Jurnal Kejuruteraan 32(1) 2020: 9-16
https://doi.org/10.17576/jkukm-2020-32(1)-02

Development of Fuzzy Logic-Base Diagnosis Expert System for Typhoid Fever

Hezekiah O. Adeyemi[a*], Simon A. Naboth[a], Sodiq O. Yusuf[a], Oluwabunmi M. Dada[a] & Peter O. Alao[b]
[a]*Department of Mechanical Engineering, Olabisi Onabanjo University, Agoiwoye, Nigeria*
[d]*Department of Electrical and Electronic Engineering, Olabisi Onabanjo University, Nigeria*
**Corresponding author: adeyemi.hezekiah@oouagoiwoye.edu.ng*

Received 14 November 2018, Received in revised form 19 May 2019
Accepted 17 July 2019, Available online 28 February 2020

ABSTRACT

Typhoid fever (TyF), caused by salmonella typhoid bacteria, represents one of the main public health challenge in various parts of the world. It is often treatable when diagnosed early, but if left untreated could lead to other medical complications. This study proposed an artificial intelligence means (arim) for diagnosis of TyF. The objectives are to find out the leading risk factors for TyF, develop fuzzy logic base-expert system, called Typhoid Responsive Expert System (TyRes), that can predict the ailment from symptoms and use TyRes to predict TyF in patients. Two sets of questionnaires were used for data collection. 325 copies were administered to the patients in 25 hospitals in Lagos, Abeokuta and Ifo, South-west Nigeria. Another set of 200 copies were administered to human medical experts (hme), 70 doctors and 140 qualified nurses, to capture hme knowledge about TyF and its symptoms. The data was analysed using Chi-Square to identify the main symptoms spotted by most of the hme. TyRes was implemented in Matlab 2015a using the main factors as input variables. Vomiting, high-temperature, weakness, abdominal-pains and loss-of-appetite were the input variables used to develop TyRes. When tested to predict TyF in 25 patients, 76% accuracy was derived when comparing hme predictions with TyRes results. It can be concluded that TyRes can mimic hme by 76% of all TyF predictions. The arim is considered reliable and can be used at home, school and health centres where hme are scarce.

Keywords: Typhoid fever; expert system; symptoms; patients

INTRODUCTION

Typhoid fever (TyF) is a serious infection marked by intestinal inflammation and ulceration (Anthony, 2017). TyF is common in many developing countries (Crump et al., 2010). When left untreated, TyF could lead to medical complication like intestinal haemorrhaging which may require major surgeries and may lead to death (Okpokpong et al., 2017).

Globally, TyF is an important cause of morbidity and mortality in many parts of the world, with a suggested figure between 12-33 million cases resulting to 216,000-600,000 deaths every year (Pang et al., 1995; De Roeck et al. 2007). TyF affects about 12.5 million persons in developing country each year. The outbreaks of typhoid fever are frequently reported from Africa and countries in Southeast Asia. It occurs most often in children and young adults. In 2013 alone about 161,000 deaths in south-central and Southeast Asia was reported (WHO 2007; Crump 2010).

According to Srikantiah et al. (2007), the leading risk factor causing TyF include hygiene habits, poor sanitation conditions, proximity to flying insects feeding on faeces, contact with someone who recently suffered from TyF, achlorhydria, immuno suppressive illnesses such as AIDS, crowded housing, consumption of raw fruits and vegetables contaminated with sewage, prolonged illness, being a health care worker, being a clinical microbiologist who handles salmonella typhi, Childhood.

The commencement of TyF symptoms manifest 1-21 days after exposure. TyFmay be suspected in patients if there is constant high fever (in more than seven days), abdominal expression like pain, vomiting and/or constipation among others and either of: weakness, poor hunger, chest with rose spots, and abnormal heart rate. While small children may experience diarrhoea, it is possible that adult or older children and adults may suffer from constipation (Evanson & Mike 2008)

Many similar studies showed that diseases like TyF remain a main public health challenge (Morel, 2000; Seising, 2006). Some of the several diagnostic techniques for TyF include; laboratory, computer aided, human experts' among others (Benedikt et al. 2011). Human medical experts' (hme) diagnosis of TyF however are common in many developing countries. According to Atun (2004), human experts have some limitations; inability to hold huge amounts of information, inability to give patient satisfaction, fatigue/wear and age as the year's pass, slow at making decision, have impediment to work in dangerous hazardous or environments high level of human errors, (Atun 2004). hme that can accurately diagnosis TyF are scarce most especially in many rural areas. Hence Atun, (2004) mentioned that there is the need for adequate provision for another means of diagnosis of TyF as a supplementary system.

