistical methods. For achieving the objectives of the study, two main AI techniques i.e. *Simplified ANFIS with subtractive clustering* and *ANFIS integrated with FCM* have been employed. The overall architecture for the proposed methodology is shown in Fig. 1.

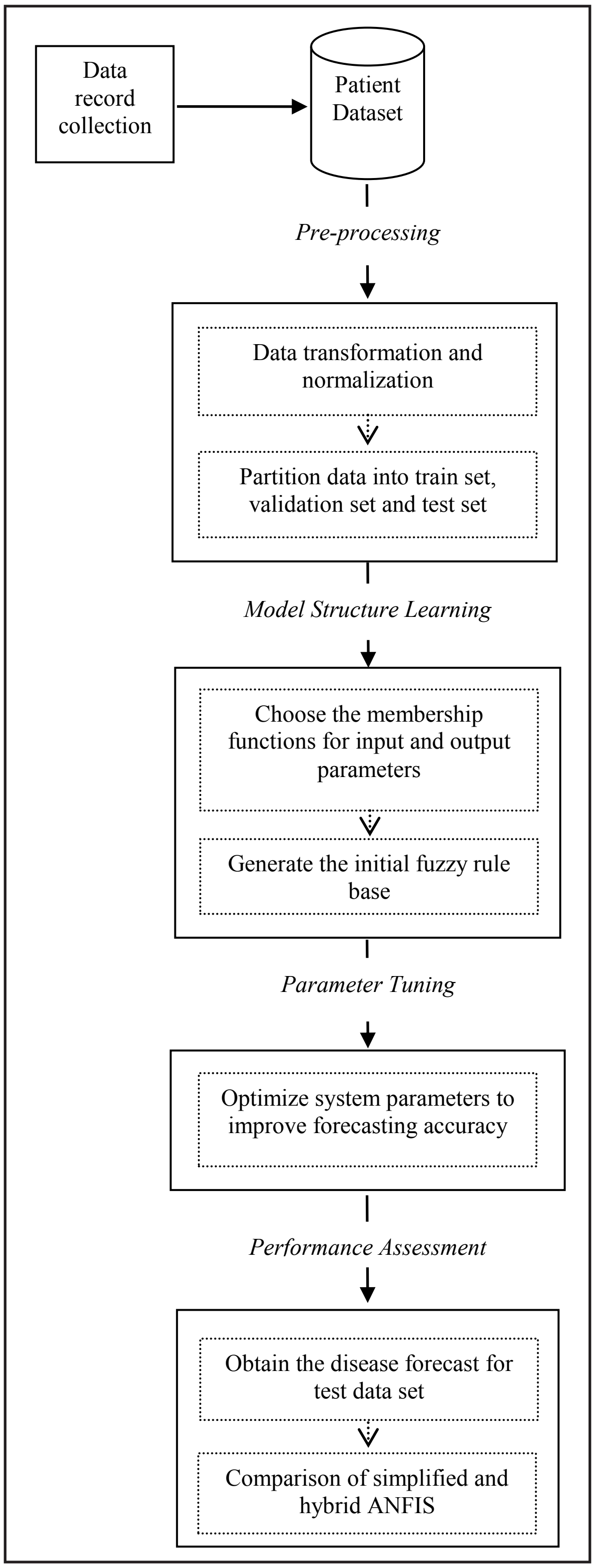

Fig. 1: Architecture of the Proposed System

TABLE I: CLINICAL PARAMETERS IN DATASET

S. No.	Parameter	Description
1	Age	Age of the patients
2	Gender	Sex of the patients
3	Total_Bilirubin	Total Billirubin in mg/dL
4	Direct_Bilirubin	Conjugated Billirubin in mg/dL
5	Alkaline_Phosphotase	ALP in IU/L
6	Alamine_Aminotrans-ferase	ALT in IU/L
7	Aspartate_Amino-transferase	AST in IU/L
8	Total_Protiens	Total Proteins g/dL
9	Albumin	Albumin in g/dL
10	Albumin-Globulin Ratio	A/G ratio

A. Adative Neuro Fuzzy Inference System (ANFIS)

Neuro-fuzzy system is a machine learning technique introduced to get better a fuzzy system automatically by exploiting the learning algorithms from neural network. It integrates the human reasoning ability of fuzzy logic and learning capability of neural network for tuning the parameters of fuzzy logic. The framework of NFS is shown in Fig. 2. In this architecture, the fuzzy interface accepts the input in the form of linguistic statements and generates the vector to be given to neural network that can be trained by learning algorithm to yield desired decisions. In this study, linguistic statements are given in the form of if-else rule base that will be generated by Fuzzy Inference System (FIS) and hybrid learning algorithm is implemented and the final decision to be taken is whether the patient has liver disease or not.

