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Research Paper

A Fuzzy Expert System for the Management of Malaria

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Abstract: *Malaria represents major public health problems in the tropics. The harmful effects of malaria parasites to the human body cannot be underestimated. In this paper, a fuzzy expert system for the management of malaria (FESMM) was presented for providing decision support platform to malaria researchers, physicians and other healthcare practitioners in malaria endemic regions. The developed FESMM 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). The Root Sum Square of drawing inference was employed to infer the data from the fuzzy rules developed. 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 Centre of Gravity (CoG). The fuzzy expert system was designed based on clinical observations, medical diagnosis and the expert's knowledge. We selected 35 patients with malaria and computed the results that were in the range of predefined limit by the domain experts.*

Keywords: Malaria, Fuzzy Logic, Knowledge base, Medical Diagnosis, Fuzzy Expert System.

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1. Introduction

As a predominant environmental health problem in Africa, malaria constitutes a great threat to the existence of many communities. The harmful effects of malaria parasites to the human body cannot be underestimated. Malaria is a parasitic disease caused mainly by *plasmodium falciparum*. *P. falciparum* and three other malaria parasites that infect human (*p. vivax*, *p.ovale*, and *p. malariae)* are transmitted by more that a dozen species of Anopheles mosquitoes widely

in the tropics [3] and [6]. Malaria is the commonest cause of mortality in the tropics [26] and [27]. Today's world is one with increasing access to intelligent systems. In recent time, Artificial Intelligent methods have significantly been used in medical applications and research efforts have been concentrated on medical expert systems as complementary solution to conventional technique for finding solution to medical problems [10] and [11]. 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. The diagnosis of tropical diseases involves several levels of uncertainty and imprecision [17].The task of disease diagnosis and management is complex because of the numerous variables involved. It is made more so because of a lot of imprecision and uncertainties. Patients cannot describe exactly how they feel, doctors and nurses cannot tell exactly what they observe, and laboratories results are dotted with some errors caused either by the carelessness of technicians or malfunctioning of the instrument. Medical researchers cannot precisely characterize how diseases alter the normal functioning of the body [46] and [47]. All these complexities in medical practice make traditional quantitative approaches of analysis inappropriate. Computer tools help to organize, store and retrieve appropriate medical knowledge needed by the practitioner in dealing with each difficult case and suggesting appropriate diagnosis, prognosis, therapeutic decisions and decision-making technique [46]. An Expert System (ES) is an intelligent computer program that uses the knowledge-base of one or more experts and inference procedures for problem solving [20]. Figure 1 below depicts a typical ES architecture. Human experts solve problems by using a combination of factual knowledge and reasoning ability. In an expert system, theses two essentials are contained in two separate but related components: a knowledge base and an inference engine. The knowledge-base provides specific facts and rules about the subject and the inference engine provides the reasoning ability that enables the expert system to form conclusions. Expert systems also provide additional tools in the form of user interface and explanation facilities. User interfaces, as with any application, enable people to form queries, provide information and interact with the system. Explanation facilities, a fascinating part of expert systems, enable the systems to explain or justify their conclusions, and they enable developers to check on the operation of the system themselves.
The application of fuzzy concepts to medical diagnosis of some diseases are discussed in [10], [11] , [29], and [48].

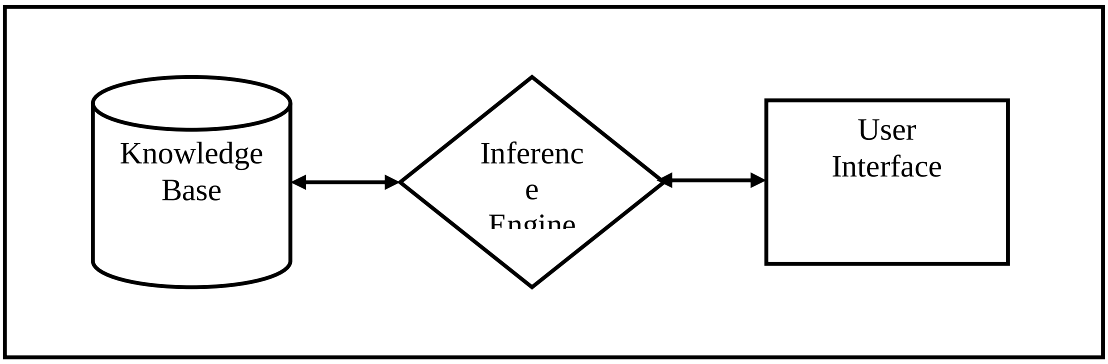

Figure 1: Architecture of an Expert System

In most tropical countries, most of which are developing countries, medical personnels and facilities are not adequate for effective tackling of tropical diseases. In rural areas, medical attention is grossly inadequate [52]. Among all the soft computing techniques, the concept of fuzzy logic is adopted in this research mainly due to it capability to makes decisions in an

environment of imprecision, uncertainty and incompleteness of information. In addition, another advantage of choosing fuzzy logic is due to the fact that, fuzzy logic resembles human decision making with its ability to work from approximate reasoning and ultimately find a precise solution. Fuzzy expert systems incorporate elements of fuzzy logic, which is a logically consistent way of reasoning that can cope with uncertainty, vagueness and imprecision inherent in medical diagnosis [25].
In this research, we developed a fuzzy expert system for the management of malaria (FESMM). FESMM was design based on clinical observations, medical diagnosis and the expert's knowledge. The objective of the system is to provide a decision support platform to malaria researchers, physicians and other healthcare practitioners in malaria endemic regions. In addition, the system will assist medical personnel in the tedious and complication task of diagnosing and further provide a scheme that will assist medical personnel especially in rural areas, where there are shortages of doctors, thereby, offering primary health care to the people.

2. Literature Review

Intelligence systems have become vital in the growth and survival of healthcare sector. Recently, much research effort has been concentrated in designing intelligence systems. Several related work have shown that tropical diseases remains a major public health problem in the tropics. [4] and [53]. However, concerted efforts are continually been made to control the spread and transmission of tropical diseases within and between communities. In the work carried out by [26], it was reported that monthly malaria incidence rates and vector densities were used for surveillance and adaptive tuning of the environmental management strategies; which resulted in a high level of performance. Within 3-5 years, malaria-related mortality, morbidity and incidence rates were reduced by 70-95%. In a recent study, it was concluded that malaria control programme that emphasized environmental management were highly effective in reducing morbidity and mortality [22]. In another study carried out by [27], the economic payoffs of malaria control strategies were highlighted. The used of expert systems in medical applications is inevitable. This can be found in [16], [31], [35], and [36]. A good number of expert systems have been development on tropical diseases. [13] developed an expert system on tropical diseases to assist paramedical staff during training and in the diagnosis of many common diseases presented at their clinics. In another study carried out by [54], an expert system on endemic tropical diseases was developed. The purpose of the system was to be a source of knowledge for doctors, and for medical students, on the diagnosis of some of the major tropical endemic diseases. [8] designed a paper to support clinical decision making. The paper focuses on the distinction between three types of clinical decision support tools: for information management, focusing attention, and patient-specific consultation.. Other expert systems for medical diagnosis and treatment of some tropical diseases are presented in [9], [37], [38], [40], [42], and [44].

[15] explained the importance of setting priority for health research. They present a paper on "Strategy emphasis for tropical disease research: a TDR perspective. In their paper, the aim was to prioritize research in neglected tropical disease than high-profile tropical diseases. An analytical method that is based on the prioritization framework of the Global Forum of Health Research was used for data analysis. [4] Emphasize the recognition that research is critical in the fight against tropical disease. However, the limited resources available can fund only a fraction of the promising research opportunities. Hence, prioritization is essential for health research and

considerable effort has gone into developing effective prioritization mechanisms. [4], [19] and [21]. Tropical disease research (TDR) Special Programme for Research and Training in Tropical Diseases, was created in 1995 to address the need for research into neglected tropical disease that represent major public health problems in developing countries [4].

