

Fuzzy based Model study of ICU Patient for Respiratory Distress Conditions

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Abstract : In this paper, the potential e-health application of fuzzy models for determining the severity of respiratory distress in an intensive care unit patient is explored. Fuzzy multi-criteria decision-making models are utilized in two scenarios: one where all features are equally important and criteria do not interact, and another where criteria interact. The practical implementation of both approaches is discussed. The Bellman-Zadeh approach is employed in the first scenario, while the Choquet integral is used in the second. Suggestions for future research on the telemedicine application are also highlighted.

Index Terms - Fuzzy Models, E-Health, Telemedicine, ICU and Respiratory.

I. INTRODUCTION

E-health technologies are a vital component of Internet society technology, focusing on healthcare practices supported by electronic processes and communication. Telemedicine, a rapidly advancing field in clinical medicine, involves the transfer of medical information through interactive audiovisual media for consultations and remote medical procedures. The paper concentrates on assessing the severity of respiratory distress in an intensive care patient using fuzzy models, with a telemedicine application in mind. Disease severity is a key aspect of medical interest, encompassing all symptoms and impairments caused by the disease under analysis. The objective of severity evaluation is to establish standardized indicators for a uniform assessment of patients' conditions. Medical examiners evaluate disease severity based on objective measurements and symptom quantification. Clinical severity rating scales commonly rely on simple additive scoring, which is widely accepted due to its ease of administration.

The current medical rating scales lack graded logic functions and other beneficial features of soft computing decision models. This paper aims to showcase how soft computing methods and corresponding software tools can serve as valuable resources in medical assessment. Fuzzy sets theory provides numerous aggregation operators for combining membership values that represent uncertain information, which is crucial for various systems including fuzzy expert systems and decision-making systems. Fuzzy decision-making systems are commonly used in applications of fuzzy sets theory to model complex and undefined systems, emphasizing the significance of the aggregation process in fuzzy information. An example where fuzzy modeling is essential is in determining the severity of respiratory distress. The utilization of fuzzy sets theory in decision-making processes related to respiratory distress severity was initially suggested in [1], with a detailed software implementation described in [2]. Intelligent medical systems can describe a patient's condition using numerical values, text, and multimedia data such as images. A patient experiencing respiratory distress can be characterized by symptoms with numerical values, verbal descriptions (Breathing), and images (chest radiograph - Rö). A suitable model to handle this diverse data is a fuzzy model. Various simplified fuzzy models for assessing the severity of respiratory distress, along with their applications, have been discussed in [2]. This paper also explores the potential for further implementation and enhancement of the application.

In the discrete finite case, the consideration of nonadditive integrals defines a class of aggregation functions that allow for criteria interaction modeling. The concept of fuzzy measure, also known as the Choquet capacity, is utilized in this context. The Choquet integral has been proposed as an aggregation operator for information fusion and pattern classification [3]. A discriminative training algorithm for Choquet-integral based fusion operators is described in [4]. This algorithm is then applied to a landmine detection problem and compared to other techniques. Fuzzy sets theory has not only generated widely accepted applications such as fuzzy-logic controllers, but it has also provided strong motivation for research on aggregation operators. The results of this research are of great importance not only for fuzzy modeling but also for the evaluation of disease severity, as seen in the example of peripheral neuropathy [5]. Fuzzy based logic is dealt in detail in [13] and [14], decision rules using artificial intelligence is referred in [14] to [16]. Section 2 of this paper focuses on a practical problem: determining the severity of respiratory distress in a patient in an intensive care unit. The theoretical basis of the model, which utilizes the Choquet integral, is presented in Section 3. This model is built upon fuzzy measures theory and interaction representation. The results are discussed in Section 4, while Section 5 addresses the problem of implementing the model on the Internet. Finally, the paper concludes with the findings and highlights possible avenues for future work.

II Implemented Methodology.

