

**SAKARYA UNIVERSITY  
INSTITUTE OF SCIENCE AND TECHNOLOGY**

**A FUZZY KNOWLEDGE BASED SYSTEM FOR  
CLINICAL DIAGNOSIS OF TROPICAL FEVER**

**M.Sc. THESIS**

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**Department : COMPUTER AND INFORMATION  
ENGINEERING**  
**Field of Science : COMPUTER AND INFORMATION  
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**Supervisor : Asst. Prof. Dr. Murat İSKEFİYELİ**

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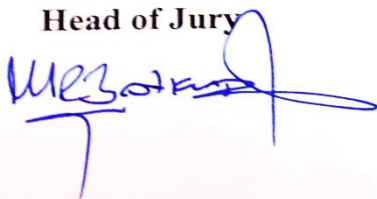
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## TABLE OF CONTENTS

ACKNOWLEDGEMENT .....	ii
TABLE OF CONTENTS .....	iii
LIST OF SYMBOLS AND ABBREVIATIONS .....	vi
LIST OF FIGURES.....	vii
SUMMARY .....	viii
ÖZET .....	ix

### CHAPTER 1.

INTRODUCTION.....	1
1.1. Introduction .....	1
1.2. Problem Statement .....	2
1.3. Objective .....	4
1.4. Scope And Limitation Of The Study.....	4
1.5. Organization Of The Thesis .....	5

### CHAPTER 2.

OVERVIEW OF FEVER IN SUB SAHARAN AFRICA .....	6
2.1. Fever And Sub-Saharan Africa .....	6
2.2. Typhoid Fever .....	7
2.2.1. The transmission of typhoid fever.....	8
2.2.2. Typhoid fever as a disease.....	8
2.2.2.1. Clinical features .....	9
2.2.2.2. Laboratory diagnosis of typhoid fever.....	9
2.2.3. Typhoid fever in Sub-Saharan Africa.....	10
2.3. Malaria .....	11

2.3.1. The transmission of malaria .....	11
2.3.2. Malaria fever as a disease .....	12
2.3.2.1. Clinical features of malaria.....	13
2.3.2.2. Microscopic diagnosis of malaria.....	14
2.3.3. Malaria in Sub-Saharan Africa.....	15
2.4. Differentiating Malaria And Typhoid By Signs And Symptoms .....	16
2.5. Summary .....	17

### CHAPTER 3.

A REVIEW ON KNOWLEDGE BASED SYSTEMS AND FUZZY LOGIC .....	18
3.1. Knowledge Based Systems .....	18
3.1.1. Architecture of a knowledge based system.....	19
3.1.1. The knowledge engineering process .....	20
3.1.1.1. Knowledge acquisition .....	21
3.1.1.2. Knowledge verifications and validations .....	21
3.1.1.3. Knowledge representation .....	22
3.1.2. Knowledge based systems in medicine.....	23
3.2. Fuzzy Logic .....	24
3.2.1. Fuzzy logic in medicine .....	26
3.2.2. Fuzzy sets.....	28
3.2.3. Fuzzy inference system.....	30
3.2.4. Matlab Fuzzy Logic Toolbox.....	37
3.3. Summary .....	38

### CHAPTER 4.

THE TROPFEV SYSTEM.....	39
4.1. Introduction .....	39
4.2. Architecture Of The TROPFEV System.....	40
4.3. TROPFEV System Development Process .....	41
4.3.1. Fever domain knowledge source identification .....	42
4.3.2. Fever knowledge acquisition .....	43
4.3.2.1. Group category .....	44
4.3.2.2. Symptoms related malaria .....	45

4.3.2.3. Related symptoms of malaria and typhoid fever .....	45
4.3.2.4. Symptoms related typhoid fever .....	47
4.3.3. Fever knowledge representation .....	47
4.3.4. Designing the TROPFEV fuzzy inference system .....	48
4.3.4.1. Defining system input and output variables .....	48
4.3.4.2. Linguistic variables and membership functions .....	50
4.3.4.3. Defining fuzzy rules of the system .....	54
4.4. Summary .....	55
CHAPTER 5.	
IMPLEMENTATION OF THE SYSTEM .....	56
5.1. Implementation Of The TROPFEV System In Matlab .....	56
5.1.1. Input fever variables in the FIS editor .....	58
5.1.2. Editing membership functions in the editor .....	60
5.1.3. Inserting rules in the Rule Editor .....	61
5.1.4. Design interface in Matlab GUI .....	62
5.1.5. Testing and evaluation of the system .....	63
5.1.5.1. Testing from the system interface .....	64
5.1.5.2. Metrics evaluation .....	66
5.1.5.3. Discussion of system results .....	67
CHAPTER 6.	
CONCLUSION AND RECOMMENDATIONS .....	70
REFERENCES .....	72
ANNEX .....	77
RESUME .....	80

## LIST OF SYMBOLS AND ABBREVIATIONS

AI	: Artificial intelligence
FIS	: Fuzzy inference system
FL	: Fuzzy logic
GOU	: Government of Uganda
KA	: Knowledge acquisition
KB	: Knowledge based
KBS	: Knowledge-based system
KR	: Knowledge representation
MARA	: Mapping malaria risk in Africa
MF	: Membership function
MOH	: Ministry of health
RHS	: Right hand side.
SSA	: Sub-Saharan Africa
TROPFEV	: A fuzzy knowledge based system for diagnosis of tropical fever
UCG	: Uganda clinical guidelines.
WHO	: World health organization

## LIST OF FIGURES

Figure 2.1. A map of sub-Saharan Africa. ....	7
Figure 2.2. Countries and areas at risk of malaria transmission .....	12
Figure 2.3. Simplified diagram showing malaria parasite life cycle.....	13
Figure 3.1. Architecture of a knowledge based system .....	20
Figure 3.2. Development of a Knowledge-Based System .....	20
Figure 3.3. Four common types of continuous membership functions.....	29
Figure 3.4. Components of a fuzzy inference system .....	31
Figure 3.5. Mamdani fuzzy inference method .....	34
Figure 3.6. Defuzzification schemes to derive a crisp output .....	36
Figure 4.3. Graph showing membership function for age .....	50
Figure 4.4. Graph showing membership function for pregnancy .....	51
Figure 4.5. Graph showing membership function for malaise and Fever.....	51
Figure 4.6. Graph showing membership function for pain .....	52
Figure 4.7. Graph showing membership function for altered mental state.....	52
Figure 4.8. Graph showing membership function for Table 4.12 variables .....	53
Figure 4.9. Graph showing membership function of the output .....	54
Figure 5.1. TROPFEV implementation tasks in Matlab 2012 a .....	57
Figure 5.2. TROPFEV inference system in FIS editor .....	59
Figure 5.3. Membership Functions for input and the output variables in Matlab.....	61
Figure 5.4. TROPFEV rules in matlab fuzzy rule editor .....	62
Figure 5.5. Designing of the interface in matlab.....	63
Figure 5.6. Testing the TROPFEV system from interface.....	66
Figure 5.7. Results of the evaluation.....	70



## SUMMARY

Keywords: Knowledge based systems, Fuzzy logic, Medical diagnosis, malaria, Typhoid fever, Tropical fever

Malaria and typhoid fever are major tropical fever infections. Both are responsible for significant morbidity, mortality and economic loss in the region. Typhoid fever is estimated to cause 725 incident cases and 7 deaths per 100,000 people in the year and on the other side 90% of the total world malaria deaths occur in the Sub-Saharan Africa.

The two diseases malaria and typhoid fever have several diagnosis features with overlapping signs and symptoms which are a task in medical diagnosis. Fuzzy logic that lies on the fuzzy set theory and similar to human reasoning is widely used for human-related sciences, and successfully solves many problems. Medical diagnosis is one of these attractive applications, which requires classification and decision making tasks. It uses natural language to represent data into computer systems where complications in diagnosis features such as vagueness are perfectly handled.

This thesis describes the use of fuzzy logic to design a knowledge based system for clinical diagnosis of malaria and typhoid fever (TROPFEV) in Sub-Saharan Africa. Knowledge was extracted from the documentary of UCG-2012 (Uganda Clinical Guidelines 2012) prepared by the ministry of healthy in Uganda as well as consulting medical experts. The knowledge acquired from these resources is modelled, represented using fuzzy rule based reasoning and implemented in Matlab 2012 a. According to the collected knowledge, 21 diagnosis features have been organised with their situations or severity during fever infections to build the system. The user is expected to get the answer of complicated malaria, uncomplicated malaria, complicated typhoid, uncomplicated typhoid or unknown fever.

For testing and evaluating its performance, the results of the TROPFEV system were compared with the results of diagnosis made by a real doctor. The difference in results between expert diagnosis and system diagnosis showed that the expert system have similarity with the real experts with 86% accuracy.

In conclusion, the use of fuzzy logic in medical diagnosis can be emphasized because it provides an efficient way to assist inexperienced physicians to arrive at the final diagnosis of fever more quickly and efficiently. This is because fuzzy logic applies fuzzy sets to handle vagueness existing in symptoms.

# BULANIK BİLGİ TABANLI TROPİKAL ATEŞ KLİNİK TEŞHİSİ

## ÖZET

Anahtar kelimeler: Bilgi tabanlı sistemler, Bulanık mantık, Tıbbi teşhis, Sıtma, Tifo ateşi, Tropikal ateşi

Sıtma ve tifo Sahra-altı Afrika'nın en büyük tropikal ateş enfeksiyonlarıdır. Her ikisi de bölgenin hastalık, ölüm ve ekonomik kayıplarının sebebidir. Tifo ateşi sebebiyle, her 100.000 kişiden 725 tifo vakasına yakalanmakta ve bu hastalardan da 7 adedi ölümle sonuçlandığı tahmin edilmektedir ve Dünya'nın sıtma ölümlerinin %90'ı Sahra-altı Afrika'da meydana gelmektedir.

Bu iki hastalığın teşhisinde önemli olan çok sayıda belirti bulunması ve birçoğunun da ortak olması dolayısıyla teşhis zorlaşmaktadır. Bulanık küme teorisine ve insan gibi sonuçlandırma üzerine dayanan bulanık mantık, insani bilimlerde yaygın olarak kullanılmakta ve birçok problemi başarılı bir şekilde çözmektedir. Sınıflandırma ve karar verme görevlerine ihtiyaç duyulan tıbbi teşhis bu cazip uygulamalardan biridir. Belirsizliklerin olduğu teşhis özelliklerindeki karmaşıklıklar bilgisayar sistemlerinde kullanılan doğal dil ile üstesinden gelinmiştir.

Bu çalışmada, Sahra-altı Afrika'da sıtma ve tifo ateşinin klinik teşhisi için bilgi tabanlı teşhis sisteminin (TROPFEV) tasarımında bulanık mantık kullanımı anlatılmaktadır. Bilgiler, tıp uzmanları danışmanlığında Uganda Sağlık Bakanlığı tarafından hazırlanan UCG-2012'den (Uganda Klinik Klavuzu 2012) çıkarım yapılmıştır. Bu kaynaklardan edinilmiş bilgiler modellenip, bulanık kural tabanlı mantık kullanılarak tanımlanmış ve Matlab 2012a gerçekleştirilmiştir. Toplanan bilgilere göre, 21 adet teşhis özellikleri, ateş hastalığının durumuna ya da şiddetine göre sistemi oluşturmak için düzenlenmiştir. Kullanıcı, karmaşık-sıtma, karmaşık olmayan-sıtma, karmaşık-tifo, karmaşık olmayan-tifo veya bilinmeyen ateş cevabını sistemden beklemektedir.

Test ve performansını değerlendirmek için, TROPFEV sistemin sonuçları ile doktor tarafından yapılan teşhis sonuçlarıyla karşılaştırılmıştır. Uzman teşhisleri ve sistem teşhisleri arasındaki % 86 oranında doğruluk olduğunu görülmüştür.

Sonuç olarak, tıbbi teşhis için tecrübesiz hekimlerin teşhislerine daha hızlı ve verimli bir şekilde teşhis koyabilmek için yardımcı olması amacıyla bulanık mantık kullanımına ağırlık verilebilir. Çünkü bulanık mantık belirtilerdeki kesin olmama sıkıntılarının üstesinden gelebilmek için bulanıklık kümelerini kullanır ve bir sınıflandırmaya ilişkilendirir.



## **CHAPTER 1. INTRODUCTION**

This chapter briefly describes the fuzzy knowledge based System for clinical diagnosis of tropical fever (TROPFEV). In this chapter, there are five sections which include the introduction of the project and problem statement related to this project. Third section is the objectives to be achieved and fourth section is the scopes. Last section is the thesis organization.

### **1.1. Introduction**

Tropical Fevers are those diseases that cause fever in the tropics. Fever is one of the most common medical signs and is characterized by an elevation of body temperature above the normal range due to an increase in the temperature regulatory set-point [1]. It is a common and very prominent presenting symptom of many tropical diseases, including many important parasitic infections. Although there are other infections that present with fever as a symptom in tropical Africa, the word fever in this research has been used to mean malaria and typhoid fever since these two are the main cause fever in Sub Saharan Africa (SSA).

Medical diagnosis is a categorization task that allows physicians to make prediction about features of clinical situations and to determine appropriate course of action. It involves identification of abnormal condition that afflicts a specific patient, based on manifested clinical data or lesions. It also involves a complex decision process that involves a lot of vagueness and uncertainty management, especially when the disease has multiple symptoms like malaria and typhoid fever which almost have similar symptoms and signs. If the final diagnosis agrees with a disease that afflicts a patient, the diagnostic process is correct; otherwise, a misdiagnosis occurs. Accurate diagnosis often aids therapy administration and as well improves the health status of patients [2].

Computer technology can make things easier to doctors by generating case-specific advice for diagnostic decision making when medical knowledge for a certain disease is embedded into knowledge based systems (KBSs). A KBS uses knowledge embedded in a knowledge base to solve complex problems. Likewise, medical knowledge about a disease can be programmed in such systems and be used by any other medical personnel anywhere at any time. These systems can improve the qualities of health service and reduce the shortage of manpower in the medical sector [3].

Fuzzy logic that lies on the fuzzy set theory [4-5] and similar to human reasoning is a powerful reasoning technique when representing medical knowledge in KBSs. It can represent medical diagnosis knowledge with in KBSs and retrieve when needed without difficulty. It uses natural language to represent data into computer systems where complications in diagnosis features such as vagueness are perfectly handled. Fuzzy diagnosis systems are good at offering linguistic concept with excellent approximation to medical texts [6] providing reliable decision and classification systems in medicine.

## **1.2. Problem Statement**

In Sub Saharan Area, Malaria and typhoid fever are considered the main existing infections with Fever as a common symptom among patients and their prevalence in the area is a burden in medical diagnosis. Malaria as the main cause of fever is one of the leading causes of morbidity and mortality in the tropics with approximately 3,000 deaths each day (90% of the world malaria deaths) [7]. It is the most important and widespread of the tropical deadly diseases. These conditions when occur in the SSA present symptoms that overlap, and thus become 'confusable'. Accurate and timely diagnosis of these conditions is considered absolutely essential in their eventual prevention, and management .In 2010, typhoid fever was estimated to cause 725 incident cases and 7 deaths per 100,000 person years in sub-Saharan Africa [8].These two infections constitute conditions that are of concern to health authorities, physicians, and the community at large, because of difficulties in their early diagnosis and associated mortality rates. In order to do this, physicians are expected

to manage an incredible amount of information, which can sometimes become unwieldy, so as to understand the symptoms the clients are experiencing, put them together and arrive at an early diagnosis.

Uganda clinical guidelines 2012 [9], gives guiding principles to physicians when diagnosing malaria and typhoid fever. These includes laboratory and clinical (signs and symptoms) methods however, the scarcity of laboratories in the rural areas of SSA where 70% of the population lives [10] is a predicament in the medical domain. It makes clinical diagnosis a mostly used form of judgment for malaria and typhoid fever with in region. During diagnosis, physicians use medical knowledge, clinical guidelines and experience to make decisions according to clinical features of a patient yet symptoms presented as an effect of malaria are not easy to be classified from those existing as an effect of typhoid fever [11- 12]. The guidelines [9] provided are not algorithms but combined circumstances as a fever patient might appear before a doctor.

The severity and complexity of the diagnosis features creates severe complications in the diagnosis sector and it might be difficult for all physicians to remember all of them in their brains. There is also considerations of different conditions and grades during diagnosis. An example is a diagnosis of malaria in children, where a physician is required to know whether he/she is bellow or above five years then considers states like high or low temperature, mild or severe vomiting and so on. Such situations need to take careful measures before final decisions because a right diagnosis leads to a right treatment. The large number of fever patients, low medical facilities, vagueness and fuzziness mixed up with the diagnosis features creates stress not only to physicians but also to patients. Some Patients may be unsuccessful to see doctors at an appropriate time because of the long line in the few available government hospitals, long time spent on patients, in addition to inadequate number of medical experts to patients affecting most of the under-developed countries. The two diseases are life-threatening and therefore should be treated early in their course [9] by using all possible methods.

Medical KBS can help hospitals and doctors to improve quality of care, efficiency and reduce costs and help with compliance issues mandated by the government or insurance companies. They can also direct physicians to quicker and correct diagnosis hence reducing the rate of diagnostic errors in medicine [13-14].

### **1.3. Objective**

The overall aim of this research is to model and represent knowledge retrieved from the Uganda clinical guideline 2012 [9] using fuzzy logic and develop a knowledge based system for clinical diagnosis of malaria and typhoid fever. The purpose of the system is to simplify the work of medical experts in the tropical medicine by providing a good decision platform for these two diseases. The system will be able to classify the type of fever and its status as uncomplicated or complicated according to the selected diagnosis features.

The TROPFEV system interface is designed in such a way that it can be used by anyone who understands English. The patient or medical assistant or any other person will only need to select symptoms and their severity from which the system will be able to tell him whether is suffering from uncomplicated/mild malaria, complicated/severe malaria, uncomplicated/mild typhoid fever complicated/severe typhoid fever or unknown fever if the selected symptoms don't match with the system rules.

The system can assist researchers in artificial intelligence, fuzzy logic, knowledge based systems and medical personnel within the SSA where there is prevalence of limited medical experts.

### **1.4. Scope And Limitation Of The Study**

Even though there are a number of different approaches for designing knowledge based system, this study focuses only on a fuzzy rule based approach. The focus area of this study is in Uganda using the Uganda clinical guideline 2012.

The study is limited to design a knowledge based system for only malaria and Typhoid fever although there are some other fever related diseases in the area. The study also focuses on diagnosis using symptoms and not the laboratory approach.

### **1.5. Organization Of The Thesis**

The study is organized into six chapters. Chapter one is the introduction part, which contains a brief background of the study, the second chapter describes the background of the two diseases, their cause effect and diagnosis. Review of literature on the knowledge based systems and fuzzy logic, their application in medical domain are presented in chapter three. Chapter 4 discusses knowledge acquisition and representation and development process. Chapter five deals with implementation of the TROPFEV system using Matlab fuzzy logic tool, its results and evaluation. Finally, chapter 6 focuses on the conclusion and recommendation based on the results of the research finding for further research work in the domain.



## **CHAPTER 2. OVERVIEW OF FEVER IN SUB SAHARAN AFRICA**

This chapter talks about basic information about malaria and typhoid fever in the Sub-Saharan Africa (SSA). Section 2.2 explains fever and the Sub-Saharan region in Section 2.3 and 2.4 presents the facts about typhoid fever and malaria, their causes, transmission, clinical features and their dominance in the SSA. In Section 2.5 the clinical differences between the two diseases are discussed and finally a summary for this Chapter in 2.6.

### **2.1. Fever And Sub-Saharan Africa**

Fever also known as pyrexia and as explained in chapter 1 is one of the most common medical signs and is characterized by an elevation of body temperature above the normal range of 36.5–37.5 °C [97.7–99.5 °F] due to an increase in the temperature regulatory set-point [1]. Malaria, typhoid fever, Brucellosis and yellow fever are some of the considered existing infections with Fever as a common symptom in the Sub-Saharan Africa (SSA). Sub-Saharan Africa is, geographically, the area of the continent of Africa that lies south of the Sahara Desert. Politically, it consists of all African countries that are fully or partially located south of the Sahara (excluding Sudan) [15]. Figure 2.1 shows map of the Sub-Saharan Africa. These infections pose a lot of challenges to global health and wellbeing due to their high morbidity and mortality rates; a challenge that has been attributed to poor medical infrastructure, poor diagnosis and management of these diseases. These conditions are known to present with similar symptoms at different stages of their pathogenesis and thus can become “confusable” with each other.

As mentioned in chapter one, we considered typhoid fever and malaria in this research.

