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A Fuzzy Logic Expert System for Diagnosing EHF and Evaluating its Risk Level

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***Abstract* – The complex nature of Ebola hemorrhagic fever (EHF), particularly at the early stages of its outbreak, makes it difficult to diagnose because it manifests symptoms that are similar to those commonly associated with other diseases. Diagnostic decisions of physicians are therefore subjective, calling for an intelligent system for the diagnosis of EHF. This study proposes a fuzzy logic system that takes account of human limitations of medical professionals in the diagnosis of EHF and evaluation of its Risk Level in patients. To achieve the aim of the study, a fuzzy logic-controlled system was designed and implemented using MATLAB fuzzy logic tool box. Input variables to the fuzzy logic controller are (i) patient's symptoms (PS), (ii) laboratory test results (TR), (iii) patient's itinerary history (PH), and (iv) number of days since initial infection (ND). The proposed system, which is able to diagnose EHF and evaluate its risk level in patients, shows varying output values as the input parameters vary; with TR having a dominant effect on the results. Fuzzy Logic is proved here to be a powerful tool to design computer-based health diagnostics systems to deal with vagueness or imprecision in disease diagnosis. The fuzzy logic system designed in this study addresses the limitations that are usually associated with the subjective decisions of physicians in the orthodox procedures of diagnosing EHF and evaluating its risk levels in patients.**

Keywords - Ebola, Diagnosis, Risk Level, Fuzzy Logic Controller

I INTRODUCTION

Ebola virus has been identified as a pathogen that causes severe and often deadly illnesses in humans and non-human primates. The disease it causes, though known generally as "Ebola hemorrhagic fever" (EHF), is referred to as "Ebola virus disease" (EVD) by the World Health Organization (WHO). Ebola virus disease first erupted in 1976 in Yambuku village (near Ebola River) in Mongala district in northern Zaire (now Democratic Republic of Congo, DRC) [1,2]. In the same year, there was an outbreak also in Sudan. Ebola viruses that caused these diseases later became known as Zaire and Sudan virus, respectively. Other species of the virus known today are the Reston virus, Taï Forest virus and Bundibugyo virus [3]. Of these five known species, only the Reston virus affects the non-human primates but not humans [4].

Fatality in Ebola Haemorrhagic Fever (EHF) ranges from 50% to 90% death rate in humans and other mammals like monkeys, chimpanzees, etc. [5,6].

The effect of EVD outbreak is severe, resulting in 28,610 total cases and 11,308 deaths in Guinea, Liberia, and Sierra Leone as reported by WHO as at March 27, 2016 [7]. Outbreaks of the virus have been reported in different countries at different times with varying degrees of fatality. According to [8], the fatality from outbreak in Yambuku in 1976 was 88%, while it was 53% and 65% in Sudan in 1976 and 1979 respectively. Some other countries of the world like the UK and USA experienced outbreak of the virus in 2014 with fatality cases of 0% and 25% respectively. A Chronology of Ebola virus disease outbreak in different countries between 1976 and 2016 with their species, cases, death and fatality rate is shown in Table 1.

Table 1: Chronology of previous Ebola virus disease outbreaks (Source: WHO Factsheet [7]