A fuzzy multicriteria decision-making model is being applied in a medical context. The criteria used for early diagnosis of ARDS (acute respiratory distress syndrome) include clinical aspects of breathing, chest radiograph, arterial partial tension of oxygen (PaO₂), arterial partial tension of carbon dioxide (PaCO₂), and alveolar-arterial oxygen tension difference (A-aDO₂). These criteria serve as an example, and it is evident that a real medical system would require the consideration of additional criteria. Table I provides the progression of changes observed in various phases of ARDS. The "Phase" column in Table I represents different stages, with N indicating the normal condition of a patient, I representing the first (least severe) phase of respiratory distress, II denoting

the second phase of respiratory distress (subclinical), III representing the third phase (established respiratory distress), and IV indicating the fourth phase of distress (severe respiratory failure), which is not discussed in this paper due to medical reasons. The features Breathing and R_ö are expressed verbally and assigned subjective membership degrees using fuzzy sets theory. On the other hand, other features are characterized by approximate intervals of numerical values. To interpret these features as fuzzy sets, denoted as 'x is approximately in the interval [b, c]', they can be described using an ordered quadruple $A = (a, b, c, d)$, which represents a fuzzy trapezoidal number. It is important to note that in order to obtain an accurate score for a patient based on the criteria of Breathing and R_ö, the development of two pattern recognition systems is necessary for a usable medical system. The first system would be utilized to describe Breathing, while the second system (a computer vision system) would provide data to the fuzzy model regarding the feature R_ö.

Table I – Decision making parameters for determining the severity of ARDS

Table II_ Fuzzy Decision Parameters for determining severity of ARDS

TABLE I. DECISION-MAKING PARAMETERS FOR DETERMINING THE SEVERITY OF ARDS

Phase	Breathing	R _ö	PaO ₂	PaCO ₂	A-aDO ₂
N	-	-	80 – 100	35 – 45	5 – 10
I	normal	no changes	70 – 90	30 – 40	20 – 40
II	mild to moderate tachypnea	minimal infiltrates	60 – 80	25 – 35	30 – 50
III	increasing tachypnea	confluence of infiltrates	50 – 60	20 – 35	40 – 60
IV	obvious respiratory failure	generalized infiltrates	35 – 55	40 – 55	50 – 80

TABLE II. FUZZY DECISION PARAMETERS FOR DETERMINING THE SEVERITY OF ARDS

Phase	PaO ₂	PaCO ₂	A-aO ₂
N	(70,80,100,110)	(30,35,45,50)	(0,5,10,15)
I	(50,70,90,110)	(25,30,40,45)	(10,20,40,50)
II	(40,60,80,100)	(20,25,35,40)	(20,30,50,60)
III	(40,50,60,70)	(10,20,35,45)	(30,40,60,70)
IV	(30,35,55,60)	(30,40,55,65)	(40,50,80,90)

Table I provides the characteristic values of the criteria used to determine the severity of respiratory distress.[6][7] These values are represented by fuzzy intervals based on experience. Table II presents the specific values for each criterion. When considering ARDS syndrome, all the criteria (symptoms) are equally important. In this case, the Bellman-Zadeh's decision-making principle can be applied. This principle states that for a set of criteria C_j , where j ranges from 1 to m , and an object x described by a sequence of feature values, the overall performance of the object is determined by its weakest manifestation.[8][9]

From the set of alternatives D_i , where i ranges from 1 to N , the alternative D^* is chosen. This alternative represents the object x with the highest overall performance, taking into account all the criteria. In a fuzzy case, the membership degree value $\mu_j(x)$ indicates the extent to which a criterion C_j is fulfilled by an object x . The value $\mu_j(x)$ represents the score for the j -th criterion.

The desired decision, or the phase of the syndrome, is determined by the degree to which an object x maximally satisfies all the criteria. This can be calculated using equation (1):

$$D^*(x) = i \max \{ \min [\mu_1(x), \dots, \mu_m(x)] \}. \quad (1)$$

In the specific problem being considered, the criteria are as follows:

C1 - Breathing, C2 - R_ö, C3 - PaO₂, C4 - PaCO₂, and C5 - A-aDO₂.

These criteria are associated with features (symptoms) and are used to classify a patient's condition into one of the following phases:

D1 - N (normal conditions), D2 - I, D3 - II, D4 - III, and D5 - IV.

