Diagnosis of Hepatitis using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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ABSTRACT
Hepatitis B is one of the liver diseases that is difficult to discover at an early stage of its attack and prominent public health problem. As at 2017, medical statistic recorded that over 23 million of Nigerians were living with Hepatitis B. Several decision support systems used in diagnosing liver diseases derived their efficiencies from artificial intelligence techniques in tackling the challenges facing physician in respect to complexity of the numerous variables involved in liver diseases diagnosis. In this paper, Adaptive Neuro-Fuzzy Inference System (ANFIS) was employed to invoke neural network that provided structures for fuzzy inference engine (FIE) in order to learn information about the normalized dataset on hepatitis B. The neural network (NN) triggers backpropagation and least square methods for tuning the membership functions at the fuzzification stage while the center of area (COA) was used as defuzzification method to compute the weighted average of the fuzzy set and intensity level of the disease for each record. The system was implemented with technical computing language, MATHLAB, on a dataset that consists of 155 instances and 20 attributes of which only the most five liver function tests (LFTs) attributes were selected as input parameters and the corresponding linguistic values and intensity levels were generated as output in order to identify the severity level of the infection. After the system was evaluated, the performance metric gave accuracy of 90.2%.

General Terms
Neural Networks, Fuzzy Logic, Linguistic Values, Liver Function Test, Adaptive Neuro-Fuzzy Inference System

Keywords
Hepatitis B, Intensity Level, Decision Support System

1. INTRODUCTION
The relevance of intelligence systems in medical diagnosis is tremendously increasing. Information taken from patients and decisions of experts are the most important factors in diagnosis of diseases (Neshat and Zadeh, 2013). The increase in scientific knowledge and computer technology is of great benefits to medical practitioners, in diagnosing life-threatening diseases and administering treatment for patients. The most commonly known liver disease, hepatitis B is a condition when a liver is inflamed as a result of viral infection. Among the possible causes are wrong intake of medications and drugs, toxins, and excessive alcohol. Hepatitis B could also be transmitted through infectious body fluids and sexual intercourse with infected person (Friedman, 2004).

Artificial intelligence in medicine is essentially concerned with the development of artificial-based techniques programs that relate disease entities with patients' symptoms in form of a model in order to provide a basis for series of diagnosis and precise therapy recommendations for medical management. Numerous researches have shown that, the most successful applications in artificial intelligence (AI) are clinical decision support system used to diagnose patients with liver and kidney related diseases (Neshat and Yaghobi, 2009).

Neuro-fuzzy is an integral aspect of artificial intelligence, which combines the strength of neural network and fuzzy logic together by utilizing the approximation method of neural-network to compute the parameters of a fuzzy system (Obi and Imianvan, 2011). Obviously, medical field has explored a quite number of techniques and methods provided by artificial intelligence for emergency care units and surgical operations Yardimci (2001). Several researches have been conducted on fuzzy-based expert system for diagnosis of diseases while neural network models have also been explored by experts for prediction and classification of liver diseases diseases.

The task of disease diagnosis and management is complex because of the numerous variables involved. The traditional method of diagnosing liver diseases is characterized with a lot of subjective decision-making, and logical thinking of medical practitioners, which lead to inappropriate use of inefficient tool (Smita et al. 2012). One of the key problems encountered in the medical field during the course of delivering proper diagnosis of liver disease is the inability of the physicians to derive comprehensive information as a result of available imprecise medical data set.

Therefore, in this paper, an Adaptive Neuro-Fuzzy Inference System (ANFIS) based model is being used to develop architecture model as problem solving for classifying and determining the intensity levels of hepatitis liver disease. The main objectives are to implement and evaluate the proposed architecture model with performance metrics. The general architecture of ANFIS as a classifier model is presented in Section 2. In Section 3, few related works regarding the use of Neural Network, Fuzzy Logic and Neuro- Fuzzy model based architecture in diagnosing liver diseases are reviewed. while the methodology adopted for the proposed architecture model is systematically presented in Section 4. In section 5, the metrics used to evaluate the performance of the proposed model are presented while the implementation and discussion of results are drawn in section 6.

2. OVERVIEW OF ANFIS ARCHITECTURE MODEL
ANFIS adopt a neural network technique that can adjust the membership functions parameters and linguistic rules directly from data in order to enhance the system performance. The ANFIS architecture contains a five-layer feedforward neural

network as shown in Figure 1. ANFIS is a hybrid intelligent system which implements a Sugeno fuzzy inference system for a systematic approach to generating fuzzy rules from a given input-output dataset (Negnevitsky, 2005).