Year	Country	Ebola virus species	Cases	Deaths	Case fatality
2015	Italy	Zaire	1	0	0%
2014	DRC	Zaire	66	49	74%
2014	Spain	Zaire	1	0	0%
2014	UK	Zaire	1	0	0%
2014	USA	Zaire	4	1	25%
2014	Senegal	Zaire	1	0	0%
2014	Mali	Zaire	8	6	75%
2014	Nigeria	Zaire	20	8	40%
2014-2016	Sierra Leone	Zaire	14124*	3956*	28%
2014-2016	Liberia	Zaire	10675*	4809*	45%
2014-2016	Guinea	Zaire	3811*	2543*	67%
2012	Democratic Republic of Congo	Bundibugyo	57	29	51%
2012	Uganda	Sudan	7	4	57%
2012	Uganda	Sudan	24	17	71%
2011	Uganda	Sudan	1	1	100%
2008	Democratic Republic of Congo	Zaire	32	14	44%
2007	Uganda	Bundibugyo	149	37	25%
2007	Democratic Republic of Congo	Zaire	264	187	71%
2005	Congo	Zaire	12	10	83%
2004	Sudan	Sudan	17	7	41%
2003 (Nov-Dec)	Congo	Zaire	35	29	83%
2003 (Jan-Apr)	Congo	Zaire	143	128	90%
2001-2002	Congo	Zaire	59	44	75%
2001-2002	Gabon	Zaire	65	53	82%
2000	Uganda	Sudan	425	224	53%
1996	South Africa (ex-Gabon)	Zaire	1	1	100%
1996 (Jul-Dec)	Gabon	Zaire	60	45	75%
1996 (Jan-Apr)	Gabon	Zaire	31	21	68%
1995	Democratic Republic of Congo	Zaire	315	254	81%
1994	Côte d'Ivoire	Taï Forest	1	0	0%
1994	Gabon	Zaire	52	31	60%
1979	Sudan	Sudan	34	22	65%
1977	Democratic Republic of Congo	Zaire	1	1	100%
1976	Sudan	Sudan	284	151	53%
1976	Democratic Republic of Congo	Zaire	318	280	88%

* Include Suspect, Probable and Confirmed EVD cases

Ebola virus disease (EVD), being very lethal and contagious [9], can be contracted from physical contact with the body or fluid (such as saliva, urine, stool/faeces, breast milk, semen) from an infected person or animal [2]. After infection, symptoms of the disease can manifest in patients `within four to ten days, though it could manifest as early as two days or as late as twenty-one days after exposure [5,10,11].

To manage and respond to the risks and consequences of the disease, surveillance systems are usually put in place to enable health care workers as well as members of the public to report to relevant authorities, any cases of febrile illness or death that are suspected to be connected with EVD [6].

Control of the spread and diagnosis of Ebola has become very challenging and problematic because outbreaks of hemorrhagic fevers in humans occur sporadically and irregularly, and are not easily predicted [12]. At the early stages of an outbreak, there is usually a similarity between its symptoms and those of other diseases [13,14] such as typhoid fever, cholera, malaria, etc. [15,16]. One of the control measures that have been employed over time to limit the spread of EVD involves performing clinical experiments on patients suspected to have been infected with the virus. Other control measures in recent times include isolation of suspected, probable, confirmed and most severely ill patients in separate tents in an area designated as high-risk area.

Movements into and out of the high-risk area are controlled by the health care workers who determine who goes into the area, how frequently, and for what length of time [17,18].

Mutua et al. [19] analyzed the commonly reactive approaches used in the management and containment of past Ebola outbreaks, and suggested that combining pre-emptive strategies with reactive ones will lead to having better knowledge about the disease, and better preparation against and better response to future outbreaks.

To diagnose Ebola virus, physicians subject patients to a number of laboratory tests to isolate the virus by cell culture of clinical specimens [20]. Other considerations include patients' symptoms (PS), patient itinerary history (PH), and the number of days since initial infection (ND). A patient may be suspected of EHF infection if his/her itinerary history (PH) reveals that he/she has travelled to a country within 21 days after the World Health Organization (WHO) has reported cases of outbreak of EHF in that country. The number of days since initial infection (ND) also affects the risk level. The subjective, vague and imprecise judgment of the physician in respect of the diagnosis of EHF and its risk level determination is usually based on these four parameters. This paper presents a Fuzzy Logic Control-based system for intelligent diagnosis of EHF and its risk-level evaluation in patients.

II MATERIALS AND METHODS

Fuzzy logic, being a powerful tool for knowledge representation in computational intelligence, and an effective framework for dealing with vagueness, imprecision and subjectivity in human decisions, has been employed successfully in the diagnosis of Malaria and Dengue disease [21], Jaundice [22], Mental illness [23], Breast Cancer [24], Diabetes [25], Brain disease [26], as well as in the prediction of Heart disease [27], etc. Safdari et al. [28] developed a 90% accuracy fuzzy expert system that could be used in hospitals for the prediction of the risk of neonatal death among infants within 0 to 28 days of age. Since Fuzzy logic techniques deal with qualitative and approximate reasoning, they act as the force that enables experts and decision support systems to effectively mimic the human mind [29]. Baheti [30] reviews the use of fuzzy-logic-based expert systems in the diagnosis of various diseases with a view to revealing the importance and the breakthrough in the use of computer in the diagnosis of diseases in human.