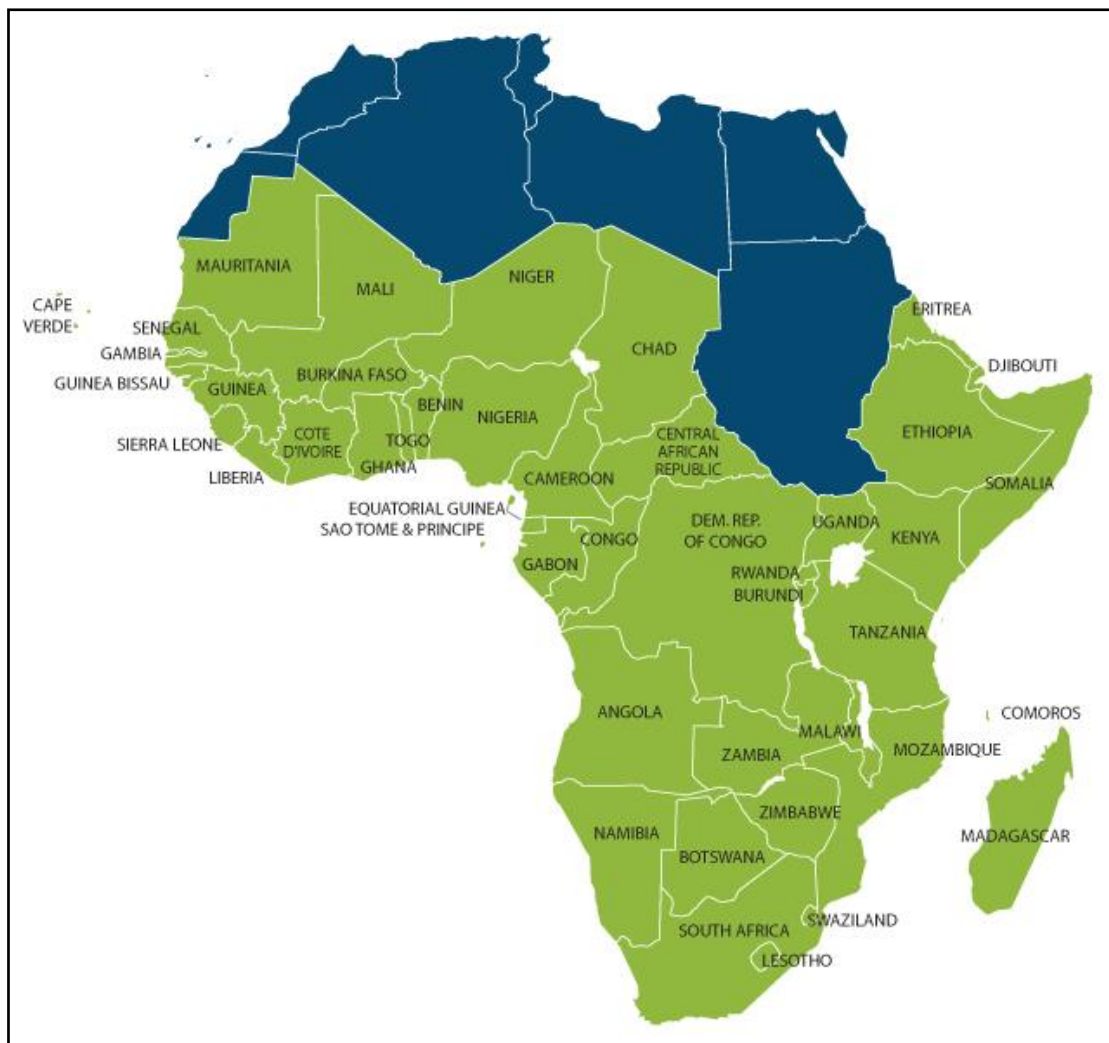


Figure 2.1. A map of sub-Saharan Africa. Source Export-Import Bank of the United States, 2012.

## 2.2. Typhoid Fever

Typhoid fever also known as Enteric Fever simply as typhoid is a common worldwide bacterial disease transmitted by the ingestion of food or water contaminated with the faeces of an infected person, which contain the bacterium *Salmonella Typhi* [16]. Typhoid fever is caused by *Salmonella typhi* [16] and can also be caused by *Salmonella paratyphi*, a related bacterium that usually causes a less severe illness. The bacteria are deposited in water or food by a human carrier and are then spread to other people in the area. The disease has received various names, such as gastric fever, abdominal typhus, slow fever, nervous fever and pythogenic fever. The name typhoid means "resembling typhus" and comes from the neuropsychiatric

symptoms common to typhoid and typhus. Despite this similarity of their names, typhoid fever and typhus are distinct diseases and are caused by different species of bacteria [17].

### **2.2.1. The transmission of typhoid fever**

Humans are the only natural host and reservoir. Typhoid and paratyphoid germs are passed in the faeces and urine of infected people. People become infected after eating food or drinking beverages that have been handled by a person who is infected or by drinking water that has been contaminated by sewage containing the bacteria. Once the bacteria enter the person's body they multiply and spread from the intestines, into the bloodstream. Even after recovery from typhoid or paratyphoid, a small number of individuals (called carriers) continue to carry the bacteria. These people can be a source of infection for others. The transmission of typhoid and paratyphoid in less-industrialized countries may be due to contaminated food or water. In some countries, shellfish taken from sewage-contaminated beds is an important route of infection. Where water quality is high, and chlorinated water piped into the house is widely available, transmission is more likely to occur via food contaminated by carriers handling food.

### **2.2.2. Typhoid fever as a disease**

During an acute infection, *S. typhi* multiplies in mononuclear phagocytic cells before being released into the bloodstream. After ingestion in food or water, typhoid organisms pass through the pylorus and reach the small intestine. They rapidly penetrate the mucosal epithelium via either microfold cells or enterocytes and arrive in the lamina propria, where they rapidly elicit an influx of macrophages [Mp] that ingest the bacilli but do not generally kill them. Some bacilli remain within Mp of the small intestinal lymphoid tissue. Other typhoid bacilli are drained into mesenteric lymph nodes where there is further multiplication and ingestion by Mp. It is believed that typhoid bacilli reach the bloodstream principally by lymph drainage from mesenteric nodes, after which they enter the thoracic duct and then the general circulation. As a result of this silent primary bacteraemia the pathogen reaches an

intracellular haven within 24 hours after ingestion throughout the organs of the reticuloendothelial system [spleen, liver, bone marrow, etc.], where it resides during the incubation period, usually of 8 to 14 days. Clinical illness is accompanied by a fairly sustained but low level of secondary bacteraemia [18].

#### **2.2.2.1. Clinical features**

According to the Uganda clinical guidelines [9], the signs and symptoms of typhoid fever are as follows;

1. Gradual onset of chills and malaise
2. Headache
3. Anorexia ( loss of appetite)
4. Epistaxis (nose bleed)
5. Backache (back pain)
6. Constipation or diarrhea
7. Abdominal pain and tenderness are prominent features
8. Temperature rises in steps
9. Relative bradycardia
10. Delirium and stupor
11. Tender splenomegaly
12. Complicated typhoid may include perforation of the gut

#### **2.2.2.2. Laboratory diagnosis of typhoid fever**

The definitive diagnosis of typhoid fever depends on the isolation of *S. typhi* from blood, bone marrow or a specific anatomical lesion. Blood culture is the mainstay of the diagnosis of this disease. Bone marrow aspirate culture is the gold standard for the diagnosis of typhoid fever [19] and is particularly valuable for patients who have been previously treated, who have a long history of illness and for whom there has been a negative blood culture with the recommended volume of blood.

### 2.2.3. Typhoid fever in Sub-Saharan Africa

Typhoid fever continues to be a common problem in developing countries where it is associated with high morbidity and mortality. In sub-Saharan Africa, surveillance for typhoid fever is hampered by the lack of laboratory resources for rapid diagnosis, culture confirmation and antimicrobial susceptibility testing. Nonetheless, in 2010, typhoid fever was estimated to cause 725 incident cases and 7 deaths per 100,000 person years in sub-Saharan Africa [20]. However, the actual figure is not really known as few studies have been done to confirm the actual number of cases in most of SSA. In SSA the burden of typhoid fever is largely unknown mainly because credible measures of disease incidence, which inherently require confirmed diagnosis of typhoid based on blood or bone marrow culture, is almost non-existent in many endemic countries where laboratory capacity is frequently limited [21]. However, a number of hospital-based surveillance and case reports from several African countries suggests that typhoid is indeed a major public health concern, especially among school-age children.

Efforts for prevention and outbreak control are challenged by limited access to safe drinking water and sanitation and by a lack of resources to initiate typhoid immunization. A comprehensive approach to typhoid fever prevention including laboratory and epidemiologic capacity building, investments in water, sanitation and hygiene and reconsideration of the role of currently available vaccines could significantly reduce the disease burden. Targeted vaccination using currently available typhoid vaccines should be considered as a short- to intermediate-term risk reduction strategy for high-risk groups across sub Saharan Africa.

The major challenges to the management of typhoid fever are diverse and formidable; especially in the sub Saharan Africa. The following are some of the challenges for managing typhoid fever in this region;

1. Poor Sanitation
2. PoTable Water
3. Health Education

4. Confounding Diseases
5. Personal and Communal Hygiene
6. Laboratory Facilities
7. Lack of enough medical experts

### **2.3. Malaria**

Malaria is a mosquito-borne infectious disease of humans and other animals caused by parasitic protozoans (a type of single cell microorganism) of the Plasmodium type [22]. Commonly, the disease is transmitted via a bite from an infected female Anopheles mosquito, which introduces the organisms from its saliva into a person's circulatory system. Malaria parasites belong to the genus Plasmodium (phylum Apicomplexa). In humans, malaria is caused by *P. falciparum*, *P. malariae*, *P. ovale*, *P. vivax* and *P. Knowlesi* [23]. Among those infected, *P. falciparum* is the most common species identified (~75%) followed by *P. vivax* (~20%) [24].

#### **2.3.1. The transmission of malaria**

Malaria is transmitted exclusively through the bites of Anopheles mosquitoes. The intensity of transmission depends on factors related to the parasite, the vector, the human host, and the environment. Transmission is more intense in places where the mosquito lifespan is longer (so that the parasite has time to complete its development inside the mosquito) and where it prefers to bite humans rather than other animals. For example, the long lifespan and strong human-biting habit of the African vector species is the main reason why more than 90% of the world's malaria deaths are in Africa.

Malaria is prevalent in tropical and subtropical regions because of rainfall, warm temperatures and stagnant waters provide habitats ideal for mosquito larvae. Disease transmission can be reduced by preventing mosquito bites by using mosquito nets and insect repellents, or with mosquito-control measures such as spraying insecticides and draining standing water. Figure 2.2 shows the global distribution of malaria in the world.

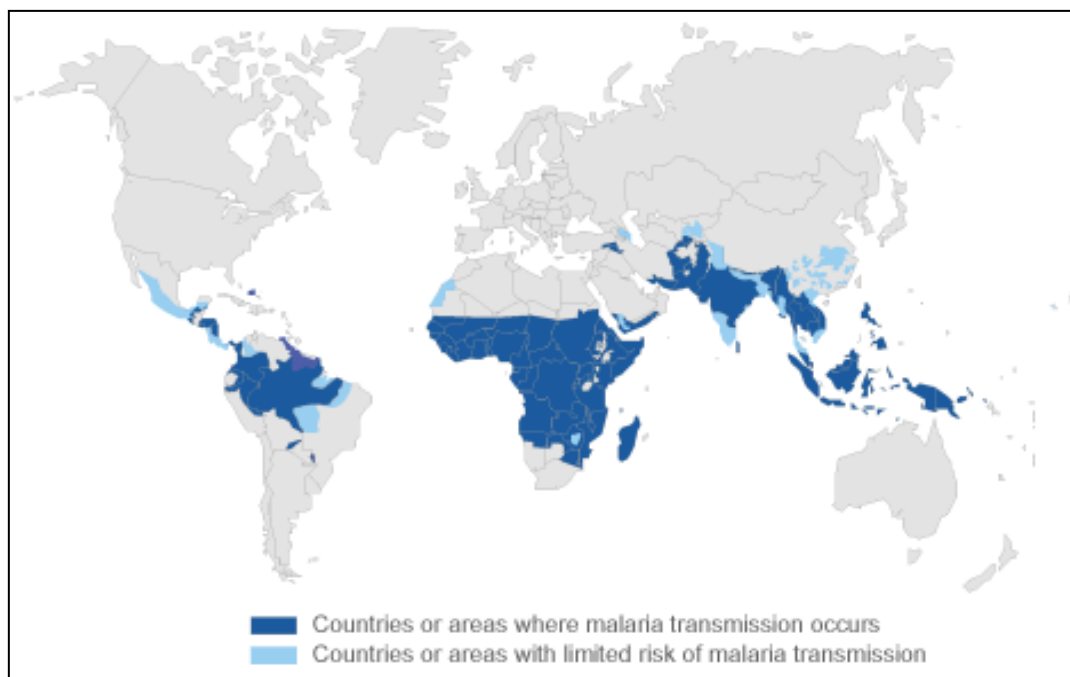


Figure 2.2. Countries and areas at risk of malaria transmission, 2011[25]

### 2.3.2. Malaria fever as a disease

A mosquito causes infection by taking a blood meal. First, sporozoites enter the bloodstream, and migrate to the liver. They infect liver cells, where they multiply into merozoites, rupture the liver cells, and return to the bloodstream. Then, the merozoites infect red blood cells, where they develop into ring forms, trophozoites and schizonts that in turn produce further merozoites. Sexual forms are also produced, which, if taken up by a mosquito, will infect the insect and continue the life cycle.

As shown in Figure 2.3, Plasmodium species infected female Anopheline mosquito injects sporozoites by biting on a human skin, and the sporozoites migrate to the liver, where they pass through Kupffer's cells and invade hepatocytes to form liver merozoites. The merozoites invade erythrocytes in the blood stream and develop through rings, trophozoites, and schizonts and subsequently replicate to produce more merozoites that invade other erythrocytes to perpetuate the asexual blood stage life cycle.

While in the blood stage, some intra-erythrocytic stages differentiate and become female and male gametocytes, that can subsequently be taken up by a mosquito upon feeding and develop into gametes that fuse and form zygotes. The zygote then develops to form sporozoites that can be injected to a human host and the cycle is completed as shown in Figure 2.3. In rare occasions malaria can be transmitted from an infected mother to the newborn through the placenta (in utero transmission) or during delivery (congenital malaria), however such cases have been shown to be rather low.

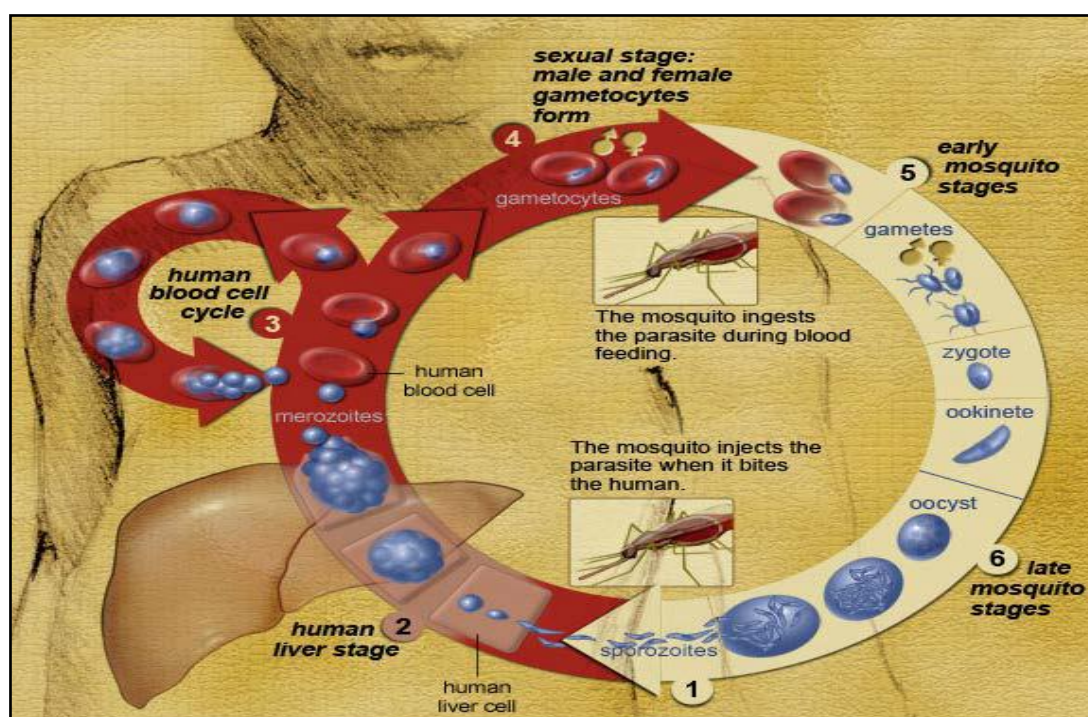


Figure 2.3. Simplified diagram showing malaria parasite life cycle in human host [26].

### 2.3.2.1. Clinical features of malaria

According to the Uganda clinical guidelines 2012 [9], the signs and symptoms of malaria are as in Table 2.1.



Table 2.1. Symptoms and signs of uncomplicated malaria based on UCG 2012

Symptoms in children under 5 years	Symptoms in older
Fever or a history of fever Loss of appetite Weakness Lethargy Vomiting Fever or a history of fever Loss of appetite	Fever or a history of fever Loss of appetite Lethargy Nausea Vomiting Headache Joint muscle pains
<b>Signs of Uncomplicated Malaria</b>	
Raised body temperature (above 37.5oC) Mild anaemia (mild pallor of palms and mucous membranes in children). Dehydration (dry mouth, coated tongue, and sunken eyes in children). Enlarged spleen.	

Table 2.2. Symptoms and signs of complicated malaria based on UCG 2012

Common symptoms of severe malaria.	Danger signs of severe illness
Change of behaviour, confusion, or drowsiness Altered level of consciousness or coma Convulsions Hypoglycemia Acidosis Difficulty in breathing Pulmonary oedema or respiratory distress syndrome Acute renal failure Severe anaemia Dizziness, tiredness, pallor Shock Haemoglobinuria Oliguria with very dark urine (coca-cola or coffee- colour) Jaundice Bleeding tendency Prostration Severe vomiting Threatening abortion (Such as uterine contractions and vaginal bleeding)	Convulsions or fits within the last two days or at present Not able to drink or breastfeed Vomiting everything Altered mental state (lethargy, drowsiness, unconsciousness, or confusion) Prostration or extreme weakness (unable to stand or sit without support) Severe respiratory distress or difficulty in breathing Severe anaemia (severe pallor of palms and mucous membranes) Severe dehydration (sunken eyes, coated tongue, lethargy, inability to drink)

### 2.3.2.2. Microscopic diagnosis of malaria

WHO recommends prompt parasite-based diagnosis by microscopy or malaria rapid diagnostic test (RDT) in all patients suspected of malaria before antimalarial treatment is administered. Light microscopy entails visualization of the malaria

parasites in a thick or thin smear of the patient's blood. Malaria microscopy allows the identification of different malaria-causing parasites (*P. falciparum*, *P. vivax*, *P. malariae* and *P. ovale*), various parasite stages, including gametocytes, and the quantification of parasite density to monitor response to treatment. Microscopy is the method of choice for the investigation of malaria treatment failures. Giemsa is the classical stain used for malaria microscopy, and diagnosis requires examination of both thin and thick films from the same patient. Light microscopy is the diagnostic standard against which other diagnostic methods have traditionally been measured.

### **2.3.3. Malaria in Sub-Saharan Africa**

Human Malaria is a serious problem in SSA and the risk exists throughout the region. It is a real fact that most malaria cases and deaths occur in sub-Saharan Africa. This is because the majority of infections in Africa are caused by *Plasmodium falciparum*, the most dangerous of the four human malaria parasites. It is also because the most effective malaria vector – the mosquito *Anopheles gambiae* is the most widespread in this region and the most difficult to control. This region has some of the poorest countries of the world with 90% of deaths occurring [approximately 3,000 deaths each] day [27]. The disease remains one of the leading causes of morbidity and mortality in the tropics. It is the most important and widespread of the tropical deadly diseases.

Human immunity is an important factor, especially among adults in areas of moderate or intense transmission conditions. Partial immunity is developed over years of exposure, and while it never provides complete protection, it does reduce the risk that malaria infection will cause severe disease. For this reason, most malaria deaths in Africa occur in young children, whereas in areas with less transmission and low immunity, all age groups are at risk according to MARA (Mapping Malaria Risk in Africa). It exacts a heavy toll of illness and death on children and pregnant women.

Diagnosis of malaria in SSA is also a problem. A few hours delay in treatment can mean the difference between life and death. The gold standard for diagnosing malaria

which visualise parasites directly in a blood film requires a laboratory set-up with a good microscope, reagents, slides and a trained microscopist. However, in many malaria-endemic countries, most of the smaller health facilities do not have laboratories, so malaria is commonly diagnosed on clinical findings in this region [28].

The economic burden resulting from malaria is considerable. Malaria-related costs in the region total USD 12 billion annually, equating to an average loss of 1.3% of gross domestic product [GDP] growth per year across countries on the African continent. This financial burden impacts families as well. The average household expenditure on malaria is roughly 10% of the yearly spend [29]. Exacerbating the healthcare costs that directly impact local and national economies are indirect costs resulting from the malaria burden. Lost productivity due to illness and time in patient care, lost education for students, teachers, and facilitators, costs related to long-term physical disability, and even increased family size due to increased fertility compensation for high child mortality all contribute to the economic impact of malaria.

