DOI: http://dx.doi.org/10.26483/ijarcs.v12i1.6682

Volume 12, No. 1, January-February 2021

ISSN No. 0976-5697

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

INTERVAL TYPE II FUZZY EXPERT SYSTEM FOR DIAGNOSIS VISCERAL LEISHMANIASIS

Yosef Berhanu Buladie
Sudan University of Science and Technology,
College of Computer Science and Information Technology
Sudan

Lars Rune Christensen (PhD)
Associate professor and head
IT-University of Copenhagen
Denmark

Abstract: Leishmaniasis is neglected tropical a protozoan infectious disease caused by Leishmania parasites. VL (also known as Kala-Azar) is the most severechronicform of Leishmaniasis, almost always fatal if untreated. The annual burden of VL in Ethiopia is estimated to be between 4,500 and 5,000 cases. In a medical environment, incomplete information and imprecise are driven to making an incorrect medical decision and maximize the rate of morbidity and mortality. Fuzzy logic technology enables to provide a simple way to attain to a certain conclusion from vague, imprecise and ambiguous medical data. Clinical suspicion of VL is complex because of its clinical manifestation are shared by other commonly occurring tropical disease like malaria, typhoid and tuberculosis.Several studies were conducted on VL, nevertheless, no one addresses the VL diagnosis using learning capacity. This thesis, we developed and investigated the application of an intelligent interval Type-2 Fuzzy Logic Expert System for diagnosis Visceral Leishmaniasis (VLDES) to assist health workers easy diagnosis a patient and decision-makers to prevent the expansion epidemic. The Type-2 Fuzzy Logic System would be clear to present a highly interpretable and transparent model that is very suitable for the handling uncertainties in the input factors and converting the accumulated data to linguistic formats. First we acquired well organized domain expert knowledge via interview questions and relevant document from the university of Gondar Kala-Azar Treatment and Research center. Secondly, we defined the parameters of fuzzy membership functions of Type-1 Fuzzy Logic System mentioned based on domain knowledge with intensive discussion. Finally, we employed to define uncertainty of the Footprint of Uncertainty (FOU) percentage of Interval Type-2 Fuzzy Logic System. We obtained 93.33% classification accuracy, 90%+ sensitivity and 96%+ specificity usingthirty patients (5 mild,5 moderate, 10 sever and 10 very sever VL patients)as testing case. This show that the proposed Interval Type-2 Fuzzy Logic Classification System provides a more interpretable model that Diagnosis VL.

Keywords:Fuzzy logic, Type-1 fuzzy logic, Type-2 fuzzy logic, Interval Tyep-2 fuzzy logic, Visceral Leishmaniasis

1. INTRODUCTION

Leishmaniasis, a Parasitology disease caused by protozoan Leishmania parasites and transmitted between humans and other mammalian hosts by female phlebotomine sandflies[1, 2]. Leishmaniasis consists of four main clinical syndromes: cutaneous leishmaniasis, mucocutaneousleishmaniasis (also known as espundia), visceral Leishmaniasis (VL; also known as Kala-Azar); and post-Kala-Azar Dermal Leishmaniasis (PKDL)[3].

According to (WHO, 2015) report, Leishmaniasis is prevalent in 89 countries across the world, affecting an estimated 12 million people with approximately 2 million new cases per year .VL is the most severe form of Leishmaniasis, almost always fatal if untreated and is characterized by a range of symptoms, including fever, weight loss, anemia, weakness, hepatomegaly, lymphadenopathy and splenomegaly. VL human cases occur in seven countries, namely Brazil, India, Ethiopia, South Sudan, and Sudan, Kenya, Somalia. Eastern Africa has the second highest number of VL cases, after the Indian Subcontinent [4, 5].

Ethiopia is one of the ten high burden countries for Leishmaniasis. It is estimated that the annual burden of VL ranges from 4,500 to 5,000 cases and population at risk is more than 3.2 million. Some of the factors found to be associated with the spread include population movements to and from endemic focus areas that are known in agro ecological zones, with wide open plains covered by bush scrubs and Acacia woodland [6, 7].

The government of Ethiopia, like other Leishmaniasis endemic countries, has taken many steps, pushing forward the response to disease and many lives saved as a result. However, there remains a great need for increased preventative measures and accessibility to early diagnosis and effective treatment if the disease is ever to be eliminated According to[8] the treatment of the disease is poorly established because of most of the rural health worker treats the Leishmaniasis like one of resistance tropical diseases like malaria and tuberculosis. In the result of this many people are dying[6-10].

Fuzzy logic is useful for real world problem where there are different kinds of uncertainty. Uncertainty is mostly observed in medical cases during diagnosis, because the symptoms and related signs of the patients are subjective, which are not able to be expressed in the conventional logic and also symptoms have different level of measurement. A fuzzy set is an extension of a conventional set. It has elements belonging to it to some degree of membership. This degree varies from 0 to 1. In conventional logic, the degree of membership is either 0 for non-membership or 1 for complete membership. Fuzziness results from imprecise boundaries of fuzzy sets. It is based on emulating human thinking where elements are linguistic variables. Fuzzy sets represent common sense linguistic labels like slow, fast, small, large, heavy, low, medium, high, tall, etc[11].

Type-1 and type-2 fuzzy sets were introduced by Zadeh in 1965 and 1975 respectively. Both are handling the process/manipulate data and information affected by uncertainty/imprecision. In especially type-2 fuzzy sets were essentially 'fuzzy fuzzy' sets where the fuzzy degree of membership is a type-1 fuzzy set[12-14].

According to Global health, 2014 report ,identify technology gap is one of the priority research area to eliminate Visceral Leishmaniasis[15]. Therefore, this study is one of the technological approach to solve the problem of VL diagnosis confusion and mange treatment track.

Developing anexpert system would reduce the repetition of the task, the burden of human expert and waiting time of patients in the hospital. The expert system could be used to assist human expert by providing the required knowledge at the right time for decision making.

The main contribution of this work is the design of the better interval type-2 fuzzy expert system, which is better than the design of the type-1,type 2 fuzzy system.