[33] analyzed and evaluated Decision Support Systems and Expert Systems which are used as support for clinical decisions as well as possibilities to improve the integration and enable the greater accommodation of these systems in today's system of the health care. These authors came to the following conclusions: tools that are used in the clinical decision systems are formulated according to technical availability, and in that way their use is limited, and especially their integration with contemporary systems for quality health care. Therefore, the development of new systems for clinical decision support is necessary.

[45] developed a computer aided fuzzy medical diagnostic system and concluded that such a system is not effective in accurate diagnosis but efficient.

[9] developed a framework for the application of knowledge technology to the management of tropical diseases. The aim of the system was to assist medical expert in the tedious and complicated task of diagnosing and providing treatment for tropical diseases. The system provided a scheme that will assist medical personnel in rural areas, where there are shortage of doctors, in the process of offering primary health care to the people. In the same perspective, [3] developed a fuzzy expert system approach using multiple experts for dynamic follow-up of endemic diseases. In their paper, architecture of LEPDIAG – a knowledge-based system for on-line diagnosis and for monitoring prognosis of leprosy was presented. The important features of LEPDIAG that were been detailed are a multiple expert environment, a homeostatic expert containing the model of immune reaction, a performance evaluator that can compare the observed signs and symptoms with those predicted by the homeostatic expert and a prognostic expert which optimizes the management schedule for the patients. The entire system is built around fuzzy-expert system building toolset to deal with the imprecise knowledge.

The application of fuzzy logic concepts to medical diagnosis of some diseases are also discussed in [31] and [45].

A good number of expert systems have been designed for the diagnosis and treatment of some diseases. They are presented in [5], [14], [18], [24], [32], [34], [49], and [51].

A medical expert system for managing tropical diseases was proposed by [2]. 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.

[41], 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.

An expert system for malaria environmental diagnosis by [43] was developed for providing decision support to malaria researchers, institutes and other healthcare practitioners in malaria endemic regions of the world. The motivation of the work was due to the insufficient malaria control measures in existence and the need to provide novel approaches towards malaria control. Several papers have successfully explained the benefits and challenges of using clinical decision support systems. [10] 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 (DSS) 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 [39] and [42], [10] 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 system using fuzzy have designed as found in [7], [25], [30], [52], and [55].

While good attempts have been made at designing systems for diagnosing tropical diseases, it is very clear that the system have some drawbacks, which necessitated the used of soft computing technique. The need to arrive at the most accurate diagnosis of malaria is the need for the application of soft computing techniques in the diagnosis process, because intelligent systems are known to improve practitioner performance and improve patient outcome, thereby improving the quality of healthcare.

3. Materials and Methods:

3.1 Data

Specialist Hospital Gombe and Specialist Hospital Yola in Nigeria were used for data collection. We selected 35 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 malaria (FESMM).

3.2 Fuzzy Logic

As stated by [28], Fuzzy logic is determined as a set of mathematical principles for knowledge representation based on degrees of membership rather than on crisp membership of classical binary logic. This powerful tool to tackle imprecision and uncertainty was initially introduced by [28] to improved tractability, robustness and low-cost solutions for real world problems. Fuzzy sets have been applied in many fields in which uncertainty plays a key role. Medical diagnosis is an excellent example of vagueness and uncertainty. Fuzzy set theory is a response to the demand for ideas and approaches for handling nonstatistical uncertainty [28].

A fuzzy set is a set with fuzzy boundaries. Defined fuzzy sets or classes for each variable allows intermediate grades of membership in them, which means each set could have elements that belongs partially to it; the degree of belonging is called membership functions ranging from 0 to 1. If X is the Universe of discourse and its elements are denoted as x, in contrast with crisp set, then the fuzzy set A of X has characteristics function associated to it. The fuzzy set is represented by a membership function, defined as follows:

$$\mu_A : X \to [0,1] \qquad - - - - - - - - - - - \quad (1)$$

$$\mu_A(X) \;=\; 1 \quad \text{if } x \text{ is totally in A}$$

$$\mu_A(X) = o \quad \text{if } x \text{ is not in A}$$
$$o < \mu_A(X) < 1 \quad \text{if } x \text{ is partially in A.}$$

$\mu_A(X)$ expresses to which the value *x* belongs to the fuzzy set A. The value o corresponds to the absolute non-membership and the value 1 corresponds to the absolute membership.

Therefore, a fuzzy membership function $\mu_A(X)$ indicates the degree of belonging to some element x of the universe of discourse X. It maps each element of X to a membership grade between 0 and 1 in various shapes such as Triangular, Trapezoidal, Sigmoid and Gaussian. Triangular membership function which is widely used will be used in this research. Triangular membership function can be calculated as follows:

$$\mu_A(X) = \begin{cases} 0 & if\ x \le a \\ \frac{x-a}{c-a} & if\ x \in [a,c] \\ \frac{b-x}{c-b} & if\ x \in [b,c] \\ 0 & if\ x \ge c \end{cases} \qquad - - - - - - - - - - - - \quad (2)$$

where *a, b,* and *c* have been defined by experts doctors. Figure 2 below shows a crisp and a fuzzy representation of a fuzzy set defined by triangular membership function of the attribute age of a patient.

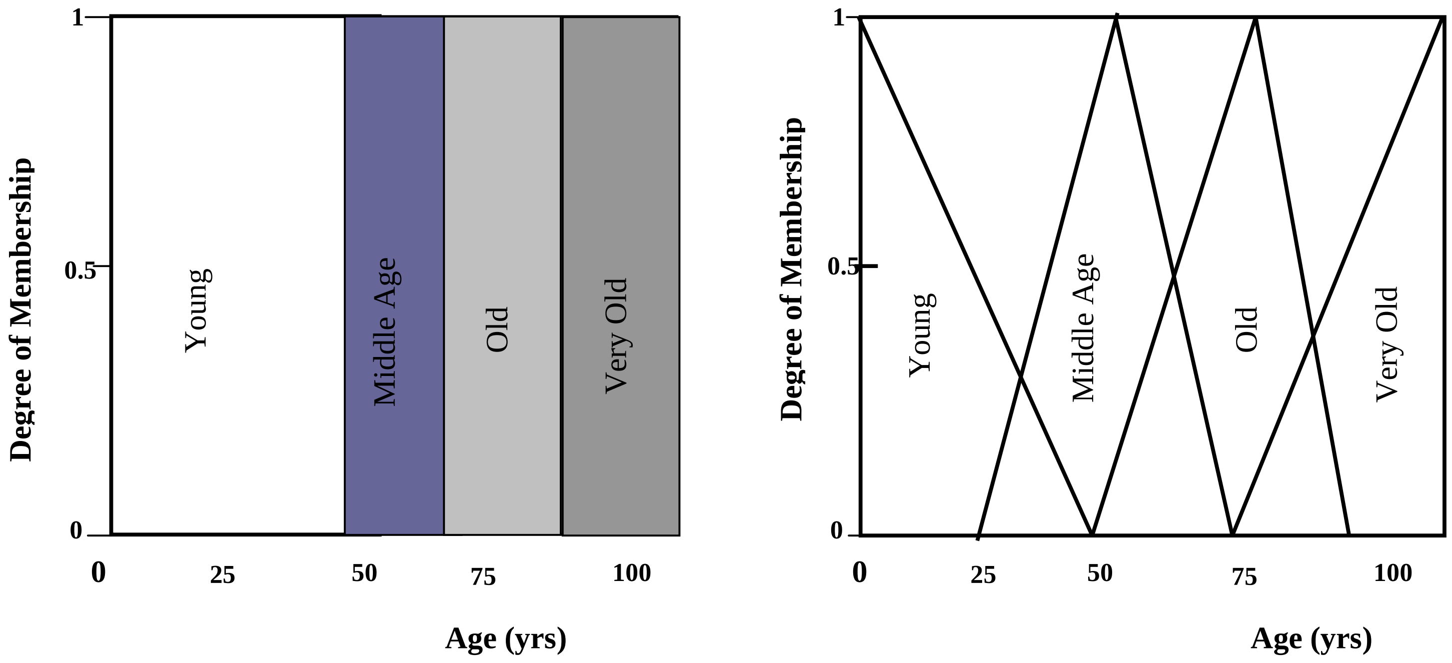

Figure 2: Crisp (left) and fuzzy (right) sets of Young, Middle Age, Old and Very Old (Crisp and Fuzzy set of Patients' Age with their Linguistics Variables)

For the linguistics variable young, the values a, b, and c are 25, 50 and 75 respectively. Ability to represent linguistic variables is a prominent feature of fuzzy logic model since they can convert numeric values to linguistic variables which are highly understandable to final system users.