The need to adequately detect and diagnose TyF cannot be overstated and the fact that symptoms displayed by one person who suffers TyF, may not be present in another person, makes accurate diagnosis more difficult (Okpokpong et al. 2017). Different researchers are exploiting intelligence systems to grow and survive healthcare sector. Expert systems have been developed in research efforts as complementary solution to many medical problems (Luger et al. 2009). An expert system is an intelligent computer program that makes use of the knowledge base of some selected human experts for solving problems. The knowledge-based supplies definite certainties and rules related to the subject. The inference engine gives the reasoning intelligence that permits the expert system to arrive at conclusions (Adekoya et al. 2008). Among several efforts, Craven (2001) focused on entity recognition for diseases and its treatment using Hidden Markov. Rosario et al. (2004) introduced the machine learning approach for identifying disease- focused on entity recognition for diseases and treatment. Mordechai and Tom (2004) proposed new algorithms such as learning algorithm for recognizing and choosing situations in free-text medical reports. Bouton et al. (2016) developed an Intelligence system to recover the management of movement in quadriplegia patients. Dilsizian and Siegel (2014) narrated the use of artificial intelligence system to analyse the heart disease with cardiac image. Long et al. (2017) develop the ocular image data to analyse congenital cataract disease, According to Viraj et al. (2018), many of these devices lack the express power to do accurate diagnosis.

Fuzzy logic is reported as a better system for accurate diagnosis of ailment (Okpokpong et al. 2017). Fuzzy logic, introduced by LotfiZadeh, is used to stem the theory of sectional truth, in circumstances where the truth rate is found between total true and outright false. According to Nitin et al. (2013) the advantages of fuzzy logic are numerous, some of which include: an intelligent approach with simplicity, easy to understand, user-friendly among others. Fuzzy Logic is easy to understand, data are easily gotten, there is always high degree of accuracy unlike others where there may be no guarantee of success.

Different expert systems have been developed with fuzzy logic procedures to better solve problem related with human health. Among many attempt, a fuzzy expert system for malaria control was proposed to provide backings (in decision making process) for healthcare practitioners in malaria endemic (Djam et al. 2011). Fernando et al. (2002) introduced a fuzzy linguistic model for assessing the prospect of neonatal death. A fuzzy expert system for cholera contro was proposed by Umoh et al., (2013). Igodan et al. (2013) presented a model of a web-based system with fuzzy logic for diagnosis and therapy of HIV/AIDs. Tsipouras (2008) proposed a fuzzy rule-based artificial intelligence device for coronary artery disease diagnosis.

Further research efforts at solving medical related problem in human race is required to enhance health and safety of human race. In line with this view, this study aim at developing a fes for diagnosis of TyF. The objectives are to capture hme knowledge to identify the leading risk factors for TyF, develop Typhoid Responsive Expert System (TyRes) that can predict the ailment from symptoms and use TyRes to predict TyF in patients. It is expected that TyRes will serve as a unique, common and inexpensive artificial intelligent medical device which can provide health information to different categories of users.

MATERIAL AND METHOD

STUDY DESIGN AND DATA COLLECTION TO DEVELOP TYPHOID RESPONSIVE EXPERT SYSTEM

The cross-sectional design involves possibility of selecting subjects base on their health conditions. Hence the study is completely a case-control of popular health status (Harvey et al. 2007). As reported by Waters et al. (1998), dependable measurements are possible if standardized techniques are followed in measurement. For accuracy, well informed personnel were engaged to measure the relevant variables among the hme and TyF patients. Two sets of questionnaires were used to collect relevant data. 325 copies were administered to patients admitted in 25 hospitals for TyF treatment in Lagos, Abeokuta and Ifo, South-west Nigeria. Another set of 200 copies were administered to hme; 70 doctors and 140 qualified nurses, to capture hme knowledge about TyF and its symptoms

CAPTURING HUMAN EXPERTS KNOWLEDGE ON SYMPTOMS OF TYPHOID FEVER

The Knowledge-Base of the expert system is an important factor in the operation of artificial intelligent systems. The system knowledge-base has correct image of the domain experts' know-how. The structure expertise is based on facts jointly agreed upon by all experts involved in the study.

