Date of publication JUN-30, 2025, date of current version MAR-20, 2025.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.24.2.4019

Methodology for Building Fuzzy Knowledge Bases to Support Medical Decisions

MARIANNA SHARKADI[1], NELLI MALYAR-GAZDA[2], MYKOLA MALYAR[1]
[1]Department of cybernetics and applied mathematics, Uzhhorod National University, Uzhhorod, CO 88000 Ukraine
[2]Department of Anaesthesiology and Intensive Care,
The Borsod-Abauj-Zemplen County Hospital and University Teaching Hospital, Miskolc, CO 3526 Hungary

Corresponding author: Marianna Sharkadi (e-mail: marianna.sharkadi@uzhnu.edu.ua).

ABSTRACT The article examines key aspects of applying artificial intelligence theory – especially fuzzy logic techniques – to address decision-making challenges in medicine under uncertain conditions. It provides an in-depth methodology for developing fuzzy knowledge bases tailored to the unique characteristics of medical data, taking into account its multifactorial complexity and inherent variability. Emphasis is placed on how fuzzy models enhance processes such as diagnosis, continuous monitoring of patients, and risk evaluation related to anesthetic management before surgery. In particular, the study highlights the necessity of second-order fuzzy logic models, which enable dynamic and flexible data processing while balancing analytical precision with clarity for healthcare professionals. The paper illustrates the use of expert insights formatted as "If-Then" linguistic rules to clarify the relationships among various physiological parameters. Additionally, it outlines procedures for constructing membership functions, implementing second-order fuzzy sets, and applying fuzzy inference algorithms. These approaches demonstrate that integrating fuzzy logic into medical diagnostics not only improves the reliability of preoperative anesthetic risk assessments but also minimizes decision-making errors and optimizes patient treatment protocols.

KEYWORDS fuzzy sets; fuzzy knowledge base; fuzzy modelling; fuzzy inference system.

I. INTRODUCTION

Today, the theory of artificial intelligence is widely used in a variety of human activities, including medicine.

A special characteristic of medical computer systems is that they are united by a medical decision support system in a fuzzy uncertain environment. The diagnosis of a disease usually includes several levels of uncertainty and fuzziness [1]. Uncertainty is of great importance for science and fuzzy logic in our time as it is a way of modeling and communicating using natural language.

The use of fuzzy modeling methods based on observable data allows for a compromise between the accuracy of classification and the interpretability of the result.

Solving the problem of classification of observed data requires solving the following tasks: selection of informative features; formation of a knowledge base, i.e., (development of) fuzzy rules; optimization of parameters of membership functions.

The main component of the fuzzy classification model is the knowledge base of fuzzy rules.

Today, computer-based clinical decision support systems for disease detection and patient monitoring are being developed and implemented [2-5], which are able to provide clinicians with personalized assessments and/or recommendations to assist in medical decision-making. Such systems are usually based on easily interpretable linguistic "If-Then" rules. Such decision-making systems are human-oriented and based on the apparatus of fuzzy set theory [5-13], which is the basis for the development of computer diagnostic systems [14-18].

In the development of computer diagnostic systems, artificial intelligence methods are often used, such as neural networks [19, 20], the nearest neighbor method [21, 22], genetic algorithms [23, 24], support vector machines [25, 26].

Here is an overview of some sources of building fuzzy knowledge bases in the medical field for diagnosing various diseases.

In their work [31], P. Kora and co-authors described a fuzzy knowledge base for determining the risk of coronary heart disease that includes 44 rules. The input features are cholesterol, blood pressure, physical activity, age, body mass index, smoking, and diabetes. The disease state is divided into three risk classes: healthy, early-stage, and advanced-stage of disease.

D. Pal and co-authors [33] proposed a developed expert system using primary and clinical information from patients to stratify the risk of coronary heart disease. The input features for the fuzzy system were formed through interviews with cardiologists: age, smoking, body mass index, hypertension, diabetes, lipid profile, chest pain. Each input variable is described by a trapezoidal membership function. The output is a fuzzy variable "risk" that takes on a fuzzy value: low, medium, high.

Paper [32] presents a fuzzy decision support system for diagnosing coronary heart disease that takes into account the accuracy of decision making and its interpretation. A. Lahsasna and co-authors proposed to extend the structure of fuzzy rules by introducing the degree of its importance and certainty in the THEN part of the rule, so that the doctor can check the validity of each rule and determine whether to take this rule into account. The authors used a "winner-take-all" inference strategy, i.e., a decision is made on the basis of one rule, IF the IF part of this rule is most appropriate to describe a particular risk factor. The proposed features allow the doctor to understand the relationship between risk factors and diagnosis and accurately determine the presence of coronary heart disease.

