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Comparison of Mamdani and Sugeno Fuzzy Interference Systems for the Breast Cancer Risk

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***Abstract*—**Breast cancer is a major health burden worldwide being a major cause of death amongst women. In this paper, Fuzzy Inference Systems (FIS) are developed for the evaluation of breast cancer risk using Mamdani-type and Sugeno-type models. The paper outlines the basic difference between Mamdani-type FIS and Sugeno-type FIS. The results demonstrated the performance comparison of the two systems and the advantages of using Sugeno- type over Mamdani-type.

***Keywords*—**Breast cancer diagnosis, Fuzzy Inference System (FIS), Fuzzy Logic, fuzzy intelligent technique.

I. Introduction

CANCER of the breast is a major health burden worldwide. Despite the billions of dollars spent on breast cancer research, incidence rates have been climbing steadily in industrialized countries since the 1940s [3]. Female breast cancer represents one in ten of all new cancers diagnosed and almost one in four cancers diagnosed in women worldwide. Every year, more than 1.1 million women are diagnosed with breast cancer and the numbers of women being diagnosed annually worldwide has almost doubled since 1975 [4]. Cancer management using consequent screening programs, which allow early detection and timely, optimal and varied methods of treatment, is a widely used and successful way of attempting to reduce morbidity and mortality [3]. Moreover, clinical Oncologists make diagnostic decisions about breast cancer patients based on past professional experience and knowledge, intelligent techniques are possibly the only class of automatic techniques powerful enough to emulate the expert’s choice. Due to their stable behavior in the presence of noise, imprecision and uncertainty, these techniques could potentially obtain better results than classical methods [5], [6]. Recognizing the broad relevance of this problem in cancer management and diagnostic decisions, this work aims to address the evaluation problem of breast cancer risk.

Recently, soft-computing techniques such as Fuzzy logic and Neural Networks techniques have been applied successfully to different applications for decision support systems. These techniques have many features that make them a particularly appealing and promising approach. Neural networks, which model the low-level structure of the human brain, can learn from experience and easily adapt to changing environments. Fuzzy logic, which reproduce the approximate reasoning process of the human mind by representing knowledge via linguistic if-then rules, allow for precise output inference starting from imprecise input. The aim of this paper is to describe different types of fuzzy logic systems that could be used for the evaluation of breast cancer risk.

This paper is organized as follows. In Section II we describe the concept of FIS with the difference between Mamdani-type and Sugeno-type FIS. Section III and Section IV describe the development of Mamdani-type FIS and Sugeno-type FIS, respectively. Experimental results and discussions are presented in Section V along with a comparative performance analysis involving the two types of fuzzy logic systems. Finally, Section VI provides some concluding remarks.

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II. Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping from given input(s) to output(s) using fuzzy logic. This mapping provides a basis from which decisions can be made, or patterns discerned. It has found successful applications in a wide variety of fields, such as automatic control, data classification, decision analysis, expert systems, time series prediction, robotics, and pattern recognition [8]. Because of its multidisciplinary nature, the fuzzy inference system is known by numerous others names, such as fuzzy-rule-based system, fuzzy expert system, fuzzy model, fuzzy associative memory, fuzzy logic controller and simply (and ambiguously) fuzzy system.

A fuzzy inference system with crisp inputs and outputs implements a nonlinear mapping from its inputs space to output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behavior of the mapping. In particular, the antecedent of a rule defines a fuzzy region in the input space, while the consequent specifies the output in the fuzzy region. Basically a fuzzy inference system is composed of five functional blocks as shown in Fig. 1. The Structure of the Fuzzy Inference system is described as follows.

