ADDIS ABABA UNIVERSITY
SCHOOL OF GRADUATE STUDIES
FACULTY OF INFORMATICS
DEPARTMENT OF INFORMATION SCIENCE

THE POTENTIAL FOR APPLYING KNOWLEDGE BASE SYSTEM FOR DIAGNOSIS OF ACUTE RESPIRATORY TRACT INFECTIONS

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A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN INFORMATION SCIENCE

MAY, 2010

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MAY, 2010

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ACKNOWLEDGMENT

This thesis is the result of a lot of effort, enthusiasm and hard work. I would like to thank many people for their kindness and assistance during my thesis writing. I sincerely thank Ato Tibebe Beshah, my adviser, who advised and encouraged me every step of the way to ensure its success. I wouldn't have finished this thesis without his support and drive.

I am also grateful to those people who provided me with information, comments, corrections and criticisms pertaining to the preparation of my thesis. These individuals include Dr. Milion Meshesha and Ato Mekuria Demissie (environmental protection expert at Arada Kifle-ketema).

The support of the people at Dagmawi-minilik hospital, Black-lion hospital and Meshualekia middle-level clinic is truly appreciated. A special thanks is due to w/rt Birhane.

This study has come about with the help of many friends who gave me both support and much useful encouragement. Particular mention should be made of my best friend Selamawit Mengesha, Meseret Ayano, Wondwosen Mekuria, Temesgen Ashenafi and Efrem Ayele and his family.

Finally, I would like to thank my family members for their constant support and encouragement. Without their support, the work on this thesis would never have been completed. I especially thank Dad and Mom for raising me and inspiring me all the time.

Above all, I would like to thank God for all His endless blessings and supportive to complete this work..

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LIST OF ACRONYMS

AC:	Accuracy
AE-CB/COPD	Acute Exacerbation of Chronic Bronchitis/Chronic Obstructive Pulmonary Disease
AI:	Artificial Intelligence
AIM:	Artificial Intelligence in Medicine
ARTI:	Acute Respiratory Tract Infections
ARI:	Acute Respiratory Infection
ALRTI:	Acute Lower Respiratory Tract Infections
AURTI:	Acute Upper Respiratory Tract Infections
ARTIKoBS:	Acute Respiratory Tract Infections Knowledge Base System
CKBS:	Clinical Knowledge Base Systems
DEC:	Digital Equipment Cooperation
DT:	Decision Tree
ES:	Expert System
FDRE:	Federal Democratic Republic of Ethiopia
FP:	False Positive
FN:	False Negative
GUI:	Graphical User Interface
IN:	Inference Network
KA:	Knowledge Acquisition
KBS:	Knowledge Base System
MoH:	Ministry of Health
PF:	Pulmonary Function
PROLOG:	PROgram LOGic
PUFF:	Pulmonary Function system
RSV:	Respiratory Syncytial Viruses
STI:	Sexual Transmitted Infections
TN:	True Negative
URTI:	Upper Respiratory Tract Infections
USD:	United States Dollar
URTI:	Upper Respiratory Tract Infections
WHO:	World Health Organization

ABSTRACT

Knowledge base systems exercise information technology to acquire and utilize combined human expertise. The technology can be very useful to institutions with clear objectives, rules and problems to provide consistent answers for repetitive decision-making, processes and tasks.

Knowledge base systems should be adopted and updated periodically to cater for the new discoveries, and to enhance benefits by addressing the new changes in the clinical diagnostic activities.

This research was done to preserve human expert level knowledge on the diagnosis of acute respiratory tract infections so that to make available such expert-knowledge for diagnostic activities.

The system, also, could be useful especially in the medical environment where knowledge experts are few, often in scarcity and often soon retire before their expertise is documented.

Facts that constituted the global criteria for the knowledgebase were gathered from expert physicians, pharmacists and nurses at the hospital of Dagmawi-minilik and Meshualekia middle-level clinic, Addis Ababa, review of guidelines, manuals, journals of respiratory infections, and online resources.

The system uses backward chaining with inference network and decision trees modeling structures basing on facts to draw logical conclusions from the initial states to the final states using respiratory diagnostic functions.

For the prototype development, Prolog programming language has been used. The performance of the prototype system is evaluated on qualitative bases. The result is encouraging to design a practical KBS for ARTI diagnosis.

Lastly, further studies should be done in artificial intelligence to solve the problem of rare expertise in the diagnosis of respiratory infections.

CHAPTER ONE

INTRODUCTION

1.1. Background to the Study

Acute Respiratory Tract Infections (ARTIs) are infections of the respiratory tract and the alveoli of the lungs caused by invasion of viruses, bacteria and fungi (Bermann, 2004). According to World Health Organization (WHO, 2009) ARTI is clinically categorized, as acute upper respiratory tract infections (AURTIs) and acute lower respiratory tract infections (ALRTIs). Acute Respiratory Tract Infection (ARTI) continues to be a major cause of morbidity and mortality world wide in general and developing countries in particular according to WHO report (2009). More recent review also indicated that most of those who die from ARTIs are young children (Ostroff, 2006). Besides this, in developing countries, in every 7 seconds, a child under 5 years of age dies because of acute respiratory infection usually pneumonia (WHO, 2008). Out of the 12.9 million deaths of peoples that occurred in 1990, some 4.3 million were attributed to ARTIs (WHO, 2008). Moreover, very recent review by Muhe (2009) estimated that 1.9 million children deaths per year are due to ARTIs.

In Ethiopia, Acute Respiratory Tract Infections are now spreading widely. It is the primary cause of visits to health clinics and outpatient hospital clinic. The main problem is that up to now, the countries haven't had a diagnosing method that is good enough to confirm or exclude ARTI. In addition, most Ethiopians are living in countryside where there is no enough of facilities for diagnosis and treatment (WHO, 2009).

In diagnosing ARTI, doctors have to cope with many difficulties: patient's symptoms are usually unclear and the similarities in symptom aspect between lung tuberculosis and other infections. Even if the bacteria and the virus are often found in the patients, the diagnosis' result depends not only on patient's symptoms but also strongly on doctor's experiences. Therefore, there are many mistakes in diagnosing and treating ARTI which cause the high rate of patient's death and the wide spread of the infections (WHO, 2009). In addition, it was indicated from one study that the physicians found in the country none of them had had any training in the management of ARTI other than what they had learnt at medical school, whether in Addis Ababa or in their previous experiences (WHO, 2009). This indicates that there is no any standard protocol for diagnosis and drug use, limited provision of health education for the community regarding ARTI, inappropriate methods of providing health care, risk factors and the proper time to seek medical assistance for treatment (WHO, 2008).

On the other hand, a number of difficulties have been encountered in developing countries like Ethiopia. First, in clinical decision making, a physician cannot make a diagnosis with high accuracy due to lack of modern equipment caused by restricted financial resources. Second, there are not sufficient good physicians to serve the whole population. Third, in the country, traditional medicine and techniques are also employed which are based on experience which is often not documented for the next generation of doctors (MoH, 2008).

Knowledge base systems (KBS) are artificial intelligence based tools designed to provide expert level solutions in a narrow based problem area. Frenster (1989) stated that KBS provide pre-selected rules for decision-making within specialized domains of knowledge but are limited by the fixed choices and by the date of the expert opinions embodied in the decision rules. However, according to Duda and Shortliffe (1983), knowledge base systems must be understandable and flexible enough to accommodate new knowledge. They act as data points out of which a cumulative body of knowledge commonly derived from human experts is developed. The human knowledge is made of a body of facts of the real world. With this, KBS can explain the reasoning process through back-traces and forward chaining and handle high levels of confidence and uncertainty, which provides an additional feature difficult to conventional programming.

The knowledge of knowledge base systems is represented as data or rules that appear in syntax as physical patterns in electronic form in the knowledge base. The knowledge is represented as production rules in the form of condition-action pairs of IF—THEN format (Turban and Aronson, 1990). Therefore, from the syntax and semantics of these rules the inference of an agent that uses a particular language is derived. Sound inference is got if the inference steps respect the semantics of the sentences they operate upon in the knowledgebase (Russell and Norvig, 2004). But conventional computer programs perform tasks by use of conventional decision-making logic, which are represented in the symbolic state.

Knowledge base systems have become widely useful application in many complex tasks. Their ability to use domain knowledge to speedily solve difficult problems makes them indispensible in, for example, medical diagnostics, manufacturing and agricultural industry and in finance and banking. Shortliffe (1974) described knowledge base system to be often more effective than other computer-based advising systems because they are goal oriented, efficient, adaptive, and able to explain their information requests and suggestions. This is one of the reasons therefore that they are widely applied, greatly marketable and of high commercial value in the developed world today (Russell and Norvig, 2004).

According to Eom (1996), a survey which was conducted on 440 knowledge base systems in business revealed that many knowledge base systems have profound impact which includes shrinking time for tasks from days to hours, minutes, or seconds. The non-quantifiable benefits include improved customer satisfaction, quality of products and services, and accurate and consistent decision making. Knowledge base systems make complex equipment easier to operate. According to Perkins (2006) for example STEAMER is an early KBS intended to train inexperienced workers operate complex ship engines. They have the additional advantage of operating in hazardous environments where humans would be exposed to various risks like in humid, toxic environment such as a nuclear power plant that has been malfunctioned. Besides, knowledge base system can provide training to novices; by enabling them to get more experience with time. The explanatory portion can also serve as a teaching device together with the notices and explanations put in the knowledgebase. They can be further be used for enhancement of intelligent capabilities to other information systems. Finally, one of the great benefits of knowledge base systems is the easy transfer from one geographical location to another. For example the Web is used extensively to disseminate information to its users in remote locations (Stefic, 2008).

Knowledge base systems have been developed for various fields such as medicine, agriculture, education, manufacturing industries, banking, finance and accounting. In medicine, diagnosis of patient complicated conditions, clinical laboratory identification of infectious diseases and recommendation of treatment, surgery, emergencies, drugs and toxicology and dentistry are some of the domains for knowledge base system development. Applications in these domains use symbolic knowledge and the problem solving methods are qualitative reasoning techniques that relate items through judgmental rules as well as through theoretical laws and definitions Frenster (1989). Diagnosis of patients with ARTI symptoms is usually based on clinical findings and anamnesis, while less frequently diagnosis is confirmed by laboratory analysis. Unfortunately, symptoms and clinical findings of different pathogens are variable and heavily overlap, even between viral and bacterial infections

(Perkins, 2006). In this case, identification of the infection would base on serious consultations with text books, journals and knowledge experts. Should this fail, the infection is reported as unidentified. The failure to identify the infection leaves a questionable gap in the diagnosis process.

Currently, the tasks of diagnosing problems associated with acute respiratory tract infections, particularly in Addis Ababa, are basically carried out by human expert's i.e. professional medical experts like physicians and nurses rather than using diagnosing computing. Human expertise in such a specialized area is quite limited and expensive. Furthermore, human experts may not always be available in all situations where they are needed. Although there are limitations in capturing and creating artificial expertise through building knowledge based system, there are benefits of artificial expertise as given in the following comparison table by Waterman (2001):

Human Expertise	**Artificial Expertise**
Perishable	Permanent
Difficult to transfer	Easy to transfer
Difficult to document	Easy to document
Unpredictable	Consistent
Expensive	Affordable

Table 1.1 Comparing human and artificial expertise

The development of medical knowledge base systems is a great milestone to such complex level problems. Knowledge base systems may make a better choice than human expertise because they are available all the time, can have collective expertise from different content resources, and do not suffer from biases and other human frailties.

The goal of this research is to assess and analyze the magnitude of the problem of acute respiratory tract infections and develop a prototype knowledge based system for medical applications in the knowledge domain of diagnosis of acute respiratory tract infections. The emphasis of this research is to provide a broad view of diagnosis of ARTI by capturing the knowledge of human experts and using a symptomatic approach. The advantage of a symptomatic approach is that the type of infection can be identified by using symptoms of the patients. As mentioned above, the process of diagnosis has been traditionally carried out by human experts/specialists and the use of computerized systems exhibiting artificial intelligence is a relatively new technology in an attempt to provide a systematic as well as efficient diagnosis process.

Recent developments in knowledge based systems allow users to conveniently interrogate a computer program as if it were an expert. A knowledge base system for diagnosis of Acute Respiratory Tract Infection is implemented through this thesis as a prototype rule based system using Prolog implementation tool. By integrating the different expert's knowledge, the prototype knowledge base system has the power to provide diagnosis of ARTI, which can assist health trainees, medical staff, specialists as well as their top management personnel regarding the probable problems of respiratory tract infections. The knowledge base system will be particularly of great assistance to the new comers who are not familiar with the field and will facilitate them in gaining a better understanding of the causes of the problems and in making decision for any necessary action.

1.2. Statement of the problem and Justification

Acute Respiratory Tract Infections (ARTIs) are the single most common infective cause of death in Ethiopia. A lack of diagnostic tests, limited access to effective treatment and some traditional healing practices exacerbated the impact of respiratory infections in the country. The rapid urbanization of populations has increased the risk of transmitting respiratory pathogens. A combination of poverty and overcrowding in per urban zones of rapidly expanding cities in the country promotes the epidemic spread of acute respiratory infections. Up to half the patients attending hospital outpatient departments in Ethiopia have acute respiratory tract infections (ARTIs). In many places, limited access to diagnostic services and a lack of effective therapeutic agents may contribute to a higher severity of acute respiratory infections, expanding global burden of respiratory infections and the need for intervention for immediate solution (WHO, 2009).

In Ethiopia, the problems of ARTI in terms of morbidity and mortality have not been sufficiently described to health planners. However, reports of ARTI's are limited to hospitals and a few community based surveys. Besides, reports have indicated that ARTI account for

33% of infant mortality and 20% of mortality among children younger than age 5 (Lulu Muhe, 2007).

According to Ministry of Health report in 2009, Influenza and respiratory syncytial viruses markedly increase mortality in infants and in elderly. Generally, respiratory syncytial virus (RSV) is more severe in infants, where as influenza is more severe in elderly people. The viruses are responsible for most of the ARTI deaths in the country. Here mortality is not usually direct consequences of influenza or RSV infection but a result of complications, such as bacterial pneumonia. So making control of such infections, therefore, is vitally important in reducing its rate of dispersion. In respond to this, the Federal Democratic Republic of Ethiopia (FDRE) develops a strategy in view of the benefits of effective and timely treatment of ARTI together with the cases of Sexual Transmitted Diseases (STI) and paid special attention to the diagnosis of most vulnerable groups like children and adults in rural areas of the country (FDRE, 1998). Though the Ministry of Health (MoH) has placed a great emphasis on integrated systems especially at the rural primary health care level for patient management of ARTI, health services are unavailable or too far away and too expensive.

The challenges of ARTI intervention can be related to two major factors: Socio-cultural factors and Health care system factors.

Socio-Cultural Factors

Various social and cultural factors were recognized in ARTI diagnosis and treatment in Ethiopia including social problems, feeling of improvement, inadequate knowledge (lack of knowledge about the cause and effect of the infections,) reluctance to seek health care, preference for alternative health services such as traditional healers, and failure to take the full, prescribed course of treatment for ARTI (Johannes, 2004). This indicates that a fundamental understanding of the socio-cultural factor in ARTI intervention is essential for an effective diagnosis and treatment of the disease.

Health Care System Factor

Ethiopia’s health care system is among the least developed in sub-Saharan Africa and is not, at present, able to effectively cope with the significant health problems facing the country.

The country's health care system is in crises with more than half of the country having no access to health care at all (WHO, 2009). There is just one doctor to every 100,000 people in the country and other trained medical staff such as nurses is in equally short supply. There is a lack of physical access to even basic health care facilities in rural areas (Johannes, 2004).

Total outpatient utilization of government health facilities in Ethiopia suggests that, on average, there are about 0.25 visits per person per year. A household survey on health care utilization found that only 10 percent of persons reporting illness actually obtained treatment for their conditions from any health facility, government or private. Utilization by the rural population (9.5 percent), as compared to 14 percent in urban areas, is lower than the national average. The findings further show that the three most important determinants of whether treatment is sought are:

- The cost of treatment
- The distance from, or absence of, the health care facility
- The quality of the facility
- Inadequate and poorly maintained infrastructure and equipment,
- Scarcity of trained health personnel

Though instructing the society through different approaches are some initiatives, it could not be solved substantially because of the above reasons and great amount of investment and time is needed.

Knowledge-based systems are designed to give expert-level, problem-specific advice in the areas of medical data interpretation, patient monitoring, disease diagnosis, treatment selection, prognosis, and patient management. They capture and make available the knowledge of experts and by applying that knowledge to patient data-emulate and assist in the decision making behavior of medical and administrative personnel. Research in medical expert and knowledge-based systems and the development of such systems is most significant to the broad realm of quality assurance and cost containment in medicine. The growing complexity the management of different diagnosis problems makes the application of such systems more and more indispensible. Provided that they are used correctly, these systems can reduce much of the repetitive and specialized mental efforts make by the treating physician and enable them to devote his or her attention to the personal care of the patient (Englimore et.al, 2007).

Evidently, there is no any knowledge based system done for diagnosing Acute Respiratory Tract Infections (ARTIs). But, there is one medical expert system done at Pacific Medical Center in San Francisco to diagnose the presence and severity of lung disease and produce reports for the patient's file (Stefic, 2008). The system is named as PUFF (Pulmonary Function expert system). A lung disease is one of the respiratory disease occurred at the respiratory system of the human body. This respiratory disease includes diseases of the lung, pleural cavity, bronchial, trachea, and acute respiratory tract and of the nerves and muscles of breathing (WHO, 2008). PUFF only interprets measurements from respiratory tests administered to patients in pulmonary (lung) function laboratory. The laboratory includes equipment designed to measure the volume of the lungs, the ability of the patient to move air into and out of the lungs, and the ability of the lungs to get oxygen into the blood and carbondioxide out. The pulmonary physiologist interprets these measurements in order to determine the presence and severity of lung disease in the patient. PUFF's task is to interpret such a set of pulmonary function (PF) test results, and to produce a set of interpretation statements and a diagnosis for the patient (Stefic, 2008). So, this indicate that even if PUFF is intended for the diagnostic activity of the lung disease which is among the different respiratory diseases, there is no knowledge based system developed for diagnosing acute respiratory tract infections as one of respiratory diseases.

Hence, the present research designed a prototype knowledge-based system that can support the diagnosis and case management activities for ARTI and the research will hopefully provide the alternative to the traditional way of offering ARTI case management approach so that it will be comfortable and pleasing to the society.

The proposed KBS, therefore, will have the benefit of:

- Much lower in cost compared with paying an expert or a team of specialists.
- Unlike human expert, the KBS to be built will be available anytime, anywhere the person needs it.
- Encourage the society to take early diagnosis and medication
- Simple, rapid, and inexpensive
- Easy of accessing information

1.3. Objectives of the Study

1.3.1. General Objective

The primary objective of the proposed study was to design and develop a prototype knowledge-based system and explore the applicability of knowledge management for diagnosis of Acute Respiratory Tract Infections (ARTIs)

1.3.2. Specific Objectives

The research has the specific objectives:

- To assess and analyze the magnitude of the problem
- To acquire the necessary tacit and explicit knowledge using primary and secondary sources
- To review literature on related works and assess techniques and tools for designing knowledge-based system as well as to identify the challenges associated with ARTI
- To model and represent knowledge using appropriate knowledge representation methods
- To design and develop a prototype knowledge based system that demonstrates the capacity of the system to give diagnosis in ARTI
- To test the reliability and performance of the new system using appropriate cases
- To recommend future researches for further work in similar area

1.4. Scope and Limitations of the Study

The central focus of this research was to design and develop a prototype knowledge base system in the diagnosis and management of ARTI. This Knowledge Based System was built using knowledge acquired from expertise in the area and supplemented by the information guideline which is outlined by the Ministry of Health, Ethiopia.

There are limitations in the study. The first one is chronic respiratory tract infections did not be considered in the study because though chronic infections are parts of respiratory tract infections, it takes more time to demonstrate the experiment. The other limitation is the non-availability and affordability of commercial prototype development shells, as a result, using the free programming language lacks some important features that help a lot in prototype development. If these limitations were not the case, the result of the study would be better.

1.5. Significance of the Study

The study was done to provide a quick and accurate diagnosis of acute respiratory tract infections for quick reference in the absence of experts. It is expected to improve performance standards and to provide quality results. Knowledge experts are few and often unavailable such that identification of infections may often fail. Therefore, it is the belief that a knowledge base system developed for the diagnosis of acute respiratory tract infections is likely to help solve the problem. The knowledge base system may in future be extended to other hospitals, especially rural areas where knowledge experts are rarely found. The system is expected, therefore, to ensure diagnostic simplicity, cost reduction and enforcement of standards in patient care management.

The knowledge base was developed using the knowledge from different human experts and textbook references for the expertise to be preserved for use in case the experts soon retire.
The system can be scaled up to diagnose more respiratory infections, for example, chronic respiratory tract infections. This provision is expected to help different health institutions since they are few of them in this country that can maintain a variety of conventional respiratory diagnostic standards. It will also be beneficial for training students and research purposes. The immediate beneficiaries of the study are societal groups that have access to personal computers in private or public sectors.

The knowledge base system to be designed will be applicable for giving consultation to people who wish to know about Respiratory Tract Infections. The system can be used in clinics and any health care centers that provide diagnosis and/or management of ARTI. It can also be used as a tool for giving information to make them aware about the importance of knowing major ARTI diagnosis and management without them having to go to a medical institution where the management is actually done. This can be very useful in terms of handling such vital information to people wherever they are.

At a large scale, the system can be integrated to tele-centers, woreda and health-net, and Internet-café or modified to be available on-line so any body that has access to the Internet can benefit from having the option of getting an automated diagnosis and management of ARTI.

1.6. Organization of the Thesis

The thesis is organized into six chapters. The first chapter presents the basic introduction, statement of the problem with justification, objectives of the study, the scope and limitations, and the significance of this research work.

The second chapter goes through the review of related literatures which provides the background material for this thesis. An overview of knowledge based systems, including the concepts, major approaches, implementation tool and validation, have been given in detail. Specialized literature on acute respiratory tract infections and their diagnosis in Ethiopia have also been covered. Work related to this research is examined. It starts with looking at general applications of knowledge base systems then follows with specific applications and work on knowledge base systems in medicine.

In the third chapter, the research design and methodology phase of the study explained in detail. Here, the study design, area, and population, sample size, sampling procedure, data collection and analysis, processes of KBS development for ARTI diagnosis, and the implementation tool was described.

The fourth chapter briefly describes the result of the preliminary assessment which was conducted to assess the magnitude of the problem of acute respiratory tract infections. In this chapter mostly occurred illnesses of acute respiratory tract infections in Addis Ababa and their distribution by sex and age group, sources of care treatment (health responses) to ARTI, barriers to treating patients with ARTI cases and proposed solution are briefly explained.

The fifth chapter focuses on the knowledge acquisition task. In this part, extracting knowledge from different sources, elicitation of knowledge and structuring and modelling the knowledge using inference network and decision tree has been made.

The six chapter deals with rules creation, rules validation, and the rule base representation of the acquired knowledge and development of the system for achieving the objectives of the study. The testing and evaluation of the system is also presented. Based on the performance evaluated, findings are briefly discussed to show the strength and weakness of the system.

In chapter seven general conclusions and suggestions for future work are presented. This chapter summarizes the whole theme of the research and its results.

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

Artificial intelligence (AI) is directed towards building a machine and improving our understanding of intelligence. One of the most successful applications of artificial intelligence reasoning techniques using facts and rules has been in building knowledge base systems that embody knowledge about a specialized field of human endeavor, such as medicine, engineering, or business. AI programs that achieve expert-level competence in solving problems by bringing to bear a body of knowledge are called knowledge based systems or expert systems (Adrian et.al, 1992). Often, the term expert systems are reserved for programs whose knowledge gathered from textbooks or non-experts. Some successes have been achieved in mimicking specific areas of human mental activity. For instance, machines are now able to play chess at the highest level, to interpret spoken sentences and to diagnose medical and technical complaints. In achieving these modest successes, research into artificial intelligence (together with other branches of computer science) has resulted in the development of several useful computing tools (Adrian et.al, 1992).

As one part of artificial intelligence research, understanding the notion of Knowledge Based System/KBS/ requires conceptualizing its theory, definition and other explanation (Stuart et.al, 1995). So, this chapter explores about Knowledge Base System and its applications especially in health sector though the spectrum of applications of KBS is so wide. The chapter also explains briefly some highlights about Acute Respiratory Tract Infections (ARTI).

2.2. Knowledge Base System

2.2.1. An overview of KBS

Knowledge Based Systems/KBS/ are computer programs that are derived from a branch of computer science research called Artificial Intelligence (AI). AI's scientific goal is to understand intelligence by building computer programs that exhibit intelligent behavior. It is concerned with the concepts and methods of symbolic inference, or reasoning, by a computer, and how the knowledge used to make those inferences will be represented inside the machine (Engelmore et.al, 2003).

The term intelligence covers many cognitive skills, including the ability to solve problems, learn, and understand language; AI addresses all of those. But most progress to date in AI has been made in the area of problem solving i.e, concepts and methods for building programs that reason about problems rather than calculate a solution.

Knowledge-based systems are computer programs designed to solve problems, generate new information (such as a diagnosis), or provide advice, using a knowledge base and an inference mechanism. Most systems include a user interface and some explanation capability as well. Knowledge-based systems are characterized as focusing on the accumulation, representation, and use of knowledge specific to a particular task, but addressed the expanded views of such systems made possible by the ability to use the same knowledge in several different ways (Engelmore et.al, 2003).

More often than not, the two terms, Expert Systems (ES) and Knowledge Based Systems (KBS), are used synonymously. Taken together, they represent the most widespread type of AI application (Engelmore et.al, 2003).

Krishnamoorthy and Rajeev (1996) differentiated between "knowledge-based systems" and "expert systems," commenting that for many applications there may not be any uniquely qualified human experts, so that it is inappropriate to speak of the development of programs approximating the level of experts. They defined a knowledge-based system as an AI program whose performance depends more on the explicit presence of a large body of knowledge than on the possession of ingenious computational procedures. On the other hand, by expert system we mean a knowledge-based system whose performance is intended to rival that of human experts (Krishnamoorthy et.al, 1996).

In all cases, knowledge-based systems are considered to be distinct from programs based primarily on mathematical models, statistical techniques, or pattern matching, although some knowledge-based systems may incorporate statistical components along with knowledge bases in an effort to account for uncertainty (Adrian et.al, 1992). The knowledge base is clearly the critical and distinguishing element characterizing these decision-support systems.

The area of knowledge base systems has blossomed over the past decade from merely academic interest into a useful technology. Numerous people have defined KBS from various perspectives. Some of these are:

"A Knowledge Base System is software that uses artificial intelligence or expert system techniques in problem solving processes. It incorporates a store (database) of expert knowledge with couplings and linkages designed to facilitate its retrieval in response to specific queries, or to transfer expertise from one domain of knowledge to another (Stuart et.al, 1995)."

Nilsson (1998) describes knowledge base systems as follows.

"Knowledge base systems are software systems that have structured knowledge about a field of expertise. They are able to solve some problems within their domain by using knowledge derived from experts in the field" (Nilsson, 1998).