In the forward pass, neuron outputs are calculated layer by layer and the consequent parameters are identified by the least squares estimator (LSE) to obtain the final single output. The forward pass operation on each layer is described below:

Layer 1: Known as a fuzzification layer, define the membership grades for each set of input and depends on the fuzzy membership function chosen. For example, Gaussian MF the output of the ith node of Layer 1 is

$O_{1,\,i} = \mu_{Ai}(x) = \exp\left(-\frac{1}{2}\left(\frac{x1-\mathrm{ci}}{\sigma i}\right)^2\right)$

Where the parameter $\{\ \sigma i, ci\ \}$ is called a premise parameter set, the centre and width of the ith fuzzy set A_i, respectively.

Layer 2: Is the output nodes are the firing strength of the rule as the product of the membership grades.

$O_2,\ i = w_i = \mu_{Ai}(x1) * \mu_{Bi}(x2)$

Layer 3: This is called the 'normalised firing strengths', where the output of the ith nodes equals the ratio of the ith rule's firing strength to the sum of all rules' firing strength.

Layer 4: i^{th} nodes output is

$O_4,i = \ddot{w}_i f_i = \ddot{w}(p_i x + q_i y + r_i)$

where p, q, and r is a set of consequent parameters which can be identified using the Least Square Estimation (LSE).

Layer 5: The single output, calculates the overall output as the summation of all incoming signals, represented as

$O_5,i = \sum_i \ddot{w}ifi$

The LSE is used to minimise the squared error $\| AX - B\|^2$, where A is the outputs produced by Layer 3, B is a target output and X is the unknown consequent value which can be obtained using pseudo-inverse of X:

$$X^* = (A^T A)^{-1} A^T B$$

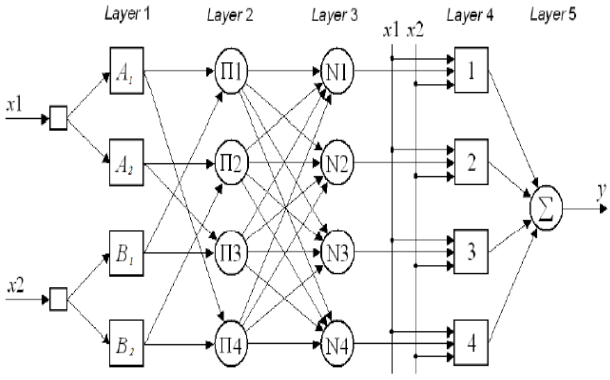

Figure 1: Adaptive Neuro-Fuzzy Inference System (Jang, 1993)

3. REVIEW OF RELATED WORKS

There is no doubt about the numerous researches that have been carried out in the area of artificial intelligence in medicine. A tremendous advancement in software and hardware industries has provided opportunities for computer scientist researchers to explore every aspect of artificial intelligence methods and techniques in building relevant systems, and devices for medical practioners. Karthikkalyan (2014) demonstrated a framework built with ANN and multilayer perceptron that classified liver diseases with improved accuracy performance. The model inputs were obtained from liver ultrasound images and employed MLP to detect the traits of any liver disease. In the study, the training of the dataset yielded 90% while testing validation yielded 95%. Olaniyi and Adnan (2013) designed an artificial neural network based model that used back propagation neural network based model that used backpropagation method of 10 hidden neurons and radial basis neural network of 20 hidden neurons, with only 6 inputs and one output to diagnose liver diseases into healthy and unhealthy liver. The dataset was obtained from BUPA in UCI Machine Learning Repository and the proposed model achieved 63% accuracy using backpropagation and 70% accuracy using radial basis technique. A similar work was proposed in Bahramirad et al. (2013), with the same input attributes and technique, the accuracy of 73% and 67% were obtained for radial basis and backpropagation technique respectively.

