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Addressing Medical Diagnosis Errors in the Upper Respiratory Tract Infection Using Fuzzy Inference System

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ABSTRACT

In this study a fuzzy inference system was developed to assist medical practitioners in the diagnosis of upper respiratory tract infections. The rule base for the fuzzy inference system was designed with the help of medical experts. Fuzzy inference system was used because upper respiratory tract infections are often mistaken for allergy to a particular condition in the environment by the patient thereby making it difficult to diagnosis accurately. The use of fuzzy logic in the design of the diagnostic system in this study was intended to provide a dependable and cheap means of diagnosing upper respiratory tract infections. The inference system was tested with four patients in the presence of a medical personnel and results obtained indicted that the inference system was able to arrive at the same diagnosis as the medical personnel when all the seven input parameter (symptoms) used in the design of the fuzzy inference system were taken into consideration.

Keywords: Upper Respiratory tract infections, Fuzzy inference systems, symptoms, diagnosis

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1. INTRODUCTION

Nigeria as a country has many contagious infectious diseases. One of the diseases suffered by people primarily is contagious infections in the respiratory tract, which includes the upper respiratory tract infection and infections of the lower respiratory tract (Simoes et al., 2006). Respiratory tract infections are infections on any part of the respiratory tract, from the nose, middle ear, pharynx (throat), voice box (larynx), bronchi, and pulmonary. Diagnosis of infectious diseases of respiratory tract is usually performed by a physician based on symptoms suffered by the patients. Medical practitioners exhibit variation in decision making because of their approach to dealing with uncertainties and vagueness in the information and knowledge available to them (Sikchi et al., 2013). The diagnostic decisions also depend upon experience, expertise and perception of the practitioner. As the complexity of a system increases, it is not easy to follow a particular path of diagnosis without any mistake (Sikchi et al., 2013). Symptoms like dry cough, Globus (lump sensation in the throat), Tickle throat might actually be associated to some other infections in the respiratory tract not putting into consideration that the same symptoms might be for chronic throat clearing.

Upper respiratory tract infection (URTI) has been recognized as one of the most common medical problems in the daily lives of people worldwide. A strong confirmation for the prevention of URTI is rather inadequate, and thus, the patients take preventive measures on the basis of their own experience or preferences. However, URTI is referred to as a viral infection (Akher and Al Johani, 2011) causing inflammation and infection in the nose and throat. URTIs are contagious which remain for few hours to 2-3 days of exposure. Also, the symptoms have been known to last from 7-10 days, but reports have shown that the symptoms may last even longer. URTI has been regarded as a nonspecific term that is used to describe acute infections involving the nose, paranasal sinuses, pharynx, larynx, trachea, and bronchi (Rohilla et al., 2013). Various signs and Ssymptoms of upper respiratory tract infection include running nose, sneezing, coughing, sore throat, fever and even vomiting. However, while upper respiratory tract infections have been suggested to be mild and self-limiting, they have been reported to lead to life threatening complications.

Nowadays, medical diagnostic processes can be carried out with the aid of computer related technologies which are on the increase daily. These systems are mostly based on the principles of Artificial Intelligence. In the medical field, many Decision Support Systems (DSS) have been designed, such as Dxplain, Quick Medical Reference, Isabel, Refiner Series System and PMA which assist medical practitioner in their decisions for diagnosis and treatment of different diseases (Awotunde et al., 2014). Fuzzy logic presents powerful reasoning methods that can handle uncertainties and vagueness (Sikehi and Sikehi, 2016). Fuzzy logic resembles human reasoning in its use of imprecise information to generate decisions (Ping and Zhu, 2008). Unlike classical logic which requires a deep understanding of a system, exact equations, and precise numeric values, fuzzy logic incorporates an alternative way of thinking, which allows modeling complex systems using a higher level of abstraction originating from our knowledge and experience (Macwan and Sajjan, 2013).