A fuzzy expert system for diagnosing hypertension [34] uses age, body mass index, blood pressure, and heart rate as input parameters. Based on the expert's knowledge, the diagnostic process is formed, as well as linguistic variables and their values.

In addition, a comparative analysis was conducted with conventional machine learning classifiers. The results show that while deep learning approaches demonstrate higher accuracy on large data sets, fuzzy systems provide more interpretable and flexible decision-making capabilities, especially in handling uncertainty and linguistic reasoning.

Fuzzy logic, on the other hand, provides a structured, rule-based system that allows for transparent decision-making, a crucial aspect in a clinical setting where explainability is essential. This hybrid approach ensures that accuracy and interpretability are balanced to support medical decision-making.

This review shows that modern medical diagnostics is a complex process that requires the accumulation of knowledge and clinical experience of medical professionals and patient data in conditions where information from patients can change dynamically and contain redundant and interrelated symptoms from several types of disease.

In such cases, it is advisable to use computer systems based on fuzzy mathematics to help clinicians, which allows them to work with both poorly formalized information and qualitative data.

The problems faced by specialists in the medical field are related to the situation when it is impossible to take into account all the parameters, and the required number of parameters cannot be determined, i.e., there are only significant parameters, while the final solution is considered, which may be approximate.

Such problems include the tasks of diagnosing and predicting the consequences of the disease, choosing a strategy and tactics of treatment, determining the level of patient readiness for surgery, etc.

To solve such problems in conditions where the description of medical data has a qualitative form, it will be appropriate to build fuzzy logic systems that have the ability to describe existing statements of medical professionals.

As a rule, the formation of fuzzy knowledge bases, the choice of the type of membership functions and the number of input parameters will significantly depend on the degree of participation of medical specialists and laboratory information.

To date, the share of surgical interventions performed in one-day surgery in European countries is 80%, while in Ukraine this figure does not exceed 60%. A necessary prerequisite for increasing the number of surgical interventions in one-day surgery is the most optimal preoperative anesthetic preparation of the patient.

The use of the proposed approach will reduce the financial burden on the medical system as a whole and on individual medical institutions in particular

This paper proposes the use of a mathematical apparatus using second-order fuzzy sets and the profile of a fuzzy knowledge base built for an anesthesiologist to make a decision on determining the level of patient readiness for elective surgery, in particular, conducting this intervention in the context of "one-day surgery".

II. MATERIAL AND METHODS

The object of the study is the processes that affect the level of patient's condition in preparation for elective intervention in modern conditions.

The main hypothesis of the study is to improve the quality of reflection of the subject area of the medical field by building fuzzy knowledge bases using interval membership functions of the second order for an anesthesiologist when admitting a patient to elective (planned) surgery.

The main tools for using fuzzy set theory are the construction of membership functions and a fuzzy knowledge base. In the theory of fuzzy sets, the membership function plays a significant role, since it is the main characteristic of a fuzzy object, and all actions with fuzzy objects are performed through operations with their membership functions. As a rule, the membership function is built either on the basis of statistical information or with the participation of an expert (group of experts). In the first case, the membership function should have a frequency interpretation, in the second case, the degree of membership is approximately equal to the intensity of the manifestation of a certain property. A knowledge base is a fuzzy rule with certain parameters, such as change intervals and membership functions, which can be formed using an expert method. In this case, the values of the fuzzy rule parameters are set manually by an expert. In another approach, the parameters of fuzzy rules are determined by machine learning methods on data from sets of retrospective examples.

The problem of medical diagnosis, as a task of determining the level of a patient's condition, can be formulated as a classification problem. Such a problem can be solved by finding the appropriate mathematical function F, which corresponds to a set of symptoms $X=\{x_1, x_2, \dots, x_n\} = \{x_i,\ i=\overline{1,n}\}$ with a certain class label k_j:

$$F(X): X \to k_j. \tag{1}$$

It is proposed to use a fuzzy modeling approach in the form of the function F, which is based on the use of certain rules for the observation data.

This approach allows for a compromise between classification accuracy and interpretation of the result.

The task of classification is to predict the class of an object by its feature vector. Let the set of features $X = \{x_1, x_2, \dots, x_n\} = \{x_i,\ i = \overline{1,n}\}$ and the set of classes $K = \{k_1, k_2, \dots, k_m\} = \{k_j,\ j = \overline{1,m}\}$.