Hence, the expert system will be supported tools to health care worker for diagnosis VL. The system primarily contains knowledge and experience of specialized doctors' full knowledge and make it real advancing system for those health workers, which serves as a means of easy ways of knowledge transfer. Therefore, the community of Ethiopia gets timely diagnosis and treatment, this is a good opportunity to enhance the quality of health care who lives rural areas and achieving the goal of Millennium Goal.

This paper is organized as section 1 describes the background and need of the study, section 2 describe on the related work, Section 3 talked the overview fuzzy logic, section 4 described knowledge acquisition Section 5 detail proposed system and discussion of the result and final conclusion on rest section.

2. RELATED WORK

Several numbers of researches have been conducted successfully on design Interval type-2 fuzzy expert model for the diagnosis and treatment of diseases. Some of them that are related to the proposed problem discussed here below:

In [16] this study explored the application of Interval Type-2 Fuzzy Logic Systems (IT2FLSs) to gas turbine fault diagnosis. The study compared the performance of IT2FLS to IT1FLS classification in terms of success rate, reliability against measurement uncertainty, incipient fault diagnosis, robustness against instrumentation failure, generally it perform an average accuracy above 99%. The result of this research showed that the application of IT2FLS improves the capability of diagnosis and finding fault.

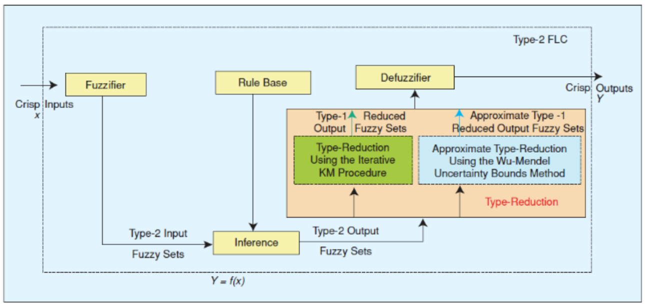

Figure 1: The interval type-2 FLC

Abdolkarimzadeh et al. [17] presented an Interval type-II fuzzy rule-based expert system as the best and moderated health worker assistance system for diagnosing chronic kidneys disease. The classification accuracy of the proposed system for diagnosis of chronic kidney disease was obtained about 90%. The results that were obtained show that interval Type-II fuzzy has the ability to diagnose Chronic Kidney Disease.

Asl et al. [18] applied type 2 fuzzy expert system to the high uncertain and vague medical diagnosis of Leukemia. Diagnosis Leukemia disease has always been a challenge for physicians. In this system, we use Mamdani-style inference that has high interpretability to clarify the results of system to experts. The classification accuracy of the type-2 fuzzy system for Leukemia diagnosis has obtained about 94% which demonstrate its capability for helping experts to early diagnosis of the disease.

A work on a fuzzy expert system for the management of malaria (FESM) was executed in [19]. The concerned system was described as capable of providing a decision support platform to malaria researchers, medical doctors and other healthcare practitioners in malaria endemic regions. This developed system was composed of knowledge based, the fuzzifier, the inference engine and defuzzifier. The developed used a triangular typed membership function for the fuzzification of scalar inputs, a fuzzy inference method of root sum square (RSS) and finally, the defuzzifier employed the popular and effective center of gravity method of defuzzification. In this study 35 selected patients of malaria were diagnosed.

Due to high uncertainty in the medical data, Type-2 fuzzy (IT2FLS) is able to consider much linguistic uncertainty and considering the uncertainty in the membership functions. In addition, it is a new and current method in medical diagnosis. As an example, in[20], interval Type-2 fuzzy were used to recognized patterns of Fatal Heart Rate (FHR) for predicting fatal well-being in medical antenatal care system. The output of the study is a system that used for classifying diagnosis of fetal health. As per researcher knowledge, few kinds of researches are conducted with the combination of soft computing techniquesthat play a vital role in the improvement of the system performance of IT2FLS. For example, Najafi et al. [21]Used fuzzy C-means (FCM) clustering algorithm to improve the performance of IT2FLS in the classification of Celiac Disease (CD).

3. OVERVIEW OF FUZZY LOGIC

3.1. Fuzzy Logic System

The fuzzy logic System has a set of relations between measurable inputs and outputs as fuzzy sets model. Another general definition of a fuzzy logic system (FLS) is noted by Mendel to be a nonlinear mapping of an input data vector into an output data vector [22, 23].

3.1.1. Type-1 Fuzzy logic system

Type-1 fuzzy set introduced by Zadeh in 1965 [24]. It is a successful method of modelling uncertainty, vagueness and imprecision more than forty years. Type-1 fuzzy sets can handle uncertainty by utilizes precise membership functions which is uncertainties for the user as them believes. Even if, It has been applied more than forty years and success full many different applications. It has the limitation to cope with large amounts of the uncertainties of the real world. Real world applications are characterized by high levels of linguistic and numerical uncertainties. Hence, the traditional type-1 using type-1 sets cannot directly handle such uncertainties to produce a new generation of fuzzy controllers with improved performance for many applications, which require a high level of uncertainties [25]. Hence, A type-2 FLS can handle higher uncertainty levels to produce improved performance [26].

3.1.2. Interval Type-2 Fuzzy logic system

Type-2 fuzzy sets, introduced again by Zadeh in the year 1975, are used for modelling levels of uncertainty and imprecision in a better way which traditional fuzzy logic(type-1) struggles [27]. Later in the year 2001, Mandel introduced a new concept which type-2 fuzzy set can be characterized with an upper membership function and a lower membership function [23]. The interval between these two functions represents the footprint of uncertainty (FOU). Itprovidesan additional degree of freedom that can make it possible to directly model and handle the uncertainties[28].

The architecture of a type-2 FLS is illustrated in Figure where the interconnection of the five components (fuzzifier, rules, inference engine, type-reducer and defuzzifier) is shown. Different from type-1 FLSs, type-2 FLSs have the additional block labelled as *type-reducer*, which is an extension of a type-1 defuzzification procedure and represents a mapping of a type-2 fuzzy set into a type-1 fuzzy set [23]. After the type-reduction process, the type-reduced sets are defuzzified to obtain crisp outputs.