A group of patients CT liver images was evaluated in Obayya et al (2016) ANFIS model that was used to classify liver tumor as benign or malignant. In their work, the CT liver images passed through various transformation stages such as; enhancement and improvement of image quality as the first stage, the use of extraction algorithms based on thresholding for extraction of liver as the input for the fourth stage where the ANFIS classifier trained the extracted features using back propagation gradient descent method and least square method. The two types of features i.e (texture feature and discrete wavelet transformation) were used separately to evaluate the performance of the model. DWT features recorded 96% accuracy while the texture feature obtained an accuracy of 90%. In the proposed Adaptive Neuro Fuzzy Inference System (ANFIS) of Rajamani and Rathika (2015), the primary objective of the model was tailored toward detection of liver cancer in patients with the help of 2-D CT images as input parameters through ANFIS algorithm to generate final optimal result. The summary of other related works are presented in Table 1. Deductions from the reviewed literature are as followed;

i. The hybridized models have better accuracy performance than individual technique base models.
ii. Most of the output of the existing models only classified as the presence or absence of liver disease.

The computation of the intensity levels of the identified liver diseases are ignored in the existing models which serve as a notable gap found in the existing paper.

4 THE METHODOLOGY FOR THE PROPOSED MODEL

The adopted methodology for this study is divided into three major phases:

A. Dataset description
B. Linguistic variables definition

C. Preprocessing of linguistic values (Input parameters)
D. Neuro-Fuzzy engine i.e. ANFIS
- Fuzzy engine
- Neural Network (NN)

The proposed architecture model is presented in Figure 2. In Fig. 2, the liver function test in the dataset for hepatitis disease is normalized in order to re-scale the selected five attributes values in the dataset into the range of 0 and 1 through normalization function. Specific percentage values are assigned independently for both training and testing data before the ANFIS invokes neural network (NN) to provide structures for fuzzy inference engine to learn information about the normalized data. The neural network triggers backpropagation and least square methods in order to tune the Gaussian membership function at the fuzzification stage to design fuzzy set for the linguistic variables. The rule-base combines the effort of fuzzy inference engine to modify the input linguistic variables. At the output stage , center of area COA is used as deffuzification method to calculate the weighted average of the fuzzy set and convert the linguistic output to crisps for computation of intensity levels of the disease.

4.1 Dataset Descriptions

The dataset for Hepatitis B was obtained from Carnegie-Mellon University database, Yugoslavia. It was donated by Jozef Stefan Institute. It consists of 20 attributes having total number of 155 instances. For the purpose of this research, the interpretation and analysis of the five selected attributes was carried out by hematologists. The five attributes used as input parameters are Ascites, Bilirubin, Alk-Phosphate, SGOT, and Albumin while Histology attribute was used as output. The output field is classified as mild and severe.

4.2 Linguistic Variables with Range Limits and Corresponding Values

The input variables are important parameters of the dataset which are investigated to form basis for disease diagnosis. In this study, two medical experts that specialize in liver disease diagnosis, offered assistance in analyzing the attributes in the dataset and designed fuzzy membership expressions for hepatitis as presented in Table 2.

4.3 Preprocessing of linguistic values (Input parameters)

Transformation of attributes values into more meaningful values that can sustain and maintain numerical stability to produce best optimal solution is highly needed before the commencement of simulation on those data. This process is referred to as Normalization. It is essential to re-scale all the attributes values in the dataset into the range of 0 and 1 by using the formula below:

$$X_{new} = ((X - X_{min}) / (X_{max} - X_{min}))$$

Where x = the real value in the column

x_{min} = the lowest value in column

x_{max} = the highest value in the column

x_{new} = the normalized value

4.4 Neuro-Fuzzy engine i.e. ANFIS

The proposed model adopted ANFIS The combination of advantages of neural-network and fuzzy system are integrated to produce hybrid system that can learn, adapt and deal with large amount of imprecise numerical data.

Algorithm Header: ANFIS_Components ( )

The ANFIS-based algorithm developed for the proposed model is given below

Step 1: Input FIS parameter parameters: mf, mftype, epochMax, errorGoal, iniStep

```
no_mf := 3
mf_type := gaussmf
epoch_max := 200
error_goal := 0
initial_step_size := 0.01
```

Step 2: Execution of normalization function by using Equation below

$$X_{new} = ((X - X_{min}) / (X_{max} - X_{min}))$$

Step 3: Input percentage value for training dataset and testing dataset

Step 4: Neural Network is invoked to provide structures for Fuzzy Inference Engine FIS to learn information about the normalized dataset.