"A Knowledge Based System is a problem solving and decision making system based on knowledge of its task and logical rules or procedures for using knowledge. Both the knowledge and the logic are obtained from the experience of a specialist in the area. It is also a program that emulates the interaction a user might have with a human expert to solve a problem. The end user provides input by selecting one or more answers from a list or by entering data. The program will ask questions until it has reached a conclusion. The conclusion may be the selection of a single solution or list of possible solutions arranged in order of likelihood. The program can explain how it arrived at its conclusion and why" (Zili et.al, 2003).

"Knowledge-Based Systems focuses on systems that use knowledge-based techniques to support human decision-making, learning and action." (Nilsson, 1998)

The basic concepts of the above definitions describe as KBS is a computer program designed to simulate the problem solving behavior of a human to support decision-making, learning and action by deriving knowledge from experts.

2.3 Knowledge Based System Architecture

The knowledge based system structure is composed of the following main components as illustrated in the figure below (Nilsson, 1998).

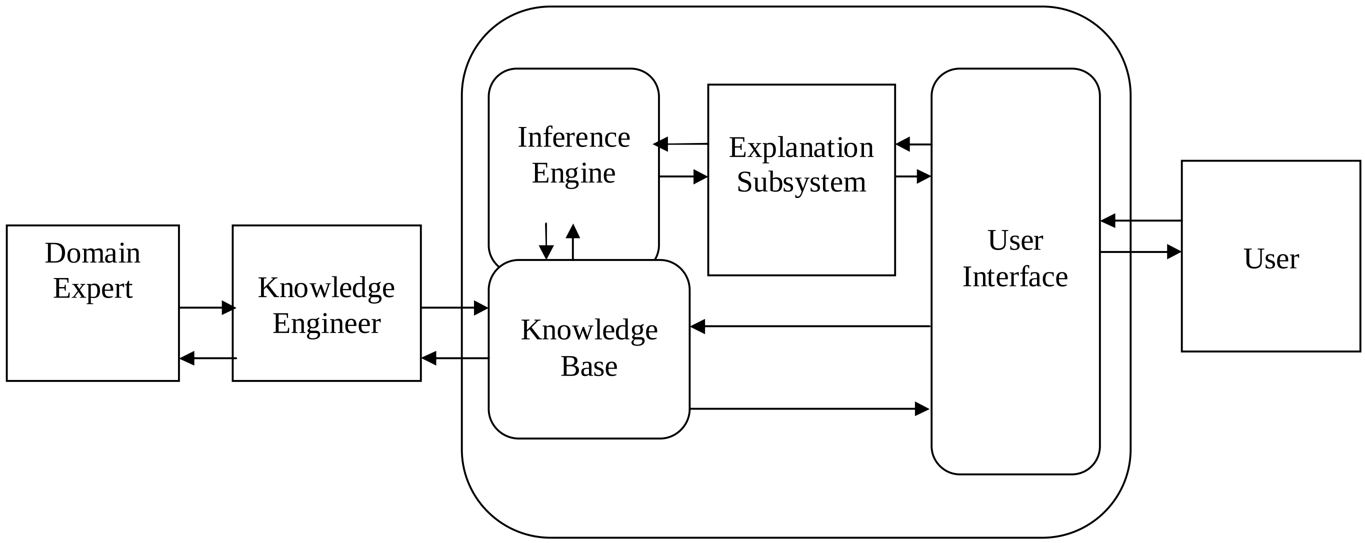


Figure 2.1: Basic Structure of Knowledge Based System

- **User interface:** The user can interact with the knowledge base system via user interface. User can enter commands, respond to questions, etc. Advanced interfaces make heavy use of pop-menus, natural language, GUI or any other style of interaction.

- **Inference Engine:** It is also known as rule interpreter and is the problem-solving component. It allows new inferences to be made from the case specific data and the knowledge in the knowledge base. These new facts represent conclusions about the state of the domain given the observations.

  The inference engine implements the recognized act cycle of the production system; this control may be either data-driven or goal-driven. Inference engines are of two kinds: categorical and non-categorical (Luger and Stubblefield, 2006). A non-categorical inference engine calculates confidence level for each conclusion it reaches, where as categorical inference engine does not.

  There are two main methods of reasoning when using inference rules:

  - *Forward chaining* starts with the data available and uses the inference rules to conclude more data until a desired goal is reached. An inference engine using forward chaining searches the inference rules until it finds one in which the if clause is known to be true. It then concludes the then clause and adds this information to its data. It would continue to do this until a goal is reached. Because the data available determines which inference rules are used, this method is also called data driven.

- *Backward chaining* starts with a list of goals and works backwards to see if there is data which will allow it to conclude any of these goals. An inference engine using backward chaining would search the inference rules until it finds one which has a then clause that matches a desired goal. If the if clause of that inference rule is not known to be true, then it is added to the list of goals.

  Backward chaining inference is practical when there are a reasonable number of possible final answers, as in the case of a diagnostic or identification system i.e., the aim of the system is to pick the best choice from many enumerated possibilities (Amzi, 2000). For example, diagnostic systems fit this model since the aim of the system is to pick the correct diagnosis.

  Backward chaining is useful in situations where the quantity of data is potentially very large and where some specific characteristic of the system under consideration is of interest. If there is not much knowledge what the conclusion might be, or there is some specific hypothesis to test, forward chaining systems may be inefficient. In principle, we can use the same set of rules for both forward and backward chaining. In the case of backward chaining, since the main concern is with matching the conclusion of a rule against some goal that is to be proved, the ‘then’ (consequent) part of the rule is usually not expressed as an action to take but merely as a state, which will be true if the antecedent part(s) are true (Krishnamoorthy et.al, 1996).

- **Knowledge Base:** A store of factual and heuristic knowledge. It holds the expertise that the system can deploy and is constructed by the knowledge engineer in consultation with the domain expert. For many knowledge based systems, knowledge representation is through the use of production rules, frames and semantic nets.
- **Explanation Facility:** A subsystem that explains the system's actions. The explanation can range from how the final or intermediate solutions were arrived to justifying the need for additional data.

- **Domain Expert:** is an expert who input the Knowledge into the system during the development and the knowledge acquisition processes.

- **User:** is a person (expert or otherwise) who uses the system for support. The end user usually sees an expert system through an interactive dialogue that proceeds in a dialogue involving questions by the system and answer input by the user.

The explicit separation of knowledge from control makes it easier to add new knowledge either during program development or in the light of experience during the program's lifetime. There is an analogy with the brain, whose control processes (the inference engine) are approximately unchanging in their nature, even though individual behaviour is continually modified by new knowledge and experience (updating the knowledge base). The knowledge is represented explicitly in the knowledge base, not implicitly within the structure of a program. Thus the knowledge can be altered with relative ease. The inference engine uses the knowledge base to tackle a particular task in an analogous fashion to a conventional program using a data file.

2.4 Merits of Knowledge Base Systems

According to Nilsson (1998), the following table depicts some of the merits of knowledge base system over that of conventional computer systems.

Knowledge Base Systems	**Conventional Computer Systems**
Knowledge base is clearly separated from the processing mechanism	Information and its processing are usually combined in one specific program
Programs may make mistakes	Program does not make mistakes
Explanations is part of most knowledge base systems	Do not explain why input data are required or how conclusions were drawn
Changes in the rule are easy to accomplish	Changes in the program are tedious
System can operate with only a few rules	The system operates only when completed
Execution is done by using heuristics and logic	Execution is done on a step-by-step (Algorithmic basis)
Can operate with incomplete or uncertain information	Needs complete information to operate
Effective manipulation of large knowledge base	Effective manipulation of large database
Representation and use of knowledge	Representation and use of data
Effectiveness is the major goal	Efficiency is the major goal
Capture, magnify and distribute	Capture, magnify and distribute
Access to judgment and knowledge	Access to numeric data or to information

Table 2.1 Comparison of Knowledge Base Systems and Conventional Computer Systems

2.5 Application of Knowledge Base Systems in Medicine

Knowledge-based systems are the commonest type of Artificial Intelligence in Medicine (AIM) systems in routine clinical use. They contain medical knowledge, usually about a very specifically defined task, and are able to reason with data from individual patients to come up with reasoned conclusions. Although there are many variations, the knowledge within a knowledge base system is typically represented in the form of a set of rules (Coiera et.al, 2003).

According to Coiera (2003), there are many different types of clinical task to which knowledge base systems can be applied.

- **Generating alerts and reminders:** in so-called real-time situations, a knowledge base system attached to a monitor can warn of changes in a patient's condition. In less acute circumstances, it might scan laboratory test results or drug orders and send reminders or warnings through an e-mail system.

- **Diagnostic assistance:** when a patient's case is complex, rate or the person making the diagnosis is simply inexperienced, a knowledge base system can help come up with likely diagnosis based on patient data.

- **Therapy critiquing and planning:** systems can either look for inconsistencies, errors and omissions in an existing treatment plan, or can be used to formulate a treatment based upon a patient's specific condition and accepted treatment guidelines.

- **Agents for information retrieval:** software agents can be sent to search for and retrieve information, for example, on the Internet, which is considered relevant to a particular problem. The agent contains knowledge about its user's preferences and needs, and may need to have medical knowledge to be able to assess the importance and utility of what it finds.

- **Image recognition and Interpretation:** many medical images can now be automatically interpreted, from plane x-rays through to more complex images like angiograms, Computerized Tomogram (CT) and Magnetic Resonance Imaging (MRI) scans. This is of value in mass-screenings for example, when the system can flag potentially abnormal images for detailed human attention (Coieral et.al, 2003).

Examples of some of these knowledge base systems are as follows.

- **MYCIN** was one of the first successful expert system to demonstrate the feasibility of developing intelligent programs with performance rivaling that of a human expert. MYCINs' task was the diagnosis of bacterial infectious diseases and the suggestion of suitable therapies (Coieral et.al, 2003).

- **PUFF** is an expert System for the interpretation of pulmonary function tests for patients with lung disease. PUFF went into production at Pacific Presbyterian Medical Centre in San Francisco in 1977 (Coieral et.al, 2003).

- **INTERNIST** is developed by Jack Myers and Harry Pople at the University of Pittsburgh. The INTERNIST is a knowledge-based medical diagnostic program based on Dr. Myers' clinical knowledge and is designed to help doctors diagnose their patients' ailments (Coieral et.al, 2003).

- **Germ Watcher** checks for hospital-acquired (nosocomial) infections, which represent a significant cause of prolonged inpatient days and additional hospital charges. Microbiology culture data from the hospital's laboratory system are monitored by Germ Watcher, using a rule-base containing a combination of national criteria and local hospital infection control policy (Coieral et.al, 2003).

2.6 Objectives of Medical Knowledge Base Systems

Motivations for the development of KBS in medicine have been numerous. Assisting physicians in making diagnoses and treatment recommendations is the most commonly found application of KBS in medicine. A physician may have knowledge of most diseases, but, due to the extensive number of diseases, a physician could benefit from the support provided by the knowledge base system to quickly isolate the disease (Coieral et.al, 2003). Specifically, the goals of developing KBS for medicine are as follows:

- To improve the accuracy of clinical diagnosis through approaches those are systematic, complete, and able to integrate data from the diverse sources (Amzi, 2000).
- To improve the reliability of clinical decisions by avoiding unwarranted influences of similar but not identical cases (Adrian et.al, 1992).
- To improve the cost efficiency of tests and therapies by balancing the expenses of time, inconvenience against benefits, and risks of definitive actions (Coieral et.al, 2003).
- To improve our understanding of the structure of medical knowledge, with the associated development of techniques for identifying inconsistencies and inadequacies in that knowledge (Nilsson, 1998).
- To improve our understanding of clinical decision-making in order to improve medical teaching and to make the system more effective and easier to understand (Nilsson, 1998).

2.7 Knowledge Representation

Knowledge Representation is the method used to encode knowledge in Intelligent Systems. An Intelligent System is an engineered system which has a purpose and uses techniques of artificial intelligence to fulfill its task (Adrian et.al, 1992). It can best be understood in terms of five distinct roles it plays and expressed each as crucial to the task at hand (Amzi, 2000).

- A knowledge representation is most fundamentally a surrogate, a substitute for the thing itself, used to enable an entity to determine consequences by thinking rather than acting, i.e., by reasoning about the world rather than taking action in it.
- It is a set of ontological commitments, i.e., an answer to the question: in what terms should I think about the world?
- It is a fragmentary theory of intelligent reasoning, expressed in terms of three components:

  (i) the representation's fundamental conception of intelligent reasoning,

  (ii) the set of inferences the representation sanctions,

  (iii) the set of inferences it recommends.
- It is a medium for pragmatically efficient computation, i.e., the computational environment in which thinking is accomplished. One contribution to this pragmatic efficiency is supplied by the guidance a representation provides for organizing information so as to facilitate making the recommended inferences.
- It is a medium of human expression, i.e., a language in which we say things about the world.

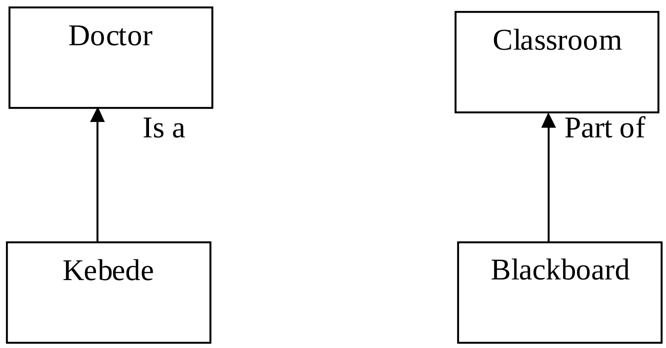
In building a knowledge base, several methods of knowledge representation can be used. However, the most widely used knowledge representation techniques include semantic networks, frames and rules.

2.7.1. Semantic Networks

A semantic network is often used as a form of knowledge representation. It is a directed graph consisting of vertices which represent concepts and edges which represent semantic relations between the concepts and for describing semantic relationships between knowledge items in a knowledge base (Amzi, 2000).

The most common relationships (suitable for object-oriented case) is shown in figure 2.2.

- "is a": object 'A' is an instance of object 'B' when object 'A' "is_a" object 'B' holds. For instance, "is a": Kebede is an instance of Doctor when Kebede "is a" Doctor holds.
- "part of": object 'A' is a part of or an attribute of object 'B' when object 'A' "part_of" object 'B' holds. For instance, "part of": Blackboard is a part of or an attribute of Classroom when Blackboard "part of" Classroom holds.



Kebede is a Doctor Blackboard is part of classroom

Is_a(Kebede, Doctor) Part_of(Blackboard, Classroom)

Figure 2.2: Example for semantic network

Semantic networks involve nodes and links between nodes. The nodes represent objects or concepts and the links represent relations between nodes. The links are directed and labeled; thus, a semantic network is a directed graph. In print, the nodes are usually represented by circles or boxes and the links are drawn as arrows between the boxes. The structure of the network defines its meaning. The meanings are merely which node has a pointer to which other node. The network defines a set of binary relations on a set of nodes (Stuart et.al, 1995).

2.7.2. Frames

A frame is a collection of slots (attributes) that characterizes an object. Each slot may be filled with a value, a default, another frame, or procedures. Embedding procedure within a frame is called procedural attachment.

A frame is a complex data structure representing a stereotyped situation, such as an object, an activity, or a person. Slots are frame-like structures for representing stereotyped sequences of events or values (Adrian et.al, 1992).

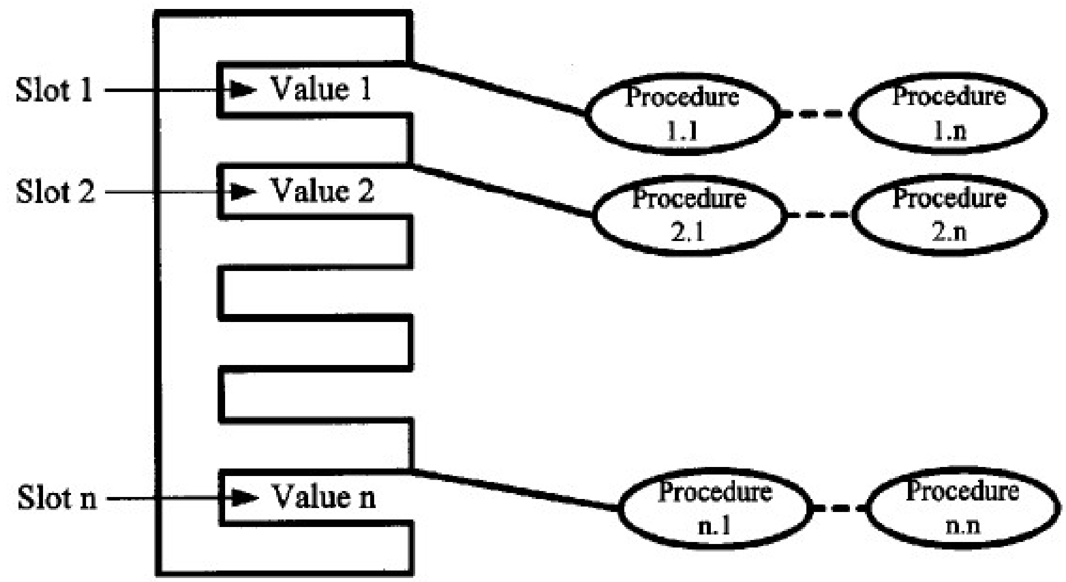


Figure 2.3: Frames and Slots (Adopted from Adrian et.al (1992))

For example, in a frame that describes a bank account, the slots can be used to represent the account number, the account type, and the account balance. Generally, a frame is composed of a concept, one or more slots, one or more values, and one or more attached procedures as depicted in figure 2.3 above.

Figure 2.4 below shows a set of frames that represent information about bank accounts. A bank representative opens the account file for a customer by soliciting, entering, and verifying all the required information. The associated knowledge base system then automatically triggers an attached procedure that asks the representative to select a transaction type (for example, add a new customer, update customer information, delete a customer, and so on). The knowledge base system then responds by triggering the appropriate procedure (Adrian et.al, 1992).

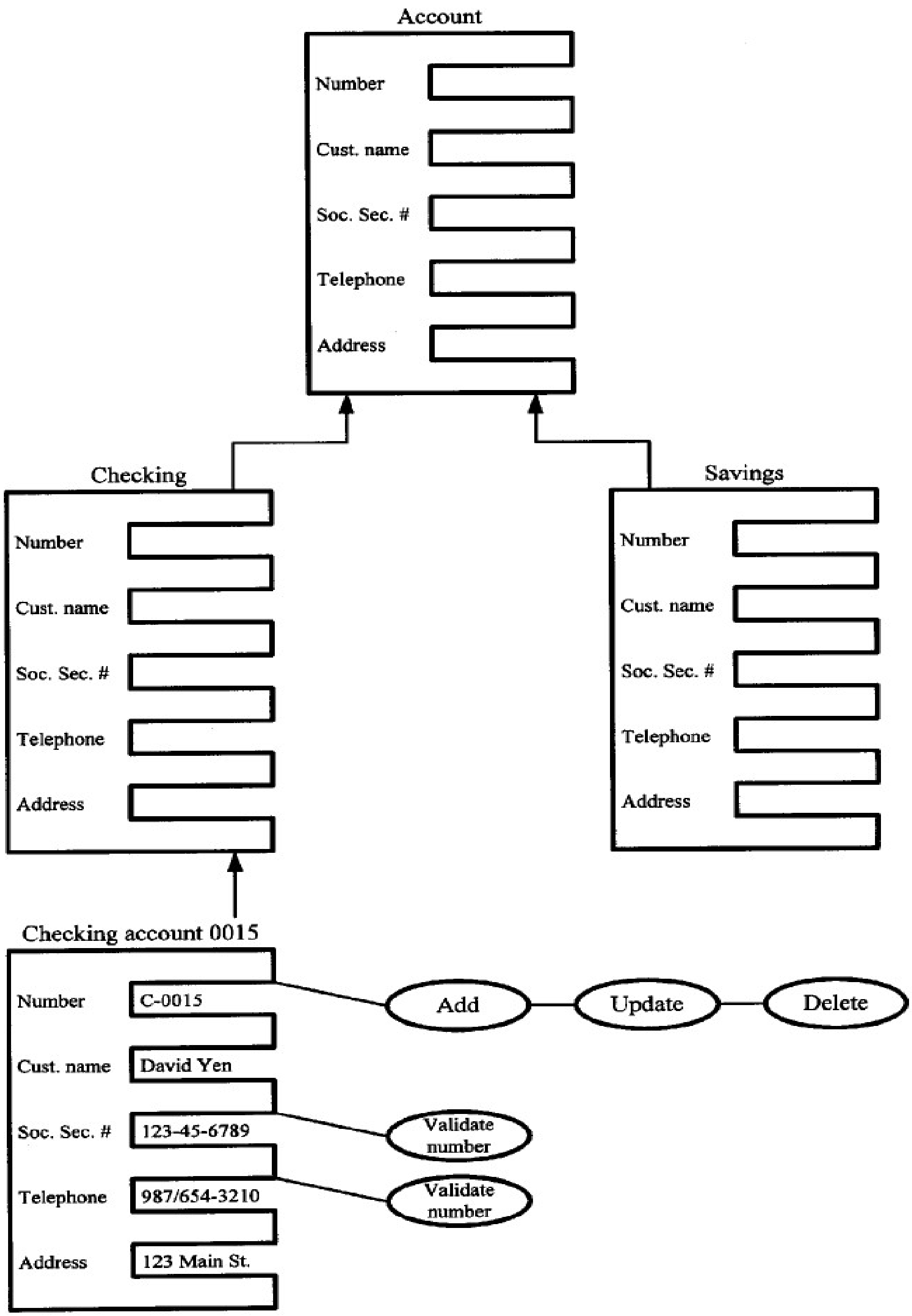


Figure 2.4: A set of frames that represent information about bank accounts (Adopted from Adrian et.al (1992)).

A frame is similar to an object. A slot holds properties or attributes, a value is an actual instance of a particular property, and an attached procedure is similar to a method.

Using frames and slots facilitates certain predetermined information processing activities (such as add, delete, or update an account) and organizes the knowledge for easy retrieval, reference, and maintenance. Not all real-world situations can be resolved by predetermined logic, however, and new situations (e.g., adding a new feature such as a debit card) are not easily accommodated without major changes to the frames and slots structure (Adrian et.al, 1992).

2.7.3. Rules

Rules are the most applicable and relatively easer way of knowledge representation in the development of a knowledge based system. A rule based system consists of a set of IF-THEN rules, a set of facts and an interpreter controlling the application of the rules, given the facts. So, a rule consists of three components, i.e., working memory i.e., a fact base, rule base and interpreter. The fact base contains the information that the system has gained about the problem thus far. The rules base contains information that applies to all the problems that the system may be asked to solve. The interpreter solves the control problem, i.e., decide which rule to execute on each selection-execute cycle (Adrian et.al, 1992).

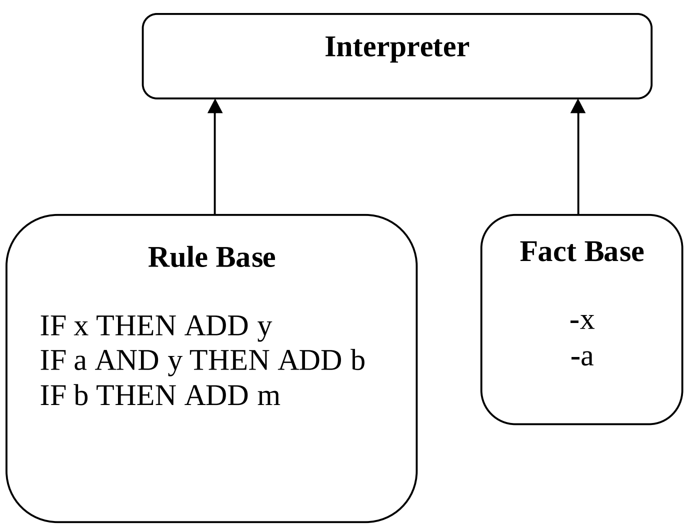


Figure 2.5: Rule based system architecture

These if-then rule statements are used to formulate the conditional statements that comprise the complete knowledge base. A single if-then rule assumes the form ‘if x is A then y is B’ and the if-part of the rule ‘x is A’ is called the antecedent or premise, while the then-part of the rule ‘y is B’ is called the consequent or conclusion.

2.8 Evaluation of knowledge-based system

While the nature, scope, and number of prototype applications of KBS have increased exponentially, knowledge-based systems that are operational are still few and far between (Reich et.al, 1998). A significant bottleneck that is frequently encountered in the transition phase from a prototype to an operational system is the lack of a rigorous and unified framework for testing knowledge-based systems (Reich et.al, 1998). If the accuracy and reliability of a KBS cannot be established, then the purpose of developing an "intelligent system" is defeated (Reich et.al, 1998). Developers of knowledge-based systems often find themselves seriously handicapped by the lack of tools and techniques to validate, verify, test, and evaluate knowledge-based systems. Inadequate test tools can cause human and financial loss, may result in lawsuits, and may cause expert systems to be viewed as a non-viable technology for critical applications (Reich et.al, 1998).

According to Anumba and Scott (2001), the evaluation of a knowledge-based system (KBS) is an important aspect of knowledge-based system development that is required to prove whether or not a system fulfils its original objectives. It is defined as the "process of examining a KBS's ability to solve real world problems in a particular domain". Two fundamental elements of evaluation have been identified, namely validation and verification. Validation refers to "building the right system", whereas verification refers to "building systems right".

The evaluation activity involves exploring the code, and examining the reasoning processes, intermediate results and conclusions of the system, to help detect errors as early as possible in the development cycle. The progress of a system can be monitored by considering the following questions:

- Is the knowledge representation scheme adequate or does it needs to be extended or modified?
- Is the system coming up with the right answers and for the right reasons?
- Is the embedded knowledge consistent with the experts?
- Is it easy for users to interact with the system?
- What facilities and capabilities do the users need?

The above questions indicate that, as the system is being constantly revised, by incorporating feedback from users and expert collaborators, the KBS evolves. Every time a rule in the knowledge base is changed, added or deleted, or the code of the reasoning program is modified or extended, or the knowledge representation scheme is refined, then action has been taken in response to an informal evaluation. In addition to the questions above, other checking mechanism are the following:

- the quality of the system's decisions and advice;
- the correctness of the reasoning techniques used;
- the quality of human-computer interaction;
- the system's efficiency; and
- its cost effectiveness.

Evaluation strategies to assess the effectiveness of knowledge based systems enable strengths and limitations of systems to be accurately articulated. Evaluations of knowledge based systems have often been performed in an ad-hoc manner without regard to theoretical concepts associated with the nature of measurement and the identification of appropriate evaluation strategies. Evaluation strategies for clinical knowledge based systems (CKBS) need to apply to systems that represent knowledge in various ways including rule base systems.

According to Reich et.al, (1998), the determination of appropriate criteria for a comprehensive evaluation cannot be done without a conceptualization of the nature of knowledge. He claims knowledge can be defined in two ways; structurally and functionally. In the structural definition, knowledge is a static entity that includes facts, rules and models that represent real world phenomena. This definition of knowledge enables the direct measurement of knowledge.

