

Elderly People Health Monitoring System using Fuzzy Rule Based Approach

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Abstract

Monitoring the health condition of elderly people is a complex problem that involves different medical units and requires continuous monitoring. Besides there is the case if we realistically assume that there does not exist a set of rules that are readily acceptable to all human experts. The parameters used in identifying the medical conditions of a patient are really a vague, subjective measure rather than an objective measure. A more effective system is needed as the electronic patient records become more and more easily accessible in various health organizations such as hospitals, medical centers and insurance companies. These data provide a new source of information that has great potentials in monitoring the health condition of Elderly people. In this paper we have developed a fuzzy inference engine for finding risk factor of elderly People. The reasoning is based on a fuzzy inference system implemented using MATLAB. Fuzzy logic is used to represent, interpret, and compute vague and/or subjective information which is very common in medicine. The Detector is a fuzzy rule-based system. Using clinical information of more than 500 patients treated at the Tafila Technical University Medical Center, we have generated preliminary simulated detection results.

Keywords

Fuzzy Logic, Inference system, Monitoring system, Risk factor.

1. Introduction

In our previous work [1, 2], we proposed a multi-agent system for monitoring the health condition of elderly people. An agent is assigned to a physician to play an assist role. Through the study, we encounter the interesting problem of how the agents should make a decision about the medical condition of an elderly people.

Actually, detecting the risk factor of elderly people is one of the first steps toward monitoring the health condition of elderly people in a multi-agent setting. Evaluating the health condition of elderly people is technically a complex problem. There is no consensus on the definition of the 'ideal' early warning score system. This is the case if we realistically assume that there does not exist a set of evaluation rules that are readily acceptable to all the users of the agents (i.e., physicians). This is because physicians often disagree one another owing to their knowledge and experiences and there is no "ground true" to indicate which physician is right or wrong.

Current monitoring systems are based on clinical judgment and traditional medical signs including heart rate, blood oxygen saturation, respiratory rate, blood pressure, and temperature [3]. One of the currently widely tool used in practice is the "Modified Early Warning Score," [4] or MEWS which was first introduced in 2001 [5,6]. The Scoring in MEWS is based on Respiratory rate, Heart rate, Systolic blood pressure, Conscious level, Temperature and AVPU score (A for 'alert', V for 'reacting to vocal stimuli', P for 'reacting to pain', U for 'unconscious').

The assessment of the MEWS scores is a relatively subjective. Also, the range of sensitivities and specificities are dependent on the cutoff score used and the MEWS requires some training to be accurate. A score is given to a specific range of values for each of the vital signs in a table. The score for each parameter is summed up and recorded to give the MEWS score. A score of five or more shows high

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chance of death or admission to an intensive care unit is required. A score of zero shows that the patient case is normal, a score that is more than zero and less than five shows that the patient is in a Low Risk. Figure 1 shows MEWS sheet used by nurses to help monitor their patients in CHRISTUS Santa Rosa Hospital in San Antonio, Texas.

	3	2	1	0	1	2	3
RR/ per minute		< 8		9-14	15-20	21-29	> 30
HR/ per Minute		< 40	40-50	51-100	101-110	111-129	> 129
Systolic BP	< 70	71-80	81-100	101-199		> 200	
Conscious Level (AVPU)			New Agitation Confusion	Alert	Responds to Voice	Responds to Pain	Un-responsive
Temp F}		< 95.0	95.1-96.8	96.9-100.4	100.5-101.3	> 101.3	
Hourly Urine (for 2 Hours)	< 10 cc/hr	< 30 cc/hr	< 45 cc/hr				
							

Figure 1: Modified Early Warning Score (MEWS) sheet [7].

In this paper Fuzzy logic [8] is used to represent, interpret, and compute vague and/or subjective information of health condition factors. Fuzzy logic is a well-established methodology that is effective for systematic handling of deterministic uncertainty and subjective information. It has been successfully used to solve challenging industrial and medical problems in practice, some of which are very difficult to solve without it. Using Fuzzy rule based approach will enhance the monitoring performance of elderly people.

In this paper the reasoning is implemented using MATLAB Fuzzy toolbox. The detecting task of the proposed system is performed by the Inference Engine that evaluates all the rules in a knowledge base and combines the weighted consequents of all relevant rules into a single output fuzzy set that shows the risk factor of an elderly patient. That set is then defuzzified to produce a crisp emission status value. The developed Fuzzy system is experience-based as experience plays a key role in the design of the evaluator.

2. The Developed Fuzzy Rule Approach

We have designed and developed a “Fuzzy Monitor Assistant System”. Fuzzy logic is a well-established methodology that is effective for systematic handling of deterministic uncertainty and subjective information. Fuzzy logic is useful especially when a mathematical model of a system is not available and rules of the thumb from domain experts are available. It has been successfully used to solve challenging industrial and medical problems in practice, some of which are very difficult to solve without it. The Assistant system is a common rule-based system that uses fuzzy sets theory.