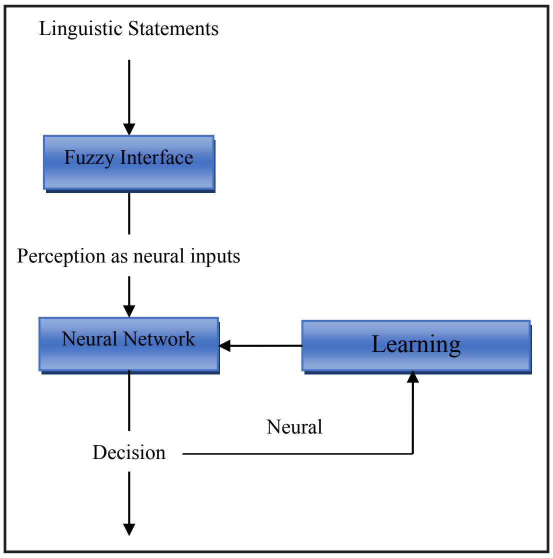

Fig. 2: Framework of Neuro-Fuzzy System

NFS can be implemented in various architectures like ANFIS, FALCON, GARIC, FINEST, etc. But ANFIS is mostly preferred architecture as it can be applied to different practical applications in varied areas of optimization and forecasting as it provides better prediction [12]. It can also approximate non-linear function with numerous input and output parameters due to which it is recognized as universal approximator or estimator. Adaptive Neuro-Fuzzy Inference System (ANFIS) is a five-layered architecture as shown in Fig. 3 and described mathematically as under:

Consider two inputs x and y and one output Z with two fuzzy if-then rules defined as under:

Rule 1: If x is A_1 and y is B_1, then $Z_1=p_1x + q_1y + r$

Rule 2: If x is A_2 and y is B_2, then $Z_2=p_2x + q_2y + r_2$

Let A_k, B_k (k = 1, 2) be two fuzzy sets in the antecedent, and p_k, q_k, r_k (k = 1, 2) are the design parameters that are to determined during the training process using learning algorithm. In this work, *hybrid learning* method has been used.

Layer 1: every k^{th} node is an adaptive node and performs fuzzification operation on linguistic variables:

$$O_k^1 = \mu_{Ak}(x), \qquad k=1, 2$$

$$O_k^1 = \mu_{Bk-2}(y), \qquad k=3, 4$$

where, μ( ) is the any fuzzy membership function. It can be Bell shaped, Gaussian function or any other function depending upon the problem to be solved. In the current study, Gaussian membership function has been used.

Layer 2: The firing strength of a rule for each k^{th} unit in this layer is calculated by multiplying the input signals and the output is provided as:

$$O_k^2 = W_k = \mu_{Ak}(x).\ \mu_{Bk}(y), \qquad k=1, 2$$

Layer 3: This layer performs the normalization on the firing strengths of each unit as:

$$O_k^3 = \overline{W_K} = W_K / (W_1 + W_2), \qquad k=1, 2$$

Layer 4: This layer evaluates the following expression for each unit as:

$$O_k^4 = \overline{W_K}.\ Z_k = \overline{W_K}.\ (p_k x + q_k y + r_k) \qquad k=1,2$$

Layer 5: The final output is calculated as:

$$Z = O_k^5 = \sum \overline{W_K}.\ Z_k$$

$$Z= \sum \overline{W_K}.\ (p_k x + q_k y + r_k) \qquad k=1,2$$

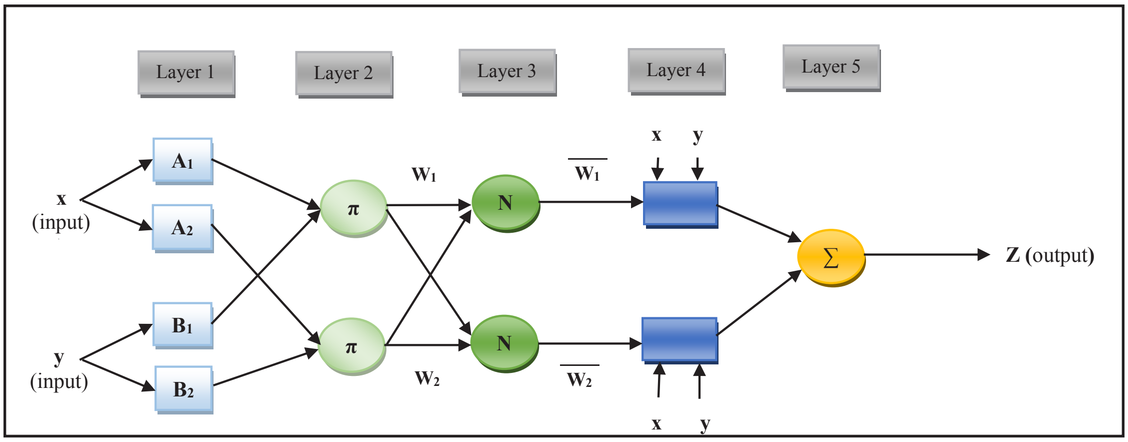

Fig. 3: ANFIS Architecture

B. Fuzzy C-Means (FCM)

The Fuzzy C-Means (FCM) is a clustering algorithm developed by Dunn and later on improved by Bezdek, in which every data point in the data set fits to many clusters but with different probabilities of membership (instead of fitting to only one cluster as in other clustering techniques) [13]. For each datum, the summation of the probabilities of membership for all clusters should be one. This algorithm consists of the steps: randomly choose the cluster centers, calculation of fuzzy membership function, computation of fuzzy center and repeat the 2nd and 3rd steps until minimum value of J_p is achieved.

For each iteration, FCM tend to minimize the following objective function:

$$J_p = \sum_{x=1}^{N}\sum_{y=1}^{M} \mu_{xy}^{p} z_x - d_y{}^2$$

where,

N represents total number of records in the data set, M points to number of clusters and p represents the fuzzy partition matrix exponent in order to regulate the fuzzy overlap grading, with $p > 1$. Fuzzy overlap represents how fuzzy the boundaries between clusters are, that is the number of data points that have significant membership in more than one cluster.

Z_x is the x^{th} datum or the record whereas d_y points to center of the y^{th} cluster. μ_{xy} represents degree of belongingness of z_x datum to y^{th} cluster.

||*|| represents norm operation computing the similar relationship between any measured data and the center of the cluster [13].

V. Result and Discussion

To attain the objectives of the study, the experiments in Matlab 2013a have been performed. Firstly, the Liver diagnostic system has been implemented using simplified ANFIS with 10 input parameters and 01 output parameter and 08 rules have been generated. The ANFIS model generated is shown in Fig. 4 and the parameters values for this model are presented in Table II.

In second phase of the study, the diagnostic system for liver disorder has been implemented using ANFIS with FCM and it resulted in 8 input parameters and 01 output parameter and 08 rules have been generated. The error occurred in training and testing phases for both simplified ANFIS and integrated ANFIs with FCM is shown in Fig. 5, 6 and 7. Finally, the performance results for both the techniques are presented in Table III.

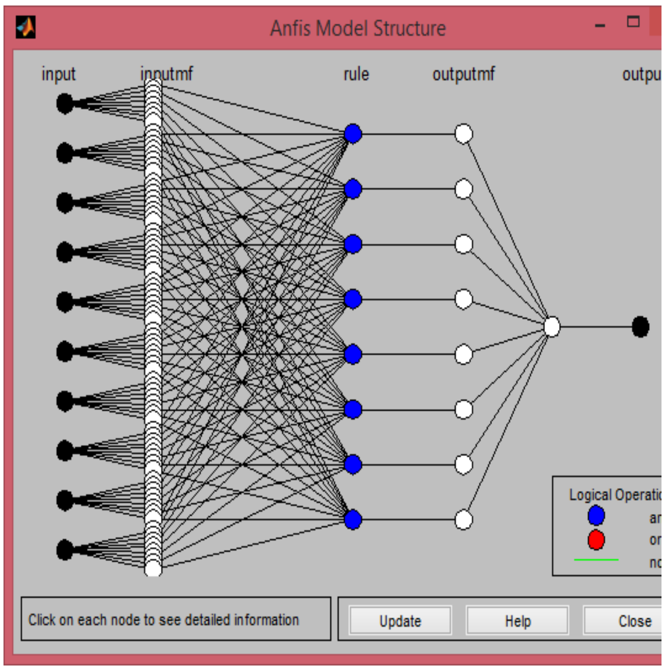

Fig. 4: ANFIS Model

TABLE II: PARAMETERS FOR ANFIS MODEL

Parameter	Value
Type	Sugeno
AND Rule	prod
OR Rule	Probor
Membership Function	Gaussian
Implication Rule	prod
Aggregation Rule	Max
De-fuzzification Rule	wtaver
Input	[1 x 10] struct
Output	[1 x 1] stucut
Rule	[1 x 8] struct
Learning Rule	Back propagation and least square method