Fuzzy logic is usually used for building fuzzy rules that can be easily understood by humans. Therefore, it is common to describe fuzzy variables as linguistic variables. The linguistics variables that we will use in this research are mild, moderate, severe and very severe for both the input and output parameters in the fuzzy model. By using those linguistic variable, fuzzy if-then rules which are the main output of the fuzzy system would be set up: generally presented in the form of: if *x* is A then *y* is B where *x* and *y* are linguistic variables and A and B are linguistic values, determined by their fuzzy sets. The first part of the rule is called the antecedent, and can consist of multiple parts with the operators AND or OR between them. The latter part is called the consequent, and can also include several outputs.

3.3 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 and Specialist hospital Yola in Nigeria. The developed system, christened "Fuzzy Expert System for the Management of Malaria (FESMM)" has an architecture presented in figure 3 below. The development FESMM involves fuzzification, inference engine and defuzzification. FESMM is a rule based system that uses fuzzy (approaximate) logic rather that Boolean logic. It was developed based on the following key components:

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

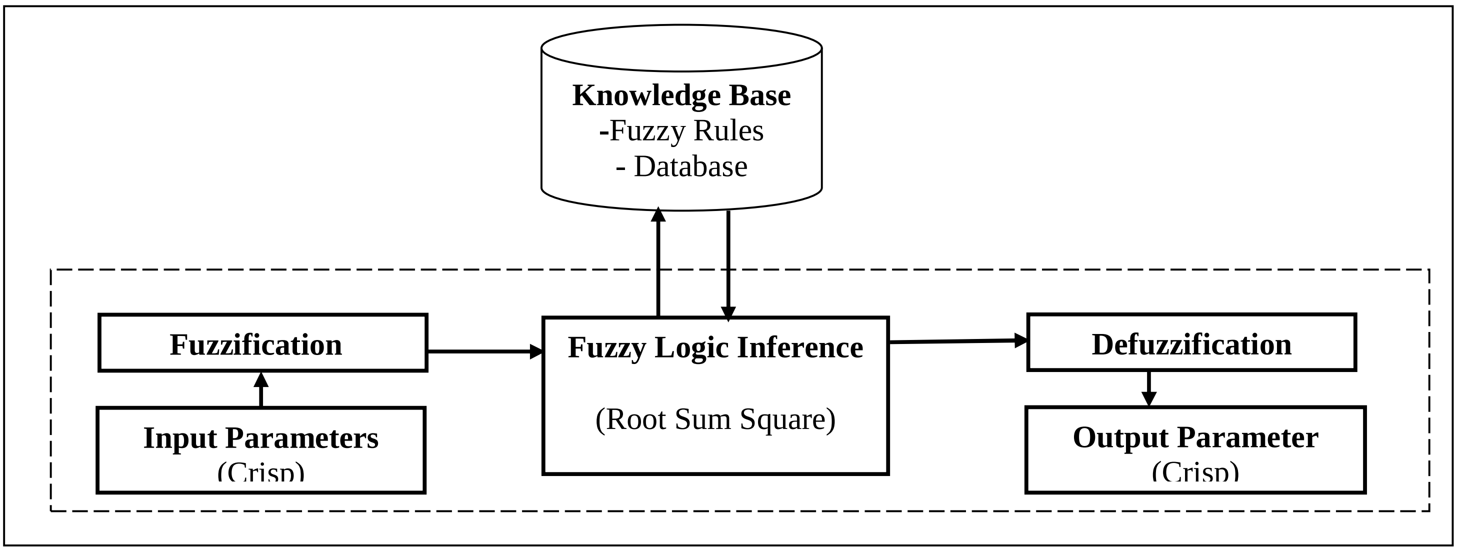

Figure 3: Architecture of FESMM

3.3.1 THE ALGORITHM FOR FUZZY DIAGNOSIS

The developed algorithm for the fuzzy diagnostic process of malaria is:

Step 1: Input signs and symptoms of patient complaint into the system. Where **m** = number of signs and symptoms.

Step 2: Search the knowledge-base for the disease **d,** which has the signs and symptoms identified.

Step 3: Get the weighing factors (wf) (the associated degree of intensity)
wf = 1, 2, 3, 4
Where 1 = Mild, 2 = Moderate, 3 = Severe, 4 = Very Severe.

Step 4: Apply fuzzy rules.

Step 5: Map fuzzy inputs into their respective weighing factors to determine their degree of membership.

Step 6: Determine the rule base evaluating (non-minimum values).

Step 7: Determine the firing strength of the rules R.

Step 8: Calculate the degree of truth R, of each rules by evaluating the nonzero minimum value.

Step 9: Compute the intensity of the disease.

Step 10: Output fuzzy diagnosis.

The flow diagram for the contributing algorithm above is shown in figure 4 below:

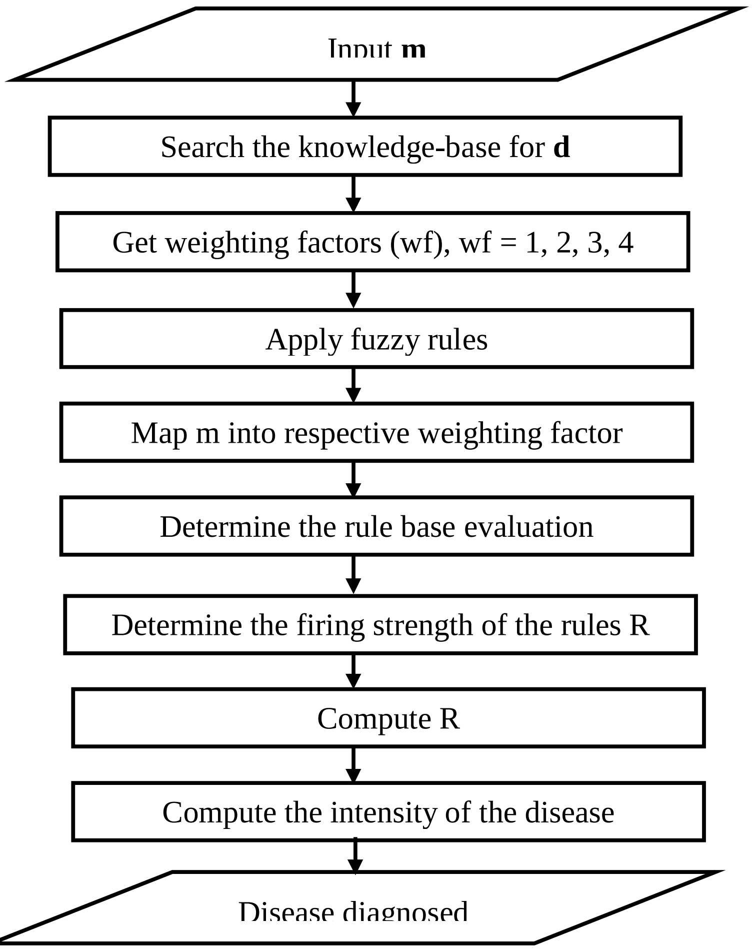

Figure 4: Flow Diagram of Fuzzy Diagnosis of Malaria

3.3.2 The Knowledge-Base of FESMM

Knowledge is a key factor in the performance of intelligent systems. The knowledge-base of FESMM 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, malaria as a known tropical disease is considered.