The reasoning is based on fuzzy logic. The structure of the Assistant System (Figure 2) includes four components: Fuzzifier, Inference Engine, Knowledge Base, and Defuzzifier. The Fuzzifier translates crisp inputs into fuzzy values. The Inference Engine is the part that controls the process of deriving conclusions. It applies a fuzzy reasoning mechanism to obtain a fuzzy output using rules and the fuzzy values. The Knowledge Base contains a set of fuzzy IF-THEN rules and a set of membership functions of fuzzy sets. These rules represent the knowledge that the PA possesses. The Defuzzifier converts the fuzzy output into a crisp value that best represents the out fuzzy set. The Defuzzifier uses the center of gravity scheme. The implication methods used in the proposed system are min (minimum), which truncates the individual output fuzzy sets, and max (maximum), which scales the resulted output fuzzy sets. The input to the implication process is a single number given by antecedent.

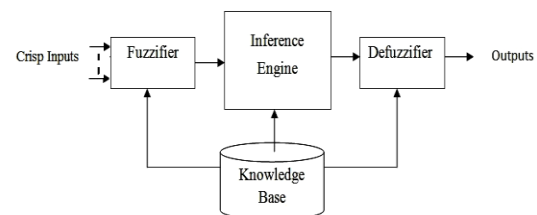


Figure 2: Block Diagram of the proposed Fuzzy system.

The monitoring task is performed by the Inference Engine that evaluates all the rules in the rule base and combines the weighted consequents of all relevant rules into a single output fuzzy set. That set is then defuzzified to produce a crisp similarity value.

The “Fuzzy Monitor Assistant System” is experience-based as experience plays a key role in the design of it. The similarity rules are used to build the Knowledge Base. The Assistant system uses a number of parameters related to physician experience. They include age, gender, medications, morbidities (chronic and acute), diagnoses, and laboratory test results.

The input and output variables will be defined in order to be used by the Fuzzy Inference Engine, and each variable is fuzzified by input fuzzy sets. The fuzzy sets used in fuzzifying the Input and Output variables are shown in Table 1. Bell fuzzy sets are specified by three parameters a, b and c while the gaussian fuzzy set is specified by two parameters a and b and trapezoidal fuzzy set is specified by four parameters a, b, c, and d.

Table 1: Definitions of fuzzy sets used in the developed system

Fuzzy Set Type	Fuzzy Set Definition
Trapezoidal	$\mu_{Trap}(x) = \begin{cases} 0, & a < x \\ -\frac{1}{b-a}(a-x), & a \leq x \leq b \\ \frac{1}{d-c}(d-x), & c \leq x \leq d \\ 0, & d < x \end{cases}$
Bell	$\mu_B(x) = \frac{1}{1 + \left \frac{a-x}{b} \right ^{2c}}, \quad c > 0$
Gaussian	$\mu_G(x) = e^{-\frac{(a-x)^2}{2b^2}}$
Triangular	$\mu_T(x) = \begin{cases} -\frac{1}{a-b}(a-x), & a \leq x \leq b \\ \frac{1}{c-b}(c-x), & b \leq x \leq c \\ 0, & otherwise \end{cases}$

The developed fuzzy monitoring system is based on 10 cues: Laboratory Tests Degree of Abnormality, Abnormality in Blood Pressure, Heart Rate, SPO2 Level, Blood Sugar Level, Temperature, Age, Triglycerides, High-density lipoproteins (HDL), Low-density lipoproteins (LDL). The cues represent

the higher-level information that is obtained from the patients’ elementary data. ‘

The detection rules that use the above cues were acquired through the joint efforts of the engineering and medical team members. The detection rules are mentioned in details the following sections.

2.1 Laboratory Test Abnormality Detection Rules

As a first step the abnormality of laboratory tests are studied and analyzed. The abnormality of the laboratory tests is a very important factor in measuring the risk of elderly people. Most people with an adverse event in the early stages feel well and have no specific findings on physical examination that would inform a health care provider. This place a large emphasis on laboratory tests to diagnose, predict or evaluate a medical problem since they are indicative of extensive problems in the patient. The liver for example is one of the organs that can be affected from medications. The liver has several functions and it is usually called the body’s manufacturing and filtering unit. The Alanine Aminotransferase (ALT) and Aspartate Aminotransferase (AST) laboratory test are typically used to evaluate liver functions or liver injury. Elevation of these tests is reflects a damage to the liver cell. Another example is the CK test. The elevation of CK laboratory result rise when muscle or heart cells are injured. Abnormality of a laboratory test shows the degree of elevation of a laboratory test result. Potassium laboratory test reflects the functionality of the muscles, heart, and nerves. For each laboratory test, the laboratory result will be converted to its abnormality value. The interpretation of abnormality value of laboratory test results is very important to understand the situation of the patients. The abnormality value will be zero for the laboratory results in normal ranges. For other ranges, The Abnormality value will be calculated using fuzzy Inference system. The laboratory results will be the input to the system and the Abnormality value will be the output. Both the input and the output are fuzzy variables.

To get the degree of the abnormality of the potassium laboratory test, the laboratory result will be converted to its abnormality value. The abnormality value will be zero for a laboratory result in the normal ranges. For other values, the abnormality value will be calculated using fuzzy rules. The laboratory results will be the input to the system and the abnormality

value will be the output. Both the input and the output are fuzzy variables. There are three fuzzy sets for the input variable Potassium Laboratory Test Value- Low, Medium, and High (Figure 3), and three fuzzy sets for the output variable Abnormality in Potassium Laboratory Test- Low, Medium, and High (Figure 4). Here are the rules:

- If Potassium Laboratory Test Value is *Low*, then Abnormality in Potassium Laboratory Test is *Low*.
- If Potassium Laboratory Test Value is *Medium*, then Abnormality in Potassium Laboratory Test is *Medium*.
- If Potassium Laboratory Test Value is *High*, then Abnormality in Potassium Laboratory Test is *High*.

