A Decision Support System for Tuberculosis Diagnosis.

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ABSTRACT

In this paper, a fuzzy expert system for tuberculosis diagnosis was developed for providing decision support platform to tuberculosis researchers, physicians, and other healthcare practitioners in tropical medicine. The combination of inadequate expertise and sometimes the complexity of medical practices exponentially increase the morbidity and mortality rates of tuberculosis patients. The task of arriving at an accurate medical diagnosis may sometimes become very complex and cumbersome. Fuzzy logic technology provides a simple way to arrive at a definite conclusion from vague, imprecise and ambiguous medical data. In order to achieve this, a study of the knowledge base system for tuberculosis was undertaken and the system was developed using fuzzy logic technology.

The developed system composed of four components which include the knowledge base, the fuzzification, the inference engine and defuzzification components. The fuzzy inference method employed in this research is the Root Sum Square (RSS). Triangular membership function was used to show the degree of participation of each input parameter and the defuzzification technique employed in this research is the Center of Gravity (CoG). The fuzzy expert system was designed based on clinical observations, medical diagnosis and the expert's knowledge. We selected 30 patients with tuberculosis and computed the results that were in the range of predefined limits by the domain experts.

(Keywords: tuberculosis, fuzzy logic, knowledge base, fuzzy inference, fuzzification, defuzzification, medical diagnosis, fuzzy expert system)

INTRODUCTION

Tuberculosis (TB) is still a major public-health difficulty in the tropics. The combination of inadequate expertise and sometimes the complexity of medical practices exponentially increase the morbidity and mortality rates of tuberculosis patients. The task of arriving at an accurate medical diagnosis may sometimes become very complex and cumbersome. Fuzzy logic technology provides a simple way to arrive at a definite conclusion from vague, imprecise and ambiguous medical data (Zadeh, 1965). The task of medical diagnostic process is complex, and can become unwieldy and complicated especially when variable variables involved are numerous and patient presenting symptoms are non-specific (Djam and Kimbi, 2011). Djam and Kimbi (2011) recognized that a very important task in achieving hospital efficiency is to optimize the diagnostic process in terms of the number and duration of patients examination, with corresponding accuracy, sensitivity and specificity, as this is known to reduce morbidity and mortality rates, control costs and improved both doctor-patient and community facility relationship.

The emergence of information technology (IT) has opened unprecedented opportunities in health care delivery system as the demand for intelligent and knowledge-based systems has increased as modern medical practices become more knowledge-intensive (Djam and Kimbi, 2011). Physician intuitively exercise knowledge obtained from previous patients' symptoms. In everyday practice, the amount of medical knowledge grows steadily, such that it may become difficult for physicians to keep up with all the essential information gained. To quickly and accurately diagnose a patient, there is a critical need in employing computerized technologies to assist in diagnosis and access the related information. Computer-assisted technology is certainly helpful for inexperienced physicians in making medical diagnosis as well as for experienced physicians in supporting complex decisions. The complexity of medical practices makes traditional approaches of analysis inappropriate. Computer–assisted technology has become an attractive tool to help physicians in retrieving medical information as well as in making decision faced in today's medical complications. Most medical diagnosis is full of imprecision and uncertainty. Fuzzy logic which is one of the soft computing techniques can render precise what is imprecise inherent in medical diagnosis (Prasad, 2000).

The need to arrive at the most accurate medical diagnosis in very timely manner is heightened in the case of TB and other tropical diseases, as it is understood that quick and accurate diagnosis and timely initiation of treatment is sine-qua-non to the reduction of complication. Early diagnosis and prompt treatment of TB is a major strategy for TB control. In order to improve the possibility of early and accurate diagnosis of TB, there is the need for the application of artificial intelligent techniques in the diagnosis process, because these are known to improved practitioner performance.

In this research, we developed a fuzzy expert system for the diagnosing tuberculosis. The objective of the system is to provide a decision support platform to tuberculosis researchers, physicians and other healthcare practitioners in the tropics.

Fuzzy Logic as a Soft Computing Tool

Fuzzy logic is one of the methods of soft computing. Soft computing is a computational method that is tolerant to sub-optimality, impreciseness, vagueness and thus giving quick, simple and sufficient good solutions (Chen and Chen, 1994). It is widely accepted that the main components of soft computing are fuzzy logic, probabilistic reasoning, neural computing, and genetic algorithms. Fuzzy logic was adopted in this research because it is a powerful tool for dealing with the problem of knowledge representation in an environment of uncertainty and imprecision.

Soft computing methods can be used in an uncertain economic decision environment to deal with the vagueness of human thought and the difficulties in estimating inputs. Fuzzy logic has been used to bridge the gap between traditional approaches of diagnosis and computer-assisted diagnosis by handling the issues of vagueness, imprecision and ambiguity inherent in medical diagnosis. Every trustworthy expert knows that his or her medical knowledge and resulting diagnosis are pervaded by uncertainty with imprecise formulations. Fuzzy logic as a soft computing tool was conceived with the formulation of vague knowledge in mind together with rules of inference; it provides a powerful framework for the combination of evidence and deduction of consequences based on knowledge specified in sly-logistic form. Fuzzification and defuzzification of a fuzzy expert system allow the treatment of uncertainty inherent in medical diagnosis. Therefore, to overcome this uncertainty in tuberculosis diagnosis, a fuzzy expert system is designed to provide decision support tool to health practitioners.