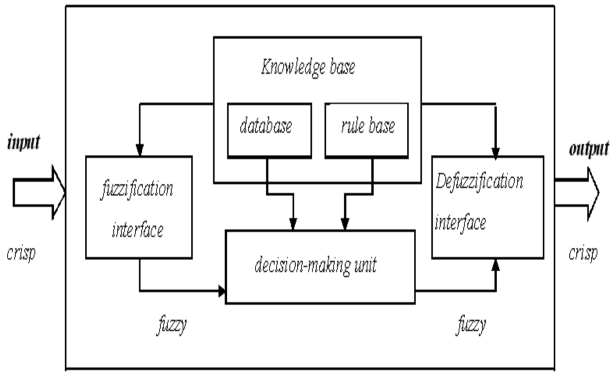

Fig. 1 Structure of the Fuzzy Inference system

- A rule base containing a number of fuzzy if-then rules.
- A database which defines the membership functions of the fuzzy sets used in fuzzy rules.
- A decision-making unit which performs the inference operations on the rules.
- A fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values.
- A defuzzification interface which transform the fuzzy results of the inference into a crisp output.

The rule base and the database are jointly referred to as the knowledge base. Fuzzy if-then rules or fuzzy conditional statements are expressions of the form: If x is A Then y is B. where, x and y are input and output linguistic variables. A and B are labels of the fuzzy sets characterized by appropriate membership functions. A is the premise and B is the consequent parts of the fuzzy rule. Fuzzy values A and B are described by the membership functions. The forms of membership functions are different and problem depended.

The steps of fuzzy reasoning (inference operations upon fuzzy IF–THEN rules) performed by FISs are described as follows

- Compare the input variables with the membership functions on the antecedent part to obtain the membership values of each linguistic label (this step is often called fuzzification).
- Combine (usually multiplication or min) the membership values on the premise part to get firing strength (weight) of each rule.
- Generate the qualified consequents (either fuzzy or crisp) of each rule depending on the firing strength.
- Aggregate the qualified consequents to produce a crisp output (This step is called defuzzification).

The most common types of fuzzy reasoning that have been introduced in the literature and applied to different applications are Mamdani and Sugeno type models [1], [8]. The most fundamental difference between Mamdani-type FIS and Sugeno-type FIS is the way the crisp output is generated from the fuzzy inputs. Mamdani-type FIS uses the technique of defuzzification of a fuzzy output, while Sugeno-type FIS uses weighted average to compute the crisp output. Hence, Mamdani FIS has output membership functions whereas Sugeno FIS has no output membership functions. Mamdani-type is widely accepted for capturing expert knowledge [2]. It allows describing the expertise in more intuitive, more human-like manner. However, Mamdani-type entails a substantial computational burden. On the other hand, Sugeno method is computationally efficient and works well with optimization and adaptive techniques, which makes it very attractive in different applications. Mamdani-type FIS is less flexible in system design in comparison to Sugeno-type FIS as latter can be integrated with ANFIS tool to optimize the outputs.

III. Development of Mamdani-Type FIS

The proposed FIS for the evaluation of breast cancer risk consists of two inputs: age and tumor surface. The system has one output that indicates the risk of breast cancer in percentage. The age and the tumor surface (i.e., tumor size) of patients are selected as input variables for the fuzzy system due to the most relevance factors decided by clinicians [6], [7]. The breast cancer risk factor is the output of the FIS. The age and the tumor size are taken to be in ranges of 0 to 80 years and 0 to 8000 pixels, respectively. Each of the selected input and output variables is described by a set of three linguistic fuzzy values, defined by a Gaussian membership function, thus allowing the fuzzification procedure to convert the measured numerical value into one of the fuzzy values. Figs. 2-4 illustrate the age, the tumor size, and the risk of cancer represented by the Gaussian membership functions, respectively.