The data used to develop TyRes depended upon the opinion of the medical experts handling the TyF treatments. The knowledge of the hme about TyF and its symptoms were captured. Chi-Square test was conducted to check for the agreement of the hme on the reported symptoms and/ or significance of the reported factors of typhoid. This is presented in Table 1.

TABLE 1. Statistics-symptoms of typhoid fever for Experts

Symptoms	Chi-Square	Df	Asymp. Sig
Fever sustained over days	40.909a	17	.001
Rash with rose color	34.831	20	.021
Weakness	43.091c	14	.001
Abdominal pain	35.33d	15	.002
Constipation	59.746e	18	,001
Confusion	34.000f	15	.003
Diarrhea	30.000d	15	.012
Loss of appetite	55.69d	15	.001
Vomiting	74.182a	17	.001
Cough	52.60g	18	.001
Sore throat	57.862h	21	.001

IDENTIFYING COMMON SYMPTOMS OF TYPHOID FEVER AMONG PATIENTS

Two hundred and twenty five 225 patients admitted into hospital for TyF were involved in the study. The patients were asked to indicate the symptoms noted from one week to the time of their admission into the clinic. Chi-Square test was also conducted to check for the similarity and significance of the various factors reported by the patients. The responses and outcome of the test is shown in Table 2

FUZZIFICATION OF INPUT DATA

In the fuzzification phase, the inputs agreed upon by hme were converted from crisp form into degrees of match. fuzzifiers are in four categories, these are engaged in the process of fuzzification trapezoid, triangular, singleton, and gaussian. Among others Traingular fuzzifier is common in use and was adopted in this study. The input parameters were selected into the horizontal axis and protruding vertically to the upper boundary of membership function which helps to take readings of the membership level (Djam et al. 2011).

The input members for the system are the symptoms commonly reported by hme and also confirmed by the patients. Each input member has a membership function which in this case, is the severity of the symptom.

The fuzzified crisp input variables are detailed in Tables 3 to 7.

TABLE 2. Test Statistics for Patient

	Symptoms	Chi-Square	Df	Asymp. Sig
A	Fever sustained over days	42.522a	3	.001
B	Rash with rose color	12.062b	4	.017
C	Weakness	17.17c	2	.002
D	Abdominal pain	8.667d	4	.002
E	Constipation	59.746e	4	.070
F	Confusion	15.500f	4	.004
G	Diarrhea	30.500d	4	.014
H	Loss of appetite	10.60	4	.001
I	Vomiting	18.415a	3	.001
J	Cough	18.41g	4	.027
K	Sore throat	16.857h	4	.025

TABLE 3. Fuzzy set of input variable "Temperature"

S/N	Range (°C)	Interval	Linguistic Term
1	<35.0	0, 10, 20, 36	LOW
2	36.5–37.5	35, 36, 37.5, 38	NORMAL
3	>37.5 or 41.5	37, 40, 41.5, 41.5	HIGH

Modified version of the range of temperature of a human being by Laupland (2009)

TABLE 4. Fuzzy set of input variable "Pain"

S/N	Range	Interval	Linguistic Term
1	0	0,0,0,0	No Pain
2	1-3	0,1,3,4	Minor Pain
3	4-6	3,4,6,7	Moderate Pain
4	7-10	6,7,9,10	Severe Pain

Modified version of the study results of pain felt in human by Warren (2003).

TABLE 5. Fuzzy set of input variable "Vomiting"

S/N	Range	Interval	Linguistic Term
1	0	0,0,0,0	No
2	1-2	0,1,2,3	Mild
3	3-4	2,3,4,5	Moderate
4	5-6	4,5,6,7	Severe

Modified version of the study results of vomiting in human by Rehodes. (1996).

TABLE 6. Fuzzy set of input variable "Weakness"

S/N	Range	Interval	Linguistic Term
1	0	0,0,0	Strong
2	0-1	0,1,1	Weak

Modified version of the study results of weakness felt in human by Saguil (2005).

TABLE 7. Fuzzy set of input variable "Loss of appetite"

S/N	Range	Interval	Linguistic Term
1	0-10	0, 6, 10, 11	Breakfast
2	12-16	10, 11, 13, 17	Lunch
3	17-21	16, 17, 20, 24	Dinner

Modified version of the study results of weakness felt in human by Larson (2003); Kosner (2014); Chambers et al., (2016).