3.3.3 Fuzzification

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 [30]. Traingular 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.
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 (3) to (6) 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:

Table 1: Range of Fuzzy Values

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

Fuzzification begins with the transformation of the raw data using the functions that are expressed in equations (3) to (6) 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 (3) to (6) below. These formulas are determined by aid of both the expert doctors in the field of tropical medicine and literature.

$$\mu_{Mild}(X)=\begin{cases}0 & if \quad x \le 0.1\\ \dfrac{x-0.1}{0.2} & if \quad 0.1 \le x \le 0.3\\ \dfrac{0.2-x}{0.1} & if \quad 0.2 \le x \le 0.3\\ 0 & if \quad x \ge .0.2\end{cases} \qquad - - - - - - - \quad (3)$$

$$\mu_{Moderate}(X)=\begin{cases}0 & if \quad x \le 0.3\\ \dfrac{x-0.3}{0.3} & if \quad 0.3 \le x \le 0.6\\ \dfrac{0.45-x}{0.15} & if \quad 0.45 \le x \le 0.6\\ 0 & if \quad x \ge .0.45\end{cases} \qquad - - - - - - - \quad (4)$$

$$\mu_{Severe}(X)=\begin{cases}0 & if \quad x \le 0.5\\ \dfrac{x-0.6}{0.2} & if \quad 0.6 \le x \le 0.8\\ \dfrac{0.7-x}{0.1} & if \quad 0.7 \le x \le 0.8\\ 0 & if \quad x \ge .0.7\end{cases} \qquad - - - - - - - \quad (5)$$

$$\mu_{Very\ Severe}(X)=\begin{cases}0 & if \quad x \le 0.8\\ \dfrac{x-0.1}{0.2} & if \quad 0.8 \le x \le 1.0\\ \dfrac{0.2-x}{0.1} & if \quad 0.9 \le x \le 1.0\\ 0 & if \quad x \le 1.0\end{cases} \qquad - - - - - - - \quad (6)$$

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 (five medical doctors). The knowledge-base of FESMM has so many fuzzy rules designed with the aid of combination theory: only the valid rules where chosen by the domain experts. Table 2 shows some of the sample fuzzy rules for malaria.

Table 2: Fuzzy Rule Base for Malaria

Rule No	Fever	Headache	Nausea	Vomiting	Jaundice	Enlarge Liver	Joint Pain	Body Weakness	Dizziness	Loss of Appetite	MP	Conclusion
1	Mild	Mild	Mild	Mild	Mild	Mild	Mild	Mild	Severe	Mild	Mild	Mild
2	Moderate	Mild	Mild	Mild	Mild	Mild	Moderate	Moderate	Severe	Severe	Moderate	Moderate
3	Severe	Moderate	Mild	Mild	Mild	Mild	Mild	Severe	Severe	Severe	Moderate	Severe
4	Very Severe	Mild	Mild	Mild	Mild	Mild	Severe	Severe	Mild	Mild	Severe	Very Severe
5	Moderate	Mild	Mild	Moderate	Mild	Mild	Moderate	Moderate	Moderate	Severe	Moderate	Moderate
6	Mild	Moderate	Moderate	Mild	Mild	Mild	Mild	Mild	Moderate	Mild	Mild	Mild
7	Mild	Mild	Moderate	Moderate	Mild	Mild	Severe	Severe	Moderate	Moderate	Moderate	Severe
8	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
9	Moderate	Mild	Moderate	Moderate	Mild	Severe	Moderate	Moderate	Severe	Moderate	Moderate	Moderate
10	Mild	Mild	Moderate	Moderate	Mild	Moderate	Mild	Mild	Mild	Mild	Mild	Mild
11	Severe	Severe	Severe	Severe	Severe	Severe	Severe	Very Severe	Severe	Severe	Moderate	Very Severe
12	Moderate	Severe	Moderate	Severe	Moderate	Severe	Moderate	Severe	Moderate	Mild	Moderate	Severe
13	Mild	moderate	Moderate	Moderate	Mild	Mild	Mild	Moderate	Mild	Moderate	Moderate	Moderate
14	Severe	Severe	Moderate	Severe	Severe	Severe	Severe	Severe	Moderate	Moderate	Severe	Severe
15	Mild	Mild	Mild	Moderate	Mild	Mild	Mild	Severe	Mild	Severe	Moderate	Severe
16	Very Severe	Moderate	Mild	Moderate	Severe	moderate	Mild	Very Severe	Severe	Mild	Moderate	Very Severe
17	Mild	Very Severe	Moderate	Moderate	Mild	moderate	Mild	Moderate	Very Severe	Mild	Moderate	Very Severe
18	Moderate	Very Severe	Very Severe	Mild	Severe	Severe	Moderate	Severe	Very Severe	Very Severe	Severe	Very Severe
19	Moderate	Moderate	Moderate	Moderate	Mild	Mild	moderate	Moderate	moderate	Moderate	Moderate	Moderate
20	Very Severe	Severe	Severe	Severe	Severe	Severe	Severe	Severe	Severe	Severe	Moderate	Very severe

Some of the rules (Rules 1, Rules 2, Rules 5, Rule 8, Rules 10, Rule 13, Rules 15, Rules 18 and Rule 20) can be interpreted as follows:

Rule1: IF fever = mild and headache = mild and nausea = mild and vomiting = mild and jaundice = mild and enlarge liver = mild and joint pain = mild and body weakness = mild, and dizziness = severe, and loss of appetite = mild and MP = mild THEN malaria = mild.

Rule 2: IF fever = moderate and headache = mild and nausea = mild and vomiting = mild and jaundice = mild and enlarge liver = mild and joint pain = moderate and body weakness = severe and dizziness = very severe, and loss of appetite = severe and MP = moderate THEN malaria = moderate.

Rule 5: IF fever = moderate and headache = mild and nausea = mild and vomiting = moderate and jaundice = mild and enlarge liver = mild and joint pain = moderate and body weakness = moderate and dizziness = moderate and loss of appetite = severe and MP = moderate THEN malaria = moderate.

Rule 8: IF fever = moderate and headache = moderate and nausea = moderate and vomiting = moderate and jaundice = moderate and enlarge liver = moderate and joint pain = moderate and body weakness = moderate and dizziness = moderate and loss of appetite = moderate and MP = moderate THEN malaria = moderate.

Rule 10: IF fever = mild and headache = mild and nausea = moderate and vomiting = moderate and jaundice = mild and enlarge liver = moderate and joint pain = mild and body weakness = mild and dizziness = mild and loss of appetite = mild and MP = mild THEN malaria = mild.

Rule 13: IF fever = mild and headache = moderate and nausea = moderate and vomiting = moderate and jaundice = mild and enlarge liver = mild and joint pain = mild and body weakness = moderate and dizziness = mild and loss of appetite = moderate and MP = moderate THEN malaria = moderate.

Rule 15: IF fever = mild and headache = mild and nausea = mild and vomiting = moderate and jaundice = mild and enlarge liver = mild and joint pain = mild and body weakness = severe and dizziness = mild and loss of appetite = severe and MP = moderate THEN malaria = severe.

Rule 18: IF fever = moderate and headache = Very Severe and nausea = Very Severe and vomiting = mild and jaundice = Severe and enlarge liver = Severe and joint pain = moderate and body weakness = severe and dizziness = very severe, and loss of appetite = very severe and MP = severe THEN malaria = very severe.

Rule 20: IF fever = very severe and headache = severe and nausea = severe and vomiting = moderate and jaundice = severe and enlarge liver = severe and joint pain = severe and body weakness = severe and dizziness = severe and loss of appetite = severe and MP = moderate THEN malaria = very severe.

A rule is said to fire if any of the precedence parameters (mild, moderate, severe, very severe) evaluate to true (1); other, if all the parameters evaluate to false (0), it does not fire.

3.3.4 FUZZY INFERENCE

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 [30]. The core of decision making output is process by the inference engine using the rules contained in the rule base. The fuzzy inference engine uses the rules in the knowledge-base and derives conclusion base on the rules. FESMM inference engine uses a forward chaining mechanism to search the knowledge for the symptoms of a disease. For each rule, the inference mechanism looks up the membership values in the condition of the rule. Fuzzy inputs are mapped into their respective weighting factors and their associated linguistic variables to determine their degree of membership. The aggregation operator is used to calculate the degree of fulfillment or firing strength of a rule.