Human thought is fuzzy in nature, complete with uncertainties, ambiguities and contradictions (Labrunda and Labrunda, 2008). Two experts might not place the same level of importance on the same piece of information (Labrunda and Labrunda, 2008). According to Aristotelian logic, for a given proposition or state, only two logic values are proposed: true-false, black-white, 1-0. In real life, things are not either black or white but most of the times are grey. Thus in many practical situations, it is convenient to consider intermediate logical values. Fortunately, the traditional idealistic mathematical approach has been improved to accommodate partial truth by the introduction of fuzzy set theory invented by Professor Lotfi A. Zadeh (Zadeh, 1973, 1975, 2008).

Unlike classical set theory, fuzzy set theory is flexible which focuses on the degree of being a member of a set (Hazarika and Dixit, 2015). This simple notion leads to new concepts and ideas through which more realistic mathematical representation can be achieved in describing events observed with uncertainty. Fuzzy logic is a qualitative computational approach which describes uncertainty or partial truth. Using fuzzy logic in medical diagnosis is a promising technique that can easily capture the required medical knowledge and come up with sound diagnostics decisions. Starting from the pioneering publication of Lotfi Zadeh in 1965 (Zadeh, 1965), fuzzy sets have been applied to many fields in which uncertainty plays a key role (Kuncheva, L. I. and Steimann, F. (1999). The diagnosis of disease involves several levels of uncertainty and imprecision, and it is inherent in medicine (Torres and Nieto, 2006). A single disease may manifest itself quite differently, depending on the patient, and with different intensities. A single symptom may correspond to different diseases. On the other hand, several diseases present in a patient may interact and interfere with the usual description of any of the diseases (Torres and Nieto, 2006). The complexity of medical practice makes traditional quantitative approaches of analysis inappropriate. In medicine, the lack of information, and its imprecision, and, many times, contradictory natures are common facts.

The sources of uncertainty can be classified as follows: (1) Information about the patient, (2) Medical history of the patient, which is supplied by the patient and/or his/her family. This is usually highly subjective and imprecise, (3) Physical examination. The physician usually obtains objective data, but in some cases the boundary between normal and pathological status is not sharp, (4) Results of laboratory and other diagnostic tests, but they are also subject to some mistakes, and even to improper behavior of the patient prior to the examination, (5) The patient may include simulated, exaggerated, understated symptoms, or may even fail to mention some of them (Abbod, et al., 2001). The application of fuzzy logic in medicine gained momentum in last two decades when the usefulness of this technique was realized to correlate with the fuzzy nature of this field. Some notable works reported in this field includes those of Eklund et al. (1994), Abbod (2001) and Yoshizawa et al. (1994).

2. MATERIALS AND METHODS

The data used in the study was collected at the Lead City hospital, Ibadan, Oyo State, Nigeria and this included the direct interview of consultants in general medicine. The data collected include various methods for diagnosing infections in the upper respiratory tract and the various signs and symptoms. The following upper respiratory tract symptoms were considered: Fever, Nasal Discharge, Sore Throat, Spit Color, Smelling Catarrh, Difficulty in Breathing and Blood Pressure. Membership Functions are used to map non fuzzy input values to fuzzy linguistic terms such as High, Very high, Average and Low. The mapping allows the use of membership function to quantify the non-fuzzy inputs in linguistic terms. The representation of membership functions graphically may include different shapes such as trapezoidal, Gaussian and piecewise linear. The triangular membership function graph is defined by a lower limit **a**, an upper limit **b**, and a value **m**, where **a < m < b** as shown in figure 1.