3.2. Overview fuzzy expert system

The human brainhas several thousand of knowledge and most complex and least understood part of the human body. Development of systems that able to capture and redistribute domain expert knowledge, wisdom and intelligences [29]. The expert system is a computer program that simulates human knowledge and experience in a particular field where there is a shortage of expert knowledge [30]. Knowledge based systems (KBS) is sophisticated, interactive computer programs which use high quality, specialized knowledge in some narrow problem domain to solve complex problems in that domain [31].

The Expert system is derived from the field of artificial intelligence as well as one of the main family members. Artificial intelligence intends to understand human intelligence behavior like cognitive skill thinking, problem solving, learning, understanding, emotion, consciousness, intuition and creativity and building of computer programs that are capable of simulation or acting one or more of those behaviors [32].

Expert systems are designed to solve complex problems at the level of a human expert by using specialized knowledge represented a set of rules. A fuzzy expert system (FES) is an expert system which include set of fuzzy rules and membership functions [33].

A fuzzy expert system is an expert system, which consists of fuzzification, fuzzy logic inference, knowledge base (combination of fuzzy rules and database), and defuzzification subsystems [19].

Inference engine is brain of expert system that control, interpret, analyzes and processes the rules. Tracing rule forest to arrive a conclusion is the key task of inference engine [30].

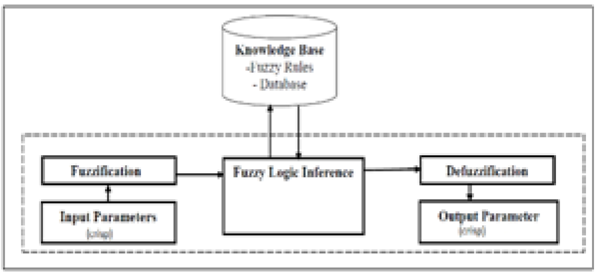

Figure: 2 Architecture of fuzzy expert system

The purpose of the inference engine is to seek information and relationships from the knowledge base and to provide answers, predictions, and suggestions in the way a human expert would. The inference engine must find the right facts, interpretations, and rules and assemble them correctly [34].

4. KNOWLEDGE ACQUISITION

Knowledge is the most important element of any expert system. Knowledge can be classified in many different ways. Tacit knowledge, explicit knowledge, hidden knowledge, factual knowledge, procedural knowledge, commonsense knowledge, domain knowledge, Meta knowledge, etc[35, 36].

4.1. Knowledge Acquisition from Domain Experts

The main problem of KBSs is acquiring knowledge from human specialist. It is a difficult cumbersome and long activity [37].

The data for this work was collected from university of Gondar kalaAzar research center. Knowledge of the domain area was collected through interviewing and Mixed (structured and unstructured) questionnaire.

4.1.1. Interviewing The Domain Experts

Interview is one of the knowledge elicitation techniques. Interview can be structured, semi structured and unstructured.Primary sources of knowledge are collected from human experts by interviewing them in the domain area at university of Gondar Kala-Azar Research Center. One of the main focuses of this research is eliciting relevant tacit knowledge from the domain experts, were selected from each case teams as per the recommendation of the medical director of the hospital by applying purposive sampling technique.

4.1.2. Knowledge Acquisition from Questionnaire

The data collected by interview was not clearly enough so the researcher decided to use another approach which is using questionnaire.

Mixed Questionnaires were used to gather information about disease and to see the views of the health experts on system.

Most of the questions in the questionnaire were open questions (unstructured) because it allows the respondent to express their views and ideas openly and without any restriction. The questionnaires were distributed to the experts mentioned above.

4.1.3. Knowledge Acquisition from Relevant Document

Document analysis has been carried out to acquire explicit knowledge. For the sake of getting deeper insight about the characteristics of oilseed crops and to strengthen the information obtained from experts through interview and questionnaire documents were reviewed.

Book and guideline from WHO Expert Committee on the Control of Leishmaniases and Guideline for diagnosis, treatment & prevention of Leishmaniasis in Ethiopia, were reviewed to get information about Kala-Azar diseases and treatment, Different Articles from the internet on disease have been reviewed.

4.2. Knowledge Modelling

Knowledge modelling is a cross disciplinary approach to capture and model knowledge into a reusable format for the purpose of preserving, improving, sharing, aggregating and processing knowledge to simulate intelligence [38].

4.2.1. Rules Representation

The predominant means of representing the vast amount of problem specific knowledge in KBS has been by production rules. Production rules are of the form 'situation » action', i.e. they are syllogisms of the form 'IF a certain situation holds THEN take a particular action’. The IF portion of the rule is called the antecedent and the THEN portion, the consequent of the rule. The reasoning mechanism of KBS (Inference Engine) uses these IF THEN rules to arrive at a conclusion, establish the validity of a fact, etc [13].

Expert knowledge is often represented in the form of rules or as data within the computer. Rule-based expert systems have played an important role in modern intelligent systems and their applications in strategic goal setting, planning, design, scheduling, fault monitoring, diagnosis and soon.

4.2.1.1. Formula fuzzy rules (fuzzy rules generation)

Apply the fuzzy operator and formulation of rules, done by if-then fuzzy rules based on expert knowledge.

The development of such an expert system usually requires a domain expert, who knows how to solve the problem at hand. Fuzzy rule-based systems, in addition to handling of uncertainties, also have several additional capabilities. Here approximate numerical values can be specified as fuzzy numbers. Based on the descriptions of the input and output variables, 256 rules were constructed by selecting an item in each input and output variable box and one connection (AND).

The fuzzy rules are defined for the dimensional pattern problem in the following form

R_1: IF x_1 is A_1 and ... and x_n is A_n THEN y is B_1 (1)

Where l=(1,2,3,… M), M is the total of number of rules, x_j: (j=1,2,3…n) are the input variables, y is an output variable and A_1 and B_1 are fuzzy sets that are characterized by membership functions and $A_1(x_j)$ and B_1(y) respectively.

