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FUZZY MODEL FOR INTELLECTUALIZING MEDICAL KNOWLEDGE

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ABSTRACT

Context. The research is devoted to the development of a flexible mathematical apparatus for the intellectualisation of knowledge in the medical field. As a rule, human thinking is based on inaccurate, approximate data, the analysis of which allows us to formulate clear decisions. In cases where there is no exact mathematical model of an object, or the model is difficult to implement, it is advisable to use a fuzzy logic apparatus. The article is aimed at expanding the range of knowledge of researchers working in the field of medical diagnostics.

Objective. The aim of the study is to improve the quality of reflection of the subject area of the medical sphere on the basis of building type-2 fuzzy knowledge bases with interval membership functions.

Method. The article describes an approach to formalising the knowledge of a medical specialist using second-order fuzzy sets, which allows taking into account the uncertainty and vagueness inherent in medical data and solving the problem of interpreting the results obtained.

Results. The developed approach is implemented on a specific problem faced by an anaesthetist when admitting a patient to elective (planned) surgery.

Conclusions. Experimental studies have shown that the presented type-2 fuzzy model with interval membership functions allows to adequately reflect the input medical variables of a qualitative nature and take into account both the knowledge of a specialist in medical practice and research medical and biological data. The acquired results hold substantial practical importance for medical practitioners, especially anesthetists, as they lead to enhanced patient assessments, error reduction, and tailored recommendations. This research fosters the advancement of intelligent systems capable of positively influencing clinical practices and improving patient outcomes within the realm of medical diagnostics.

KEYWORDS: fuzzy clustering, medical diagnostics, membership functions of the second kind.

ABBREVIATIONS

ASA is the American Society of Anaesthesiologists;
FOU is a footprint of uncertainty;
FS-1 is a first-order fuzzy set;
FS-2 is a second-order fuzzy set;
LMF is a lower membership function;
MET is a metabolic equivalent;
MF is a membership function;
UMF is an upper membership function.

NOMENCLATURE

A is a fuzzy set;
A_{ij} is a linguistic term;
X is the set of features;
x_i is an i-th element of the set X;
K is the set of classes;
k_j is a class label, j-th element of the set K;
$F(X)$ is a fuzzy classifier;
$J_{x'}$ is a primary membership function;
μ is a membership function;
$\mu(x^*)$ is the value of the membership function at a particular point;
$\mu_{\tilde{A}}(x')$ is the secondary membership function;
n, m – number of elements in the set;
P is a number of rules;
R_{pj} is a product rule;
x is the primary variable;
x^* is specific value of the indicator;
u is the secondary variable.

INTRODUCTION

Modern information technologies are widely used in many areas of human activity, in particular, they are being intensively implemented in the daily practice of healthcare. Fuzzy modelling is one of the most popular and rapidly developing areas in the field of modern methods of managing poorly formalized objects.

The massive introduction of digital technologies in the modern world demonstrates successful results, in particular in the diagnosis of socially significant diseases. The use of computer systems by a practitioner requires continuous improvement of both the doctor's knowledge and the systems as a whole. Both subjective and objective factors should be taken into account. Subjective factors include physician errors in examination and diagnosis. Objective factors include, first of all, the constant increase in the number of criteria that must be taken into account and analysed by a doctor when making a medical decision, which significantly exaggerate the cognitive capabilities of a person, as well as the lack of time for decision-making. To solve these problems, it is advisable to introduce intelligent systems based on artificial intelligence technologies into clinical medicine. Such systems are able to provide clinicians with personalized assess-

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ments and/or recommendations to assist them in making medical decisions.

Intelligent decision-making systems should be focused on the knowledge of a specialist doctor and be based on a set of explicit, understandable, easily interpretable linguistic "IF-THEN" rules. As a rule, in the process of assessing a patient's condition, medical practice uses linguistic terms such as "high fever", "old age", "low blood pressure", which are intuitive and well aligned with the doctor's thinking and judgement, and can be used to describe uncertain and inaccurate information. These properties encourage researchers to use fuzzy logic theory in intelligent decision support systems.