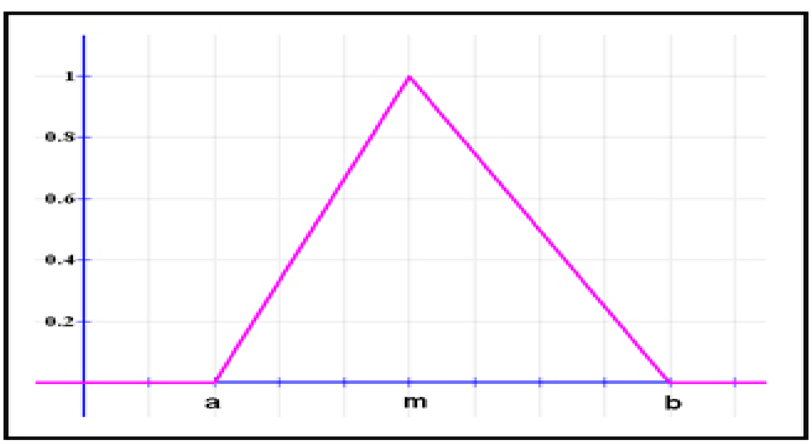

Figure 1: Feature of Membership functions (Source: eMathTeacher, 2016.)

Triangular fuzzifiers were used for changing the scalar values to fuzzy sets in the range of 0 and 1. Figure 2 and figure 3 present the representation of the membership functions for fever and blood pressure. Table 1 presents the decision making matrix for the diagnosis of upper respiratory tract infections.