OUTPUT VARIABLES

The output of the system is a diagnosis of whether or not the patient has TyF. The output variable, the TyF risk value, has three membership functions, Mild, Moderate and Severe as shown in Table 8.

TABLE 8. Fuzzy set of out variables "Risk"

S/N	Intervals	Linguistic Variables
1	0, 0.2, 0.4	Mild
2	0.32, 0.505, 0.7	Moderate
3	0.6, 0.8, 1	Severe

INFERENCE ENGINE COMPONENT OF TYRES

The fuzzy inference engine engages the rules in the knowledge-base and comes up with an output depending on the rules. For each rule, the inference mechanism locates the membership rates in the situation of the rule. Fuzzy inputs are generalized into their related linguistic variables and corresponding weighting factors to ascertain their membership levels. The aggregation operator is employed to compute a rule firing power. The sets in fuzzy rules commonly have many antecedents which are joined together using fuzzy logical operators like OR, AND and NOT with different meanings to their narrations: while 'AND' engages minimum weight of all the antecedents, 'OR' makes use of the maximum rate. The 'IF' segment is referred to as the "antecedent" and the 'THEN' is known as the "consequent" (Tsoukalas, 1993).

DEVELOPMENT OF "IF THEN RULE" FOR TYRES

USE OF MATRIX TABLE

The rules used to control TyRes were generated by the use of a matrix table shown in Table 9. With the help of the matrix table, there were 288 rules generated by interpolating each of the inputs variables in conjunction with each other to generate the possible outputs. Each small box of the table represents the possible generated rule in each section

Inference rules are a collection of IF-THEN rules that form the basis for decision making in the system. Below are some inference rules used in the system;

i. If (LOW-Temp.) and (NO-vomiting) and (Loss-of-appetite till BREAKFAST) and (weakness-YES) and (NO-pain) then (RISK is MILD)
ii. If (HIGH-Temp.) and (SEVERE- vomiting) and (Loss-of-appetite till LUNCH) and (weakness-NO) and (NO-pain) then (RISK is MODERATE)
iii. If (NORMAL-Temp.) and (SEVERE-vomiting) and (Loss-of-Appetite till LUNCH) and (weakness-YES) and (NO-pain) then (RISK is MODERATE)
iv. If (NORMAL-Temp.) and (MILD-vomiting) and (Loss-of-Appetite till DINNER) and (weakness-YES) and (MODERATE-pain) then (RISK is MODERATE)
v. If (HIGH-Temp.) and (SEVERE-vomiting) and (Loss-of-Appetite till LUNCH) and (weakness-NO) and (MODERATE-pain) then (RISK is SEVERE)
vi. If (HIGH-Temp.)) and (SEVERE-vomiting) and (Loss-of-Appetite till LUNCH) and (weakness-YES) and (MODERATE-pain) then (RISK is SEVERE)
vii. If (HIGH-Temp.)) and (SEVERE-vomiting) and (Loss-of-Appetite till LUNCH) and (weakness-NO) and (SEVERAL-pain) then (RISK is SEVERE)
viii. If (HIGH-Temp.) and (NO-vomiting) and (Loss-of-Appetite till DINNER) and (weakness-NO) and (NO-pain) then (RISK is MILD)
ix. If (HIGH-Temp.) and (NO-vomiting) and (Loss-of-Appetite till DINNER) and (weakness-YES) and (MODERATE-pain) then (RISK is MODERATE)

DEFUZZIFICATION

The input which the inference engine of the system understands is a fuzzy set. The output need be converted to a language that man can understand. Hence the defuzzification process has a whole number. Some defuzzification methods are suggested, among which are: center-of-sums, centre-of-area (CoG), max-criterion and mean of maxima (Djam et al. 2011). The CoG defuzzification technique is like the expression for computing the center of density. The density of mass is however exchanged with the values of membership function.

$$COG = \frac{\int \mu A(x) x \delta x}{\int \mu A(x) \delta x} \qquad (1)$$

Where μ = Membership value and x_i = centre of membership function. This method was engaged in this research because it is easy calculate and relatively dependable.