For this research, we have decided to apply fuzzy logical AND to evaluate the composite firing strength of the rules.

In practice, the fuzzy rules sets usually have several antecedents that are combined using fuzzy logical operators, such as AND, OR and NOT, though their definitions tend to vary: AND simply uses minimum weight of all the antecedents, while OR uses the maximum value. There is also the NOT operator that subtracts a membership function from 1 to give the “complementary” function. The IF part of a rule is called the “antecedent” and the THEN part is called the “consequent” [30].

For the purpose of this research, the AND operator is used to combine the antecedent parts of the rules.

The degree of truth (R) of the rules are determined for each rule by evaluating the nonzero minimum values using the AND operator. 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 [56]. The inference engine technique employed in this research is the Root Sum Square (RSS). RSS is given by the formula in equation (7):

$$\sqrt{\sum R^2} = \sqrt{\left(R_1^2 + R_2^2 + R_3^2 + \ldots R_n^2\right)} \qquad - - - - - - \quad (7)$$

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. Examples of the rule base evaluation for patient number 001 and patient number 035 are presented in section table 6 and table 7 below. The RRS of drawing inference was found to be the most suitable technique to infer data from the rules developed.

3.3.5 DEFUZZIFICATION

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 and four common defuzzification techniques are: center-of-area (gravity), center-of-sums, max-criterion and mean of maxima. According to [1], 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 [23]. The center-of-gravity (CoG) often uses discrete variables so that CoG, Y' can be approximated to overcome its disadvantage as shown in equation (8) below 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:

$$\mathrm{CoG}(Y') = \frac{\sum \mu_Y(x_i)x_i}{\sum \mu_Y(x_i)} \qquad - - - - - - - \quad (8)$$

Where $\mu_Y(x_i)$ = 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.

3.3.6 RESEARCH EXPERIMENT

We considered a set of five diseases **D**, and the expert doctors defined a set of signs and symptoms **M** relevant to a particular tropical disease.

D = $\{d_1, d_2, d_3, d_4, d_5\}$ where d_1, d_2, d_3, d_4, d_5 represents the five tropical diseases under consideration.

M = $\{m_1, m_2, m_3, m_4 \ldots m_n\}$ where $m_1, m_2, m_3, m_4 \ldots m_n$ represents the signs and symptoms of a particular tropical disease.

To specify the signs/symptoms intensity for a particular patient, the expert doctors applied weighing factors to the set **M**, thereby assigning fuzzy values to the signs/symptoms. The fuzzy values are selected from the fuzzy set:

{Mild (1), Moderate (2), Severe (3), Very Severe (4)}

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

Table 3: Rating of Patients on Malaria Diagnosis Variables

Patient No.	Fever	Headache	Nausea	Vomiting	Jaundice	Enlarge Liver	Joint Pain	Body Weakness	Dizziness	Loss of Appetite	Mp
001	4	3	3	2	2	3	2	2	4	4	3
002	3	2	3	3	3	2	4	3	3	4	2
003	4	3	3	3	3	3	3	2	2	3	2
004	1	2	3	2	2	-	3	-	2	3	3
005	2	4	2	4	1	2	3	-	3	3	3
006	1	4	2	2	3	2	2	3	3	3	3
007	4	4	3	2	1	2	2	4	-	3	2
008	4	2	3	3	2	2	3	4	2	2	2
009	4	2	4	3	2	2	3	3	2	3	2
010	4	3	2	3	1	2	4	3	3	1	3
011	3	1	2	2	3	-	2	2	1	2	2
012	3	3	3	2	3	2	1	3	3	2	2
013	3	2	2	2	1	3	2	2	4	2	2
014	2	2	3	3	2	2	2	4	4	1	3
015	2	1	2	3	1	3	1	3	3	2	2
016	1	3	2	2	2	2	2	3	3	3	2
017	2	2	3	4	3	3	3	4	2	2	2
018	4	3	3	2	2	-	2	1	3	4	3
019	3	2	1	3	3	2	2	3	2	3	2
020	4	3	2	4	2	1	2	2	4	2	3
021	2	4	1	3	3	2	2	3	3	2	3
022	1	4	3	2	2	3	3	2	3	3	3
023	2	2	2	2	2	2	2	2	3	3	3
024	3	3	4	3	1	1	3	2	2	2	2
025	4	2	2	2	2	2	4	2	3	1	3
026	1	2	2	2	2	2	4	1	3	3	2
027	2	2	1	3	1	-	3	2	1	3	2
028	3	2	4	2	2	2	3	3	1	4	3
029	4	3	3	2	2	2	2	2	2	4	2
030	3	3	3	1	2	4	3	3	3	3	3
031	2	3	3	2	3	4	2	2	2	3	4
032	4	4	3	2	2	2	3	3	4	2	4
033	4	3	-	-	3	2	3	2	3	3	2
034	4	1	-	2	3	2	2	4	2	2	2
035	3	2	2	2	-	2	-	2	2	4	2

From the above table 3, it is still vague and ambiguous to have a patient has low or moderate fever, moderate headache, low nausea, etc. It is of paramount importance to define the degree to which one can say that sign/symptom is low, moderate, severe and severe. This is done with the help of a fuzzifier. The fuzzifier employed in this research is the triangular fuzzifier (see equation (2) above.

Table 4 below define the degree to which one can say the signs, symptoms and investigation is mild, moderate, severe, or very severe.

For example, a patient complains that he has joint pain especially at nights, so a medical doctor assigns 3 (out of 4) value to his joint pain, and supplies it to the system, the will in turn recognize this as severe joint pain, and evaluate the degree of severity as (3-1)/4 = 0.5 using triangular fuzzifier to obtain the triangular fuzzy numbers.

Triangular fuzzy values for signs/symptoms and investigation of table 3 above are shown in table 4 below:

Table 4: Triangular Fuzzy Numbers for Malaria

Patient No.	**Fever**	**Headache**	**Nausea**	**Vomiting**	**Jaundice**	**Enlarge Liver**	**Joint Pain**	**Body Weakness**	**Dizziness**	**Loss of Appetite**	**Mp**
001	0.75	0.5	0.5	0.25	0.25	0.5	0.25	0.25	0.75	0.75	0.5
002	0.5	0.25	0.5	0.5	0.5	0.25	0.75	0.5	0.5	0.75	0.25
003	0.75	0.5	0.5	0.5	0.5	0.5	0.5	0.25	0.25	0.5	0.25
004	0.0	0.25	0.5	0.25	0.25	0.0	0.5	0.0	0.25	0.5	0.5
005	0.25	0.75	0.25	0.75	0.0	0.25	0.5	0.0	0.5	0.5	0.5
006	0.0	0.75	0.25	0.25	0.5	0.25	0.25	0.5	0.5	0.5	0.5
007	0.75	0.75	0.5	0.25	0.0	0.25	0.25	0.75	0.0	0.5	0.25
008	0.75	0.25	0.5	0.5	0.25	0.25	0.5	0.75	0.25	0.25	0.25
009	0.75	0.25	0.75	0.5	0.25	0.25	0.5	0.5	0.25	0.5	0.25
010	0.75	0.5	0.25	0.5	0.0	0.25	0.75	0.5	0.5	0.0	0.5
011	0.5	0.0	0.25	0.25	0.5	0.0	0.25	0.25	0.0	0.25	0.25
012	0.5	0.5	0.5	0.25	0.5	0.25	0.0	0.5	0.5	0.25	0.25
013	0.5	0.25	0.25	0.25	0.0	0.5	0.25	0.25	0.75	0.25	0.25
014	0.25	0.25	0.5	0.5	0.25	0.25	0.25	0.75	0.75	0.0	0.5
015	0.25	0.0	0.25	0.5	0.0	0.5	0.0	0.5	0.5	0.25	0.25
016	0.0	0.5	0.25	0.25	0.25	0.25	0.25	0.5	0.5	0.5	0.25
017	0.25	0.25	0.5	0.75	0.5	0.5	0.5	0.75	0.25	0.25	0.25
018	0.75	0.5	0.5	0.25	0.25	0.0	0.25	0.0	0.5	0.75	0.5
019	0.5	0.25	0.0	0.5	0.5	0.25	0.25	0.5	0.25	0.5	0.25
020	0.75	0.5	0.25	0.75	0.25	0.0	0.25	0.25	0.75	0.25	0.5
021	0.25	0.75	0.0	0.5	0.5	0.25	0.25	0.5	0.5	0.25	0.5
022	0.0	0.75	0.5	0.25	0.25	0.5	0.5	0.25	0.5	0.5	0.5
023	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.5	0.5	0.5
024	0.5	3	4	0.25	0.0	0.0	0.5	0.25	0.25	0.25	0.25
025	0.75	0.25	0.25	0.25	0.25	0.25	0.75	0.25	0.5	0.0	0.5
026	0.0	0.25	0.25	0.25	0.25	0.25	0.75	0.0	0.5	0.5	0.25
027	0.25	0.25	0.0	0.5	0.0	0.0	0.5	0.25	0.0	0.5	0.25
028	0.5	0.25	0.75	0.25	0.25	0.25	0.5	0.5	0.0	0.75	0.5
029	0.75	0.5	0.5	0.25	0.25	0.25	0.25	0.25	0.25	0.75	0.25
030	0.5	0.5	0.5	0.0	0.25	0.75	0.5	0.5	0.5	0.5	0.5
031	0.25	0.5	0.5	0.25	0.5	0.75	0.25	0.25	0.25	0.5	0.75
032	0.75	0.5	0.5	0.25	0.25	0.25	0.5	0.5	0.75	0.25	0.75
033	0.75	0.5	0.0	0.0	0.5	0.25	0.5	0.25	0.5	0.5	0.25
034	0.75	0.0	0.0	0.25	0.5	0.25	0.25	0.75	0.25	0.25	0.25
035	0.5	0.25	0.25	0.25	0.0	0.25	0.0	0.25	0.25	0.75	0.25