The next step in the fuzzification process is the development of fuzzy rules. The fuzzy rules for this research were developed with the assistance of domain experts and cases which defined by WHO. Some of rules listed blow

1. fever >2 week is very sever and living or traveling VL endemic area is yes certainly and enlarged lymph nodes (Splenomegaly or Hepatomegaly) is very sever and loss of weight is very sever and anemia is very sever THEN VL suspicion is very sever
2. fever >2 week is very sever and living or traveling VL endemic area is yes certainly and enlarged lymph nodes (Splenomegaly or Hepatomegaly) is very sever and loss of weight is very sever and anemia is sever THEN VL suspicion is very sever
3. fever >2 week is sever and living or traveling VL endemic area is yes certainly and enlarged lymph nodes (Splenomegaly or Hepatomegaly) is sever and loss of weight is sever and anemia is sever THEN VL suspicion is sever
4. fever >2 week is sever and living or traveling VL endemic area is yes certainly and enlarged lymph nodes (Splenomegaly or Hepatomegaly) is sever and loss of weight is sever and anemia is sever THEN VL suspicion is sever
5. fever >2 week is sever and living or traveling VL endemic area is yes possibly and enlarged lymph nodes (Splenomegaly or Hepatomegaly) is sever and loss of weight is very sever and anemia is very sever THEN VL suspicion is moderate
6. fever >2 week is moderate and living or traveling VL endemic area is yes certainly and enlarged lymph nodes (Splenomegaly or Hepatomegaly) is very sever and loss of weight is sever and anemia is sever THEN VL suspicion is moderate
7. fever >2 week is moderate and living or traveling VL endemic area is yes possibly and enlarged lymph nodes (Splenomegaly or Hepatomegaly) is very sever and loss of weight is very sever and anemia is very sever THEN VL suspicion is moderate
8. fever >2 week is mild and living or traveling VL endemic area is possibly No and enlarged lymph nodes (Splenomegaly or Hepatomegaly) is very sever and loss

of weight is very sever and anemia is very sever THEN VL suspicion is mild

4.3. Attribute Selection

On the basis of domain experts' knowledge, we identified 5 input and variables. The following table 1 shows the detail description

Table1: input and output variable description

	Variable Name	Description
Input variable	Fever > weeks	Persist fever more than two weeks
	Living or traveling to endemic area	Living or traveling history of a patient to the endemic areas
	Splenomegaly	Enlargement of spleen, liver or lymph node
	weight loss	The patient of weight
	Anaemia	Patient that shows the clinical symptom of Anaemia
output variable	VL diagnosis suspicion	Suspicion level of Visceral Leishmaniasis

5. PROPOSED FUZZY EXPERT SYSTEM FOR DIAGNOSIS VL

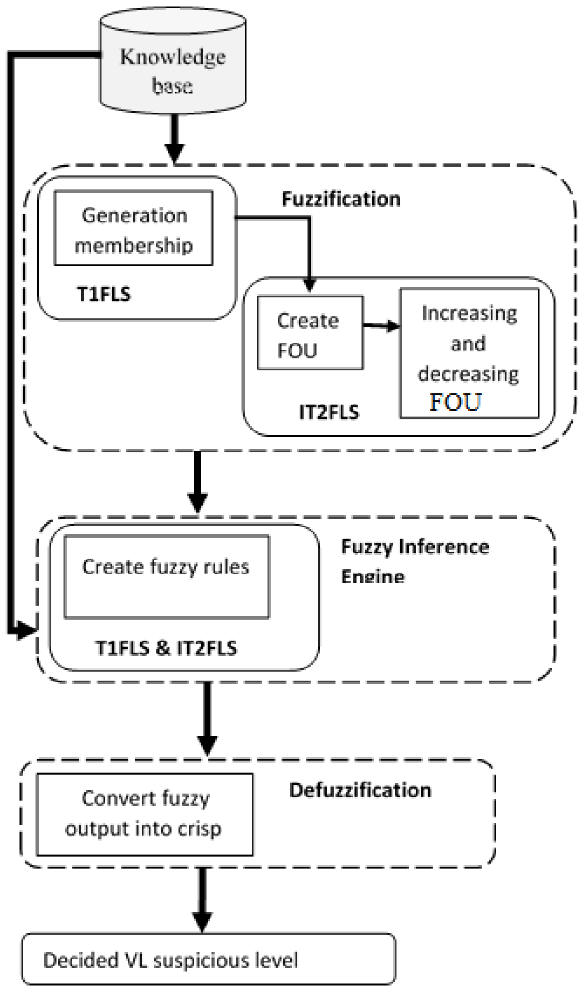

Figure 3: proposed fuzzy expert system

As we state on the above, we organized and represented knowledge to the proposed fuzzy logic-based system for diagnosis of VL. Explained detailed in the following subsections **Step 1: Fuzzification**

The first step in the development of fuzzy logic based expert system is to construct fuzzy sets for the parameters. Based the equation (2 and 3) and intensive discussion of domain expert ,thetriangular and trapezoidal are functions of a vector, *x* and depends on three scalar parameters *a*, *b* and *c*, as given by [39].

$$f(x;a,b,c) = \begin{cases} 0, & if\ x \le a \\ \frac{x-a}{b-a} & if\ a \le x \le b \\ \frac{c-x}{c-b} & if\ b \le x \le c \\ 0 & if\ c \le x \end{cases} \quad (2)$$

$$f(x;a,b,c,d) = \begin{cases} 0, & if\ x < a\ or\ x > d \\ \frac{x-a}{b-a} & if\ a \le x \le b \\ 1 & if\ b \le x \le c \\ \frac{d-x}{d-c} & if\ c \le x \le d \end{cases} \quad (3)$$

On the basis of domain experts' knowledge, both input and output parameters selected for this research were described with four linguistic variables (mild, moderate, severe and very severe) for 6 variables and (certainly No, possibly No, possibly Yes and certainly Yes) for the variable living and traveling to endemic areas. The range of fuzzy value for each linguistic is shown in table 1 below as per the domain expert recommendation:

Table 2: Range of Fuzzy Values

Variable	Linguistic Label	Membership function	Parameters
Fever > weeks	Mild	Trapezoidal	[0 0 0.1 0.3]
	Moderate	Triangular	[0.2 0.4 0.6]
	Sever	Triangular	[0.5 0.7 0.8]
	Very sever	Trapezoidal	[0.7 0.9 1 1]
Living or traveling to endemic area	Mild	Trapezoidal	[0 0 0.2 0.3]
	Moderate	Triangular	[0.1 0.6 0.8]
	Sever	Triangular	[0.4 0.7 0.9]
	Very sever	Trapezoidal	[0.7 0.9 1 1]
Splenomegal y	Mild	Trapezoidal	[0 0 0.2 0.3]
	Moderate	Triangular	[0.05 0.5 0.7]
	Sever	Triangular	[0.4 0.7 0.9]
	Very sever	Trapezoidal	[0.55 0.75 1 1]
weight loss	Mild	Trapezoidal	[0 0 0.1 0.3]
	Moderate	Triangular	[0.1 0.4 0.65]
	Sever	Triangular	[0.35 0.6 0.9
	Very sever	Trapezoidal	[0.5 0.7 1 1]
Anaemia	Mild	Trapezoidal	[0 0 0.3 0.35]
	Moderate	Triangular	[0.1 0.35 0.65]
	Sever	Triangular	[0.3 0.6 0.85]
	Very sever	Trapezoidal	[0.55 0.75 1 1]
VL diagnosis suspicion	Mild	Trapezoidal	[0 0 0.1 0.3]
	Moderate	Triangular	[0.05 0.5 0.75]
	Sever	Triangular	[0.4 0.65 0.8]
	Very sever	Trapezoidal	[0.55 0.75 1 1]

In this study, each input and output represented by two triangular and two trapezoidal membership functions such as *mild*, *moderate*, *sever* and *Very sever* by determined the membership parameters The membership function of T1FLS extracted from domain knowledge rules. The type-1 membership functions for inputs and output variables for VL suspicion decision system represented in Figures4 (A), (B) and (C) show 2 input sample and output.

Step 2: Transforming Type-1 Membership Functions to Interval Type-2 Membership Functions

Triangle Interval Type-2 Membership Functions with Uncertainty $a \in [a_1, a_2]$, $b \in [b_1, b_2]$ and $c \in [c_1, c_2]$

To make a fuzzy system, you must first determine the input and output linguistic variables, in this case, we have two inputs and one output

The Equation (2 and 3) represents the triangle and trapezoidal Interval Type-2 Membership Functions with Uncertainty.

$\mu(x) = \mu(x)$, $\mu(x)$= itritype2(x, $[a_1, b_1, c_1, a_2, b_2, c_2]$), where $a_1 < a_2$, $b_1 < b_2$, $c_1 < c_2$ (4)

$$\mu_1(x) = \max\left(\min\left(\frac{x - a_1}{b_1 - a_1}, \frac{c_1 - x}{c_1 - b_1}\right), 0\right) \quad (5)$$

$$\mu_2(x) = \max\left(\min\left(\frac{x - a_2}{b_2 - a_2}, \frac{c_2 - x}{c_2 - b_2}\right), 0\right) \quad (6)$$

$$\mu(x) = \max\begin{Bmatrix} (\mu_1(x), \mu_2(x)) \forall\, x \notin (b_1, b_2) \\ 1 \qquad\qquad \forall\, x \notin (b_1, b_2) \end{Bmatrix} \quad (7)$$

$$\mu(x) = \min(\mu_1(x), \mu_2(x)) \quad (8)$$

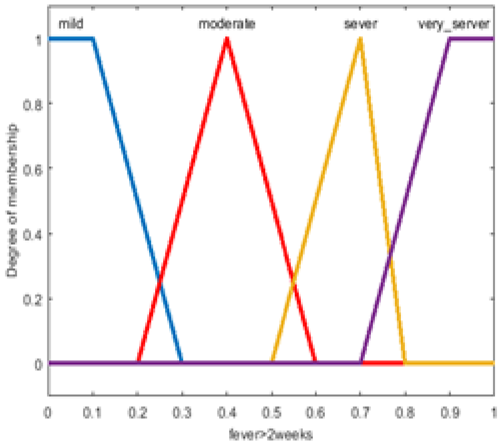

Figure 4 (A) Fuzzy set for fever more than 2 weeks

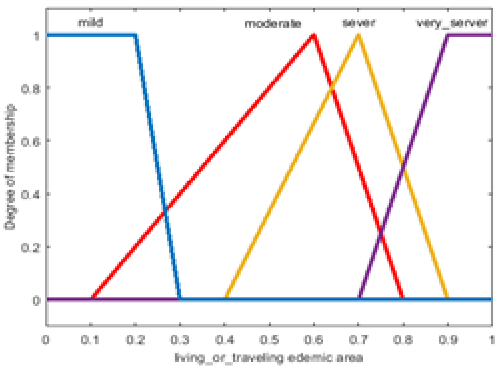

Figure 4 (B) Fuzzy set for Living or travelling history at endemic area

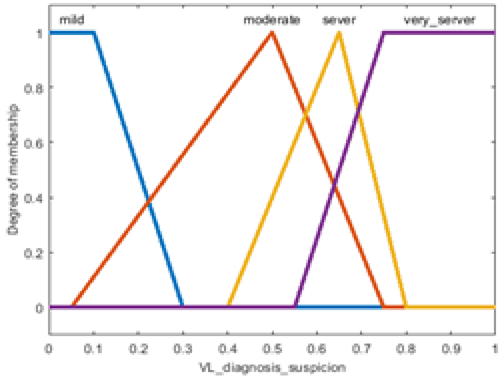

Figure 4 (C) Fuzzy set for output VL diagnosis Suspicion

In order to construct the upper and lower membership function based on equation 5 and 6and we employedto defined uncertainty of FOU in percentage 10, 20 and 30 percentage from type-1 fuzzy sets. The table 3 and figure5(A), (B) and (C) shows the 20 % uncertainty.