TABLE 9. Matrix Table to generate applicable rules for TyRes

				VARIABLE 1: VOMITING			
				NO	MILD	MODERATE	SEVERE
				VARIABLE 2: PAIN			
				NO	MILD	MODERATE	SEVERE
				VARIABLE 3: WEAKNESS			
				WEAK		STRONG	
VARIABLE 1: TEMPERATURE	LOW	VARIABLE 1: APPETTITE	BREAKFAST	24 output	24 output	24 output	24 output
	MODERATE		LUNCH	24 output	24 output	24 output	24 output
	HIGH		DINER	24 output	24 output	24 output	24 output

RESULTS AND DISCUSSION

MEMBERSHIP FUNCTIONS OF INPUT VARIABLES

Each input member has a membership function which in this case, is the severity of the symptom.

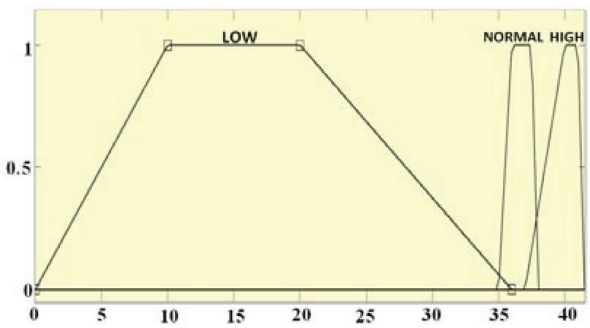

FIGURE 1. Input variable temperature

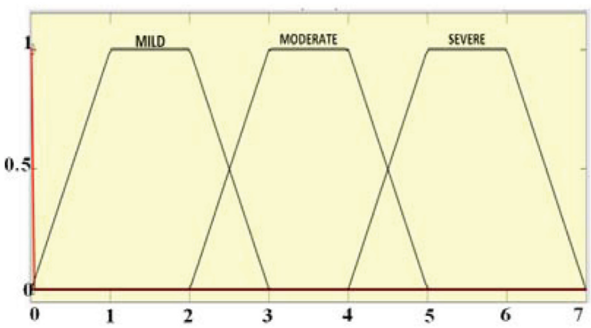

FIGURE 2. Input variable 'vomiting'

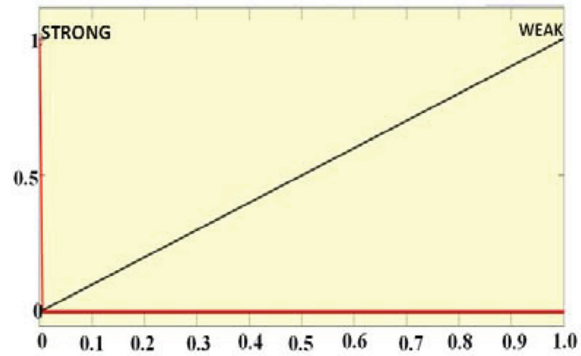

FIGURE 4 Input variable 'weakness'

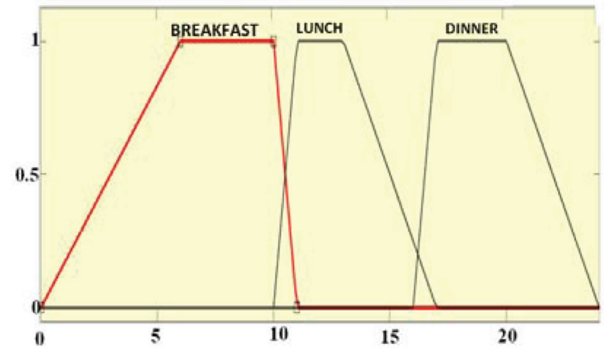

FIGURE 3. Input variable 'loss of appetite'

TYRES OUTPUT INTERFACE

Figure 6 is the interface of TyRes. It shows the possible relationship between each of the input variables parameters with their respective numerical values and the possible outcome (Risk value) using Tyres.