Step 5: NN will triggers backpropagation algorithm and least square methods to tune membership functions at the fuzzification stage

Step 6: The rule-base combines the effort of FIS to modify the input linguistic variables while Gaussian membership function is used to design the fuzzy sets for the variables as presented in equation below

$$\mu_{Ai}(x) = \exp(-((c_i - x)^2 / (2\sigma_i^2))$$

Where c_i represents the centre, ∂_i represents the width of the ith fuzzy set A^i

Table 1: Overview of AI techniques used for liver diagnosis

S/N	Authors	Years	Input Parameters	Methods Or Technique	Output Descriptions	Accuracy %
1	Ayushi et al.	2017	LFT(Liver Function Tests)	SVM (Support Vector Machine	Presence & Non-presence of hepatitis	83.16
		2017		KSVN (Kernel Support Vector Machine)		85.16
		2017		KKNN		84.14
2	Vaidya et al.	2017	LFTs	Neuro-Fuzzy	Healthy & Non-healthy of liver	Not considered
3	Ferokhzad & Ebrahimi	2016	LFTs	Neuro-Fuzzy (ANFIS)	Healthy & Non-healthy of liver	83

4	Obayya et al.	2016	LFTs	ANFIS	Healthy & Non-healthy of liver	90
5	Cetin et al.	2015	LFTs	ANN (Artificial Neural Network)	Presence & Non presence of hepatitis	91.9
6	Rajamani and Rathika	2015	LFTs	ANFIS	Prediction of presence liver cancer	Not considered
7	Satarkar & Ali	2014	LFTs	Fuzzy Logic	Classification of cirrhosis disease into (low, immediate, high)	Not considered
8	Kulluk et al.	2013	LFTs	ANN and FL	Healthy & Non-healthy of liver	85.6
9	Olaniyi & Adnan	2013	LFTs	ANN	Healthy & Non-healthy of liver	63.0
10	Chang et al.	2010	LFTs	Integration of CBR, DM, FL and GA	Healthy & Non-healthy of liver	81.6
11	Li & Liu	2010	LFTs	ANN and FL	Presence & Non presence of hepatitis	70.78
12	Atiya et al.	2009	LFTs	KNN	Presence & Non presence of hepatitis	75
13	Neshat & Yaghobi	2009	LFTs	ANFIS	Presence & Non presence of hepatitis	96.4
14	Neshat et al.	2008	LFTs	FL	Presence & Non presence of hepatitis	91.0

Step 7: Membership functions and associated parameters map inputs through the output membership function and associated parameters to output.

Step 8: Gradient vector facilitated adjustment of the parameters associated with membership functions to enhance effective modeling of input/output data for every set of specific parameters.

Step 9: Deffuzifier uses equation below to convert the linguistic output to crisps. Center of Area or Centroid (COA), COA method was adopted to calculate the weighted average of the fuzzy set in the system