Table 3: 20 % uncertainty degree of fuzzy parameters

Variable	Linguistic Label	20% FOU Lower parameter	20% FOU Upper parameter
Fever > weeks	Mild	[0 0 0.09 0.27]	[0 0 0.11 0.33]
	Moderate	[0.22 0.4 0.54]	[0.18 0.4 0.66]
	Sever	[0.55 0.7 0.72]	[0.45 0.7 0.88]
	Very sever	[0.77 0.99 1 1]	[0.63 0.81 1 1]
Living or traveling to endemic area	Mild	[0 0 0.22 0.33]	[0 0 0.18 0.27]
	Moderate	[0.11 0.6 0.72]	[0.09 0.6 0.88]
	Sever	[0.44 0.7 0.81]	[0.36 0.7 0.99]
	Very sever	[0.77 0.99 1 1]	[0.63 0.81 1 1]
Splenomegal y	Mild	[0 0 0.18 0.27]	[0 0 0.22 0.33]
	Moderate	[0.055 0.5 0.63]	[0.045 0.5 0.77]
	Sever	[0.44 0.7 0.81]	[0.36 0.7 0.99]
	Very sever	[0.6 0.82 1 1]	[0.49 0.67 1 1]
weight loss	Mild	[0 0 0.09 0.27]	[0 0 0.11 0.33]
	Moderate	[0.11 0.4 0.71]	[0.09 0.4 0.58]
	Sever	[0.38 0.6 0.81]	[0.31 0.6 0.99]
	Very sever	[0.55 0.77 1 1]	[0.45 0.63 1 1]
Anaemia	Mild	[0 0 0.27 0.31]	[0 0 0.33 0.38]
	Moderate	[0.11 0.35 0.58]	[0.09 0.35 0.71]
	Sever	[0.33 0.6 0.76]	[0.27 0.6 0.93]
	Very sever	[0.6 0.82 1 1]	[0.49 0.67 1 1]
VL diagnosis suspicion	Mild	[0 0 0.09 0.27]	[0 0 0.11 0.33]
	Moderate	[0.055 0.5 0.67]	[0.45 0.5 0.82]
	Sever	[0.44 0.65 0.72]	[0.36 0.65 0.88]
	Very sever	[0.6 0.82 1 1]	[0.49 0.67 1 1]

6. RESULTS

The proposed system was evaluate the performance using thirty patients as test case from university of Gondar hospital. From total patients twenty of them are VL patients treated under university of Gondar kala-Azar research treatment center. So, the researcher taken those patients as ten sever and ten very sever who are VL relapse patients, 5 is belong to moderate their symptom are very related VL but they were identified by laboratory test 3 of them has VL the rest two are free, other five are not VL patients as mild but they are chronic internal patients in University of Gondar hospital.

Our results based on real patient data confirm that the fuzzy logic expert system can represent the expert's thinking in a satisfactory manner in handling complex trade-offs. Fuzzy logic systems are excellent in handling ambiguous and imprecise information prevalent in medical diagnosis. The essence of the study was to ascertain the degree to which fuzzy methodology represents the exact diagnosis of the patient as compared with those of medical doctors. Table 4 below shows the data matrix of thirty patients of fuzzy expert system prediction verses the actual real data.

Table 4: Confusion matrix of the proposed system

Fuzzy expert prediction	Actual				
	Type I				
	VL suspicion	mild	moderate	sever	Very sever
	mild	3	0	0	0
	moderate	1	3	1	1
	sever	1	1	8	1
	Very sever	0	0	1	8
	Type II 10% uncertainty				
	mild	4	0	0	0
	moderate	1	4	1	0
	sever	0	1	9	1
	Very sever	0	0	0	9
	Type II 20% uncertainty				
	mild	4	0	0	0
	moderate	1	4	1	0
	sever	0	1	9	0
	Very sever	0	0	0	10
	Type II 30% uncertainty				
	mild	4	0	0	0
	moderate	1	4	0	0
	sever	0	1	10	0
	Very sever	0	0	0	10

Based on these results we obtain the overall classification accuracy (OCA), Sensitivity (Sn), Weighted Average Sensitivity (WASn), Specificity (Sp) and Weighted Average Specificity (WASp) for which we use the following equations:

$$OCA = \frac{\sum_{i=1}^{n} TP(x_i)}{\sum_{i=1}^{n} TP(X_i) + \sum_{i=1}^{n} TN(x_i)} \quad 9$$

$$Sn\,(x_i) = \frac{TP(x_i)}{TP(x_i) + \sum_{i=1}^{n} FN(x_i)} \quad 10$$

$$WASn = \sum_{i=1}^{n} \left(\frac{actualinstance\, x_i}{total} * Sn(x_i) \right) \quad 11$$

$$Sp(x_i) = \frac{\sum_{i=1}^{n} TN(x_i)}{\sum_{i=1}^{n} TN(X_i) + \sum_{i=1}^{n} FP(x_i)} \quad 12$$

$$WASp = \sum_{i=1}^{n} \left(\frac{actualinstance\, x_i}{total} * Sp(x_i) \right) \quad 13$$

Table 5: summary result

	Type I	Type II 10% uncertainty	Type II 20% uncertainty	Type II 30% uncertainty
OCA	73.33%	86.67%	90%	93.33%
WASn	70%	85%	87.50%	90%
WASp	91.47%	95.54%	97.13%	98.72%

Where:

- TP is the set True Positive a class, patients in a class classified correctly;
- FN is the set False Negative a class, sum of patients in the actual instances of a class exclude TP of a class;
- FP is the set False Positive a class, sum of patients in the predicted instances of a class exclude TP of a class;
- TN is the set True Negative a class, sum of all patients exclude sum of actual and predicted instance of a class;
- x_i is the test result or instance for the i^{th} individual class

In general, on the experiments performed with the different architectures, it gives the possibility of being able to compare each one of the results and reach the conclusion that the best architecture is the one that is composed of type-2 high uncertainty, with 256 fuzzy rules and Mamdani type. Table 4 show the summary result. It performed 93.33% correctly classify, 90%+ sensitivity that indicates all of the patients class were correctly identified. Moreover, specificity determine 96%+ of the patients who are not belongs to class were correctly identified. Hence, the designed fuzzy expert system provides a decision support tool for medical practitioners and other health workers.

7. DISCUSSION

This work is focused on analyzing each of the possible architectures of type-1, type-2 fuzzy and interval type 2 fuzzy systems, in order to obtain the best classifier with the least possible error at the moment of making the kalaAzar suspicion classification.