LITERATURE REVIEW

A good number of expert systems have been designed for the diagnosis and treatment of some diseases. They are presented in (Classen, 1998), (Perreault and Mrtzeger, 1999), (Yan et al., 2006). (McCaffery et al., 2007), (Pignone, 2007), (Street, 2007), (Pietka, 2008), (Thomson et al., 2007), and (Tadic et al., 2009).

A medical expert system for managing tropical diseases was proposed by (Adekoya et al., 2008). The proposed Medical Expert Solution (MES) system was to assist medical doctors to diagnose symptoms related to a given tropical disease, suggests the likely ailment, and advances possible treatment based on the MES diagnosis. The MES uses a knowledge-base which composes of two knowledge structures; namely symptoms and disease. The MES inference engine uses a forward chaining mechanism to search the knowledge-base for symptoms of a disease and its associate therapy which matches the query supplied by the patient. The MES is useful for people who do not have access to medical facilities and also by those who need first-aid solution before seeing medical consultant.

Obot and Uzoka (2008) designed a fuzzy rule-based framework for the management of tropical diseases. The objective of the research was to apply the concept of fuzzy logic technology to determine the degree of severity on tropical diseases. The root sum square of drawing inference was employed to infer the data from the rules developed. Center-of-gravity method was used for defuzzification.

Several papers have successfully explained the benefits and challenges of using clinical decision support systems. Uzoka et al. (2010) designed a Clinical Decision Support System (DSS) in the diagnosis of malaria. A case comparison of two soft computing methodologies. The purpose of this study is to make the case for the utility of decision support systems in the diagnosis of malaria and to conduct a case comparison of the effectiveness of the fuzzy and the AHP methodologies in the medical diagnosis of malaria, in order to provide a framework for determining the appropriate kernel in a fuzzy-AHP hybrid system. In the same context as in Obot et al. (2010), Uzoka and Barker (2010) equally designed an experimental comparison of fuzzy logic and analytic hierarchy process for medical decision support systems. The results of the study indicated a non-statistically significant relative superiority of the fuzzy technology over the AHP technology. Other medical expert systems using fuzzy have been designed (Hudson and Cohen, 1994), (Kuncheva and Steimann, 1999), (Wainer and Sandri, 1999), (Tohal and Ngah, 2007), (Sharareh et al., 2010) and (Djam and Kimbi, 2011).

MATERIALS AND METHODS

Data

Specialist Hospital Gombe in Nigeria was used for data collection. We selected 30 patients, aged between 15 and 75. In this sequel, we made an honest attempt to incorporate fuzzy techniques and develop a fuzzy expert system for the management of tuberculosis.

FUZZY EXPERT SYSTEM

The success of a Fuzzy Expert System depends upon the opinion of the domain experts on various issues related to the study. The domain experts identified were from Specialist hospital Gombe in Nigeria. The developed Fuzzy Expert System for the Management of tuberculosis has an architecture presented in Figure 1 below.

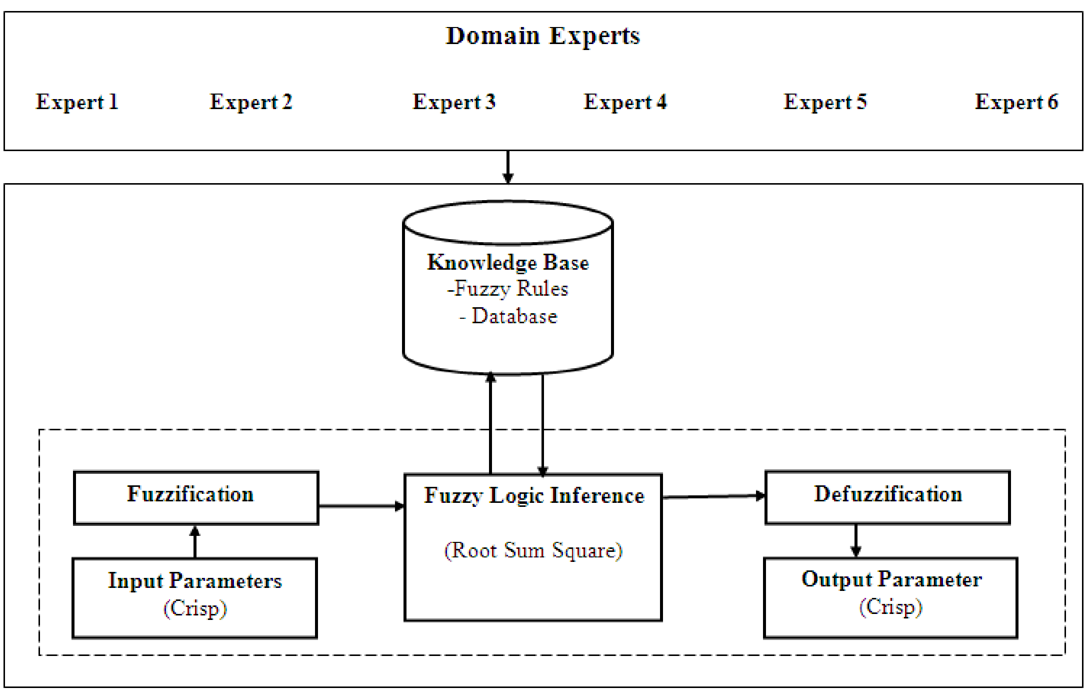

Figure 1: Architecture of the System.