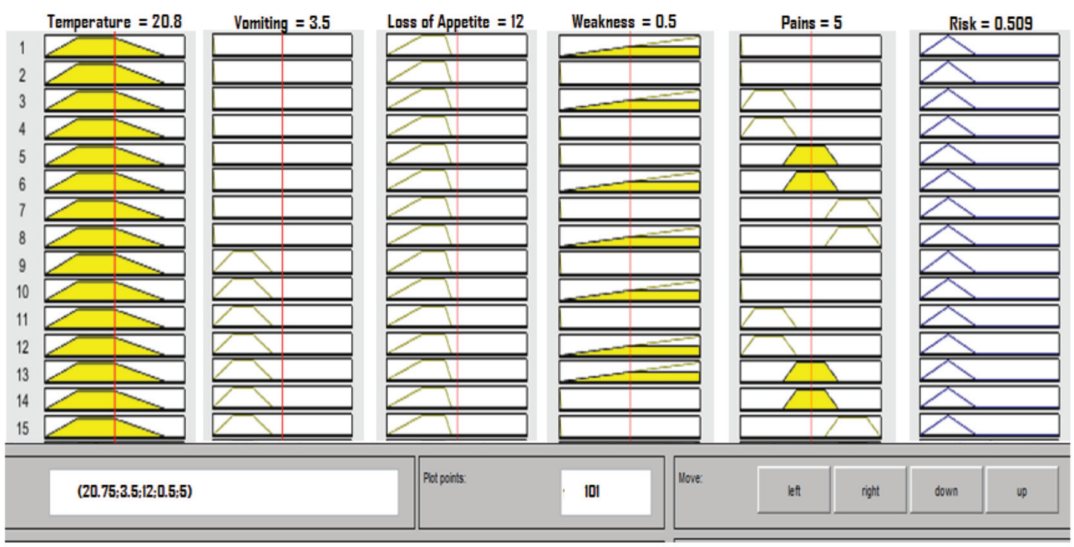

FIGURE 6. Output of the active rule and risk value for a case diagnosis for a typhoid fever patient

VALIDATION OF THE DEVELOPED EXPERT SYSTEM

Comparison was made with hme diagnosis results to ascertain the performance of TyRes

Table 10 shows 25 validation data samples set apart from the questionnaire conducted among the hospitalized patients, the comparison results of hme diagnosis results and the predictions of TyRes using the same five input variables (temperature, weakness, vomiting, pains and loss of appetite).

It was observed that for the hme, the possible risk assessment of typhoid result on sample 1 was 0.345 This is interpreted, in Table 8, as 'moderate.' The output of the TyRes was 0.509 which is also interpreted as 'moderate.' The similarity in the diagnosis of the 25 samples by TyRes and hme were noted in every other samples except in samples 3, 9, 16, 20, 22 and 25.

For sample 3, the diagnosis of the hme was 1.0 (severe) and for TyRes was 0.508 (moderate). The reason why samples 3, 9, 16, 20, 22 and 25 had different linguistic interpretations when compared with hme opinions may be because hmeprovid different opinions of risk of ailments under same condition depending on their feelings. The hmeopinions may change with time. This is not likely with TyRes which is constant in judgement base on the expert knowledge captured into its data base. The data base can be adjusted and /or improved upon. The variations not witstanding, 19 out of 25 samples (76%) diagnosis of the TyRes agreed totally with hme.

The proposed artificial intelligent device has been tested and it can be proven to have good percentage of diagnosis accuracy compared to hme. Any category of personnel can use TyRes interface; The interface shows the relationship between each of the inputs to the possible output (both in numerical value and graphical display). To get the new output, at the bottom left corner of the interface, values of the input variables in the order of 'body temperature,' 'vomiting frequency' 'level of loss of appetite,' 'degree of weakness' and 'body pain' are specified. Each value is separated from each other by using a comma. When the system is prompted, it will display the possible output value at the left right corner of the interface. The value generated is compared with Table 8 for linguistic interpretation.

TyRes can be applied in any clinic most expecially in the rural areas where hme are scarce. Acceptance of TyRes will improve health, reduce mortality rate in the society and helps economic growth. As part of the limitation of this study, the TyResis developed for diagnosis of Typhoid fever only. For future improvement, the system can be further enhanced such that, apart from generating the risk value (in

TABLE 10. Showing comparison between the diagnosis results of human medical experts and TyRes