Fuzzy classification is represented as a function that assigns a class label to a point in the input feature space with a calculated degree of confidence:

$$F(X): X_1 \times X_2 \times \ldots \times X_n \to [0,1]^n. \tag{2}$$

The basis of fuzzy classification is the following productive rule:

$$R_{pj}: IF x_1 = A_{1j} \& x_2 = A_{2j} \& \ldots \& x_{nj} = A_{nj}\ THEN\ class = k_j, \tag{3}$$

where A_{ij} is a linguistic term that characterizes the i -th feature in the j -th rule and is defined by its membership function $\mu_{A_{ij}}(x_i)$ at the point x_i, $p = \overline{1,P}$, P is the number of rules.

A class is defined by the rule for which the If-part maximally matches the description given by the input vector X:

$$class = k_{j^*}, j^* = arg \max_{1 \le j \le m} \prod_{i=1}^{n} \mu_{A_{ij}}(x_i). \tag{4}$$

The construction of a fuzzy classification requires solving the following tasks: selection of informative features, formalization of knowledge, formulation of a fuzzy rule base, and optimization of the parameters of the membership function.

The problem of selecting informative features is to find such input attributes from the dataset that most realistically reflect the patient's condition and the doctors' understanding of the result. These can be statistical, theoretical, information and metaheuristic methods.

The formalization of knowledge is a problem whose solution is to build a model that adequately reflects the information of the subject area.

An important tool for building decision-making models for tasks that are poorly formalized and operate with expert information is the apparatus of fuzzy sets and fuzzy logic [27]. The formalization of expert knowledge through fuzzy sets includes appropriate procedures for creating membership functions. These procedures are the key to decision-making, since the quality of the decision depends on the adequacy of the membership function that represents the expert knowledge. The choice of the type of fuzzy set to build membership functions and the corresponding fuzzy model poses the researcher with the task of optimal choice [30].

Defining a membership function is the first and very important step for further work with fuzzy sets. The membership function can be built on the basis of statistical data or with the participation of an expert or a group of experts. Many scientists, starting with L. Zadeh, have devoted their research to the problem of constructing membership functions, which is a key concept in fuzzy logic. Depending on the degree of fuzziness that is taken into account when building a fuzzy model, there are type 1 fuzzy models, general type 2 models, and interval type 2 models [28].

Type 1 fuzzy models, which are based on first-order fuzzy sets, use membership functions with clear membership degrees and produce only a point (clear) value at the output. Lotfi Zadeh proposed a convenient interpretation of type 1 fuzzy sets in solving practical problems:

$$A = \{(x, \mu_A(x))|x \epsilon X, 0 \le \mu_A(x) \le 1\}, \tag{5}$$

where X is an universal set, and $\mu_A(x)$ is a function of the membership of element x in the set A, which is a subset of the universal set.

Based on the first-order fuzzy sets, various models, methods, and algorithms have been developed to address uncertainty. However, the analysis of these methods and models shows that they often do not provide complete solutions due to insufficiently justified choice of modeling parameters, requiring multiple implementations to select the optimal parameters.

The concept of fuzzy sets of the second-order (fuzzy sets type-2) was introduced by the founder of fuzzy logic L. Zadeh in 1975. Second-order fuzzy sets were understood as “fuzzy” sets in which the degree of membership is a fuzzy set of the first order.

The use of fuzzy sets with fuzzy membership functions is associated with the concept of linguistic truth, for example, with such values as true, quite true, very true, more or less true, and so on, and fuzzy sets whose degree of membership is described by such linguistic terms as low, medium, high, very low, not low and not high, etc. on the other hand.

In practice, a distinction is made between general and interval second-order fuzzy sets, which are based on the first-order fuzzy sets.

Paper [6] described the second-order fuzzy sets using lower and upper membership functions (MF). Each of these functions can be represented as a first-order fuzzy set. The interval between these two functions is the footprint of uncertainty (FOU) [5], which is the main characteristic of a second-order fuzzy set (FS-2). The footprint of uncertainty describes the blurring of the first-order membership function, which is fully represented by its two limiting functions: lower (LMF) and upper (UMF), which are first-order fuzzy sets (FS-1) (Fig. 1).

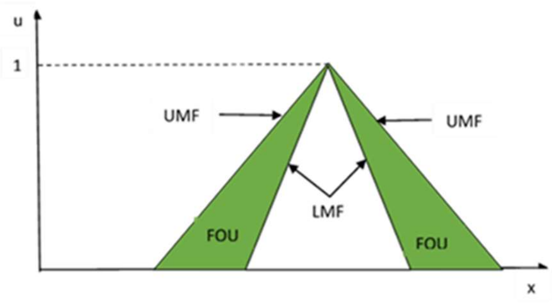

Figure 1. Type-2 membership function.

The introduction of fuzziness in the membership function makes it possible to bring the fuzzy model closer to human thinking and perception and reduce the risk of errors arising from the lack of consideration of questionable points located near the boundaries of the function. One of the main tasks is to determine the size of the uncertainty trace, as it affects the accuracy of the model and the time required for computations in computer systems. Obviously, the size of the uncertainty depends on the type of membership functions used.