Architecture of a fuzzy logic expert system proposed in this study, for diagnosing EHF and evaluation of its risk level, is presented in Fig. 1. It comprises of an interface module that enables the physician to input patients' PS, TR, ND and PH values to the Knowledge-Base Expert System module. The Knowledge-Base Expert System consists of the Fuzzy Logic Controller (FLC) and the Decision Support Engine (DSE).

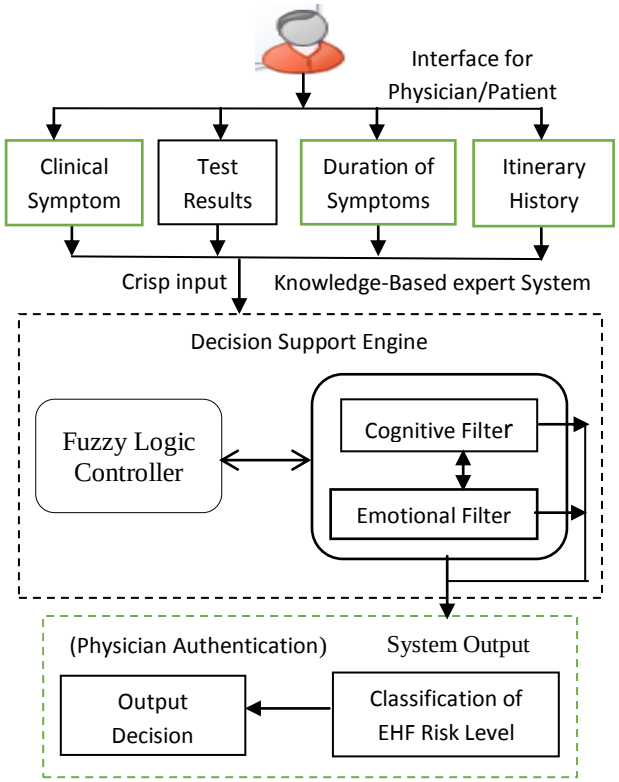

Figure 1: Architecture of Neuro-fuzzy Expert System for the diagnosis of EHF

The structure of the fuzzy logic controller, shown in Fig. 2 comprises a Fuzzifier, Knowledge Base, Inference Engine and a Defuzzifier.

The fuzzifier receives crisp numerical input data in the form of linguistic variables, namely, PS, TR, ND and PH, which it transforms into appropriate values of linguistic labels of the fuzzy sets.

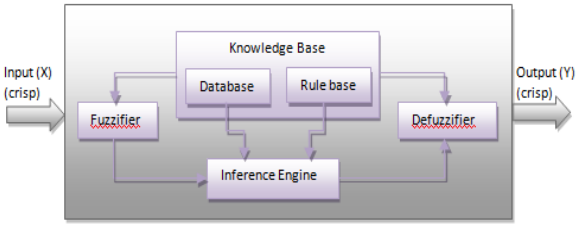

Figure 2: Fuzzy Logic Controller

Suppose $\boldsymbol{f}$ is a fuzzy set of diagnosis categories in $\boldsymbol{F}$ (Universe of Discourse) and $\boldsymbol{x_i}$ represents an element in $\boldsymbol{f}$, the fuzzy set $\boldsymbol{f}$ is expressed as in equations 1 and 2:

$$f = \{(x_i \mu_f(x_i))|x_i) \in F, \quad \mu_f(x_i) \in [0.1]\} \quad (1)$$

$$\mu_f: F \rightarrow M_f \quad . \quad . \quad . \quad (2)$$

where $\mu_f(x_i)$ is the membership function(i.e., the degree of belonging) of x in the fuzzy set f.