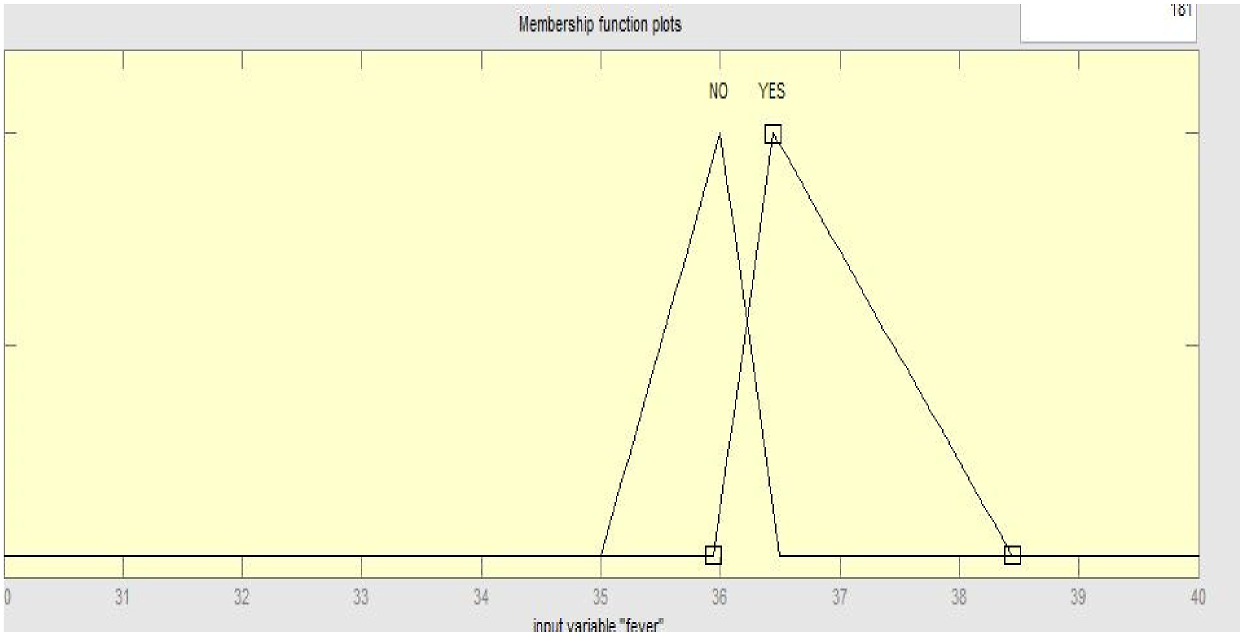

Figure 2: Representation of fuzzy membership function for fever

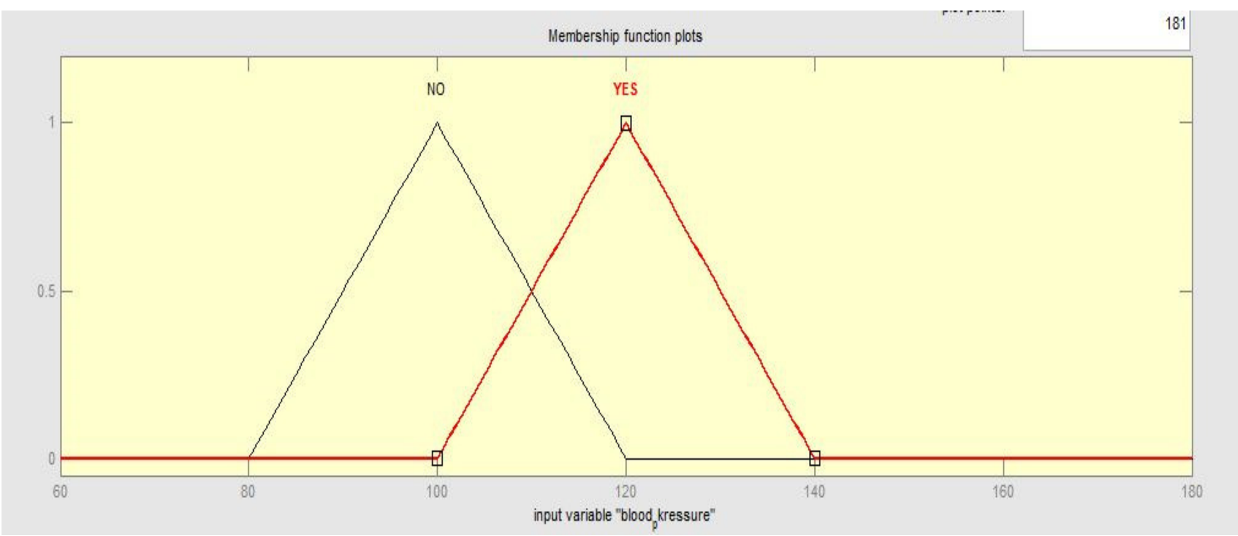

Figure 3: Representation of fuzzy membership function for blood pressure

Table 1: Decision Making Matrix for the diagnosis of upper respiratory tract infections

FEVER	NASAL DISCHARGE	SORE THROAT	DIFFICULTY IN BREATHING	SMELLING CATARRH	COLORED SPIT	BLOOD PRESSURE	INFERENCE
0.25	0.25	0.25	0.25	0.25	0.25	0.25	NO
0.25	0.25	0.25	0.25	0.25	0.25	0.75	NO
0.25	0.25	0.25	0.25	0.25	0.75	0.25	NO
0.25	0.25	0.25	0.25	0.25	0.75	0.75	NO
0.25	0.25	0.25	0.25	0.75	0.25	0.25	NO
0.25	0.25	0.25	0.25	0.75	0.25	0.75	NO
0.25	0.25	0.25	0.25	0.75	0.75	0.25	NO
0.25	0.25	0.25	0.25	0.75	0.75	0.75	YES
0.25	0.25	0.25	0.75	0.25	0.25	0.25	NO
0.25	0.25	0.25	0.75	0.25	0.25	0.75	NO
0.25	0.25	0.25	0.75	0.25	0.75	0.25	NO
0.25	0.25	0.25	0.75	0.25	0.75	0.75	NO
0.25	0.25	0.25	0.75	0.75	0.25	0.25	NO
0.25	0.25	0.25	0.75	0.75	0.25	0.75	NO
0.25	0.25	0.25	0.75	0.75	0.75	0.25	YES
0.25	0.25	0.25	0.75	0.75	0.75	0.75	YES
0.25	0.25	0.75	0.25	0.25	0.25	0.25	NO
0.25	0.25	0.75	0.25	0.25	0.25	0.75	NO
0.25	0.25	0.75	0.25	0.25	0.75	0.25	NO
0.25	0.25	0.75	0.25	0.25	0.75	0.75	NO
0.25	0.25	0.75	0.25	0.75	0.25	0.25	NO
0.25	0.25	0.75	0.25	0.75	0.25	0.75	NO
0.25	0.25	0.75	0.25	0.75	0.75	0.25	YES
0.25	0.25	0.75	0.25	0.75	0.75	0.75	YES
0.25	0.25	0.75	0.75	0.25	0.25	0.25	YES
0.25	0.25	0.75	0.75	0.25	0.25	0.75	NO