The membership function of a general second-order fuzzy set is depicted in a three-dimensional model in Figure 2, where the third dimension of the membership function at each point in the two-dimensional domain represents the so-called "footprint of uncertainty" (FOU).

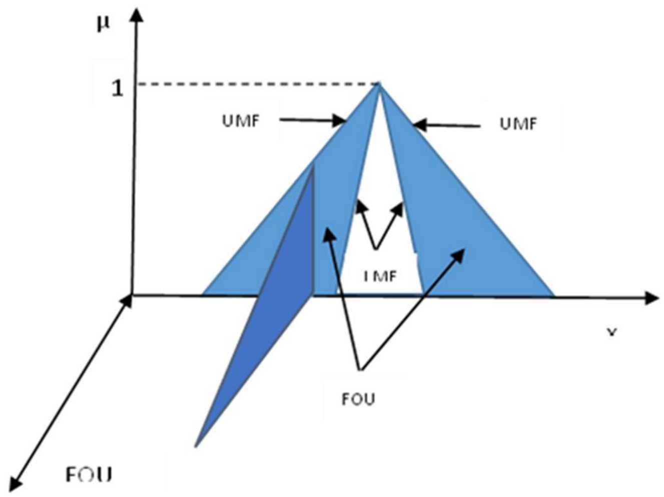

Figure 2. Uncertainty trace of a type 2 fuzzy set.

Second-order fuzzy sets are characterized by the blurring of the boundaries of the membership function (MF) and the way the degrees of membership are distributed by the values of the arguments. Blurring the boundaries is the first step in the transition from type 1 to type 2 fuzzy sets.

Theoretically, we can choose any type of membership function, it is unlimited, but the most common in practical use are Gaussian, triangular, trapezoidal, and bell-shaped membership functions.

From the theoretical point of view, there are two types of the second type of membership functions: interval and general. If for any value of the argument from the universe over the entire interval, from the lower degree of membership to the upper, the value of the FN is unchanged, then this type of FN is unified (homogeneous), and a fuzzy set with this type of FN is called an interval fuzzy set of the second order. And if for any value of the argument from the universe in the specified interval, the value of the FN changes, then the fuzzy set with this type of FN is called a second-order fuzzy set of general form.

III. RESULTS

In most practical tasks of medical diagnostics, the synthesis of fuzzy knowledge bases and the construction of fuzzy models in the context of qualitative data depend on the ability of a medical specialist to formalize his knowledge and understand the importance of the parameters provided to the developer for the further design of a fuzzy logic system.

Let us demonstrate the use of this approach when making a decision by an anesthesiologist. We will give an example of signs by which the patient's physical condition is assessed before elective (planned) surgical interventions.

The difficulty of determining the patient's condition is often associated with the presence of excessive information and interrelated symptoms, especially if the patient suffers from several diseases. Often, the biggest challenge for a doctor is to structure the available information and identify the most important so-called "sign" signs or symptoms. It is especially difficult to qualitatively assess a patient's condition before surgery. An adequately determined condition allows us to predict the duration of a patient's possible hospital stay. Timely corrected deviations in the patient's condition can optimize the financial burden on medical institutions and the healthcare system as a whole, as well as improve the quality and duration of the patient's life.

According to the global practice, patients undergo a mandatory examination by an anesthesiologist before an elective (planned) intervention. As a result of the examination, recommendations will be given regarding the risk of anesthesia for this patient, the patient's suitability for a particular volume of surgery, the conditions under which this surgery can be performed (one-day surgery or the availability of inpatient department), the need for additional examinations (laboratory or instrumental) or correction of treatment or directly certain vital signs (for example, hemoglobin level, arterial blood pressure level, etc.

In the vast majority of cases, the task of assessing preoperative anesthetic risk is extremely difficult for a physician due to the availability of a huge amount of information, which is often subjective, confusing, interrelated, and in many cases even mutually exclusive.

Today, anesthesia outpatient appointments are based on the world-famous system proposed by the American Society of Anesthesiologists (ASA) [29], which provides for 6 risk classes.

The physical status of patients according to the ASA classification is an assessment of the patient's condition before surgery, endoscopy or other manipulation. There are 6 classes of physical status: from a healthy patient to a patient in an extremely serious condition.

ASA I - Healthy patient (does not smoke, drinks alcohol in small quantities).

ASA II - Patient with mild systemic disease (mild disease only without significant functional limitations). Examples include (but are not limited to): smoker, social alcoholic, pregnant, obese (<30 BMI <40), compensated diabetes mellitus, controlled hypertension, mild respiratory disease.