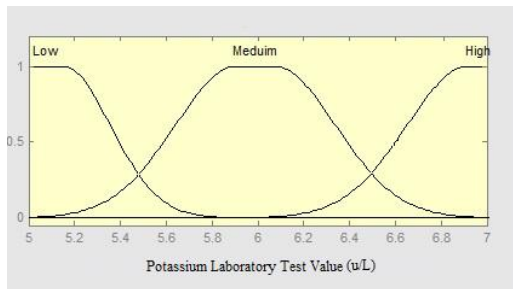


Figure 3: Fuzzy sets for Potassium Laboratory Test Value.

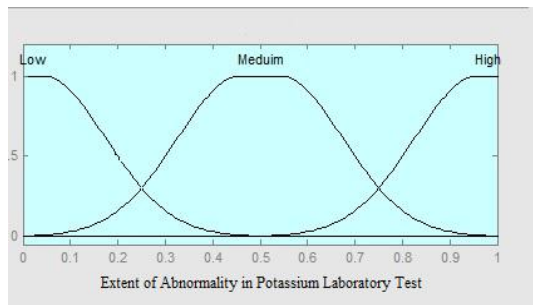


Figure 4: Fuzzy sets for Abnormality in Potassium Laboratory Test.

Creatinine laboratory test measures the amount of Creatinine in blood. This test is used to evaluate kidney function. The rules used to determine Abnormality in Creatinine Laboratory Test are as follows,

- If Creatinine Laboratory Test Value is *Low*, then Abnormality in Creatinine Laboratory Test is *Low*.

- If Creatinine Laboratory Test Value is *High*, then Abnormality in Creatinine Laboratory Test is *High*.

The two fuzzy variables used to determine Abnormality in Creatinine Laboratory Test are characterized by bell fuzzy sets (Figure 5 and Figure 6).

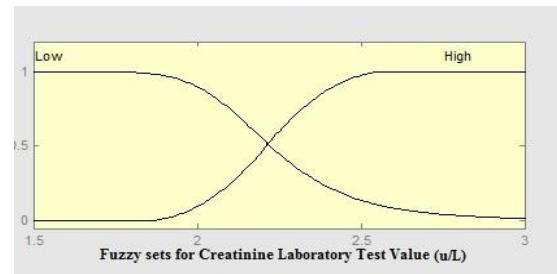


Figure 5: Fuzzy sets for Creatinine Laboratory Test Value.

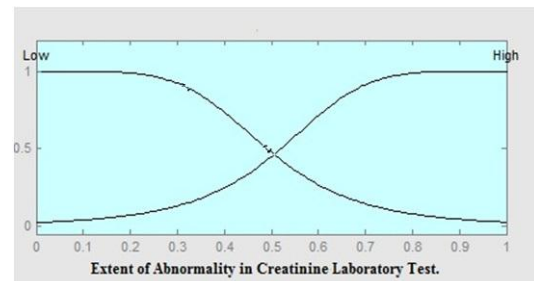


Figure 6: Fuzzy sets for Abnormality in Creatinine Laboratory Test.

For example for the laboratory test AST, there are five fuzzy sets for the variable Laboratory Test Value as input- Very Low, Low, Medium, High and Very High (Figure 7), and five fuzzy sets as output to define the variable Abnormality in Laboratory Test: Very Low, Low, Medium, High and Very High (Figure 8).

The rules used to determine Abnormality in AST Laboratory Test are as follows,

- If AST Laboratory Test Value is *Very Low*, then Abnormality in AST Laboratory Test is *Very Low*.
- If AST Laboratory Test Value is *Low*, then Abnormality in AST Laboratory Test is *Low*.

- If AST Laboratory Test Value is *Medium*, then Abnormality in AST Laboratory Test is *Medium*.
- If AST Laboratory Test Value is *High*, then Abnormality in AST Laboratory Test is *High*.
- If AST Laboratory Test Value is *Very High*, then Abnormality in AST Laboratory Test is *Very High*.

These fuzzy rules are extracted from the knowledge provided by the physicians in our team.

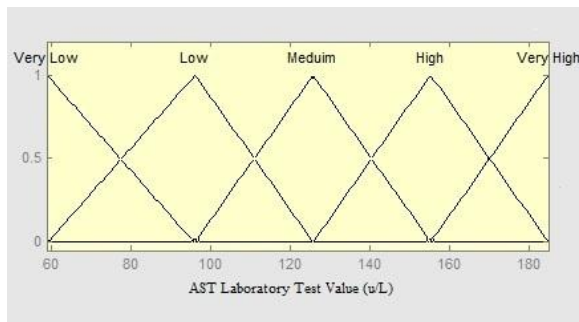


Figure 7: Fuzzy sets for AST Laboratory Test Value.