When admitting a patient to surgery, the anaesthetist must comprehensively examine the patient, i.e. objectively examine the patient's condition, analyse laboratory, *X*-ray and other types of examinations, and take into account the presence of other diseases of the patient. Processing a large amount of information about a patient is a complex task that an intelligent decision support system can help solve.

The object of study is the development of a flexible mathematical apparatus for intellectualizing knowledge in the medical field, with a specific focus on medical diagnostics.

The subject of study is the intellectualization of knowledge in the medical field.

This paper proposes the use of a mathematical apparatus using second-order fuzzy sets to determine the class of a patient's readiness for surgery.

1 PROBLEM STATEMENT

The problems faced by medical professionals are related to the situation when all parameters cannot be taken into account, 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 a disease, choosing a treatment strategy and tactics, 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 solve this problem, it is proposed to use type-2 fuzzy models with interval membership functions[1], which are adequately applied in the medical field and are capable of taking into account both the knowledge of a medical expert and laboratory biomedical data in the context of descriptive, qualitative data.

The problem of medical diagnosis can be formulated as a classification problem. Such a problem can be solved by finding an appropriate classifier, i.e. a mathematical function F, that corresponds to a set of symptoms $X = \{x_1, x_2, ..., x_n\} = \{x_i, i = \overline{1,n}\}$ with a certain class label k_j:

$$F(X): X \to k_j .$$

It is proposed to use a fuzzy modelling approach based on observation data as a classifier. Such an 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 $X = \{x_1, x_2, ..., x_n\} = \{x_i, i = \overline{1,n}\}$ and the set of classes $K = \{k_1, k_2, ..., k_m\} = \{k_j, j = \overline{1,m}\}$.

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

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

The basis of a fuzzy classifier is a product rule of the following form:

$$R_{pj}: \text{IF } x_1 = A_{1j} \text{ and } x_2 = A_{2j} \text{ and...and } x_n = A_{nj} \text{ THEN } class = k_j .$$

The class is defined by the rule for which the IF-part maximally corresponds to the description given by the input vector *X*:

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

The construction of fuzzy classifiers 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.

2 REVIEW OF THE LITERATURE

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 personalised assessments and/or

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recommendations to assist in medical decision-making. As a rule, such systems are 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 neighbours method [21, 22], genetic algorithms [23, 24], support vector machines [25, 26].

3 MATERIALS AND METHODS

The theory of fuzzy sets and fuzzy logic systems makes it possible to build decision-making models for tasks that are poorly formalized and operate with expert information[27].

To formalize expert knowledge through fuzzy sets, appropriate procedures for creating membership functions are required. These procedures are a key stage of decision-making, as 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 for the construction of membership functions and the corresponding fuzzy model poses the researcher with the task of optimal choice [30].

The issue of constructing membership functions is one of the key issues in fuzzy logic, and many scientists, starting with L. Zadeh, have devoted their research to it. In the theory of fuzzy sets, the membership function is the main characteristic of a fuzzy object, and all operations with fuzzy objects are performed through their membership functions. 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. Depending on this, we get a frequency or expert interpretation.

Depending on the degree of fuzziness of fuzzy sets, which is taken into account when building a fuzzy model, we distinguish between 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 values of 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:

$$A = \{(x, \mu_A(x)) \mid x \in X, 0 \le \mu_A(x) \le 1\}.$$

Based on first-order fuzzy sets, various models and algorithms have been developed to address uncertainty, such as the model for assessing the effectiveness of investment projects [4]. However, the analysis of these methods and models shows that they often do not provide complete solutions due to insufficiently justified choice of modelling parameters, requiring multiple implementations to select the optimal parameters.

There are general and interval second-order fuzzy sets. General and interval type-2 fuzzy models are based on second-order fuzzy sets.