In the functional definition, knowledge has a purpose and cannot be measured directly but only indirectly by measuring the behavior of a system that has knowledge. This view of knowledge has been preferred to the structural view by a number of researchers including Newell (2004). Defining knowledge as a structural entity alone is quite limiting. Reich et.al, (1998) maintains that only with simple knowledge representation schemes and simple inference mechanisms can a prediction about the expected performance of a system be reasonable. Such a prediction becomes increasingly difficult once the knowledge schema becomes complex.

There are benefits inherent in the structural view of knowledge for the evaluation of intelligent systems despite limitations raised by Reich et. al, (1998). Inspection of rules, facts and inferences made is certainly useful in the testing phase of rule based systems development. Furthermore, the size of the rule set is often used as an indication of the performance of the system. A knowledge base consisting of 80,000 rules is very large and the system that infers with such a set is likely to make sophisticated inferences (Reich et.al, 1998).

In addition to the structural/functional knowledge dichotomy, criteria for the evaluation of knowledge based systems can be based on quantitative or qualitative metrics. A count of the number of rules in a rule based knowledge based systems is quantitative while an end user opinion is qualitative. Furthermore, both qualitative and quantitative criteria can be discovered for knowledge that is structural and also for knowledge that is functional.

The extent to which a knowledge base is readable or transparent to knowledge engineers is important because maintenance is difficult with knowledge bases that are overly complex or ill-structured. This is qualitative measure and assumes the structural view of knowledge. Quantitative measures that assume functional knowledge are more commonly used in evaluating knowledge based systems. The Mycin system of Shortliffe et al (2000) was evaluated by comparing diagnoses, with those of specialists. Buchanan et al (1996) advocate user acceptance as an appropriate evaluation criteria for their intelligent system in the medical domain. User acceptance is a useful criterion because ultimately, the benefits of the system will only be realized to the extent that user's actually engage the system.

Most developers employ the use of qualitative techniques such as the common process of running test cases through the proposed system and comparing the system's output with known results (Moore and Miles, 1991). Quantitative techniques are rarely used and are considered inappropriate for the evaluation of a KBS (Moore and Miles, 1991). This is mainly because these approaches would not normally be used for the evaluation of human expertise. Generally, KBS developers desire to assess their KBSs at a similar level to human experts, and therefore adopt qualitative techniques. The most commonly employed qualitative techniques to evaluate KBSs are outlined below (O'Keefe et al., 1987, Hayes-Roth et al., 1983):

- Visual interaction: this test allows the expert to make comments while interacting with the system, altering parameters as desired.

- Predictive validation: this test involves the use of historic test cases. The KBS is driven by past data to obtain a set of conclusions. These conclusions are compared with that of the historic case or with expert performance.
- Black box testing: information is added to a piece of code and sections of, or the whole system. Results are predicted and are compared with the actual results of the system.
- Sensitivity analysis: this test consists of systematically changing a system's input variables and parameters over a range of interest to observe the effect upon system performance.

The above list highlights the main techniques considered useful for the evaluation of a knowledge-based system.

2.8.1 Measurement System

Burns and Grove (2001) describe measurement as "the process of assigning numbers to objects or events to situations in accord with some rule." According to the authors, a component of measurement is instrumentation, which is the application of specific rules to the development of a measurement device or instrument and the instrument is selected to examine a specific variable in the study. The purpose is to produce trustworthy evidence that can be used in evaluating the outcomes of the research study.

A measurement system must be defined that will accurately characterize how well the method followed in the development of the KBS is performing compared to the human medical expert. Any decision that the system makes will be either correct or incorrect according to the experts; however, because there could be multiple, ordered rate classifications, more information than correct/incorrect can be captured.

Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data. The simplest type of classification problem is binary classification. In binary classification, the target attribute has only two possible values: for example, high infection or low infection. Multiclass targets have more than two values: for example, low, medium, high, or unknown infection.

A confusion matrix, a popular measurement tool for medical diagnosis, displays the distribution of the records in terms of their actual classes and their predicted classes. It is statistical measures of the performance of a binary classification test which indicates the quality of the current model (Anumba and Scott, 2001). As an example, the following confusion matrix is depicted for two possible outcomes p (positive) and n (negative).

		Actual		
		p	n	Total
Predicted	p'	true positive	false postive	P
	n'	false negative	true negative	N
	total	P'	N'	

Table 2.2: Confusion Matrix (Adopted from Anumba and Scott (2001))

The confusion matrix defines two parameters. These parameters, as shown in table 3.1, are:

1. *Sensitivity (also called recall rate)* - measures the proportion of actual positives which are correctly identified as such (for example, the percentage of sick people who are infected);
2. *Specificity* – measures the proportion of negatives which are correctly identified (for example, the percentage of well people who are identified as not having the infection);

2.9 Acute Respiratory Tract Infections/ARTI/

2.9.1. Introduction

Despite decades of dramatic progress in their treatment and prevention, infectious diseases remain a major cause of death and debility and are responsible for worsening the living conditions of many millions of people around the world. Acute Respiratory Tract Infections are among the one which is the most common causes of illnesses in the world and have reaching health, social and economical consequences (WHO, 2008).

Infectious diseases of the respiratory tract are a major cause of morbidity and mortality worldwide. About 4 million deaths from acute lower respiratory infections (ALRI) occur throughout the world annually. The severity and fatality of ARI is much greater in the developing nations and amongst socially and economically deprived groups in the developed countries (WHO, 2008).

In developing countries, acute respiratory tract infections are the leading cause of morbidity. The cost of these infections is enormous because of lost earnings and the cost of treatment.

They kill 4 million people every year in developing countries, and most of these deaths are caused by pneumonia. ARTI are responsible for 8.2% of the world's total burden of disability and premature death (WHO, 2008).

Acute lower respiratory infections cause 19% of all deaths among children younger than 5 years and adults and 8.2% of all disability and premature mortality (as measured by disability-adjusted life years). In developing countries, pneumonia kills 3 million people every year, and other acute respiratory tract infections kill another million people. This huge mortality goes virtually unnoticed, despite the fact that it is equivalent to a jumbo jet carrying 400 people crashing every hour, day after day (WHO, 2009).

2.10. Acute Respiratory Tract Infections in Ethiopia

In Ethiopia, Acute Respiratory Tract Infections are now spreading widely. It is the primary cause of visits to health clinics and outpatient hospital clinic. The main problem is that up to now, the countries haven't had a diagnosing method that is good enough to confirm or exclude ARTI. In addition, most Ethiopians are living in countryside where there is not enough of facilities for diagnosis and treatment (WHO, 2009).

In diagnosing of ARTI, doctors have to cope with many difficulties: patient's symptoms are usually unclear and the similarities in symptom aspect between lung tuberculosis and other infections. Even if the bacteria and the virus are often found in the patients, the diagnosis' result depends not only on patient's symptoms but also strongly on doctor's experiences. Therefore, there are many mistakes in diagnosing and treating ARTI which cause the high rate of patient's death and the wide spread of the infections (WHO, 2009).

On the other hand, a number of difficulties have been encountered in developing countries like Ethiopia. First, in clinical decision making, a physician cannot make a diagnosis with high accuracy due to lack of modern equipment caused by restricted financial resources. Second, there are not sufficient good physicians to serve the whole population. Third, in the country, traditional medicine and techniques are also employed which are based on experience which is often not documented for the next generation of doctors (MoH, 2008).

In its complications and impacts, according to MoH (2009), ARTI are of public health concern following to STI (Sexually Transmitted Infections) in Ethiopia not only because of their high prevalence, but also their potential to cause serious complications in infected people who are not treated in a timely and effective way. In addition, especially pneumonia, are known to facilitate for complications like HIV/AIDS on the patient. Most of the health consequences of ARTI tend to occur in children of age less than 12. This is because they have not yet built up immunity to the many viruses that can cause infections like colds. In addition, untreated ARTI could lead to loss of life. Specially those people who live in countryside, due to lack of health care facilities like clinics and hospitals, the severity of the infections tends to rise two fold than people who live in urban areas (WHO, 2009).

2.11 Diagnosis of ARTI in Ethiopia

ARTI is a major public health problem in Ethiopia. In Addis Ababa hospitals and health centers, upper respiratory tract infections were diagnosed in 31% of the illnesses seen. This was the most frequent diagnosis, followed by gastrointestinal tract disorders (10%); all other diagnoses were less than 10% (Dakubo et.al, 2009). In a study of the pattern of patients room visits in different hospital's in Addis Ababa, respiratory diseases accounted for 66.6% of 30 067 cases. Upper respiratory tract infection was responsible for 32.5% of cases, bronchial asthma for 16.5%, and acute tonsillitis for 8.2% and pneumonia for 2.4% of the cases (Bashour et.al, 2008).

The diagnostic procedures and treatment of ARTI in Ethiopia indicated that there is an overuse or inappropriate X-ray, complete blood count and culture as well as other tests. The use of X-ray for 77% of the ARTI cases is a case in point. In addition, the use of antibiotics and other drugs appears to be high. It is envisaged that a national ARTI program launched in 2009 by Ministry of Health (MoH) reduces the inappropriate use of drugs significantly and hence reduces the cost of ARTI management. But, decreasing the number of antibiotics used and preventing inappropriate use were also leads to less community resistance to the antibiotics, which is an important issue. It has been found that at least one-third of patients attending primary health care centers in Addis Ababa failed to comply with short-term antibiotic therapy (Dakubo et.al, 2009), which could be dangerous. Many studies have been conducted in Ethiopia on prescribing patterns (Bashour et.al, 2008) and it is important that the principles of proper antibiotic therapy be followed and is part of continuing medical education (Lye MS et al, 2008).

Physicians found in the country none of them had had any training in the management of ARTI other than what they had learnt at medical school, whether in Addis Ababa or in their previous experiences (WHO, 2009). In addition, there is no any standard protocol for diagnosis and drug use, limited provision of health education for the community regarding

ARTI, inappropriate methods of providing health care, risk factors and the proper time to seek medical assistance for treatment (WHO, 2008).

2.12. Knowledge Base Systems and ARTI

Like explained above, artificial intelligence is a branch of computer science emphasizing on building software and making hardware to have human-like intelligence (Coiera et al, 2004). One of the artificial intelligence applications used for commercial is medical knowledge base system. The application of KBS in clinical decision making process is based on the reason that there are increased symptoms and medicines while doctors have limitations to remember all the symptoms and medicines, as well as dosage of medicines. Accordingly, the KBS is needed to assist doctors in diagnosing particular disease based on its symptoms. The result of diagnosing, then, is adjusting to patient condition in deciding medical treatment (Zili et al, 2003).

The aim of the study is to apply the knowledge base system as a tool to diagnose ARTI. In diagnosing ARTI, it is expected that the KBS can assist doctor to determine properly the medical treatment. It can also permit paramedic to do as doctor in facing cases properly in accordance knowledge and inferring procedure.

A knowledge-base system goes one step further and not only provides information but also interprets it to the same level as a human expert would. Therefore, knowledge base systems offer good possibilities for application to diagnosis. However, development of such a system requires 'tools and techniques other than the development of a conventional system. The development of knowledge-base systems in medicine is still in an early stage (Coiera et.al, 2004).' There are some knowledge-base systems developed for diagnosis of different diseases like MYCIN, INTERNIST etc. As of my best knowledge no descriptions were found of knowledge base system developed for diagnosis of respiratory tract infections.

Knowledge base systems are widely used in developed countries but their applications are limited in developing counties. In fact, KBS should be used more in developing countries for many reasons. But one main reason is there are large numbers of well-trained technicians but there are limited numbers of professional experts such as engineer and medical doctor. On the other hand, the available KBS programs and KBS shells are effective, inexpensive and PC based applications. Most of these modern KBS software are user friendly and extremely powerful such that the size of KBS is only limited by the capacity of computer (Coiera et al, 2004).

Considering the excessive amount of and many kinds of acute respiratory tract infections and symptoms, in the other side the doctor's memory for remembering all kind of these infections and symptoms is very restricted. So, it is needed KBS as an auxiliary tool for the doctor in diagnosing a disease based on its symptoms and other factors. The diagnose result will become a basis of medicine usage on patient as medical treatment; and to tackle such problem effectively ordinary systems should be changed in a way that the diagnosis functions that is previously done by different health workers in all of the health service delivery systems like at the health post, health center, district hospital, and regional or referral hospital, must be systematized by computer operation. Undeniably, knowledge base systems are at the tracks which are coming in a fully functional way to alleviate such problems. It can improve the rate of the accuracy diagnosis of physician with the auxiliary help of this system, which have the obvious meaning in low the mortality and high the survival rate, and has strong practical values and further social benefits.

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

To undertake a scientific study, all the components should fit together in a meaningful whole. To achieve this goal, the researcher needs to draw up a design, the strategy for conducting the study or the plan to obtain answers to the research questions. Burns and Grove (2001) describe the research design as a “blueprint for conducting a study that maximizes control over factors” that could interfere with the validity of the findings. Polit et al (2001) also described the research design as the “research investigation in a logical and systematic way.” It spells out the strategy the researcher plans to adopt to develop information that is accurate and interpretable. The research design guides the researcher in planning and implementing the study to achieve the intended goal. The control provided by the design increases the probability that the study results are accurate reflections of the real situations.

Polit et al (2001) also added that research methodology is a technique used to structure a study and gather and analyze the data in the course of the research investigation and consists of a set of orderly, disciplined procedures to acquire information. This section of the thesis describes the research design and methodology employed for the purpose of collecting required data to assess the magnitude of the problem and acquire necessary knowledge, to explain processes of KBS development for ARTI diagnosis, to discuss on the implementation tool used in order to conduct experiment to achieve sustainable reductions in rates of the common ARTI.

3.2. Study Design

To discover an alternative approach for the diagnosis and management of ARTI, one should have pertinent and precise knowledge about ARTI. Koal (2006) stated that descriptive survey approach become particularly useful where one needs to understand some particular information which presents a complete description of a phenomenon with in its context. In addition Burns and Grove (2001) state that descriptive designs help to identify problems in current practice with a view to improve practice outcomes.

The purpose of descriptive survey research is the “exploration and description of real-life situations” and to provide information of the elements as they occur (O'Leary, 2001). Thus, the descriptive survey method is suitable to be employed in this investigation to understand the way how to manage and to asses the diagnosis session associated with ARTI. It is also thought appropriate to generate adequate information for the experiment to develop an alternative approach to diagnose and manage ARTI. Therefore, descriptive study supported by qualitative approach was conducted in selected health institutions, in Addis Ababa from February 2010 to April 2010. The study was conducted for preliminary assessment of acute respiratory tract infections in Addis Ababa.

3.3. Study Area

The study was conducted in Addis Ababa, which is the capital city of Ethiopia. At the time of the study the city was divided into ten Kifle Ketemas (sub-cities) under which 100 kebeles (smallest administrative units) are included. Addis Ababa has the best health coverage in the country which is 88.25%. There are 24 hospitals, 23 health centers, and 456 clinics in the city.

3.4. Study Population

The target population in this study represents the medical experts who were diagnosing patients with ARTI cases and patients who were vulnerable for ARTI and admitted to hospital and clinic for ARTI diagnosis and aged above 18 years at the selected health institutions.

3.4.1. Inclusion and Exclusion Criteria

All persons who were unable to hear, unconscious and mentally disabled were excluded from the source population.

3.5 Sampling Procedure and Sample Size

Burns and Grove (2001) describe sampling procedure as “the characteristics essential for membership in the target population”. Purposeful sampling procedure was employed and Dagmawi-Minilik Hospital and Meshwalekia middle-level clinic were purposefully selected from 24 hospitals and 456 clinics in Addis Ababa. Burns and Grove (2001) define purposive sampling as “judgmental sampling that makes the conscious selection by the researcher of certain subjects or elements to include in the study”.

Dagmawi-Minilik hospital is situated in Yeka Kefele Ketema to the northern part of Addis Ababa. Meshwalekia middle-level clinic is situated in Kirkos Kefele Ketema to the eastern part of Addis Ababa. Both health institutions provide health care services for out-patients and in-patients specially Dagmawi-Minilik hospital serving as teaching for health sciences. The staffs are highly qualified and the hospital and the clinic are well equipped with modern laboratory. These health institutions are selected purposively. This selection is based on the following conditions:

i. ARTI cases are commonly seen in hospitals and especially in middle-level clinics.

ii. Easy access of ARTI expertise, patients and stand alone computer in examination rooms.

iii. Many people are available irrespective of sex or age which includes qualified ARTI expertise and high ARTI vulnerable groups.

The reason why other hospitals and clinics were not included was that different hospitals and clinics follow the same procedures and guidelines to diagnose and manage ARTI cases and many patients who were vulnerable to ARTI cases could be found in the above selected hospital and clinic.

Given that the intent of the descriptive survey in this research was to assess the magnitude of acute respiratory tract infections, all study experts and patients were selected using stringent criteria, including their knowledge and experience in healthcare and patient safety for the experts and age and years of schooling completed for the patients. In addition, the following criteria were utilized for inclusion of medical experts in this preliminary assessment:
(a) Medical experts who had been involved in patient healthcare and ARTI management;
(b) Medical experts who had been using WHO ARTI case management guideline;

The number of experts with such qualifications was fairly limited (n = 6 (three experts from Dagmawi-Minilik hospital and three experts from Meshualekia middle-level clinic)) and the sample of patient participants was small (n = 30 (fifteen patients from Dagmawi-Minilik hospital and fifteen patients from Meshualekia middle-level clinic)).

3.6. Data collection

Burns and Grove (2001), define data collection as “the precise systematic gathering of information relevant to specific research objectives or questions”. According to Burns and Grove (2001), data can be collected in several ways depending on the study and can include a variety of methods; however, the research objectives must be accomplished with the instrument used.

For the purpose of collecting data for this research, primary and secondary sources of data were used. As primary sources, medical experts in health including drug advisors, physicians and pharmacists from Dagmawi-Minilik Hospital and Meshwalekia middle-level clinic and patients were interviewed to understand the dimension of ARTI. Besides, guideline for ARTI Prevention and Management published by Ministry of Health Ethiopia (MoH, 2009), related documents, books and journals were assessed as secondary sources of data.

3.7. Data Analysis and Presentation

Narrative analysis was selected as the primary analytic framework for the research. Narrative constitutes a data unit that reliably reflects the interdiscursive mix of decoded information and internalized value and belief systems regarding various domains of social life, including health and disease (Viney et al, 1991).

From the researcher’s point of view narrative analysis can have either a descriptive or an explanatory purpose. If the purpose is descriptive, the aim is “to produce an accurate description of the interpretive narrative accounts individuals or groups use to make sequences of events in their lives or organizations meaningful” (Polkinghorne, 1988). An explanatory purpose would be to account for the connection between events in a causal sense and to provide the necessary accounts that supply the connections (Clandanin & Connelly, 2000). In this research the purpose is descriptive and interdiscursive, particularly to describe the magnitude of Acute Respiratory Tract Infections (ARTI). The result obtained from this narrative analysis shows the magnitude of the problem and the diagnosis session associated with ARTI which in turn useful to understand how medical experts manage ARTI cases and design and implement the proposed knowledge base system accordingly.

3.8. Processes of KBS Development (Knowledge Engineering) for ARTI Diagnosis

The process of knowledge base system development or, knowledge engineering, is the extraction, articulation and computerization of knowledge. It can be represented by four highly interdependent and overlapping phases as described below. The common phases are problem selection, knowledge acquisition, knowledge presentation, and knowledge application (Stuart et al, 1995).

- **Problem Selection**: The most critical step in developing a knowledge base system is identifying a suitable problem. KBS's are best suited to problems that require experience, knowledge, judgment, and complex interactions to arrive at a solution (O'Leary, 2001). For many medical situations the importance of diagnosis as a task requiring computer support in routine clinical situations receives equal emphasis with other clinical tasks. The clinical care of a particular patient often proceeds in distinct phases, such as diagnosis before therapy, or prevention of disease before onset of disease, or rehabilitation of the patient after therapy of the patient (O'Leary, 2001).

  It is obvious that diagnosis is only one of the many problems in clinical medicine. When a patient's case is complex (or rare) or the person making the diagnosis is inexperienced, KBS's helps by giving likely diagnosis based on patient's data. KBS's are also used to train and practice clinicians and students on various medical tasks (Polit et al, 2001).

  One of the first tests to determine if a subject area is suitable for KBS is whether the solution of the problem requires the knowledge and expertise of a human expert. From the result obtained in the preliminary assessment conducted in two health institutions in Addis Ababa, a high mortality due to severity of the acute respiratory tract infections is great enough and it has been evidenced that some solution should be devised (the result obtained from the survey research will be provided in the next section of this thesis). As this research suggests, the successful implementation of KBS may offset cost of development. The KBS solution could be also valuable as a constant source of expertise for decision makers in medical, available at all times and to all physicians as well as people on ARTI management aspects.

- **Knowledge Acquisition**: Once the problem is identified the knowledge acquisition phase of KBS development is carried out. Knowledge acquisition is the accumulation, transfer, and transformation of problem-solving expertise from some knowledge source to a computer program for constructing or expanding knowledge base (O'Leary, 2001). The task in this phase is to have the knowledge which the expert uses to solve the problem displayed in a logical fashion so that it can be coded into the computer (Polit et al, 2001). In here, the typical resource is knowledge.

  For this research two sources are utilized for knowledge acquisition in the domain of ARTI diagnosis: technical literature and interviews with domain experts from Dagmawi-Minilik Hospital and Meshualekia middle-level clinic. The medical experts were selected only from Dagmawi-Minilik Hospital and Meshualekia middle-level clinic primarily because all the other medical experts from different hospitals and clinics use the same ARTI case management guideline and procedure. On the other hand, the technical literatures include sources such as guidelines, manuals, journals, conference proceedings, and medical text books. These sources are generally well organized and ready to use. There are several guidelines and manuals as well as text books which attempted to document the general management of Acute Respiratory Tract Infections. These sources were extensively used to extract initial knowledge about the problem. The knowledge extracted from these sources is very important but usually insufficient for diagnosing ARTI. This is why the second source, interviews with domain experts, is crucial. It comprises knowledge from experience in managing ARTI cases.

- **Knowledge Representation**: Its purpose is to organize the required knowledge into a form that the knowledge base system can readily access for decision making, planning, recognizing objects and situations, analyzing scenes, drawing conclusions, and other cognitive functions. Representing knowledge and mimicking the decision-making behavior of domain experts is a central problem in the development of medical knowledge-based systems (Anumba and Scott, 2001). The chosen representation scheme should cover all pieces of the domain knowledge. Reusability and shareability of the knowledge are other desirable features, since the development of useful knowledge bases is a very time and cost consuming process (Gashing, J. et al, 2000).

In this research a knowledge representation technique that best matches the way the expert mentally models the diagnosis of ARTI was required. So, from the different knowledge reasoning techniques like case-based and frame-based reasoning, a rule-based reasoning was chosen to design the KBS because it is the most common way to represent the acquired knowledge and has got a lot of research interest in medicine over the last decades (Aroyo, 2006; Christer, 1991); and the following approach was applied:

If (X) Then (Y)

In the domain problem there are a number of symptoms (i.e., patient data) that all contribute in diagnosing the infections. IF-THEN rules are used for representing of ARTI. Moreover, the piece of knowledge represented by the production rule is relevant to the line of reasoning being developed. If the IF part of the rule is satisfied, consequently, the THEN part can be concluded, or its problem-solving action taken.
In relation to this, backward chaining is used in this research because the expert first considers some conclusions and then attempts to prove it by searching for supporting information since the expert is mainly concerned with proving some hypothesis or recommendations.

- **Knowledge Application**: this includes the testing and evaluation phase which is to verify the reasoning and/or inference process. The prototype knowledge base system must be tested and evaluated to determine internal consistency in the logic and to confirm that it was built according to planned specifications (O'Leary, 2001). The evaluation of medical knowledge based systems is important, and it is also difficult because there is no generally accepted methodology for carrying out this evaluation. The major aspect in the evaluation of a medical knowledge-based system is to find out whether the system is safe and legal, and to study the impact of the system on patients and the organization (Adrion et al., 2002). An important step of system evaluation which should involve people is to validate the system or determine that it behaves like a human expert (O'Leary, 2001). Adrion *et al.* (2002) define validation as "the determination of the correctness of the system with respect to the user needs and requirements".

  There are several methods for knowledge base systems validation which vary from the simple ones such as using test cases and sensitivity analysis to the more sophisticated such as using simulation and statistical techniques (Gashing, J. et al, 2000). The choice of the appropriate validation method depends on factors such as: the type of the problem handled by the system, the availability of human experts, case studies, time and money, and the development stage of the system. Using test cases is the present predominant method for knowledge base systems validation (O'Leary, 2001).

The diagnosis phase of the prototype knowledge base system was validated using test cases. Due to data limitations, all cases were signalized. The cases were solved by both the system and medical experts who are responsible for diagnosing ARTI in Dagmawi-Minilik Hospital and Meshualekia middle-level clinic. The system results were then shown to the experts who were asked to assess the agreement between their results and those of the system. The fact that the experts solved the test cases before seeing the results of the system is very important to eliminate any bias. The experts were asked to select one of five agreement scales: Perfect Agreement, Strong Agreement, Fair Agreement, Slight Agreement, and No Agreement. In determining a rating for the agreement between the system results and the experts, two factors were considered: whether the infections and countermeasures (diagnosis) were correctly identified by the system and the corresponding degree of belief associated with each correctly identified infections or countermeasure (diagnosis).

An important issue in the testing and evaluation process is the definition of the minimal acceptable standards that will permit a system to be regarded as a success (Gashing, J. et al, 2000). So, in order to achieve the objective of the study each chapter of the development phase was revised with previously selected medical experts using semi-structured interview. For this research, from the most commonly employed qualitative techniques to evaluate KBSs, visual interaction and predictive validation techniques were used to test the prototype knowledge base system performance.

The visual interaction test allows the expert to make comments while interacting with the system and the predictive validation test involves the use of historic test cases and comparing the system’s output with known results (Anumba and Scott, 2001). For this experiment, using random sampling technique, the users of the system were classified into two different groups. The first group incorporates 12 (twelve) medical persons in which 6 (six) from Dagmawi-Minilik Hospital and 6 (six) from Meshualekia middle-level clinic who were using the system as an ARTI counselor (junior and senior physicians); and the second group includes seven patients (four from Dagmawi-Minilik Hospital and three from Meshualekia middle-level clinic) and five voluntary system users.

On the other hand, evaluation using test cases was conducted mainly by the researcher and, at the same time, with each one of the twelve experts. The main aim of predictive validation is to test the prototype knowledge base system performance to diagnose ARTI syndromes. Using rough estimation, expected to be enough to prove and demonstrate the systems' capabilities, twenty-five historical test cases were selected from ARTI archives which are used to compare the diagnosis of the past with that of the system and the experts. These cases were selected by the expert evaluators using random sampling technique so that no bias would be introduced into the evaluation process. Then, of those historical test cases, using proportionate stratified sampling techniques four cases were selected for testing the prototype to ensure the performance of the system with that of the experts. Proportionate stratified sampling technique helps in selecting cases randomly by stratifying the cases in terms of curable or non curable ARTI. For each selected historical cases, ranking was set by the evaluator expert to check whether the system is consistent with that of the experts. Unstructured questionnaires were conducted in conjunction with entering the cases into the system, to help ascertain the expert's view on the systems' performance.