The development system involves fuzzification, inference engine and defuzzification. The Fuzzy Expert System is a decision support system that provides decision support platform to health care researchers in tropical medicine. The designed system is a rule based system that uses fuzzy logic rather that Boolean logic. It was developed based on the following key components:

- Knowledge-Base component
- Fuzzification Component
- Inference Engine Component
- Defuzzification Component

Logical System Modeling

Unified Modeling Language (UML) as an object oriented tool was used to capture and model some of the functionalities in the system. UML is an excellent tool for modeling objects and the relationship between the objects and classes (Kendall and Kendall, 2002).

The UML approach helps to depict the system in many different views thus giving a quick structural representation of the system. Figure 2, Figure 3, and Figure 4, show the class diagram, sequence diagram and activity diagram of the system, respectively.

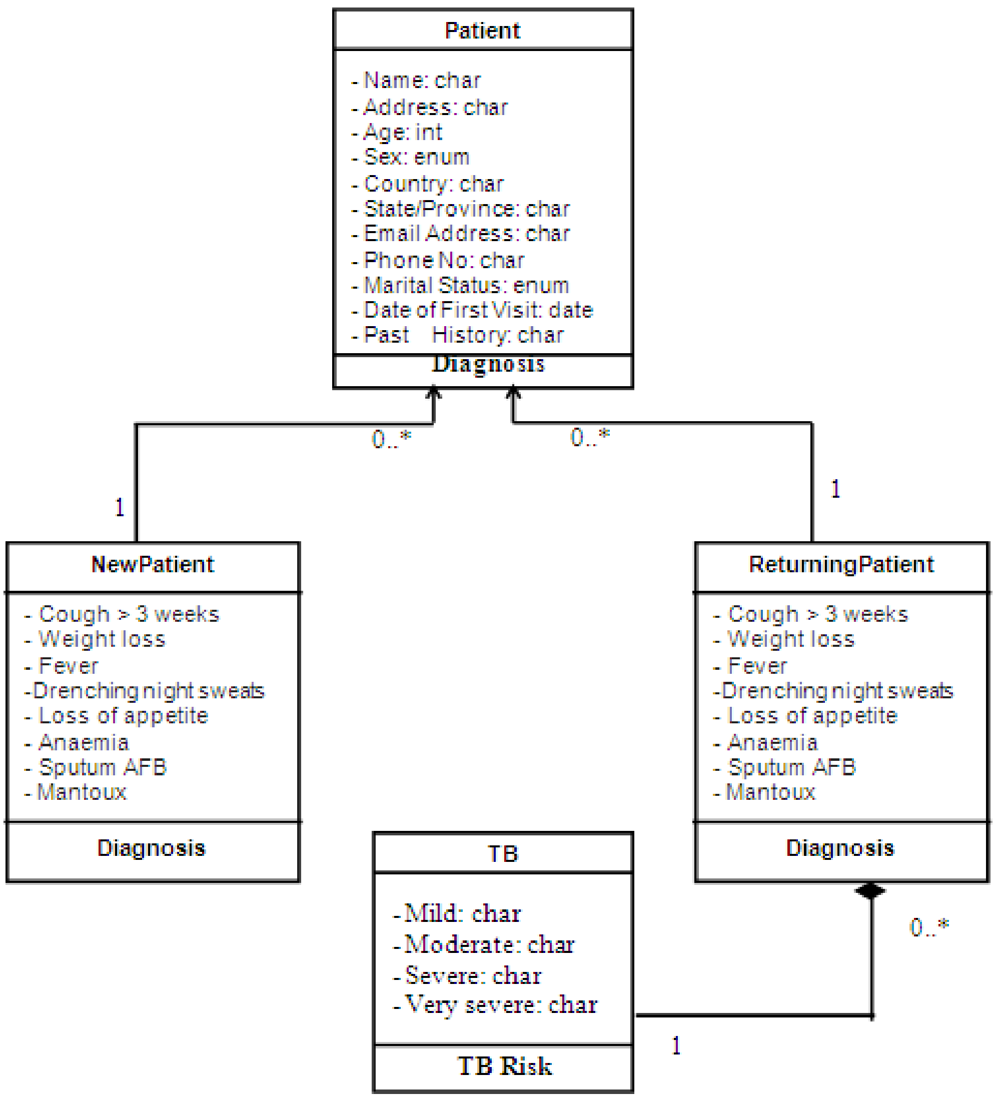

Figure 2: Class Diagram Showing Attributes Generalization and Composition Association.