From equations 3 to 6, $M_f = \{0, 1\}$ if f is a crisp set; conversely, $\{0<M_f< 1\}$ if f is a fuzzy set.

$$\mu_f: x \rightarrow [0, 1] \quad (3)$$

$$\mu_f(x) = 1 \text{ if } x \text{ is totally in } f \quad (4)$$

$$\mu_f(x) = 0 \text{ if } x \text{ is not in } f \text{ at all} \quad (5)$$

$$0 < \mu_f(x) < 1 \quad \text{if } x \text{ is partially in } f \quad (6)$$

$\mu_f(x)$ maps all elements of F to a membership grade from 0 and 1 in various shapes called Triangular, Trapezoidal, Bell Curve, Gaussian, etc. membership functions. The Triangular membership function shown in Fig. 3 is adopted in this study because of its simplicity and ease of use.

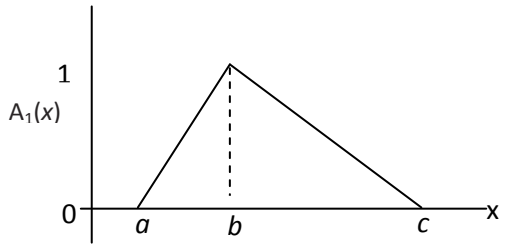

Figure 3: Triangular Membership Function

Membership functions are determined at various points on the triangle by use of equation (7).

$$\text{Triangle}(x;a,b,c) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \\ 0 & x > c \end{cases} \quad (7)$$

where 'a' and 'c' respectively set the left and right "feet," or base points of the triangle, while b sets the location of the triangle peak.

The Knowledge Base of the fuzzy logic controller comprises a database and a rule base. The membership function of an element in a fuzzy set is defined in the database module. The rule base comprises the set of fuzzy production rules, which represent the control policy and goals of the domain experts by means of control rules expressed in linguistic terms. The control rules are formulated in an "IF–THEN" format that makes learning and adaptation easier, and outputs better; consequently resulting in a system that relies less on expert knowledge within the particular domain knowledge [31,32]. Given the diagnosis category, the antecedent (the IF …) part of the rules, and the consequence or "firing strength" (the THEN …) part, determine the EHF Risk Level (EHF-RL). A patient's EHF-RL would be classified into 'No EHF Risk', 'Very Low EHF Risk', 'Low EHF Risk', 'High EHF Risk' or 'Very High EHF Risk' as shown in Table 2.

TABLE 2: OUTPUT FUZZY SET

Diagnosis Categories	Fuzzy Values
T-1 (No EHF Risk)	0.0< x < 0.2
T-2 (Low EHF Risk)	0.2 < x < 0.3
T-3 (Moderate EHF Risk)	0.3< x < 0.5
T-4 (High EHF Risk)	0.5< x < 0.7
T-5 (Very High EHF Risk)	0.7< x ≤ 1.0

A rule fires if any of the precedence diagnosis categories evaluates to true (i.e., 1); else, it does not fire if all the diagnosis categories evaluate to false (i.e., 0). Examples of the structure of the rules in the rule base are:

If (PS is Mild) and (TR is V-Mild) and (ND is Short) and (PH is Unsafe) then (EHF-RL is T-2)
If (PS is V-Severe) and (TR is V-Mild) and (ND is Short) and (PH is V-Unsafe) then (EHF-RL is T-3)
If (PS is Deadly) and (TR is High) and (ND is V-Short) and (PH is Disastrous) then (EHF-RL is T-5)

Decision-making process takes place in the Inference Engine of the fuzzy logic controller. The engine mimics decision-making process in humans and infers fuzzy control actions by utilising fuzzy implication and linguistic rules. The output of the fuzzy inference engine process is a fuzzy set.

The Defuzzifier converts inferred fuzzy control actions from the fuzzy inference engine into crisp control action that is outputted from the controller in the real life domain.

The decision support engine of Figure 1 is driven by the inference mechanism of the fuzzy logic controller. The output from the inference engine of the fuzzy logic controller is fed into the cognitive filter of the decision support engine and applies the objective rules to determine if a patient is Ebola virus infected or not. This result is inputted into the emotional filter where the subjective rules in the domain of study are applied appropriately to rank the patient's EHF_Risk Level.

The proposed fuzzy control system, with input linguistic variables PS, TR, ND and PH, was implemented using the Fuzzy logic toolbox in MATLAB 7.10.0.499 (R2010) software. Each linguistic variable was fuzzified into linguistic terms to explain it at different levels within scale 0 – 1. Linguistic variable PS, fuzzified into four linguistic terms: mild', 'severe', 'very severe' and 'deadly', has

values ranging from 1 – 32 as shown in the membership function of Fig. 4.