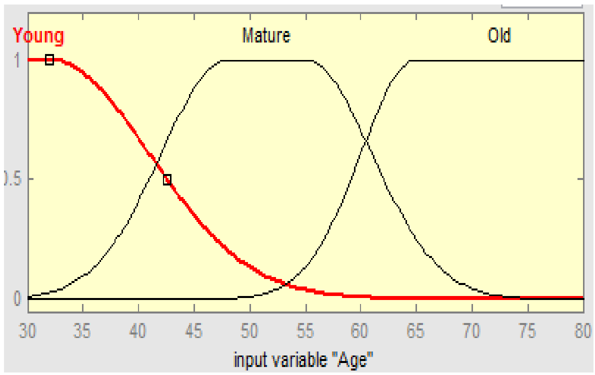

Fig. 2 Age membership functions

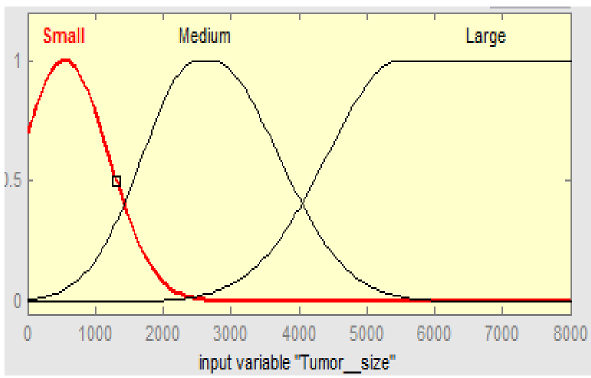

Fig. 3 Tumor membership functions

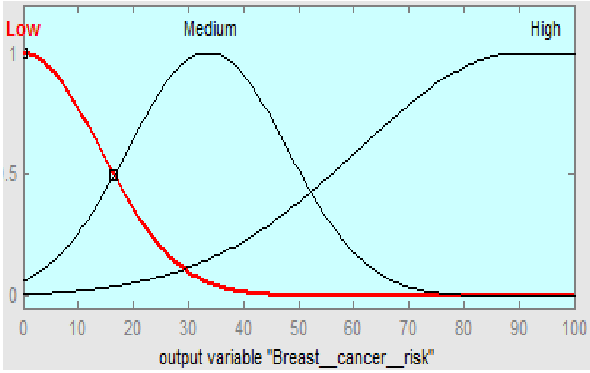

Fig. 4 Breast cancer risk membership functions

The fuzzy inference rules for risk evaluation are derived from the clinical experience and illustrated in Table I [6]. These rules will be applied to the inputs and the output of the Mamdani-type FIS and Sugeno-type FIS.

TABLE I
FUZZY INFERENCE RULES IN A MATRIX FORM

Size	Age: *Young*	Age: *Mature*	Age: *Old*
Small	Low	Low	Low
Medium	Medium	Medium	Medium
Large	High	High	High

By using the graphical user interface of the Fuzzy Logic Toolbox [9], the fuzzy inference systemfor the Mamdani- type is shown in Fig. 5.

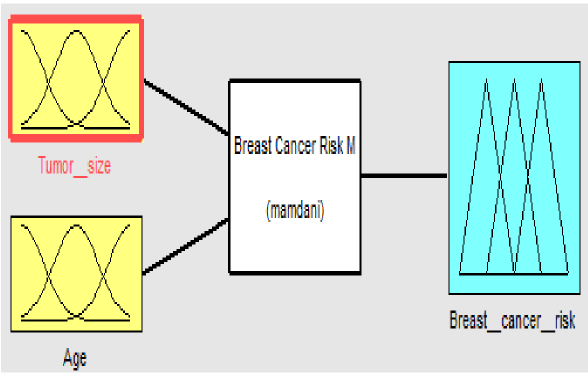

Fig. 5 Mamdani- type FIS

IV. Development of Sugeno-TypeFIS

The initial steps and the setting of Sugeno-type FIS are same as of Mamdni-type FIS. It also consists of two inputs from the age and the tumor size, and produces one output that indicates the risk of breast cancer. Each of the selected input variables is described by a set of three linguistic fuzzy values, defined by a Gaussian membership function,as in the case of Mamdani-type fuzzy inference system(as already shown in Figs. 2-3). Unlike the output value range of the Mamdani-type fuzzy inference system, the range of Sugeno-type output is between 0 and 1.The output of this system can only be either constant or linear in this FIS, so three linguistic fuzzy values for the output are "Low", "Medium", and "High" which can be constant as shown in Table II. The rule base for Sugeno-type FIS is the same as for Mamdani-type FIS as shown in Table I.