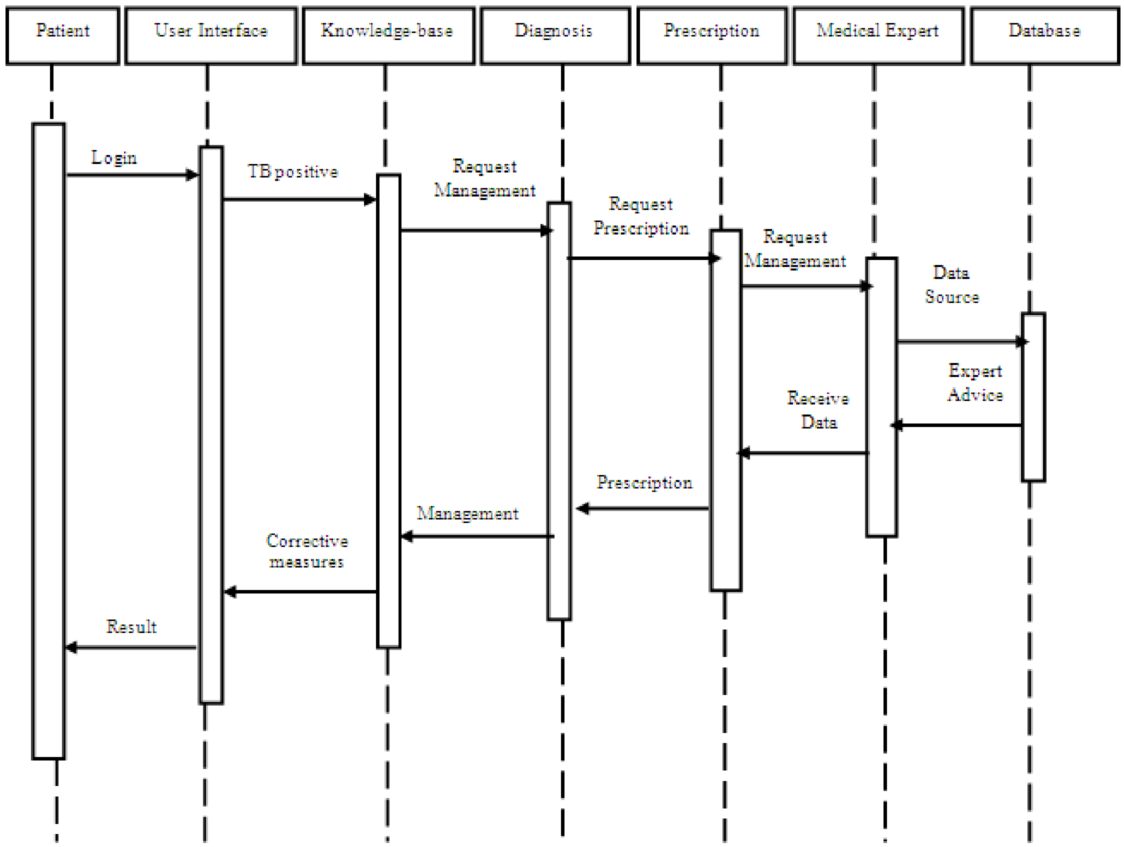

Figure 3: Sequence Diagram for the System
(Source: Djam and Kimbi, 2011).

Activity Diagram for the Developed System

Activity diagrams are used to graphically depict the sequential flow of activities of the developed system. The activity diagram in Figure 4 below describes the work flow of activity of the system.

Knowledge-Base Component

Knowledge is a key factor in the performance of intelligent systems. The knowledge-base of the system is composed of structured and concise representation of the knowledge of domain experts of tropical medicine. The structure knowledge is concerned with facts, rules and events of tropical diseases, which were commonly agreed upon by experts in the field of tropical medicine. For the purpose of this research, TB as a known tropical disease, is considered. The knowledge-base of the designed system has 256 fuzzy rules which were developed with the help of six domain experts.

Fuzzification Component

Fuzzification is the process of changing a real scalar value into a fuzzy value. This is achieved with different types of fuzzifiers. There are generally four types of fuzzifiers, which are used for the fuzzification process. They are: Trapezoidal fuzzifier, Triangular fuzzifiers, Singleton fuzzifier, and Gaussian fuzzifier (Tsoukalas and Uhrig, 1993). Triangular fuzzifier which is widely used will be used in this research. Fuzzification of data is carried out by selecting input parameters into the horizontal axis and projecting vertically to the upper boundary of membership function to determine the degree of membership.