In relation with this, in order to posses the true quality of the model used in the prototype knowledge base system performance test, confusion matrix is used in this research. Confusion Matrix displays the distribution of the records in terms of their actual classes and their predicted classes. It indicates the quality of the current model (Anumba and Scott, 2001).

3.9. Implementation Tool

As a programming tool, prolog language is used to demonstrate the potential of the prototype knowledge base system in diagnosing Acute Respiratory Tract Infections (ARTI). Its name is derived from the phrase "PROgramming in LOGic". Prolog is a full, industry-standard programming language, ideally suited to writing rules. The choice of Prolog is due to three major features of the language that are not commonly found in other languages: rule-based programming, built-in pattern matching, and backtracking execution. The rule-based programming allows the program code to be written in a form which is more declarative than procedural. This is made possible by the built-in pattern matching and backtracking which automatically provide for the flow of control in the program. Together these features make it possible to elegantly implement many types of knowledge-based systems (Liddle, 1999). In addition, Prolog is not a difficult language to learn.

CHAPTER FOUR

RESULTS OF THE PRILIMINIARY ASSESSMENT

4.1. Introduction

Acute respiratory Tract Infections (ARTI) are a leading cause of mortality in adults and children under five in the developing world, accounting for more than three million deaths annually, 80 percent from pneumonia. In Ethiopia, ARTI are now spreading widely. In its complications and impacts, according to MoH (2009), ARTI are of public health concern following to STI (Sexually Transmitted Infections) in the country not only because of their high prevalence, but also their potential to cause serious complications in infected people who are not treated in a timely and effective way. For example, pneumonia is known to facilitate for complications like HIV/AIDS on the patient.

The severity of ARTI is also a great concern in Addis Ababa. So, for preliminary assessment of the magnitude of acute respiratory tract infections in the capital city and to understand the way how to manage and to asses the diagnosis session associated with ARTI, descriptive study supported by qualitative approach was conducted in Dagmawi-Minilik Hospital and Meshwalekia middle-level clinic from February 2010 to April 2010 and the result of the survey has also provided as below. This preliminary assessment was appropriate to create a good ground about the magnitude and extent of acute respiratory tract infections for the experiment to develop an alternative approach to diagnose and manage ARTI.

4.2. The Research Instrument

The preliminary interview guide used cultural and biomedical knowledge to structure questions that would elicit a clear understanding of ARTI in Addis Ababa. After two days of pre-testing this interview guide in the field setting, the researcher revised and developed a final instrument (Appendix 4) which elicited three categories of information from respondents:

1. Illnesses which is mostly occurs in adults and children (Question 1);

2. Sources of patients care in and away from their home (Question 2-4);

3. Narratives of ARTI-related illnesses that explain how the health institutions define, diagnose, and respond to ARTI in adults and children (Questions 5-6).

All of the questions in the interview guide were designed to elicit qualitative data. The emphasis was placed on the quality of the data, and a good interview provided understanding and depth in at least one dimension of ARTI beliefs and behaviors. As such, it was more important for researcher to obtain good narratives from respondents about an ARTI-related event in patients than to receive a brief answer to every question in the interview guide.

4.3. Findings

4.3.1. Characteristics of the Respondents

The cooperation of the hospital and clinic staff and the patients made it possible for the researcher to conduct more interviews than anticipated. The researcher conducted interviews of 30 individuals in Dagmawi-minilik hospital and Meshualekia middle-level clinic. Although the majority of patient respondents were married mothers of children under the age of five, also included were grandmothers and fathers who came for medication in the two health institutions.

The population requiring health care in the selected health institutions was predominantly female (62%). Female predominance, which is universal, is significant and could be explained by the fact that women are more anxious of their health, or maybe more vulnerable because of their reproductive health life (e.g., child bearing, genital activities, post partum). In addition, they are probably more available than men to attend the health centers or more able to manage the long waiting time at the health settings (Silva et al, 1998).

Children aged less than 15 years accounted for 33.1%, and those aged 65 years and over accounted for 13.7% of the surveyed consultations (Figure 1). The age-sex distribution of the study population showed that among young people aged less than 25 years, patients were predominantly male. In contrast, patients aged 25-64 years were predominantly female and the sex distribution of those aged 65 years and over was equally distributed (Figure 1). Most of the respondents didn’t recognized different types of ARTI illness terms, had children who had a past case of ARTI, and knew about or had used different types of traditional medicines to treat ARTI on their children.

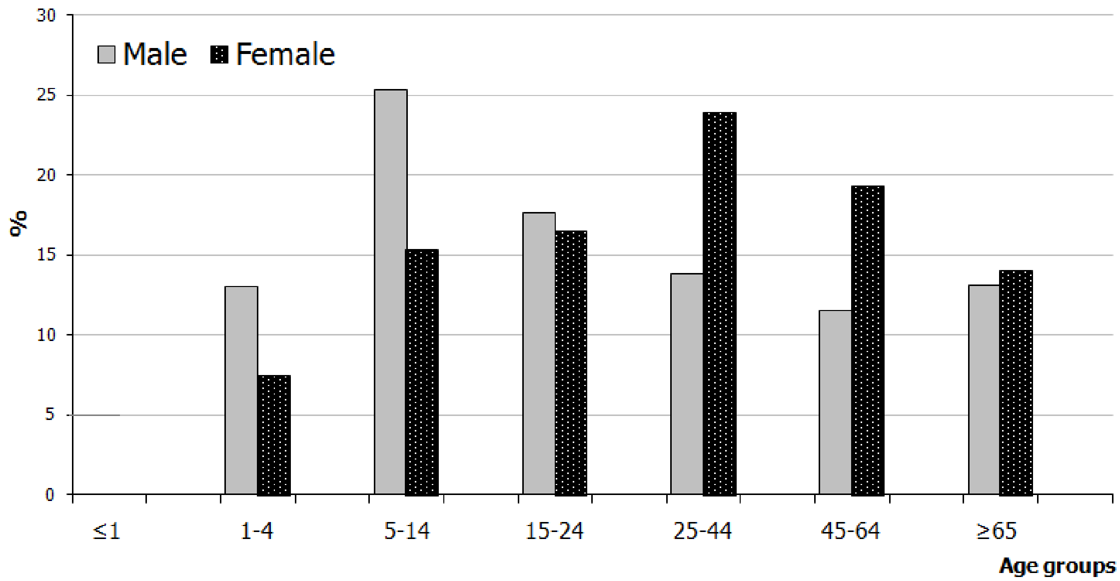


Figure 4.1: Age and Sex distribution of study population

4.3.2. Health Problems which are mostly occurs on the patients

4.3.2.1. Distribution of health problems by Sex Group

Respiratory tract infections came in first place for both genders. However, skin diseases, which are ranked second, were also prevalent in males and digestive problems in females. The genital affections and psychological problems were at the bottom of the list for both genders, making them the less identified affections in health institutions.

4.3.2.2. Distribution of health problems by age group

The distribution of health problems managed on the selected health institutions was variable with age. Up to 24 years, the top three identified problems were respiratory tract infections, such as tonsillitis, acute upper respiratory infection, and acute bronchitis and pneumonia which are infections of the lower respiratory tract. Among children, under 5 years of age, the frequency of respiratory tract infections was more than 60%, whereas digestive affections, such as diarrhoea, gastrointestinal infections, worms and parasites, came next and constituted 14%. For adults 25-44 years of age, respiratory tract infections remained the most frequent problem (34%).

For the age group of 45-64 years, acute bronchitis and pneumonia was the top health problem (14.2%), followed by diabetes (9.3%) and uncomplicated hypertension (8.5%).

Elderly population aged 65 years and over was characterized by an increase of chronic affections. High blood pressure was the most common disease (22.4%) and diabetes mellitus came in third place (7.9%). In addition, respiratory tract infections and locomotive illnesses were also frequent and presented, together, almost 30%.

4.3.3. Acute Respiratory Tract Infections Illnesses showed in Addis Ababa

There is a specific comprehension of ARTI in the city as the data suggests. To discuss ARTI, one must refer to its upper and lower domain. The researcher found two basic uses of this term: a literal meaning (any infection of the respiratory tract) and a more general meaning reserved for describing any illness or ailment. When the respondents asked to name the types of ARTI they know about, some of the list included gunfan (common cold), tonsil (acute Pharyngitis (tonsilitis)), sinus (acute bacterial sinusitis), bierd (pneumonia) and bierd kewugatina kesal gar (acute bronchitis) (Table 4.1). The patient may have one of these illnesses, or suffer from a combination of two or more.

4.3.3.1. Categories of Severity for ARTI Illnesses

In contrast to the biomedical definition of acute respiratory tract infections, is the respondent's conceptualization of ARTI in Addis Ababa. Within the category of ARTI, some illnesses were considered a normal part of the patients growing up process. These illnesses include yetirs meblat, gunfan, nift, muket and masnetes. Respondents indicated that these illnesses come and go without the need for any serious treatment. The researcher labeled them as ordinary ARTI-illnesses. More serious illnesses which can cause ARTI includes tikusat, mastawek, yebierd himem, yekusil simiet, yejoro himem, yeayin mekilat, yehod kurtet, yedikam simeit and sal.

In this study, yebierd himem (pneumonia), yetonsil himem (acute pharyngitis), sinus (acute bacterial sinusitis), gunfan (common cold) and bierd kewugatina kesal gar (acute bronchitis) have been assigned into the subcategory most serious respiratory tract infections for these reasons: respondents reported that an infection like common cold could lead to other complication like pneumonia and TB (tuberculosis) and the other illnesses could be life-threatening and lead to a patients death. Furthermore, customary beliefs about the etiology of these illnesses are associated with the realm of the supernatural, presenting a challenge to health education efforts. The following table illustrates these common illnesses of ARTI.

Amharic Term	**English Term**
A. Illnesses and Symptoms Related to the Normal Growing Experience	
yetirs meblat	(teething)
gunfan	(coughing)
Nift	(mucous)
muket	(temperature, body heat)
masnetes	(sneezing)
B. Serious, Life Threatening ARTI Symptoms and Illnesses	
tikusat	(fever)
mastawek	(vomiting)
yebierd himem	(pneumonia pain)
yekusil simiet	(sores)
yejoro himem	(ear pain)
bierd kewugatina kesal gar	(acute bronchitis)
yeayin mekilat	(red eyes)
yehod kurtet	(stomachache)
yedikam simeit	(fatigue or tiredness)
deret lay yemisema sal	(cold illness which feels on the chest)
gunfan	(common cold)
sinus	(acute bacterial sinusitis)
C. Core ARTI Terminology	
gunfan	(common cold)
tonsil	(acute phryngitis)
sinus	(acute bacterial sinusitis)
bierd	(pneumonia)
bierd kewugatina kesal gar	(acute bronchitis)

Table 4.1 ARTI Illness Terms

4.3.4. Health Response to ARTI in Adults and Children

4.3.4.1. Sources for Care Treatment and Options in patients home

The most immediate sources of care are those found in or near the home. Parents have a cluster of accessible and familiar sources in their village to assist them when their children become ill. These sources include relatives and sometimes the nearby clinic.

The child's mother or father may gather herbs, leaves, or roots used for medicines. The child's mother or paternal grandmother may prepare a herbal medicine from boiling leaves or herbs. The herbal treatments mentioned most often for yebierd himem (pneumonia), tonsil (acute pharyngitis) and bierd kewugatina kesal gar (acute bronchitis). After these herbs are boiled, the caretaker (the parent) holds the sick patient near the steam rising from the mixture to make the patient inhale the vapors. An inhalation tent may be made by spreading a cloth over the heads of the caretaker and the patient to make the inhalation process more efficient. In the interview of patients in Dagmawi-minilik hospital and Meshualekia middle-level clinic, all were aware of this common treatment. In fact, they dispersed momentarily to search for the herbs growing near the entrance to their house. Male and female medical experts in the two health institutions also knew the herbs and their use.

These peoples also use over-the-counter medicines to treat patient with ARTI. The respondents said that there are trade stores or small shops that sell over-the-counter medicines such as paracetamol, aspirin, and cough mixtures. These medicines are dispensed by store owners and clerks.

4.3.4.2. Sources of Care away from Home

For people living in the capital city, transportation to the hospital or clinic for critical illness is difficult. Most of the time, peoples couldn’t get vehicles to transport patients to the nearest hospital. Obtaining treatment from traditional healers and herbalists may require money.

Throughout the interviews, people often spoke of the prohibitive cost of taking a patient to the health centers. However, even if traditional healers charge more than the health centers, people still seek their help. For example, one woman confided that unlike the clinic staff, some traditional healers will allow payment by installments rather than "cash on the line".

The steps individuals take to seek help vary from the most immediate to the more distant form of help. Families usually started treating their children with ARTI at home using home remedies or over the counter medicines. If a second level of care is needed, they either continued home care, using the advice of a more experienced mother or a village herbalist, or changed to another source of care (e.g., the hospital, clinic or the traditional healer). As trust is developed in a method or person, money seems to become a less significant factor.

4.3.4.3. Sources for Care Diagnosis and Treatment in health institutions

Health problems in the capital city (Addis Ababa) showed that acute respiratory tract infections were the most prevalent problem. Some questions should be asked, such as, how are respiratory tract infections being taken care of in health institutions, and how do medical experts diagnose, and respond to acute respiratory tract infections? It has been showed from the responses analyzed from 2 physicians, 2 nurses, and 2 nurse-clinicians that WHO recommendations on the management of ARTI were not fully followed by most of the medical experts for the management of a patient with mild ARTI and severe acute lower respiratory tract infection (ALRI), but by only small amount for the management of moderate ALRI.

In diagnosing of ARTI, doctors faced with many difficulties: patient's symptoms are usually unclear and the similarities in symptom aspect between lung tuberculosis and other infections. Even if the bacteria and the virus are often found in the patients, the diagnosis' result depends not only on patient's symptoms but also strongly on doctor's experiences. Therefore, there were many mistakes in diagnosing and treating ARTI which caused the high rate of patient's death and the wide spread of other complications.

It has also been showed from the research that medical experts tend to prescribe antibiotics for respiratory infections based on clinical arguments or merely to satisfy patients' demand for antibiotic prescriptions. In addition, antibiotics were prescribed by the experts in the surveyed health institutions to most of the consulting patients of whom more than half percent did not require antibiotics. The number of prescribed medicines as well as the non-respect of the therapeutic instructions constituted a potentially dangerous practice.

The researcher identified two major, potentially correctable, difficulties in the current diagnostic decision making process in the two selected health institutions. Firstly, in combining the demographic items and clinical symptoms and signs related to illnesses, the physicians tended to underestimate the likelihood of serious infections. There are too many relevant signs and symptoms for doctors to assimilate effectively; instead, they tended to discount the information and underestimate the probability of serious infection. As such, the full diagnostic value of current clinical tests was often not reached. Secondly, where near patient tests were available, such as acute respiratory tract infections and chest radiograph for pneumonia, errors in interpretation meant that serious infections was left untreated at the initial presentation.

4.3.5. Conclusion

Acute Respiratory Tract Infections are now spreading widely. In the capital city, infections like common cold, pneumonia, acute bacterial sinusitis, acute pharyngitis and acute bronchitis are the primary cause of visits to health clinics and outpatient hospital clinic. The danger was that the bacteria and the virus which causes the infections could ruin patient's health and even killed them. It has been showed from the assessment that the city hasn't had a diagnosing method that is good enough to confirm or exclude ARTI. The data gathered from the medical experts in the two health institutions indicated that upper respiratory tract infections were diagnosed in 31% of the illnesses seen. This was the most frequent diagnosis, followed by gastrointestinal tract disorders (10%); all other diagnoses were less than 10%. In a study of the pattern of patients room visits in different hospital's in Addis Ababa, respiratory diseases accounted for 66.6% of 30 067 cases. Upper respiratory tract infection was responsible for 32.5% of cases, bronchial asthma for 16.5%, and acute tonsillitis for 8.2% and pneumonia for 2.4% of the cases. The primary strategy for preventing mortality from acute respiratory tract infections is treatment: antibiotics, which can be administered at home, or hospitalization with oxygen support for severe cases. But it has been found that at least one-third of patients attending primary health care centers in Addis Ababa because of ARTI failed to comply with short-term antibiotic therapy, which could be dangerous.

During the assessment various social and cultural factors were also recognized in ARTI diagnosis and treatment in Addis Ababa including social problems, feeling of improvement, inadequate knowledge (lack of knowledge about the cause and effect of the infections,) reluctance to seek health care, preference for alternative health services such as traditional healers, and failure to take the full, prescribed course of treatment for ARTI. In places where peoples live in condensed environment, the hazards of ARTI have national ramifications. ARTI could also become the most common reason for interference with the performance of individual's daily activities. In addition, they are difficult to be prevented due to the ease spreading of the infection from person to person, or even to the larger community. Those people who are infected by ARTI could spread the infections to others, which could caused these people to miss their work or school and could increase the total cost incurred by illness (due to antibiotic usage, other medications usage, an increased rate of physician visits, and potentially hospitalization). The problems associated with these illnesses became more complicated since ARTI are one of the most transmissible diseases, associated with high secondary attack rates, especially via household contacts.

It has also been noticed from the assessment that there were barriers to treating patients with ARTI cases with the appropriate medication and these are classified into three levels: at the household level, at the community level and at the health facility level.

At the Household Level: Knowledge and Practices of Parent/Caretaker

- Failure to recognize signs and symptoms of severe ARTI which can upgrade to chronic illness such as chronic Pharyngitis and chronic bronchitis
- Severe disease may be attributed to causes such as spirits; traditional healers consulted
- Lack of money for hospital or clinic visit, transport to hospital or clinic, antibiotics

At the Community Level

- Lack of transport to health facilities
- Antibiotics not available
- Inaccurate information about how to take antibiotics

At the Health facility Level

- Antibiotics not in stock or out of date
- Inappropriate methods of providing health care
- No standard protocol for diagnosis and drug use

The above information indicates that a fundamental understanding of the socio-cultural factor in ARTI intervention is essential for an effective diagnosis and treatment of the disease.

Though instructing the society through different approaches are some initiatives, it could not be solved substantially because of the above reasons and great amount of investment and time is needed. So, some solution is required that ensures the patient with acute respiratory tract infections are treated with safe, that services are accessible and affordable, and that both families and providers have the knowledge and skills to manage sick patients appropriately.
So to get such solution, ordinary systems should be changed in a way that the diagnosis functions that is previously done by different health workers in all of the health service delivery systems like at the health post, health center, district hospital, and regional or referral hospital, must be systematized by computer operation.

In many diagnostic situations, the number of variables to consider and give proper weight is simply overwhelming. Doctors are affected too much by their quirky recent experience. They rely upon heuristics which are useful shortcuts but often inaccurate. And there are gaps in their knowledge. Doctors rely upon some combination of using a systematic algorithmic approach and gestalt diagnostic judgment. But they can suffer from the fact that humans are inherently poor at statistics, and their intuitions lead them astray. For example, physicians overestimate the predictive value of clinical signs that may be present with a specific disease, but also common in the healthy population. Basically – there are too many variables for doctors to consider, so they tend to simplify things by discounting some variables, and this leads to error. Computers, however, don't get overwhelmed; they just do what given to them and they are far better at weighing multiple variables using precise evidence-based statistics – that is, once the proper model has been developed.

Undeniably, knowledge base systems are at the tracks which are coming in a fully functional way to alleviate such problems. It can improve the rate of the accurate diagnosis of physician with the auxiliary help of this system, which have the obvious meaning in lowering the mortality and high survival rate, and has strong practical values and further social benefits. These systems can help reduce mistakes and optimize care. In the new era of cost control in medicine, it should also be considered that such systems can potentially save a great deal of health care birr's. But this does not mean that computers will be practicing medicine anytime soon. Physicians are needed to gather data from patients, and human judgment is needed for things like – how sick does this person look. Also, clinical decision making is still beyond current software technology – that level of artificial intelligence is not here. Knowledge base systems are meant to aid experts, not replace them.

As stated in the preliminary assessment result, the application of knowledge base system is based on the reason that there are increased symptoms of ARTI and medicines for the management of ARTI while doctors have limitations to remember all the symptoms and medicines, as well as dosage of medicines. Accordingly, the KBS is needed to assist doctors in diagnosing particular disease based on its symptoms. In addition, it can assist doctor to determine properly the medical treatment and can permit paramedic to do as doctor in facing cases properly in accordance knowledge and inferring procedure. The result of diagnosing, then, is adjusting to patient condition in deciding medical treatment and the knowledge reside on the system can be assessed and updated regularly.

CHAPTER FIVE

KNOWLEDGE ACQUISITION AND MODELING

5.1. Introduction

Knowledge Acquisition as one of KBS development process deals about collecting relevant pieces of knowledge and information from experts. Knowledge required for designing KBS for ARTI diagnosis is acquired through interviews. In this chapter knowledge modeling of the knowledge acquired using decision tree and inference network modeling is presented. These modeling techniques clearly show the flow of knowledge in the course of decision making.

5.2. Conventional versus Knowledge-based ARTI Diagnosis

Diagnosis is and will be the most important problem of medicine, and the accuracy of diagnosis determines mainly the success in clinical decision making (Hodhod, 2002). As the human body is very complicated and it is characterized by practically infinite number of disease symptoms, symptoms and clinic of a disease are greatly influenced by the individual features of a patient and knowledge of specialists are limited (Salem et.al, 2001).

After computers appeared, works related to attempts to formalize the diagnosis process boomed. The results of these works mainly did not come up to expectations and rare successes are connected either with relative simplicity of the problem (to differentiate diseases sufficiently remote from each other in the symptoms space) or with its inadequate simplification. As a result, at best models diagnosing a disease not worse than an average doctor appeared (Long, 2001).

Principal difficulties in simulation of "large" systems (to which medical diagnosis systems also belong) made it necessary to look for roundabout ways. One of these ways being developed intensively at present is the creation of knowledge-based medical systems. A knowledge base system is a computer system which incorporates formalized knowledge of specialists in a certain concrete subject and is able to take expert decisions within this subject (to solve problems in such a way as a man-expert would do it) (Salem et.al, 2001).

To achieve effective and efficient ARTI management, patients should receive effective curative care and prevention education. This is accomplished by increasing awareness of risk and encouraging health care seeking behavior (MoH, 2008). However, the conventional ways of ARTI diagnosis are not knowledge-driven. This makes the ARTI diagnosis insufficient to meet the current needs. In case of knowledge-driven approach for disease management, clinical prediction rules are created by medical practitioners based on their knowledge and clinical experience. Such expert-generated rules are then evaluated and refined in clinical tests. Once verified, these knowledge-driven rules are used to expedite diagnosis and treatment for the disease. For example, conventional ways do not provide any awareness even though most people with ARTI are unaware of their risk.

In most of the health care facilities like hospitals and middle-level clinics, the conventional approach of ARTI diagnosis starts with receiving patient request for allocation of patient card to ARTI expert. In these health care facilities, the patient is obliged to pay money for the diagnosis by the expert. Then, based on the patients' history, the medical expert prescribes the necessary medication. After all, the treatment used by the patient may fail because of lack of appropriate information, which in turn leads to drug resistance behavior and other ARTI complications.

The conventional approach involves complicated knowledge flow and a lot of paper work, and as such time is needed for the ARTI expert to manage the patient. In the process, useful information may be missed due to human error. Since, experience and skill are main ingredients of tacit knowledge; it is difficult to make the knowledge of the expert shareable. The quality of patient diagnosis and management is heavily relying on the know-how, experience and qualification of the expert (Hodhod, 2002). Moreover, the patient diagnosis and management of common ARTI can only be provided during the office hours.

On the other hand, for the knowledge-based ARTI diagnosis approach, the processes of risk awareness and/or diagnosis of ARTI, from the time the person requested till he/she gets advice or medicine prescription is accomplished by the knowledge base system. According to the methodology adopted for this research, such system is developed at three stages, which includes knowledge acquisition perspective, diagnosis representation perspective and performance measurement perspective. The knowledge acquisition perspective will be discussed in the remainder of this chapter and the other two will be discussed on the next chapters. For the purpose of this study, this knowledge base system is named as **A**cute **R**espiratory **T**ract **I**nfections **K**nowledge **B**ase **S**ystem (ARTIKoBS).

5.3. Knowledge Acquisition

Knowledge acquisition (KA) has come to be seen as a bottleneck in the process of building knowledge base systems (Fraser, 2001). Knowledge acquisition refers to the task of endowing expert systems with knowledge. It is the accumulation, transfer, and transformation of problem-solving expertise from some knowledge source to a computer program for constructing or expanding knowledge base (Salem et.al, 2001). The task in this phase is to have the knowledge which the expert uses to solve the problem displayed in a logical fashion so that it can be coded into the computer. In here, the typical resource is knowledge (Milton, 2008). In KBS development knowledge acquisition is a stage in which the knowledge engineer captures both tacit and explicit knowledge in the domain area so as to build a KB (Long, 2001).

Efficiency of operation of the knowledge base system depends in the first place on quantity and quality of the information available in its knowledge base (Salem et.al, 2001). The problem of knowledge acquisition for medical knowledge bases is one of the most severe obstacles to the application of knowledge base system to practical medical problems. Knowledge acquisition has long been known as a bottleneck to the diffusion of computer-based tools in a variety of fields (Milton, 2008), but the difficulty is especially great for medical knowledge bases (Fraser, 2001). The medical field presents a combination or imprecise causal knowledge, very large amounts of information, and potentially life-threatening consequences of incorrect conclusions (Milton, 2008). These factors combine to make medical knowledge bases harder to build and maintain that knowledge bases for most other applications (Sriram, 1984).

Knowledge acquisition in clinical medicine is dominated by the handling of information. A physician performing a diagnostic or therapeutic task extracts data from the current patient comparing it with information on similar cases and referring it to his clinical experience. In this process, he/she uses medical knowledge: terminological knowledge, causal knowledge, strategic knowledge, etc. This knowledge stems from his/her own experience and from the communication with his clinical colleagues (Nelson, 1982).

The building blocks of medical knowledge base are the concepts: entity of disease, syndrome, symptom, clinical examination, etc. This conceptual layer is built up during knowledge acquisition by medical experts and knowledge engineers together.

According to Yang (2005), the most important issues arise in connection with knowledge acquisition are as follows:

- Most knowledge is in the minds of experts
- Experts have vast amounts of knowledge
- Experts have a lot of tacit knowledge
    - They don't know all that they know and use
    - Tacit knowledge is hard to describe
- Experts are very busy and valuable people
- Each expert doesn't know everything
- Knowledge has a "shelf life"

Because of these issues, the following techniques are often proposed to simplify the task of getting valuable knowledge from experts (Bechhofer, 2006):

- Take experts off the job for short time periods
- Allow non-experts to understand the knowledge
- Focus on the essential knowledge
- Can capture tacit knowledge
- Allow knowledge to be collated from different experts
- Allow knowledge to be validated and maintained

5.3.1. Knowledge Elicitation

Knowledge elicitation is the transfer and transformation of problem-solving expertise and domain knowledge from a source into a program and it is the most key part of the knowledge acquisition process (Benchimol, Levine and Pomerol, 1999).