Two linguistic variables (YES and NO) were used for setting up the IF THEN rules which interprets the decision making matrix. The fuzzy rules obtained are presented:

Rule 001	If fever is NO and Nasal discharge is NO and Sore throat is NO and difficulty in breathing is NO and smelling catarrh is NO and colored spit is NO and blood pressure is NO then Upper respiratory tract infections is NO.
Rule 002	If fever is NO and Nasal discharge is NO and Sore throat is NO and difficulty in breathing is NO and smelling catarrh is YES and colored spit is YES and blood pressure is YES then Upper respiratory tract infections is YES.
Rule 003	If fever is NO and Nasal discharge is NO and sore throat is NO and difficulty in breathing is YES and smelling catarrh is NO and colored spit is NO and blood pressure is NO then upper respiratory tract infection is NO.
Rule 004	If fever is NO and Nasal discharge is NO and sore throat is NO and difficulty in breathing is YES and smelling catarrh is YES and colored spit is YES and blood pressure is NO the upper respiratory tract infections is YES.
Rule 005	If fever is NO and Nasal discharge is NO and sore throat is NO and difficulty in breathing is YES and smelling catarrh is YES and colored spit is YES and blood pressure is YES the upper respiratory tract infections is YES.
Rule 006	If fever is NO and Nasal discharge is NO and sore throat is YES and difficulty in breathing is NO and smelling catarrh is YES and colored spit is NO and blood pressure is YES then upper respiratory tract infections is NO.
Rule 007	If fever is NO and Nasal discharge is NO and sore throat is YES and difficulty in breathing is YES and smelling catarrh is NO and colored spit is YES and blood pressure is NO then upper respiratory tract infection is YES.
Rule 008	If fever is YES and Nasal discharge NO and sore throat is NO and difficulty in breathing is NO and smelling catarrh is NO and colored spit is NO and blood pressure is NO then upper respiratory tract infection is NO.
Rule 009	If fever is YES and Nasal discharge is NO and sore throat is YES and difficulty in breathing is NO and smelling catarrh is YES and colored spit is NO and blood pressure is YES.

Rule 010	If fever is YES and Nasal discharge is YES and sore throat is NO and difficulty in breathing is NO and smelling catarrh is NO and colored spit is NO and blood pressure is NO then upper respiratory tract infection is NO.
Rule 011	If fever is YES and Nasal discharge is YES and sore throat is NO and difficulty in breathing is NO and smelling catarrh is NO and colored spit is YES and blood pressure is YES then upper respiratory tract infection is NO.
Rule 012	If fever is YES and Nasal discharge is YES and sore throat NO and difficulty in breathing is YES and smelling catarrh is NO and colored spit is NO and blood pressure is YES then upper respiratory tract infection is YES.
Rule 013	If fever is YES and Nasal discharge is YES and sore throat is NO and difficulty in breathing is YES and smelling catarrh is YES and colored spit is YES and blood pressure is YES then upper respiratory tract infection is YES.
Rule 014	If fever is YES and Nasal discharge is YES and sore throat is YES and difficulty in breathing is NO and smelling catarrh is YES and colored spit is YES and blood pressure is NO then upper respiratory tract infection is NO.
Rule 015	If fever is YES and Nasal discharge is YES and sore throat is YES and difficulty in breathing is NO and smelling catarrh is YES and colored spit is YES and blood pressure is YES then upper respiratory tract infection is YES.
Rule 016	If fever is YES and Nasal discharge is YES and sore throat is YES and difficulty in breathing is YES and smelling catarrh is YES and spit color is NO and blood pressure is NO then upper respiratory tract infection is YES.
Rule 017	If fever is YES and Nasal discharge is YES and sore throat is YES and difficulty in breathing is YES and smelling catarrh is YES and spit color is YES and blood pressure is NO then upper respiratory tract infection is YES.
Rule 018	If fever is YES and Nasal discharge is YES and sore throat is NO and difficulty in breathing is NO and smelling catarrh is NO and spit color is YES and blood pressure is YES the upper respiratory tract infection is NO.
Rule 019	If fever is NO and Nasal discharge is YES and sore throat is YES and difficulty in breathing is NO and smelling catarrh is NO and spit color is NO and blood pressure is NO then upper respiratory tract infection is NO.