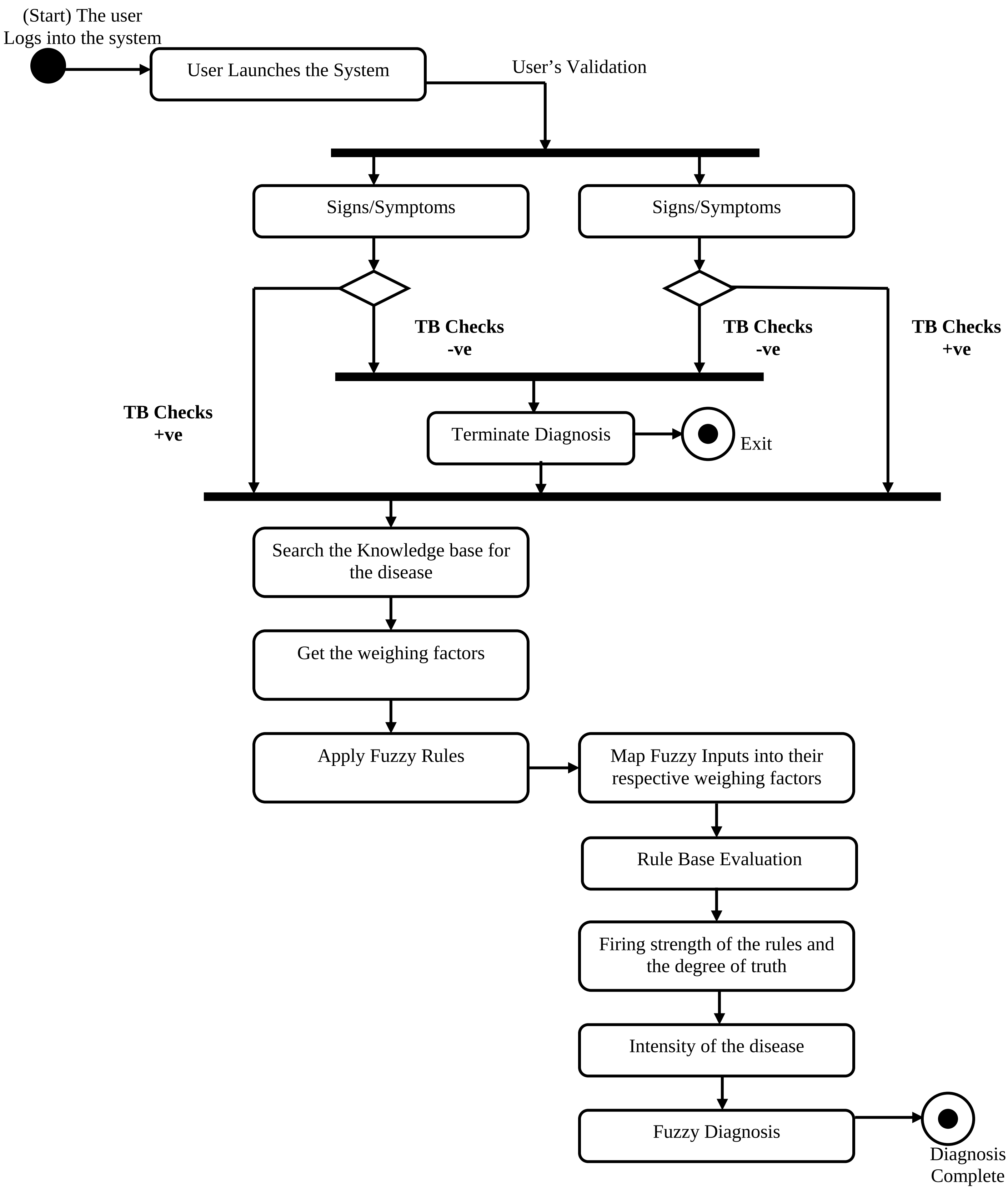

Figure 4: Activity Diagram for the Developed System.

The first step in the development of fuzzy logic based expert system is to construct fuzzy sets for the parameters. This is shown in Equations (1) to (4) below. 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). The range of fuzzy value for each linguistic is shown in Table 1 below: Fuzzification begins with the transformation of the raw data using the functions that are expressed in Equations (1) to (4) below.

During the process, linguistic variables are evaluated using triangular membership function and are accompany by associated degree of membership ranging from 0 to 1 as shown in equations (1) to (4) below. These formulas are determined by aid of both the expert doctors in the field of tropical medicine and literature.

Table 1: Range of Fuzzy Values.

Linguistic Variables	Fuzzy Values
Mild	$0.1 \leq x \leq 0.3$
Moderate	$0.3 \leq x \leq 0.6$
Severe	$0.6 \leq x \leq 0.8$
Very Severe	$0.8 \leq x \leq 1.0$

$$\mu_{Mild}(X) = \begin{cases} 0 & if \quad x \leq 0.1 \\ \dfrac{x-0.1}{0.2} & if \quad 0.1 \leq x \leq 0.3 \\ \dfrac{0.2-x}{0.1} & if \quad 0.2 \leq x \leq 0.3 \\ 0 & if \quad x \geq .0.2 \end{cases} \qquad - - - - - - \quad (1)$$

$$\mu_{Moderate}(X) = \begin{cases} 0 & if \quad x \leq 0.3 \\ \dfrac{x-0.3}{0.3} & if \quad 0.3 \leq x \leq 0.6 \\ \dfrac{0.45-x}{0.15} & if \quad 0.45 \leq x \leq 0.6 \\ 0 & if \quad x \geq .0.45 \end{cases} \qquad - - - - - - \quad (2)$$

$$\mu_{Severe}(X) = \begin{cases} 0 & if \quad x \leq 0.5 \\ \dfrac{x-0.6}{0.2} & if \quad 0.6 \leq x \leq 0.8 \\ \dfrac{0.7-x}{0.1} & if \quad 0.7 \leq x \leq 0.8 \\ 0 & if \quad x \geq .0.7 \end{cases} \qquad - - - - - - \quad (3)$$

$$\mu_{Very\ Severe}(X)=\begin{cases}0 & if \quad x \le 0.8 \\ \dfrac{x-0.1}{0.2} & if \quad 0.8 \le x \le 1.0 \\ \dfrac{0.2-x}{0.1} & if \quad 0.9 \le x \le 1.0 \\ 0 & if \quad x \le 1.0\end{cases} \qquad ------ \quad (4)$$

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 (six medical doctors). The knowledge-base of the designed system has 256 fuzzy rules.

Table 2 below shows sample fuzzy rule base for TB. The rule base for TB has cough > 3 weeks, weight loss, fever, drenching night sweats, loss of appetite, anaemia, sputum AFB, and Mantoux as input parameters to the system. From the expert knowledge, these input parameters were used to generate 256 rules for the rule base for TB.

Some of the rules (Rules 20, Rules 30, Rules 60, Rule 80, Rules 110, Rule 140, Rules 160, Rules 200 and Rule 256) can be interpreted as follows:

Rule 20: IF cough > 3 weeks = severe and weight loss = severe and fever = severe and drenching night sweats = mild and loss of appetite = severe and anaemia = mild and sputum AFB = severe and mantoux = moderate THEN TB = very severe.

Rule 30: IF cough > 3 weeks = moderate and weight loss = moderate and fever = moderate and drenching night sweats = moderate and loss of appetite = moderate and anaemia = moderate and sputum AFB = moderate and mantoux = moderate THEN TB = moderate.

Rule 60: IF cough > 3 weeks = mild and weight loss = mild and fever = mild and drenching night sweats = mild and loss of appetite = mild and anaemia = mild and sputum AFB = mild and mantoux = mild THEN TB = mild.

