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IMPLEMENTATION OF INTELLIGENT BIOMEDICAL DIAGNOSTICS BASED ON THE FUZZY INFERENCE SYSTEM

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Abstract. Intelligent biomedical diagnosis system is one of the most active research areas nowadays. Use of artificial intelligence and computer technologies in diagnosis and treatment of illnesses or training of fitness has highly increased. Heart disease diagnosis is a challenging task which can offer automated prediction about the heart disease of patient so that further treatment can be made easy. In this article the fuzzy logic based heart disease diagnosis system is analyzed on base sixth risk that affect on heart disease risk.

Keywords: fuzzy logic, fuzzy expert systems, fuzzy inference system, making decision.

Introduction

In several areas of biomedical domain, including prediction of the effectiveness of surgical procedures, medical tests and the discovery of relationships among clinical and diagnosis data, data mining techniques have been applied. Modern-day medical diagnosis is a very composite process, entailing precise patient data, a philosophical understanding of the medical literature and many years of clinical experience. The health care data which, unfortunately, are not «mined» to discover hidden information for effective decision-making are collected in a huge amount by the health care industry. Use of artificial intelligence or computer technology in the fields of medicine area diagnosis and treatment of illnesses has highly increased. The biomedical field has a challenging field because of very high complexity and uncertainty. Therefore, the use of intelligent systems such as fuzzy logic has been developed. Because of the many and uncertain risk factors in the heart disease risks, sometimes heart disease diagnosis is hard for experts. In the other word, there exists no strict boundary between what is Healthy and what is diseased, thus distinguish is uncertain and vague.

There are huge data management tools available within health care systems, but analysis tools are not sufficient to discover hidden relationships amongst the data. Most of the medical information is vague, imprecise and uncertain. Medical diagnosis is a complicated task that requires operating accurately and efficiently.

Fuzzy set theory and fuzzy logic have a number of characteristics that make them highly suitable for modeling uncertain information upon which medical concept forming, patient state interpretation, and diagnostic as well as therapeutic decision making is usually based. Firstly, medical entities such as symptoms, signs, test results, diseases and diagnoses, therapeutic and prognostic information can be defined as fuzzy sets. The inherent vagueness of these entities will thus be conserved. Secondly, fuzzy logic offers reasoning methods capable of drawing strict as well as approximate inferences. Medicine demands this broad range of possibilities because the body of medical theory includes definitional, causal, statistical, and heuristic knowledge. Practical medicine even has to accept incomplete medical theories where only vague and uncertain empirical information guides the necessary medical procedures. Finally, fuzzy automata maybe used as high level patient monitoring devices with real time access to medical information systems.

The advantages of fuzzy logic are its simplicity, flexibility of combining conventional control techniques, ability to model nonlinear functions and imprecise information, use of empirical knowledge and dependency on heuristics.

A fuzzy logic system is mainly comprised of four components: fuzzifier, defuzzifier, fuzzy rule base and fuzzy inference engine. these components are arranged as follows in any fuzzy logic system, (Fig. 1).

Fuzzification is the first process that takes place in the FLS. A numeric or crisp input value is given to the fuzzifier. The crisp input value is required to be converted to the corresponding fuzzy value as the rules for determining the result, are defined for fuzzy inputs. This task is performed by the fuzzifier and then the fuzzy input values are supplied to the fuzzy inference engine, which is responsible for computing the set of outputs based on the IF-THEN rules defined in the fuzzy rule base.