ASA III - Patient with severe systemic disease (significant limitations of functional activity). Examples include (but are not limited to): poorly controlled hypertension or subcompensated diabetes mellitus, COPD, morbid obesity (BMI ≥40), active hepatitis, alcohol dependence or abuse, implanted pacemaker, moderate reduction in cardiac output fraction, chronic renal failure requiring regular scheduled hemodialysis. A history (more than 3 months) of myocardial infarction, stroke, transient ischemic attack, coronary heart disease or stenting.

ASA IV - A patient with a severe systemic disease that poses a permanent threat to life. Examples include, but are not limited to: myocardial infarction, stroke, transient ischemic attack, coronary artery disease or stenting, current myocardial ischemia or severe heart valve dysfunction, severe ejection fraction reduction, sepsis, DIC, acute or chronic renal failure, and irregular hemodialysis.

ASA V - Dying patient. Surgery for vital indications. Examples include (but are not limited to): aortic aneurysm rupture, severe polytrauma, intracranial hemorrhage, acute intestinal ischemia with concomitant severe cardiac pathology or multiple organ failure.

ASA VI - Brain death has been established, organs are removed for donor purposes.

However, the first three classes are most often used for elective interventions. Patients belonging to the first two classes are considered suitable for elective interventions of one-day surgery.

Here are the normal values of the indicators used in the examination of the patient.

1. Metabolic equivalent. Metabolic equivalent (MET) is a unit of measurement of the body's energy needs, which is used during the treadmill test to assess the functional abilities of a person (i.e., his/her tolerance to physical activity).

The baseline value (1 MET) is the metabolic rate at rest (under the conditions of basal metabolism), which is 1 kcal/kg/h. Thus, 2 METs correspond to a load that causes a 2-fold increase in the body's energy requirement compared to the resting state. Activity that requires energy expenditure of 2-4 MET (slow walk, doing routine housework, etc.) is considered light, while running and climbing uphill can be accompanied by an increase in energy demand of up to 10 or more MET.

The functional capacity of a person unable to perform a load of more than 5 MET during a treadmill test is considered to be reduced, which is associated with a more difficult prognosis, while the ability to perform a load above this level indicates a favorable outcome.

The Borg Scale is used to assess the perceived exertion of physical activity, i.e., how much a person feels their body is working. The perceived strain is based on the physical sensations that a person experiences during physical activity, including an increase in heart rate, increased respiratory rate, increased sweating, and muscle fatigue. In its original form, the scale started at 6 points and reached 20, which corresponded to a heart rate of 60 to 200. In recent years, an updated scale from 1 to 10 points, the so-called Newer scale, has been used.

2. Laboratory parameters:

2.1. Complete blood count:

Hemoglobin 120 - 160 g/l (90-180),

Red blood cells 4.1- 5.2 T/l (2.5-7.0)

Leukocytes 4.4-11.3 G/l (2-20.0)

Platelets 140- 400 G/l (75-600)

2.2. Kidneys and their functioning:

Creatinine 38-85 mmol/l (30-200)

GFR (glomerular filtration rate) - more than 90 ml/min/1.73 m2 (less than 25)

2.3. Homeostasis:

Potassium 3.5-5.1 mmol/l (3-6)

Sodium 137-150 mmol/l (130-155)

Sugar 3.7-6.2 mmol/l (3.2-9.0)

3. Echocardioscopy, if available (LVEF%, normal 55-75%, life-threatening if less than 55%).

4. Coagulogram (blood clotting).

4.1. INR 0.80-1.20 (0.6-1.4).

4.2. Fibrinogen 1.8-3.5 g/l (1.2-5.0).

The first task in building a fuzzy classification is the selection of information features. Let us consider several “iconic” signs that an anesthesiologist usually uses during his examination:

1. Age of the patient;
2. Mass index;
3.The presence of bad habits (smoking);
4. Level of tolerated physical activity;
5. The level of blood pressure;
6. ECG (abnormalities or not);
7. Hemoglobin level;
8. Platelet count;
9. Sugar level;
10. Glomerular filtration rate;
11. Potassium level.

The second task is to formalize the knowledge. Here are the linguistic values that these features can take.