The concept of fuzzy sets of the second order (fuzzy sets type-2) was given 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 main reason for considering fuzzy sets with fuzzy membership functions is the close relationship that exists between the concept of linguistic truth, for example, with such values on the one hand as true, completely true, very true, more or less true, and so on, and fuzzy sets, the degree of membership of which is described by such linguistic terms as low, medium, high, very low, not low and not high, etc. on the other hand.

In [6], second-order fuzzy sets are described using the 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 (SF-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).

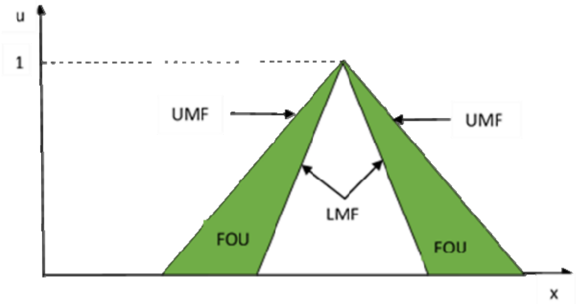

Figure 1 – Type-2 membership function

The introduction of fuzziness in the membership function makes it possible to bring the fuzzy model closer to human thinking and perception. Reality is interpreted differently by different people, and the same word can have different meanings for different individuals, especially when it comes to evaluation statements. Therefore, it is important to avoid a strict correspondence between the values of the degree of membership by expanding the range of uncertainty for each value of the interval. This helps to 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 function used.

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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).

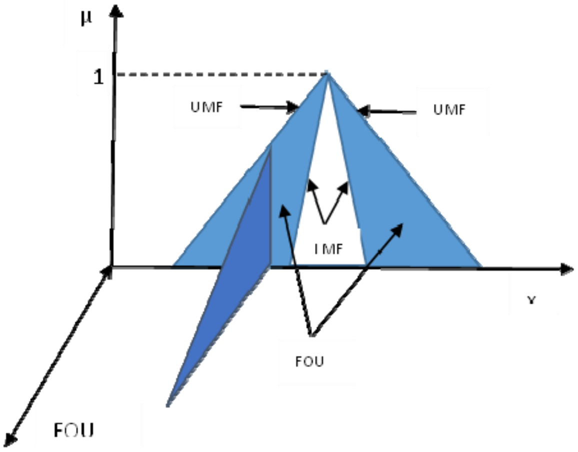

Figure 2 – Uncertainty trace of a type 2 fuzzy set

In theory, you can choose any type of membership function, it is unlimited. However, for type 2 fuzzy sets, the most common are Gaussian, triangular, trapezoidal, and bell-shaped membership functions.

Second-order fuzzy sets are characterised by the blurred boundaries of the membership function (MF) and the way the degrees of membership are distributed to the values of the arguments. Blurring the boundaries is the first step in the transition from type 1 to type 2 fuzzy sets. At the next stage, it is important to choose the type of membership function, just like for type 1 fuzzy sets.

There are two types of FS-2. 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 FS-2 is unchanged, then this type of FS-2 is unified (homogeneous). A fuzzy set with such a type of FS-2 is called an interval fuzzy set of the second order (IFS-2).

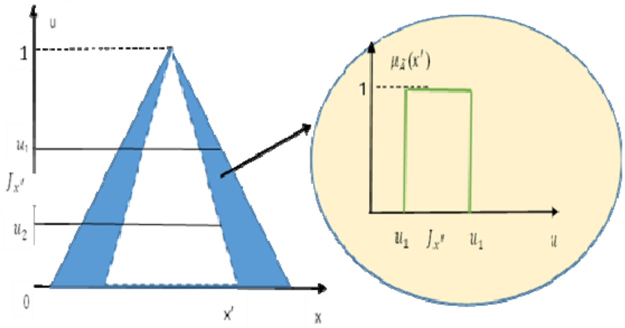

Figure 3 – Interval fuzzy set of the second order

Interval fuzzy models of type 2 use membership functions built on the basis of fuzzy sets with interval values of membership degrees (Fig. 3).