Step 10: Algorithm terminates

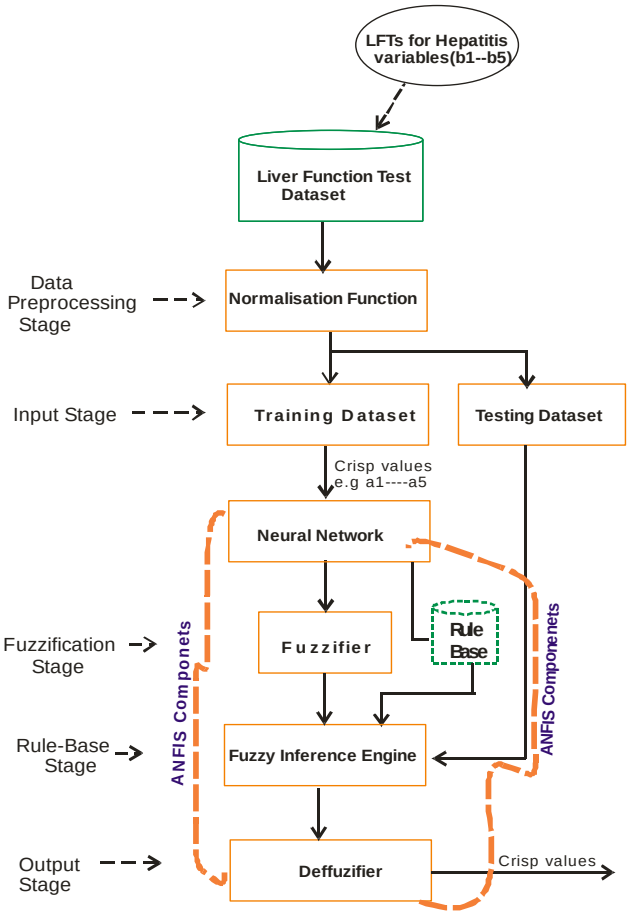

Fig. 2: ANFIS-Based Architecture Model for Diagnosis of Hepatitis B disease

Table 2: Description of linguistic variables for Hepatitis B

S/N	Input Variables	Description	Moderate	Severe
1	Total Bilirubin	Blood test to measure abile pigment cleared from the blood by the liver	$11 \leq X \leq 45$	$45 < X$
2	Alk-Phosphates	Test to measure quantity of blood protein found in bile duct cell membranes.	$40 \leq X \leq 60$	$60 < X$
3	SGOT	Test to measure enzymes that catalyze protein transformations within hepatocytes	$30 \leq X \leq 50$	$50 < X$
4	Albumin	Test to measure a protein in the serum that transports substances.	$28 \leq X \leq 35$	$28 > X$
5	Ascites	Clinical test to examine if liver is perfectly working.	$1 \leq X \leq 4$	$4 < X$

5. METRICS USED TO EVALUATE THE MODEL PERFORMANCE

The performance of the developed model, GADMLD, is evaluated by using confusion matrix. Confusion matrix is used in order to predict the number of correct and incorrect prediction made generated by the model when compared to the actual outcomes (target value) in the data.

a. TP (True Positive): When the outcome is appropriately classified as positive when it is really positive.

b. TN (True Negative): When the outcome is appropriately classified as negative when it is really negative.

c. FP (False Positive): When the outcome is incorrectly classified as positive when it is really negative.

d. FN (False Negative): When the outcome is appropriately classified as negative when it is really positive.

e. Accuracy: This is the measure that gives the proportion of the total number of predictions that were correct.

f. Precision: This is the proportion of positive cases that were correctly identified.

g. Sensitivity: This refers to the proportion of actual positive cases which are correctly identified.

h. Specificity: This explains the proportion of actual negative cases which are correctly identified.

6. IMPLEMENTATION AND DISCUSSION OF RESULTS

6.1 Implementation

The architecture model was simulated with MathLab 2015 version. Out of 164 total data used, only 40% of 164 (66) are used for training. After it was trained for 200 epochs, the following results are generated and also indicated in Figure 3.

MSE (Mean Square Error) = 0.11768
RMSE (Root Mean Square Error) = 0.34305
Error Mean = -3.143e-005
Error St.D = 0.34567

The MSE is interpreted as the measure of closeness of an output line to the specified data point (target line). The RMSE is computed as an average of distance between the target line and output line along the vertical line while the Error Mean measures the accuracy of the model.

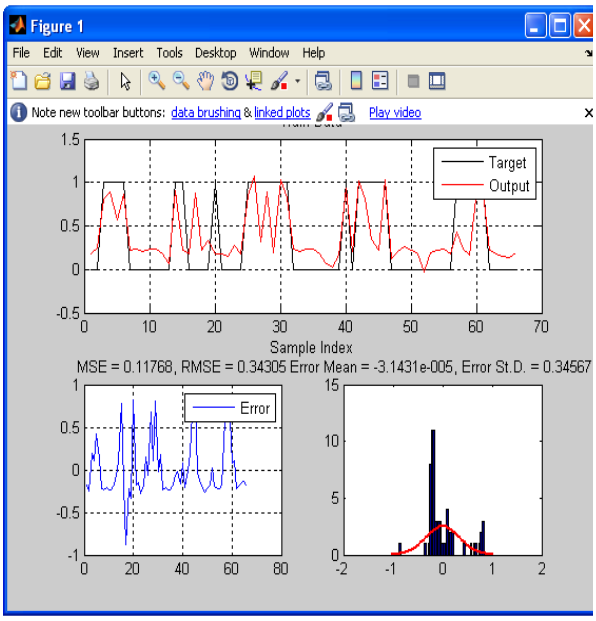

Fig. 3: Graph of Simulation Result of Hepatitis Dataset Training

60% of the total numbers of 164 records (i.e. 98 records) in the dataset were selected randomly for testing and evaluating the proposed model, the simulated graph result is presented in Fig. 4. The following results are generated as follows;