TABLE 3: INPUT VARIABLE PS

Linguistic Term	Parameters		
Mild	**1.12**	**4.08**	**7.00**
Severe	**4.90**	**8.16**	**15.00**
Very Severe	**9.00**	**14.90**	**20.00**
Deadly	**15.00**	**23.35**	**32.00**

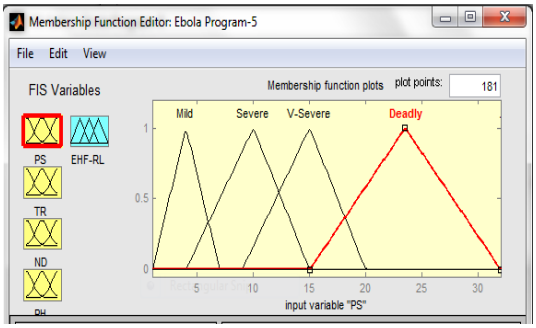

Figure 4: Membership Function for PS

Linguistic variable TR with values from 1 – 5, was fuzzified into four linguistic terms: 'very mild', 'mild', 'high' and 'very high' shown in Table 4, and depicted in the membership representation of fig. 5.

TABLE 4: INPUT LINGUISTIC VARIABLE TR

Linguistic Term	Parameters		
Very Mild	**1.00**	**1.63**	**2.25**
Mild	**1.50**	**2.25**	**3.00**
High	**2.25**	**3.15**	**4.00**
Very High	**3.00**	**4.00**	**5.00**

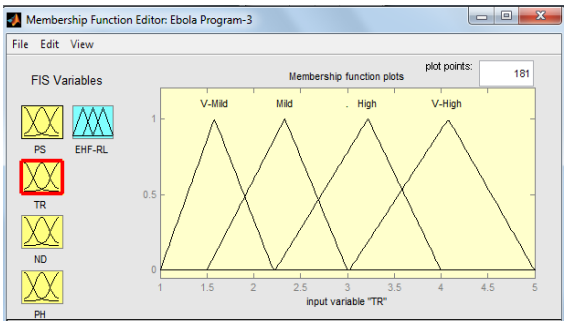

Figure 5: Membership Function for TR

Values of linguistic variable ND ranges from 1 – 21, fuzzified into four linguistic terms: 'very short', 'short', 'long', 'very long' shown in Table 5, represented by the membership functions of Fig. 6.

TABLE 5: INPUT LINGUISTIC VARIABLE ND

Linguistic Term	Parameters		
Very Short	**1.00**	**2.50**	**4.00**
Short	**3.00**	**5.50**	**8.00**
Long	**6.00**	**10.00**	**14.00**
Very Long	**10.00**	**15.50**	**21.00**

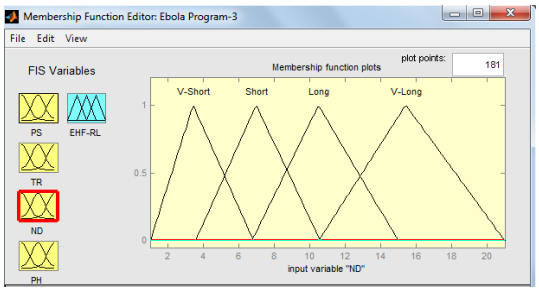

Fig. 6: Membership Function for ND

Table 6 shows Linguistic variable PH with its linguistic terms ('mild', 'unsafe', 'very unsafe' and 'disastrous') varying from 1 – 5, as pictured in the membership functions of Fig. 7.