These models, unlike type 1 fuzzy models, provide point and interval values at the output. They cope well with various types of uncertainties and require significantly less computational resources than general type 2 fuzzy models. For example, studies [6–8] provide examples of the use of interval membership functions to solve practical problems.

If, for any value of the argument from the universe in the specified interval, the value of the FN-2 changes, then a fuzzy set with this type of FN-2 is called a second-order fuzzy set of general form.

The second-order membership function in the general (heterogeneous) form can be defined by:

– type 1 characteristics (primary variable and membership function);

– type 2 characteristics (secondary variable and membership function).

Type 2 characteristics define the parameters of the vertical section of the second-order membership function (Fig. 4).

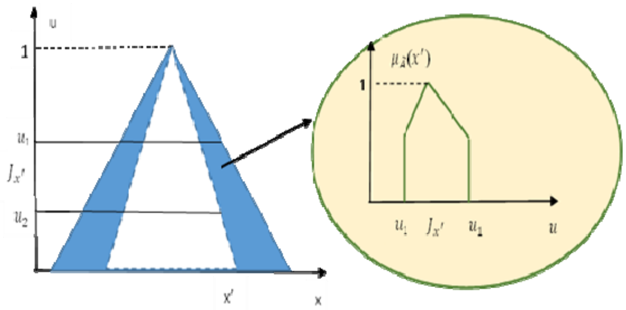

Figure 4 – General second-order fuzzy set

Fig. 4 shows the main characteristics of the second-order membership function in general (heterogeneous) form.

The heterogeneous type of second-order membership function is not used very often due to the high cost of computation, although it has a large number of degrees of freedom. Therefore, expert systems are mostly based on the interval type of second-order fuzzy sets. They allow you to use all the features of interval computing and have a wide range of practical applications.

It is also important to distinguish between different types of uncertainty when constructing membership functions in fuzzy systems, such as intra-uncertainty and inter-uncertainty. Intra-uncertainty arises due to insufficient knowledge or fuzzy expert judgement. Inter-expert uncertainty results from different estimates by several experts. Intra-uncertainty can be described by a second-order fuzzy set, and inter-uncertainty by combining several FS-2 [7].

4 EXPERIMENTS

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

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The construction of type-2 fuzzy knowledge bases with interval membership functions for solving the problem of medical diagnosis and prognosis of disease states consists of two main stages. The first stage is designed to generate a fuzzy model based on sample *X*, which is actually verified data from medical practice of the results of a patient's disease examination.

Let's demonstrate the use of this approach when making a decision by an anaesthetist. Here is an example of signs that are used to assess the patient's physical condition during elective (planned) surgical interventions:

1) Physical status. In the provision of anaesthetic care, the classification proposed by the American Society of Anaesthesiologists (ASA) is most often used for assessment [29]. 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 5 classes of physical status: from a healthy patient to a patient in an extremely serious condition.

ASA I – Healthy patient (non-smoker, low alcohol drinker).

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

ASA III – Patient with a 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, chronic renal failure requiring regular scheduled haemodialysis. A history (more than 3 months) of myocardial infarction, stroke, transient ischaemic 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 ischaemic attack, coronary artery disease or stenting, ongoing myocardial ischaemia or severe heart valve dysfunction, severe ejection fraction reduction, sepsis, DIC, acute or chronic renal failure, with irregular haemodialysis.

ASA V – Dying patient. Surgery for vital indications. Examples include (but are not limited to): ruptured aortic aneurysm, severe polytrauma, intracranial haemorrhage, acute intestinal ischaemia with concomitant severe cardiac disease or multiple organ failure.