The membership degrees $\mu_j(x)$, where j ranges from 1 to 5, for each phase and the given numerical values of symptoms are determined using trapezoidal membership functions, as described in [1]. These values are proInstead of using Bellman-Zadeh's decision-making principle, one can utilize a nonadditive set function on a finite set of criteria as an alternative. This approach enables the definition of weights not only on each criterion but also on each subset of criteria, allowing for modeling criteria interaction.[10] [12]

III. Set Function Based Approach

The concept of a fuzzy measure (or the Choquet capacity) is employed for this purpose.

$$Ch_{\mu}(\mathbf{x}) := \sum_{i=1}^m (x_{(i)} - x_{(i-1)}) \mu(\{(i), \dots, (m)\}). \quad (2)$$

A fuzzy measure (or the Choquet capacity) on $C = \{C_1, \dots, C_m\}$ is a monotonic set function $\mu: P(C) \rightarrow [0, 1]$, where $P(C)$ represents the power set of the set C . It is important to note that $\mu(\emptyset) = 0$ and $\mu(C) = 1$. Monotonicity implies that $\mu(S) \leq \mu(T)$, whenever $S \subseteq T \subseteq C$. The interpretation of $\mu(S)$ can be understood as the weight associated with the subset S of criteria. In this scenario, the discrete Choquet integral [3], [7] serves as a suitable aggregation operator. In equation (2), the symbol $(\cdot)$ in the indices denotes a permutation of the elements of C such that $x(1) \leq \dots \leq x(m)$ and $x(0) = 0$. By utilizing the Choquet integral and considering the patient's symptoms, the rank of phases can be determined, and the ARDS phase of the patient under consideration is identified as the phase with the highest global evaluation. The Choquet integral allows for the expression of physician's preferences.vided in Table II

Table III – Symptoms for a patient\
Table IV – Decision making table for a patient

TABLE III. SYMPTOMS (FEATURES) FOR A PATIENT

Breathing	Ro	PaO2	PaCO2	A-aDO2
increasing tachypnea	confluence of infiltrates	50	32	31

TABLE IV. DECISION-MAKING TABLE FOR A PATIENT

Phase	Breathing	Ro	PaO2	PaCO2	A-aDO2
N	0	0	0	0.4	0
I	0	0	0	1	1
II	0.2	0.3	0.5	1	1
III	1	1	1	1	0.1

IV. Sample illustration

Based on the data provided in Table III, the decision-making table in Table IV is utilized. According to the model referenced in [1], respiratory distress falls under phase II. The physician's preferences indicate that Breathing and R_o are less significant compared to PaO₂ and PaCO₂, which should be prioritized. This preference highlights a synergy between PaO₂ and PaCO₂, emphasizing their combined importance. The fuzzy measure representation of these preferences is as follows:

For the first preference,

$$(\text{Breathing}) = \mu(R_o) = 0.1, \mu(\text{PaO}_2) = \mu(\text{PaCO}_2) = \mu(\text{A-aDO}_2) = 0.2.$$