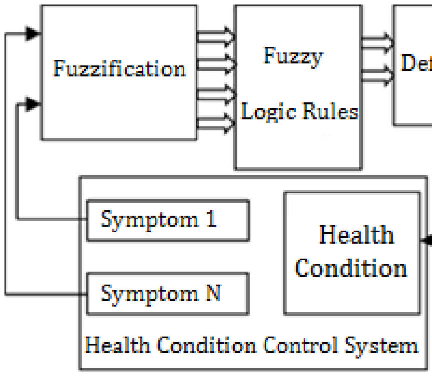

Fig. 1. Block diagram of health condition using fuzzy logic system

Usually, when more than one inputs are required, AND operator is used to combine them. The last process in the fuzzy logic system is defuzzification. It converts the fuzzy output values into their corresponding crisp values. There are different methods for fuzzification and defuzzification. Some widely used fuzzifiers are Singleton fuzzifier, Gaussian fuzzifier and trapezoidal or triangle fuzzifier. Singleton fuzzifier is the simplest fuzzifier which basically assigns a precise value to the given input and hence no fuzziness is introduced by fuzzification in this case. Gaussian and Triangular fuzzifiers are used to suppress the noise in the given inputs. Examples of defuzzifiers are maximum defuzzifier, mean of maxima defuzzifier, centroid defuzzifier, height defuzzifier, modified height defuzzifier, center of sets and center of sums.

Dataset for design of fuzzy system

Dataset for the designed system is collected from various Hospitals and by consulting the expert in the field of heart disease [1, 2]. The purpose of this dataset is to diagnose the presence or absence of heart disease given the results of various medical tests carried out on a patient. This system uses 6 attributes for input and 1 attribute for output.

The Input attributes are chest pain type, blood pressure, cholesterol, blood sugar, maximum heart rate and old peak (ST depression induced by exercise relative to rest). The output field refers to the presence of heart disease in the patient. It is integer value from 0 (no presence) to 1; increasing value shows increasing heart disease risk. Fuzzy logic is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than precise. In contrast with binary sets having binary logic, also known as crisp logic, the fuzzy logic variables may have a membership value of only 0 or 1. Firstly there is a need to make a dataset to decide the range of parameters on which the heart diseases are depending.

Chest pain. In input attribute Chest pain, we choose five different membership functions which are very low, low, moderate, high and very high. The range of this attribute is given in Table 1 and on Fig. 2.

Table 1. **Classification of chest pain**

Input Field	Range	Fuzzy set
CHEST PAIN	1-3	Typical angina
	3-5	Atypical angina
	5-7	Non-anginal
	7-9	Asymptomatic

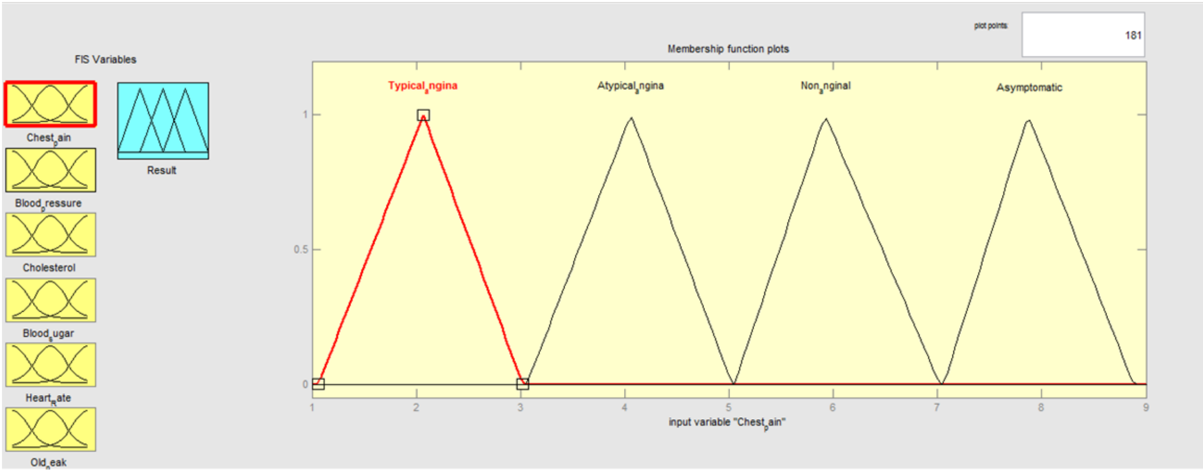

Fig. 2. Membership functions of chest pain

Blood pressure. We choose five different membership functions for input attribute blood pressure and are named as very low, low medium, high and very high. This can also be shown in Table 2 and on Fig. 3.