1. Age under 40 is young, 40-58 is middle-aged, 59-75 is old;

2. Body mass index...<25 - normal, 25-32 - overweight, more than 33 - obese;

3. Bad habits: smoking - no (<0.6), yes (0.3-1.0);

4. Physical activity - no (<0.6) - MET <5, yes (0.3-1.0) - MET > 5-6-7;

5. Systolic blood pressure <135 - normal, 136-159 - elevated, 160-200 - high;

6. ECG - normal, there are abnormalities;

7. Hemoglobin level 120-140 - normal, 90-120 - intermediate, <90 - low;

8. Platelet count 150-350 - normal, 100-150 and 350-450 - intermediate, less than 100 and more than 450 - pathological changes;

9. Sugar 3.3-5.5 - normal, 5.5-8.5 - intermediate, less than 3.2 and more than 9 - pathological changes;

10. GFR more than 90 - normal, 75-90 - moderate changes, less than 75 - pathological deterioration;

11. Potassium level 3.3-5.5 - normal, 3.0-3.3 and 5.5-5.9 - moderate changes, less than 3 and more than 6 - severe pathological changes.

The analysis of the information on the indicators [35-37] has shown that it is advisable to use the apparatus of fuzzy set theory to interpret them, since the values of these indicators are blurred. Among piecewise linear functions, the most commonly used are the so-called “triangular” and “trapezoidal” membership functions. The first type of function is usually used to formalize uncertainties such as “approximately equal” and “average value”, and the second type is used to represent uncertainty such as “located in the interval”.

To model the first six features, we will use first-order membership functions. An example of a membership function is shown in Fig. 3.

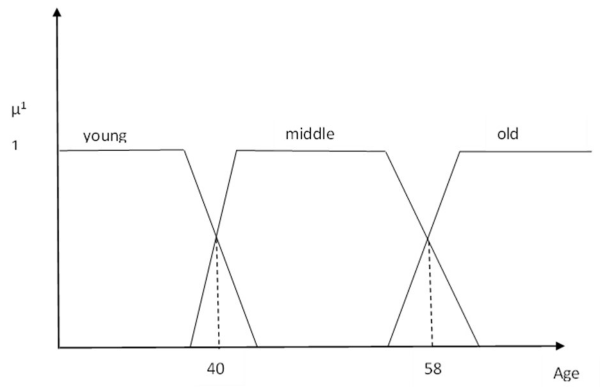

Figure. 3. Input linguistic variable “age”.

Features 7, 8, 9, 10, 11 should be modeled using second-order membership functions. To describe the values of these indicators, we will use the second-order trapezoidal membership functions.

$$\mu = \begin{cases} 0, & x \le a_1 \\ \dfrac{x-a_1}{b_1-a_1}, & a_1 \le x \le a_2 \quad (UMF) \\ \dfrac{x-a_2}{b_1-a_2}, & a_2 \le x \le b_1 \quad (LMF) \\ 1, & b_1 \le x \le b_2 \quad (Norm) \\ \dfrac{c_1-x}{c_1-b_2}, & b_2 \le x \le c_1 \quad (LMF) \\ \dfrac{c_2-x}{c_2-b_2}, & c_1 \le x \le c_2 \quad (UMF) \\ 0, & x \ge c_2 \end{cases}$$

Examples of membership functions for features and terms are shown in Fig. 4.

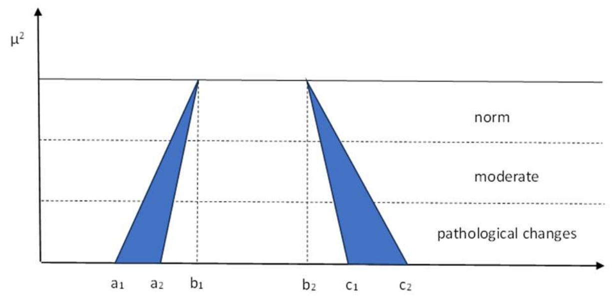

Figure 4. Input linguistic variables for features 7, 8, 9, 10, 11.

The next task is to form a fuzzy rule base. For example, here is a profile of 10 rules.

1. IF (age is young) AND (body mass index is normal) AND (physical activity is yes) AND (smoking is no) AND (blood pressure is normal) AND (ECG is normal) AND (hemoglobin is normal) AND (platelets are normal) AND (sugar is normal) AND (GFR - normal) AND (potassium - normal) THEN ASA I, the risk of anesthesia is low, the patient is suitable for a one-day elective intervention.

2. IF (age is average) AND (BMI is normal) AND (exercise is yes) AND (smoking is no) AND (blood pressure is normal) AND (ECG is normal) AND (hemoglobin is normal) AND (platelets are normal) AND (glucose is normal) AND (GFR - normal) AND (potassium - normal) THEN ASA I, the risk of anesthesia is low, the patient is suitable for a one-day elective intervention.

3. IF (age is young) AND (body mass index is normal) AND (exercise is yes) AND (smoking is no) AND (blood pressure is normal) AND (ECG is normal) AND (hemoglobin is intermediate) AND (platelets are normal) AND (glucose is normal) AND (GFR - normal) AND (potassium - normal) THEN ASA I, the risk of anesthesia is low, the patient is suitable for a one-day elective intervention.