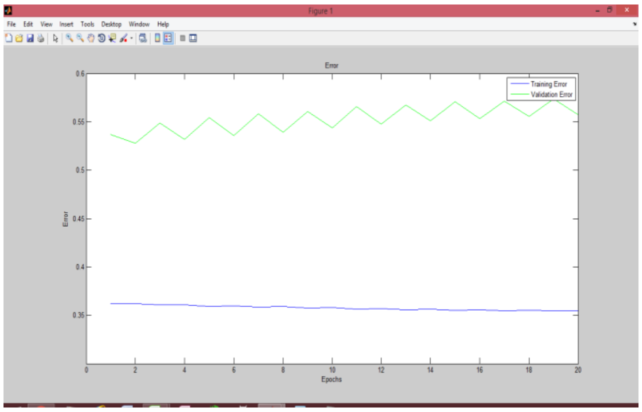

Fig. 5: Error Plot During Training and Validation Phase Using ANFIS

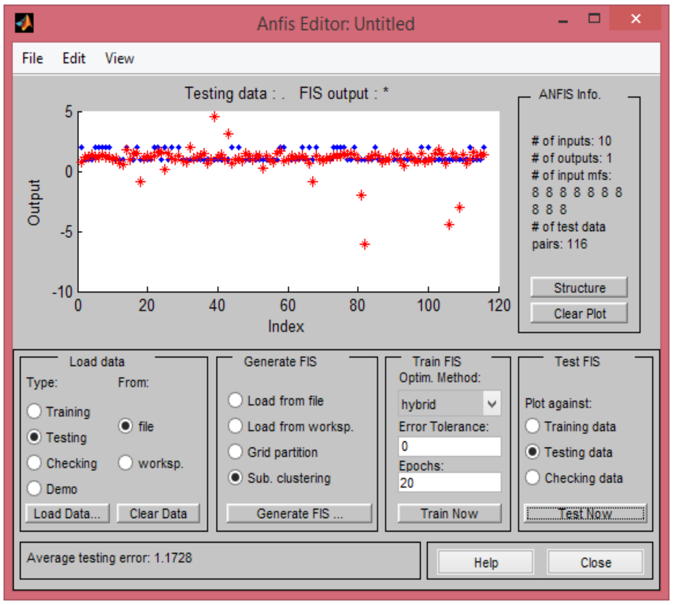

Fig. 6: Error Plot During Testing Phase Using ANFIS

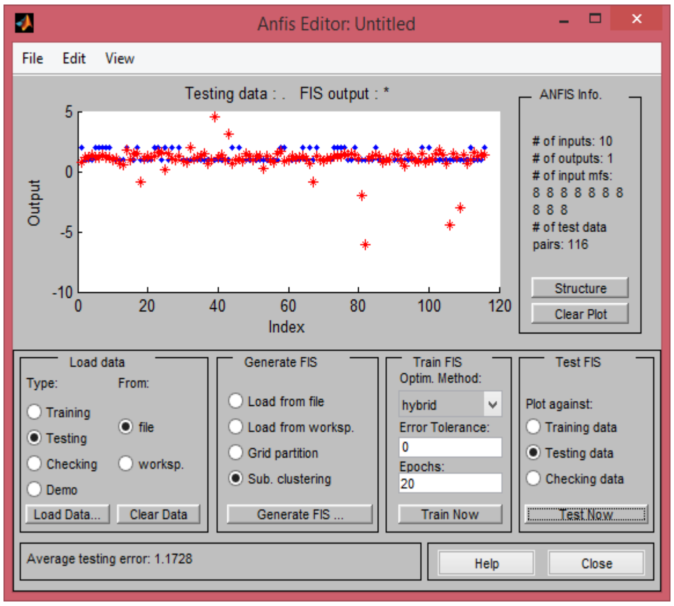

Fig. 7: Error Plot During Training Phase Using ANFIS with FCM

TABLE III: EVALUATION OF SIMPLIFIED ANFIS WITH ANFIS INTEGRATED WITH FCM

Error	ANFIS	ANFIS with FCM
Training RMSE	0.355	0.3877
Validation Error during training	0.5278	0.4869
Validation error during testing	.57394	0.4636
Testing RMSE	1.1728	0.4414

VI. CONCLUSION

In this work, it has been found out that the proposed methodology is able to diagnose the liver disorder with better accuracy. It can also be seen that the performance of a hybrid model of ANFIS is better than simplified ANFIS model. The experimental results show that the proposed hybrid technique ANFIS with FCM have a high accuracy in terms of error in predicting the liver disease on the liver disease dataset. We can use such hybrid techniques for other disease datasets as well as for health care issues too.

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