Table 2. **Classification of blood pressure**

Input Field	Range	Fuzzy set
BLOOD PRESSURE	<117 mmHg	low
	129–147 mmHg	medium
	139–160 mmHg	high
	>173 mmHg	very high

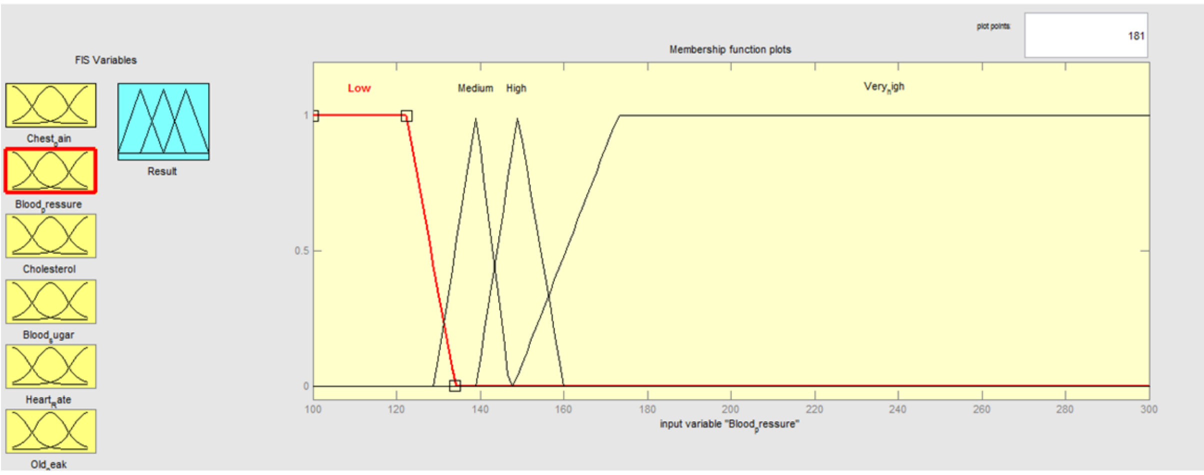

Fig. 3. Membership functions of blood pressure

Cholesterol. Cholesterol has salient affect on the result and can change it easily. Authors chose five different membership functions for input attribute cholesterol. The range and membership function of this attribute is shown in Table 3 and on Fig. 4.

Table 3. **Classification of cholesterol**

Input Field	Range	Fuzzy set
CHOLOSTEROL	<136 mg/dl	low
	188–250 mg/dl	medium
	217–307 mg/dl	high
	>342 mg/dl	very high