TABLE 6: INPUT LINGUISTIC VARIABLE PH

Linguistic Term	Parameters		
Mild	**1.00**	**1.65**	**2.30**
Unsafe	**1.50**	**2.35**	**3.20**
Very Unsafe	**2.30**	**3.20**	**4.10**
Disastrous	**3.20**	**4.10**	**5.00**

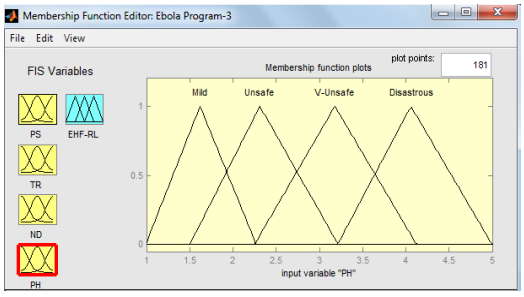

Figure 7: Membership Function for PH

Based on the descriptions of the input and output variables defined with the fuzzy inference system, rules were generated using the AND operator. The

specified weight to a rule is assumed to be unity (1). Given the set of Input values, the rules which satisfied the operational logic were utilised to generate the output for the Inference Engine. The inference engine mechanism searches the membership values in the condition of each rule and processes the crucial decision-making output denoted as EHF-RL (i.e. EHF Risk Level). The output derived from each rule is aggregated and then defuzzified as described.

III RESULTS AND DISCUSSION

Table 7 shows some EHF Risk Level (EHF_RL) results (on a scale of 0 – 1) generated from the training of the FIS, using test cases of PS, TR, ND and PH input values. Each of the crisp numerical input data of these linguistic variables was

TABLE 7: RESULTS OF SOME OF THE TRAINING AND TEST CASES

S/No	PS	TR	ND	PH	EHF-RISK LEVEL	
					VALUE	LINGUISTIC TERM
1.	1.72	1.17	1.47	1.17	0.100	No Risk
2.	1.80	2.21	2.00	2.00	0.197	No Risk
3.	2.34	2.21	2.30	2.20	0.211	Low Risk
4.	11.67	2.50	12.25	2.75	0.431	Moderate Risk
5.	12.45	2.50	12.25	2.75	0.431	Moderate Risk
6.	12.74	2.50	12.25	2.75	0.431	Moderate Risk
7.	28.77	2.50	12.25	2.75	0.439	Moderate Risk
8.	29.65	2.50	12.25	2.75	0.451	Moderate Risk
9.	8.34	2.20	11.50	3.50	0.290	Low Risk
10.	10.67	2.86	11.50	3.00	0.447	Moderate Risk
11.	11.58	3.00	11.50	3.00	0.488	Moderate Risk
12.	19.84	3.65	11.50	3.00	0.610	High Risk
13.	20.23	3.85	11.50	3.00	0.629	High Risk
14.	8.13	3.27	10.64	2.12	0.468	Moderate Risk
15.	9.15	3.27	10.64	2.44	0.465	Moderate Risk
16.	10.32	3.27	10.64	2.76	0.476	Moderate Risk
17.	13.32	3.27	10.64	2.97	0.525	High Risk
18.	15.61	3.27	10.64	3.00	0.601	High Risk
19.	17.43	3.27	10.64	3.22	0.665	High Risk
20.	15.97	2.34	2.20	3.80	0.503	High Risk
21.	15.97	2.82	12.32	3.80	0.576	High Risk
22.	15.97	3.11	13.73	3.80	0.644	High Risk
23.	15.97	3.87	17.45	3.80	0.670	High Risk
24.	15.97	4.11	18.78	3.80	0.686	High Risk
25.	15.97	4.97	20.00	3.80	0.751	Very High Risk
26.	17.34	2.45	14.68	2.00	0.431	Moderate Risk
27.	17.34	2.72	14.68	2.20	0.473	Moderate Risk
28.	17.34	2.85	14.68	2.54	0.486	Moderate Risk
29.	17.34	3.35	14.68	3.00	0.667	High Risk
30.	17.34	3.67	14.68	3.45	0.722	Very High Risk
31.	17.34	3.67	14.68	3.65	0.725	Very High Risk
32.	18.50	3.20	2.50	2.50	0.486	Moderate Risk
33.	18.50	3.20	3.10	2.67	0.526	High Risk
34.	18.50	3.20	7.75	2.85	0.563	High Risk
35.	18.50	3.20	15.17	3.28	0.711	Very High Risk
36.	18.50	3.20	18.46	3.90	0.767	Very High Risk
37.	25.39	2.30	10.20	2.10	0.279	Low Risk
38.	25.79	3.90	18.62	3.80	0.806	Very High Risk
39.	27.34	2.10	9.67	1.95	0.250	Low Risk
40.	27.78	3.78	16.84	3.33	0.779	Very High Risk
41.	28.40	2.34	10.06	2.15	0.305	Moderate Risk
42.	29.25	1.98	12.23	1.76	0.247	Low Risk
43.	30.88	3.96	20.70	3.87	0.761	Very High Risk
44.	31.23	1.85	8.00	1.65	0.250	Low Risk
45.	31.88	4.54	20.37	4.95	0.850	Very High Risk