The fuzzy inference engine maps the fuzzy inputs to their respective weighting factors and their associated linguistic variables to determine their degree of membership. The aggregation operator is used to calculate the degree of fulfillment or firing strength of a rule. Fuzzy rule sets have several antecedents that are combined using fuzzy logical operators, such as AND, OR and NOT, though their definitions vary. AND simply uses minimum weight of all the antecedents, while OR uses the maximum value. There is also the NOT operator that subtracts a membership function from 1 to give the complementary function. The degree of truth of the rules were determined for each rule in the fuzzy rules database by evaluating the nonzero minimum values using the AND operator The inference engine evaluates all the rules in the rules base and combines the weighted consequences of all the relevant variables into a single fuzzy set. There are two types of inference techniques: In forward chaining the inference strategy begins with a set of known facts, derives new facts using rules whose premises match the known facts, and continues this process until a goal state is reached or until no further rules have premises that match the known or derived facts. In backward chaining the inference strategy attempts to prove a hypothesis by gathering supporting information.

The Mamdani Inference method was used. The fuzzy inference engine used a forward chaining mechanism to search for the symptoms of upper respiratory tract infections and then derives conclusions based on the rules in the knowledge-base. Defuzzification is the process of converting the fuzzy output from the inference engine to a crisp value. The input to the defuzzification process is a fuzzy set while the output of the defuzzification process is a single number (crisp output). There are six commonly used defuzzifying methods: Centroid of Area (COA), Bisector of Area (BOA), Mean of Maximum (MOM), Smallest of Maximum (SOM), Largest of Maximum (LOM) and Fuzzy c-means (FCM). The Centroid of Area which is also called Center of Area or Center of Gravity technique was used for defuzzification. The technique finds the center of area of the fuzzy output distribution and returns a single output number. This is the most commonly used technique because of its high level of simplicity and accuracy.

3. RESULTS AND DISCUSSION

The upper respiratory tract diagnosis Fuzzy Inference System was developed using the fuzzy logic toolbox of MATLAB R2013a. Seven membership classes which represent the input variables (Blood Pressure, Fever, Sore Throat, Smelling Catarrh, Colored Spit, Difficulty in Breathing and Nasal Discharge) and output variables were modeled using the triangular membership function. The schematic diagram of the fuzzy inference system is presented in Figure 4.