Aroyo (2006) suggests that clearly understanding the existing system and identifying the actual problem can help to design the right solution which ultimately alleviate the knowledge bottleneck in that field. In this research, various experts in health including drug advisors and physicians from different hospitals and pharmacies were interviewed to understand the dimension of ARTI. Interview is selected as a method to acquire knowledge because as

Olson and Rueter (2005) describes it is the most common method for eliciting knowledge from the expert.

In conversation, the expert reveals the objects he/she thinks about, how they are related or organized, and the process he/she goes through in making a judgment, solving a problem, or designing a solution (Olson and Rueter, 2005). Of those, to acquire knowledge for the use of this research, only six ARTI experts are selected using purposeful sampling technique. Profiles of experts who participated in knowledge elicitation process are presented in table 5.1 below.

No.	Specialty	Experience	Degree
1	Physician	12 year	M.D.
2	Nurse	6 year	12+2
3	Nurse	7 year	Diploma
4	Pharmacist	10 year	Diploma
5	Physician	6 year	M.D.
6	Pharmacist	2 year	Diploma

Table 5.1 Profiles of the experts participated in interviews

Discussion with the experts indicated that all of them generally undertaking ARTI diagnosis using Ministry of Health guideline (MoH (2009)). In addition to the experts, additional knowledge has been acquired by the researcher from the Internet, books, medical journals, diagnosis guidelines, and manuals.

Important parameters were identified by a thorough examination of the expertise acquired from the medical experts and the guidelines. Based on the suggestions of the expertise, the concepts were refined and all experts agreed that, the five most commonly encountered acute upper and acute lower respiratory tract infections are Common Cold, Acute Bacterial Sinusitis, Pharyngitis, Pneumonia and Acute Bronchitis.

5.3.2. Knowledge Modelling

Knowledge modelling is a central activity in knowledge base system construction. It is a technique that helps to clarify the structure of a knowledge-intensive task (Miller, 1985). Knowledge base system construction methods typically provide tools for knowledge analysis in the form of so-called conceptual models of knowledge or simply knowledge models. According to Anteneh W. (2004), a knowledge model provides an implementation independent specification of knowledge in any application method. It is a representation of domain-specific knowledge in the manner in which the expert thinks (Christer, 1991). Typically, a knowledge model provides formats for writing down both static domain knowledge (rules, classes, relations) as well as reasoning strategies in which this domain knowledge is used to solve a particular problem.

- *Domain Knowledge* specifies the domain-specific knowledge and information types (e.g., medications) that we want to talk about in an application.

- *Task/Inference Knowledge* describes what goal(s) an application pursues (e.g., diagnosis), and how these goals can be realised through a decomposition into subtasks and (ultimately) inferences. This "how" aspect includes a description of the dynamic behavior of tasks, i.e., their internal control. Inference knowledge describes the basic inference steps that we want to make using the domain knowledge. Inferences are best seen as the building blocks of the reasoning machine. The reasoning task is described through a hierarchical decomposition of functions or processes.

The decision making problem of predicting the infection from ART infections is a complex process, because of the numerous elements/parameters (such as symptoms, signs, physical examination etc.) involved in its operation, and a permanent attention is demanded.
The knowledge used for the building of the knowledge base system is specified in one module, i.e. knowledge regarding ARTI patients needing diagnosis for the first time based on the infection to be diagnosed. For such problem the decision tree and inference network structure is investigating to handle with the problem of ARTI during the patient admission into the hospital or clinic.

Expertise from a single expert is usually limited in both quality and scope. If a body of partial knowledge could be pooled together from multiple experts or “semi-experts," knowledge acquisition, the longstanding bottleneck in knowledge engineering would be resolved (Hayes-Roth et.al, 1983). To make such an approach, Decision Tree (DT) and Inference Network (IN) are a good representation.

A decision tree is composed of nodes, leaves and branches. Inside the nodes some decision occur that transfer control via any of its branches to other nodes or leaves (Richardson, 2000). A binary decision tree is one where each node of the tree has only two transition branches.

Typically, these binary trees are used to implement knowledge systems where you answer yes/no questions. The hierarchical nature of medical diagnostic problems adapts very naturally to binary decision trees (Richardson, 2000). Usually the heuristics dictate that one problem leads to consequences that in turn lead to other problems and that eventually leads to a cause and a reasonable guess or solution to the problem (Bechhofer, 2006).
Decision trees can be easily transformed into corresponding rule bases with a little help from the knowledge engineers. When used in clinical diagnosis, a classical decision tree usually starts from making a decision on one main symptom of the patient. According to different results ("Yes" or "No") of the first step, this tree will go towards separate directions and make decisions on other symptoms. Eventually it will lead to several potential diseases which the patient possibly has.

On the other hand, inference networks are basically a Bayesian Network which are graphical tools used to facilitate the qualitative structuring of uncertain knowledge and provide a framework for encoding of probabilistic relations in a form guaranteed to be coherent (Richardson, 2000). Rules can be combined with facts to deduce new facts or arrive at conclusions. This process is known as inference. We can view an inference as a process of constructing a network tree structure whose nodes are the clauses used in rules and whose branches are arrows connecting the clauses. The branching in such a tree reflects the structure of a set of rules used in an inference. The tree so constructed is referred to be an inference network (IN) (Christer, 1991).
In this research, the attention primarily has focused on the process of making medical diagnoses. In medical science, patients have symptoms that prompt them to see a doctor. In other words, symptoms are comprised of the observations reported by patients and the observations of doctors while examining patients. The identification of the underlying cause of symptoms is crucial and improves the chance of proper diagnosis of the disease and prescribing the correct treatment.

In the inference network the behavior (in this case the type of infection) to be modeled is situated at the top in the decision making process, whose reasoning implies to reach a predefined goal, coming from one or more initial states (the initial states in this case are symptoms which helps to identify the infection). Therefore, the reasoning system will be more efficient when a least number of transitions to reach the final goal are achieved. Thus, increasing the efficiency implies to minimize intermediate states, and that is represented in the organization of the knowledge base. So, As for the reasoning process an inference tree starts from decisions on symptoms of the infection, and ends up with a final decision about that infection at the root. The reasoning goes from Nodes to higher-level Rules, and finally leads to the conclusion/root. Since the symptoms are placed at the lowest level of an inference tree, the decisions on the lowest level will form the decisions on higher levels.

Inference network for KBS was chosen because of the nature of the application due to the reason that prediction of infections in ARTI is a complex process with sufficient interacting parameters and inference networks are suitable for this kind of problem, through the available experience and accumulated knowledge from experts, the easy for use and the low time requirement.

In this type of domain (medical diagnostic problems) higher level alternatives at the top nodes are examined first and then a narrowing process begins until an answer is found. A decision tree and inference network could be both a knowledge representation and a reasoning method (Tomsovic, 1985). Both modeling methods has an advantages of being very efficient, compact, and relatively easy to implement (Nelson, 1982). They are selected for this research because of their cognitive nature that allows a human expert to easily comprehend the solution of a problem. They can be used in medical diagnoses as visual and analytical tools to represent decision-making methods and their consequences. Usually those consequences could be chance event outcomes, resource costs, and utilities (Nelson, 1982). Generally, the decision tree and inference network modeling has two outstanding advantages, which are its ease of use and simplicity to explain the facts to supervising physician (Tomsovic, 1985).

Both structures have a feature of easily used and simplicity to suggest clear decision. The decision tree structure starts at the clinical problem box and works through step-by-step until it arrives at an exit box at the end of a branch and the inference network structure was used in this research to identify each infections based on the symptoms given.

The initial phase for both approaches (inference network and decision tree) was to identify the elements in the domain, that is, the major types of acute respiratory tract infections and the symptoms of each infections using inference network, and finally representing qualitative evidential links between these elements using decision tree structure. The research considered several diagnoses of acute respiratory tract infections like antibiotics, pill, injection, Syrup, Tablet etc. It also considered several concepts like sore throat, earache, coughing, nausea, heartbeat, headache, teeth pain, ear pain, abnormal lung, abnormality at heart etc which are basically symptoms of ARTI; and objects like lung, heart, bronchial tubes, mucus, throat, cells, tissue, nasal cavity, trachea, oral cavity, larynx and pharynx on which the infections are shown. Appendix 2 lists some of the selected elements of the problem. The inference net was derived from the expertise gathered from the medical experts (tacit knowledge) and from exploring different secondary resources like documents and manuals (explicit knowledge), and further discussion with the expert. These networks allow the decomposition of the expert's domain knowledge into separable local relationships.

The initial inference net has 8 nodes. Figure 5.1 shows a fragment of the inference net for the major elements in the domain.

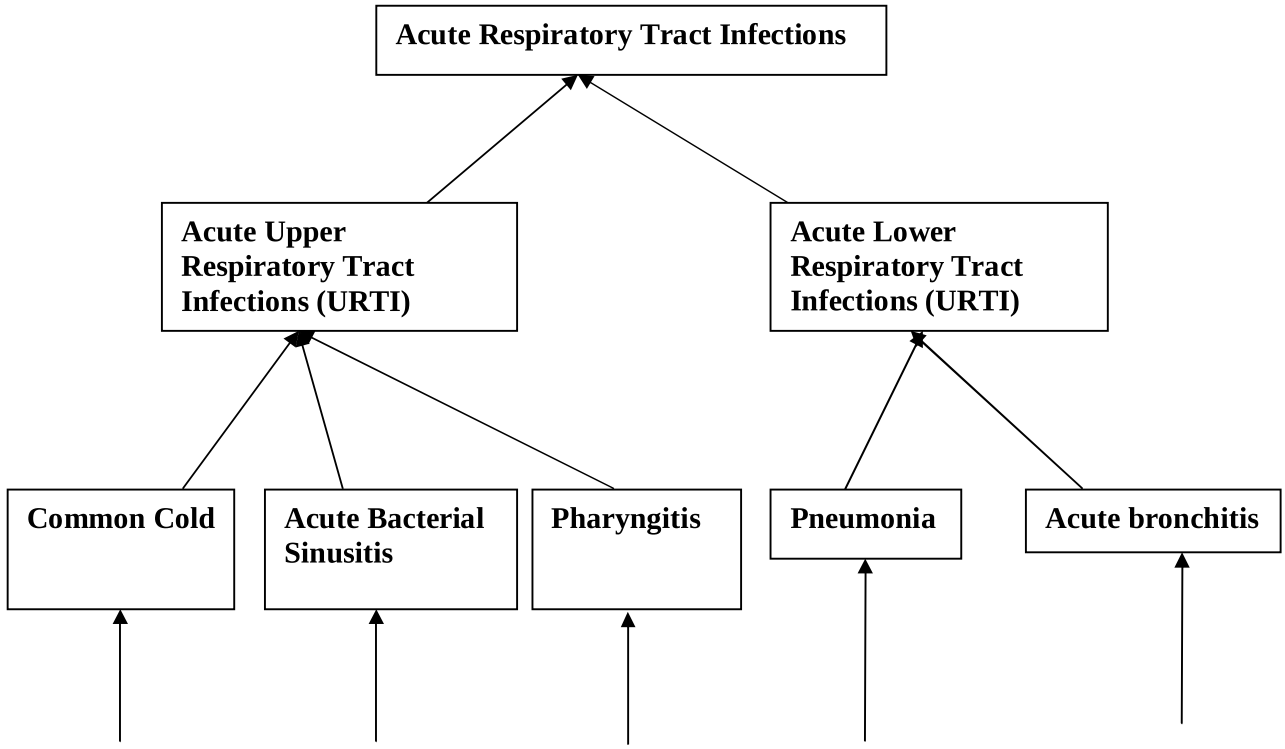


Figure 5.1: Inference network for Acute Respiratory Tract Infections

It has been mentioned above that from the knowledge gathered and expert's confirmation, the five most commonly encountered acute upper and acute lower respiratory infections are common cold, acute bacterial sinusitis, pharyngitis, pneumonia and acute bronchitis. The above inference network shows these five most common ART infections.

In the inference net, the direction of the links corresponds to the anticipated direction of inference, from evidence to major infections. In this approach, the directed links help in the subsequent encoding of the relationships. For the KBS approach, arrows converging on a node indicate a potential diagnostic rule with the antecedent nodes to appear in the condition and the destination node to appear in the action.

As shown in the above figure broad diagnosis of acute respiratory tract infection (ARTI) includes the two principal sub-diagnoses of acute lower respiratory tract infection (ALRTI) and acute upper respiratory tract infection (AURTI), although it is often difficult to distinguish between them.

5.3.2.1. Acute Upper respiratory tract infections (AURTIs)

Acute Upper respiratory tract infections (AURTIs) are the most widespread infectious illnesses in Ethiopia. They are common acute infections involving the nose, paranasal sinuses, pharynx, larynx, trachea, and bronchi. It is usually identified by the community as a common cold (Bauman and Burns (2000). AURTIs can be defined as an acute febrile illness with cough, sore throat, or hoarseness, which are very common in the community and are one of the major reasons for appointments to primary care physicians, particularly during the winter season (Fleming *et al*., 2001).

According to the findings Bauman and Burns (2000), AURTIs are the most common acute illness found in an outpatient setting which have a wide range of clinical manifestation that may vary from the common cold (mild and self-limiting) to a life threatening disease, such as epiglottitis. Viruses such as influenza A and B viruses, adenovirus, respiratory syncytial virus, parainfluenza viruses, and Epstein Barr virus are some of the main etiologies for AURTIs. The main bacteria that are responsible for causing AURTIs include *Chlamydia pneumoniae, Legionella spp., Mycoplasma pneumoniae, Haemophilus influenzae,* and *Streptococcus pneumoniae*.

5.3.2.1.1. Common AURT Infections and their Inference Network Structure

5.3.2.1.1.1. Common Cold

The common cold is considered to be an acute illness of the URTIs and it is caused either by respiratory syncytial viruses that are capable of repeatedly infecting an individual or rhinoviruses that initiate infection only once. These viruses are experienced by people of all age’s worldwide (Monto, 2002). The common cold is characterized by malaise, sore throat, and low-grade fever, especially at the first time of onset. This illness can affect persons of all ages and are considered to represent a self-limited syndrome (Bauman and Burns, 2000). The figure below shows the inference net for *common cold* upper respiratory tract infection.

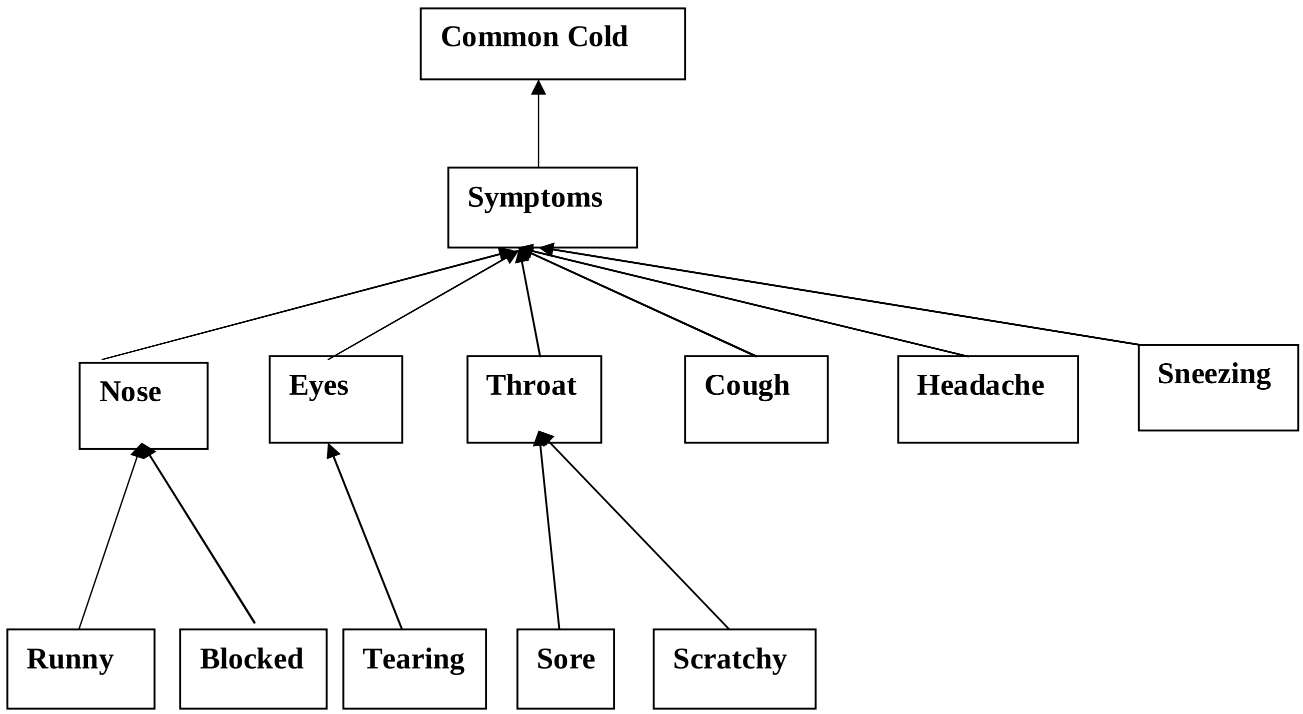


Figure 5.2: Inference network for common cold

In figure 5.2 the forward path in the inference network shows that from the basic symptoms runny and blocked nose, sore and scratchy throat, tearing eyes, coughing, headache and sneezing could lead to common cold upper respiratory tract infection. The inference net here is used to implicate the infection type based on the given symptoms.

5.3.2.1.1.2. Acute bacterial sinusitis

Acute bacterial sinusitis is a common infection of the paranasal sinuses that is usually associated with inflammation of the nasal and sinus mucosa. Sinus disease has been shown to occur in 90% of patients with the common cold. In the first few days of infection, the symptoms are likely to be due to a viral cause that leads to upper respiratory tract infection, but this infection may later become complicated by a bacterial infection. The main pathogens responsible for bacterial infection are *Streptococcus pneumonia*, *Haemophilus influenza*, and *Moraxella catarrhalis*, although *Staphylococcus aureus* and *Streptococcus pyogenes* are isolated in rare cases (Bamberger and Jackson, 2001). Some physicians suspect acute bacterial sinusitis when cold or influenza-like illnesses persist for several days, and associated mainly with nasal congestion, sinus discomfort or tenderness, fever, headache, maxillary toothache, and facial pain. Figure 5.3 shows the inference net for *acute bacterial* *sinusitis* upper respiratory tract infection. In the figure, as in the inference net for common cold, the forward path shows that congested and stuffiness nasal symptom, teeth pain, ear pain, coughing, bad breathing, nausea, and eye becomes red could lead to acute bacterial sinusitis upper respiratory infection.

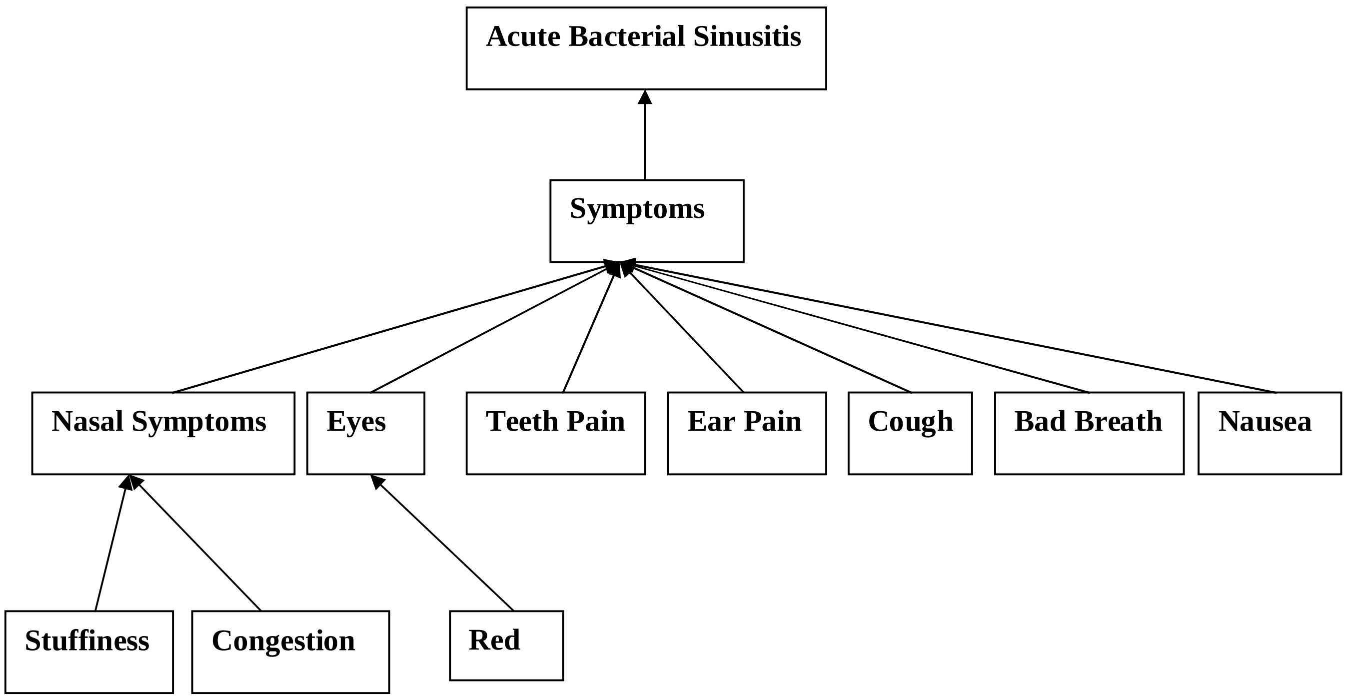


Figure 5.3: Inference network for Acute Bacterial Sinusitis

5.3.2.1.1.3. Acute Pharyngitis

Acute Pharyngitis is the most common cause of sore throat, leading to an increasing number of family visits to physicians as well as ambulatory pediatric care visits. Streptococcus pyogens is considered to be the main causative agent of pharyngitis in both children and adults (Bamberger and Jackson, 2001). Acute pharyngitis is usually caused by a viral infection. It's often caused by the same viral infection that causes the common cold. The symptoms of acute pharyngitis usually last for a week or less.

Figure 5.4 shows the inference net for *acute pharyngitis* upper respiratory tract infection.

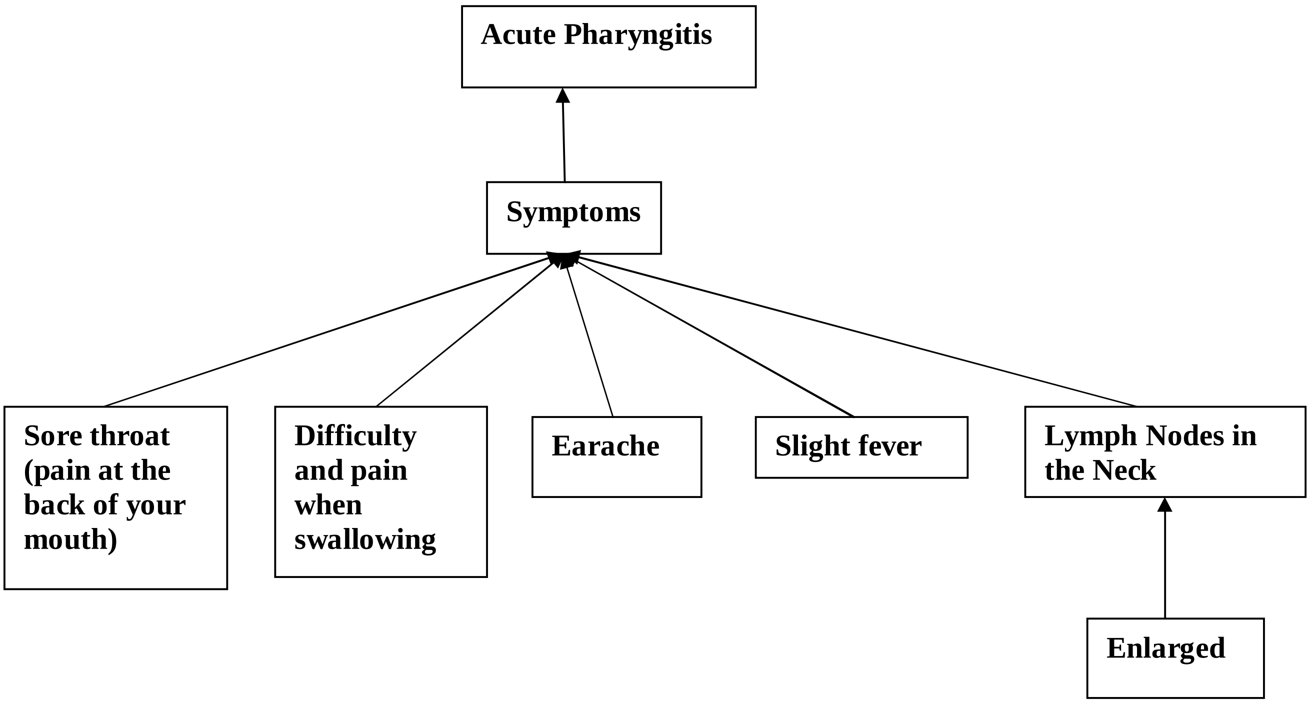


Figure 5.4: Inference network for Acute Pharyngitis

In the figure, the forward path shows that sore throat, difficulty in swallowing, earache, slight fever, and enlarged lymph node at the neck could lead to acute pharyngitis upper respiratory infection.

5.3.2.2. Acute lower respiratory tract infections

The meaning of the word *acute* in *acute respiratory tract infection* refers to new, or has just started recently and the words *lower respiratory tract* means actually in the lungs, like the bronchi and below. This refers to pneumonia or bronchitis.

Acute lower respiratory tract infections are a persistent and pervasive public health problem. They cause a greater burden of disease worldwide than human immunodeficiency virus infection, malaria, cancer, or heart attacks (Fleming *et al.*, 2001). The spectrum of disease ranges from a mild mucosal colonisation or infection, an acute bronchitis or acute exacerbation of chronic bronchitis/chronic obstructive pulmonary disease (AE-CB/COPD), to an overwhelming parenchymal infection with the patient presenting with a severe pneumonia. *Streptococcus pneumoniae* and *Haemophilus influenza* have been found to be predominant cause of ALRTI (Bamberger and Jackson, 2001).

5.3.2.2.1. Common ALRT Infections and their Inference Network Structure

5.3.2.2.1.1. Acute (typical) Pneumonia

Acute (typical) Pneumonia is an infection of the alveoli or the walls of the alveolar sacs. It is a serious infection of the small bronchioles and alveoli that can involve the pleura. It is very life-threatening in the elderly or people with illnesses that affect the immune system. It is also the leading cause of death in children less than fives years of age. The common causes of pneumonia are dependent on the immune status of the patient, the location where the patient acquired the pneumonia, the age of the patient, and the type of pneumonia the patient manifests. However, the most common cause of acute (typical) pneumonia is *pneumococcal bacteria, Streptococcus pneumoniae* accounts for 2/3 of *bacteremic pneumonias* (Bamberger and Jackson, 2001).

Figure 5.5 shows the inference net for acute (typical) pneumonia lower respiratory tract infection. In the figure the forward path in the inference network shows that runny nose and chills, green mucus, shaking chills, muscle aches, rapid heart beat, and fatigue could lead to pneumonia acute lower respiratory tract infection.