In the work entitled Design expert system for diagnosis visceral Leishmaniasis using fuzzy interval type II fuzzy system with a new computational method, the design of a type-II fuzzy classifier was carried out with the triangular and trapezoidal membership functions and the appropriate fuzzy rules based on the knowledge of an expert in tropicaldisease.

In this work, we decided to design type-1 and type-2 fuzzy classifiers using triangular and trapezoidal membership functions in order to compare the different architectures with which the experiments were carried out. These are shown in the results section and all this in order to obtain the architecture with the lowest classification error rate.

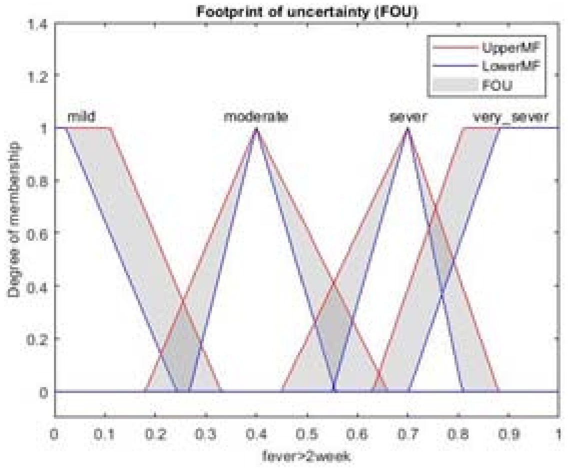

Figure 5 (A) Fuzzy set for fever more than weeks

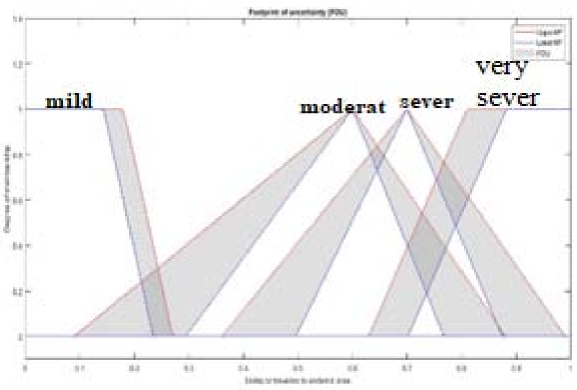

Figure 5 (B) Fuzzy set for living and travelling endemic area

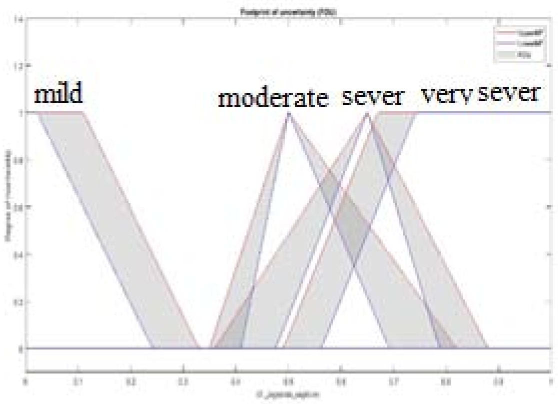

Figure 5 (C) Fuzzy set for output VL diagnosis Suspicion

It is important to emphasize that the use of type-2 fuzzy systems can help to improve the results, that is why the contribution of this work is was to find a better classification architecture based on interval type-2 fuzzy systems since the management of uncertainty in their membership functions helped to give a more adequate classification.

8. CONCLUSIONS

In this work, we experiment with different architectures designed based on fuzzy logic and evolutionary computing techniques, which belong to the artificial intelligence area. The design of the interval type-2 fuzzy systems enables making decisions based on a structure built from the knowledge of an expert, which is specified by membership functions and fuzzy rules and these are made based on different architectures.

Based on the information obtained in the tables shown above, we can conclude that the best architectures are interval type II having maximum FOU or increasing the degree of uncertainty. It is important to note that each of the fuzzy systems was tested with thirty patients, ten sever and ten very sever who are VL relapse patients, five is belong to moderate their symptom are very related VL but they were identified by laboratory test three of them has VL the rest two are free, other five are not VL patients as mild but they are chronic internal patients in University of Gondar hospital. The contribution of this work is the design of the type-2 fuzzy system with triangular and trapezoidal membership functions, which is better than the design of the type-1 fuzzy system, it is also important to mention that the results obtained in the type-2 fuzzy systems are also better than type-1 and also the high uncertainty score high classification accuracy, sensitivity and specificity.However the design with the best result is achieved in this work with a 93.33% classification accuracy, 90%+ sensitivity and 96%+ specificity.

ACKNOWLEDGMENT

Let me give thanks to the owner of this supernatural power and creature of the entire universe, almighty GOD. My immense gratitude is to my advisor Dr. Lars Rune Christensen for his critical comments, encouragement and guidance on throughout the completion of this work. I would like to express my appreciation to Dr. Rezika Mohamed head of University of Gondar VL Research and Treatment center and all staffs staff members. I am also grateful to my sponsor institution University of Gondar, Ethiopia to giving educational opportunities at Sudan. It is my pleasure to express my gratitude to Sudan University of Science and Technology for doing my PhD.

REFERENCE

1. Desjeux, P.J.C.i., microbiology and i. diseases, Leishmaniasis: current situation and new perspectives. 2004. **27**(5): p. 305-318.
2. Bates, P.A., Transmission of Leishmania metacyclic promastigotes by phlebotomine sand flies. International journal for parasitology, 2007. **37**(10): p. 1097-1106.
3. Chappuis, F., et al., Visceral leishmaniasis: what are the needs for diagnosis, treatment and control? Nature reviews microbiology, 2007. **5**(11): p. 873-882.
4. Organization, W.H., Leishmaniasis fact sheet. WHO: Geneva, Switzerland, Available: http://www.who.int/mediacentre/factsheets/fs375/en/. Accessed 15 June 2017., 2017.
5. Consortium, M., Leishmaniasis control in eastern Africa: Past and present efforts and future needs. Situation and gap analysis, 2010. **86**.
6. Hurissa, Z., et al., Clinical characteristics and treatment outcome of patients with visceral leishmaniasis and HIV co-infection in northwest Ethiopia. Tropical Medicine & International Health, 2010. **15**(7): p. 848-855.