Rule 80: IF cough > 3 weeks = moderate and weight loss = moderate and fever = moderate and drenching night sweats = very severe and loss of appetite = mild and anaemia = moderate and sputum AFB = severe and mantoux = moderate THEN TB = moderate.

Rule 110: IF cough > 3 weeks = moderate and weight loss = mild and fever = moderate and drenching night sweats = mild and loss of appetite = moderate and anaemia = mild and sputum AFB = moderate and mantoux = mild THEN TB = moderate.

Rule 140: IF cough > 3 weeks = severe and weight loss = severe and fever = severe and drenching night sweats = moderate and loss of appetite = moderate and anaemia = moderate and sputum AFB = very severe and mantoux = mild THEN TB = very severe.

Rule 160: IF cough > 3 weeks = mild and weight loss = moderate and fever = mild and drenching night sweats = mild and loss of appetite = moderate and anaemia = mild and sputum AFB = mild and mantoux = mild THEN TB = mild.

Rule 200: IF cough > 3 weeks = mild and weight loss = moderate and fever = severe and drenching night sweats = moderate and loss of appetite = moderate and anaemia = mild and sputum AFB = moderate and mantoux = moderate THEN TB = moderate.

Rule 256: IF cough > 3 weeks = mild and weight loss = mild and fever = severe and drenching night sweats = severe and loss of appetite = severe and anaemia = severe and sputum AFB = severe and mantoux = severe THEN TB = severe.

Table 2: Fuzzy Rule base for TB.

Rule No	IF								THEN
	Cough>3 weeks	**Weight loss**	**Fever**	**Drenching night sweats**	**Loss of appetite**	**Anaemia**	**Sputum AFB**	**Mantoux**	**Conclusion**
1	Severe	Severe	Severe	Mild	Severe	Mild	Severe	Moderate	Very Severe
20	Moderate	Mild	Mild	Mild	Mild	Mild	Mild	Mild	Mild
30	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
40	Very Severe	Severe	Severe	Severe	Severe	Severe	Severe	Severe	Very Severe
50	Very Severe	Severe	Very Severe	Moderate	Moderate	Moderate	Mild	Mild	Very Severe
60	Mild	Mild	Mild	Mild	Mild	Mild	Mild	Mild	Mild
70	Severe	Mild	Severe	Mild	Severe	Mild	Very Severe	Moderate	Severe
80	Moderate	Moderate	Moderate	Very Severe	Mild	Moderate	Severe	Moderate	Very Severe
90	Very Severe	Moderate	Moderate	Moderate	Mild	Moderate	Moderate	Mild	Severe
100	Severe	Severe	Severe	Moderate	Moderate	Moderate	Mild	Mild	Severe
110	Moderate	Mild	Moderate	Mild	Moderate	Mild	Moderate	Mild	Moderate
120	Mild	Mild	Mild	Mild	Moderate	Moderate	Moderate	Mild	Mild
130	Mild	Mild	Moderate	Moderate	Moderate	Mild	Severe	Moderate	Moderate
140	Severe	Severe	Severe	Moderate	Moderate	Moderate	Very Severe	Mild	Very Severe
150	Moderate	Moderate	Moderate	Severe	Mild	Moderate	Mild	Moderate	Moderate
160	Mild	Moderate	Mild	Mild	Moderate	Mild	Mild	Mild	Mild
170	Moderate	Severe	Severe	Severe	Mild	Moderate	Severe	Severe	Severe
200	Mild	Moderate	Severe	Moderate	Moderate	Mild	Moderate	Moderate	Moderate
240	Severe	Severe	Mild	Mild	Moderate	Moderate	Moderate	Mild	Moderate
256	Mild	Mild	Severe	Severe	Severe	Severe	Severe	Severe	Severe

Fuzzy Inference Component

The process of drawing conclusion from existing data is called inference. Fuzzy inference is the process of mapping from a given input to an output using the theory of fuzzy sets (Tsoukalas and Uhrig, 1993). The fuzzy inference engine uses the rules in the knowledge-base and derives conclusion base on the rules. The inference engine for the designed system uses a forward chaining mechanism to search the knowledge for the symptoms of a disease. The inference engine evaluates all the rules in the rules base and combines the weighted consequences of all the relevant (fired) into a single fuzzy set (Melek and Sadeghian, 2009). The inference engine technique employed in this research is the Root Sum Square (RSS). RSS is given by the formula in Equation (5):

$$\sqrt{\sum R^2} = \sqrt{\left(R_1^2 + R_2^2 + R_3^2 + \ldots R_n^2\right)} \qquad (5)$$

Where $R_1^2 + R_2^2 + R_3^2 + \ldots R_n^2$ are strength values (truth values) of different rules which share the same conclusion (i.e., R = value of firing rule). RSS combines method combines the effects of all applicable rules, scales the functions at their respective magnitudes and compute the “fuzzy” centroid of the composite area. This method is more complicated mathematically than other methods, but selected for this research since it gives the best weighted influence to all firing rules. An example of the rule base evaluation for patient number 003 is presented in Table 5 below. The RSS of drawing inference was found to be the most suitable technique to infer data from the rules developed.

Defuzzification Component

The defuzzification process translates the output from the inference engine into crisp output. This is due to the fact that, the output from the inference engine is usually a fuzzy set while for most medical applications, crisp values are required. The input to the defuzzification process is a fuzzy set while the output of the defuzzification process is a single number (crisp output). Many defuzzification techniques are proposed. Four common defuzzification techniques are: center-of-area (gravity), center-of-sums, max-criterion and mean of maxima. According to (Abraham and Nath, 2000), max-criterion produces the point at which the possibility distribution of the action reaches a maximum value and it the simplest to implement.