4. IF (age is young) AND (body mass index is overweight) AND (physical activity is yes) AND (smoking is yes) AND (blood pressure is normal) AND (ECG is normal) AND (hemoglobin is normal) AND (platelets are normal) AND (sugar - normal) AND (GFR - normal) AND (potassium - normal.) THEN ASA II, the risk of anesthetic support is medium, the patient is conditionally suitable for a one-day elective intervention.

5. IF (age is young) AND (body mass index is overweight) AND (physical activity is yes) AND (smoking is yes) AND (blood pressure is elevated) AND (ECG is normal) AND (hemoglobin is normal) AND (platelets are normal) AND (sugar is normal) AND (GFR - normal) AND (potassium - normal) THEN ASA II, the risk of anesthetic support is average, the patient is conditionally suitable for a one-day elective intervention, which is necessary for the examination.

6. IF (age is young) AND (body mass index is overweight) AND (physical activity is yes) AND (smoking is yes) AND (blood pressure is elevated) AND (ECG is abnormal.) AND (hemoglobin is normal) AND (platelets are normal.) AND (sugar is normal) AND (GFR - normal) AND (potassium - normal.) THEN ASA II, the risk of anesthetic support is medium, the patient is conditionally suitable for a one-day elective intervention required before the examination.

7. IF (age is young) AND (body mass index is overweight) AND (physical activity is yes) AND (smoking is yes) AND (blood pressure is high) AND (ECG is abnormal) AND (hemoglobin is normal) AND (platelets are normal) AND (sugar is normal) AND (GFR - normal) AND (potassium - normal.) THEN ASA II, the risk of anesthetic support is medium, the patient is conditionally suitable for a one-day elective intervention, which is necessary for the examination.

8. IF (age is young) AND (body mass index is overweight) AND (physical activity is yes) AND (smoking is yes) AND (blood pressure is high) AND (ECG is normal) AND (hemoglobin is low) AND (platelets are normal) AND (sugar is normal) AND (GFR - normal) AND (potassium - normal) THEN ASA II, the risk of anesthetic support is medium, the patient is conditionally suitable for a one-day elective intervention, correction of indicators is necessary.

9. IF (age is average) AND (body mass index is overweight) AND (physical activity is yes) AND (smoking is yes) AND (blood pressure is elevated.) AND (ECG is normal) AND (hemoglobin is low) AND (platelets are normal.) AND (sugar is elevated) AND (GFR - moderate changes) AND (potassium - normal) THEN ASA III, the risk of anesthetic support is high, the patient is unsuitable for a one-day elective intervention, correction of indicators is necessary.

10. IF (age is average) AND (body mass index is overweight) AND (physical activity is not) AND (smoking is) AND (blood pressure is elevated.) AND (ECG is abnormal) AND (hemoglobin is intermediate) AND (platelets are normal) AND (sugar is elevated) AND (GFR - moderate changes) AND (potassium - normal.) THEN ASA III, anesthetic risk is high, the patient is unsuitable for a one-day elective intervention, and the patient should be evaluated before the examination.

IV. CONCLUSIONS

Based on the expert's knowledge, the significant signs are selected, which, as a rule, are most often used by an anesthesiologist during the examination process to make a decision when admitting a patient to elective surgery. The well-known system for assessing the patient's physical condition proposed by the American Society of Anesthesiologists (ASA), which provides for the presence of 6 risk classes, is presented.

We propose an improved second-order fuzzy inference system specifically designed for risk assessment in anesthesiology. Unlike conventional fuzzy models that rely on static membership functions, our system uses dynamically adapted fuzzy sets that adjust to specific patient parameters.

In traditional fuzzy models, hemoglobin levels were classified as “low” if they were below 90 g/L, “intermediate” if they were between 90-120 g/L, and “normal” if they were above 120 g/L. In the proposed model, these thresholds dynamically change depending on the patient's age and comorbidities. A 70-year-old diabetic patient may have a higher threshold for “low” hemoglobin than a 25-year-old healthy patient.