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

The addition of the letter "E" indicates the urgency of surgical intervention. An emergency situation is defined as existing when a delay in treating the patient will lead to a significant increase in the threat to life. For example: ASA I E, II E, III E or IV E. ASA V class is usually always ASA V E. There is no ASA VI E class. The Borg Scale is used to assess a patient's exercise tolerance.

2) Metabolic equivalent. A metabolic equivalent (MET) is a unit of measurement of the body's energy needs that is used during a treadmill test to assess a person's functional abilities (i.e., their tolerance to physical activity).

The baseline value (1 MET) is the metabolic rate at complete rest (under basal metabolic conditions), which is 1 kcal/kg/h. Thus, 2 MET corresponds to a load that causes a 2-fold increase in the body's energy requirement compared to the resting state. Activity requiring 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 severe prognosis, while the ability to perform a load above this level indicates a favourable 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. Perceived exertion 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 went up to 20, which corresponded to a heart rate of 60 to 200. In recent years, an updated scale from 1 to 10b, the so-called Newman scale, has been used.

3) Laboratory parameters:

Complete blood count:

Haemoglobin 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)

Kidneys and their functioning:

Creatinine 38–85 μmol/l (30–200)

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

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)

4) Echocardioscopy, if available (LVEF%, normal 55–75%, poor if less than 55%).

5) Coagulogram (blood coagulation).

INR 0.80–1.20 (0.6–1.4).

Fibrinogen 1.8–3.5 g/l (1.2–5.0).

In addition to the above permissible values of indicators for signs of 3–5 groups, there are normative values, which, like personal indicators of patient's symptoms, depend on gender, age, clinical, biochemical and other parameters of comorbidities, which complicates decision-making depending on different stages of the life cycle. Such a relationship of parameters and symptom indicators can be set not only analytically, but also algorithmically by building various models of functioning systems.

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Information on the first and second signs is obtained by interviewing the patient. The scores should correspond to the following levels:

– ASA (class I, II, if class III, the indicators will need to be assessed more carefully);

– MET (4 or more is ideal, less than 4 should be considered whether to allow elective intervention, if so, to set a higher risk of anaesthesia).

The analysis of the information regarding the indicators of groups 3–5 showed that it is advisable to use the apparatus of fuzzy set theory to interpret them, since, as you can see, the values of these indicators are blurred. Among the 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 formalise uncertainties such as "approximately equal" and "average", and the second type is used to represent uncertainties such as "located in an interval".

To describe the values of these indicators, we will use second-order trapezoidal membership functions (Fig. 5):

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

5 RESULTS

As an example, consider the application of this approach in determining the degree of fuzziness for the indicator "sugar" of group 3. Homeostasis using second-order fuzzy sets.

For example, a normal blood sugar level in men aged two to 60 years is considered to be in the range of 74–106 mg/dl (4.1–5.9 mmol/l). According to the permissible values, this indicator "sugar" can be in the range of 3.7–6.2 mmol/l (3.2–9.0 mmol/l). Let's describe the value of this indicator using a second-order trapezoidal membership function:

$$\mu = \begin{cases} 0, \ x \le 3.2; \\ \dfrac{x-3{,}2}{0{,}9}, 3.2 \le x \le 3.7; \\ \dfrac{x-3.7}{0.4}, 3.7 \le x \le 4.1; \\ 1, \ 4.1 \le x \le 5.9; \\ \dfrac{6.2-x}{0.3}, \ 5.9 \le x \le 6.2; \\ \dfrac{9-x}{3.1}, \ 6.2 \le x \le 9.0; \\ 0, \ x \ge 9.0. \end{cases}$$

The result of the graphical representation is shown in Figure 6.