The center-of-area (also referred as center-of-gravity or the centroid method) is the most widely used technique because when it is used, the defuzzified values tend to move smoothly around the fuzzy output region, thus giving a more accurate representation of fuzzy set of any shape (Cochron and Chen, 2005). The center-of-gravity (CoG) often uses discrete variables so that CoG, Y' can be approximated to overcome its disadvantage as shown in Equation (6) which uses weighted average of the centers of the fuzzy set instead of integration. The CoG is an averaging technique. The CoG defuzzification method is similar to the formula for calculating the center of gravity in physics. The difference is that, density of mass is replaced by the membership values. The CoG formula is given as:

$$\mathrm{CoG}\left(Y'\right) = \frac{\sum \mu_Y\left(x_i\right)x_i}{\sum \mu_Y\left(x_i\right)} \qquad (6)$$

where $\mu_Y\left(x_i\right)$=Membership value in the membership function and,

x_i = center of membership function.

The approach is adopted in this research because it is computationally simple and intuitively plausible (Djam and Kimbi, 2011).

RESEARCH EXPERIMENT

Patients’ state of health (with respect to TB) was evaluated by the domain experts based on signs, symptoms and investigations. The intensity of signs, symptoms and investigation was rated as mild (1), moderate (2), severe (3), and very severe (4). Table 3 shows the weights assigned to patients after an interactive session with the expert doctors.

Table 4 below define the degree to which one can say the signs, symptoms and investigations is mild, moderate, severe, or very severe. Triangular fuzzy values for signs, symptoms and investigations of table 3 above are shown in Table 4.

From the above Table 4, the interactive session entered for patient number 003 is as follows:

Cough > 3 weeks	Severe	0.5
Weight loss	None	0.0
Fever	Moderate	0.25
Drenching night sweats	Moderate	0.25
Loss of appetite	None	0.0
Anaemia	Severe	0.5
Sputum AFB	Moderate	0.25
Mantoux	Moderate	0.25

Table 3: Weights assigned to Patients on TB Diagnosis Variables.

Patient No.	Cough >3 weeks	Weight loss	Fever	Drenching night sweats	Loss of appetite	Anaemia	Sputum AFB	Mantoux
001	4	3	3	2	2	2	2	2
002	4	2	3	3	-	2	4	3
003	3	1	2	2	-	3	2	2
004	3	3	3	2	2	-	3	-
005	3	3	2	4	1	2	3	-
006	3	3	2	2	3	2	2	3
007	3	2	3	2	1	2	2	4
008	2	2	3	3	2	2	3	4
009	3	2	4	3	2	2	3	3
010	1	3	2	3	1	2	4	3
011	2	2	2	2	3	-	2	2
012	2	2	3	2	3	2	3	3
013	4	4	2	2	1	3	2	2
014	3	3	3	3	2	2	2	4
015	3	2	4	3	2	3	4	3
016	3	2	2	2	2	2	2	3
017	3	2	3	4	3	3	3	4
018	4	3	3	2	2	-	2	2
019	3	2	1	3	3	2	2	2
020	2	3	2	4	2	1	2	2
021	2	3	1	3	3	2	2	3
022	3	3	3	2	2	3	3	2
023	3	3	2	2	2	2	2	2
024	2	2	4	3	-	-	2	2
025	3	3	2	2	2	2	4	2
026	3	2	2	2	2	2	4	3
027	3	2	1	3	-	-	3	2
028	4	3	4	2	2	2	3	3
029	4	2	3	2	2	2	2	2
030	3	3	3	1	2	4	3	3

Table 4: Triangular Fuzzy Numbers for TB.

Patient No.	Cough >3 weeks	Weight loss	Fever	Drenching night sweats	Loss of appetite	Anaemia	Sputum AFB	Mantoux
001	0.75	0.5	0.5	0.25	0.25	0.25	0.25	0.25
002	0.75	0.25	0.5	0.5	0.0	0.25	0.75	0.53
003	0.5	0.0	0.25	0.25	0.0	0.5	0.25	0.25
004	0.5	0.5	0.5	0.25	0.25	0.0	0.5	0.0
005	0.5	0.5	0.25	0.75	0.0	0.25	0.5	0.0
006	0.5	0.5	0.25	0.25	0.5	0.25	0.25	0.5
007	0.5	0.25	0.5	0.25	0.0	0.25	0.25	0.75
008	0.25	0.25	0.5	0.5	0.25	0.25	0.5	0.75
009	0.5	0.25	0.75	0.5	0.25	0.25	0.5	0.5
010	0.0	0.5	0.25	0.5	0.0	0.25	0.75	0.5
011	0.25	0.25	0.25	0.25	0.5	0.0	0.25	0.25
012	0.25	0.25	0.5	0.25	0.5	0.25	0.5	0.5
013	0.75	0.75	0.25	0.25	0.0	0.5	0.25	0.25
014	0.5	0.5	0.5	0.5	0.25	0.25	0.25	0.75
015	0.5	0.25	0.75	0.5	0.25	0.5	0.74	0.5
016	0.5	0.25	0.25	0.25	0.25	0.25	0.25	0.5
017	0.5	0.25	0.5	0.75	0.5	0.5	0.5	0.75
018	0.75	0.5	0.5	0.25	0.25	0.0	0.25	0.25
019	0.5	0.25	0.0	0.5	0.5	0.25	0.25	0.25
020	0.25	0.5	0.25	0.75	0.25	0.0	0.25	0.25
021	0.25	0.5	0.0	0.5	0.5	0.25	0.25	0.5
022	0.5	0.5	0.5	0.25	0.25	0.5	0.5	0.25
023	0.5	0.5	0.25	0.25	0.25	0.25	0.25	0.25
024	0.25	0.25	0.74	0.5	0.0	0.0	0.25	0.25
025	0.5	0.5	0.25	0.25	0.25	0.25	0.74	0.25
026	0.5	0.25	0.25	0.24	0.25	0.25	0.754	0.5
027	0.5	0.25	0.0	0.5	0.0	0.0	0.5	0.25
028	0.75	0.5	0.75	0.25	0.25	0.25	0.5	0.5
029	0.75	0.25	0.5	0.25	0.25	0.25	0.25	0.25
030	0.5	0.5	0.5	0.0	0.25	0.75	0.5	0.5