An approach to formalizing knowledge that reflects the information of the subject area of an anesthesiologist based on the use of fuzzy mathematics tools is proposed. For fuzzy feature modeling, fuzzy sets of the first and second order are used, which allows us to adequately describe the input linguistic variables. For example, we present the second-order membership function for the indicator “potassium”:

$$\mu = \begin{cases} 0, & x \leq 3{,}0; \\ \dfrac{x-3{,}0}{0{,}5}, & 3{,}0 \leq x \leq 3{,}3; \\ \dfrac{x-3{,}3}{0{,}2}, & 3{,}3 \leq x \leq 3{,}5; \\ 1, & 3{,}5 \leq x \leq 5{,}1; \\ \dfrac{5{,}5-x}{0{,}4}, & 5{,}1 \leq x \leq 5{,}5; \\ \dfrac{6-x}{0{,}9}, & 5{,}5 \leq x \leq 6.0; \\ 0, & x \geq 6{,}0. \end{cases}$$

Let us say that the value of the indicator “Potassium” for a particular patient is x* = 5.4 mmol/L, then the value of the primary membership function of the second order is lower (LMF) and upper (UMF). Accordingly, the value of the secondary membership function (triangular), see Fig. 5.

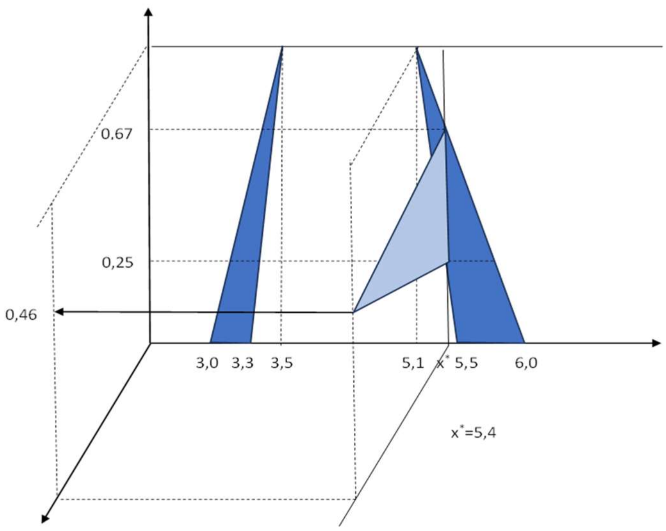

Figure. 5. Interval fuzzy set of type-2 for the indicator “potassium”.

Based on the fuzzy knowledge base consisting of 10 rules, the following conclusions of the anesthesia examination were obtained:

1. The risk of anesthetic management is low, the patient is suitable for a one-day elective intervention, ASAI status.

2. The risk of anesthetic support is medium, the patient is conditionally suitable for a one-day elective intervention, ASAII status level:

A) with pre-examination;

B) with correction of vital signs or correction of treatment.

3. The risk of anesthetic support is high, not suitable for elective one-day intervention, ASAIII level. Suitable for surgical intervention:

A) with pre-examination;

B) with correction of vital signs or correction of treatment.

Based on the expert experience of an anesthesiologist, 11 key signs for assessing the preoperative condition of a patient are identified and the normative values of the corresponding indicators are given. The membership functions for first- and second-order fuzzy sets used to describe input linguistic variables in a computer-based intelligent decision-making system based on a fuzzy knowledge base with 10 rules are considered. Examples of first- and second-order membership functions characterizing different types of indicators are presented. Based on the results of the research, conclusions are formulated regarding the anesthetic examination of the patient. The fuzzy knowledge base and the list of key features are open, which makes it possible to supplement, correct and modify them.

Experimental validation was conducted using real medical data. The evaluation focused on key performance indicators such as sensitivity, specificity, and accuracy.

Unlike deep learning, the fuzzy model allowed medical professionals to trace the reasoning behind each classification.

The sensitivity (ability to correctly identify high-risk patients) was 84%, and the specificity (correct identification of low-risk patients) was 89%. These results confirm that the system is reliable for clinical decision support.

Thus, the proposed second-order fuzzy inference system improves the adaptability of the model, providing a more accurate preoperative risk assessment. In addition, this research extends traditional fuzzy knowledge bases by integrating an expert-driven rule optimization process.

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MARIANNA SHARKADI, Ph.D. in Economics, Associate Professor at the Department of Cybernetics and Applied Mathematics, Uzhhorod National University, Uzhhorod, Ukraine. Her research interests encompass mathematical modeling of socio-economic systems, fuzzy modeling, and intelligent decision-making systems.

NELLI MALYAR-GAZDA, Ph.D. in Medicine, Anesthesiologist at the Department of Anesthesiology and Intensive Care, The Borsod-Abauj-Zemplen County Hospital and University Teaching Hospital, Miskolc, Hungary. Her research interests include anesthesiology, emergency conditions, determination of the patient's readiness for elective surgery.

MYKOLA MALYAR, Doctor of Technical Sciences, Professor at the Department of Cybernetics and Applied Mathematics, Dean of the Faculty of Mathematics and Digital Technologies, Uzhhorod National University, Uzhhorod, Ukraine. His research interests encompass computer modeling of socio-economic systems, decision theory, data mining, fuzzy modeling, artificial intelligence systems.