#### **2.4. Differentiating Malaria And Typhoid By Signs And Symptoms**

Since antiquity, clinicians have had difficulty in differentiating typhoid fever from malaria because of some overlapping clinical features. Because the inability of physicians to clinically differentiate these two entities, they used the term 'typhomalaria' as a diagnosis for acute fevers without localizing signs. Osler [12] clearly differentiated malaria from typhoid fever by clinical criteria alone. By recognizing and appreciating the characteristic clinical features and his observations remain valid and useful today. Osler appreciated the differences in height of fever/rapidity of onset in differentiating malaria from early typhoid fever. He correctly observed that fever in malaria rises quickly and attains high levels (38.9 to 41.1°C). Typhoid fever has a plateau fever pattern that rises slowly during the second/third week.

According to Osler, the fever curve in typhoid increases slowly stepwise over the first few days and is followed by a pulse temperature deficit as the infection progressed. Both typhoid fever and malaria are accompanied by a prominent headache. Both malaria and typhoid fever have few, if any localizing signs such as rose spots (in typhoid fever). Splenomegaly is common to both infections. Osler also cited Malaria begins with multiple shaking chills, whereas typhoid fever begins with a single morning shaking chill. In malaria, chills are followed by spiking fevers. Except for the initial shaking chill, chills are not common with typhoid fever. In malaria, chills precede the fever followed by profuse diaphoresis and profound malaise followed by complete recovery between attacks. Osler also appreciated the clinical features of malaria and typhoid fever using non specific laboratory tests.

## **2.5. Summary**

We had a brief overview of malaria and typhoid fever in this chapter. The two diseases are great concern in the SSA region where the main used type of diagnosis is clinical diagnosis though both infections have their golden types of diagnosis. Some symptoms and signs overlap among the two diseases with vagueness and this is a task to clinicians when it comes to classification and decision making more so in rural areas where the biggest type of population lives. The two diseases appear in complicated and uncomplicated forms according to the available signs and symptoms on the patient. Final diagnosis is not easy at all since a physician has to consider different diagnosis features. This type of problems can be handled by transferring this medical knowledge into computer decision systems. In the next chapter, we explain knowledge based systems and fuzzy logic as a solution for decision making.

## **CHAPTER 3. A REVIEW ON KNOWLEDGE BASED SYSTEMS AND FUZZY LOGIC**

This chapter provides a literature review on knowledge based systems (KBS) and fuzzy logic. In KBS section, KBSs are defined, their architecture described, knowledge base engineering processes reviewed and lastly KBSs in medicine described. In fuzzy logic section, general description of fuzzy logic, its application in medicine, fuzzy sets and fuzzy inference system are presented.

### **3.1. Knowledge Based Systems**

A Knowledge-Based System, one of the major branches of artificial intelligence [AI], is a computer program that reasons and uses a knowledge base to solve complex problems. AI is an area of problem solving; concepts and methods for building programs that reason about problems rather than calculating a solution. KBS can act as an expert on demand without wasting time, anytime and anywhere. The term is broad and is used to refer to many different kinds of systems. KBSs can advise, analyze, categorize, communicate, consult, design, diagnose, explain, explore, forecast, form concepts, identify, interpret, justify, learn, manage, monitor, plan, present, retrieve, schedule, test, tutor, etc. The one common theme that unites all knowledge based systems is an attempt to represent knowledge explicitly via tools such as ontologies and rules rather than implicitly via code the way a conventional computer program does. A knowledge based system has at least one and usually two types of sub-systems: a knowledge base and an inference engine [30]. The knowledge base represents facts about the world, often in some form of subsumption ontology. The inference engine represents logical assertions and conditions about the world, usually represented via IF-THEN rules [31].

The phrase knowledge-based system is generally employed to denote information systems in which some symbolic representation of human knowledge of a domain is applied, usually to some extent resembling human reasoning, to solve actual problems in the domain. Examples of problem domains include medical diagnosis, patient monitoring systems, and so on. As this knowledge is often derived from experts in a particular field, and early knowledge-based systems were actually developed in close collaboration with experts, the term expert system was the term used in the early days to refer to these systems. As human experts use their knowledge in a particular field of expertise to solve day today activities, in the same way, knowledge based system handles problems; the computer needs an internal model of the world using the stored knowledge. All information is stored in such a way that it is readily accessible. To design knowledge based system, the expert knowledge was represented in a way that it supported for reasoning mechanism in computer languages. Representing knowledge into the expert system could offer potential advantages over human expertise. Because, knowledge based systems can use the acquired knowledge permanently, consistently, easy to transfer and document expert knowledge [32].

Knowledge, however, can also be extracted from literature. Moreover, not all domains of specific expert systems may be viewed as specialists' fields. As a consequence, some people prefer to make a distinction between expert systems and knowledge-based systems. In their view the latter are more general than the former as the former should always concern a specialist's field. In this research, we used the general term knowledge-based systems.

### **3.1.1. Architecture of a knowledge based system**

Figure 3.1 below shows the building blocks of knowledge based system architecture adopted from [33].

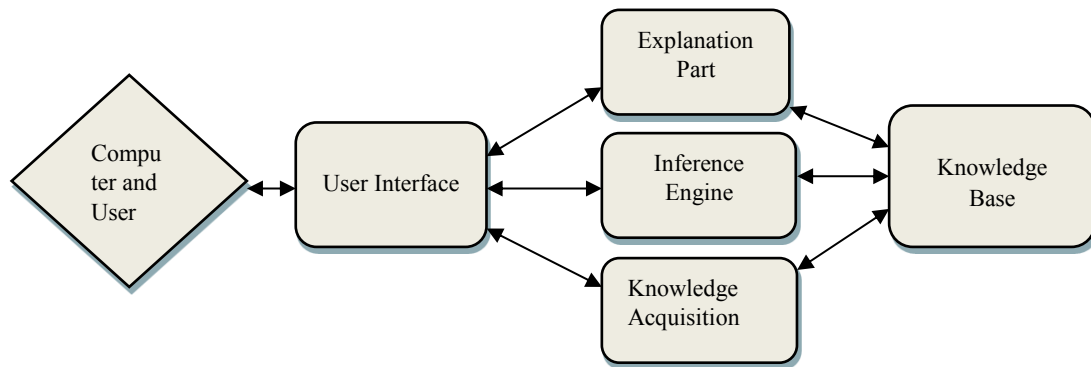


Figure 3.1. Architecture of a knowledge based system

The architecture of knowledge based system consists of different components such as Knowledge Base, Knowledge acquisition module, inference engine, user interface and explanation module. The Knowledge Base contains all relevant knowledge acquired from Domain experts. Knowledge also acquired from the user during their interaction with the system. The knowledge acquisition module helps in the collection process of knowledge from the set of human experts as shown in Figure above. The inference engines formulate questions and assert the answers provided by the user in a natural language form. It provides a mechanism for conveying recommendations to the end user. The explanation module provides a brief description.

### 3.1.1. The knowledge engineering process

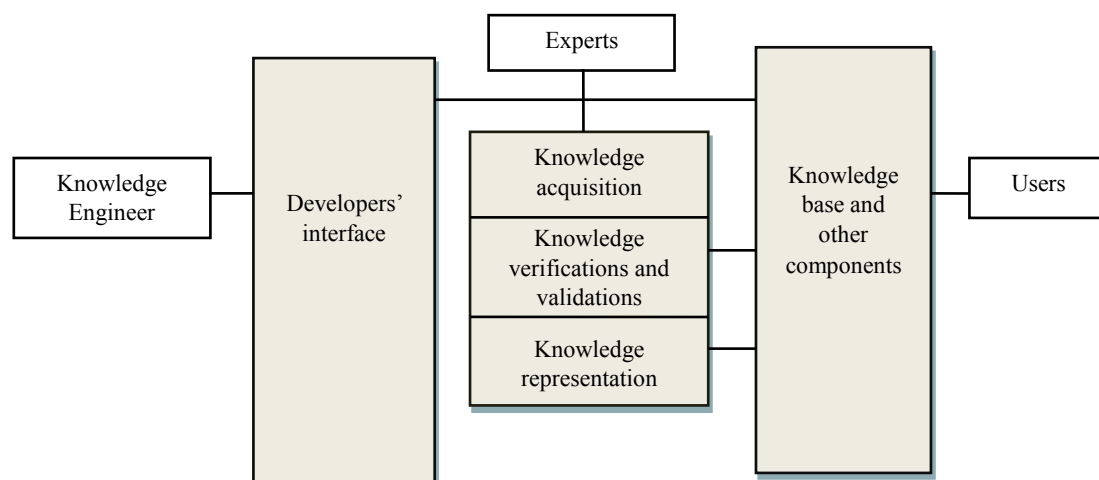


Figure 3.2. Development of a Knowledge-Based System [34]

The development of knowledge based system is the integration of many components. Figure 3.2. below shows the overview of knowledge based system development process [34].

#### **3.1.1.1. Knowledge acquisition**

Knowledge acquisition is the process of acquiring relevant knowledge from human experts, books, documents, sensors, or computer files. Knowledge acquisition and is considered a bottleneck [35] because it is time- and labor-intensive. The knowledge can be specific to the problem domain or to the problem-solving procedures, it can be general knowledge (e.g., knowledge about a certain disease) or it can be meta-knowledge (knowledge about knowledge). Knowledge acquisition is the bottleneck in knowledge based system development today. Because, the trustworthiness and the performance of the knowledge based system mainly depends upon the acquired knowledge [36].

The knowledge acquisition process incorporates different methods such as interviews, questionnaires, record reviews and observation to acquire factual and explicit knowledge [37]. The performance of the expert systems depends upon the reliability, validity and accuracy of the elicited knowledge. The process of knowledge elicitation is affected by different contributing factors such as communication between the expert and ability of knowledge engineer [38].

Therefore, effective elicitation techniques facilitate to acquire relevant knowledge form domain experts. The commonly used knowledge acquisition techniques include interviews, observations and document analysis [39].

#### **3.1.1.2. Knowledge verifications and validations**

Validation refers to building the right system, that is, determining whether the system does what it was meant to do and at an acceptable level of accuracy. Validating a knowledge based system involves confirming that the KBS performs the desired task with a sufficient level of expertise.



Verification refers to building the system "right", that is, determining whether the system implementation correctly corresponds to its specification. Therefore verifying an expert system means confirming the program accurately implements the acquired expert knowledge as documented.

### **3.1.1.3. Knowledge representation**

Elicited knowledge has to be represented in a knowledge base in such form that will not only be efficient to retrieve and manipulate by the knowledge based system but also amendable to the user or knowledge engineer. This activity involves preparation of a knowledge map and encoding of knowledge in the knowledge base. Knowledge can be represented in various ways: logic, semantic networks, frames model-based representation and rule based representation, each of which can be used for knowledge representation. Logic is a study of correct inference, which is elegant, simple and has sound mathematical basis [40]. The semantic network is a graph-based representation with nodes and arcs [41]. Nodes are objects in the real world and the links show how objects are associated with each other [40]. The frame-based knowledge representation is an object-based representation method. A frame is a description of an object and inside the frame knowledge is described in slots [42]. The rule-based representation consists of conditions (IF-THEN) evaluating to true or false and actions to be taken depending on the results of the conditions [42], which form rules in certain domain.

In this research, fuzzy logic rules have been used. They are made of simple IF-THEN rules and condition-action, if a condition is met, corresponding rule is fired and action is taken. If more than one condition is met, corresponding rules are fired, and due to this conflict, no action is taken until a conflict resolution method results in selecting one rule, and then it performs the action of that rule. Their modularity, simplicity, and good performance are what make them most often used in simple domains. The next section of this chapter will discuss fuzzy logic.

### 3.1.2. Knowledge based systems in medicine

Knowledge-based systems can be applied in medical domain when knowledge about a specific task in medicine is programmed into these systems. KBSs in the medical domain can be designed to give expert-level, problem-specific advice in the areas of medical data interpretation, patient monitoring, disease diagnosis, decision support, treatment selection, prognosis, and patient management. They capture medical texts, knowledge of experts and assist in the decision-making.

Research in medical knowledge-based systems and their development is most significant to the broad monarchy of quality assurance and cost containment in medicine. The growing complexity of the fund of knowledge makes the application of such systems more and more crucial. Patients may use internet based medical KBSs or computers installed in hospitals and answer questions about their symptoms and signs then get directed to the right clinical departments without any involvement of a medical attendant. In such an environment, a doctor will not waste much time asking questions to a patient, he will have to proceed to further examinations. This saves money and time by influencing expert, allowing other junior medical attendants to function at higher level and advancing reliability.

Therefore medical KBS;

1. Can reduce much of the repetitive and specialized mental efforts made by the treating physician and enable him or her to devote his or her attention to the personal care of the patient.
2. Can guide the user to gather easily the patient information, based on those information points that can lead to a possible diagnose and to the adapted treatment of the diseases.
3. They guide the user during the medical examination (physical) that will be done on the patient showing the definitions, images, sounds and/or videos of the signs associated to their disease and verify that the doctor does not forget to examine none of the criteria diagnoses even though is the first time that he sees or knows this sign.
4. They can lead to a better medical quality and improve patient care.

5. Provide comprehensive quality management with consideration of medical working processes and administrative conditions.
6. Clinical patient management KBSs help to monitor patient's measured and derived medical data and generate reminders, warnings, and alerts during the automatic processing of medical protocols and guidelines.

Although knowledge based systems can perform allot of tasks in medicine, as seen above, our research is mainly concerned with diagnosis. Diagnosis KBS in the medical domain are normally known as diagnostic decision support systems (DDSSs) or medical diagnosis systems (MDSs). They can direct physicians and doctors to quicker and correct diagnosis and reduce the rate of diagnostic errors in medicine [13-14]. Such systems are more appropriate in the SSA where life threatening malaria and typhoid fever are predominant and endemic.

Knowledge based systems in the medical history include MYCIN, a program to advise physicians on antimicrobial selection for patients with bacteremia or meningitis [43 -44]; the Present Illness Program (PIP), a system that gathered data and generated hypotheses about disease processes in patients with renal disease[45]; INTERNIST-1, a large system to assist with diagnosing complex problems in general internal medicine[46] ,and CASNET, an ophthalmology advisor designed to assess disease states and to recommend management for patients with glaucoma [47] .

### **3.2. Fuzzy Logic**

There are a number of knowledge based reasoning methods that can be used when building KBSs. The well-known reasoning approaches are ontology based reasoning, semantic network, neural network, fuzzy logic, case based reasoning and rule based reasoning. For the purpose of this research work, fuzzy logic is discussed.

Fuzzy logic (FL) is a form of many-valued logic; it deals with reasoning that is approximate rather than fixed and exact. Compared to traditional binary sets (where variables may take on true or false values); FL variables may have a truth value that ranges in degree between 0 and 1. It has been extended to handle the concept of

partial truth, where the truth value may range between completely true and completely false [48]. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. Irrationality can be described in terms of what is known as the fuzzjective [49].

In a normal Boolean representation, a person can be sick or healthy. The problem with this representation is that there must be a clean cut-off for where illness begins and ends. If 100% were set as the cut-off for being healthy, someone with a healthy of 99% would be considered not healthy. Such differentiation does not fully represent the world in which we live because our world is not discrete. To compound the problem, human beings often think and speak using general, imprecise language where the characteristics of things, such as healthiness, are subjective in nature. In FL we may assume that a person is 100% healthy, 80% healthy, 50% healthy and use words like very health, fairly healthy and somehow healthy. Fuzzy logic captures the meaning of the imprecise, or fuzzy, statements inherent to human thinking and represents them in a manner that enables a system to solve problems.

In fuzzy based systems, the fundamental of the decision making is the approximate reasoning, which is a rule-based system. Knowledge representation in a rule-based system is done by means of IF...THEN rules. Furthermore, approximate reasoning systems allow fuzzy inputs, fuzzy antecedents, and fuzzy consequents. "Informally, by approximate or, equivalently, fuzzy reasoning, we mean the process or processes by which a possibly imprecise conclusion is deduced from a collection of imprecise premises. Such reasoning is, for the most part, qualitative rather than quantitative in nature and almost all of it falls outside of the domain of applicability of classical logic", [50]. This fuzzy representation allows a closer match with many of the important concepts of practical affairs, which lack the sharp boundaries assumed by classical logic.

The concept of fuzzy sets was introduced by Zadeh [4] in 1965 as a generalization of classical sets. While in classical set theory an element is either a member of a set or not, fuzzy sets allow graded memberships of elements. Zadeh generalized the  $\{0, 1\}$ -valued (or, in other words crisp) characteristic function of classical sets to the unit

interval. This way, objects may belong to a set to any degree between 0 and 1. The framework of fuzzy sets fully contains the framework of crisp sets. As a consequence of the generalization, fuzzy sets only possess a part of crisp set properties. According to Zadeh, the essential characteristics of fuzzy logic are:

1. Exact reasoning is viewed as a limiting case of approximate reasoning.
2. Everything is a matter of degree.
3. Any logic system can be fuzzified.
4. Knowledge is interpreted as a collection of equivalent and fuzzy constraints on a collection of variables.
5. Inference is viewed as a process of propagation of fuzzy constraints.

### **3.2.1. Fuzzy logic in medicine**

Doctors rely on gained knowledge and experience in making decisions though most medical concepts are uncertain. The inexact nature of medical concepts and their relationships requires a strong reasoning technique that can handle problems involved in the medical knowledge. For example, in the diagnosis of malaria, the degree of vomiting, dehydration, fever, anaemia and other diagnosis features imply a certain conclusion by the physician. Some may occur in different states as mild, medium, severe, or low, high, very high etc and doctors can always conclude as uncomplicated or complicated malaria according to the situation. FL provides linguistic approach with an excellent approximation to texts.

FL is also an important technique in handling uncertainty within the medical knowledge. Uncertainty is a situation where the information available to the decision makers is imprecise to be summarized by a probabilistic measure. It can be due to lack of knowledge or insufficient information, vagueness, no specificity and conflict in the information. Uncertainty such as biological variability of patients, patient and physician bias, error in test interpretation, differing values and opinions of patients and physicians, uncertainty surrounding decision-making etc is frequently encountered in medical practice and causes stress to patients and physicians. Fuzzy logic theory provides a very useful solution to understanding, quantifying and handling vague, ambiguous and uncertain data or knowledge. It uses fuzzy sets to

handle and analyze uncertainty of data, environmental data and FL reasoning to handle inaccurate reasoning in knowledge-based systems hence turning into precise what is imprecise in the world of medicine.

The Fuzzy Expert System has proved its usefulness significantly in the medical diagnosis for the quantitative analysis and qualitative evaluation of medical data, consequently achieving the correctness of results. Many areas in medicine have accessed the use of fuzzy logic in various applications include:

CADIAG-2 [51], was the first to use the theory of fuzzy sets in medicine. It was developed to assist the physician in diagnostics. Representation and processing of medical knowledge was a very difficult and complex task for computer systems when the first fuzzy expert system, CADIAG-2, arose in the late seventies.

Scott S. Lancaster et al. discussed the design of Fuzzy logic controller (FLC) for medical device based on software using fuzzy logic. FLC used for controlling the regulator to apply air pressure to the skin of human consisting of analogue-to-digital convertor for the collection of data, pneumatic valve and sensor to control air pressure [52].

Ch. Schuh et al. described how fuzzy logic used in medical human health care system and the medical data of patient [53].

M. Mahfouf , M.F.Abbod , D.A.Linkens et al. explained the use of fuzzy logic in the neuro medical field, fuzzy logic evaluation on the basis of facial expression and human behavior etc., surveyed different fuzzy techniques using the data analysis of medical science [54].

Adeli et al [55] designed Fuzzy expert system for the Heart Disease Diagnosis was developed. The developed system uses fuzzy logic. In their system the crisp value is fuzzified to get fuzzy values. The expert system uses those fuzzy values and the output is also fuzzy. The fuzzy output is defuzzified to get a crisp output.

### 3.2.2. Fuzzy sets

The ordinary set theory is based on the bivalent logic which allows only values of  $a = \{0, 1\}$ . That means for each point  $x$  can be clearly decided whether it belongs to the set  $a$  or not,  $x \in a$  or  $x \notin a$ . In contrast to this, the fuzzy set theory [4-5] allows all values of a function in the defined interval  $[0, 1]$ . Therefore, a partial membership of a point  $x$  of a universe set  $X$  to a fuzzy subset  $A$  is possible, whereas the fuzzy subset  $A$  (further referred to as fuzzy set) is a set of ordered pairs:

$$A = \{(x, \mu_A(x)) : x \in X; \mu_A(x) \in [0,1]\} \quad (3.1)$$

$\mu_A(x)$  is called the membership (characteristic) function of the fuzzy set  $A$  and represents the grade of membership of  $x$  in  $A$  by associating each point in  $X$  a real number of the interval  $[0,1]$ . The closer  $\mu_A(x)$  is to 1 the more point  $x$  belongs to the fuzzy set  $A$  and vice versa. Furthermore, if  $\mu_A(x)$  is equal to zero, point  $x$  does not belong to the fuzzy set  $A$ . If at least one point of a fuzzy set  $A$  has a membership value of one,  $A$  is a so-called normal fuzzy set. Fuzzy sets are often defined by a graphical diagram of its membership function. It is the key component of a fuzzy set, and all operations with fuzzy sets are defined through their membership functions. Figure 3.3 shows the four common types of continuous membership function  $\mu_A(x)$ .