transformed into fuzzy values by the fuzzifier in the Fuzzy Logic Controller (FLC). Each of the fuzzy values represents the degree of membership of the crisp value (i. e., the degree or extent to which the crisp value belongs to a fuzzy set) on a scale of 0 to 1 on the triangular membership function of Figure 3. Then fuzzy "IF-THEN-RULES" are applied by the Inference Engine of the FLC to logically compute the degree to which the input data matches the conditions of a rule. This leads to fuzzy outputs, which represent the actions to be taken by the controller in terms of the given information. The fuzzy outputs have to be transformed back to crisp values by the defuzzifier module of the FLC. MATLAB uses the "Centre of Gravity" also called the "Centroid" approach to carry out the defuzzification of the fuzzified values. Usage of the Centroid technique has a very high success rate because it gives accurate results based on weighted values of several output membership functions; hence it is commonly used. The centroid method is given by equation 8.

$$x^* = \frac{\sum_{i=1}^{n} x_i \mu_F(x_i)}{\sum_{i=1}^{n} \mu_F(x_i)} \quad . \quad . \quad (8)$$

where x^* = Fuzzy controller output variable

x_i = Sampled element

$\mu_F(x_i)$ = Membership value of sampled element

$F = \bigcup_{j=1}^{n} B^j$ = Fuzzy set

n = *n*umber of sampled values

Table 7 reveals variations in the Ebola Haemorrhagic Fever Risk Level (EHF_RL) with varying values of the input parameters (PS, TR, ND and PH). The output depends on all these parameters. Little variations are observed in the output when TR, ND and PH (Tan coloured in Table 7) are kept constant while varying PS even to a "Deadly" region value of 29.65. The output remains on a "Moderate Risk Level" — an indication that PS does not necessarily determine EHF_RL.

Keeping ND and PH (coloured Aqua in Table 7) constant, while varying PS and TR, EHF_RL increases gradually from "Moderate" to "High" risk level. This same pattern is observed when TR and ND (coloured purple in Table 7) are kept constant and PS and PH are varied.

It is however all "High" risk level, even when "Very Mild" value of TR and "Very Short" duration of ND combine with "Very High" constant values of PS and PH (shown in light green color in Table 7). This is an indication that TR and ND are very crucial in determining the risk level of EHF virus infection

With constant high values of PS and ND (light turquoise color in Table 7), the system output increases gradually from "Moderate" to "Very High" risk level; implying that TR and PH have significant effect on the risk level of EHF infection. It is also observed (as shown in light orange color in Table 7) that keeping PS and TR at a very high level also results in "High" and "Very High" EHF risk level. The very singular dominant effect of TR is observed in all the results shown. Generally, a "mild" value of TR results in either a "No" or "Low" EHF risk level irrespective of the combinations of the other input parameters. This shows that TR is the fundamental indicator of EHF_RL.

IV CONCLUSION

In this study, a fuzzy expert system to diagnose EHF and evaluate its risk level is proposed. The design is based on four judiciously chosen fuzzy input variables namely: patient's symptoms (PS), laboratory test results (TR), the number of days since initial infection (ND) and the patient's itinerary history (PH), and one output variable EHF risk level (EHF-RL) in patients. The knowledge representation and fuzzy logic rules of the proposed system are based on the experience and judgment of physicians, and reports and reviews from health associations/organizations. The EHF expert system, which can be used by both the physician and patient alike does not only diagnose for EHF but also determines the disease risk level in patients. Designing the system with fuzzy technology in comparison with classical design techniques improves results due to the fact that human factors like ambiguity, imprecision and fatigue have been addressed.

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