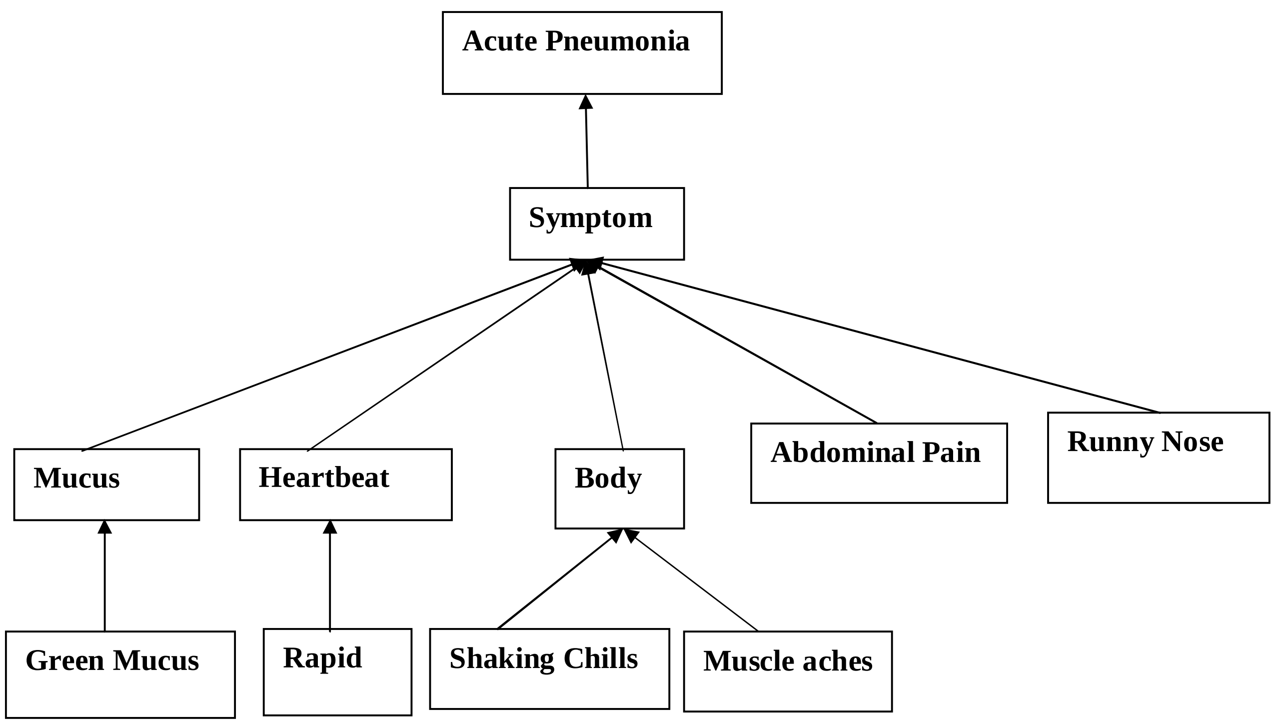


Figure 5.5: Inference network for acute (typical) Pneumonia

5.3.2.2.1.2. Acute Bronchitis

Bronchitis is an acute inflammation of the air passages within the lungs. It occurs when the trachea (windpipe) and the large and small bronchi (airways) within the lungs become inflamed because of infection or other causes (WHO, 2008).

Acute bronchitis describes the inflammation of the bronchi usually caused by a viral infection, although bacteria and chemicals also may cause acute bronchitis. Bronchiolitis is a term that describes inflammation of the smaller bronchi referred to as bronchioles. In infants, this is usually caused by respiratory syncytial viruses (RSV), and affects the small bronchi and bronchioles more than the large. In adults, other viruses as well as some bacteria can cause bronchiolitis and often manifest as a persistent cough at times productive of small plugs of mucus (Bauman and Burns, 2000).

Acute bronchitis as mentioned above is a cough that begins suddenly usually due to a viral infection involving the larger airways. Colds (also known as viral upper airway infections) often involve the throat (pharyngitis) and nasal passages, and at times the larynx (resulting in a diminished hoarse voice, also known as laryngitis).

Acute bronchitis occurs most often due to a viral infection that causes the inner lining of the bronchial tubes to become inflamed and undergo the changes that occur with any inflammation in the body. Common viruses include the rhinovirus, respiratory syncytial virus (RSV), and the influenza virus. Bacteria like *Mycoplasma, Pneumococcus, Klebsiella, Haemophilus* and Chemical irritants like tobacco smoke, gastric reflux, solvents can cause acute bronchitis (Bauman and Burns, 2000).

Figure 5.7 below shows the inference net for *Acute Bronchitis* lower respiratory tract infection.

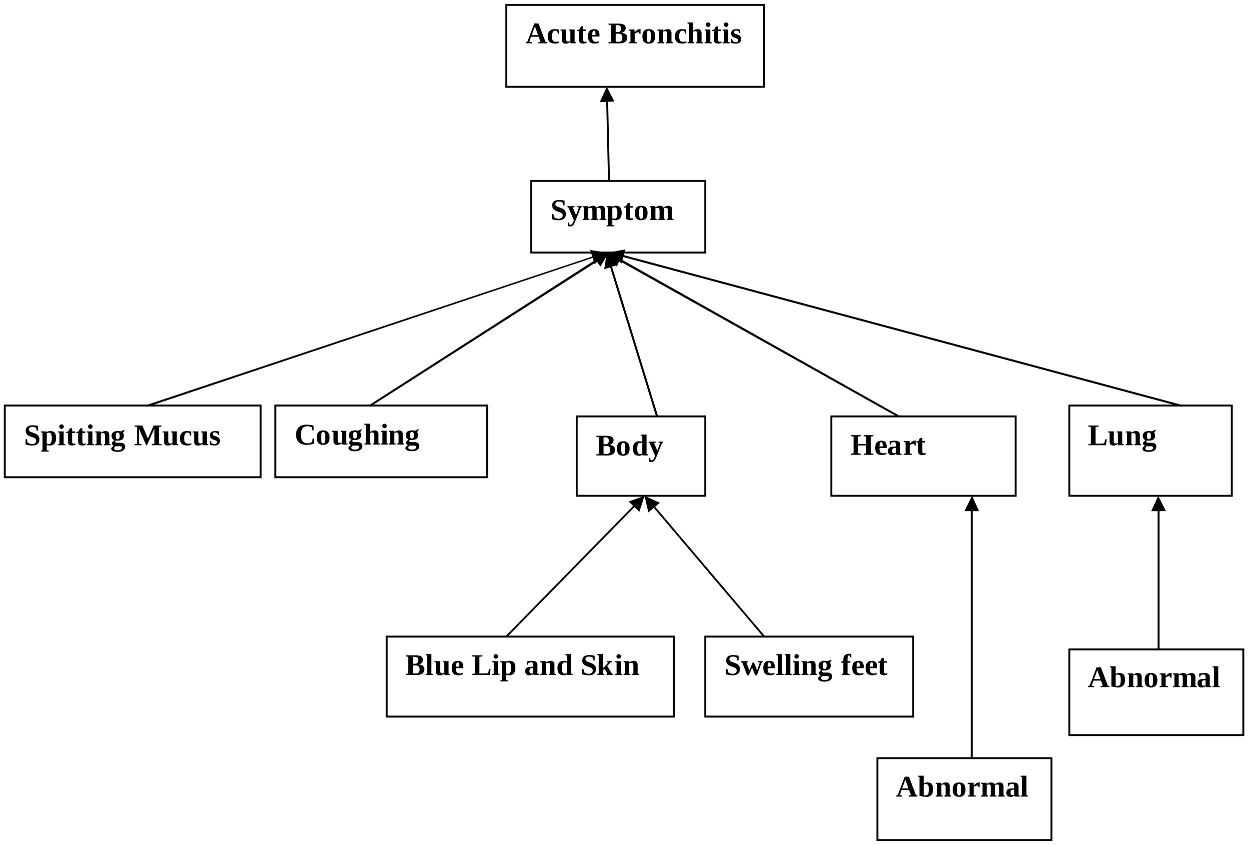


Figure 5.7: Inference network for acute (typical) bronchitis

In the figure, the forward path in the inference network shows that when lip and skin become blue, feet is swelling, cough, mucus, abnormal lung, and heart failure could lead to acute bronchitis lower respiratory tract infection.

5.3.3. Hybrid Decision Tree and Inference Network Logical View for Symptomatic Diagnosis of ARTI

It has been shown that the inference network structure used in this research has helped in making a relationship between the symptoms and the type of infection and in predicting the infection type based on the symptoms given. Through conducting lengthy interviews with the medical experts, as also depicted in each of the inference network, 28 symptoms were identified which are indicators of the five acute respiratory tract infections. These infections and their symptoms are listed in appendix 3. After this, the hybrid structure was formed between decision tree and inference network modeling structures. As explained above, in a decision tree structure the inference process involves simply walking through the algorithm, selecting the appropriate path from the answers to the questions contained in the nodes. It encodes the medical expert knowledge in the order and form in which the questions are structured. The two models (IN and DT) are generalized as depicted in appendix 1 which represents the wide-ranging paths that indicate the logical view for the diagnosis and management of ARTI based on symptoms. For example, in the hybrid structure, the first question is sore throat or painful swallowing? Depending on the answer, one of two paths is chosen. For instance, if the answer is yes, an immediate diagnosis of Acute Pharyngitis is made; if not, the decision tree structure went down hierarchically for asking another infection.

Taken together, in this chapter, the transformation process of acquiring required knowledge from human experts and knowledge collected by way of document analysis was helpful in pinpointing the specific parameters essential for the diagnosis of ARTI. From thereon it was possible to arrive at the 'Goals' and build the 'Rule Base' by framing the rules, which is discussed in the following phase.

CHAPTER SIX

THE KBS DEVELOPMENT AND EVALUATION

6.1. Introduction

The previous knowledge acquisition phase brought to light how the knowledge acquisition phase of the proposed KBS development was dealt with. In addition, the knowledge model has been developed using the top-down approach of hybrid inference network and decision tree structures. The model developed is used as a general framework to design the knowledge base. Following the knowledge acquisition process, the knowledge engineer must determine how the chunks of knowledge are to be represented in the structure of the expert system (Brule, 1986). In this knowledge representation phase the research attempts to make it amply clear how the knowledge acquired is represented in the form of a ‘Rule Base.’ Thus this phase is devoted towards constructing rules and developing a rule base, which facilitates in the application of knowledge by the system in decision making.

6.2. The System Design

The design of the prototype involves user interface, knowledge base, inference engine and the explanation facility. The knowledge acquisition and knowledge representations are carried out by the knowledge engineer. The user responds to a series of dialogs with the prototype system and after an output result, for how the system reach on the conclusion will be provided using the explanation facility.

6.2.1. Knowledge Representation

Knowledge representation is a method used to encode the knowledge for use by the KBS or it is putting the knowledge into rules or cases or patterns in the knowledge representation process (Rich & Knight, 1991). According to Aroyo (2006), it is a method of storing and processing knowledge in computer. There are a number of various available to represent expert knowledge which includes semantic net, frames, cases and rule as discussed earlier in chapter two. In this research, a representation called production rule or simple rule is used to represent the knowledge acquired. The first reason is that rules are relatively easy to understand and create from the acquired knowledge and has the advantage of naturalness of expression, modularity and restricted syntax (Brule, 1986). The other reason is that rule base representation is convenient to translate from the knowledge acquired and modeled using inference network and decision tree. The other advantage of production rule is the ease with which the inference chain may be modified. By simply adding new rules or modifying existing rules, the performance of the system can be easily modified, although as systems become larger, this modularity becomes harder to maintain (Rychener, 1976).

The if-then structure of the production rule lends a consistency to the knowledge base that is not always evident in other methodologies. Because of this uniformity, the rules can be easily explained to and understood by a human expert. The benefits of this can be easily seen in a system such as the MYCIN system (Shortliffe, 1976). The MYCIN system acts as a medical consultant, aiding in the diagnosis and selection of therapy for patients with bacteria or meningitis infections. It carries on an interactive dialogue with a physician and is capable of explaining its reasoning processes.

The term production rule in AI which is the most commonly used type of knowledge representation (Graham, 1989) serve to accurately represent the heuristics which an expert uses to resolve a particular problem. They can quite readily be represented as a series of if-then statements that relates the given information or facts in IF part to some action in the THEN part. The IF part is called the antecedent (premise or condition); and the THEN part is called the consequent (conclusion or action). Rule provides some description of how to solve a problem in relatively easy and understandable manner. Production rules are one of the most popular and widely used knowledge representation languages in medicine (Ignizio, 1991).
When the inference engine evaluates the "if' portion of a statement as true, the operative portion of the statement is added to the knowledge base. The inference engine then utilizes the data which is resident in the knowledge base and decides which rule will be applied next. This entire process then repeats itself until the end of the reasoning chain is reached.

The rules for this study are created from the knowledge acquired through the knowledge elicitation techniques used in chapter five. In other words rules are created through the transformation of inference network and decision tree modeled in the previous chapter to the if-then rules.

6.2.2. Knowledge Base Construction

All of the domain knowledge required for ARTIKoBS to function is contained in its knowledge base. This knowledge base is the collection of much of the problem solving knowledge in acute respiratory tract infections using symptomatic approach which contains rules of the form IF condition THEN action. When the condition part of a rule is satisfied, the rule is said to fire and the action part is executed. The following sample rules represents the way acquired knowledge represented in ARTIKoBS that helps to build a production system.

If there is no headaches
And there is sore at the patient throat
And there is pain at the patient ear
And the patient is not coughing
And no pain at the patient teeth
And swallowing is difficult
And there is slight fever
And there is no nausea
Then acute pharyngitis will be diagnosed

If there is headaches
And sore at the patient throat
And no pain at the patient ear
And the patient is coughing
And there is no fatigue
And the nose is blocked
And there is no nausea
And the patient eye is tearing
And the patient sneezes
Then common cold will be diagnosed

If there is headaches
And pain at the patient ear
And the patient is coughing
And there is no an ache at the muscle
And the heart is not beating rapidly
And the nose is blocked
And the patient eye is red
And pain at the patient teeth
And there is nausea
Then acute bacterial sinusitis will be diagnosed

If there is headaches
And the patient is coughing
And there is nausea
And the mucus is colored
And there is shaking chills
And there is an ache at the muscle
And the heart is beating rapidly
And there is fatigue
Then pneumonia will be diagnosed

If there is no headaches
And the patient is coughing
And there is nausea
And the mucus is colored
And there is no shaking chill
And there is an ache at the muscle
And the heart is beating rapidly
And there is fatigue
And the feet is swelling
Then acute bronchitis will be diagnosed

These rules are added to the knowledge base using prolog programming language. These rules capture common evidence of problems associated with the symptom of acute respiratory tract infections. The detail is presented in appendix 3.

6.2.3. Reasoning Mechanisms

During inference, rules are linked into chains of reasoning by the KBS which can use either backward chaining or forward chaining. Forward chaining is data-driven and investigates the consequences of the knowledge and finds the rules whose conditions are satisfied by the knowledge; whereas backward chaining is the goal-driven reasoning tries to prove a hypothesis by finding rules with the hypothesis result in its conclusion. In case where an expert first needs to gather some information and then tries to infer from it whatever can be inferred, the forward chaining inference engine is chosen. Whereas, incase when expert begins with a hypothetical solution and then attempts to find facts to prove it, the backward chaining inference engine is chosen.

The reasoning mechanism used for this research is the forward chaining because different initial rules are processed first to draw different new conclusions as refined in the following subsection. The popularity of forward-chaining or data-driven control derives largely from the fact that such reasoning mechanism can respond quickly to input from the user of the system, rather than forcing the user to wait until the program gets around to what the user wants to talk about.

In KBS development, forward-chaining is the process of establishing the facts, and seeing which conclusions are supported. The flow of control of a forward chaining system is often controlled by setting goal facts in working storage. Rules might have goals in the conditions thus ensuring the rule will only fire when that goal is being pursued. For a data driven system (forward-chaining system), the system must be initially populated with data, in contrast to the goal driven system (backward-chaining system) which gathers data as it needs it.

6.2.4. The Goals

Possible goals are derived by combining the five infections stated in the knowledge acquisition phase. During inference five top goals are used. The remaining intermediates are seen as sub goals during inference. Based on this, ARTIKoBS five goals are:

Goal 1: *Acute Pharyngitis* – this tells that based on the symptom that the user inputs, the infection that the person is infected by is acute pharyngitis.

Goal 2: *Common Cold* **-** this tells that based on the symptom that the user inputs, the infection that the person is infected by is common cold.

Goal 3: *Acute Bacterial Sinusitis* **-** this tells that based on the symptom that the user inputs, the infection that the person is infected by is acute bacterial sinusitis.

Goal 4: *Pneumonia* **-** this tells that based on the symptom that the user inputs, the infection that the person is infected by is pneumonia.

Goal 5: *Acute Bronchitis* **-** this tells that based on the symptom that the user inputs, the infection that the person is infected by is acute bronchitis.

6.2.5. Uncertainty handling in ARTIKoBS

6.2.5.1. Challenges in Medical Diagnosis Process and Knowledge Base Systems

When faced with a patient who may or may not suffer from a particular infection, a doctor cannot usually give a definite and unique identification of infection. This does not indicate a lack of ability or intelligence on the doctor's part. It is more because the only evidence which a doctor has to go on is what symptoms are observed, and this is often insufficient to identify the infection uniquely. Several infections may produce similar symptoms, in the earlier stages at least and some infections do not produce all the symptoms in the early stages. So when working backwards from all the symptoms, a doctor must consider several possibilities. It may be, of course, that some of these possibilities are more likely than others and so the result of diagnosis could well be a list of possible infections, with some indication of how likely each is. For instance, a quick examination of a patient might result in the following diagnosis:

The patient has a sore throat - very likely
The patient is coughing – very unlikely
The patient has a scratchy throat – probably
The patient feels swallowing pain - maybe

How does a doctor arrive at this sort of conclusion? The process is certainly a complex one but a doctor will make considerable use of established medical knowledge about infections, their symptoms, how common each infection is, how significant a symptom is, and so on. All this medical knowledge can be called a knowledge base. This knowledge will generally be fixed from one patient to the next. What alters with a change of patient's symptoms is that as a patient is examined, the doctor builds up a separate local knowledge base about the patient. These two knowledge bases and a third component in the doctor's diagnosis system -a reasoning mechanism performs the mental searching of the medical knowledge base, and matches it with the patient's observed symptoms in the local knowledge base. This reasoning mechanism is sometimes called the inference engine.

"Medicine is a science of uncertainty and an art of probability" (Wood, 1999). Important components of the art of medicine are skills in repeatedly making decisions, formulating appropriate judgments and being comfortable with risk and uncertainty. Medical training, with its heavy emphasis on factual learning, often assigns a lesser priority to the study of decision making (Wood, 1999).

As clinical decision making inherently requires reasoning under uncertainty, knowledge base systems will be suitable techniques for dealing with partial evidence and with uncertainty regarding the effects of proposed interventions (Shortliffe, 1987). The specific uncertainty of medical knowledge requires means for representing and dealing with different forms of uncertainty.

According to Shortliffe (1987), a characteristic of knowledge base systems distinct from conventional programs is their ability to use incomplete or incorrect data. Given only a partial data set, an expert is likely to have less than absolute certainty in his or her conclusion. The degree of certainty can be quantified in relative terms and included in the knowledge base. The certainty values are assigned by the expert during the knowledge acquisition phase of developing the system. By incorporating rules in the knowledge base with different certainty values, the system will be able to offer solutions to problems without a complete set of data (Shortliffe, 1987).

Several are diagnostic knowledge base systems whose conclusions are often weighted by certainty factors that express the degree of confidence that the system has in its conclusion (Wood, 1999). This feature enables the system to draw conclusions with incomplete data. For example, if all essential symptoms of a disease were expressed and recorded by the user during a consultation, then the maximum certainty factor would be expected (i.e. the system is absolutely certain of its conclusion). However, if a symptom is not expressed or not observed by the user, then the system would be less certain of its conclusion and would indicate the decrease in confidence with a lower than maximum certainty value. Users may also use certainty values while recording their observations. For example, if the user is not absolutely certain that a symptom is present, a less than maximum certainty value may be assigned to the response. The system then uses an algorithm inherent to the language of the knowledge base system to combine the various certainty values into a single meaningful measure of confidence in the conclusion drawn by the system.

6.2.5.2. Process of Uncertainty handling in ARTIKoBS

There are various ways in which the certainty factors can be implemented, and how they are propagated through the knowledge base systems, but they all have to deal with the same basic situations according to Shortliffe (1987):

- rules whose conclusions are uncertain;
- rules whose premises are uncertain;
- user entered data which is uncertain;
- combining uncertain premises with uncertain conclusions;
- updating uncertain working storage data with new, also uncertain information;
- establishing a threshold of uncertainty for when a premise is considered known.

ARTIKoBS medical diagnostic system was developed using prolog programming language and uses uncertainty to express the degree to which a rule matches the description of the infected patient. The uncertainty associated with each response serves as an approximate indicator of the confidence in the advice provided by the knowledge base system.

ARTIKoBS diagnoses five infections of acute respiratory tract infections. The user begins a session by inputting his/her symptoms to the system by saying yes, no, very likely, very unlikely, probably, unlikely, maybe and don't know. The knowledge base system uses certainty factor to arrive at conclusions. At the end of a session the knowledge base system displays all conclusions reached with corresponding levels of certainty. Certainty has been built into the knowledge base to help the knowledge base system reach a conclusion when there is incomplete data or unknown information.

In the real world, there is often uncertainty associated with the rules of thumb an expert uses, as well as the data supplied by the user. But the most common scheme for dealing with uncertainty is to assign a certainty factor to each piece of information in the system. The inference engine automatically updates and maintains the certainty factors as the inference proceeds.

There are eight (8) responses with their confidence factor that the user of the system is allowed to input. These certainty factors (preceded by CF) are integers which are assigned for these user responses as +100 (for definitely true or *yes* response), 0 (for *no* response), 90 (for *very likely* response), 5 (for *very unlikely* response), 80 (for *probably* response), 25 (for *unlikely* response), 60 (for *maybe* response), and null (for *don't know* response) this is because *don't know* is a response which is used to elaborate the question asked by the system and it doesn't hold any confidence factor.

The inference in ARTIKoBS does not stop after having found one possible value for problem. It finds all of the reasonable problems and reports the certainty to which they are known. These certainty factors are not probability values, but simply give some degree of weight to each answer. The above sample knowledge base from ARTIKoBS indicates how certainty information is added to the rules in the then clause and the user can only specify CFs when inputting the eight responses. These are the only two ways uncertainty gets into the system. Uncertainty associated with a particular run of the system is kept in working storage. Every time a value for an attribute is determined by a rule or a user interaction, the system saves that attribute value pair and associated CF in working storage.

The CFs in the conclusion of the rule is based on the certainty factor assigned for the premise. That is, if the conclusion has a CF of 85 and the premise is known to CF 100, then the fact which is stored in working storage has a CF of 85. The conclusion in ARTIKoBS is perfectly known since the system needs a means for determining the CF of the premise. The confidence factor assigned to each of the user responses corresponds to the CF for the premise in ARTIKoBS. When the premise of a rule is uncertain due to uncertain facts, and the conclusion is uncertain due to the specification in the rule, then the following formula is used to compute the adjusted certainty factor of the conclusion:

$$CF = RuleCF * PremiseCF / 100.$$

A threshold value for a premise is needed to prevent all of the rules from firing. The number 65 is used in ARTIKoBS as a minimum CF necessary to consider a rule for firing. This means that if working storage had:

The patient is always coughing: very likely (CF=90)

The patient nose is runny and blocked: unlikely (CF=25)

then conclusion would not fire due to the low CF associated with the premise.

ARTIKoBS was validated by comparing the responses obtained by the system to the domain expert's responses to the same acute respiratory tract infections. ARTIKoBS arrived at 71 % correct responses with 100% certainty, and 13% of the responses were correct diagnoses with less than 100% certainty.

6.2.6. The User Interface

The user interface of the system is directly used from the interface of the SWI prolog window. The facts are asked to be answered using the “yes”, “no”, “very likely”, “very unlikely”, “probably”, “unlikely”, “maybe” or “don’t know” options.

The first page of the user interface welcomes the user by displaying “Welcome to ARTIKoBS Acute Respiratory Tract Infections Knowledge Base System.” As shown in figure 5.1, the system invites the users to write “artikobs” followed by full stop and press enter key. The system first instructs the user about the options that he/she has in order to consult the system. For example, for “yes” response, the user must write y without full stop at the end of the character and press enter key and then follow the instruction. To get explanation about the question that the user is asked, the system invites the user to write d without full stop at the end of the character and press enter key.

After full consultation and diagnosis, the system prompts the user by displaying “Do you want to conduct another consultation?” If the user input y (which means yes), the system start the consultation again. If not, the system invites the user to write halt followed by full stop and press enter key to exit from the prolog window.

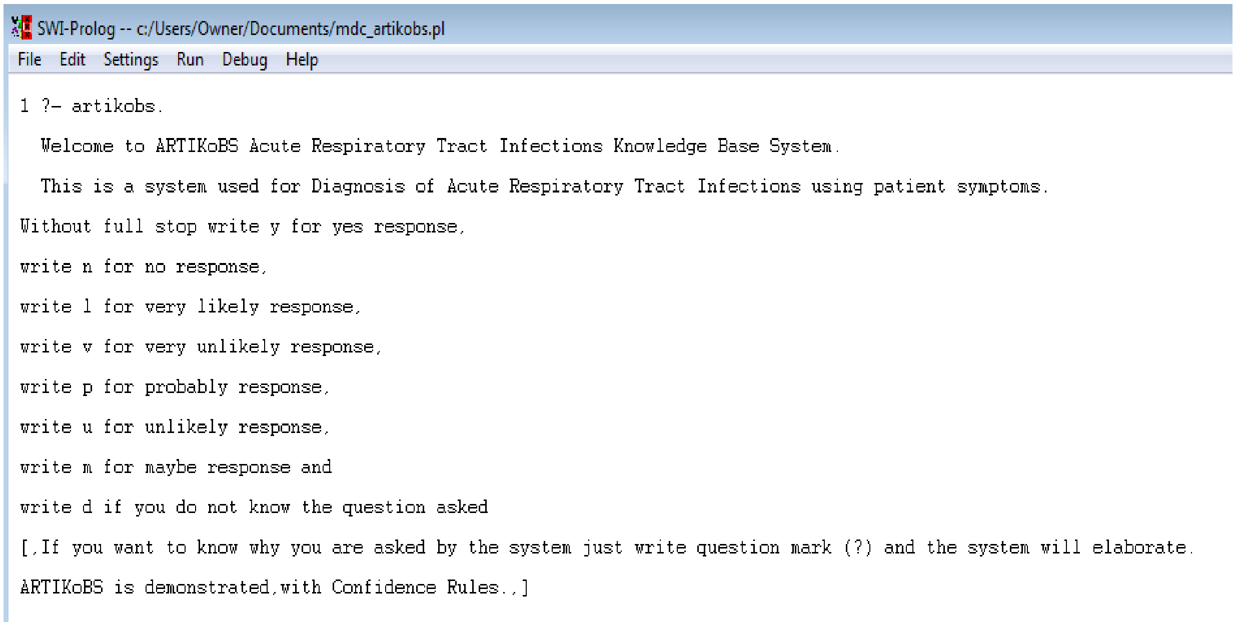


Figure 6.1: The Welcoming Window of ARTIKoBS.