Fuzzy numbers always constitute a generalization of the usual concept of numbers in fuzzy sets. The 0-level set is defined as the support  $\text{supp}(A)$  of a fuzzy number which includes all points with an  $\alpha$ -level greater than 0:

$$\text{Supp}(A) = \{x \in X; \mu_A(x) > 0\} \quad (3.2)$$

Because of Equation 3.2 any real number can be considered as a fuzzy number with a **single point** support and is called a crisp number (Figure 3.3a) instead of a fuzzy number.

The definition of **LR-fuzzy numbers** after [56] is very popular and widely-used, in particular, the simplest variants of LR-fuzzy numbers, and the triangular and trapezoidal fuzzy numbers are used in practice.

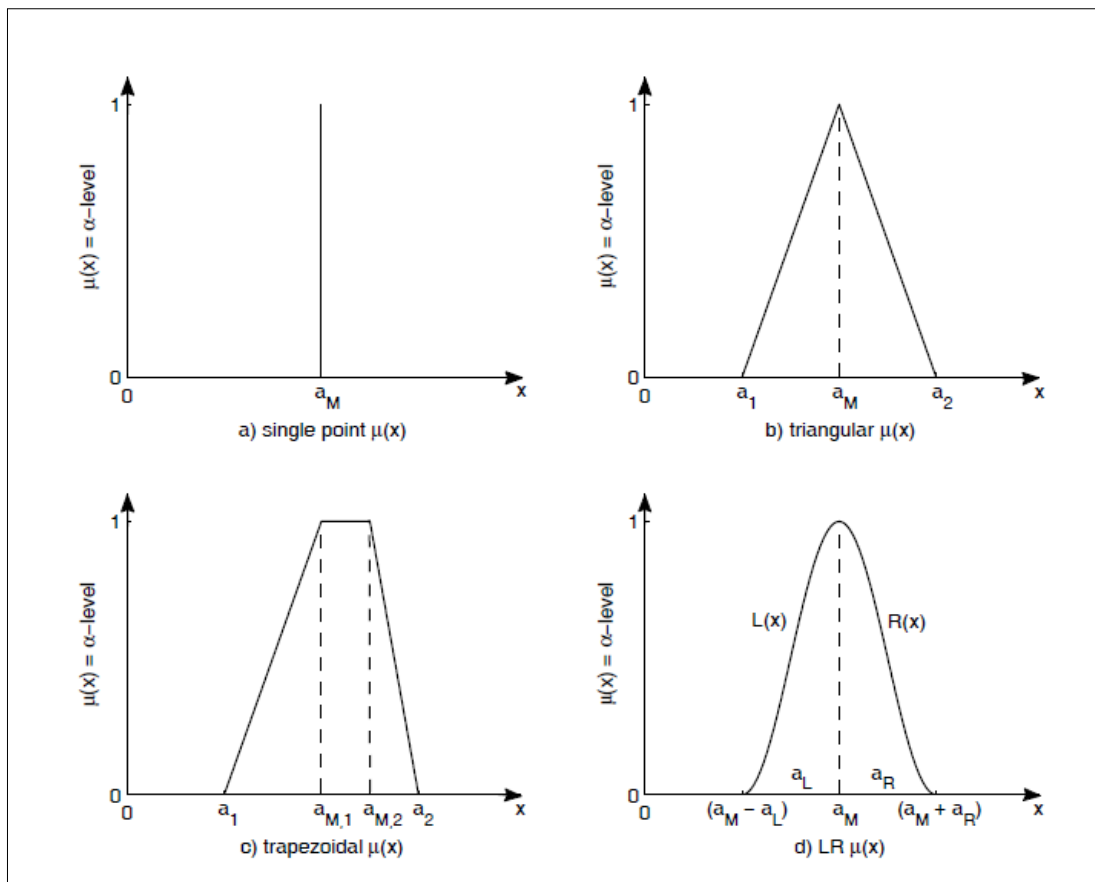


Figure 3.3. Four common types of continuous membership functions  $\mu(x)$ : a) single point, b) triangular, c) trapezoidal, and d) LR (Left - Right) where  $L(x)$  and  $R(x)$  are continuous strictly decreasing functions.

$$\mu_A(x) = \begin{cases} \mathcal{L}\left(\frac{a_M - x}{a_L}\right) & \text{if } x \in [(a_M - a_L), a_M] \\ \mathcal{R}\left(\frac{x - a_M}{a_R}\right) & \text{if } x \in [a_M, (a_M + a_R)] \\ 0 & \text{else} \end{cases} \quad (3.3)$$

where  $L(x)$  and  $R(x)$  are continuously, strictly decreasing functions defined on  $[0, 1]$  with values in  $[0, 1]$  satisfying the conditions:

$$L(x) = R(x) = 1 \text{ if } x \leq 0 \text{ and } L(x) = R(x) = 0 \text{ if } x \geq 1.$$

The support of the LR-fuzzy number  $A$  is  $\text{supp}(A) = [(a_M - a_L), (a_M + a_R)]$ .

**Triangular fuzzy number:** A triangular fuzzy number  $A$  is defined as

$A = (a_1, a_M, a_2)T$  and its membership function (Figure 3.3b) is defined by:



$$\mu_A(x) = \begin{cases} \frac{x-a_1}{a_M-a_1} & \text{if } x \in [a_1, a_M] \\ \frac{a_2-x}{a_2-a_M} & \text{if } x \in [a_M, a_2] \\ 0 & \text{else} \end{cases} \quad (3.4)$$

where  $a_1 \leq a_M \leq a_2$ .

The support of the triangular fuzzy number A is  $\text{supp}(A) = [a_1, a_2]$ .

**Trapezoidal fuzzy number:** A trapezoidal fuzzy number A is defined as

$A = (a_1, a_{M,1}, a_{M,2}, a_2)_{\mathbb{R}}$  and its membership function (Figure 3.1c) is defined by:

$$\mu_A(x) = \begin{cases} \frac{x-a_1}{a_{M,1}-a_1} & \text{if } x \in [a_1, a_{M,1}] \\ 1 & \text{if } x \in [a_{M,1}, a_{M,2}] \\ \frac{a_2-x}{a_2-a_{M,2}} & \text{if } x \in [a_{M,2}, a_2] \\ 0 & \text{else} \end{cases} \quad (3.5)$$

where  $a_1 \leq a_{M,1} \leq a_{M,2} \leq a_2$ .

The support of the trapezoidal fuzzy number A is  $\text{supp}(A) = [a_1, a_2]$ .

### 3.2.3. Fuzzy inference system

A fuzzy inference system (FIS) comprises a set of rules that employ linguistic terms similar to those used in natural language and an inference mechanism is able to extract correct conclusions from approximate data [57]. They are essentially knowledge-based systems that utilize all of the concepts that have been described in the previous sections: fuzzy logic, fuzzy IF-THEN rules and membership functions. Figure 3.4 shows the components of a fuzzy inference system: As shown in Figure 3.4, a fuzzy inference system is made up of five functional blocks.

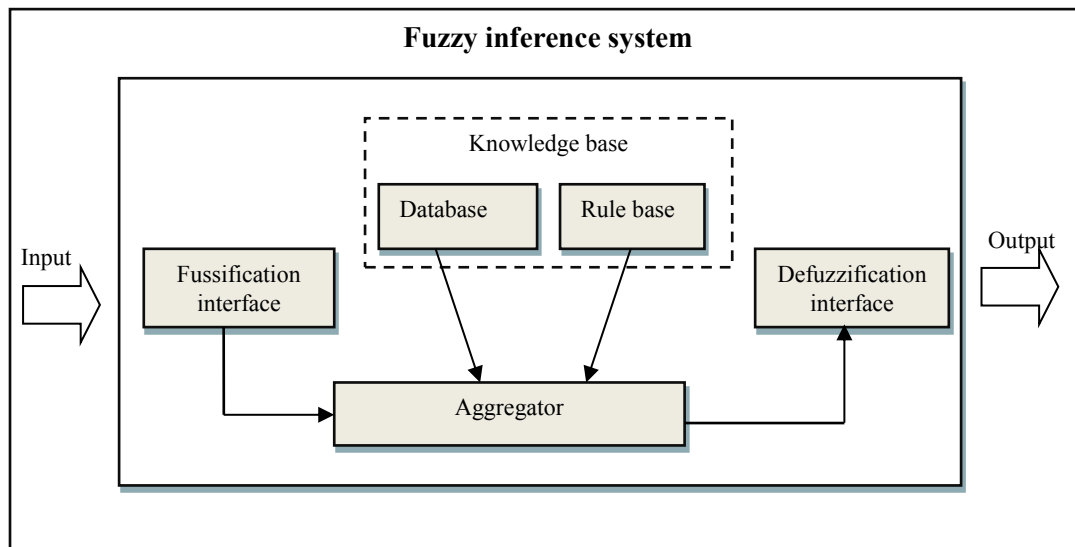


Figure 3.4. Components of a fuzzy inference system [58]

### 3.2.3.1. A fuzzification interface

This transforms the crisp inputs into degrees of match with linguistic values. The process of fuzzification is an important stage in the development of a fuzzy expert system. Fuzzification is where crisp quantities i.e. selected input variables are converted into fuzzy values. The fuzzifier converts the crisp inputs which are supplied to the system to fuzzy inputs and also determine the degree to which these inputs belong to each of the appropriate fuzzy sets. This is done using membership functions plus their relative formulas. For this research, a triangular type membership function was used and therefore equation 3.5 will be used. The purpose of the fuzzification process is to allow a fuzzy condition in a rule base to be interpreted.

### 3.2.3.2. A rule base containing a number of fuzzy IF-THEN rules

The application of fuzzy logic in real world systems is mainly used with fuzzy IF-THEN rules. In this application, conditional statements take the form of:

IF < premise > THEN < consequence >

whereby both premise and consequence are characterized by fuzzy or linguistic elements respectively. Due to their straightforward forms, fuzzy if-then rules are often employed to process information captured by human reasoning in order to

make decisions that are based on linguistic inputs. Fuzzy rules are stored in the rule base of the FIS. An example that illustrates this relationship is:

IF < vomiting is severe > THEN < malaria is severe >

where 'severe' is linguistic variable that can be characterized by membership functions. Through the use of linguistic inputs and membership functions, fuzzy IF-THEN rules can easily capture the spirit of "rule of thumb" used by humans. This is done by incorporating them in fuzzy inference systems.

Fuzzy sets operations in the rule base are done by Fuzzy Operators. These operations are generalization of crisp set operations. There is more than one possible generalization. The most widely used operations are called standard fuzzy set operations. The basic connective operations in classic set theory are those of intersection and union. These operations on characteristic functions can be generalised to fuzzy sets in more than one way [59]. However, one particular generalisation, which results in operations that are usually referred to as standard fuzzy set operations, has a special significance in fuzzy set theory.

The standard operators, intersection ( $\text{AND}$ ) min and union ( $\text{OR}$ ) max are known to define the 'strongest' (most restrictive) union and the 'weakest' (least restrictive) intersection, which make it possible to calculate fuzzy sets [60]. Typically, most fuzzy expert systems make use of these fuzzy operators and their selection can be random to an extent. The choice of operators, fuzzy intersection and fuzzy union is based on its universal application to the inference method applied to the system however an intersection operator has been chosen for this research.

### **3.2.3.3. A database which defines the membership functions**

The use of membership functions, define for each fuzzy set and each linguistic variable, the degree of membership of a crisp value in each fuzzy set. The membership function shapes differentiate the ranges suggested from the knowledge acquired, and the placement of these shapes is estimated over the universe of discourse. In addition, the number of shapes and the overlapping of these shapes is an important issue to be considered when defining membership functions.

Membership functions can take a variety of shapes. However, triangular membership functions (Figure 3.3b ) has been chosen for this system since it often provide adequate representation of the expert knowledge, while at the same time, simplifies the process of computation.

#### **3.2.3.4. An aggregator or inference engine which performs the inference operation based on the rules**

Once all crisp input and output variables have been fuzzified into their respective linguistic values, the inference engine will access the fuzzy rule base of the fuzzy inference system to derive linguistic values for the output linguistic variables. The inference engine evaluates all the rules in the rule base and merges the weighted consequences of the entire fired rule into a single fuzzy value. Fuzzy inference engine of the FIS system gets input from the rule base and the fuzzifier, and then evaluates all these input in order to produce the desired output. This means that the inputs and the outputs of the inference engine are fuzzy values and the difference between them is that the output is a single fuzzy value unlike the inputs.

#### **3.2.3.5. Defuzzification interface**

A defuzzification interface is one which converts the fuzzy results into crisp outputs. There are a number of inference techniques used in a fuzzy inference system. One of the techniques that is used mostly in various practical applications and was used in this research is the Mamdani inference technique. The Mamdani technique was introduced by Professor Ebrahim Mamdani of London University in 1975 to control kiln temperature in a cement factory. To come up with the technique, he applied a set of fuzzy rules supplied by experienced human operators rather than using theoretical formula. The technique takes the form of:

$$\text{IF } \langle x \text{ is } A \rangle \text{ AND } \langle y \text{ is } B \rangle \text{ THEN } \langle z \text{ is } C$$

where A, B, are fuzzy sets in the premise and C is a fuzzy set in the consequence. Figure 3.5 illustrates the Mamdani inference technique for a 2-input 1-output system.

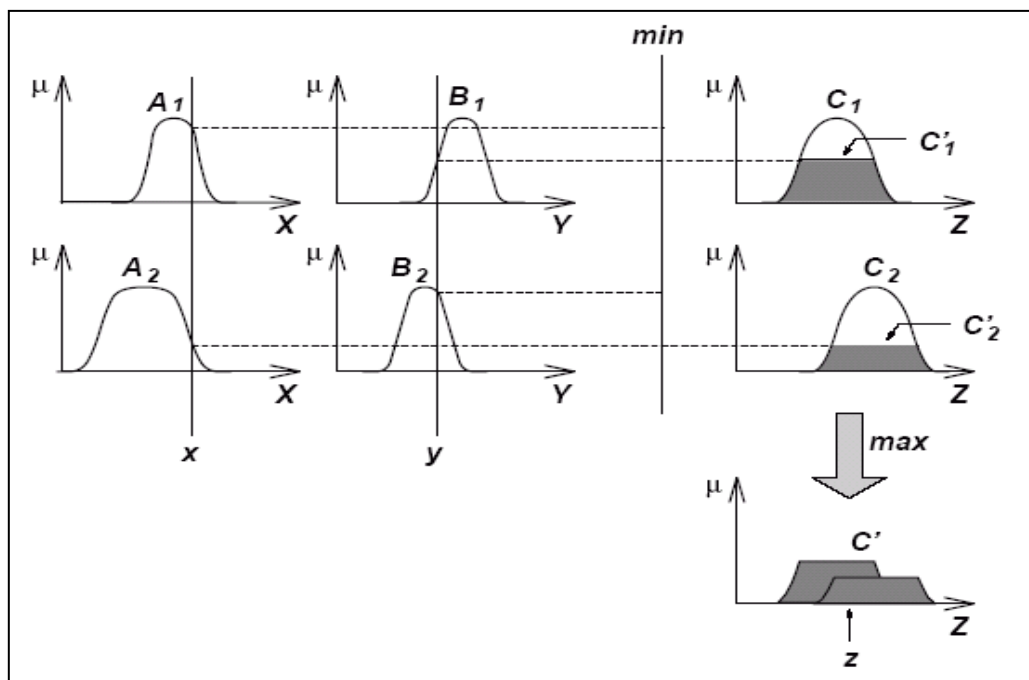


Figure 3.5. Mamdani fuzzy inference method [59]

In the above Figure,  $A_1$  and  $A_2$  represent the degree of memberships for fuzzy input  $x$  and  $B_1$  and  $B_2$  represent the degree of memberships for fuzzy input  $y$ . Use of the  $\min$  operator indicates that the minimum of these two values are mapped to fuzzy output  $z$ , indicated by areas under  $C'_1$  and  $C'_2$  respectively. The resultant, which is the area under  $C'$ , is an aggregation (union) of areas under  $C'_1$  and  $C'_2$ . In order to indicate an appropriate representative value for the final output, the aggregated output membership function has to be converted into a crisp form. The conversion is done in the defuzzification step of the inference system and can be achieved using any one of the five computational schemes:

### 3.2.3.5.1. Centroid or Centre-of-Area (COA), $z_{COA}$

This method calculates the point which is central to the area under the aggregated output membership function. It is calculated using the following equation:

$$z_{COA} = \frac{\int \mu_A(z)zdz}{\int \mu_A(z)dz} \quad (3.6)$$

where  $\mu_A(z)$  is the aggregated output membership function. This is the most commonly used defuzzification technique and is very accurate which we also used in this work. The only disadvantage of this technique is that it can be computationally difficult for complex membership functions.

### 3.2.3.5.2. Bisector of Area (BOA), zBOA

This method calculates the area under the aggregated output membership function and divides it into two equal areas. The point of division is returned as the bisector of the area. It is calculated using the following equation:

$$\int_a^{z_{BOA}} \mu_A(z) dz = \int_{z_{BOA}}^b \mu_A(z) dz \quad (2.8)$$

Where  $a=\{z|z \in Z\}$ ,  $b=\max\{z|z \in Z\}$ , and  $z_{BOA}$  is the value at which the area is divided equally by 2. This technique can also be computationally difficult if the out membership functions are complex.

### 3.2.3.5.3. Mean-of-Maximum (MOM), zMOM

This method calculates the arithmetic mean of all the maximum values of the aggregated output membership function. It is calculated using the following equation:

$$z_{MOM} = \frac{\int z dz}{\int dz} \quad (3.8)$$

### 3.2.3.5.4. Smallest-of-Maximum (SOM), zSOM

This method returns the smallest of the maximum values on the aggregated output membership function. This defuzzification technique is very fast as it doesn't require any calculations.

### 3.2.3.5.5. Largest-of-Maximum (LOM), zLOM

This method returns the largest of the maximum values on the aggregated output membership function. For the same reason as the Smallest-of-Maximum defuzzification technique, this technique is also very fast. The above methods are graphically represented in Figure 3.6:

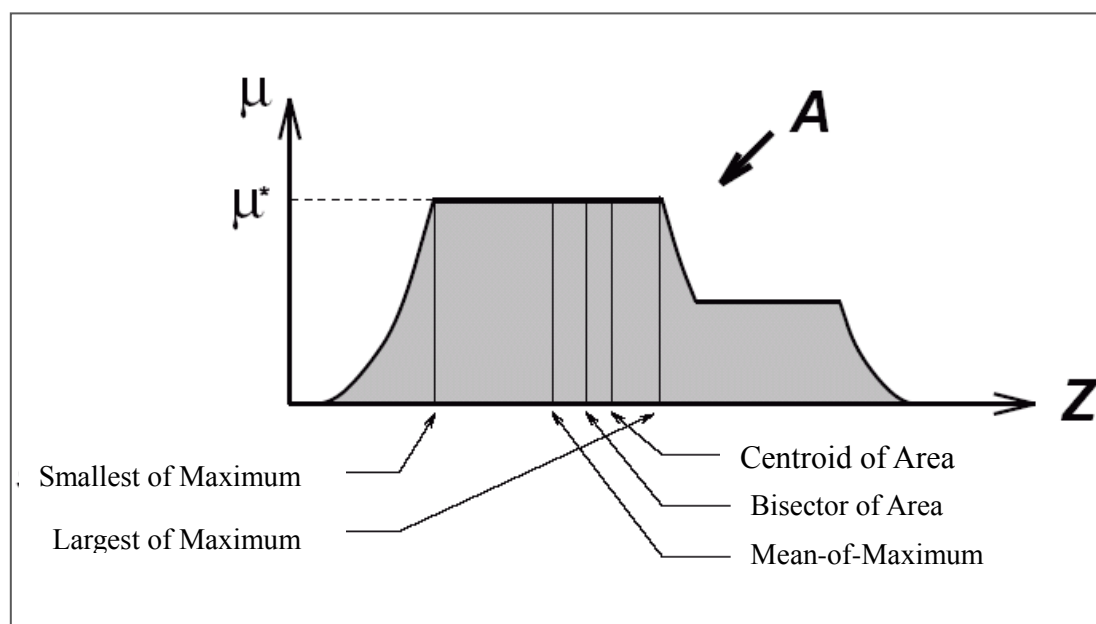


Figure 3.6. Defuzzification schemes to derive a crisp output [58]

### 3.2.3.6. Developing fuzzy inference systems

There are essentially 5 steps that one can follow in developing fuzzy inference models [58]:

1. Specify the problem and define linguistic variables used.
2. Determine fuzzy membership functions.
3. Elicit and construct fuzzy rules.
4. Encode the fuzzy membership functions, fuzzy rules and procedures to perform fuzzy inference in an expert system.
5. Evaluate the system.