Table 5: Rule Base Evaluation for Patient Number 003.

Rule No	Cough >3 weeks	Weight loss	Fever	Drenching night sweats	Loss of appetite	Anaemia	Sputum AFB	Mantoux	Conclusion	Non-zero Minimum Number
1	0.5	-	-	-	-	-	-	0.25	Very Severe	0.25
30	-	-	0.25	0.25	-	-	0.25	0.25	Moderate	0.25
40	-	-	-	-	-	0.5	-	-	Very Severe	0.5
50	-	-	-	0.25	-	-	-	-	Very Severe	0.25
70	0.5	-	-	-	-	-	-	0.25	Severe	0.25
80	-	-	0.25	--	-	-	-	0.25	Very Severe	0.25
90	-	-	0.25	0.25	-	-	0.25	-	Severe	0.25
100	0.5	-	-	0.25	-	-	-	-	Severe	0.25
110	-	-	0.25	-	-	-	0.25	-	Moderate	0.25
120	-	-	-	-	-	-	0.25	-	Mild	0.25
130	-	-	0.25	0.25	-	-	-	0.25	Moderate	0.25
140	0.5	-	-	0.25	-	-	-	-	Very Severe	0.25
150	-	-	0.25	-	-	-	-	0.25	Moderate	0.25
200	-	-	-	0.25	-	-	0.25	0.25	Moderate	0.25
240	0.5	-	-	-	-	-	0.25	-	Moderate	0.25
256	-	-	-	-	-	0.5	-	-	Severe	0.5

These values will result in the fuzzy transcript as shown in Table 5 below using the rule base for TB as presented in Table 2 above. An example for rule base evaluation for patient number 003 is presented in Table 5.

Table 5 above shows that, sixteen (16) rules where fired out for patient number 003 (i.e., 16 rules generated non-zero minimum values from the rule base for TB in Table 2).

For each of the linguistic variables: mild, moderate, severe and very severe, the respective output membership function strength (range: 0-1) from the possible rules (R1 – R256) are computed using RSS inference technique as shown in Equation (7).

The output (fuzzy set) from RSS is then defuzzified to obtain the crisp output. Defuzzifying using discrete CoG technique, we have the following as shown in Equation (8). This means that patient number 003 has severe TB with 61% possibility.

Similarly, we computed the results of all fired rules for the other 29 patients and got results that were in the range of predefined limits by the domain experts.

$$Mild = \sqrt{R120^2} = \sqrt{0.25^2} = 0.25$$

$$Moderate = \sqrt{R30^2 + R110^2 + R130^2 + R150^2 + R200^2 + R240^2} = \sqrt{0.25^2 + 0.25^2 + 0.25^2 + 0.25^2 + 0.25^2 + 0.25^2} = 0.6124 \quad - - - - (7)$$

$$Severe = \sqrt{R70^2 + R90^2 + R100^2 + R256^2} = \sqrt{0.25^2 + 0.25^2 + 0.25^2 + 0.5^2} = 0.6614$$

$$Very\ Severe = \sqrt{R1^2 + R40^2 + R50^2 + R80^2 + R140^2} = \sqrt{0.25^2 + 0.5^2 + 0.25^2 + 0.25^2 + 0.25^2} = 0.7071$$

$$Crisp\ Output = \frac{(0.25 * 0.2) + (0.6124 * 0.4) + (0.6614 * 0.65) + (0.7071 * 0.9)}{0.25 + 0.6124 + 0.6614 + 0.7071} = 0.61 = 61\% \quad - - - - (8)$$

RESULTS AND DISCUSSION

A decision support system for diagnosing TB has been developed. The study evaluated the diagnosis of thirty patients using fuzzy methodology and the results gotten were in the range of the pre-defined limits by the domain experts. 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 5 above shows the rule evaluation for patient number 003. Patient number 003 was diagnosed for severe malaria with 61% possibility. The designed fuzzy expert system provides a decision support tools to medical practitioners and other health workers.

Our results based on real patient data confirms 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 (Djam and Kimbi).

CONCLUSIONS

The used of fuzzy logic in medical diagnosis cannot be overemphasized. Fuzzy logic for medical diagnosis provides an efficient way to assist inexperienced physicians to arrive at the final diagnosis of TB more quickly and efficiently. The developed system provides decision support platform to assist TB researchers, physicians and other health practitioners in TB endemic regions. The authors believe that the approach proposed in this study, if used intelligently, could be an effective technique for diagnosing TB.

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