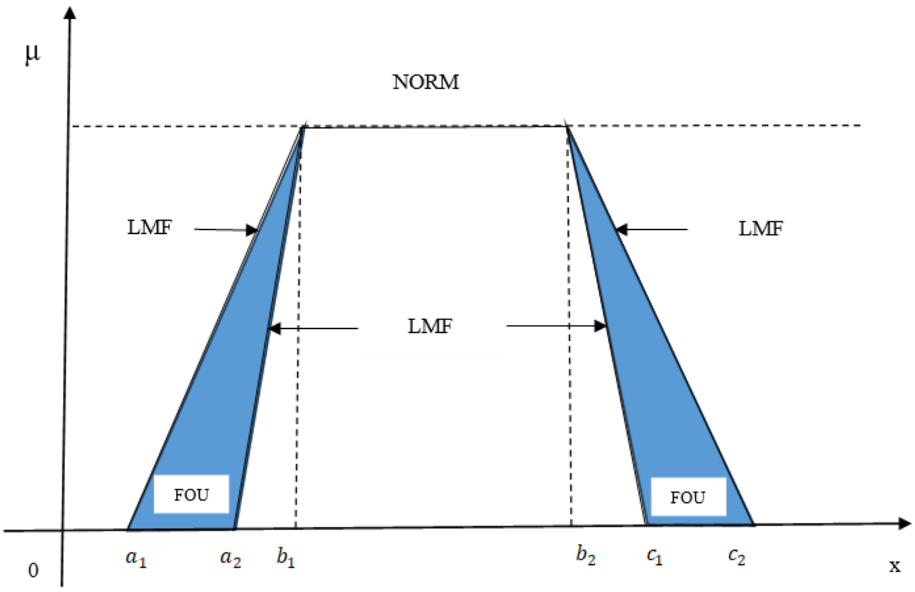

Figure 5 – General interval fuzzy set of type-2

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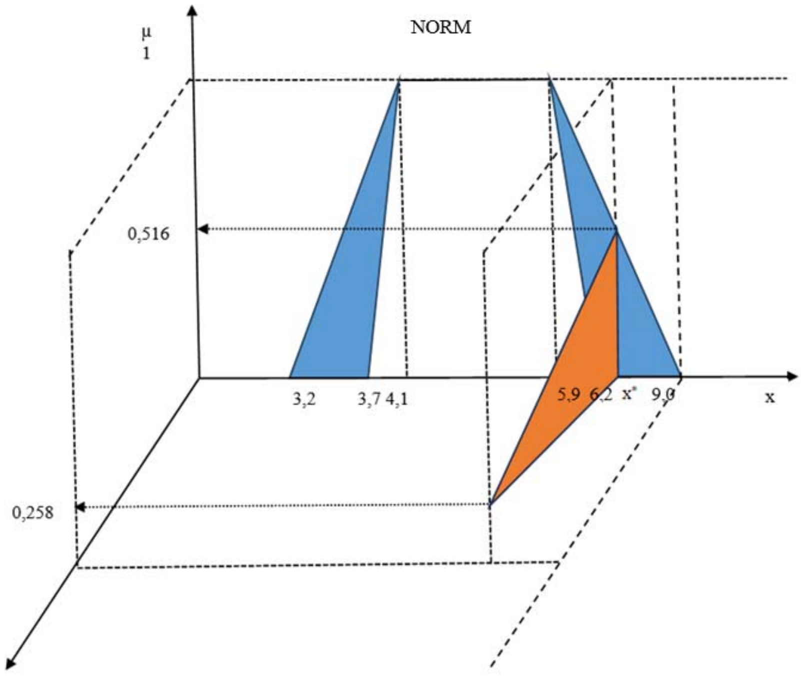

Figure 6 – Interval fuzzy set of type-2 for the indicator “sugar”

Let the value of the indicator “sugar”, for a particular patient, is x^* = 7.4 mmol/l, then the value of the primary membership function of the second order $\mu^1(x^*) \approx 0.516$, and, accordingly, the value of the secondary membership function (triangular) $\mu^2(x^*) \approx 0.258$ (Fig. 6).

Similarly, for this indicator, it is possible to build interval fuzzy sets taking into account the age and gender of the patient.