6.2.7. Explanation Facility

The explanation facility is among the important parts of ARTIKoBS. The system is capable to explain how the conclusions arrived. This means the user can ask the system for justification of conclusions or explanation why some question is used. At any point in a consultation the ARTIKoBS responds with the rules that is used for the conclusion, or the rule being considered which led to a question to the user.

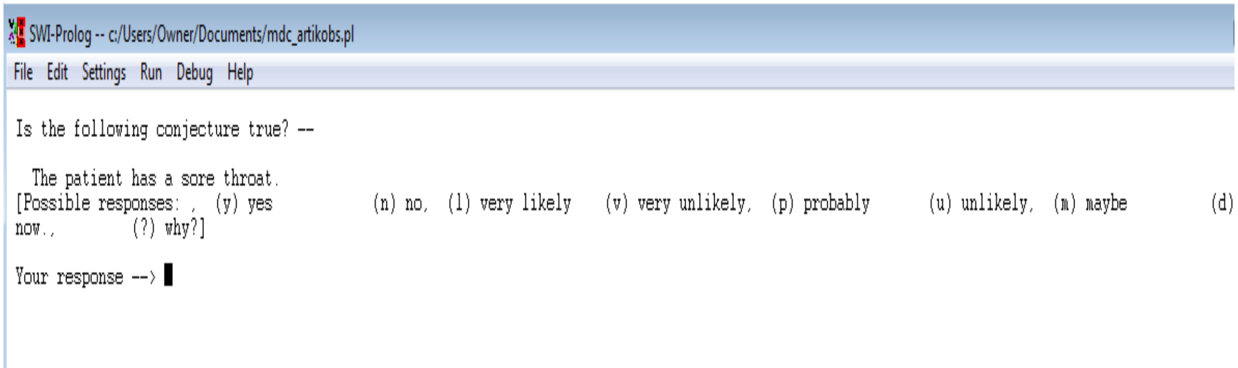
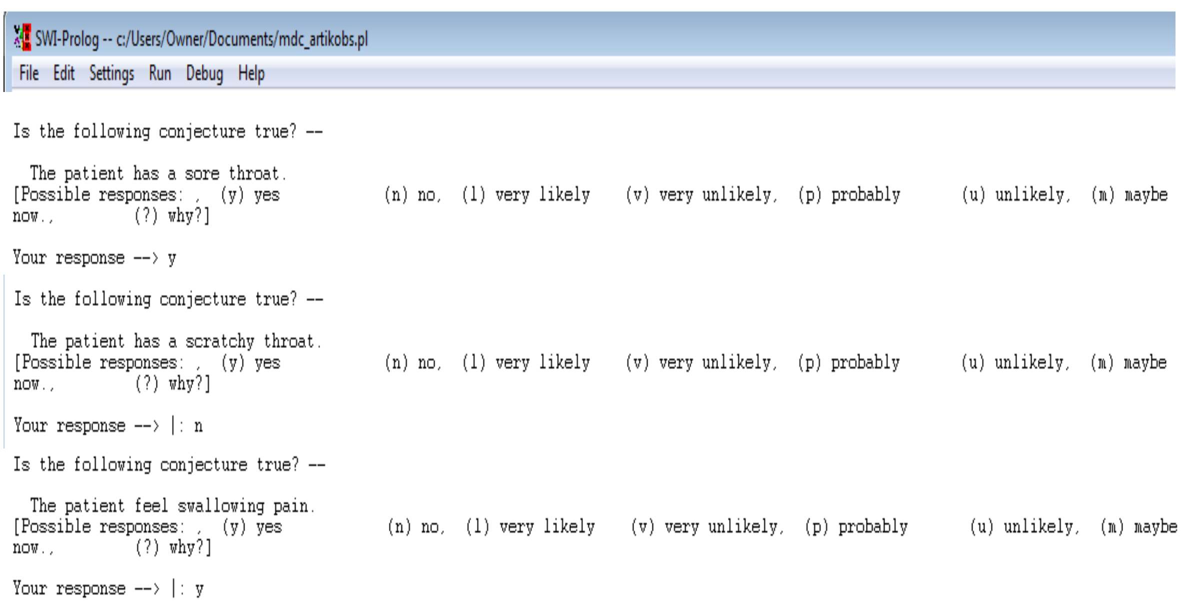


Figure 6.2: The ARTIKoBS window asking the user.

"Is the following conjuncture true?—The patient has a sore throat" is the first question asked by the system. As the hybrid decision tree and inference network logical view for symptomatic diagnosis of ARTI indicates that sore throat or painful swallowing is the first symptom where the diagnosis process was started. This question is asked by the system to identify whether the patient is infected by Acute Pharyngitis or not. In case where the response is yes, the system continues to ask more questions so that the appropriate conclusion is made. If not, the diagnosis process proceeds to other symptoms to identify and diagnose other acute respiratory tract infections. In the meantime or at the end of the consultation the system provides the necessary advices when ever appropriate.



```
Conclusion: The patient has acute pharyngitis.
Confidence in hypothesis: 90%.
Do you want an explanation?
--> |: y


The patient has acute pharyngitis.
Accepted with 90% confidence on the basis of the following
Rule: The patient has acute pharyngitis.
  with confidence of 90% if
    to confirm: The patient has a sore throat.
    to confirm: The patient feel swallowing pain.
    to disconfirm: The patient has a scratchy throat.

The patient has a sore throat. -
From what you told me, I accepted this with 100% confidence.

The patient feel swallowing pain. -
From what you told me, I accepted this with 100% confidence.

The patient has a scratchy throat. -
From what you told me, I rejected this with 100% confidence.

Press Return when ready to continue.
```

Figure 6.3: The window that give advice for user.

As shown in figure 6.3 above, the system asks questions and collects the answers. It gives intermediate advices that tells the user how he/she can proceed and what could be the results following this step. The application proceeds likewise.

6.3. Testing and Evaluation

The mass of information, data and rules which accumulate in the knowledge base over months and years of development is of little value unless the knowledge is accurate and free of contradictions. Although there will almost always be situations which occur at the limit which the system will be unable to handle, many of these can be identified through exception handling rules or through human oversight. As with a conventional software project it is advisable to test and validate the system as it is being built, rather than waiting until the system is complete.

Knowledge base errors may be more difficult to find, however they are relatively easy to correct. They come in multiple forms, from typing mistakes to referring to wrong variables or using ineffective inference strategies. Bowerman (1988) concludes that a good, strong systems-analysis approach will usually turn up the sources of the problems in a reasonable time.

The evaluation process tries to answer the questions like: are the knowledge acquisition and knowledge representation schemes adequate or do they need to be extended or modified? Is the system coming up with the right answers for the right reasons? Is the embedded knowledge consistent with the experts? Is it easy for users to interact with the system? What facilities and capabilities do the users need?

There are different techniques that are employed to KBS testing and evaluation. These techniques are classified as qualitative and quantitative. The former employs subjective comparisons of performance and the later employs statistical techniques to compare KBS performance against either test cases or human experts (Anumba and Scott, 2001).

In this research, qualitative evaluation techniques like visual interaction and predictive validation were used. Visual interaction is one of the most commonly employed qualitative techniques to evaluation KBSs (O'Keefe et al, 1987, Hayes-Roth et al, 1983). This test allows the expert to make comments while interacting with the system, altering parameters as desired. In case of predictive validation the test involves the use of historic test cases. The KBS is driven by past data to obtain a set of conclusion. These conclusions are compared with that of the historic case or with expert performance; and then the performance is judged. In addition to this, the quality of the system's decision and advice, the correctness of the reasoning techniques, the system's efficiency, and its cost effectiveness are also part of the evaluation process. The evaluation activity also involves exploring the code, examining the reasoning processes, examining intermediate results and conclusions of the system, to help detect errors as early as possible in the development. These are what were followed in the evaluation process of this research.

6.3.1. Visual Interaction

A reasonable test of the theory and implementation described here is to bring human subjects to the laboratory and determine whether they can converse sufficiently well with the machine to effectively solve problems. The purpose of the testing was to assess the performance of the system from the user perspective and to judge the human factors issues, learnability, and user response. The hypotheses were that the system would function acceptably, that user would respond positively to using the system. This section describes the design of the tests and the results obtained.

The evaluation process adopted has involved the domain experts, patients and voluntary user groups from beginning to end of the process. The experts interacted with various sections of the system by inputting several variables to check its performance and providing feedbacks on different cases. These are useful in identifying areas of knowledge missing from the system; areas of the system which are not being covered; and whether the knowledge was consistent with that of the experts and so on.

In this regard, ARTIKoBS prototype effectiveness test is applied in Dagmawi-Minilik hospital and Meshualekia middle level clinic health institutions. For this experiment, the users were classified into two different groups. The first group, using random sampling, incorporates 10 (ten) medical persons (six medical experts from Dagmawi-Minilik hospital and four medical experts from Meshualekia middle level clinic) who use the system as an ARTI counselor (junior and senior physicians) who are selected from a total of 20 experts. Of the ten selected medical persons, using purposive sampling technique, 6 experts were used as system evaluators and the other four experts were assigned to help the second group. The second group includes nine patients and voluntary ARTIKoBS users. This group was selected and evaluated by the four experts mentioned above.

The developed prototype system was deployed in nine available standalone computers in the selected health institutions and after full explanation about ARTIKoBS, the system was evaluated. The analysis of ARTIKoBS user's performance test is discussed as follows.

No.	**Infection Name**	**Gender**	**Correctly Diagnosed**	**Incorrectly Diagnosed**
1	Acute Pharyngitis	2Female	2	0
2	Common Cold	1Male, 2Female	1	2
3	Acute Bacterial Sinusitis	1Male	1	0
4	Pneumonia	1Female	1	0
5	Acute Bronchitis	2Male	1	1
Total			6	3

Table 6.1 Patient profile for ARTIKoBS user's performance test

From the data shown in the above table, of the total of nine patients, six were diagnosed correctly as ART infection cases, and the other three were diagnosed incorrectly as ART infection case.

6.3.2. Confusion Matrix

The confusion matrix is a simple square matrix that compares the relative performance of the human and the new system – the match and mismatch. The columns of the matrix correspond to the number of instances by human and the rows correspond to the number of instances by the system as a particular value (Brule, 1986). One benefit of a confusion matrix is that it is easy to see if the system is confusing two classes (i.e. commonly mislabeling one as another). For example, the following table shows the confusion matrix for a two class classifier. The entries in the confusion matrix have the following meaning in the context of our study: a is the number of correct predictions that an instance is negative, b is the number of incorrect predictions that an instance is positive, c is the number of incorrect of predictions that an instance negative, and d is the number of correct predictions that an instance is positive.

		Predicted	
		Positive	**Negative**
Actual	**Positive**	**a (True Positive)**	**b (False Positive)**
	Negative	**c (False Negative)**	**d (True Negative)**

Table 6.2 Confusion Matrix

Several standard terms have been defined for the 2 class matrix:

• The accuracy (AC) is the proportion of the total number of predictions that were correct. It is determined using the equation:

$$\mathbf{AC=a+d/a+b+c+d}$$

• The recall or true positive rate (TP) is the proportion of positive cases that were correctly identified, as calculated using the equation:

$$\mathbf{TP=a/a+b}$$

• The false positive rate (FP) is the proportion of negatives cases that were incorrectly classified as positive, as calculated using the equation:

$$\mathbf{FP=b/a+b}$$

• The true negative rate (TN) is defined as the proportion of negatives cases that were classified correctly, as calculated using the equation:

$$\mathbf{TN=d/c+d}$$

• The false negative rate (FN) is the proportion of positives cases that were incorrectly classified as negative, as calculated using the equation:

FN=c/c+d

The classification performance of the model used in this research was evaluated using three statistical measures; classification accuracy, sensitivity and specificity. These measures are defined using the values of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) as depicted in table 6.2.

- A true positive decision occurs when the positive prediction of the system coincided with a positive prediction of the medical expert or when an input is detected as a patient with ARTI diagnosed by the expert clinicians.
- A true negative decision occurs when both the system and the medical expert suggested the absence of a positive prediction or in other word, when an input is detected as normal that is labeled as a healthy person by the expert clinicians.
- False positive occurs when an input is detected as a patient that is labeled as healthy by the expert clinicians.
- Finally, false negative occurs when the system labels a positive case as negative or when an input is detected as normal with ARTI case diagnosed by the expert clinicians.
- Classification accuracy is defined as the ratio of the number of correctly classified cases and is equal to the sum of TP and TN divided by the total number of cases N.

  Accuracy=TP+TN/N

- Sensitivity refers to the rate of correctly classified positive and is equal to TP divided by the sum of TP and FN. Sensitivity may be referred as a *True Positive Rate*

  Sensitivity=TP/TP+FN

- Specificity refers to the rate of correctly classified negative and is equal to the ratio of TN to the sum of TN and FP. *False Positive Rate* equals (100-specificity).

  Specificity=TN/TN+FP

Using the output presented in table 6.3 below we see that out of the total instances which have a class “Positive”, 5 are correctly diagnosed, whereas 2 of the total instances are misdiagnosed. Likewise, out of 2 class “Negative” instances, 2 are diagnosed correctly and nothing is incorrectly diagnosed.

		Patients with ART Infections	
		Positive	**Negative**
ARTIKoBS Test	**Positive**	**True Positive = 5**	**False Positive = 2**
	Negative	**False Negative = 0**	**True Negative = 2**

Table 6.3 Confusion Matrix for ARTIKoBS user's performance experiment

From the table 6.3, the performance of the system is computed using the following equations.

Sensitivity (True Positive Rate) = TP/ (TP + FN)

= 5/ (5 + 0)

= 5/5 which is equivalent to 100%

Specificity (False Positive Rate) = TN / (FP + TN)

= 2 / (2 + 2)

= 2 / 4 which is equivalent to 50%

The Accuracy = TP + TN / N

= 5 + 2 / 9

= 0.78

= 78%

Sensitivity (true positive rate) of 100% indicates that the positive prediction of the system coincided with a positive prediction of the medical expert. This means that the system is fully functioning to identify a patient with any of the five acute respiratory tract infections and to give the necessary diagnosis.

A specificity of 50% indicates that, at initial diagnosis, ARTIKoBS correctly identifies 50% of those who do not have ARTI. It is also to mean that out of 100%, the system recognizes half percent (50%) of healthy people as healthy. This implicates that further investigations shall be undertaken to ensure high ART infections confirming rate and to recognize all health people as healthy.

The result shows the system has an accuracy of 78%. The remaining 22% is the variation between the system and the human experts. Out of the 22% the output of the human expert is found to be ‘acute bronchitis’ whereas the output using the system contains outputs, ‘pneumonia’. The variation happened because of two main reasons. The first one is related with the symptom similarity between acute bronchitis and pneumonia acute respiratory tract infections. Most of the time one of a severe complication of pneumonia is acute bronchitis. If there is coughing or hack on the patient with pneumonia infection that may not go away for a longtime, after one or two week, the infection became severe and it gave rise for acute bronchitis infection.

The other is since the system adopts rule based reasoning it couldn’t work with situation analysis while the human expert can do. The system narrows down this gap by considering case based reasoning that enable it to learn from past human practices which is not covered in this research.

6.3.3. Evaluation Using Test Cases

Evaluation using test cases (also referred to as predictive validation) is conducted mainly by the researcher and, at times, with experts present. The main aim of the predictive validation is to test ARTIKoBS ability to diagnose ART infections. Twenty five historical test cases, which are expected to be enough to prove and demonstrate the system’s capabilities, were used to compare the diagnosis of the past with that of the system and the experts. These cases were randomly selected by the expert evaluators so that no bias would be introduced into the evaluation process.

Of those historical test cases, by stratifying the cases first and then using random sampling, one from each case was selected to use at various stages of the system development to detect errors and check that the knowledge within the system was consistent with that of the experts.

The test cases used to evaluate ARTIKoBS ability were new ones which have not been used in the early stages of the system’s development. Initially, the researcher entered a number of random cases from the expert’s case files into ARTIKoBS. The cases were selected from respiratory infections department archives randomly. And this system generally dealt with the cases well. Second, test cases are entered into the system by the expert evaluators. Four test cases randomly chosen by the experts, one case evaluation for each expert and one from each case, were used for evaluation during this phase. These cases are briefly described below. Unstructured questionnaires were conducted, in conjunction with entering the cases into the system, to help ascertain the expert's views on specific aspects of the system's performance.

Other diagnostic systems usually use one unique decision tree for one main symptom of a patient. If a patient has *n* different main symptoms, then there will be *n* different decision trees for the user to go through during one diagnosis. And the results produced by *n* decision trees should be compared, and combined somehow, if they are different from each other. All of the four randomly selected test cases from patient records have more than one main symptom. That means a decision tree that comprised the five inference trees must be gone through from their roots in order to diagnose just one patient.

Case 1

Background: This case describes a 17 years old patient complain of nasal stuffiness or drainage, sore or scratchy throat, sneezing, hoarseness, cough, and a fever and headache. There was no other complain.

Summary: The system modeled the case well, and commented that if a patient has sore or scratchy throat, sneezing and cough, there is a high probability that the patient is infected by common cold acute upper respiratory tract infection and it is necessary for the patient to take the appropriate medication. This decision of the system was the same with the medical expert.

The system doesn't consider other problems except the three symptoms which cause the system to decide on the given problem. The explanation facility and remedial advice given by the system is considered reasonable. In contrast, the expert checked other symptoms which could cause common cold and advises the necessary diagnosis accordingly. He agreed that the system came up with the correct solution to the problem and gave the system an overall rating of 80 percent.

Case 2:

Background: A 28 year old female patient complains of reduced sense of smell and taste and cough.

Summary: The system identify and diagnosed the infection as acute bacterial sinusitis because the reduction of sense of smell and taste is mainly caused by the stuffiness, congestion, and a thick yellow or green discharge symptoms of acute bacterial sinusitis. The medical expert was agreed with the diagnosis provided by ARTIKoBS although he considered other symptoms like teeth and ear pain, bad breathing and nausea to come up with the decision.

The evaluator agreed fully with the advice given by ARTIKoBS. With the amount of information required for this case, including explanation facility, he considered the system to be efficient in the diagnosis process and agreed that the system has the ability to reason out and gave it an overall rating of 95 percent.

Case 3

Background: The case was a difficulty in swallowing and the patient feels scratchy on his throat and generally feeling unwell on his tonsil. There was no other history.

Summary: Both the system and the expert diagnose Acute Pharyngitis though they differ in the way they came up with the conclusion. In addition to the decision given, the expert considered slight fever as one symptom to differentiate the diagnosis from other cases. But the system came up with the decision by referring only the three symptoms. As it was specified that a slight fever is possible, not all causative agents which cause acute pharyngitis infection have a slight fever symptoms.

The assessment, treatment and health education were well represented in the system and it was commented by the evaluator that it is complete. The expert overall system rating was 95 per cent.

Case 4

Background: In this case, a female 26 year old patient complains of a cough which was dry at first (does not produce mucus) and after a few days it brings up mucus from the lungs (productive cough). There were small streaks of blood in the mucus. She was also complains of whistling noises (wheezing) when breathing and a sensation of tightness, burning, or dull pain in the chest under the breastbone that usually is worse when breathing

Summary: Although the expert diagnosed this case as acute bronchitis lower respiratory tract infection, he found it difficult to understand the diagnosis given by the system. Because ARTIKoBS diagnoses was rather an advice like “Can draw no conclusions.” This was absolutely different from the medical expert decision.

The main reason for this confusion was because ARTIKoBS diagnoses on acute bronchitis infection were based on the patient’s symptoms like swelling feet, spitting-out mucus and failure at the heart and it doesn’t considered symptoms like sensation of tightness, burning, or dull pain in the chest under the breastbone which is beyond the scope of this system. Because of this reason, the evaluator finally did not specify an overall rating of the system.

Discussion

In general, these evaluations were used to assess ARTIKoBS performance for the task for which it is designed. By comparing the problem solving approach of the knowledge base system with the medical experts decision making process, ARTIKoBS has performed an average rating of 80% and this result of the comparison shows that the designed knowledge base system has a very close clinical decision making approach to the medical experts in ARTI case management. Besides, the result implies that the evaluation of ARTIKoBS can be considered a success because it is demonstrated that the knowledge base system made accurate diagnosis and gave sufficient recommendations for each. One major problem of the prototype was that it doesn’t give possible solutions for those problems which are out of the rule.

It is also noteworthy that, as evident from the test cases, the system is able to provide (in some situations) more accurate results than that arrived at using conventional methods. In addition, the experts are visualized how future extensions of the system will significantly improve their existing ARTI symptomatic management. However, the main difficulties encountered in the evaluation were with the expert evaluators. This was mainly due to the limited time which they had available.

The knowledge representation of the prototype with rule based techniques requires to exhaustive input of facts and relationship of facts. However clinical decision making process is always changeable because of new symptoms of acute respiratory tract infections and most of the time the relation between the infections and some of these symptoms are not clearly defined. Therefore the application of the knowledge base system demands the integration of learning tools like neural network to create a general pattern for matching with new symptoms of ARTI.

The finding of the study also implicates that a diagnosis system for acute respiratory tract infections can be effectively facilitated by using knowledge base system to acquire the tacit knowledge obtained from individual and a team of medical experts with respect to the available clinical diagnosis guidelines.

The testing phase of this study has also revealed that because extensive clinical expertise and resources are required to perform evaluations, efficient yet effective methods of monitoring performance during the long-term maintenance phase of the knowledge base system life cycle must be devised. This is because of the fact that computerized medical knowledge bases must be revised constantly, and can never be considered completely finished. Consequently, even the best medical knowledge bases are subject to obsolescence unless a careful maintenance and updating process is implemented.

CHAPTER SEVEN

CONCLUSION AND RECOMMENDATIONS

This chapter marks the peak of the project work. Over and above the prime objectives of assessing the magnitude of acute respiratory tract infections and developing prototype rule based knowledge base system, this work has brought to light certain observations, which are presented by the researcher as important findings and an attempt was also made to give some meaningful suggestions.

6.1. Conclusion

Acute respiratory tract infection (ARTI) are infectious diseases of the respiratory tract which includes the two principal sub-diagnoses of acute lower respiratory tract infection (ALRTI) and acute upper respiratory tract infection (AURTI), although it is often difficult to distinguish between them. Upper respiratory tract infections (URTIs) are the most widespread infectious illnesses in Ethiopia. They are common acute infections involving the nose, paranasal sinuses, pharynx, larynx, trachea, and bronchi. It is usually identified by the community as a common cold and the other infection acute lower respiratory tract is a persistent and pervasive public health problem which surrounds in the lungs, like the bronchi and below which includes diseases like pneumonia, and bronchitis.

This study is an assessment of the magnitude of ARTI surrounding Addis Ababa and a prototype implementation of a knowledge base system for definitive isolation and identification of respiratory tract infections particularly the acute ones. The knowledge domain is got by extensive consultations with knowledge experts in the field of respiratory infections and literature review. These consultations enabled the formulation of production rules. The knowledge base system has been developed from scratch using Prolog implementation tool. The process takes time but gives freedom to the researcher to think and produce original work. It may also give guidance to a recommendation of the possible drugs susceptibility testing.

The prototype knowledge based system, ARTIKoBS has been shown to be generally successful for diagnosing acute respiratory tract infections and this rule-based system performs well in meeting the purpose and objective of the research. It provides a broad view of diagnosis of ARTI emulating the approach of human experts and uses a symptomatic approach. Through modification of existing modules or addition of new modules, the knowledge base system can be conveniently expanded in the future to cover the latest research findings and updates of standards and codes of practice.

It is noted that the performance of ARTIKoBS depends considerably on the user's input. The more the input information, the better is the chance of diagnosing the acute respiratory infections. The ARTIKoBS has been adequate in providing diagnosis of acute respiratory tract infections but it cannot perform satisfactorily in special cases outside its knowledge domain such as the chronic respiratory tract infections. The ARTIKoBS has also been able to provide useful information on each infection types and the necessary care that the patient ought to take.

Useful aspects learnt from the development of ARTIKoBS, which would also be useful for other knowledge base system developments, are summarized below:

- To develop a system like ARTIKoBS, the knowledge engineer needs to know what questions to ask of an expert so that rules may address symptoms and not causes. It is therefore necessary for the knowledge engineer to have some knowledge of the domain.
- Use of terms and jargon in medical diagnosis, which may cause problems to user, are to be avoided as far as possible. However, in practice, people including the new comers who want to use the system must understand some common terms involved in medical diagnosis works otherwise it may not be possible for them to understand the conclusions either.
- Questions to be asked of users of the ARTIKoBS must be clear and unequivocal as far as possible. By asking various questions, the system actually prompts or reminds the user of the need to carry out the various tests required.
- Experts do at times differ in opinions and there may be cases in which the experts themselves are not too certain. It would of course be unfair to expect knowledge base

systems, including ARTIKoBS, to perform at levels that human experts cannot achieve.

- The use of graphics and external program interfaces with the ARTIKoBS will be of benefit.

Knowledge base systems exercise information technology to acquire and utilize human expertise. They can be beneficial to organizations that have clear objectives, rules, and procedures by providing answers to repetitive decision-making, processes and tasks. They can also reduce employment costs, centralize the decision making process, create efficiency and reduce time needed to solve complex problems. However, the weaknesses of these systems should never be under looked such as the limited knowledge domain compared to human experts.

Knowledge based expert systems including ARTIKoBS can be a helpful and useful educational tool. ARTIKoBS is useful to health trainees, medical staff, specialists as well as their top management personnel regarding the probable problems so that early action can be taken. The ARTIKoBS will be particularly of great assistance to the new comers who are not familiar with the field and will facilitate them in gaining a better understanding of the causes of the problems and in making decision for any necessary action.

6.2. Recommendations

The following recommendations are made for further work to enhance the functionality of the prototype and/or develop a new system in a related clinical domain.

1. Although the researcher assessed the magnitude of ARTI in Addis Ababa, the assessment methods used in this study introduced biases that should be addressed. Sampling bias occurred in two health institutions of the study design selection of respondents. Since both health institutions were located in the capital city, and the research did not include respondents in the remote sections of the country, or nearby cities from the capital city. Additionally, the use of medical staffs from the two health institutions facilitated access to respondents, but their presence may have biased patient responses to the questions.

2. The knowledge domain of the “Knowledge Base System for Acute Respiratory Tract Infections diagnosis,” should be upgrade to include other side of respiratory tract infections, which is obviously the chronic ones for example, chronic bronchitis from the lower

respiratory tract infections and chronic Pharyngitis from the upper respiratory tract infections. Therefore, it would be necessary scale up the system to cater for new diseases.

3. Emphasis should be given to the verification and validation steps of the development process with possible clear criteria set to evaluate the effectiveness of the system. Misguided recommendation emanating from a poorly evaluated system could be deleterious to the patient; either no improvement is witnessed or drug toxicities would endanger the life of the patient.