From the above table 4, the interactive session entered for patient number 001 is as follows:

Fever	Very Severe	0.75
Headache	Severe	0.5
Nausea	Severe	0.5

Vomiting	Moderate	0.25
jaundice	Moderate	0.25
Enlarge liver	Severe	0.5
Joint pain	Moderate	0.25
Body weakness	Moderate	025
Dizziness	Very Severe	0.75
Loss of appetite	Very Severe	0.75
MP	Severe	0.5

These values will result in the fuzzy transcript as shown in table 5 below using the rule base for malaria as presented in table 2 above. An example for rule base evaluation for patient number 001 is presented in table 5 below:

Table 5: Rule Base Evaluation for Patient number 001

Rule No	Fever	Headache	Nausea	Vomiting	Jaundice	Enlarge Liver	Joint Pain	Body Weakness	Dizziness	Loss of Appetite	MP	Conclusion	Non-zero Minimum Value
2	-	-	-	-	-	-	0.25	0.25	-	-	-	Moderate	0.25
4	0.75	-	-	-	-	-	-	-	-	-	0.5	Very Severe	0.5
5	-	-	-	0.25	-	-	0.25	0.25	-	-	-	Moderate	0.25
7	-	-	-	0.25	-	-	-	-	-	-	-	Severe	0.25
8	-	-	-	0.25	0.25	0.5	0.25	0.25	-	-	-	Moderate	0.5
9	-	-	-	0.25	-	-	0.25	0.25	-	-	-	Moderate	0.25
10	-	-	-	0.25	-	0.5	-	-	-	-	-	Mild	0.5
11	-	-	0.5	-	-	-	-	-	-	-	-	Very Severe	0.5
12	-	0.5	-	-	0.25	-	0.25	-	-	-	-	Severe	0.5
\13	-		-	0.25	-	-	-	0.25	-	-	-	Moderate	0.25
14	-	0.5	-	-	-	-	-	-	-	-	0.5	Severe	0.5
15	-	-	-	0.25	-	-	-	-	-	-	-	Severe	0.25
16	-	-	-	0.25	-	0.5	-	-	-	-	-	Very Severe	0.5
17	-	-	-	0.25	-	0.5	-	0.25	0.75	-	-	Very Severe	0.5
18	-	-	-	-	-	-	0.25	-	0.75	0.75	0.5	Very Severe	0.5
19	-	-	-	0.25	-	-	0.25	0.25	-	-	-	Moderate	0.25
20	0.75-	0.5	0.5	-	-	-	-	-	-	-	-	Very severe	0.5

Table 5 above shows that, seventeen (17) rules where fired out for patient number 001. i.e. 17 rules generated non-zero minimum values from the fuzzy rule base for malaria 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 – R20) are computed using RSS inference technique as shown in equation (9) below:

$$
\begin{aligned}
\textit{Mild} &= \sqrt{R10^2} \\
&= \sqrt{0.5^2} \\
&= 0.5 \\
\textit{Moderate} &= \sqrt{R2^2 + R5^2 + R8^2 + R9^2 + R13^2 + R19^2} \\
&= \sqrt{0.25^2 + 0.25^2 + 0.5^2 + 0.25^2 + 0.25^2 + 0.25^2} \\
&= 0.75 \qquad ------ \quad (9) \\
\textit{Severe} &= \sqrt{R7^2 + R12^2 + R14^2 + R15^2} \\
&= \sqrt{0.25^2 + 0.5^2 + 0.5^2 + 0.25^2} \\
&= 0.7906 \\
\textit{Very Severe} &= \sqrt{R4^2 + R11^2 + R16^2 + R17^2 + R18^2 + R20^2} \\
&= \sqrt{0.5^2 + 0.5^2 + 0.5^2 + 0.5^2 + 0.5^2 + 0.5^2} \\
&= 1.2247
\end{aligned}
$$

The above 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 (10) below:

$$
\textit{Crisp Output} = \frac{(0.5*0.2)+(0.75*0.4)+(0.7906*0.65)+(1.2247*0.9)}{0.5+0.75+0.7906+1.2247}
$$

$$
= 0.62 = 62\% \qquad ----- \quad (10)
$$

This means that patient number 001 has severe malaria with 62% possibility.

The interactive session entered for patient number 035 is as follows:

Fever	Severe	0.5
Headache	Moderate	0.25
Nausea	Moderate	0.25
Vomiting	Moderate	0.25
jaundice	None	0.0
Enlarge liver	Moderate	0.25
Joint pain	None	0.0
Body weakness	Moderate	0.25
Dizziness	Moderate	0.25
Loss of appetite	Very Severe	0.75
MP	Moderate	0.25

These values will result in the fuzzy transcript as shown in table 6 below using the rule base for malaria as presented in table 2 above. An example for rule base evaluation for patient number 035 is presented in table 6 below:

Table 6: Rule Base Evaluation for Patient number 035

Rule No	Fever	Headache	Nausea	Vomiting	Jaundice	Enlarge Liver	Joint Pain	Body Weakness	Dizziness	Loss of Appetite	MP	Conclusion	Non-zero Minimum Value
2	-	-	-	-	-	-	-	0.25	-	0.75	0.25	Moderate	0.25
3	0.5	0.25	-	-	-	-	-	-	-	0.75	0.25	Severe	0.5
5	-	-	-	0.25	-	-	-	0.25	0.25	0.75	0.25	Moderate	0.25
6	-	0.25	0.25	-	-	-	-	-	0.25	-	-	Mild	0.25
7	-	-	0.25	0.25	-	-	-	-	0.25	-	0.25	Severe	0.25
8	-	0.25	0.25	0.25	-	0.25	-	0.25	0.25	-	0.25	Moderate	0.25
9	-	-	0.25	0.25	-	-	-	0.25	-	-	0.25	Moderate	0.25
10	-	-	0.25	0.25	-	0.25	-	-	-	-	-	Mild	0.25
11	0.5	-	-	-	-	-	-	-	-	0.75	0.25	Very Severe	0.5
12	-	-	0.25	-	-	-	-	-	0.25	-	0.25	Severe	0.25
13	-	0.25	0.25	0.25	-	-	-	0.25	-	-	0.25	Moderate	0.25
14	0.5	-	0.25	-	-	-	-	-	0.25	-	-	Severe	0.5
15	-	-	-	0.25	-	-	-	-	-	0.75	0.25	Severe	0.25
16	-	0.25	-	0.25	-	0.25	-	-	-	-	0.25	Very Severe	0.25
17	-	-	0.25	0.25	-	0.25	-	0.25	-	-	0.25	Very Severe	0.25
19	-	0.25	0.25	0.25	-	-	-	0.25	0.25	-	0.25	Moderate	0.25
20	-	-	-	-	-	-	-	-	-	0.75	0.25	Very severe	0.25