7. Tsegaw, T., et al., Identification of environmental parameters and risk mapping of visceral leishmaniasis in Ethiopia by using geographical information systems and a statistical approach. Geospatial health, 2013. **7**(2): p. 299-308.
8. FMoH, Guideline for diagnosis, treatment and prevention of leishmaniasis in Ethiopia. Edited by Unit NTD, 2013. **2nd Edition**(Ethiopian Federal Ministry of Health; Addis Ababa, Ethiopia.).
9. Moncaz, A., et al., Characterization of breeding sites of Phlebotomus orientalis–The vector of visceral leishmaniasis in northwestern Ethiopia. Acta tropica, 2014. **139**: p. 5-14.
10. Herrero, M., et al., Natural history of a visceral leishmaniasis outbreak in highland Ethiopia. The American journal of tropical medicine and hygiene, 2009. **81**(3): p. 373-377.
11. Vaucheret, C., S. Guadarrama, and S. Muñoz. Fuzzy Prolog: A Simple General Implementation Using (R). in International Conference on Logic for Programming Artificial Intelligence and Reasoning. 2002. Springer.
12. Siler, W. and J.J. Buckley, Fuzzy expert systems and fuzzy reasoning. 2005: John Wiley & Sons.
13. Zadeh, L.A., "Fuzzy sets" Information and Control, ed. Vol.8. 1965: Lecture Notes. pp. 338-353.
14. Liang, Q. and J.M. Mendel. Interval type-2 fuzzy logic systems. in Fuzzy Systems, 2000. FUZZ IEEE 2000. The Ninth IEEE International Conference on. 2000. IEEE.
15. Matlashewski, G., et al., Research priorities for elimination of visceral leishmaniasis. 2014. **2**(12): p. e683-e684.
16. Montazeri-Gh, M. and S.J.A.S.C. Yazdani, Application of interval type-2 fuzzy logic systems to gas turbine fault diagnosis. 2020. **96**: p. 106703.
17. Abdolkarimzadeh, M., M.F. Zarandi, and O. Castillo. Interval Type II Fuzzy Rough Set Rule Based Expert System to Diagnose Chronic Kidney Disease. in North American Fuzzy Information Processing Society Annual Conference. 2018. Springer.
18. Asl, A.A.S. and M.H.F. Zarandi. A type-2 fuzzy expert system for diagnosis of leukemia. in North American Fuzzy Information Processing Society Annual Conference. 2017. Springer.
19. Djam, X., et al., A fuzzy expert system for the management of Malaria. 2011.
20. Chourasia, V.S., A.K. Tiwari, and R.J.A.S.C. Gangopadhyay, Interval type-2 fuzzy logic based antenatal care system using phonocardiography. 2014. **14**: p. 489-497.
21. Najafi, A., et al. A novel soft computing method based on interval type-2 fuzzy logic for classification of celiac disease. in Biomedical Engineering and 2016 1st International Iranian Conference on Biomedical Engineering (ICBME), 2016 23rd Iranian Conference on. 2016. IEEE.
22. Dubois, D. and H.J.N.Y.A. Prade, Theory and application, fuzzy sets and systems. 1980.
23. Mendel, J.M., Uncertain rule-based fuzzy logic systems: introduction and new directions. 2001: Prentice Hall PTR Upper Saddle River.
24. Zadeh, L.A., Fuzzy sets. Information and control, 1965. **8**(3): p. 338-353.
25. Hagras, H., Type-2 FLCS: A new generation of fuzzy controllers IEEE Computational Intelligence Magazine, 2007. **2**(1): p. 30-43.
26. Castillo, O., et al., A comparative study of type-1 fuzzy logic systems, interval type-2 fuzzy logic systems and generalized type-2 fuzzy logic systems in control problems. Information Sciences, 2016. **354**: p. 257-274.
27. Zadeh, L.A., The concept of a linguistic variable and its application to approximate reasoning—I. Information Sciences, 1975. **8**(3): p. 199-249.
28. Chourasia, V.S., A.K. Tiwari, and R. Gangopadhyay, Interval type-2 fuzzy logic based antenatal care system using phonocardiography. Applied Soft Computing, 2014. **14**: p. 489-497.
29. Sajja, P.S., R.J.A.K.B.S.M. Akerkar, Applications, and Research, Knowledge-based systems for development. 2010. **1**: p. 1-11.
30. Tripathi, K.J.I.S.I.o.A.I.T.-N.A. and P. Applications, A review on knowledge-based expert system: Concept and architecture. 2011. **4**: p. 19-23.
31. Raman, R. and K.J.A.M. Prasad, Applications of knowledge based systems in mining engineering. 1987. **1**: p. 167.
32. Cohen, P.R. and E.A. Feigenbaum, The handbook of artificial intelligence. Vol. 3. 2014: Butterworth-Heinemann.
33. Muthukaruppan, S. and M.J. Er, A hybrid particle swarm optimization based fuzzy expert system for the diagnosis of coronary artery disease. Expert systems with Applications, 2012. **39**(14): p. 11657-11665.
34. Abraham, A.J.H.o.m.s.d., Rule-Based expert systems. 2005.
35. Vlaanderen, M.J., Automated knowledge acquisition for expert systems: An overview. 1990.
36. Oprea, M.J.E.I., On the Use of Data-Mining Techniques in Knowledge-Based Systems. 2006. **6**: p. 21-24.
37. Vale, Z.A., C.T.J.I.S.T. Leondes, and Applications, Knowledge-based systems techniques and applications in power systems control centers. 2003. **6**: p. 61-110.
38. Al-Alawi, A.I., N.Y. Al-Marzooqi, and Y.F.J.J.o.k.m. Mohammed, Organizational culture and knowledge sharing: critical success factors. 2007.
39. Barua, A., L.S. Mudunuri, and O. Kosheleva, Why trapezoidal and triangular membership functions work so well: Towards a theoretical explanation. 2013.