Finally, the system is tested to check whether it conforms to the required settings specified in the beginning. This step may prove to be laborious as various levels of

input data needs to be fed into the system and the outputs verified to the satisfaction of the expert. Tuning the system may be required and this can be done by;

1. Reviewing the model input and output variables.
2. Reviewing the membership functions. If necessary, additional membership functions may be required to be defined.
3. Providing sufficient overlaps between neighbouring membership functions. It is suggested in [60] that triangle-to-triangle and trapezoidal-to-triangle membership functions should overlap around 25% to 50% of their bases.
4. Reviewing the rules. If necessary, additional rules may be required to be defined.
5. Revising the shapes of the membership functions.

#### **3.2.4. Matlab Fuzzy Logic Toolbox**

The Fuzzy Logic Toolbox is a collection of functions built on the Matlab numeric computing environment. It provides tools for you to create and edit fuzzy inference systems within the framework of Matlab. This toolbox relies heavily on graphical user interface (GUI) tools to help you accomplish your work, although you can work entirely from the command line if you prefer. The toolbox provides three categories of tools:

1. Command line functions
2. Graphical, interactive tools
3. Simulink blocks and examples

The first category of tools is made up of functions that you can call from the command line or from your own applications. Many of these functions are Matlab M-files, series of Matlab statements that implement specialized fuzzy logic algorithms. You can view the Matlab code for these functions using the statement `type function name`. You can change the way any toolbox function works by copying and renaming the M-file, then modifying your copy. You can also extend the toolbox by adding your own M-files. Secondly, the toolbox provides a number of interactive tools that let you access many of the functions through a GUI. Together, the GUI-based tools provide an environment for fuzzy inference system design, analysis, and implementation. The third category of tools is a set of blocks for use with the



Simulink simulation software. These are specifically designed for high speed fuzzy logic inference in the Simulink environment. Key Features include;

1. Specialized GUIs for building fuzzy inference systems and viewing and analyzing results.
2. Membership functions for creating fuzzy inference systems.
3. Support for AND, OR, and NOT logic in user-defined rules.
4. Standard Mamdani and Sugeno-type fuzzy inference systems.
5. Automated membership function shaping through neuroadaptive and fuzzy clustering learning techniques.
6. Ability to embed a fuzzy inference system in a Simulink model.
7. Ability to generate embeddable C code or stand-alone executable fuzzy inference engines.

The matlab fuzzy tool has been used for implementing a fuzzy knowledge based system for clinical diagnosis of tropical fever (TROPFEV) aimed in this research.

### **3.3. Summary**

This chapter provided a literature survey on knowledge based systems and fuzzy logic. We learnt that knowledge from, experts, documents, books; published papers can be modelled and represented using knowledge based representing techniques to implement knowledge based systems. We found fuzzy logic a technique that has many applications in the medical domain and a good one for expressing medical texts more so in diagnosis. The need to arrive at the accurate and quick medical diagnosis in a timely manner is the main outcome that may reduce the burden of Tropical fever. We have selected fuzzy logic as the best technique to express tropical fever texts using its linguistic variables. We also selected matlab a fuzzy logic tool that will be used during implementation due to its simplicity.

## **CHAPTER 4. THE TROPFEV SYSTEM**

This chapter proposes a fuzzy knowledge based system for diagnosis of the two diseases. The system architecture and the developments process are explained within the chapter.

### **4.1. Introduction**

We have taken a review of knowledge based systems in the previous chapter and we discussed knowledge based systems and their application in the medical domain. We deeply reviewed fuzzy logic, its use and importance in medicine such as handling uncertainty, the possibility to use linguistic variables and so on. We also saw in chapter 2 that malaria and typhoid fever are serious infections in SSA. Clinical diagnosis is the usually used type of judgment in the region; however, decision making for patients is a bit complicated towards physicians because of various features contained in these two diseases. In this chapter, we propose a fuzzy knowledge based system for Tropical fever Diagnosis (TROPFEV) that is simple to use and can be used by both physicians and trained medical workers or even patients to know the type of fever. It uses plain English language to interact with users and no special knowledge required for individual users. It is a clinical decision support that uses symptoms and their severity or conditions to make a conclusion in an easier way than doctors do. In this situation, it can always help doctors and medical workers to make quick decisions rather than using their own brains. This saves them from stress and tiredness.

The system is also aimed to show the possibility of fuzzy logic in medical texts in a way that systems developed using the technique can reason the same way people reason. During diagnosis based on the individual's option selections, the system concludes the complicity and type of fever that is complicated malaria,

uncomplicated malaria, complicated typhoid, uncomplicated typhoid or unknown fever if the user's selected symptom options do not match with the system fuzzy rules.

#### 4.2. Architecture Of The TROPFEV System

The architecture of the proposed knowledge based Tropical fever system (TROPFEV) for the diagnosis of Tropical fever is presented in Figure 4.1. It consists of an interface via which a doctor, patient, or any other person selects symptoms and signs of the patient such as mild or severe or none for vomiting, anaemia or any other symptom. The user interface is very friendly that any user who knows English and medical fever diagnosis languages can use it.

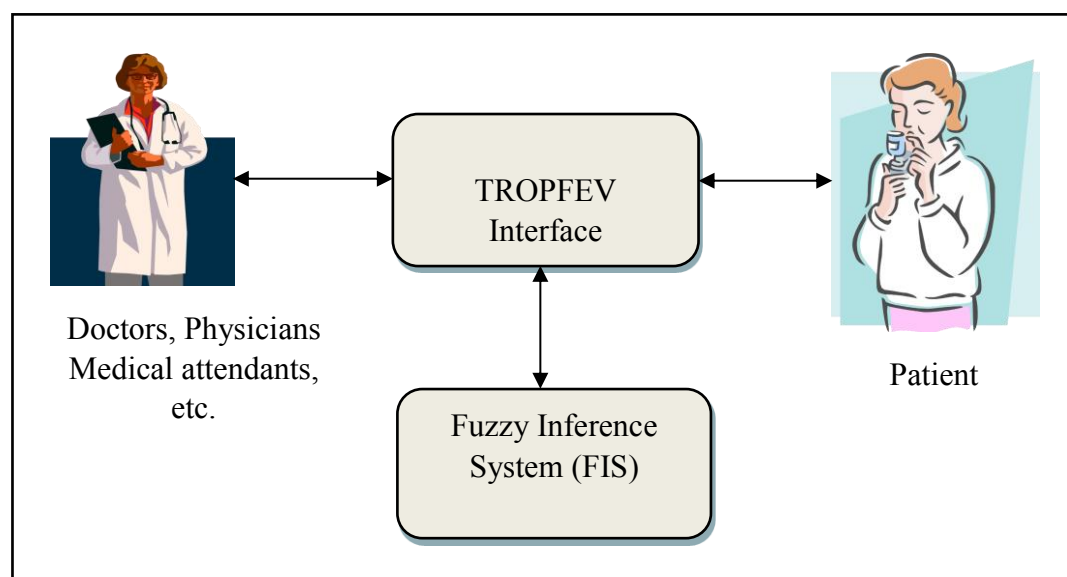


Figure 4.1. Architecture of fever system

The Fuzzy inference system (FIS) of the TROPFEV system is where the inputs selected by the doctor or patient are mapped to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made. The system uses fuzzy reasoning to map an input space into an output space. Fuzzy logic being a rule based system uses if-then rules. FIS is used to recognize the nodules depending on the input, output Fuzzy membership functions. Based on the input diagnosing features, the FIS can classify whether fever is complicated malaria, uncomplicated

malaria, complicated typhoid, uncomplicated typhoid or unknown fever. Figure 5.2 shows the fuzzy inference system of the TROPFEV system in matlab fuzzy editor.

### **4.3. TROPFEV System Development Process**

When developing knowledge based systems a number of challenges must be overcome such as detection of domain expertise in this case expertise concerning malaria and typhoid fever diagnosis, knowledge acquisition and knowledge representation and this case fuzzy rule, programming, validation, verification etc. Figure 4.2 shows the development process of the TROPFEV system. The process of TROPFEV development includes;

1. Fever domain knowledge source identification
2. Fever knowledge acquisition
3. Fever knowledge representation
4. Designing a fuzzy inference system
5. Implementation of TROPFEV fuzzy inference system
6. Verification and testing

The first four processes that is; fever domain knowledge source identification, fever knowledge acquisitions, fever knowledge representation, designing a fuzzy inference system are discussed in this very chapter will the last two are discussed in the next chapter.

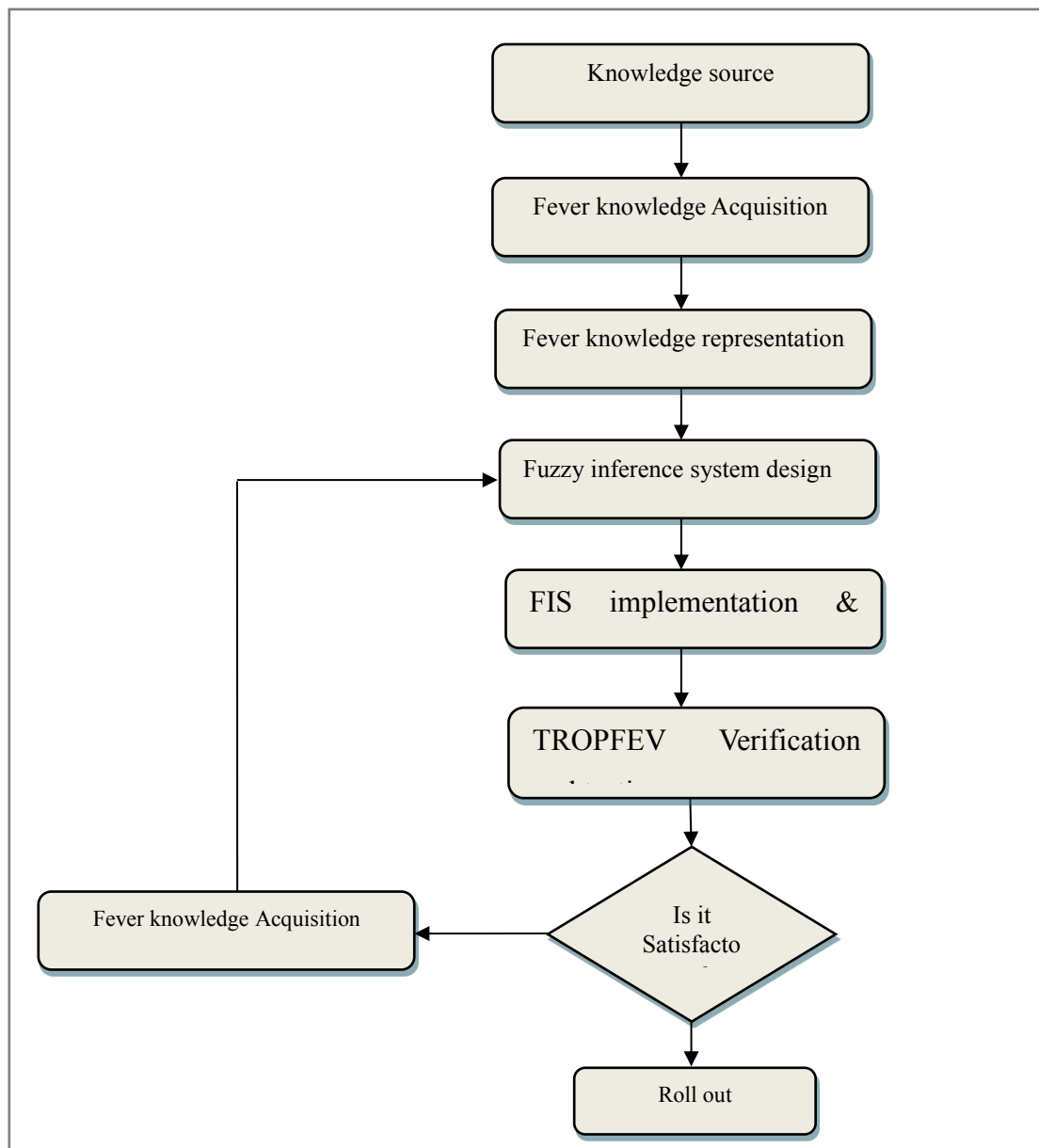


Figure 4.2. TROPFEV System Development Processes

#### 4.3.1. Fever domain knowledge source identification

The study of this research was mainly in Uganda one of the countries that are affected by malaria in Africa. The main source of knowledge concerning malaria and typhoid fever was the Uganda clinical guideline. The UCG2012 was published by the ministry of health (MoH) in Uganda. It is designed to provide updated, practical, and useful information for both upper and lower level health facilities on the diagnosis and management of common conditions present in Uganda. The UCG aims to provide easy-to-use, practical, complete, and useful information on how to correctly

diagnose and manage all common conditions that are likely to be encountered. Doctors acquire this knowledge and store them in their brains to be used when diagnosing. Because computer systems can also stockpile using mathematical techniques such as fuzzy logic, we aim in this research to extract the knowledge in this document and compute it into a fuzzy knowledge based system. Besides the UCG2012, an expert in the field of medical medicine Dr. Akusa Yuma Darlington from Arua regional referral hospital in northern Uganda was consulted. Patient cases used to test the system were also collected from the same hospital.

#### 4.3.2. Fever knowledge acquisition

The process and the meaning of knowledge Acquisition was explained in the previous chapter. There are several techniques to do knowledge acquisition from knowledge sources like interviews, observation and document analysis. The method used for this work is mainly document analysis although some experts about tropical diseases were consulted. After finding the best knowledge source for typhoid fever and malaria, knowledge from human experts and the Uganda clinical guideline concerning the two infections was elicited and structured. In tropical diagnosis of fever, good understanding of the features of malaria and typhoid fever is so important since they share some similar symptoms and signs yet final medication depends on the type of fever diagnosed. These two diseases always appear as uncomplicated or complicated (severe). Figure 4.3 show classification of malaria and typhoid fever based on the Uganda clinical guidelines 2012.

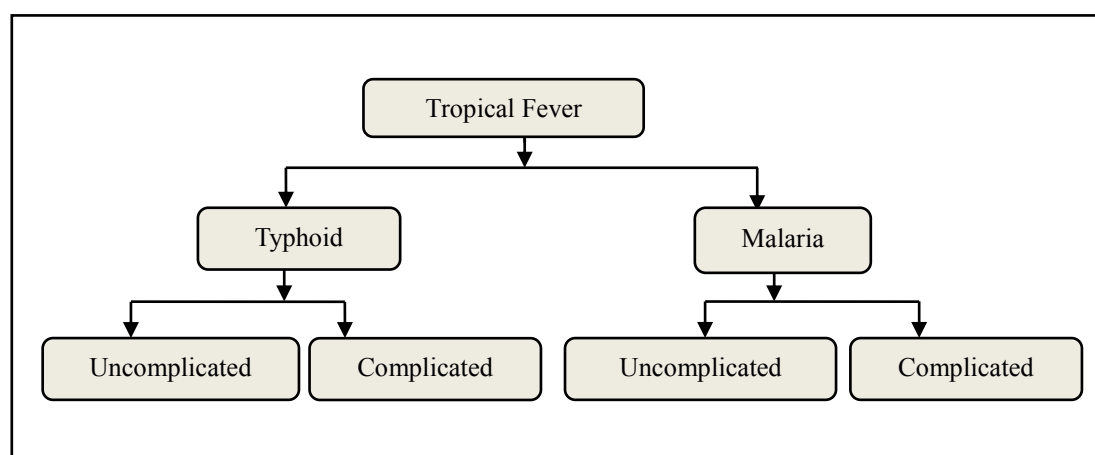


Figure 4.3. Conditions of malaria and typhoid Fever. (Based on UCG2012)

In this research, 21 features which determine the diagnosis of malaria were collected. 8 are specific to malaria where two of the 8 are categories of people that are affected by malaria while the other 6 are signs and symptoms. 8 symptoms are shared by both malaria and typhoid though some differ in the way they present and the remaining 5 are specific to typhoid fever according to the Uganda clinical guidelines 2012.

#### 4.3.2.1. Group category

The first concept of domain experts in diagnosing patients with fever is their group category. That is under five years, above 5 years and pregnant women. Experts first consider the age of the patient then ask for the related symptoms. It is clear that children below five years may experience conditions in malaria that are not experienced by adults and the reverse is also true. For example a doctor will ask a parent whether the child breast feeds well which can't be asked to adults. He may also ask pregnant women whether they experience threatening abortion symptoms which are not asked to children.

Knowing age of patient helps domain expert in trying to classify which symptoms may be faced by the victim as well as giving the right therapy. The two attributes mentioned here that is age and pregnancy are only related to malaria as mentioned in the UCG. Table 4.1 shows the two attributes.

Table 4.1. Group Category features.

S/N	Attribute (Symptom)	Explanation
1.	Age	This is the maturity of the patient. It is always considered as below 5 years or above 5 in the diagnosis of malaria.
2.	Pregnancy	It is the development of one or more offspring, known as an embryo or fetus, in a woman's uterus. It can be categorised in Trimesters. (first Trimester, second Trimester and third Trimester)

#### 4.3.2.2. Symptoms related malaria

One of the important parameters in the diagnosis of fever is to check for the signs of malaria and their severity. Most of the symptoms like Anaemia appear with high severity for complicated malaria and mild for uncomplicated malaria. Table 4.2 shows the symptoms of fever related to malaria as mentioned in the Uganda clinical guidelines 2012.

Table 4.2. Signs and symptoms of malaria

S/N	Attribute (Symptom)	Explanation
1.	Convulsions	Is a medical condition where body muscles contract and relax rapidly and repeatedly, resulting in an uncontrolled shaking of the body.
2.	Threatening Abortion	This includes vaginal bleeding that occurs in the first 20 weeks of pregnancy. Vaginal bleeding could indicate risk of miscarriage.
3.	Prostration	Extreme exhaustion or lack of energy or power. Or extreme weakness (unable to stand or sit without support)
4.	Anaemia	Anaemia is when the number of red blood cells or concentrations of hemoglobin are low a person is said to have anemia. (mild pallor of palms and mucous membranes in children)
5.	Dehydration	The act or process of freeing from water; also, the condition of a body from which the water has been removed. In malaria it includes sunken eyes, coated tongue, lethargy, inability to drink).
6.	Difficulty In Breathing	Clinically evident inability to adequately ventilate and/or oxygenate. This is currently the preferred term to use in referring to veterinary patients who present with severe respiratory difficulty.

#### 4.3.2.3. Related symptoms and signs of malaria and typhoid fever

In the diagnosis of fever in tropic Africa, the domain experts have a concept of symptoms that is used to differentiate the related symptoms and non-related



symptoms of malaria and typhoid. For the related symptoms of fever, the domain experts have a general knowledge about the common symptoms of the two diseases. During knowledge gathering and evaluation of the Uganda clinical guidelines, there are symptoms and signs that appear both on patients of malaria and typhoid fever. Some of these symptoms appear in the different form according to the type of fever such as fever which appears to both diseases, in malaria it appears as intermittent while in typhoid fever it appears in the gradual form. This can be easily classified using fuzzy sets. These symptoms are summarised in Table 4.3.

Table 4.3. Signs and symptoms of common to both malaria and typhoid

S/N	Attribute (Symptom)	Explanation
1.	Fever	It is one of the most common medical signs and is characterized by an elevation of body temperature above the normal range of 36.5–37.5 °C [97.7–99.5 °F] due to an increase in the temperature regulatory set-point. It appears as gradual in typhoid fever and intermittent in malaria.
2.	Loss Of Appetite.	This occurs when one have a reduced desire to eat. Or drink. In severe malaria, a baby may not be able to eat.
3.	Vomiting	It is known medically as emesis and informally as throwing up and numerous other terms) is the involuntary, forceful expulsion of the contents of one's stomach through the mouth and sometimes the nose
4.	Altered Mental State	An alteration in mental status refers to general changes in brain function, such as confusion, amnesia (memory loss), loss of alertness, loss of orientation (not cognizant of self, time, or place), defects in judgment or thought, poor regulation of emotions, and disruptions in perception, psychomotor skills, and behavior. This also include lethargy, drowsiness, unconsciousness, or confusion, coma, Dehydration) .In typhoid fever, this appears as Delirium and stupor
5.	Chills	Chills are feelings of coldness accompanied by shivering. They occur gradually in typhoid Chills are feelings of coldness accompanied by shivering.
6.	Headache	It is pain anywhere in the region of the head or neck. It appears in the group above 5 in the case of malaria
7.	Pain	Pain is an unpleasant feeling often caused by intense or damaging stimuli in muscles joints or back. In typhoid fever this occurs as backache.

#### 4.3.2.4. Symptoms related typhoid fever

According to Uganda clinical guidelines, Relative Bradycardia, Abdominal Pain, Malaise, and Gut Perforation are listed as the signs of typhoid fever and are not listed to malaria.