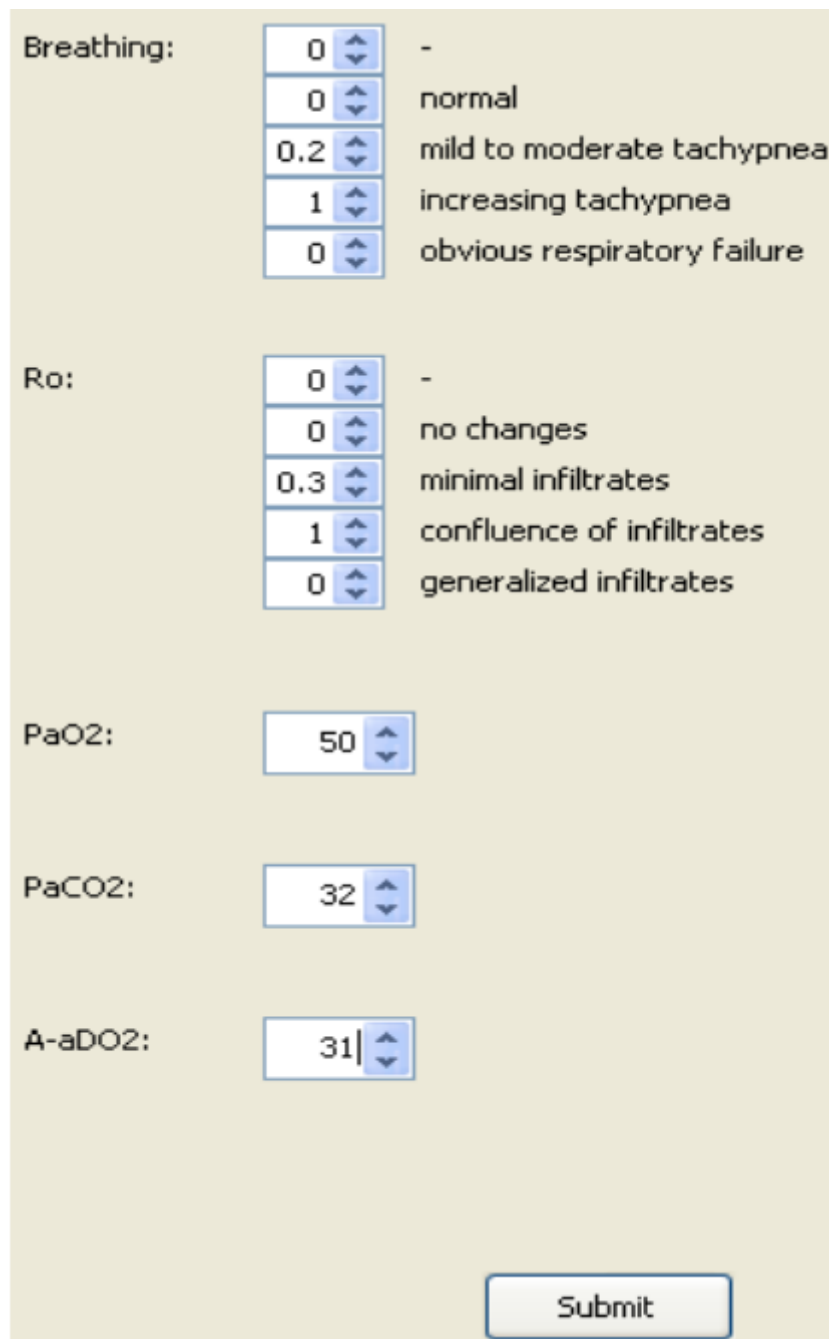
For the second preference,

$$\mu(\text{PaO}_2, \text{PaCO}_2) = 0.5, \text{ which is greater than } \mu(\text{PaO}_2) + \mu(\text{PaCO}_2) = 0.4.$$

The concept is that superadditivity indicates synergy between criteria, while subadditivity suggests redundancy. It is at the discretion of the physician to adjust these values to reflect the importance and interaction adequately. In the given example, the Choquet integral calculation for each phase requires defining v for specific subsets of criteria. The super additivity and subadditivity of the fuzzy measure are crucial in determining synergy and redundancy between criteria. The preferences in this scenario indicate synergy only between PaO₂ and PaCO₂, with additivity suggesting no synergy or redundancy. Ultimately, respiratory distress is identified as falling under phase III ($Ch_{\mu}(\text{III}) = 0.73$), differing from a scenario where symptoms perfectly meet all criteria.