Table 6 above shows that, seventeen (17) rules where fired out for patient number 035. i.e. 17 rules generated non-zero minimum values from the fuzzy rule base for malaria in table 3. 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 – R20) are computed using RSS inference technique as shown in equation (11) below:

$$
\begin{aligned}
Mild &= \sqrt{R6^2 + R10^2} \\
&= \sqrt{0.25^2 + 0.25^2} \\
&= 0.3536 \\
Moderate &= \sqrt{R2^2 + R5^2 + R8^2 + R9^2 + R13^2 + R19^2} \\
&= \sqrt{0.25^2 + 0.25^2 + 0.25^2 + 0.25^2 + 0.25^2 + 0.25^2} \\
&= 0.6124 \qquad - - - - \quad (11) \\
Severe &= \sqrt{R3^2 + R7^2 + R12^2 + R14^2 + R15^2} \\
&= \sqrt{0.5^2 + 0.25^2 + 0.25^2 + 0.5^2 + 0.25^2} \\
&= 0.8291 \\
Very\ Severe &= \sqrt{R11^2 + R16^2 + R17^2 + R20^2} \\
&= \sqrt{0.5^2 + 0.25^2 + 0.25^2 + 0.25^2} \\
&= 0.6614
\end{aligned}
$$

The above 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 (12) below:

$$Crisp\ Output = \frac{(0.3536*0.2)+(0.6124*0.4)+(0.8291*0.65)+(0.6614*0.9)}{0.3536+0.6124+0.8291+0.6614}$$
$$= 0.59 = 59\% \qquad ----\quad (12)$$

This means that patient number 035 has moderate malaria with 59% possibility
Similarly, we computed the results of all fired rules for the other 33 patients and got results that were in the range of predefined limits by the domain experts. The results for the 35 patients are presented in the appendix.

4. Results and Discussion

We have made humble attempt to implement the concept of Fuzzy Rule Based Systems that incorporated fuzzy techniques in simplifying the diagnosis of malaria. A fuzzy expert system for diagnosis malaria was developed. In the fuzzy logic implementation, the selection of fuzzifier, rule base and inference engine determined the output of FESMM. We choose triangular fuzzifier, the rule base was designed based on knowledge of domain experts (five medical doctors), and the inference technique we employed was RSS. Fuzzy logic was utilized to remove uncertainty, ambiguity and vagueness inherent in medical diagnosis.
The study evaluated the diagnosis of thirty-five 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. From the study, apart from assigning linguistics variables such as mild, moderate, severe and very severe to the diagnosis, the degree of mildness, intensity or severity are also evaluated as shown in the two cases cited. Table 5 and table 6 show the rule evaluation for patient number 001 and patient number 035. Patient number 001 was diagnosed for severe malaria with 62% possibility and patient number 035 was diagnosed for moderate malaria with 59% possibility. This will enable the medical practitioner to assign different doses of treatment to each of the two patients according to their degree of diagnosis. As seen in the results, one advantage fuzzy diagnosis has over other soft computing techniques is that it resembles human decision making with its ability to work from approximate reasoning and ultimately find a precise solution. The other patients' data were similarly computed and results for the 35 patients are presented in the appendix.

5. Conclusions

On the basis of the all presented, it can be concluded that there is no doubt whether Fuzzy Expert Systems should be applied for medical purpose. The use of fuzzy logic for medical diagnosis provides an efficient way to assist inexperienced physicians to arrive at the final diagnosis of malaria more quickly and efficiently. The developed FESMM provides decision support platform to assist malaria researchers, physicians and other health practitioners in malaria endemic regions. The authors believe that the approach proposed in this study, if used intelligently, could be an effective technique for diagnosing malaria. Further more, implementation of FESMM will reduce doctors' workload during consultation and ease other problems associated with hospital consultations.

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Appendix: Fuzzy Results

Patient Number	**% Possibility**	**Diagnosis**
001	62	Severe
002	30	Mild
003	41	Moderate
004	88	Very Severe
005	67	Severe
006	56	Moderate
007	43	Moderate
008	34	Mild
009	56	Moderate
010	78	Severe
011	81	Very Severe
012	48	Moderate
013	57	Moderate
014	34	Mild
015	56	Moderate
016	66	Severe
017	77	Severe
018	71	Severe
019	52	Moderate
020	53	Moderate
021	65	Severe
022	67	Severe
023	45	Moderate
024	39	Moderate
025	63	Severe
026	84	Very Severe
027	59	Moderate
028	77	Severe
029	58	Moderate
030	64	Severe
031	65	Severe
032	50	Moderate
033	69	Severe
034	70	Severe
035	59	Moderate

References

[1] A. Abraham and B. Nath, Hybrid intelligent systems: A review of a decade of research, *School of Computing and Information Technology, Faculty of Information Technology, Monash University, Australia, Technical Report Series*, 5(2000), 1-55.

[2] A.F. Adekoya, A.T. Akinwale and O.E.Oke, A medical expert system for managing tropical diseases. *Proceedings of the Third Conference on Science and National Development*, (2008), 74-86.

[3] B. Apurba, K.M. Arun and B. Anupam, A fuzzy expert approach using multiple experts for dynamic follow-up of endemic diseases, *Artificial Intelligence and Expert Systems*, 19(2007), 53-73.

[4] C.M. Morel, Reaching maturity – 25 years of the tropical disease research, *Parasitol Today*, 16(2000), 522-528.

[5] D.C. Classen, Clinical decision support systems to improve clinical practice and quality care. *Journal American Medicinal Associations*, *2*80(1998), 180-187.

[6] D.J. Briggs, A Framework for integrated environmental health impact assessment of systemic risks, *Environmental Health. Malaria Journal,* 7(2008), 1186-1476.

[7] D.L Hudson, and M.E. Cohen, Fuzzy logic in medical expert system, *IEEE Eng. Med. and Bio*, 12(1994). 693-698.

[8] E.H. Shortliffe, Computer programs to support clinical decision making, *Journal of the American Medical Association*, 258(1997), 61 - 66.

[9] F.M.E. Uzoka and F.O. Famuyiwa, A Framework for the application of knowledge technology to the Management of Diseases, *International Journal of Health Care Quality Assurance*, 17(2004), 194-204.

[10] F.M.E.Uzoka, J. Osuji, and O. Obot, Clinical decision support system (DSS) in the diagnosis of malaria: A case comparison of two soft computing methodologies. *Expert Systems with Applications*, 38(2010), 1537-1553.

[11] F.M.E.Uzoka and K. Barker, Expert systems and uncertainty in medical diagnosis: A proposal for fuzzy-AHP hybridisation, *International Journal of Medical Engineering and Informatics*, 2(2010), 329-342.

[12] G.I. Doukidis, and D. Foster, The potential for computer-aided diagnosis of tropical diseases in developing countries: An expert system case study, *European Journal of Operation Research*, 49(1990), 271-278.

[13] G.I. Doukidis, T. Cornford, and D. Foster, Medical expert system for developing countries: Evaluation in practice, *Expert Systems with Applications*, 7(1994), 221-233.

[14] H. Devlin, and J.K Devlin, Decision support system in patient diagnosis and treatment. *Future Rheumatology*, 2(2007), 261-263.