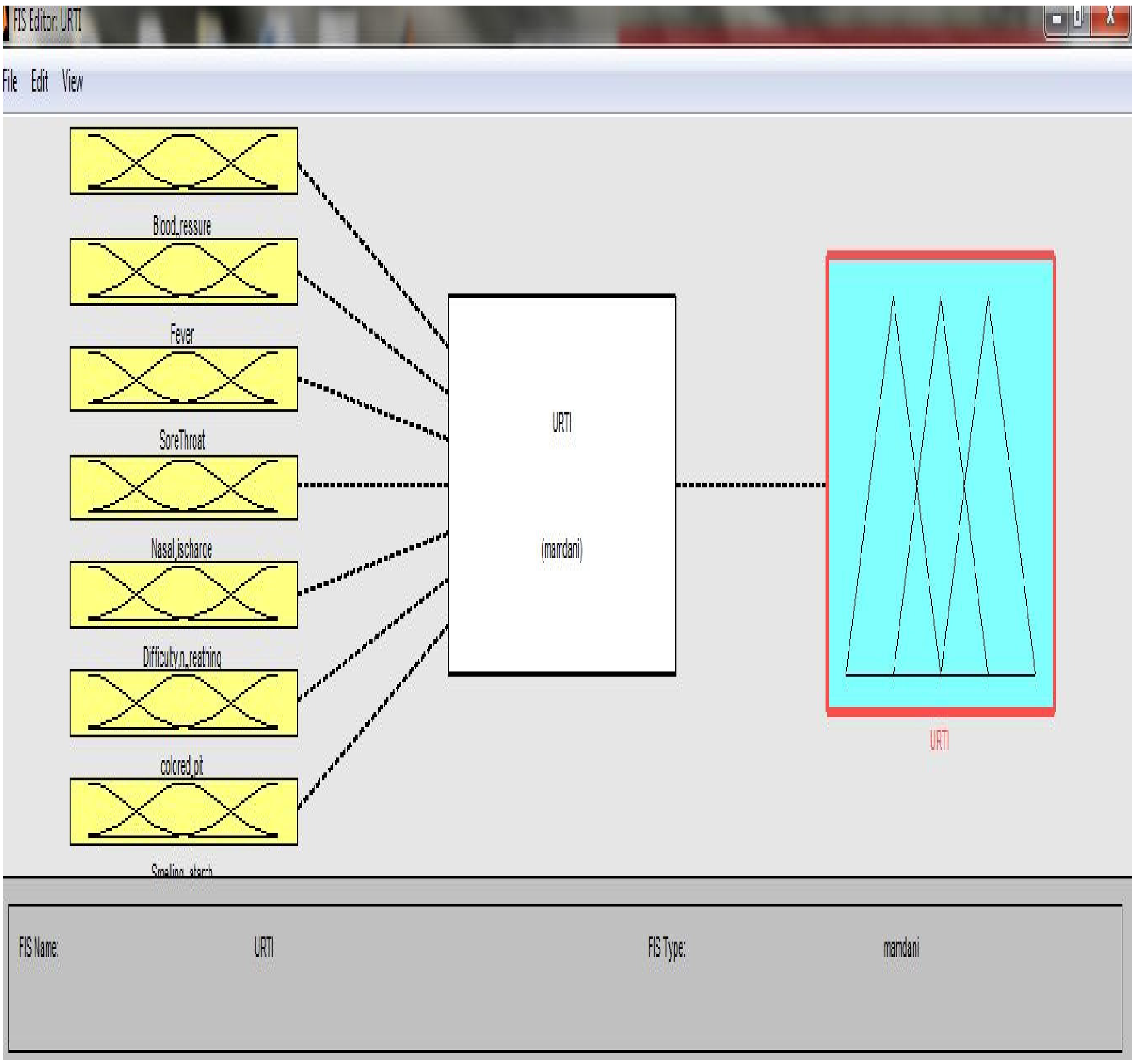

Figure 4: FIS for Upper Respiratory Tract Infection

Using the fuzzy rule editor, 128 rules were generated for the diagnoses of upper respiratory tract infection. An upper respiratory tract infection fuzzy inference system application was then developed which was used for the diagnosis from symptoms presented as shown in figure 5.