MSE (Mean Square Error) = 0.28756
RMSE (Root Mean Square Error) = 0.53625
Error Mean = 0.1215
Error St.D = 0.52498

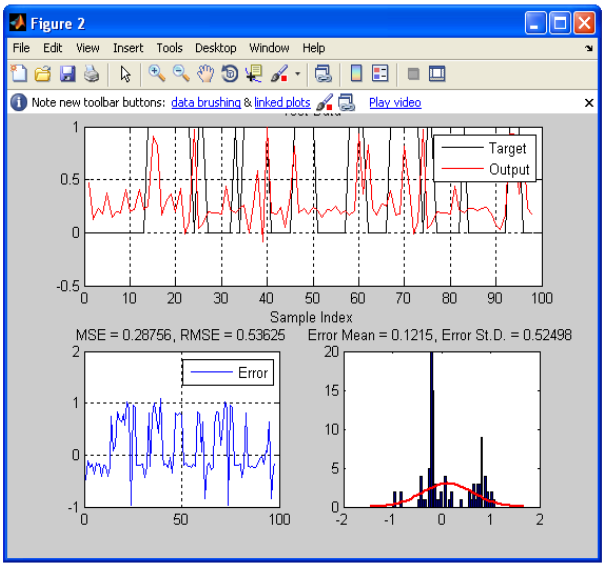

Fig. 4: Graph of Simulation Result of Hepatitis Dataset Training

6.2 Discussion of Results

In the course of simulation, 66 records were subjected for training the model, the output-target-error result generated is presented in Table 3 while 98 records were used to test the model and its output-target-error result is equally shown in Table 4 and Table 5 depicts the final output which generates Linguistic Value, Further Linguistic Value and Intensity Level.

It is clearly presented in Table 5 that out of 56 records of patients that have moderate hepatitis B infection, only 26 of them have moderate-low while 30 patients have moderate-high. Total number of 38 patients has severe infection, only 12 of them have severe-low and 26 patients have severe-high. This provides decision support services for doctors and medical practitioners for best optimal treatment to be administered on such patients. The 90.2% accuracy of the model obtained justifies the efficiency of ANFIS technique in building a medical decision system support for liver diseases diagnosis.

From Table 6, the original input parameters are the following attributes; Ascites, Bili, AlkPho, Alb, and SGOT. "Stage" as an attribute is the output classified as "1" and "2", where "1" represents moderate and "2" represents severe. Each record has its own input parameters and corresponding output. After the simulation, the extent of the infection is generated for clarity and to remove imprecise information. For Example, record 1 and record 6 have the same Further Linguistic values of "Moderate High" but the Intensity Level of record 1 is 9.1857 and record 6 has 2.2268, likewise for record 14 and record 15.

Table 3: Result on Dataset-Training

S/N	TARGET	OUTPUT	ERROR
1	0	0.172052829	-0.172052829
2	0	0.245701077	-0.245701077
3	1	0.810972348	0.189027652
4	1	0.89484333	0.10515667
5	1	0.57252434	0.42747566
6	1	0.87038497	0.12961503
7	0	0.227101621	-0.227101621
8	0	0.229706666	-0.229706666
9	0	0.207872243	-0.207872243
10	0	0.229121639	-0.229121639
11	0	0.240717178	-0.240717178
12	0	0.172564037	-0.172564037
13	0	0.070823708	-0.070823708
14	1	0.908139745	0.091860255
15	1	0.220518428	0.779481572
16	0	0.181018529	-0.181018529
17	0	0.877377191	-0.877377191
18	0	0.219340721	-0.219340721
19	0	0.338961716	-0.338961716
20	1	0.178932845	0.821067155
21	0	0.173962716	-0.173962716
22	0	0.147404718	-0.147404718
23	0	0.27752971	-0.27752971
24	0	0.174462961	-0.174462961
25	1	0.847957056	0.152042944
26	1	1.067108052	-0.067108052
27	1	0.321949661	0.678050339
.	.	.	.
.	.	.	.
66	0	0.19478625	-0.19478625