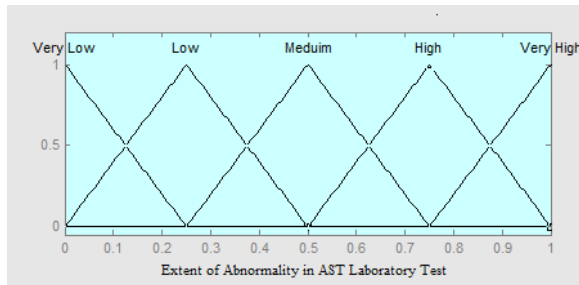


Figure 8: Fuzzy sets for Abnormality in AST Laboratory Test.

The same procedure will be followed for other laboratory tests. Here are the rules and the fuzzy sets for ALT, CK, Potassium and Creatinine laboratory tests.

The rules used to determine Abnormality in ALT Laboratory Test are as follows:

- If ALT Laboratory Test Value is *Very Low*, then Abnormality in ALT Laboratory Test is *Very Low*.

- If ALT Laboratory Test Value is *Low*, then Abnormality in ALT Laboratory Test is *Low*.
- If ALT Laboratory Test Value is *Medium*, then Abnormality in ALT Laboratory Test is *Medium*.
- If ALT Laboratory Test Value is *High*, then Abnormality in ALT Laboratory Test is *High*.
- If ALT Laboratory Test Value is *Very High*, then Abnormality in ALT Laboratory Test is *Very High*.

The fuzzy sets used to determine ALT Laboratory Test Value are shown in Figure 9. The Abnormality in ALT Laboratory is a fuzzy variable whose fuzzy sets are shown in Figure 10.

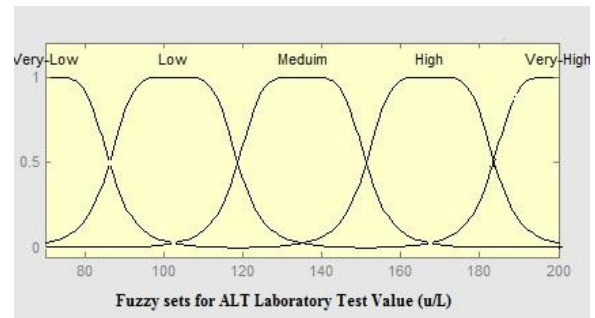


Figure 9: Fuzzy sets for ALT Laboratory Test Value.

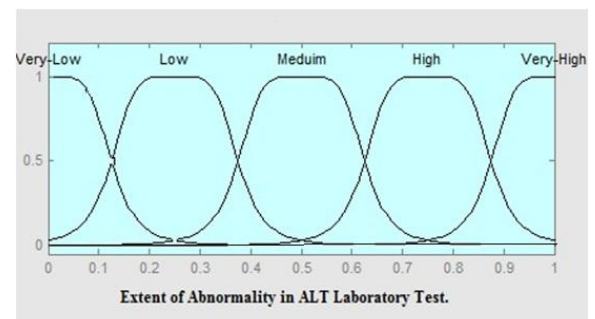


Figure 10: Fuzzy sets for Abnormality in ALT Laboratory Test.

The rules used to determine Abnormality in CK Laboratory Test are as follows,

- If CK Laboratory Test Value is *Very Low*, then Abnormality in CK Laboratory Test is *Very Low*.

- If CK Laboratory Test Value is *Low*, then Abnormality in CK Laboratory Test is *Low*.
- If CK Laboratory Test Value is *High*, then Abnormality in CK Laboratory Test is *High*.
- If CK Laboratory Test Value is *Very High*, then Abnormality in CK Laboratory Test is *Very High*.

Both CK Laboratory Test and Abnormality in Ck Laboratory are fuzzy variables and their fuzzy values are represented by bell shaped membership functions.

Figure 11 shows the CK Laboratory Test. The Abnormality in Ck Laboratory is shown in Figure 12.

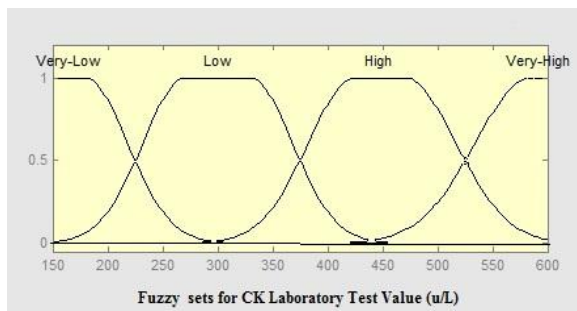


Figure 11: Fuzzy sets for CK Laboratory Test Value.

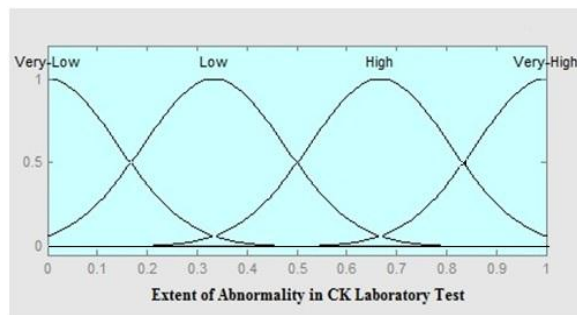


Figure 12: Fuzzy sets for Abnormality in CK Laboratory Test.