Table 4.4. Signs and symptoms of typhoid fever

S/N	Attribute (Symptom)	Explanation
1.	Relative Bradycardia	It is the resting heart rate of under 60 beats per minute (BPM).
2.	Abdominal Pain	It is a common symptom associated with transient disorders or serious disease. Diagnosing the cause of abdominal pain can be difficult, because many diseases can cause this symptom
3.	Malaise	It is a feeling of general discomfort or uneasiness, of being "out of sorts", often the first indication of an infection or other disease.
4.	Constipation	Refers to bowel movements that are infrequent or hard to pass. Constipation is a common cause of painful defecation. Severe constipation includes obstipation (failure to pass stools or gas) and fecal impaction, which can progress to bowel obstruction and become life-threatening.
5.	Gut Perforation	It is a hole that develops through the whole wall of the esophagus, stomach, small intestine, large bowel, rectum, or gallbladder.

#### 4.3.3. Fever knowledge representation

Knowledge representation incorporates findings from psychology about how humans solve problems and represent knowledge in order to design formalisms that will make complex systems easier to design and build. Knowledge representation and reasoning also incorporates findings from logic to automate various kinds of reasoning, such as the application of rules or the relations of sets and subsets. In the diagnosis of tropical fever, medical doctors in this domain make decisions according to the severity or appearance of the above mentioned diagnosis attributes. For example when a child is less than five years is having fever and he cannot breastfeed, the medical doctor concludes to have severe malaria.

Fuzzy logic, as its name suggests, is the logic underlying modes of reasoning which are approximate rather than exact. The importance of fuzzy logic derives from the fact that most modes of human reasoning-and especially common sense reasoning-are approximate in nature. It uses the “if then rules” to make conclusions and therefore it was used in this research to represent knowledge acquired from the medical sources.

#### **4.3.4. Designing the TROPFEV fuzzy inference system**

Fuzzy systems have the capability of the individual expert knowledge to make decisions. Diagnosis of tropical fever with signs is very complex because symptoms and signs for typhoid fever and malaria are almost similar. The severity and the appearance, and state of some of some symptoms determine the complicity of the two diseases. The typical steps followed in designing TROPFEV Fuzzy inference system include;

1. Defining system input and output variables
2. Linguistic variables and membership functions
3. Defining fuzzy rules of the system

##### **4.3.4.1. Defining system input and output variables**

The First step taken in designing this system was determining input and output variables. 21 input variables obtained during knowledge acquisition and 1 output variable (fever) were defined. The explanations of these input variables are detailed in the knowledge acquisition sub topic of this chapter. Table 4.5 and Table 4.6 show the input and the output variables of the fuzzy system respectively.

Table 4.5. Input variables for the TROPFEV system

S/N	Code	Attribute (Symptom)	Category
1.	AGE	Age	Group category
2.	PRE	Pregnancy	
3.	FEV	Fever	Symptoms
4.	APP	Loss Of Appetite.	
5.	CON	Convulsions	
6.	VOM	Vomiting	
7.	MEN	Altered Mental State	
8.	PRO	Prostration	
9.	ANE	Anemia	
10.	DEH	Dehydration	
11.	BRE	Difficulty in Breathing	
12.	THR	Threatening Abortion	
13.	CHI	Chills	
14.	PAI	Pain	
15.	SPL	Splenomegaly	
16.	HEA	Headache	
17.	BRA	Relative Bradycardia	
18.	ABD	Abdominal Pain	
19.	MAL	Malaise	
20.	COP	Constipation	
21.	GUP	Gut Perforation	

Table 4.6. Output variables for the TROPFEV system

S/N	Code	Variable	Explanation
1.	FEVER	Fever	Condition of fever

#### 4.3.4.2. Linguistic variables and membership functions of the system

After determining the input and output a variable of the TROPFEV fuzzy system, the next stage was to determine their membership functions. Here linguistic variables and values are expressed by means of natural language terms. The different terms or linguistic values are represented with fuzzy sets characterised by membership functions defined on the universe of discourse. Literature on membership function was discussed in chapter 3. After the analysis of the Uganda clinical guidelines and consultation of the experts in the domain of tropical medicine, the fuzzy sets of the input variables are determined as shown from Table 4.7 to Table 4.12 while Table 13 shows the output of the system. Figure 4.2 to 4.8 shows the corresponding membership functions in a triangular form. The explanation for each of these input variables can be found in Table 4.1 to Table 4.4.

Table 4.7. linguistic variables and fuzzy sets for age

Input variable	Fuzzy sets	Crisp values
Age	Bellow 5	$0 < X \leq 5$
	Above 5	$5 < X < 100$

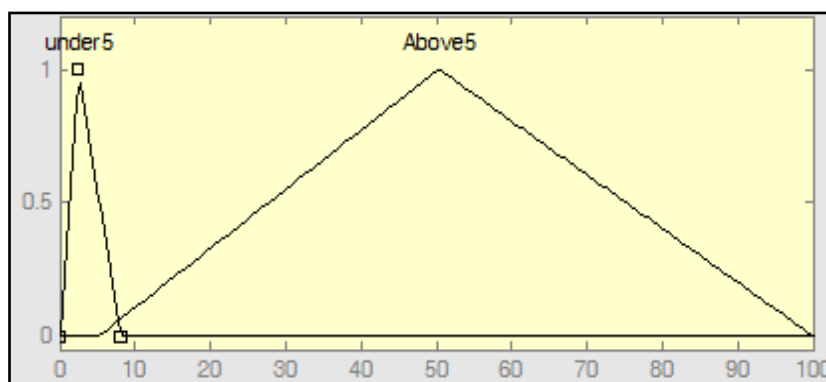


Figure 4.1. Graph showing membership function for age

Table 4.8. linguistic variables and fuzzy sets for pregnancy

Input variable	Fuzzy sets	Crisp values
Pregnancy	1 <sup>st</sup> Trimester	$1 \leq X < 12$
	2 <sup>nd</sup> Trimester	$13 \leq X < 28$
	3 <sup>rd</sup> Trimester	$29 \leq X < 40$

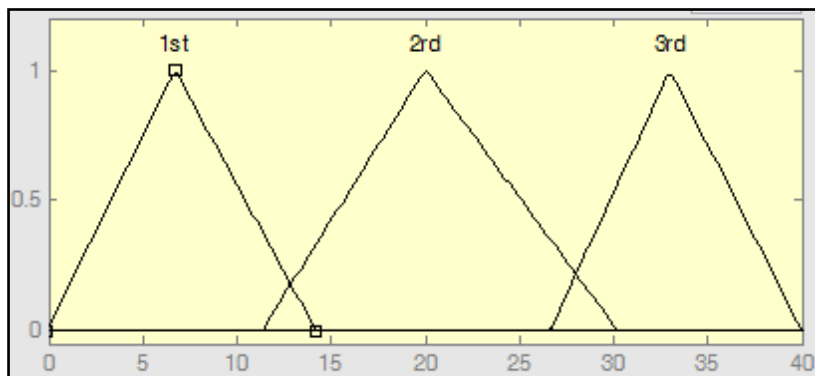


Figure 4.2. Graph showing membership function for pregnancy

Table 4.9. linguistic variables and fuzzy sets for malaise and fever

Input variable	Fuzzy sets	Crisp values
Malaise Fever	Gradual	$0 < X \leq 3$
	Intermittent	$3 < X \leq 5$

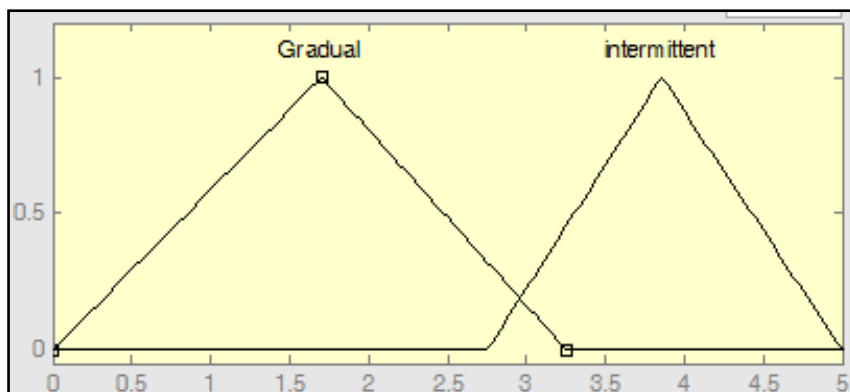


Figure 4.3. Graph showing membership function for malaise and Fever

Table 4.10. linguistic variables and fuzzy sets for pain

Input variable	Fuzzy sets	Crisp values
Pain	back	$0 < X \leq 3$
	Joint	$3 < X \leq 5$



Figure 4.4. Graph showing membership function for pain

Table 4.11. linguistic variables and fuzzy sets for pain

Input variable	Fuzzy sets	Crisp values
Altered Mental State	Lethargy	$0 < X \leq 2$
	Delirium	$2 < X \leq 3.5$
	Coma	$3.5 < X \leq 5$

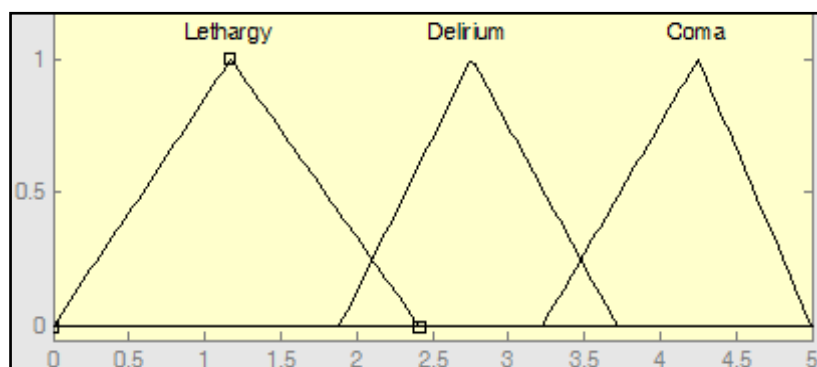


Figure 4.5. Graph showing membership function for altered mental state

Table 4.12. linguistic variables and fuzzy sets for the rest of the input variables

Input variable	Fuzzy sets	Crisp values
Loss Of Appetite. Convulsions Vomiting Prostration Anemia Dehydration	Mild	$0 < X \leq 3$
Difficulty in Breathing Threatening Abortion Splenomegaly Headache Relative Bradycardia Abdominal Pain Constipation Gut Perforation	severe	$3 < X \leq 5$

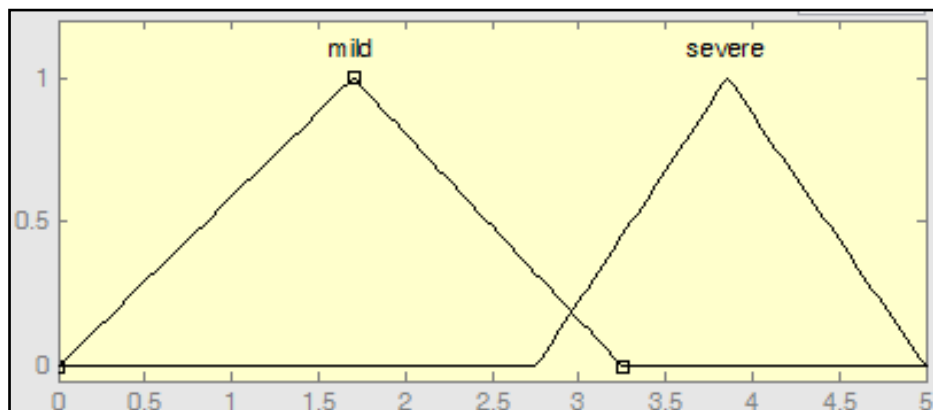


Figure 4.6. Graph showing membership function for Table 4.12 variables



Table 4.13. linguistic variables and fuzzy sets of the output

Output variables	Fuzzy sets	Crisp values
Type of fever	Uncomplicated Typhoid	$0 < X \leq 1$
	Uncomplicated Malaria	$1 < X \leq 2$
	Unknown Malaria	$2 < X \leq 3$
	Complicated Typhoid	$3 < X \leq 4$
	Complicated Malaria	$4 < X \leq 5$

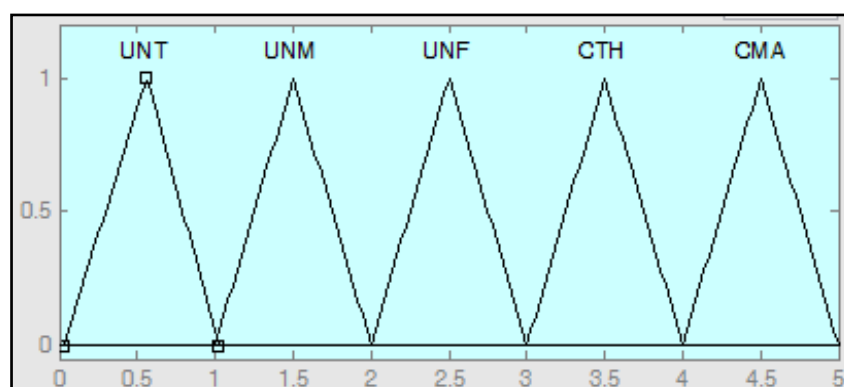


Figure 4.7. Graph showing membership function of the output

#### 4.3.4.3. Defining fuzzy rules of the system

The rule base is the main part in the fuzzy inference system and the quality of results in a fuzzy system depends on the fuzzy rules. It describes the behaviour of the fuzzy inference system, based on the linguistic terms associated with the input and output variables. It is characterized by a set of IFTHEN rules in which the antecedents (IF parts) and the consequents (THEN parts) involve linguistic variables. The rule base for TROPFEV diagnosis is a set of fuzzy rules where antecedents (IF parts) and the consequents (THEN parts) involve linguistic variables. These rules in the rule base were created considering all the possible circumstances and the conditions that were mentioned in the Uganda clinical guidelines 2012 (UCG2012) for both malaria and typhoid fever in their complicated and uncomplicated form. The knowledge about common conditions of malaria and typhoid fever in the two mentioned group category was analysed in terms of fuzzy logic rules. Rule base is the main part in

fuzzy inference system and quality of results in a fuzzy system depends on the fuzzy rules. Intermittent fever for malaria and gradual fever for typhoid fever have been considered one of the main differentiation factors for classifying the two infections. 65 rules have been generated for this work and some of them are shown in Appendix 1. The advantage of the Matlab tool is that rules are easy to edit and therefore new rules can be added in the system whenever new knowledge is acquired. Appendix 1 shows some of the rules developed using this system.

#### **4.4. Summary**

We introduced a fuzzy knowledge based system for clinical diagnosis of tropical fever to help doctors in decision making as an easier process in diagnosis. The architecture of the proposed system has been revealed in this chapter. We also mentioned the developing process for this system which included; fever domain knowledge source identification, fever knowledge acquisition, fever knowledge representation, designing a fuzzy inference system, implementation of TROPFEV prototype verification and testing although the first four processes haven't been only discussed in this chapter. The relevant knowledge was acquired from the Uganda clinical guideline 2012 in addition to consulting medical experts in the medical domain. 21 diagnosis features and five outputs of fever as uncomplicated malaria, uncomplicated typhoid, complicated malaria, complicated typhoid and unknown fever were defined in this chapter. Fuzzy logic has been chosen as a tool for presenting fever knowledge and a fuzzy inference system has been designed. Linguistic variables for each fuzzy set were identified and their membership functions were created using a triangular membership function. We aim to use fuzzy logic in this research and implement a system that can make decisions on malaria and typhoid fever just as doctors can do. We carry out the implementation and testing using matlab in the next chapter.

## **CHAPTER 5. IMPLEMENTATION OF THE SYSTEM**

In this section we implement a fuzzy inference system using a matlab fuzzy toolbox, design the TROPFEV interface using a matlab graphical user interface (GUI) and eventually testing the implemented system for its performance. The fuzzy toolbox simplifies in modelling complex system behaviours using simple logic rules, and implementing them in a fuzzy inference system. It contains the FIS Editor which displays general information about a fuzzy inference system, Membership Function Editor which lets to edit the membership functions associated with the input and output variables of the FIS and Rule Editor which enables to view and edit fuzzy rules. Testing was done using the interface that was designed containing all the diagnosis features and its fuzzy sets.

### **5.1. Implementation Of The TROPFEV System In Matlab**

This involves the implementation of the fuzzy inference system (FIS), interface and finally testing. The Fuzzy inference system of the TROPFEV system is where the inputs described in chapter 4 are mapped to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made. The system uses fuzzy reasoning to map an input space into an output space. Fuzzy logic being a rule based system uses if-then rules, FIS is used to recognize the nodules depending on the input, output Fuzzy membership functions. Based on the input diagnosing features, the FIS can classify whether fever is complicated malaria, uncomplicated malaria, complicated typhoid, uncomplicated typhoid or unknown fever.

The implementation of the TROPFEV system in matlab involves the following tasks as shown in Figure 5.1:

1. Inserting fever variables in the FIS Editor
2. Editing Membership Functions in the Editor

3. Inserting rules in the rule editor
4. Design interface in Matlab GUI
5. Test and Evaluate the TROPFEV system

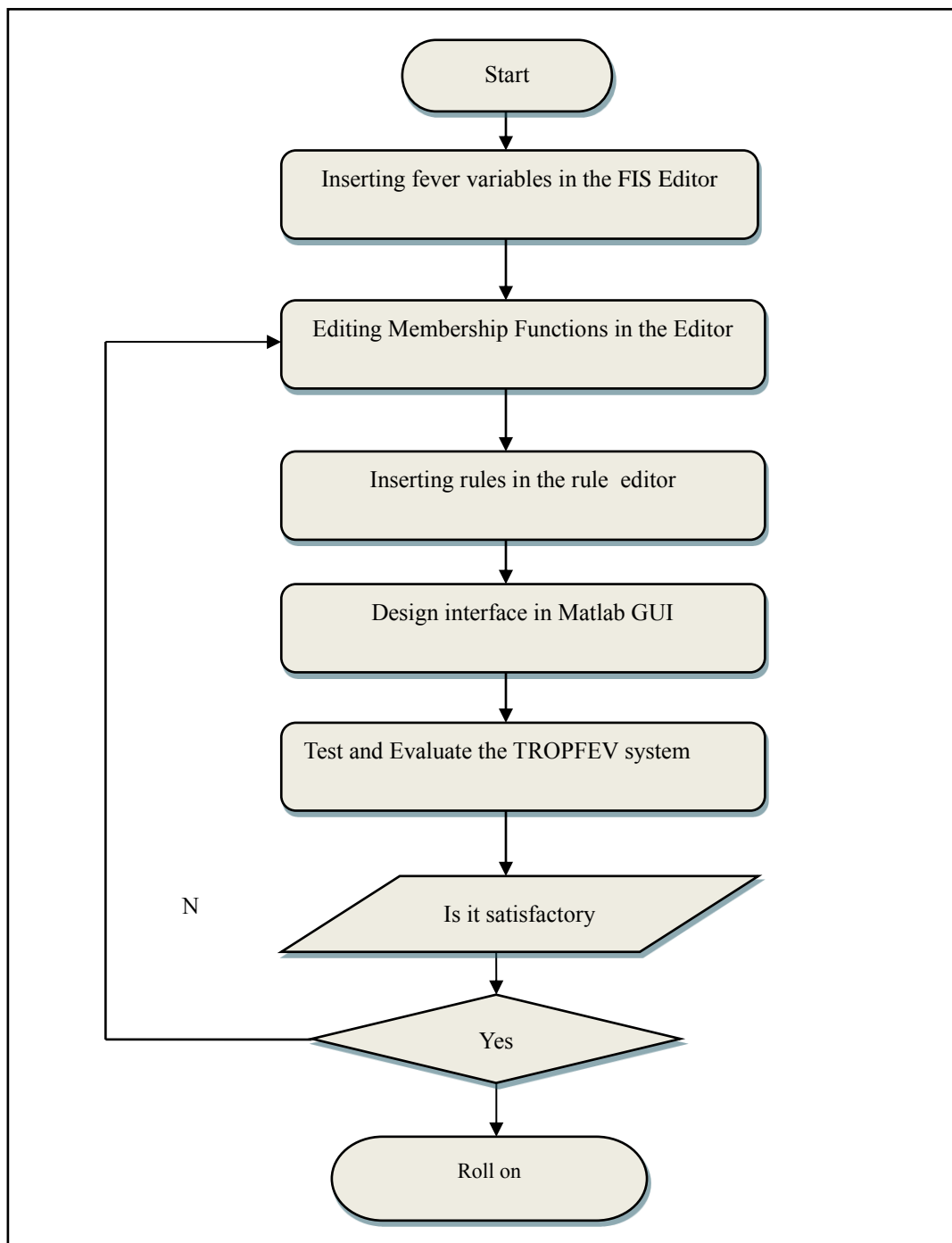
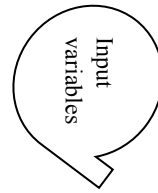