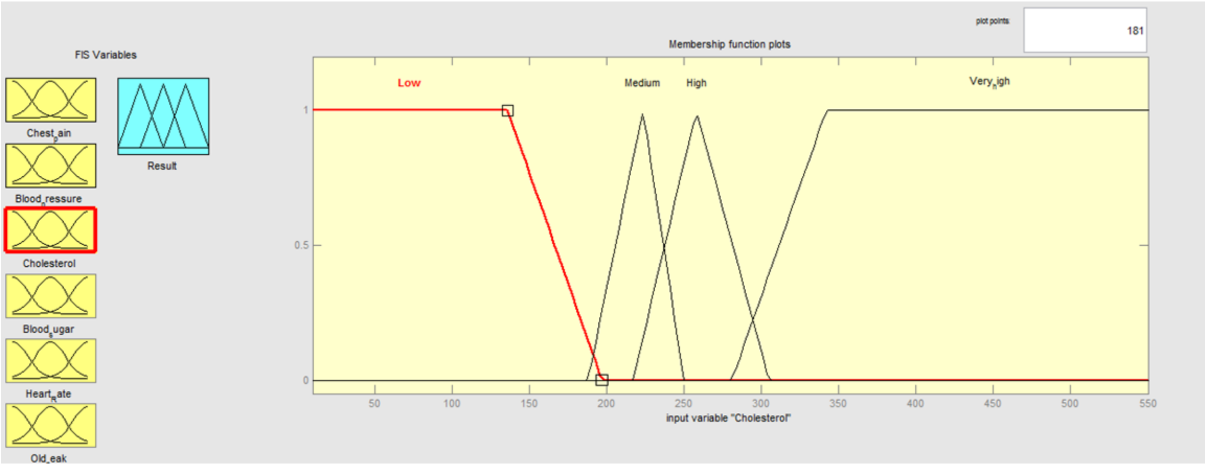

Fig. 4. Membership functions of cholesterol

Blood sugar. Blood sugar field is one of the most important factors in the diagnostics of heart disease. The input attribute blood sugar, five different membership functions were used which is given as very low, low, medium, high and very high. The range and the membership function of this attribute is given in Table 4 and on Fig. 5.

Table 4. **Classification of blood sugar**

Input Field	Range	Fuzzy set
BLOOD SUGAR	60–240 mg/dl	low
	>244	high

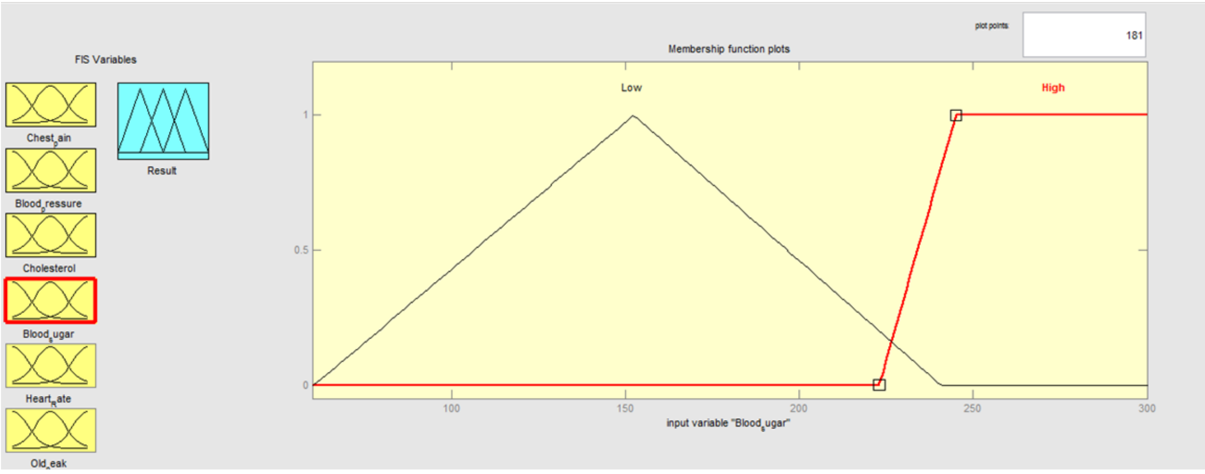

Fig. 5. Membership functions of blood sugar

Heart rate. Heart rate has five different membership functions, i.e. very low, low, medium, high and very high. The range and membership function of this attribute is given in Table 5 and on Fig. 6.

Table 5. **Classification of heart rate**

Input Field	Range	Fuzzy set
HEART RATE	<80 bpm	low
	111–194 bpm	medium
	>220 bpm	high