The aggregated laboratory abnormality is calculated as a linear combination of the corresponding sub abnormality. The aggregated Laboratory Abnormality is computed as the following:

$$\text{Laboratory Abnormality} = w_1 \times \text{Potassium Abnormality} + w_2 \times \text{Creatinine Abnormality} + w_3 \times \text{AST Abnormality} + w_4 \times \text{ALT Abnormality} + w_5 \times \text{CK Abnormality Similarity}$$

where $w_1 + w_2 + w_3 + w_4 + w_5 = 1$

The weights control the importance of the sub abnormalities. Some laboratory abnormalities are more important than the others based on the studied medical problem. This makes some weights greater than the others. In this study we deal with these sub abnormalities in equal amount of importance. The total laboratory tests degree of abnormality is represented by "Degree of Abnormality of Laboratory Tests" whose values are triangular fuzzy sets labeled as "Very High," "High," "Medium," "Low," and "Very Low". The corresponding membership function of Degree of Abnormality set is specified in Figure 13.

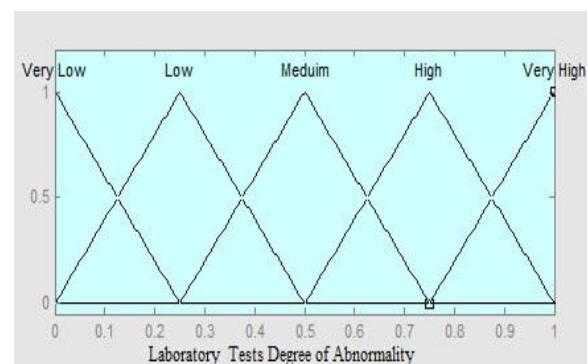


Figure 13: Membership function of Laboratory Tests Degree of Abnormality.

2.2 Blood Pressure Detection Rules

Blood pressure used in clinical environments to measure systolic and diastolic blood pressures which represent force of blood pushing the walls of the blood vessels that passed through it. The Systolic Blood Pressure (SBP) measure is the top number. It measures the pressure of the blood within the vessels when a heart contracts. The average measure for systolic is 120. The Diastolic Blood Pressure (DBP) measure is the bottom number. It is the pressure of the blood within the vessels when the heart is resting and then refilling. The average diastolic measure is 80. The normal measurement of blood pressure is 80/120.

The Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP) will be the input to the system and the abnormality value in blood pressure will be the output. Both the inputs and the output are fuzzy variables. There are three fuzzy sets for the input variable Systolic Blood Pressure (SBP) - Low, Medium, and High (Figure 14), three fuzzy sets for the input variable Diastolic Blood Pressure (DBP) - Low, Medium, and High (Figure 15), and three fuzzy

sets for the output variable Abnormality in Blood Pressure- Low, Medium, and High (Figure 16). Here are the rules:

- If Systolic Blood Pressure Value is *Low* and Diastolic Blood Pressure Value is *Low*, then Abnormality in Blood Pressure Test is *Low*.
- If Systolic Blood Pressure Value is *Low* and Diastolic Blood Pressure Value is *Medium*, then Abnormality in Blood Pressure Test is *Low*.
- If Systolic Blood Pressure Value is *Low* and Diastolic Blood Pressure Value is *High*, then Abnormality in Blood Pressure Test is *Medium*.
- If Systolic Blood Pressure Value is *Medium* and Diastolic Blood Pressure Value is *Low*, then Abnormality in Blood Pressure Test is *Medium*.
- If Systolic Blood Pressure Value is *Medium* and Diastolic Blood Pressure Value is *Medium*, then Abnormality in Blood Pressure Test is *Medium*.
- If Systolic Blood Pressure Value is *Medium* and Diastolic Blood Pressure Value is *High*, then Abnormality in Blood Pressure Test is *High*.
- If Systolic Blood Pressure Value is *High* and Diastolic Blood Pressure Value is *Low*, then Abnormality in Blood Pressure Test is *Medium*.
- If Systolic Blood Pressure Value is *High* and Diastolic Blood Pressure Value is *Medium*, then Abnormality in Blood Pressure Test is *High*.
- If Systolic Blood Pressure Value is *High* and Diastolic Blood Pressure Value is *High*, then Abnormality in Blood Pressure Test is *High*.

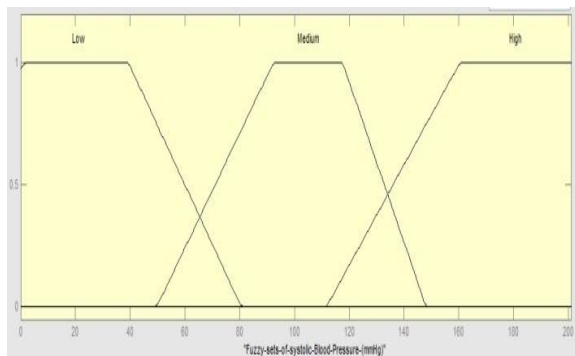


Figure 14: Membership function of Systolic Blood Pressure (SBP).

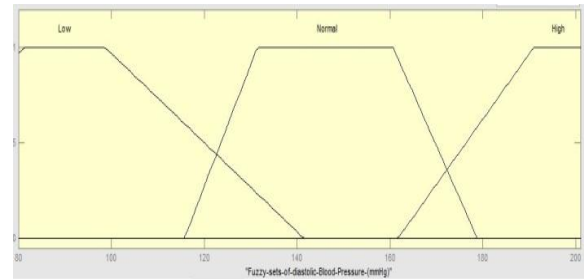


Figure 15: Membership function of Diastolic Blood Pressure (DBP).