Figure 5.1. TROPFEV implementation tasks in Matlab 2012a

### 5.1.1. Input fever variables in the FIS editor



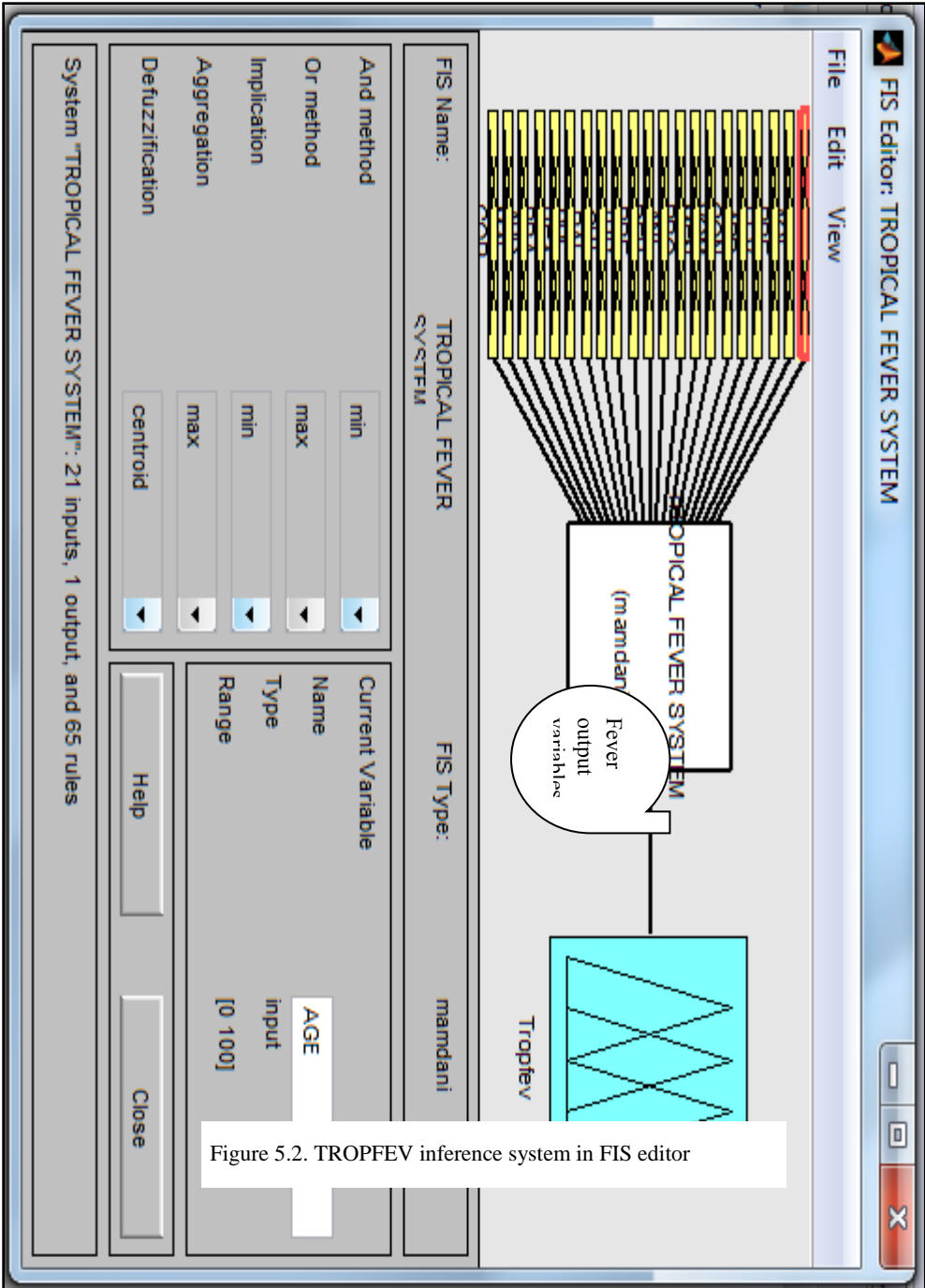


Figure 5.2. TROPFEV inference system in FIS editor

The FIS Editor provides a good interface for editing the input and output variables in Matlab. It also displays general information about a fuzzy inference system. We selected the mandani type of fuzzy inference system because it is intuitive, widespread acceptance and well suited to human input. The input of the TROPFEV system contains the 21 input variables we defined in the last chapter while the output contains the fever output variables. The TROPFEV inference system in FIS editor is shown in Figure 5.2 above.

### **5.1.2. Editing membership functions in the editor**

The Membership Functions of the TROPFEV system defined in chapter 4 were edited in the matlab membership function Editor. This editor helps in displaying and editing all of the membership functions associated with all of the input and output variables of the TROPFEV system. The diagnosis features were edited in this editor as the input variables while the conditions of fever as output variables of the system using the triangular membership function. Figure 5.3 shows input and output variables in the matlab membership function editor.

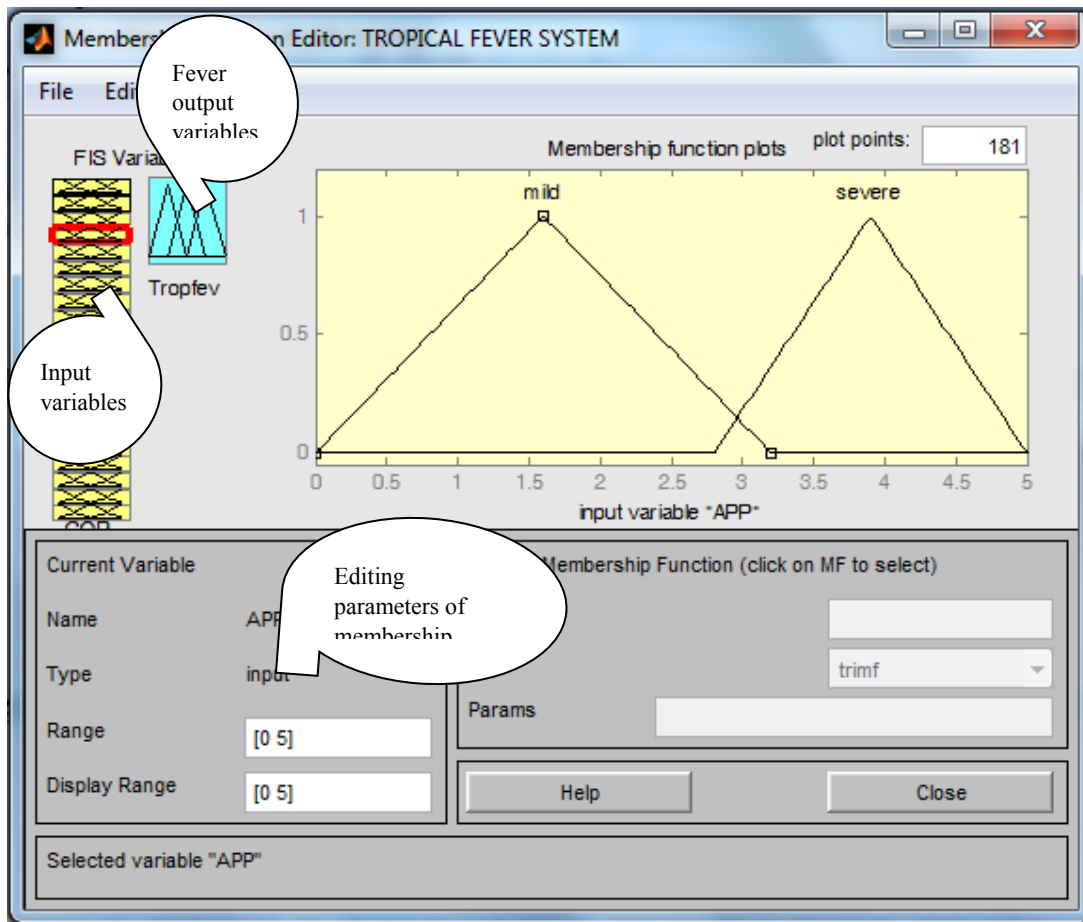


Figure 5.3. Membership Functions for input and the output variables in Matlab

### 5.1.3. Inserting rules in the Rule Editor

The rules of the TROPFEV system were constructed using the graphical Rule Editor interface. Based on the descriptions of the input and output variables defined with the FIS Editor, the Rules for diagnosis of malaria and typhoid fever were inserted in the rule editor. We chose “none” for diagnosis features that were excluded from a certain rule while the “AND” operator for intersection was used. The weights of all rules were equal and specified to “1 “.Figure 4 is shows how rules of the TROPFEV system were edited in the rule editor.



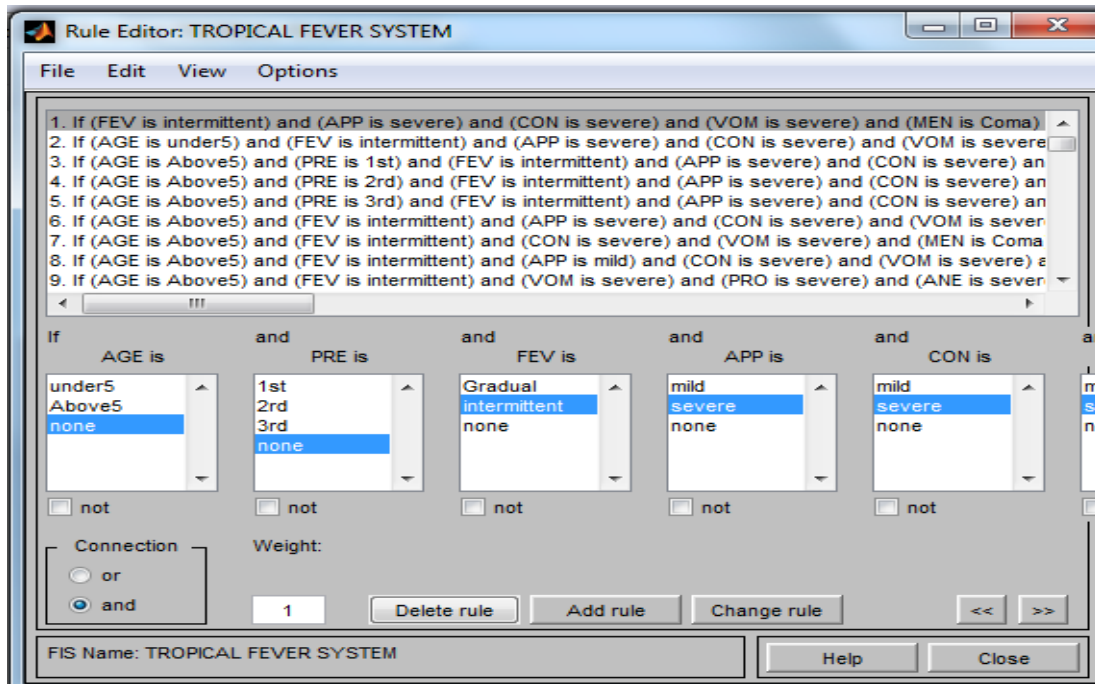


Figure 5.4. TROPFEV rules in matlab fuzzy rule editor

#### 5.1.4. Design interface in Matlab GUI

The TROPFEV system was proposed for a wide range of users who may not have any idea on programming but rather medical knowledge in tropical diagnosis and therefore an interface was designed using matlab GUI or graphical user interfaces. The user of the TROPFEV system does not have to create a script or type commands at the command line to accomplish the tasks but rather a graphical display window. The GUI typically contains controls such as menus, toolbars, buttons, and sliders. The TROPFEV system contains a panel for fever diagnosis features and a panel for results. Each diagnosis feature is indicated with its fuzzy sets and a slider which determines a value on running the TROPFEV interface. As the slider is adjusted towards the right, its values increases and a linguistic value representing such a value appears on the textbox in front of the value. Figure 5.5 shows designing of the interface in matlab and Figure 5.7 after running the interface.

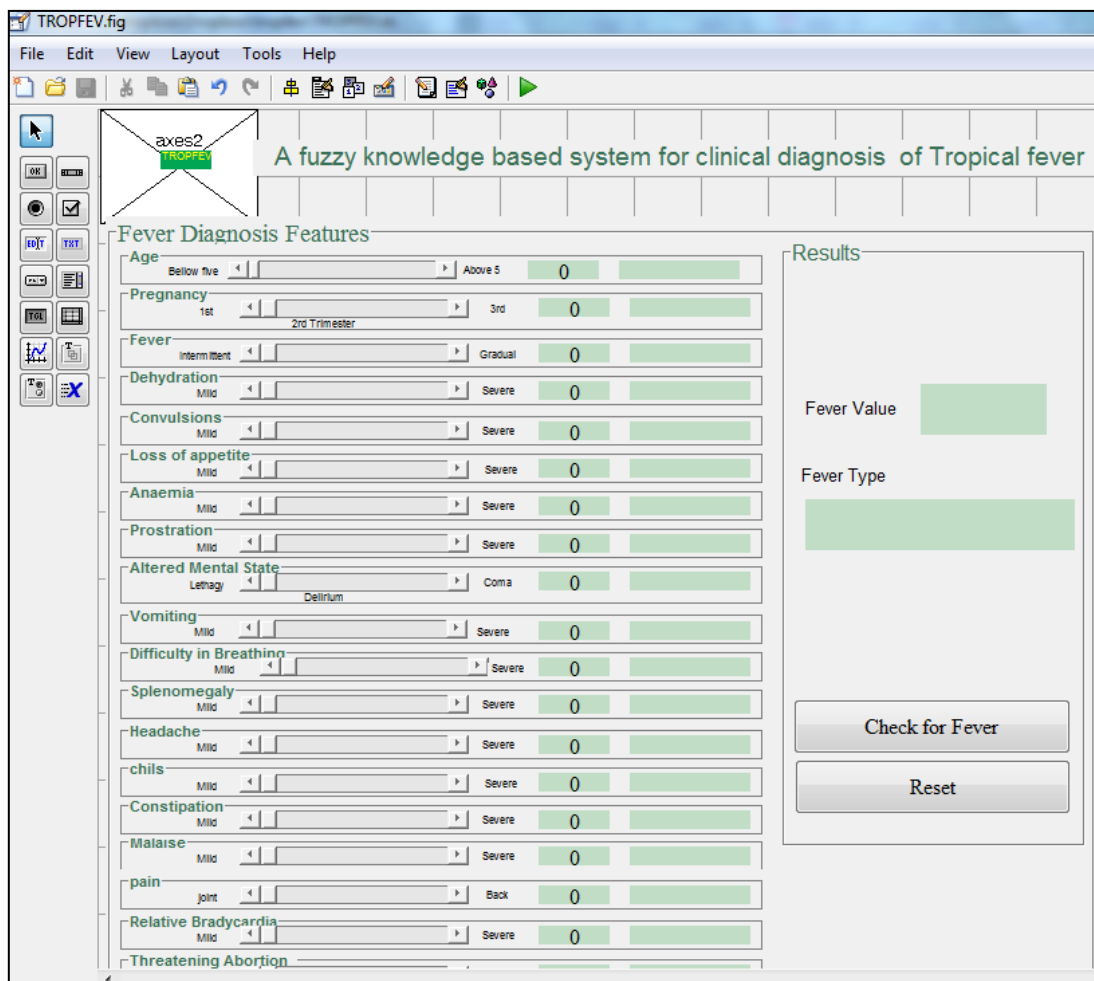


Figure 5.5. Designing of the interface in matlab

### 5.1.5. Testing and evaluation of the system

After implementing fuzzy knowledge based system the final step is testing and measuring the performance of the system whether achieves the objective or not. Testing and evaluation of the prototype knowledge based system helps the knowledge engineer to measure the whether the system achieve the propose objective or not. For the purpose of this research study, TROPFEV system is tested and evaluated based on its objective. The essences of the study was to acquire and model knowledge from document and develop a simple system in the diagnosis of tropical fever which can be used by physicians and even patients using fuzzy logic. Measurement is from the point of whether the system achieved its objective or not. In this study the performance of the system is measured by comparing the expert's results and the system results. Therefore to evaluate the TROPFEV system, the aim

is to confirm that a crisp output may be obtained from crisp inputs in order to confirm that the algorithm is capable of providing accurate answers in clear cut situations. Cases for 100 patients collected from Arua regional referral hospital in northern Uganda with the help of a medical expert have been used in testing and evaluation.

#### 5.1.5.1. Testing from the system interface

The targets for this system are medical doctors more especially in rural areas of SSA who may have little knowledge on using computers but need a decision support system to simplify their work. Therefore, designing a good user interface was one of its main special qualities. To test the system from interface, the intensities of diagnosis features (input variables) for the two diseases and their condition (output variables) were rated in relation to the crisp values of the respective fuzzy sets as explained in chapter 4. Doctor's diagnosis for uncomplicated typhoid, uncomplicated malaria, Unknown fever, complicated typhoid and complicated malaria was donated with values as 0.5, 1.5, 2.5, 3.5 and 4.5 respectively as shown in Table 5.1 because the defuzzification system adopted uses a CoA. See also Figure 4. 8. Appendix 1 shows some of the rated diagnosis features for twenty cases.

An example is case number 20 of appendix 1.A 12.5 old year boy comes to the doctor and he finds the following conditions; Fever(Intermittent), Loss of Appetite (mild) ,Vomiting(mild),Anaemia(mild), Dehydration(mild), Chills(mild), Pain(joint), Splenomegaly(mild), Headache(mild), Abdominal Pain(mild) and eventually concludes as uncompleted malaria . To test this in the system, the intensities of these conditions were rated relative to Table 3 as Fever(3.5), Loss of Appetite(2) ,Vomiting(2), Anaemia(2), Dehydration(2), Chills(mild), Pain(3.5), Splenomegaly (1), Headache(1), Abdominal Pain(2) and those which did not appear were rated with zero(0).

Table 5.1. Doctor and TROPFEV diagnosis ratings for 20 cases.

Case	Doctor's Diagnosis	Rated	TROPFEV
------	--------------------	-------	---------

01	Complicated malaria	4.5	4.5
02	Uncomplicated malaria	1.5	1.5
03	Uncomplicated malaria	1.5	1.5
04	Uncomplicated typhoid	0.5	0.5
05	Uncomplicated typhoid	0.5	0.5
06	Complicated malaria	4.5	4.5
07	Complicated malaria	4.5	4.5
08	Uncomplicated typhoid	0.5	0.5
09	Uncomplicated typhoid	0.5	0.5
10	Uncomplicated malaria	1.5	1.5
11	Uncomplicated malaria	1.5	1.5
12	Uncomplicated typhoid	0.5	0.5
13	Uncomplicated malaria	1.5	1.5
14	Uncomplicated typhoid	1.5	1.5
15	Uncomplicated malaria	1.5	2.5
16	Uncomplicated typhoid	0.5	0.5
17	Uncomplicated malaria	1.5	1.5
18	Uncomplicated malaria	1.5	1.5
19	Uncomplicated malaria	1.5	1.5
20	Uncomplicated malaria	1.5	1.5

Each intensity of the diagnosis feature was then entered into the system by adjusting the slider as shown in Figure 5.6. By placing the check button of user interface, intensities of the patient's symptoms were fuzzified by the Matlab fuzzy tool box using the triangular formula in (Equation 3.4). The fuzzified values of this case are then sent into the inference engine which determines the rule to be fired and combines the weighted consequences into a single fuzzy value. The combined fuzzy value is then defuzzified to generate a crisp value in relation to Figure 4.10. In this case 1.5 was shown as an output and this corresponds to uncomplicated malaria as shown in Figure 5.6.

**TROPFEV**  
A fuzzy knowledge based system for clinical diagnosis of Tropical fever

**Fever Diagnosis Features**

Age	Below five	Above 5	12.5	Above 5
Pregnancy	1st	2nd Trimester	0	None
Fever	Intermittent	Gradual	4	Intermittent
Dehydration	Mild	Severe	2	Mild
Convulsions	Mild	Severe	0	None
Loss of appetite	Mild	Severe	2	Mild
Anaemia	Mild	Severe	2	Mild
Prostration	Mild	Severe	0	None
Altered Mental State	Lethargy	Coma	0	None
Vomiting	Mild	Severe	2	Mild
Difficulty in Breathing	Mild	Severe	0	None
Splenomegaly	Mild	Severe	1	Mild
Headache	Mild	Severe	1	Mild
chills	Mild	Severe	1	Mild
Constipation	Mild	Severe	0	None
Malaise	Mild	Severe	0	None
pain	joint	Back	3.5	Joint
Relative Bradycardia	Mild	Severe	0	None
Threatening Abortion	Mild	Severe	0	None
Gut Perforation	Mild	Severe	0	None
Abdominal Pain	Mild	Severe	2	Mild

**Results**

Fever Value: 1.5

Fever Type: **Uncomplicated Malaria**

Buttons: Check for Fever, Reset

Figure 5.6. Testing the TROPFEV system from interface

### 5.1.5.2. Metrics evaluation

Calculation of different metrics is based on the results provided by the system and the doctor's diagnosis using a confusion matrix as provided in Table 6. Precision, recall, specificity, accuracy and MCC [62-63] of the system were calculated as 97.1%, 85%, 90%, 86% and 65.4% respectively to evaluate its performance. These are defined as follows;

1. Precision: The percentage of positive prediction made by the system that came out correct.

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (5.1)$$

2. Recall (Sensitivity): The percentage of sick patients classified correctly by the model.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \quad (5.2)$$

3. Specificity: The percentage of normal patients classified correctly by the system.

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP}) \quad (5.3)$$

4. Accuracy: The percentage of correctly classified patients.

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (5.4)$$

5. MCC: A Matthews Correlation Coefficient value [59] that calculates system's global accuracy and more specific than accuracy.

$$\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FP}) \times (\text{TP} + \text{FN}) \times (\text{TN} + \text{FP}) \times (\text{TN} + \text{FN})}} \quad (5.5)$$

Where; TP (True positive) is the number of abnormal patients correctly classified by the system, TN (True negative); the number of healthy patients correctly classified by the system, FP (False positive); the number of healthy patients wrongly classified by the system, FN (False negative); the number of abnormal patients wrongly classified by the system.