4. The knowledge base system can be linked to other hospital information systems, for example, a hospital decision support system such that diagnosis of infections and reporting of results can be done in real time. Furthermore, it should be implemented as a knowledge server on the NET to publish the expertise.

5. It would be a huge task to incorporate all needed rules in a given domain, unless the scope is narrowed purposely thereby limiting the knowledge required. In keeping with the view that knowledge is never complete, a self-learning system should be developed. That way if a rule is not there, it would be when it’s needed.

6. There should be favorable conditions for further studies and development of knowledge base systems in different medical problem areas in Ethiopia.

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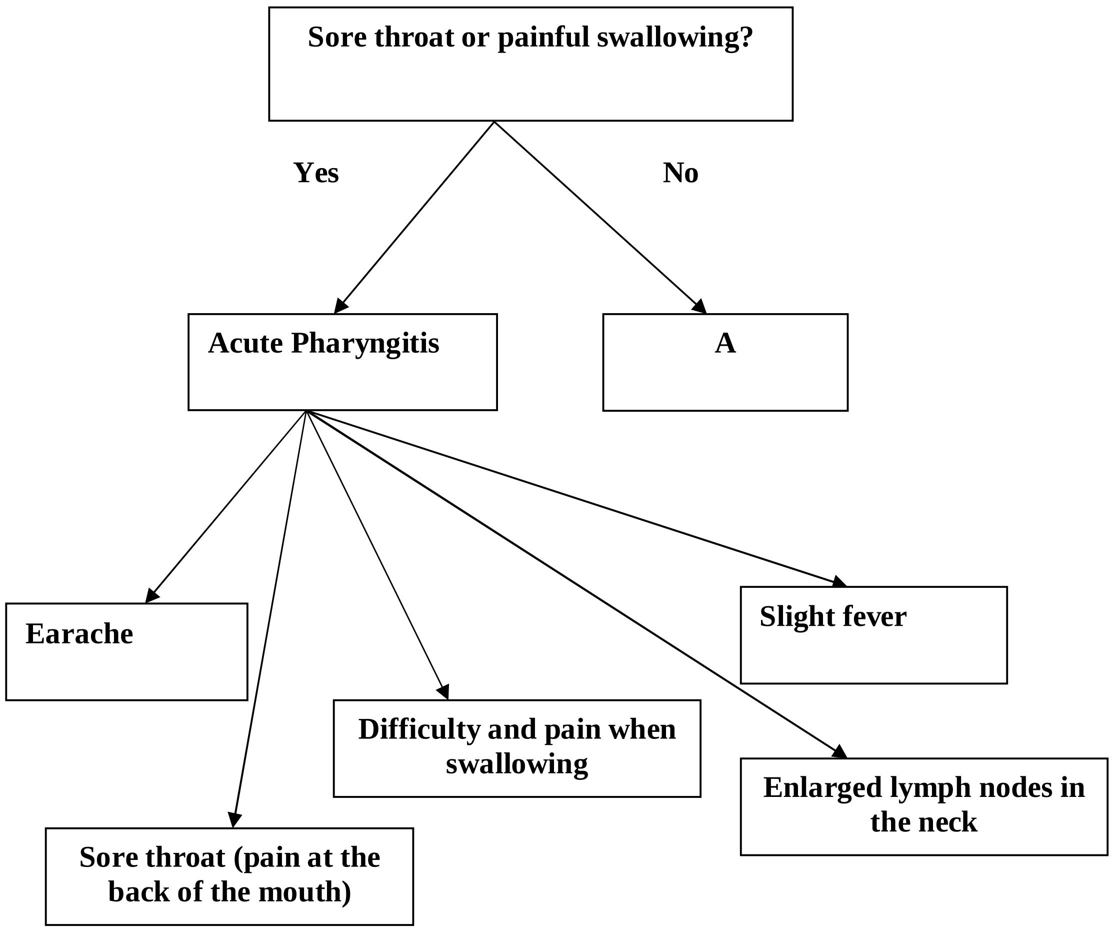
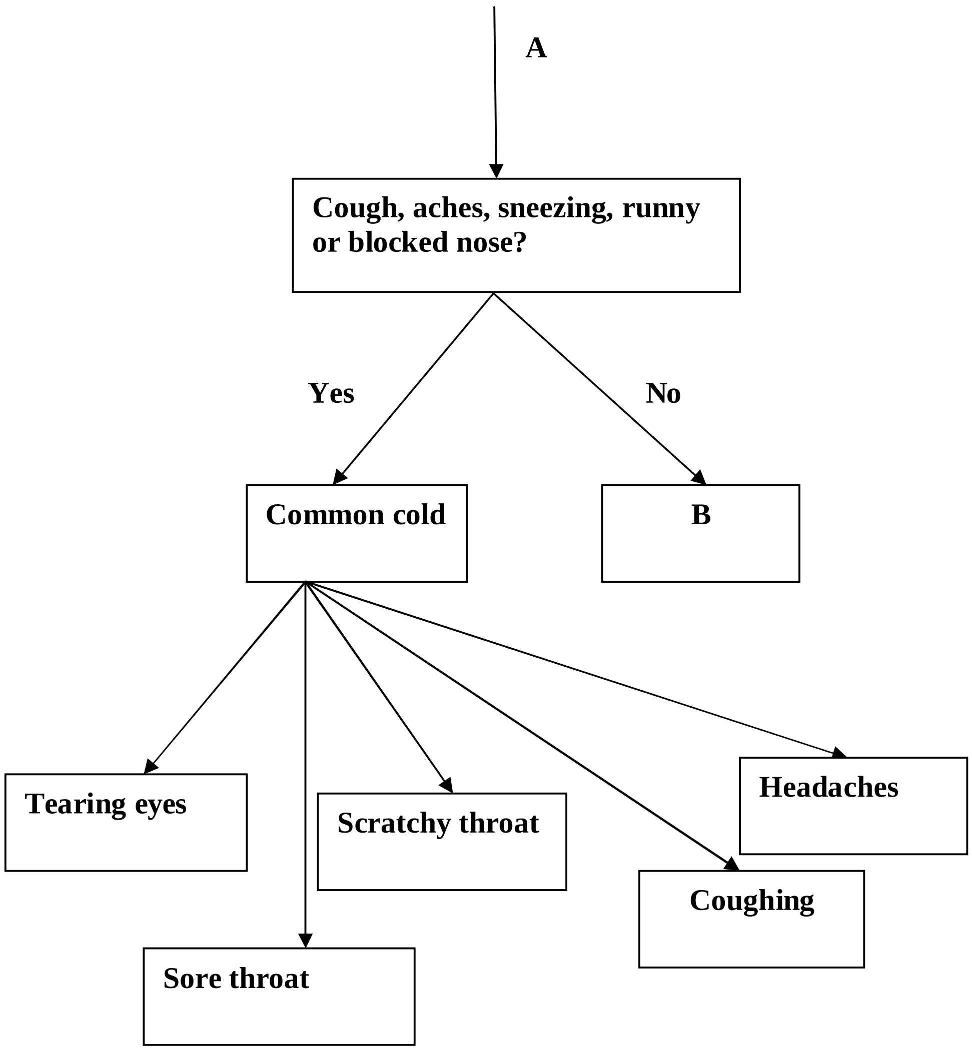
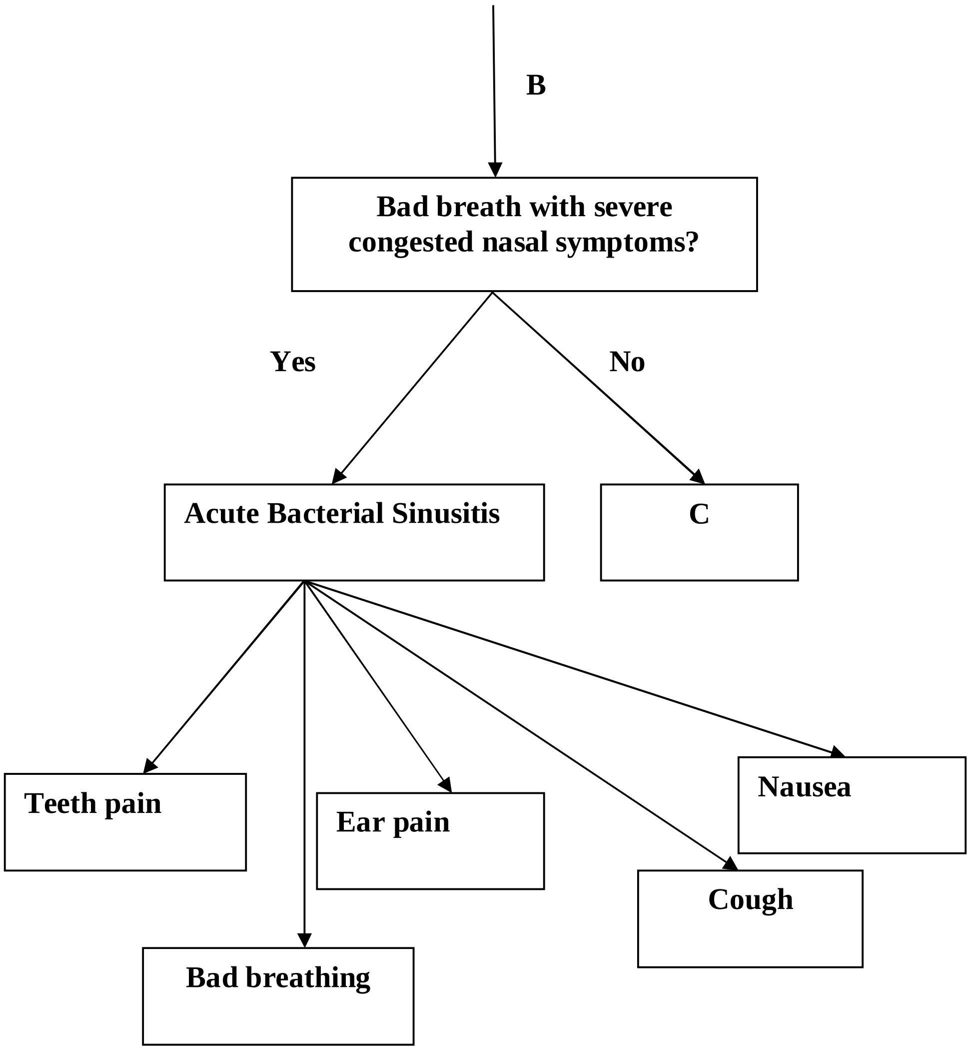
APPENDICES

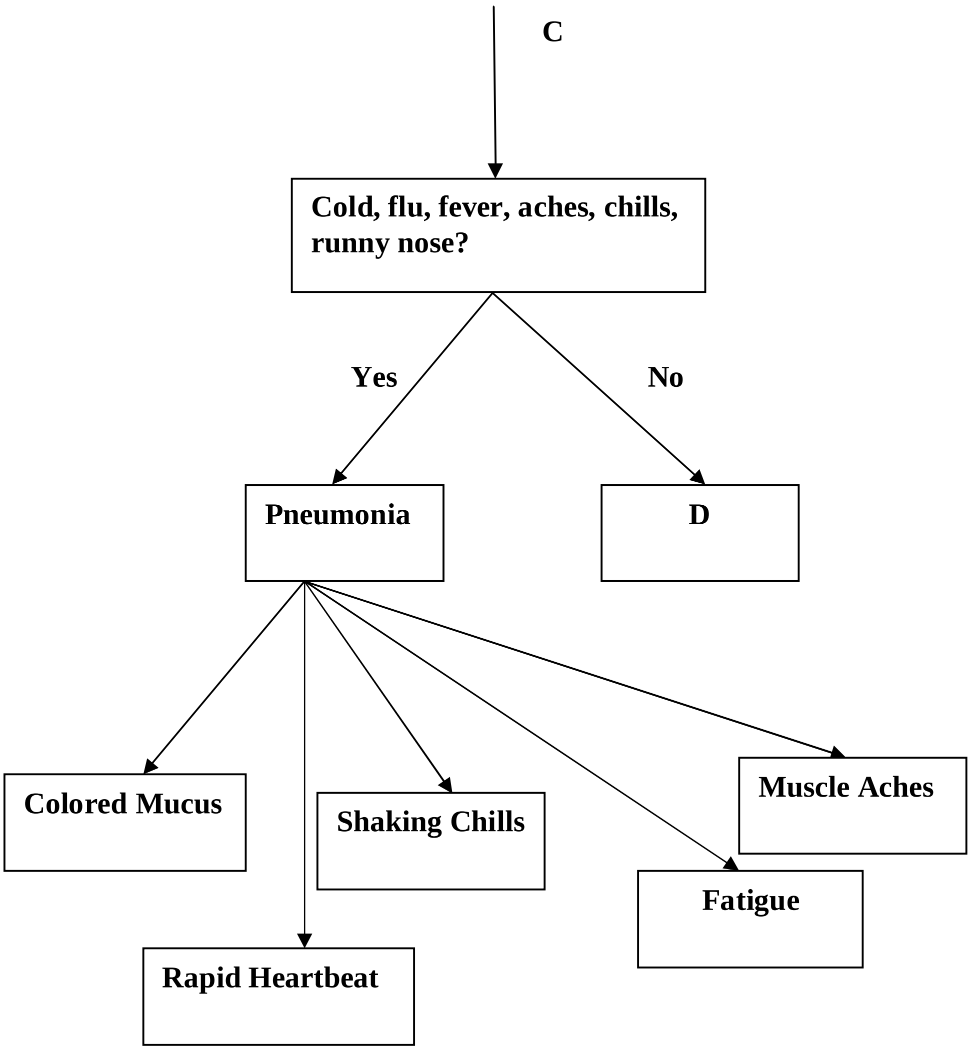
Appendix I

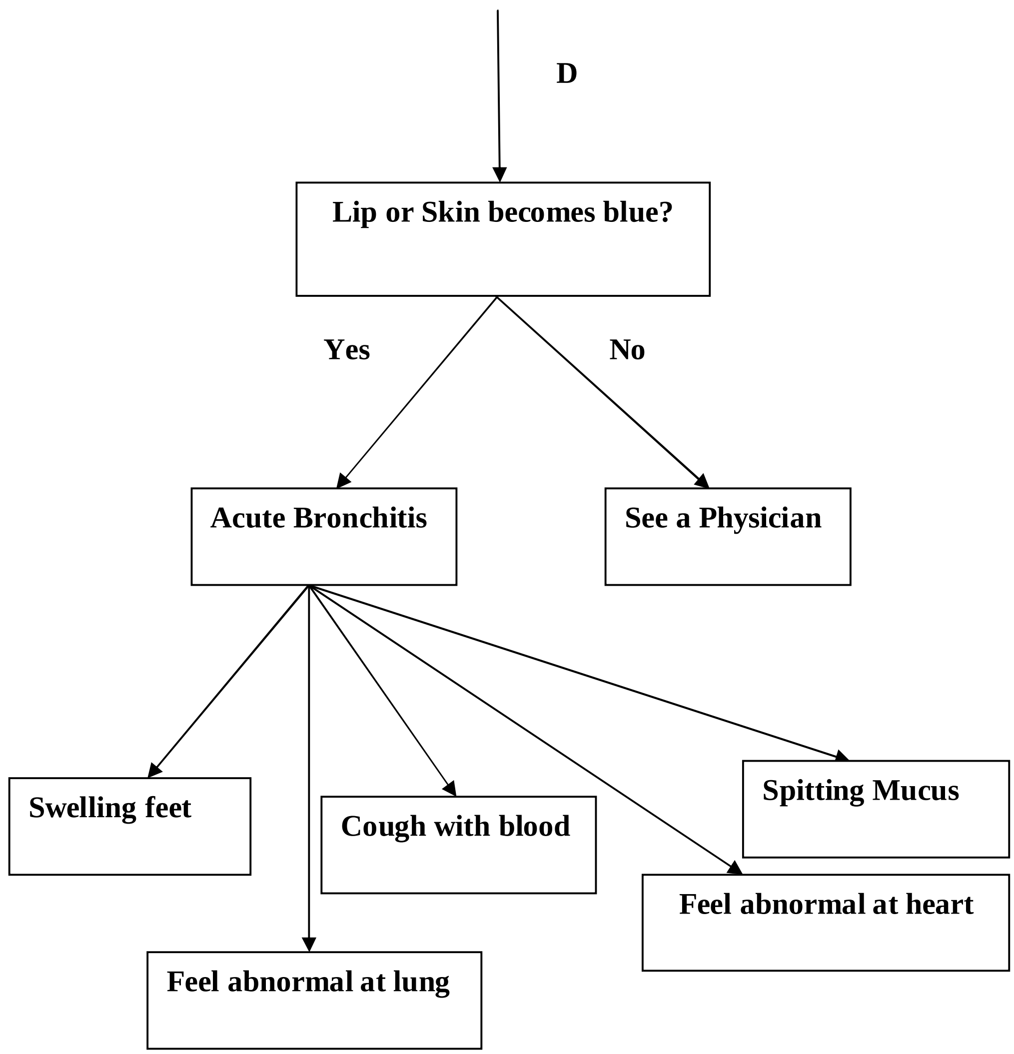
Hybrid Decision Tree and Inference Network Logical View for Symptomatic Diagnosis of ARTI




A
Cough, aches, sneezing, runny or blocked nose?
Yes
No
Common cold
B
Tearing eyes
Scratchy throat
Headaches
Coughing
Sore throat


B
Bad breath with severe congested nasal symptoms?
Yes
No
Acute Bacterial Sinusitis
C
Teeth pain
Ear pain
Nausea
Cough
Bad breathing


C
Cold, flu, fever, aches, chills, runny nose?
Yes
No
Pneumonia
D
Colored Mucus
Shaking Chills
Muscle Aches
Fatigue
Rapid Heartbeat


D
Lip or Skin becomes blue?
Yes
No
Acute Bronchitis
See a Physician
Swelling feet
Cough with blood
Spitting Mucus
Feel abnormal at heart
Feel abnormal at lung

Appendix II

Selected elements of Acute Respiratory Tract Infections

STRTEGIES	• Identify acute respiratory tract infections symptom and diagnose the infection type • Identify the treatment
CONCEPTS	• Acute Respiratory Tract Infections: Acute Pharyngitis, Common Cold, Acute Bacterial Sinusitis, Pneumonia, Acute Bronchitis • Treatment • Sore throat (pain at the back of the mouth), difficulty and pain when swallowing, earache, slight fever, enlarged lymph nodes in the neck, runny nose, blocked nose, tearing eyes, scratchy throat, coughing, headache, sneezing, congested nasal symptom, stuffiness nasal symptom, red Eyes, bad breath, nausea, green mucus, rapid heartbeat, abdominal pain, vomiting, teeth pain, ear pain, abnormal lung, abnormality at heart
OBJECTS	• Lung, heart, bronchial tubes, mucus, throat, cells, tissue, nasal cavity, trachea, oral cavity, larynx, pharynx • Antibiotics, pill, injection, Syrup, Tablet, • Hospitals, clinics

Appendix III

Symptoms of the five Acute Respiratory Tract Infections

1. **Acute Pharyngitis**

num	Symptoms
1	Sore throat
2	Swallowing pain
3	Ear aches
4	Slight fever

2. **Common Cold**

num	Symptoms
1	Blocked nose
2	Sore throat
3	Tearing eyes
4	Coughing
5	Headache
6	Sneezing

3. Acute Bacterial Sinusitis

num	Symptoms
1	Blocked nose
2	Teeth pain
3	Ear pain
4	coughing
5	Headache
6	nausea
7	Red eye

4. Pneumonia

num	Symptoms
1	Colored mucus
2	Shaking chills
3	Muscle aches
4	Rapid heartbeat
5	Fatigue
6	nausea
7	Coughing
8	headache

5. **Acute Bronchitis**

num	Symptoms
1	Swelling feet
2	Coughing
3	Colored mucus
4	Fatigue
5	Rapid heartbeat
6	Muscle aches

Appendix IV

Interview questions that help to collect information about the magnitude of ARTI in Addis Ababa

Interviewer: After introducing the research, and requesting the respondent's participation in the study, records their name, year of birth, number of children if any, years of schooling completed, sex, and any other obvious indicators of socio-economic status observed.

1. What kind of illnesses mostly occurs in patients attending this health institution?

2. Is there a traditional healer in your village? Is there a religious healer? Do you ever seek his or her help when your child or someone you know is ill? What does the healer do to help you or your family member? Can the traditional healer treat these infections? How?

3. Have you ever attended the clinic? (Why/why not?)

4. Have you ever taken any patient there?

5. Have you ever taken a patient with infection there? If yes, ask what happened. (Did the patient get better? What kind of treatment was given?)

6. Is there any reason why you would not take a patient with the five infections of ARTI (common cold, acute Pharyngitis, acute bacterial sinusitis, pneumonia or acute bronchitis) (or any other disease) to the clinic?

Appendix V

Sample Prolog Code

```
%This is a system used for Diagnosis of Acute Respiratory Tract Infections.

%to start the diagnosis write "artikobs" then "." and press "enter". Ok!

%........................Diagnosis starts........................

kb_threshold(65).
kb_hypothesis('The patient has acute pharyngitis.').
kb_hypothesis('The patient has common cold.').
kb_hypothesis('The patient has pneumonia.').
kb_hypothesis('The patient has acute bacterial sinusitis.').
kb_hypothesis('The patient has acute bronchitis.').
kb_hypothesis('Give the patient acetaminophen(Tylenol).').
kb_hypothesis('Give the patient Gargling with warm salt water.').
kb_hypothesis('Give the patient aspirin(but not for children).').
kb_hypothesis('Give the patient penicillin.').
kb_hypothesis('Give the patient antibiotics.').
kb_hypothesis('Give the patient tetracycline.').
kb_hypothesis('Give the patient erythromycin.').

c_rule('The patient has nasal congestion.',
      95,
      [],
      ['The patient is breathing through the mouth.',yes]).

c_rule('The patient has a sore throat.',
      95,
      [],
      [and,['The patient is coughing.',yes],['The inside of the patient''s throat is red.',yes]]).
 c_rule('The patient has a sore throat.',
      90,
      [],
      ['The inside of the patient''s throat is red.',yes]).
 c_rule('The patient has a sore throat.',
      75,
      [],
      ['The patient is coughing.',yes]).
c_rule('The patient has chest congestion.',
      100,
      [],
      ['There are rumbling sounds in the chest.',yes]).
c_rule('The patient feel swallowing pain.',
      90,
      [],
      ['The patient feel pain at his/her throat when he/she eat food.',yes]).
c_rule('The patient ear aches.',
      95,
      [],
```

```
    [and,['The patient feel pain at his/her ear.',yes],['The patient feels burning at his/her ear.',yes]]).
c_rule('The patient ear aches.',
    75,
    [],
    ['The patient feel pain at his/her ear.',yes]).
c_rule('The patient feel swelling feet.',
    75,
    [],
    ['The patient feel inflammation of his/her foot.',yes]).
c_rule('The patient has acute bronchitis.',
    95,
    [],
    [and,['The patient is always coughing.',yes],[and,['The patient feel bad when he/she breaths.',yes],['The patient feel shaking chills.',yes]]]).
c_rule('The patient has acute bacterial sinusitis.',
    85,
    [],
    [and,['The patient has breathing problem.',yes],[and,['The patient is coughing.',yes],['The patient has a scratchy throat.',no]]]).
c_rule('The patient has acute pharyngitis.',
    85,
    [],
    [and,['The patient has a sore throat.',yes],[and,['The patient is coughing.',no],['The patient has a scratchy throat.',no]]]).
c_rule('The patient has common cold.',
    85,
    [],
    [and,['The patient has a scratchy throat.',yes],[and,['The patient feel swallowing pain.',no],['The patient has a sore throat.',no]]]).
c_rule('The patient has pneumonia.',
    85,
    [],
    [and,['The patient feel shaking chills.',yes],[and,['The patient has chest congestion.',yes],['The patient has a sore throat.',no]]]).
c_rule('Give the patient antibiotics.',
    100,
    ['The patient has acute bronchitis.'],
    []).
kb_can_ask('The patient has nasal congestion.').
kb_can_ask('The patient has chest congestion.').
kb_can_ask('The patient has a sore throat.').
kb_can_ask('The patient has a scratchy throat.').
kb_can_ask('The patient feel swallowing pain.').
kb_can_ask('The patient ear aches.').
kb_can_ask('The patient feel ear pain.').
kb_can_ask('The patient has slight fever.').
kb_can_ask('The patient has enlarged lymph nodes.').
kb_can_ask('The patient nose is runny and blocked.').
kb_can_ask('The patient head aches.').
kb_can_ask('The patient eye tears.').
```

```
ask_confidence(Hypothesis,CF) :-
    kb_can_ask(Hypothesis),
    writeln('\nIs the following conjecture true? --\n'),
    write('  '), writeln(Hypothesis),
    writeln(['Possible responses: ',
           '  (y) yes          (n) no',
           '  (l) very likely    (v) very unlikely',
           '  (p) probably      (u) unlikely',
           '  (m) maybe         (d) don''t know.',
           '        (?) why?']),
    write('  \nYour response --> '),
    get_only([y,l,p,m,n,v,u,d,?],Reply), nl, nl,
    convert_reply_to_confidence(Reply,CF),
    !, Reply \== d,
    ask_confidence_aux(Reply,Hypothesis,CF).
explain_question :-
    current_hypothesis(Hypothesis),
    writeln('This information is needed to test the following hypothesis:'),
    writeln(Hypothesis), nl,
    writeln('Do you want further explanation?'),
    explain_question_aux,!.

explain_question :-
    writeln('This is a basic hypothesis.'),
    nl, wait.
confidence_in([Hypothesis,yes],50) :-
    assert(known(Hypothesis,50,no_evidence)), !.

confidence_in([Hypothesis,no],CF) :-
    !, confidence_in([Hypothesis,yes],CF0),
    CF is 100 - CF0.
confidence_in([and,Conjunct1,Conjunct2],CF) :-
    !, confidence_in(Conjunct1,CF1),
    confidence_in(Conjunct2,CF2),
    minimum([CF1,CF2],CF).

confidence_in([or,Disjunct1,Disjunct2],CF) :-
    !, confidence_in(Disjunct1,CF1),
    confidence_in(Disjunct2,CF2),
    maximum([CF1,CF2],CF).

evidence_that(Hypothesis,[CF,[CF1,Prerequisite,Condition]]):-
    c_rule(Hypothesis,CF1,Prerequisite,Condition),
    confirm(Prerequisite),
    confidence_in(Condition,CF2),
    CF is (CF1 * CF2)//100.

get_yes_or_no(Result) :- nl,
                write('Type Y or N:'),
                get_yes_or_no(Result).
```

```
interpret(89,yes).  % ASCII 89  = 'Y'
interpret(121,yes). % ASCII 121 = 'y'
interpret(78,no).   % ASCII 78  = 'N'
interpret(110,no).  % ASCII 110 = 'n'
```

DECLARATION

I certify that all work on thesis was carried out between March 2010 and May 2010 and it has not been submitted for any academic award at any other college, institute or university. The work presented was carried out under the supervision of Ato Tibebe Beshah. All other work in the thesis is my own except where acknowledged in the text.

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(Solomon Demissie Seifu)
15th May, 2010

This thesis has been submitted for examination with my approval as advisor.

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(Ato Tibebe Beshah)