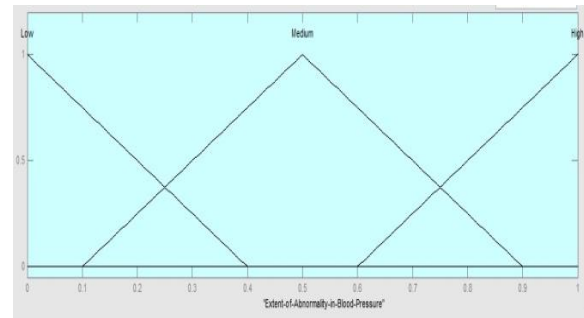


Figure 16: Membership function of the Abnormality in Blood Pressure.

2.3 Pulse Detection Rules

This is the number of times the heart beats per minute. The average heart beat rate is 80 beats per minute. The Heart Rate variables used to determine risk factor of elderly people is characterized by bell fuzzy sets (Figure 17).

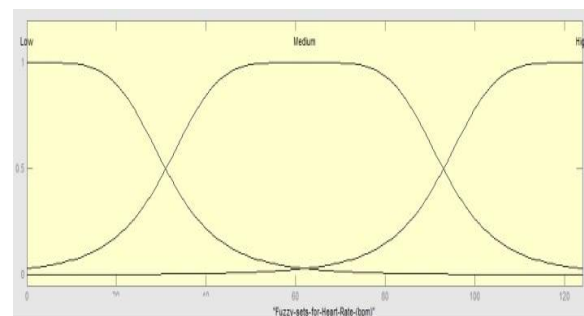


Figure 17: Membership function of Heart Rate.

2.4 blood oxygen saturation (SPO2)

SPO2 yield to a critical information that can indicate an urgent need for medical treatment, particularly in emergencies when there is a reduction in blood oxygen saturation. The average measure for the SPO2 is 97. SPO2 is a fuzzy variable and its fuzzy

values are represented by trapezoidal shaped membership functions as shown in Figure 18.

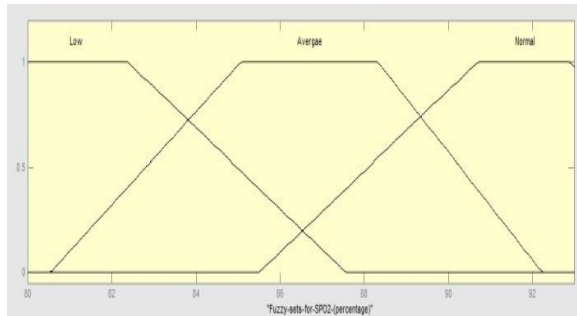


Figure 18: Membership function of SPO₂ Level.

2.5 Blood Sugar Detection Rules

Diabetes is a major, complex chronic disease. It is an abnormal rise in the concentration of blood sugar. It is caused by the hormone insulin needs. Hormones made in the body which is called insulin and glucagon help control blood glucose levels. A blood glucose test measures the amount of a sugar called glucose in a sample of a blood. Higher than normal blood glucose levels may be a sign of diabetes and if the person has diabetes, it means that the diabetes is not well controlled. For the Blood Sugar Level, there are three fuzzy sets as - Low, Normal and High (Figure 19),

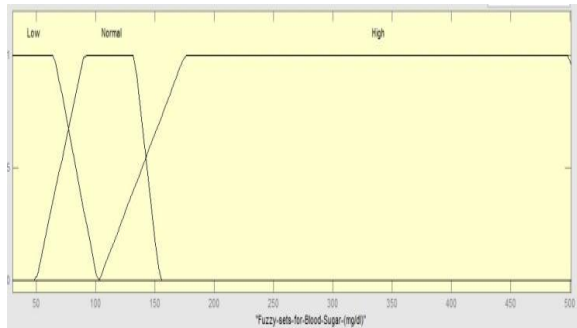


Figure 19: Membership functions of Blood Sugar Level.

2.6 Temperature Detection Rules

This input variable is divided into 4 fuzzy sets. These sets are (Low, Fever, Increase heat and increase malignant); membership functions of the 4 fuzzy sets are trapezoidal. These Memberships are shown in Figure 20.

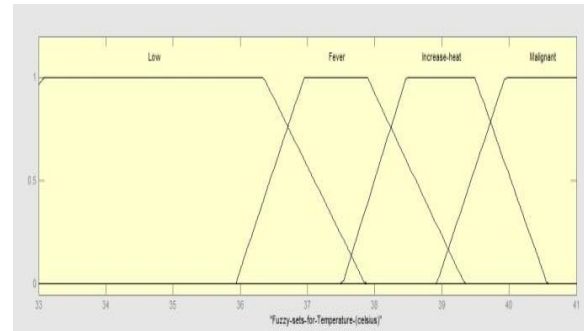


Figure 20: Membership functions of Temperature.

2.7 Age Detection Rules

The age of the patient is important because some symptoms are potentially will be considered more serious according to age. For example, acute diarrhoea in a healthy adult is not that danger. However, such symptoms in a baby could produce dehydration more quickly; elderly patients are also at a higher risk of becoming dehydrated. Age is an important factor in determining the similarity between the patients.