Table 5.2. Confusion matrix for TROPFEV system evaluation

<b>TROPFEV Testing</b>	UNT	UNM	UNF	CTH	CMA	Total	<b>Performance evaluation</b>	
UNT	22	1	1	0	0	24	Metrics	Results (%)
UNM	1	40	1	0	0	42	Precision	97.1
UNF	5	4	18	0	1	28	Recall	85
CTH	0	0	0	2	0	2	Specificity	90
CMA	0	0	0	0	4	4	Overall accuracy	86
Total	28	45	20	2	5	100	MCC	65.4

### 5.1.5.3. Discussion of system results

We have seen the simplicity of the system using the system user friendly interface in Figure 5.6. The system gives results in both numerical and the correct name of the diagnosed fever and this is what is needed by experts and medical petitioners. The slider used gives great flexibility in the selection of symptom intensities. The system

is designed with linguistic variables such as mild and severe which are mentioned in the Uganda clinical diagnosis guidelines [9] to determine the severity of malaria and typhoid fever. The linguistic variables used are the same used in the medical diagnosis and hence a simple tool for diagnosis. The TROPFEV system is aimed to help medical doctors to make a quick decision for both malaria and typhoid fever in their early and uncomplicated stages hence reducing the long waiting for doctors, problem of misdiagnosis, number of inpatients admitted in hospitals and finally but importantly reduce on the high morbidity, mortality and economic loss.

The metric evaluation values shown in Table 5.2 used 20 cases for healthy, 45 for uncomplicated malaria, 28 for uncomplicated typhoid, 2 for complicated typhoid and 5 for complicated malaria. Precision, recall specificity, overall accuracy, and Matthews Correlation Coefficient value of the system were found to be 97.1%, 90%, 85%, 86% and 65.4% respectively. From the performance evaluation metrics, it can be noted that our system has a high capability of reaching to positive outcomes. Table 5.2 shows that sensitivity is less than specificity. This specifies that the number of fever patients that is correctly classified is less than the number of healthy people that is detected as unhealthy.

To compare the TROPFEV system with others, the same clinical cases confirmed by the doctor were assigned to other two doctors in the same field for conclusion as shown in Table 5.3 and 5.4. We made sure that these doctors work in areas where clinical diagnosis is the mostly used type of judgement for the two diseases. Figure 5 shows the comparison between our system and the other two doctors. As expected, there is much similarity among physicians and the TROPFEV system. However, specificity of the two doctors is more than that of our system which is opposite for sensitivity. This indicates that our system can detect more patients than the two doctors. It is obvious from Figure 5.7 that precision from our system is different with only 1-3% from that of doctors. It is necessary to remark that though all comparisons have almost similar accuracy, TROPFEV system still shows to be more accurate.

The similarity is because the system uses fuzzy logic technique which has almost similar reasoning with human beings. Its accuracy can be improved by editing rules within the system.

Table 5.3. Confusion matrix for DOCTOR 1 evaluation

<b>DOCTOR 1 Testing</b>	UNT	UNM	UNF	CTH	CMA	Total	<b>Performance evaluation</b>	
UNT	20	1	0	0	0	21	Metrics	Results (%)
UNM	4	38	1	0	0	43	Precision	98.4
UNF	4	6	19	1	0	30	Recall	80
CTH	0	0	0	1	0	1	Specificity	95
CMA	0	0	0	0	5	5	Overall accuracy	80
Total	28	45	20	2	5	100	MCC	61.7

Table 5.4. Confusion matrix for DOCTOR 2 system evaluation

<b>DOCTOR 2 Testing</b>	UNT	UNM	UNF	CTH	CMA	Total	<b>Performance evaluation</b>	
UNT	21	1	0	0	0	22	Metrics	Results (%)
UNM	6	36		0	0	42	Precision	100
UNF	2	8	20	0	1	31	Recall	78.75
CTH	0	0	0	2	0	2	Specificity	100
CMA	0	0	0	0	4	4	Overall accuracy	83
Total	28	45	20	2	5	100	MCC	65.2



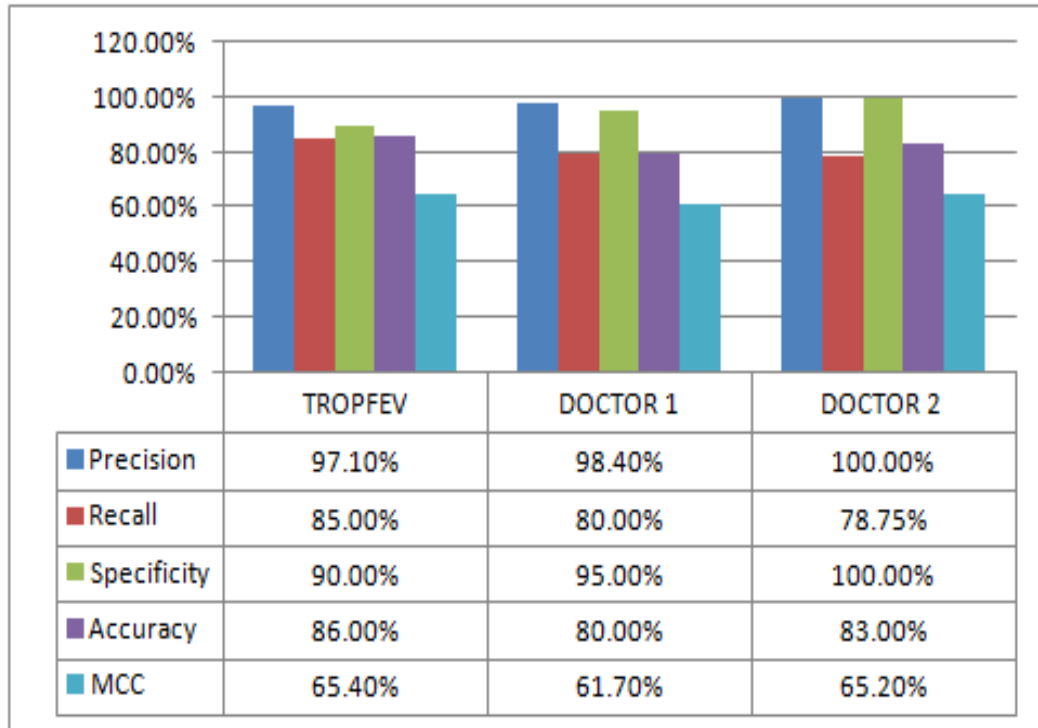


Figure 5.7. Results of the evaluation, comparison between TROPFEV system and other doctors

## **CHAPTER 6. CONCLUSION AND RECOMMENDATIONS**

In this section, I summarise some important findings in this research. In the second chapter, we had a brief overview of malaria and typhoid fever. The two diseases are great concern in SSA where the coverage of health care services remains at its infant stage. Different factors are identified such as quality of health care, shortage of skilled manpower in the area, the distribution of physician per patient, the holding capacity of hospital, overcrowded number of patient and shortage of budget. The main used type of diagnosis is clinical diagnosis in rural areas though both infections have their golden types of diagnosis which require laboratories. Symptoms and signs with vagueness overlap among the two diseases and this is a task to clinicians. We concluded that these types of problems can be handled by transferring this medical knowledge into computer decision systems for classification.

The third chapter provided a literature survey on knowledge based systems and fuzzy logic. We learnt that knowledge from, experts, documents, books; published papers can model and represented using knowledge based representing techniques to implement knowledge based systems. We also found fuzzy logic a technique that has many applications in the medical domain and a good one for expressing medical texts more so in diagnosis. The need to arrive at an accurate and quick medical diagnosis in a timely manner is the main outcome that may reduce the burden of Tropical fever. KBS can direct physicians to quicker and correct diagnosis hence reducing the rate of diagnostic errors in medical diagnosis. We selected fuzzy logic as the best technique to express tropical fever texts using its linguistic variables. We also selected matlab a fuzzy logic tool that will be used during implementation due to its simplicity.

In the fourth section, we introduced a fuzzy knowledge based system for Tropical fever diagnosis to help doctors in decision making as an easier process in diagnosis.

The architecture of the proposed system was revealed in this chapter. We also mentioned the developing process for this system which included; fever domain knowledge source identification, fever knowledge acquisition, fever knowledge representation, designing a fuzzy inference system, implementation of TROPFEV prototype verification and testing. The relevant knowledge was acquired from the Uganda clinical guideline 2012 in addition to consulting medical experts in the medical domain. 21 diagnosis features and five outcomes of fever as uncomplicated malaria, uncomplicated typhoid, complicated malaria, complicated typhoid and unknown fever were defined in this chapter. Fuzzy logic has been chosen as a tool for presenting fever knowledge and a fuzzy inference system has been designed. Linguistic variables for each fuzzy set were identified and their membership functions were created using a triangular membership function.

In the fifth section, we implemented the TROPFEV system in Matlab program. The inference system was implemented in matlab fuzzy toolbox while the interface was implemented using the Matlab Graphical User Interface. We tested the system using fever cases from Arua medical referral hospital from Uganda and we found that the most of the results were as expected.

During our study the following can be recommended;

1. Knowledge for knowledge based systems is limited from only experts but can also be obtained from documents. The use of fuzzy logic in medical diagnosis can be emphasized. It uses natural language known as linguistic variables in the place of numerical values and collects elements into similar groups where they can be dealt less precisely and hence enabling to handle even complex systems.
2. The need for tropical fever decision support systems in tropical medicine is necessary and more research should be encouraged. The system can also be integrated by adding laboratory tests for malaria and typhoid fever as well as the therapy part. Constructing such systems as web based medical expert systems can save many lives of people including tourists and remote based patients.

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## ANNEX

### Appendix 1 sample of the rules used in the rule base.

1. If (FEV is intermittent) and (APP is severe) and (CON is severe) and (VOM is severe) and (MEN is Coma) and (PRO is severe) and (ANE is severe) and (DEH is severe) and (BRE is severe) then (Tropfev is CMA) (1)
2. If (AGE is under5) and (FEV is intermittent) and (APP is severe) and (CON is severe) and (VOM is severe) and (MEN is Coma) and (PRO is severe) and (ANE is severe) and (DEH is severe) and (BRE is severe) then (Tropfev is CMA) (1)
3. If (AGE is Above5) and (PRE is 1st) and (FEV is intermittent) and (APP is severe) and (CON is severe) and (VOM is severe) and (MEN is Coma) and (PRO is severe) and (ANE is severe) and (DEH is severe) and (BRE is severe) and (THR is severe) then (Tropfev is CMA) (1)
4. If (AGE is Above5) and (PRE is 2rd) and (FEV is intermittent) and (APP is severe) and (CON is severe) and (VOM is severe) and (MEN is Coma) and (PRO is severe) and (ANE is severe) and (DEH is severe) and (BRE is severe) and (THR is severe) then (Tropfev is CMA) (1)
5. If (AGE is Above5) and (PRE is 3rd) and (FEV is intermittent) and (APP is severe) and (CON is severe) and (VOM is severe) and (MEN is Coma) and (PRO is severe) and (ANE is severe) and (DEH is severe) and (BRE is severe) and (THR is severe) then (Tropfev is CMA) (1)
6. If (AGE is Above5) and (FEV is intermittent) and (APP is severe) and (CON is severe) and (VOM is severe) and (MEN is Coma) and (PRO is severe) and (ANE is severe) and (DEH is severe) and (BRE is severe) and (THR is severe) then (Tropfev is CMA) (1)
7. If (AGE is Above5) and (FEV is intermittent) and (CON is severe) and (VOM is severe) and (MEN is Coma) and (PRO is severe) and (ANE is severe) and (DEH is severe) and (BRE is severe) and (THR is severe) then (Tropfev is CMA) (1)
57. If (AGE is under5) and (FEV is intermittent) and (APP is mild) and (MEN is Lethargy) and (PRO is mild) and (ANE is mild) and (DEH is mild) then (Tropfev is UNM) (1)
58. If (AGE is Above5) and (FEV is intermittent) and (APP is mild) and (VOM is mild) and (MEN is Lethargy) and (PRO is mild) and (ANE is mild) and (DEH is mild) and (HEA is mild) then (Tropfev is UNM) (1)
59. If (AGE is Above5) and (PRE is 2rd) and (FEV is intermittent) and (APP is mild) and (VOM is mild) and (ANE is mild) and (DEH is mild) and (CHI is mild) and (SPL is mild) and (HEA is mild) then (Tropfev is UNM) (1)
60. If (AGE is Above5) and (FEV is Gradual) and (APP is mild) and (VOM is mild) and (MEN is Delirium) and (CHI is mild) and (PAI is Muscle) and (SPL is mild) and (HEA is mild) and (MAL is Gradual) and (COP is mild) then (Tropfev is UNT) (1)
61. If (AGE is under5) and (FEV is intermittent) and (APP is mild) and (VOM is mild) then (Tropfev is UNM) (1)
62. If (AGE is under5) and (FEV is intermittent) and (APP is mild) and (VOM is mild) and (ANE is mild) and (DEH is mild) and (CHI is severe) and (HEA is mild) then (Tropfev is UNM) (1)
63. If (AGE is Above5) and (FEV is intermittent) and (APP is mild) and (VOM is mild) and (MEN is Lethargy) and (ANE is mild) and (DEH is mild) and (CHI is mild) and (SPL is mild) and (HEA is mild) and (ABD is mild) then (Tropfev is UNM) (1)
64. If (AGE is under5) and (FEV is intermittent) and (APP is mild) and (ANE is mild) and (DEH is mild) and (SPL is mild) then (Tropfev is UNM) (1)
65. If (AGE is under5) and (PRE is 2rd) and (FEV is intermittent) and (APP is mild) and (ANE is mild) and (DEH is mild) and (CHI is mild) and (PAI is Joint) and (HEA is mild) then (Tropfev is UNM) (1)

Appendix 2 Rating of patients on the Tropical fever diagnosis variables.

NO	AGE	PR E	FEV	APP	CON	VOM	MEN	PRO	AN E	DEH	BRE	THR	CHI	PAI	SPL	HEA	BRA	ABD	MA L	COP	GUP	RES ULT
01	6.6	0	4	2	0	0	0	4	4	4	2	0	1	0	0	1	0	0	0	0	0	4.5
02	10	0	4	1	2	0	0	0	2	0	0	0	2	4	2	2	0	2	0	0	0	1.5
03	1.7	0	4.5	1.5	0	2	0	0	2	0	0	0	4	0	0	0	0	0	4	0	0	1.5
04	17	0	1	2	0	1	2.5	1	0	1	0	0	0	1	1	0	0	0	1	2	0	0.5
05	23	0	2	3	0	1	2.5	1	0	2	0	0	0	1	2	2	0	0	1	2	0	0.5
06	20	0	4	0	4	1	4	1	1	1	4	0	2	4	0	0	0	0	4	0	0	4.5
07	16	0	4	4	2	1	1	4	4	3	0	0	2	0	1	2	0	1	0	0	0	4.5
00 8	42	0	3	1	0	2	2.5	2	0	2	0	0	0	0	2	1	2	2	3	2	0	0.5
09	40	0	2	2	0	1	0	0	0	2	0	0	1	2	2	1	0	0	1	2	0	0.5
10	2	0	4.5	3	1	1	0	2	1	1	0	0	0	0	0	0	0	0	0	0	0	1.5
11	4	0	4	2	0	0	0	0	2	2	0	0	0	0	2	0	0	0	0	0	0	1.5
12	65	0	1	2	0	2.5	2.5	0	0	0	0	0	2	2	2	3	2	1	1	1	0	0.5
13	1.9	0	3.5	2.5	0	0	1	3	2	1	0	0	0	0	0	0	0	0	0	0	0	1.5
14	15	0	4	2.5	0	2	1	2	2	1	0	0	0	0	0	2	0	0	0	0	0	1.5
15	20	0	3.5	3	0	2	0	0	0	3	0	0	2	0	2	1	0	4	0	0	0	2.5
16	18	0	3	3	0	2	2.5	1	0	2	0	0	2	1	2	1	2	2	2	2	0	0.5
17	2	0	3.5	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.5
18	12	0	4	2	0	2	1	1	2	1	0	0	0	0	0	2	0	0	0	0	0	1.5
19	3	0	4.5	1	0	2	0	0	1	0	0	0	4	0	0	0	0	0	4	0	0	1.5
20	12. 5	0	4	2	0	2	0	0	2	2.5	0	0	1	3.5	2	1	0	2	0	0	0	1.5

Appendix 3 membership variables after fussionification.

NO	AGE	PRE	FEV	APP	CON	VOM	MEN	PRO	ANE	DEH	BRE	THR	CHI	PAI	SPL	HEA	BRA	ABD	MAL	COP	GUP
01	0.1	0	1	0.7	0	0	0	1	1	1	0.7	0	0.6	1	0	0.6	0	0	0	0	0
02	0.1	0	1	0.6	0.7	0	0	0	0.7	0	0	0	0.7	0	1	0.7	0	0.7	0	0	0
03	0.7	0	0.5	0.9	0	0.7	0	0	0.7	0	0	0	0	0	0	0	0	0	1	0	0
04	0.3	0	0.6	0.7	0	0.6	1	0.6	0	0.6	0	0	0	0.6	0.6	0	0	0	0.6	0.7	0
05	0.4	0	0.7	0.1	0	0.6	1	0.6	0	0.7	0	0	0	0.6	1	0.7	0	0	0.6	0.7	0
06	0.3	0	1	0	1	0.6	1	0.6	0.6	0.6	1	0	0.7	1	0	0	0	0	0	0	0
07	0.2	0	1	1	0.7	0.6	1	1	1	0.1	0	0	0.7	0	0.6	0.7	0	0.6	1	0	0
08	0.8	0	0.1	0.6	0	0.7	1	0.7	0	0.7	0	0	0	0	1	0.7	0.7	0.7	0.1	0.7	0
09	0.8	0	0.7	0.7	0	0.6	0	0	0	0.7	0	0	0.6	0.7	1	0.7	0	0	0.6	0.7	0
10	0.8	0	0.5	0.7	0.6	0.6	0	0.7	0.6	0.6	0	0	0	0	0	0	0	0	0	0	0
11	0.4	0	1	0.7	0	0	0	0	0.7	0.7	0	0	0	0	1	0	0	0	0	0	0
12	0.7	0	0.6	0.7	0	0.4	1	0	0	0	0	0	0.7	0.7	1	0.1	0.7	0.6	0.6	0.6	0
13	0.8	0	0.5	0.5	0	0	1	0.1	0.7	0.6	0	0	0	0	0	0	0	0	0	0	0
14	0.2	0	1	0.5	0	0.7	1	0.7	0.7	0.7	0	0	0	0	0	0.7	0	0	0	0	0
15	0.3	0	0.1	0.7	0	0.7	1	0.7	0	0.7	0	0	0	0	1	0.6	0.7	0.7	0.1	0.7	0
16	0.3	0	0.7	0.1	0	0.7	1	0.6	0	0.7	0	0	0.7	0.6	1	0.6	0.7	0.7	0.7	0.7	0
17	0.8	0	0.5	0.7	0	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0.2	0	1	0.7	0	0.7	0	0.6	0.7	0.6	0	0	0	0	0	0.7	0	0	0	0	0
19	0.8	0	0.5	0.6	0	0.7	1	0	0.6	0	0	0	0	0	0	0	0	0	1	0	0
20	0.1	0	1	0.7	0	0.7	0	0	0.7	0.3	0	0	0.6	0.5	0.7	0.6	0	0.7	0	0	0

## **RESUME**

Sekiziyivu Ismael was born on 20.08.1984 Naggalama Uganda. He completed his high school from Naggalama Islamic Institute in 2003 and joined Uganda technical college Kichwamba where he obtained a diploma in electrical engineering in 2006. Then he joined Islamic call college Tripoli-Libya where he graduated in computer and information technology in 2010. He joined Tomer Kadikoy for Turkish language which he completed in 2012 and joined Sakarya University in Turkey to pursue a master degree in computer engineering whose final work has been represented by this thesis. Sekiziyivu Ismael speaks 5 main languages that are English, Arabic, Turkish, Swahili, and Luganda.