[15] H.F.R. Jan, B. Erik, C. Lester, M.P.D. Philippe, D.E. Howard, T.P. Kanyok, J.F. Kengeya, D.W. Kioy, K. Vasanthapuram, K., K.L. Janis, P.P. Nunn, O. Ayoade, R.G. Ridley, T.T. Yeya, Z. Fabio and C.M. Morel, Strategic emphases for tropical disease research: a TDR Perspective. *TRENDS in Parasitology,* 18(2002), 421-426.

[16] H.P. Nguyen and V. Kreinovich, Fuzzy logic and its applications in medicine. *International Journal of Medical Informatics, 62*(2001), 165-173.

[17] H.T. Nguyen and E.A. Walker, A First Course in Fuzzy Logic, Application in Intelligent System, Boston; Kluwer Academic, 1997.

[18] H. Yan, Y. Jiang, J. Zheng, C. Peng, and Q. Li, A multilayer perception-based medical decision support system for heart disease diagnosis, *Expert Systems with Applications*, 30(2006), 272-281.

[19] H. Varmus, Evaluating the burden of disease and spending the research dollars of the national institutes of health, *N. Engl. J.Med,* 340(1999), 1881-1887.

[20] J, Durkin, J. Expert System Design and Development. New Jersey: Prentice-Hall (1994).

[21] J.D. Sachs and H. Steele, Macroeconomics and health: Investing in health for economics development. *Report of the Commission on Macroeconomics and Health, WHO, Geneva* (2001).

[22] J. Keiser, B. Singer, and J. Utzinger, Reducing the burden of malaria in different eco-epidemiological setting with environmental management: a systematic review, *The Lancet Infectious Disease*, 5(2005), 695-708

[23] J. K. Cochran, J.K. and Chen, H. (2005). Fuzzy multi-criteria selection of object oriented simulation for production system analysis, *Computers and Operations Research,* 2(2005), 32, pp. 153-168.

[24] J. Pietka, J. (2008). A preliminary study of expert systems to support a patient's decision in the diagnosis of selected blood circulatory and respiratory systems' diseases. *Journal if Biocybernetics and Biomedical Engineering,* 28(2008) 65-73.

[25] J. Wainer and S. Sandri, Fuzzy temporal/categorical information in diagnosis. *Journal of Intelligent Information Systems,* 13(1999), 9-29.

[26] J. Utzinger, T. Yesim, S.H. Burton, Efficacy and Cost-effectiveness of Environmental Management for Malaria Control, *Tropical Medicine & International Health*, 6(2001), 677-687.

[27] J. Utzinger, D. Tozan, and S.B.H. Fadi, The Economic Payoffs of Integrated Malaria Control in the Zambian Copperbelt between 1930 and 1950. *Tropical Medicine & International Health*, 7(2002), 657-677.

[28] L.A. Zadeh, Fuzzy sets and systems: In fox, J. (ed.): *Proceedings Symposium on System Theory, Polytechnic Institute of Brooklyn,* (1965), 29-37.

[29] L.I Kuncheva and F. Steimann, Fuzzy medical diagnosis. *Artificial Intelligence in Medicine, Elsevier Science,* 16(1999) 121-128.

[30] L.H. Tsoukalas, and R.E. Uhrig. Fuzzy and neural approaches in Engineering, John Wiley & Son, Inc. (1993).

[31] M.F. Abdod, V.D.G. Keyserlingk, D.A. Linkens and M. Mahfouf, Survey of utilization of fuzzy technology in medicine and healthcare. *Fuzzy Sets and Systems,* 120(2001), 331-349.

[32] M. Fathi-Torbaghan and D. Meyer, MEDUSA: A fuzzy expert system for medical diagnosis of acute abdominal pain. *Method Inf Med*, 33(1994), 287-295.

[33] M. Fieschi, Medical decision support systems: Old dilemmas and new paradigms? *Method Inf Med*, 42(2003), 190-198.

[34] M. Pignone, Incorporating decision analysis in decision aids. *Medical Decisions Making,*. 27(2007, 547-549.

[35] N. Allahverdi and S. Yaldiz, (1998). Expert system application in medicine: An example of design of a pre-diagnosis expert system. *Proc. Second Turkish-German Joint Computer Application Days, Konya,* (1998), 175-192.

[36] N. Allahverdi, Expert systems. *An Artificial Intelligent Application, Istanbul: Atlas,* (2002), 248-251.

[37] O.C. Akinyokun and O.A. Adeniji, Experimental study of intelligent computer aided diagnosis and therapy, *AMSE Journal of Modeling, Simulation and Control*, 27(1991), 1-20.

[38] O.U. Obot, Knowledge-based server for diagnosis and therapy of tropical diseases. *M. Tech. Thesis, Federal University of Technology, Akure* (1999).

[39] O.U. Obot, Principles, practice and problems of knowledge acquisition in a knowledge-based system, *Nigeria Journal of Research and Production*, 5(2004), 36-42.

[40] O.U. Obot, (2006), Experimental study of knowledge representation in a knowledge-based system (a case study of diagnosis and therapy of typhoid fever), *International Journal of Physical Science, India,* 18(2010), 109-118.

[41] O.U. Obot, and F.M.E. Uzoka, Fuzzy rule-based framework for the management of tropical diseases, *International Journal of Engineering and Informatics*, 1(2008), 7-17.

[42] O.U. Obot, F.M.E. Uzoka, K. Barker and J. Osuji, An experimental comparison of fuzzy logic and analytic hierarchy process for medical decision support systems. *Computer Methods and Programs in Biomedicine,* 6, (2010), 123-130.

[43] O. Oluwagbemi, E. Adeoye, S. Fatumo, Building a computer-based expert system for malaria environmental diagnosis: An alternative malaria control Strategy, *Egyptian Computer Science Journal,* 33(2009), 55-68.

[44] O.U. Obot, Principles, practice and problems of knowledge acquisition in a knowledge-based system, *Nigeria Journal of Research and Production,* 5 (2004), 35-42.

[45] P.R. Innocent and R.I. John, Computer aided fuzzy medical diagnosis. *Information Science,* 162(2004), 81-103.

[46] P. Szolovits, R.S. Patil, and W.B. Schwartz, Artificial intelligent in medical diagnosis, *Journal of Internal Medicine*, 108 (1988), 80-87.
[47] P. Szolovits, Uncertainty and decision in medical informatics. *Methods of Information in Medicine,* 34 (1995), 111-121.

[48] R. Brause and F. Friedrich, A neuro-fuzzy approach as medical diagnostics interface, *In Proceeding of European Symposium on Artificial Neural Networks (ESANN).* 1 (2000), 201-206.

[49] R.G. Thomson, M.P. Eccles, N.I. Steen, J. Greenaway. L. Stobbart, M.L. Murtagh C.R. May, A patient decision aid to support shared decision-making on anti-thrombotic treatment of patients with a trial fibrillation: Randomized controlled trial. *Quality and Safety in Health Care,* 16(2007), 216-223.

[50] R.I. John and P.R. Innocent, Modeling Uncertainty in Clinical Diagnosis Using Fuzzy Logic. IEEE Trans Syst Man Cybern, Vol. 35(2005), 1340-1350.

[51] R.L. Street, Aiding medical decision making: A communication perspective. *Medical Decisions Making,* 27(2007), 550-553.

[52] R.N.K. Sharareh, N. Mahshid, and X. Zeng, A logistic regression model to predict high risk patients to fail in tuberculosis treatment course completion, *LAENG International Journal of Applied Mathematics,* 40 (2010), 774-778.

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

[54] S.F. Boyom, Expert system on endemic tropical diseases, *Methods of Information in Medicine,* 20(1990), 56-64

[55] S.F. Tohal, and U.K. Ngah, Computer aided medical diagnosis for the identification of malaria parasites, *IEEE -ICSCN, MIT Campus, Anna University, Chennai, India,* (2007), 521-522.

[56] W.W. Melek, and A. Sadeghian, A theoretical framework for intelligent expert systems in medical encounter evaluation. *Expert Systems*, 26(2009), 82-99.

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