Based on the literature and the physicians on our team, the age of a patient is defined by the following membership functions: Young, Med-Age, and Old. Age is represented by trapezoidal membership functions (Figure 21).

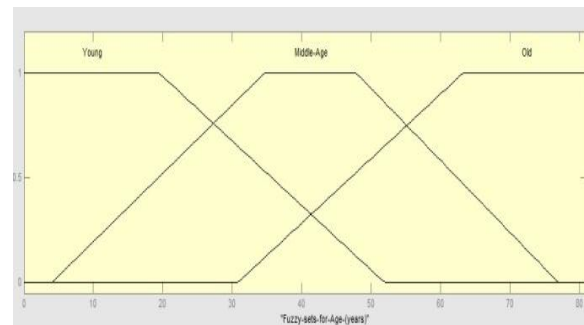


Figure 21: Membership function of Age.

2.8 Triglycerides Detection Rules

Triglycerides can also raise heart disease risk. Levels that are borderline high (150-199 mg/dL) or high (200 mg/dL or more) may need treatment in some people. This input field has four fuzzy sets (Normal, Borderling-High, High, and Very High). Figure 22 shows the membership functions of Triglycerides. Membership functions of these fuzzy sets are trapezoidal.

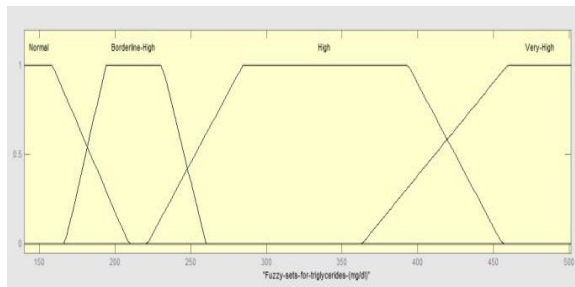


Figure 22: Membership functions of Triglycerides.

2.9 Cholesterol Detection Rules

The blood cholesterol level has a lot to do with high chances of getting heart disease. Many people with high blood cholesterol are unaware that their cholesterol level is too high because itself does not cause symptoms. High blood cholesterol is one of the major risk that leads to heart or having a heart attack. Having too much cholesterol in the blood as a result of building up fats in the walls of vein can slow down blood flow or even block the flow. There are two types:

2.9.1 High-density lipoproteins (HDL - High Density Lipoproteins)

It helps keep cholesterol from building up in the arteries. This is what is sometimes called good cholesterol or hyperplasia. Normal HDL level over 40 mg / 100 ml of blood (0.83 to 2.5 mmol / L). higher numbers for HDL are better. A level less than 40 mg/dL is low and is considered a major risk factor because it increases your risk for developing heart disease. HDL levels of 60 mg/dL or more help to lower your risk for heart disease.

2.9.2 Low-density lipoproteins (LDL-Low Density Lipoproteins)

It's the main source of cholesterol buildup and blockage in the arteries so-called some bad cholesterol or malignant, and there is an inverse relationship between the level of LDL and HDL in the blood.

The normal level of LDL in the blood less than 180 mg / 100 ml (0.5 - 3.88 mmol / L).

Both the High-density lipoproteins (HDL) and the Low-density lipoproteins (LDL) are fuzzy variables. There are three fuzzy sets for the input High-density lipoproteins (HDL) - Low, Medium, and High (Figure 23), and four fuzzy sets for the other input variable Low-density lipoproteins (LDL) Desirable,

Near Desirable, Border High, High, Dangerous (Figure 24).

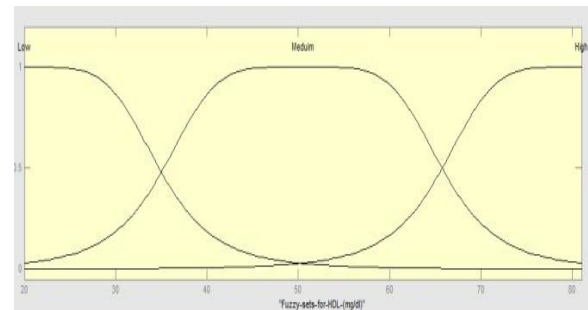


Figure 23: Fuzzy sets for High-density lipoproteins (HDL).

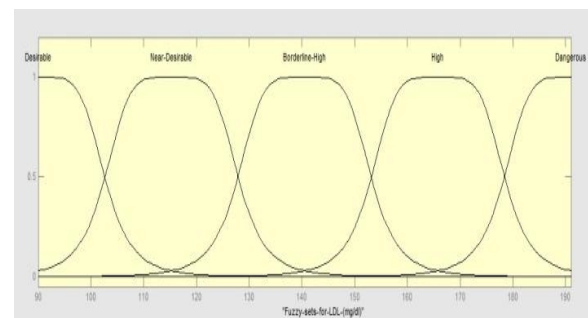


Figure 24: Low-density lipoproteins (LDL).

2.10 Elderly People Risk Factor

A risk factor is a value that shows the chance of getting a disease and/or the health risk of the patient. The strength of the risk is called "Degree of Risk". The Degree of Risk is a fuzzy variable whose values are represented by triangular fuzzy sets categorized as "Very High," "High," "Medium," "Low," and "Very Low" (Figure 25).