V. Fuzzy Model Implementation

The ARDS Advisor application, as discussed previously, was developed. The initial step in utilizing the application involves inputting values for the 5 criteria commonly used to determine the phase of respiratory distress syndrome: clinical aspects of breathing (Breathing), chest radiograph (Rö), arterial partial tension of oxygen (PaO₂), arterial partial tension of carbon dioxide (PaCO₂), and alveolar-arterial oxygen tension difference (A-aDO₂, mmHg). The first two criteria are described verbally, with the physician required to indicate the degree of truth on a scale of 0 to 1. For the remaining three criteria, the measured values for a patient must be entered. Respiratory failure phases are represented as fuzzy numbers



The interface displays five input criteria for the fuzzy model:

- Breathing:** A dropdown menu with options: 0 (normal), 0.2 (mild to moderate tachypnea), 1 (increasing tachypnea), and 0 (obvious respiratory failure).
- Ro:** A dropdown menu with options: 0 (no changes), 0.3 (minimal infiltrates), 1 (confluence of infiltrates), and 0 (generalized infiltrates).
- PaO₂:** A text input field with the value 50.
- PaCO₂:** A text input field with the value 32.
- A-aDO₂:** A text input field with the value 31.

A **Submit** button is located at the bottom right of the form.

Figure 1 – Fuzzy Model Implementation

The membership degree to each phase for each symptom is calculated based on input values. Upon clicking the Submit button, the user receives the initial result computed using the Bellman-Zadeh's decision-making principle. Clicking the Next button leads the user to the next step, where inputting additional parameters required for the Choquet integral begins. In the first step (Table 3 entries), the user is prompted to specify the importance of each individual symptom on a scale of 0 to 5. Initially, all values are set to 1, representing the average importance of equally significant symptoms. Clicking on the Next button reveals the importance indices of individual symptoms entered by the user, as well as the importance indices of all possible symptom combinations calculated using ordinary addition. This includes cases where there is no interaction between symptoms, where the importance of criteria A and B combined equals the sum of importance A and importance B.

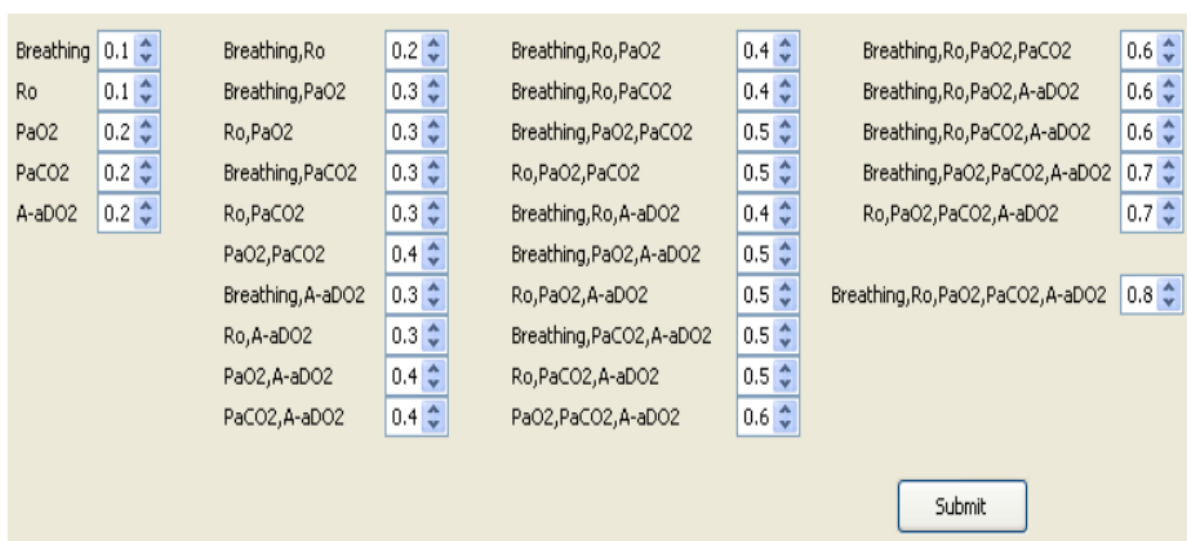
The user adjusts these values to demonstrate the interaction between criteria by following a specific principle: reducing the combined importance index if symptoms are redundant to some extent, and increasing it if the symptoms exhibit synergy. It is the

responsibility of the user to scale these values according to their perception of the interaction. In case of incorrect parameter submission, such as assigning a lower combined importance to parameters PaO₂ and PaCO₂ than the individual importance of one of them, a prompt will be issued to rectify the parameters. While users are provided with calculated values for non-interacting criteria and asked to scale them to express interaction, this task remains laborious