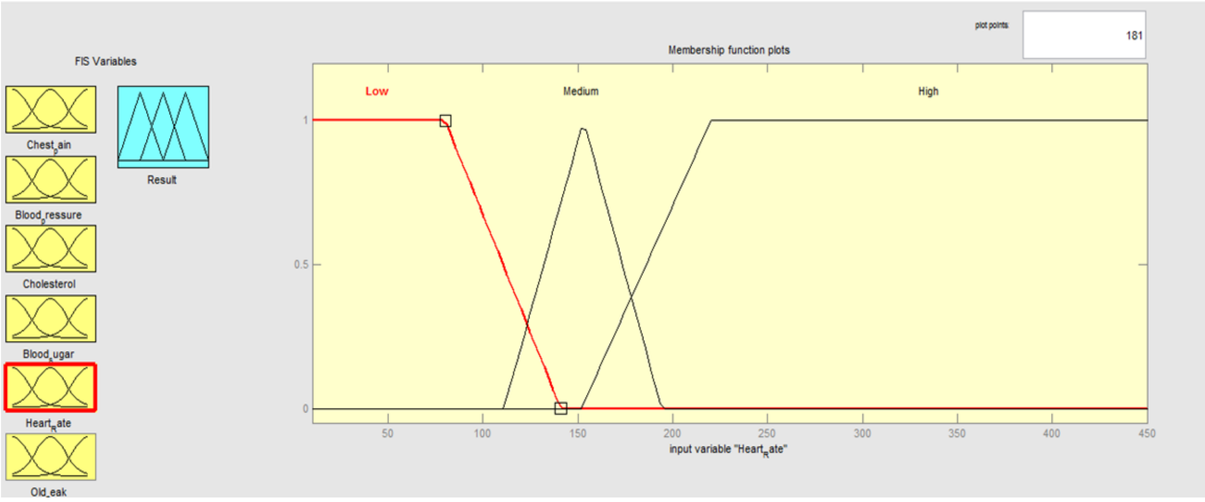

Fig. 6. Membership functions of heart rate

Old peak. This input attribute means ST depression induced by exercise relative to rest. Old peak field has 5 fuzzy sets (very low, low, medium, terrible and risk). These fuzzy sets have been shown in Table 6 with their ranges and on Fig. 7.

Table 6. **Classification of old peak**

Input Field	Range	Fuzzy set
OLD PEAK	<1	low
	1,5–4,2	risk
	>4	terrible

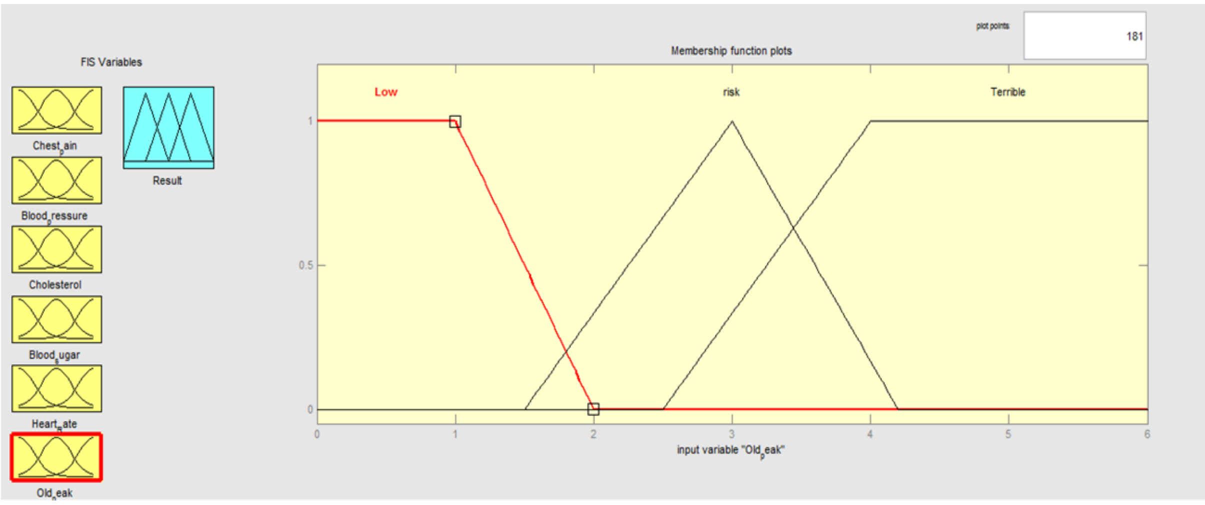

Fig. 7. Membership functions of old peak

System Testing

The system uses Mamdani inference mechanism. The result shows the presence of heart disease risk in patient. It has value from 0 (no presence) to 1. There are 4 Fuzzy sets: healthy, sick1 – low risk, sick2 – moderate risk, sick3 – high risk. Inference engine of this system is designed with the help of the expert and contains 18 dependent rules that uses forward chaining inference mechanism to accurately diagnose the heart disease risk. Centroid technique is used for defuzzification. The results of system testing have been shown in Table 7 and on Fig. 8–11.