Table 4: Result on Dataset-Testing

S/N	TARGET	OUTPUT	ERROR
1	0	0.470348439	-0.470348439
2	0	0.119738724	-0.119738724
3	0	0.233716924	-0.233716924
4	0	0.181760125	-0.181760125
5	0	0.371633188	-0.371633188
6	0	0.143992788	-0.143992788
7	0	0.193501173	-0.193501173
8	0	0.184739691	-0.184739691
9	0	0.406187582	-0.406187582
10	0	0.20111305	-0.20111305
11	0	0.214241352	-0.214241352
12	0	0.406953462	-0.406953462
13	0	0.217521825	-0.217521825
14	1	0.248443324	0.751556676
15	1	0.912254832	0.087745168
16	1	0.830294022	0.169705978
17	1	0.16598022	0.83401978
18	1	0.315385802	0.684614198
19	1	0.360653132	0.639346868
20	1	0.202366181	0.797633819
21	1	0.416180083	0.583819917
22	1	-0.015170608	1.015170608
23	1	0.104887081	0.895112919
24	0	0.977267874	-0.977267874
25	1	0.039368997	0.960631003
26	1	0.081119359	0.918880641
27	0	0.199326506	-0.199326506
.	.	.	.
.	.	.	.
98	0	-0.161426438	0.161426438

In Table 3 and Table 4, the difference between the Target value and Output value which is computed as Error in each record is mostly found to be 0.1. These are minimal errors that justify better performance of the model.

Table 5: Summary of Cumulative Intensity Rate for Hepatitis

		Low	**High**	
Hepatitis	**Moderate**	26	30	Total = 98
	Severe	15	26	

The performance of the proposed model based on the metrics used is presented in Table 7. The accuracy of 90.2% was obtained after evaluation with the liver disease dataset.

Table 6: Final Simulated Result for Testing-Records

S/N	**Ascites**	**Bili**	**ALK Pho**	**SGOT**	**Alb**	**Stage**	**Linguistic Value**	**Further Linguistic**	**Intensity Level**
1	2	0.9	76	271	4.4	1	Moderate	Mod-High	9.1857
2	2	1	45	4	5	1	Moderate	Mod-High	7.9161
3	2	1.5	100	100	5	1	Moderate	Mod-High	7.4598
4	2	1	55	45	4.1	1	Moderate	Mod-High	9.1445
5	2	2	167	242	3	1	Moderate	Mod-High	6.4017
6	2	0.6	30	24	4	1	Moderate	Mod-Low	2.2628
7	2	1	72	46	4.4	1	Moderate	Mod-Low	2.6026
8	2	0.7	85	31	4.9	1	Moderate	Mod-High	8.5223
9	2	0.7	62	224	4.2	1	Moderate	Mod-High	6.7432
10	2	0.7	100	31	4	1	Moderate	Mod-Low	4.5115
11	2	1.5	179	69	2.9	1	Moderate	Mod-High	6.9683
12	2	1.3	141	156	3.6	1	Moderate	Mod-Low	3.245
13	2	1.6	44	123	4.1	1	Moderate	Mod-High	7.0896
14	2	0.9	135	55	4	2	Severe	Sev-High	75.1557
15	1	2.5	165	64	2.8	2	Severe	Sev-Low	8.7745
16	1	1.2	118	16	2.8	2	Severe	Sev-Low	16.9706
17	2	0.6	76	18	4.4	2	Severe	Sev-High	83.402
18	2	0.9	230	117	3.4	2	Severe	Sev-High	68.4614
19	2	1.5	107	157	3.4	2	Severe	Sev-Low	63.9347

20	2	0.6	40	69	4.2	2	Severe	Sev-High	79.7634
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
98	2	0.7	71	18	4.4	1	Moderate	Mod-High	8.5482

Table 7: The Performance Evaluation Metrics used

Performance Metrics	TP	TN	FP	FN	False Positive Rate	Specificity %	Precision %	Sensitivity %	**Accuracy %**
Hepatitis	57	32	0	8	0	1	100	87.69	**90.2**

7. CONCLUSION

In this study, we have been able to develop an architecture model that combines the knowledge-base and reasoning features of fuzzy logic (FL), with self-learning capacity of artificial neural network (ANN) to diagnose Hepatitis B disease by computing the intensity levels of its attack. Medical field refers to diagnosis as an approach of recognizing a disease through the analysis of underlying physiological symptoms. Hepatitis is a chronic liver disease that can easily decompensate to cirrhosis disease if its severity is not properly checked with appropriate tools. This study can improve the quality of liver disease diagnosis and provide appropriate information for medical practitioners in the process of administering treatment. This work could be further expanded for improved optimal solutions by integrating Genetic Algorithm (GA) with ANFIS.

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