						Human Experts							
Subjects	a	b	c	D	e	x	Y	Z	F	g= f/5	H	i	J
1	3	29.5	8	2	1	1	3	2	2	0.4	Moderate	0.509	Moderate
2	2	36.7	9	1	0	1	1	1	1	0.2	Mild	0.200	Mild
3	0	40.1	13	6	1	5	5	4	5	0.9	Severe	0.508	Moderate
4	2	37.1	20	1	1	3	2	2	2	0.5	Moderate	0.508	Moderate
5	6	40.1	10	4	0	1	4	5	3	0.7	Severe	0.800	Severe
6	2	37.1	9	3	0	1	1	1	1	0.2	Mild	0.216	Mild
7	2	35.3	14	0	1	1	1	1	1	0.2	Mild	0.239	Mild
8	3	39.1	9	9	1	3	5	4	4	0.8	Severe	0.800	Severe
9	4	29.8	15	2	1	3	4	5	4	0.8	Severe	0.509	Moderate
10	3	37.2	9	0	1	1	1	3	2	0.3	Moderate	0.231	Mild
11	6	35.6	19	8	1	5	5	5	5	1.0	Severe	0.800	Severe
12	1	37.7	10	1	0	1	1	1	1	0.2	Mild	0.296	Mild
13	4	41.3	13	4	1	5	3	5	4	0.9	Severe	0.800	Severe
14	3	30.7	22	5	0	3	3	1	2	0.5	Moderate	0.500	Moderate
15	2	28.9	14	4	1	1	3	3	2	0.5	Moderate	0.509	Moderate
16	0	36.7	13	8	1	5	4	2	4	0.7	Severe	0.508	Moderate
17	5	36.8	21	5	1	5	5	4	5	0.9	Severe	0.800	Severe
18	6	37.1	15	2	0	2	4	4	3	0.7	Severe	0.8	Severe
19	1	40.0	9	2	1	1	3	1	2	0.3	Moderate	0.508	Moderate
20	6	36.5	21	1	1	3	3	3	3	0.6	Severe	0.509	Moderate
21	1	38.2	9	3	0	1	1	1	1	0.2	Mild	0.200	Mild
22	4	36.5	14	0	1	4	2	4	3	0.7	Severe	0.509	moderate
23	0	37.1	10	60	0	1	1	1	1	0.2	Mild	0.200	Mild
24	3	35.4	21	5	1	3	4	3	3	0.7	Severe	0.800	Severe
25	4	30.2	14	4	1	4	2	2	3	0.5	Severe	0.509	moderate

a = vomiting, b = temperature c = loss of apetite, d = pains e = weakness, f = numerical average g = conversion to 0-1, h = linguistic interpretation
i = experts diagnosis, j = experts diagnosis linguistic interpretation

terms of numeric value) and it should also give the linguistic interpretation on the same platform. According to Harvey et al. (2007), the cross-sectional studies used in this study may have provided limited causal inference which may end in wrongly use or undervalue data. If a patient changed location, the exposure condition may be a consequence of the disease instead of a cause.

CONCLUSION

In this project, a Typhoid Responsive Expert System (TyRes) has been proposed for diagnosis of typhoid fever. The study identified leading risk factors of typhoid fever. These includes; high fever sustained over several days, rash with rose-coloured spot, weakness, pain, constipation, confusion, diarrhoea, loss of appetite, vomiting, cough and sore throat were used. Five of these factors were used as input variables to develop TyRes. These are temperature, weakness, vomiting, pains and loss of appetite. TyRes was used for diagnosis of typhoid fever in 25 patients and an accuracy of 76% was achieved. This implies that the artificial intelligent device has a high percentage accuracy and can well mimic human medical expert diagnosis. The adoption of fuzzy logic in this study provides a new method of typhoid diagnosis especially in areas where there are few availability of human medical experts. The adoption of fuzzy logic in the development of TyRes suggested in this study is believed to be reliable, fast and an easy way of managing typhoid fever.

ACKNOWLEDGEMENT

The authors would like to thank all the personnel involved in this study. Olabisi Onabanjo University is equally appreciated for all supports rendered.

REFERENCES

Adekoya, A.F., Akinwale, A.T. & Oke, O.E.A. 2008. Medical expert system for managing tropical diseases. *Proceedings of the third conference on Science and National Development, COLNAS*, 74-86.

Anthony, L. 2017. Wordweb software. Available from http://wordweb.info/developer/.accessed [12 December 2017].

Atun, R. 2004. What are the advantages and disadvantages of restructuring a health care system to be more focused on primary care services? *Copenhagen, WHO Regional Office for Europe (Health Evidence Network report;* http://www.euro.who.int/document/e82997, accessed 20 January).

Bouton C.E., Shaikhouni A. & Annetta N.V., 2016. Restoring cortical control of functional movement in a human with quadriplegia. *Nature* 533: 247-50

Crump, J. A. & Eric, D.M. 2010. Global trends in typhoid and paratyphoid fever. *Clinical Infectious Dis*eases 50(2): 241-246.