Table 7. **Fuzzy sets range of output variable**

Input Field	Range	Fuzzy set
OUTPUT VARIABLE	<1,5	healthy
	2,5–4,5	sick1
	5,5–7,5	sick2
	>8,5	sick3

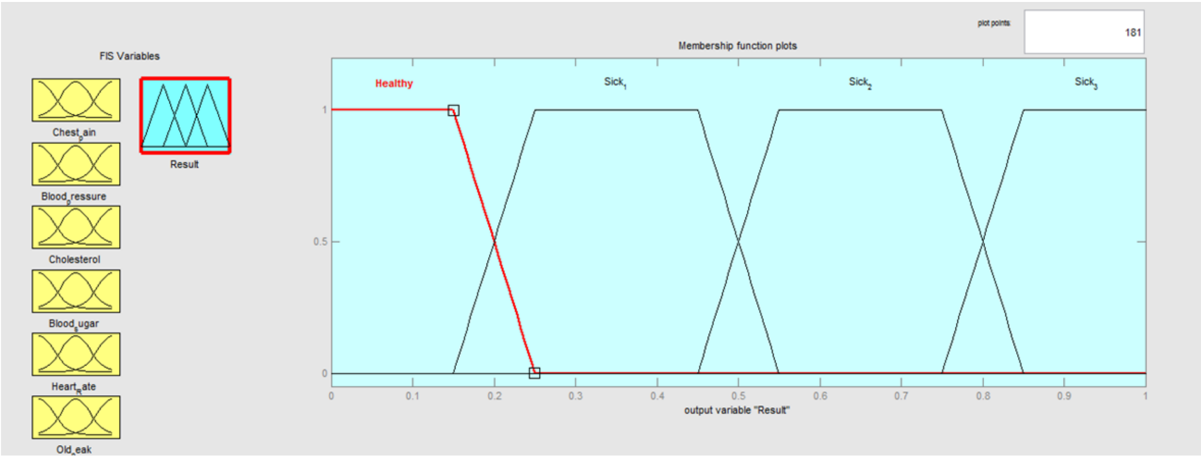

Fig. 8. Membership functions of result

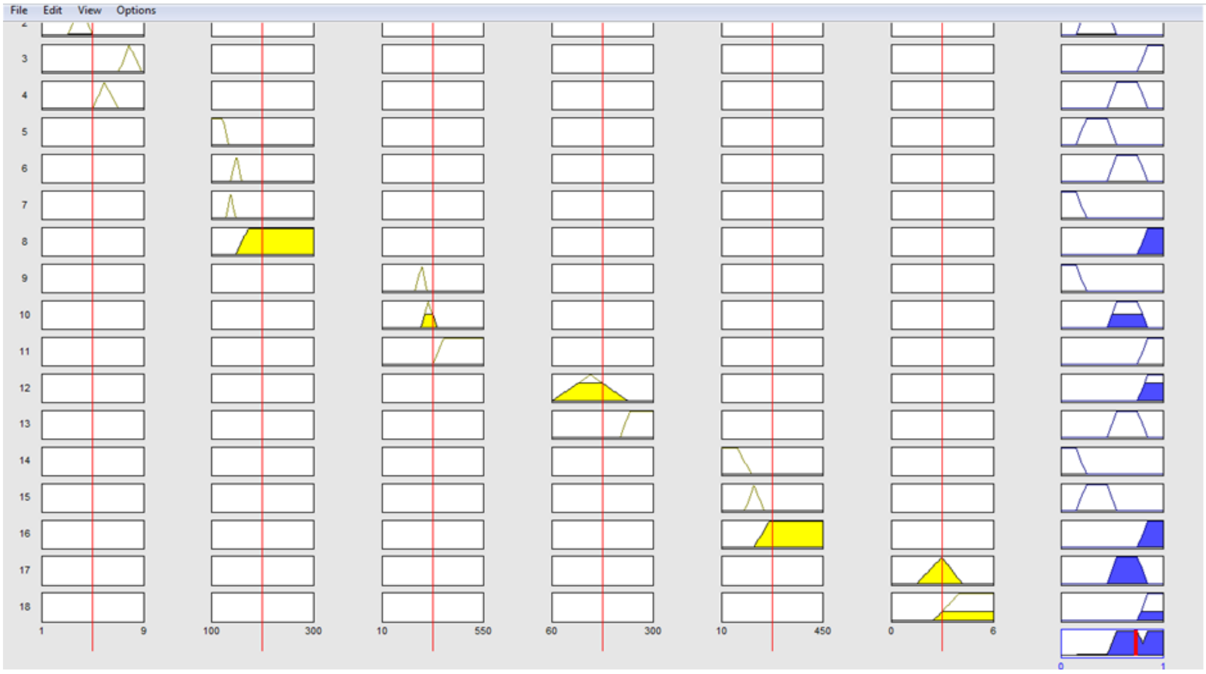

Fig. 9. Result of fuzzy system

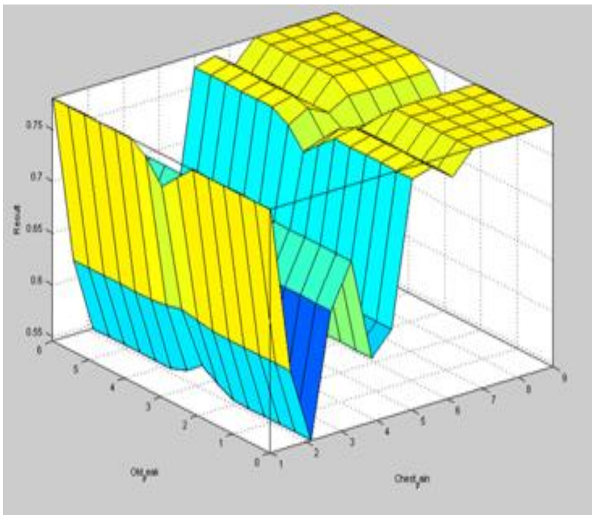

Fig. 10. Surface viewer of chest pain and old peak

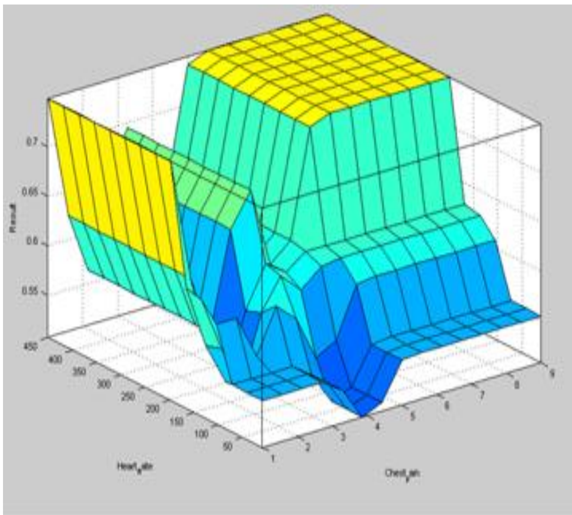

Fig. 11. Surface viewer of chest pain and heart rate

Conclusion

Analysis performed in fuzzy logic tools [3] using of the fuzzy inference system for medical diagnosis shows what this technology may be used in private life and to improve decision making about state of patients in hospitals or during the process of transporting the patient. Experimental results according to numerous studies showed that this system did quite better than non-expert and about 92 % as a well as the expert did [1].

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