TABLE II
LINGUISTIC FUZZY VALUES FOR THE CANCER RISK

Breast Cancer Risk	Constant Value
Low	0
Medium	0.5
High	1

The fuzzy inference system for the Sugeno-type is shown in Fig. 6.

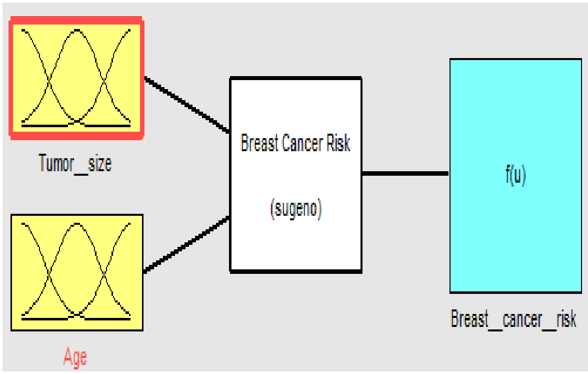

Fig. 6 Sugeno-type FIS

V. Results and Discussions

The following results were obtained during the simulation of both types fuzzy inference systems.

For Mamdani-type FIS, Fig. 7 illustrates the surface view of the three-dimensional view of the relationship between the inputs (age, tumor size) and the output (risk of breast cancer). Fig. 8 illustrates two dimensional view of the relationship between the risk of breast cancer and the age. Fig. 9 illustrates also two dimensional view of the relationship between the risk of breast cancer and the tumor size.

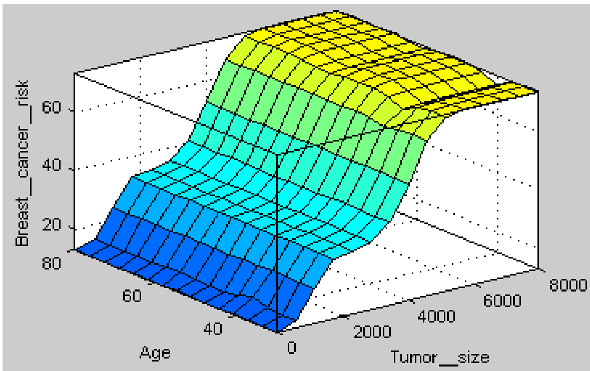

Fig. 7 Surface view of inputs and output in Mamdani-type FIS

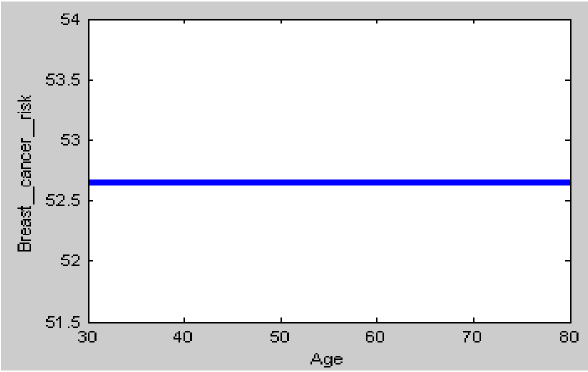

Fig. 8 Relationship between risk of cancer and age in Mamdani-type FIS

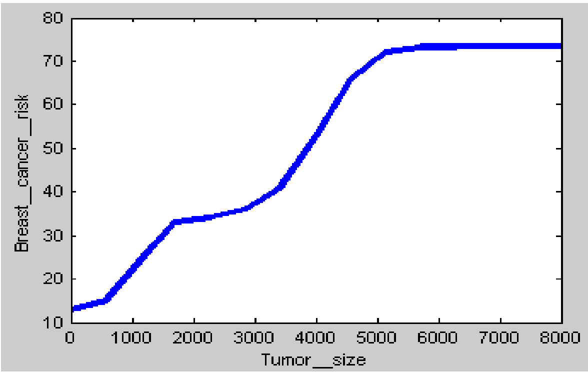

Fig. 9 Relationship between risk of cancer and tumor size in Mamdani-type FIS

For Sugeno-type FIS, Fig. 10 illustrates the surface view of the three-dimensional view of the relationship between the inputs (age, tumor size) and the output (risk of breast cancer). Fig. 11 illustrates two dimensional view of the relationship between the risk of breast cancer and the age. Fig. 12 illustrates also two dimensional view of the relationship between the risk of breast cancer and the tumor size.