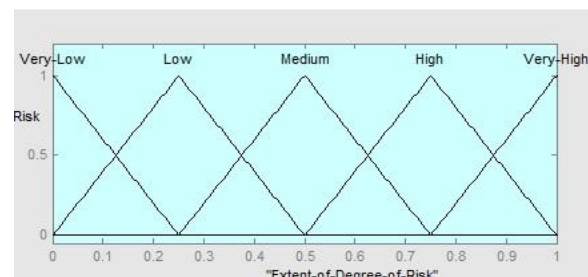


Figure 25: Membership of Degree of Risk.

Based on the experience of the physicians worked with the team, we define the fuzzy rules to link

Laboratory Tests Degree of Abnormality, Abnormality in Blood Pressure, Heart Rate, SPO2 Level, Blood Sugar Level, Temperature, Age, Triglycerides, High-density lipoproteins (HDL), Low-density lipoproteins (LDL) to Degree of Risk.

A sample of the rules used to determine Degree of Risk:

- If Laboratory Tests Degree of Abnormality is *Low*, Abnormality in Blood Pressure is *Low*, Heart Rate is *Medium*, SPO2 Level is *Normal*, Blood Sugar Level is *low*, Temperature is *Low*, Age is *Young*, Triglycerides is *Normal*, LDL is *Desirable*, HDL is *High*, then Degree of Risk is *Low*
- If Laboratory Tests Degree of Abnormality is *Very High* Abnormality in Blood Pressure is *Low*, Heart Rate is *Medium*, SPO2 Level is *Normal*, Blood Sugar Level is *low*, Temperature is *Low*, Age is *Old*, Triglycerides is *Normal*, LDL is *Very High*, HDL is *Low*, then Degree of Risk is *High*.

The selection of the weights for combining fuzzy rules in the fuzzy inference engine is a crucial issue. The weights control the importance of the corresponding factor. In case of equally importance, the weights will have the same value. The resulted Degree of Risk scores are between 0 and 1 and a higher score represents a higher health risk. The final "Degree of Risk" score is represented by 4 levels whose values are labeled as, Level 1 = "Very High Risk," Level 2 = "High Risk," Level 3 = "Moderate Risk," and Level 4="Low Risk." The interpretation of the score of Degree of Risk is shown in Table 2.

Table 2: The interpretation of the score of Degree of Risk

If You Have	You Are in Category
Heart disease, diabetes and risk score more than 0.25 Or No disease and risk score more than 0.75	Very High Risk
Heart disease, diabetes and risk score more less than 0.2 Or No disease and risk score is between 0.5-0.75	High Risk
No disease and risk score is between 0.25-0.5	Moderate Risk
No disease and risk score is between 0-0.25	Low Risk

Degree of Risk can be affected by other reasons. This includes but not limited to Cigarette smoking and Family history of early heart disease.

3. Experiments

The purpose of the simulation experiment is to examine the proposed approach. A suspect case will be provided to the developed rule-based system. To evaluate the effectiveness of the developed system, we retrieved the electronic data of 306 cases visited Tafila Technical University Medical Center for medical examination in Tafila during the time period from Jun 9, 2014 to September 30, 2014. Event data such as demographic data, patient visit data, diagnostic data, and laboratory data was retrieved for all the cases. There are 162 males and 144 females. All the data was stored in a 2007 Microsoft Access database. The resulting Degrees of Risk provided by the proposed system are shown in Table 3.

Table 3: Number of cases provided by the system

Level	Number of cases
Level 1	2
Level 2	6
Level 3	66
Level 4	232
Total Number	306

4. Conclusion

In this paper, we have developed a fuzzy ruled based approach that can be used in monitoring the health conditions of elderly people based on the received vital signs. The fuzzy system has been implemented using MATLAB software packages. Using real patient data the detection performance of the approach has been assessed.

References

- [1] Ayman M. Mansour, "A Multi-Agent Intelligent System for Monitoring Health Conditions of Elderly People", International Journal of Electrical, Robotics, Electronics and Communications Engineering, Vol.8 (6), 2014.
- [2] A. Mansour, H. Ying, P. Dews, Y. Ji, J. Yen, R. E. Miller, and R. M. Massanari, "Finding similar patients in a multi-agent environment", Fuzzy Information Processing Society (NAFIPS), 2011 Annual Meeting of the North American, 2011, pp. 1-6.

- [3] "Defining Key Health Information Technology Terms", Department Of Health & Human Services, Office Of The National Coordinator For Health Information Technology, USA, April 28, 2008.
- [4] American College Of Surgeons Committee On Trauma, "Advanced Trauma Life Support Course For Physicians," American College Of Surgeons, Chicago, IL, 1993.
- [5] Subbe C.P., Kruger M., Gemmel L. - "Validation of a modified Early Warning Score in medical admissions." Quarterly Journal of Medicine 2001; 94; 521-6.
- [6] Subbe CP, Slater A, Menon D, Gemmell L: Validation of physiological scoring systems in the accident and emergency department. Emerg Med J 2006, 23:841-845.
- [7] <http://www.christussantarosa.org/>
- [8] L. A. Zadeh, "Fuzzy sets," Information and Control, vol. 8, 1965, pp. 338-353.



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