6 DISCUSSION

The construction of second-order interval fuzzy sets for indicators of 3–5 groups will allow to formalise knowledge and generate, on the basis of research medical data, an adequate fuzzy knowledge base model for an intelligent decision support system, which will allow doctors to access not only a clinical decision adapted to a particular patient, but also a set of clinical rules on the basis of which this decision was obtained.

Experimental studies have shown the convenience and effectiveness of the proposed approach of using fuzzy interval sets of the second order to intellectualise the knowledge of an anaesthetist.

CONCLUSIONS

The knowledge obtained from experts usually contains various types of uncertainties, and the knowledge resulting from the processing of experimental data contains a significant amount of noise.

Therefore, the methods of fuzzy set theory are the most suitable for processing incomplete and contradictory information.

For a qualitative representation of the subject area under conditions of uncertainty, it is advisable to use fuzzy interval sets of the second order.

In conclusion, it should be noted that the construction of IF-THEN rules based on biomedical data will be considered in the following publications, which will be devoted to the development of fuzzy logic systems.

The scientific novelty of obtained results lies in the pioneering application of type-2 fuzzy sets with interval membership functions to address uncertainty in medical data, particularly in the domain of anesthesiology, while integrating expert knowledge and biomedical data, thereby advancing the capabilities of intelligent medical decision support systems.

The practical significance of obtained results lies in the tangible benefits for medical professionals, particularly anesthetists, in improving the quality of patient assessments, reducing errors, and providing personalized recommendations. The research contributes to the development of intelligent systems that can positively impact clinical practice and patient outcomes in the field of medical diagnostics.

Prospects for further research involve refining the proposed type-2 fuzzy model, exploring its application across diverse healthcare domains, integrating advanced technologies for real-time decision support, collaborating with medical practitioners to enhance practical utility, and investigating ethical implications, aiming to advance the field of intelligent medical decision support systems.

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НЕЧІТКА МОДЕЛЬ ІНТЕЛЕКТУАЛІЗАЦІЇ ЗНАНЬ МЕДИЧНОЇ СФЕРИ

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АНОТАЦІЯ

Актуальність. Дослідження присвячено розробці гнучкого математичного апарату для інтелектуалізації знань у медичній сфері. Як правило, людське мислення базується на неточних, наближених даних, аналіз яких дозволяє формувати чіткі рішення. У випадках коли не існує точної математичної моделі об'єкта, або модель складна для реалізації доцільно використовувати апарат нечіткої логіки. Стаття направлена на розширення діапазону знань дослідників, які працюють в області медичної діагностики.

Мета роботи – підвищення якості відображення предметної області медичної сфери на основі побудови нечітких баз знань типу-2 з інтервальними функціями належності.

Метод. Описано підхід формалізації знань фахівця медичної галузі за допомогою нечітких множин другого порядку, який дозволяє враховувати невизначеність і нечіткість, яка властива медичним даним, а також вирішувати проблему інтерпретації отриманих результатів.

Результати. Розроблений підхід реалізовано на конкретній проблемі з якою стикається лікар-анестезіолог при допуску пацієнта до елективного (планового) оперативного втручання.

Висновки. Проведені експериментальні дослідження показали, що представлена нечітка модель типу-2 з інтервальними функціями належності дозволяє адекватно відображати вхідні медичні змінні якісного характеру та враховувати, як знання фахівця з медичної практики, так і дослідні медико-біологічні дані. Отримані результати мають важливе практичне значення для лікарів-практиків, особливо анестезіологів, оскільки дозволяють покращити оцінку стану пацієнта, зменшити кількість помилок та надати індивідуальні рекомендації. Це дослідження сприяє розвитку інтелектуальних систем, здатних позитивно впливати на клінічну практику та покращувати результати лікування пацієнтів у сфері медичної діагностики.

КЛЮЧОВІ СЛОВА: нечітка кластеризація, медична діагностика, функції належності другого роду.

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