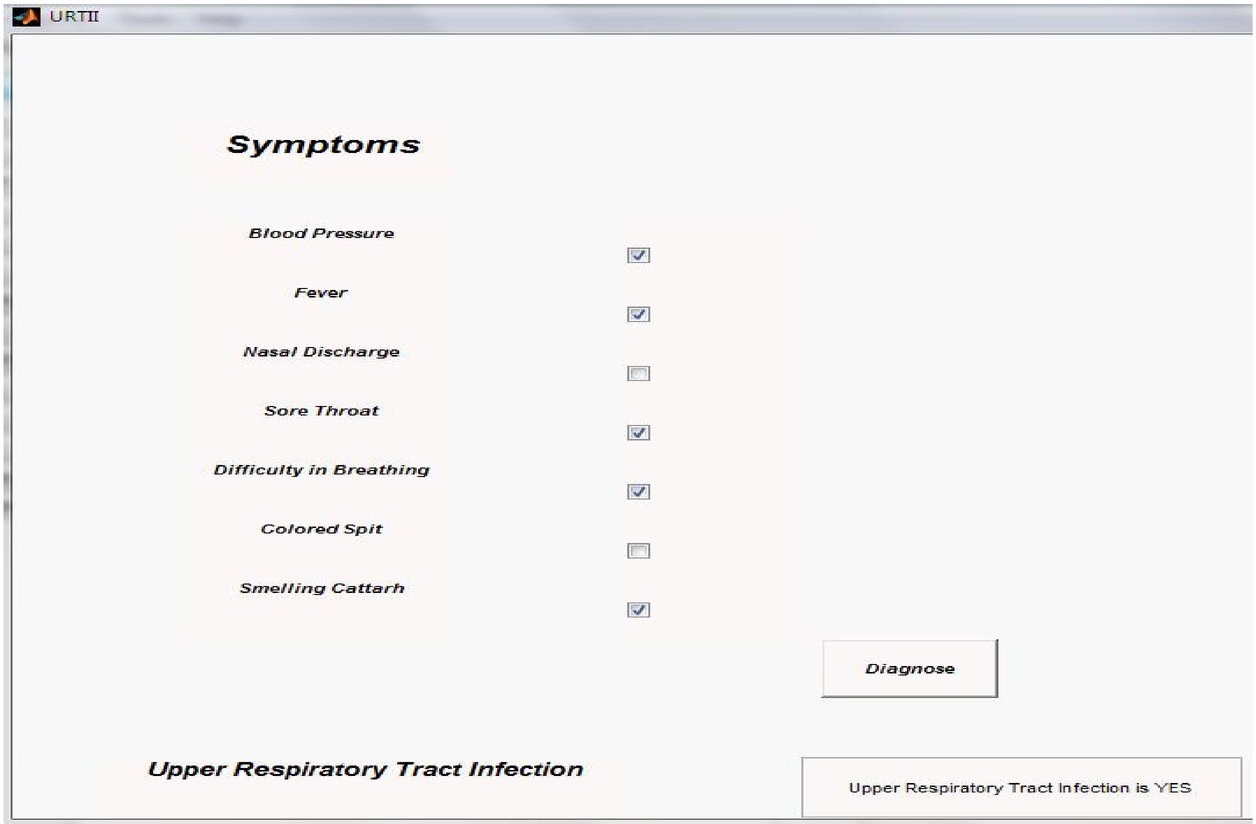

Figure 5: Graphical User Interface for the FIS diagnosis system

To get a diagnosis the relevant symptoms are ticked and the diagnose button is clicked. This activates a callback function which allows the system to check the fuzzy rule base which contains the IF THEN statements from where it draws it inference and displays the diagnose result. The fuzzy inference system was tested using the data (symptoms) presented by four patients who suffer from upper respiratory tract infections. Table 3 shows the diagnosis made by the fuzzy inference system which corresponds to the diagnosis made by the medical expert.

Table 3: Performance Evaluation for the fuzzy inference system

Blood Pressure	Fever	Nasal Discharge	Difficulty in breathing	Colored spit	Sore throat	Smelling cattarh	Diagnosis	FIS	Report
120	36.5	0.5	0.6	0.4	0.7	0.5	YES	0.51	Correct
130	36.5	0.7	0.6	0.8	0.6	0.4	YES	0.5	Correct
100	36.5	0.5	0.6	0.4	0.7	0.5	YES	0.5	Correct
120	36.5	0.7	0.6	0.6	0.7	0.4	YES	0.5	Correct

4. CONCLUSION

An upper respiratory tract fuzzy inference system for the diagnosis of upper respiratory tract infection has been developed and tested. Although the diagnosis of the ailments remains a primary duty of medical personnel, the development of an automated diagnostic system can assist in fast decision making in the diagnosis of the ailment. Furthermore work on the development of the fuzzy logic based medical diagnostic system can be the incorporation of drug prescription/treatment modules which will further help reduce problems associated with hospital consultations, especially where there are not enough medical personnel on ground to attend to patients. .

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