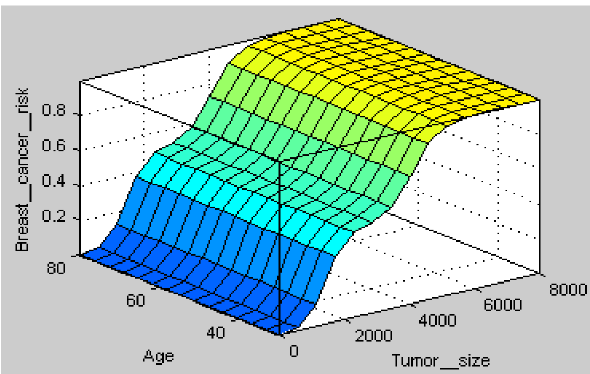

Fig. 10 Surface view of inputs and output in Sugeno-type FIS

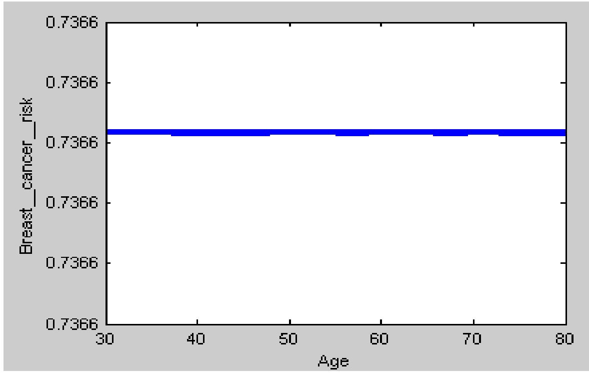

Fig. 11 Relationship between risk of cancer and age in Sugeno-type FIS

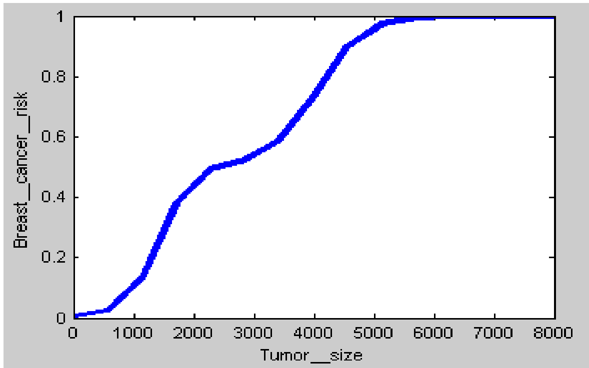

Fig. 12 Relationship between risk of cancer and tumor size in Sugeno-type FIS

As illustrates in the figures above, both inference systems (Mamdani-type and Sugeno-type) responded to operational changes as determined by the input quantities working variations with quite similar results. However, the sugeno-type FIS has a smooth operational performance than that of the mamdani-type FIS for the breast cancer evaluation. Moreover, the sugeno-type FIS works to full capacity unlike that of Mamdani-type FIS, and responds to inputs values changes quite efficiently more than the Mamdani type.

VI. Conclusion

This paper described the two most commonly used Fuzzy inference systems to evaluate the risk of breast cancer. It can be concluded that Mamdani-type FIS and Sugeno-type FIS perform quite similar, but Sugeno-type FIS allows the evaluation of risk to work at its full capacity with smooth operational performance. Although the designing of both systems is same but the output membership functions of Sugeno-type can only be either constant or linear and also the crisp output is generated in different ways for both FISs. Sugeno-type FIS has also an advantage that it can integrated with neural networks and genetic algorithm or other optimization techniques so that the system can adapt to system characteristic efficiently. However, extension of this work to compare the performance between the Fuzzy inference system and the clinical evaluation system is an interesting topic for further research. Other possible direction for research is investigating the FISs with more possible fuzzy rules.

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