De Roeck, D, Jodar, L., Clemens, J. 2007. Putting typhoid vaccination on the global health agenda. *The New England Journal of Medicine* 357:1069-1071.

Dilsizian, S.E. & Siegel, E.L. 2014. Artificial intelligence in medicine and cardiac imaging: harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. *Current Cardiology Reports* 16:441.

Djam, X.Y., Wajiga, G.M., Kimbi, Y.H. & Blamah, N.V. 2011. A Fuzzy Expert System for the Management of Malaria. *International Journal of Pure and Applied Sciences and Technology* 5(2): 84-108.

Evanson, M. & Mike, E. 2008. Typhoid fever in children in Africa. *Tropical Medicine and International Health* 13(4): 532-540.

Gulshan, V., Peng, L. & Coram, M. 2016. Development and Validation of a Deep Learning Algorithm for detection of Diabetic Retinopathy in retinal fundus photographs. *JAMA*, 316(22): 2402-2410

Harvey, C., Neil, P. & David, K., 2007. Selecting appropriate study designs to address specific research questions in occupational epidemiology. *Occupational and Environmental Medicine* 64(9): 633-638.

Igodan C. E., Akinyokun O.C., & Olabode O. 2013. Online Fuzzy-Logic Knowledge Warehousing And Mining Model For The Diagnosis And Therapy Of Hiv/Aids. *International Journal of Computational Science and Information Technology* (IJCSITY) 1(3): 27-40

Long, E., Lin, H. & Liu, Z. 2017. An artificial intelligence platform for the multihospital collaborative management of congenital cataracts. *Nature Biomedical Engineering* 1(2):0024

Luger, G. F. and Stubblefield, W. A. 2009. AI Algorithms, Data Structures, and Idioms in Prolog, Lisp, and Java. *Boston: Addison-Wesley Pearson Education*

Benedikt L., Kamala T., Shaali M. A., George, M. M., Lorenz von S., Ben, A., Ilse, C.E.H., et al. 2011. Assessment and comparative analysis of a rapid diagnostic test for the diagnosis of typhoid fever among hospitalized children in rural Tanzania. BMC Infect Dis 11, 147 doi:10.1186/1471-2334-11-147

Mordechai, A. & Tom, K., 2004. Context Sensitive Medical Information Retrieval. *Medical and Health Technology and Informatics, MEDINFO*, 282-286.

Morel, C.M. 2000. Reaching maturity – 25 years of the tropical disease research, *Parasitol Today,* 16: 522-528.

Okpokpong, N.N.C., Umar, F.I.A. & Itoro, A. 2017. Fuzzy Expert Framework for Diagnosis of Typhoid Fever. *Circulation in Computer Science* 2(9): 13-16.

Pang, T.Z., Bhutta, A., Finlay, B.B. & Altwegg, M. 1995. Typhoid fever and other salmonellosis: a continuing challenge. *Trends Microbiology* 3: 253-255.

Seising, R. 2006. From vagueness in medical thought to the foundations of fuzzy reasoning in medical diagnosis, *Artificial Intelligence in Medicine,* 38: 237-257.

Srikantiah, P. Vafokulov, S., Luby, S.P., Ishmail, T., Earhart, K. & Khodjaev, N. 2007. Epidemiology and risk factors for endemic typhoid fever in Uzbekistan. *Tropical Medicine & International Health* 12(7): 838-47.

Tsipouras, M.G. 2008. Automated diagnosis of coronary artery disease based on data mining and fuzzy modelling. *IEEE Transaction on Information Technology Biomedicine*, 12(4): 447-458.

Tsoukalas, L.H. & Uhrig, R.E. 1993. *Fuzzy and neural approaches in Engineering,* John Wiley & Son, Inc.

Umoh, U. & Ntekop, M. 2013. A Proposed Fuzzy Framework for Cholera Diagnosis and Monitoring. *International Journal of Computer Applications* 82(17): 1-10.

World Health Organization, 2011. Guidelines for the Management of Typhoid Fever. Available from http://apps.who.int/medicinedocs/documents/s20994en/s20994en.pdf . Retrieve 2017-08-28.

Viraj, B., Suja, S. Rajan, D.F., Sittig, R. O. Morgan, P. C. & Hardeep, S. 2018. *Defining and Measuring Diagnostic Uncertainty in Medicine:* A Systematic Review. Journal of General Internal Medicine 33(1): 103-115.