$$I^{\mu}(K) := \sum_{L \subseteq [m] \setminus K} \frac{(m - |L| - |K|)! |L|!}{(m - |K| + 1)!} \sum_{L' \subseteq K} (-1)^{|K| - |L'|} \mu(L' \cup L),$$

$$\forall K \subset [m], \quad (3)$$

Furthermore, if the number of symptoms in the ARDS Advisor application were to increase, it could render the application unusable as scaling alone would become overwhelming. One potential solution to this issue is that representing interaction through indices is more intuitive for decision-makers than the traditional measure representation. Grabisch defined the interaction index between any number of criteria, and further improvements could be made by utilizing algorithms for identifying fuzzy measures, such as those developed by Mori and Murofushi, as well as Grabisch. The algorithm introduced by Grabisch in particular leverages the lattice structure of coefficients for enhanced performance



Breathing	0.1	Breathing,Ro	0.2	Breathing,Ro,PaO ₂	0.4	Breathing,Ro,PaO ₂ ,PaCO ₂	0.6
Ro	0.1	Breathing,PaO ₂	0.3	Breathing,Ro,PaCO ₂	0.4	Breathing,Ro,PaO ₂ ,A-aDO ₂	0.6
PaO ₂	0.2	Ro,PaO ₂	0.3	Breathing,PaO ₂ ,PaCO ₂	0.5	Breathing,Ro,PaCO ₂ ,A-aDO ₂	0.6
PaCO ₂	0.2	Breathing,PaCO ₂	0.3	Ro,PaO ₂ ,PaCO ₂	0.5	Breathing,PaO ₂ ,PaCO ₂ ,A-aDO ₂	0.7
A-aDO ₂	0.2	Ro,PaCO ₂	0.3	Breathing,Ro,A-aDO ₂	0.4	Ro,PaO ₂ ,PaCO ₂ ,A-aDO ₂	0.7
		PaO ₂ ,PaCO ₂	0.4	Breathing,PaO ₂ ,A-aDO ₂	0.5		
		Breathing,A-aDO ₂	0.3	Ro,PaO ₂ ,A-aDO ₂	0.5	Breathing,Ro,PaO ₂ ,PaCO ₂ ,A-aDO ₂	0.8
		Ro,A-aDO ₂	0.3	Breathing,PaCO ₂ ,A-aDO ₂	0.5		
		PaO ₂ ,A-aDO ₂	0.4	Ro,PaCO ₂ ,A-aDO ₂	0.5		
		PaCO ₂ ,A-aDO ₂	0.4	PaO ₂ ,PaCO ₂ ,A-aDO ₂	0.6		

Figure 2 Fuzzy Indices

The algorithm described in this text utilizes specific terminology. The lattice of a fuzzy measure consists of interconnected nodes. The lattice is divided into horizontal layers, with the number of layers being $n + 1$. Each layer is numbered from 0 (representing the layer containing only $\mu \emptyset$) to n (representing the layer containing only μX). A path refers to a series of linked nodes, starting from $\mu \emptyset$ and ending at X . In Figure 4, the path highlighted includes μ_3 , μ_{23} , and μ_{234} . For a node in layer l , its lower neighbors (or upper neighbors) are the nodes in layer $l-1$ (or $l+1$) that are connected to it. There are l lower neighbors and $n-l$ upper neighbors. The author of the algorithm outlines it in two steps. In step 1, when given a datum x , only the coefficients on the path associated with x are modified to decrease the error, similar to a gradient descent algorithm. The modification is performed while ensuring the monotonicity property is preserved on the path. Additionally, the monotonicity of neighboring nodes is checked. This process is repeated for all learning data multiple times. In step 2, if there is an insufficient amount of learning data, certain nodes may remain unmodified. These nodes are then modified to achieve a more balanced lattice, where the distance from neighbors is as equal as possible. The underlying idea behind step 2 is that when there is no information available for certain nodes, they should be arranged in the lattice to create a homogeneous structure. Applying this (or a similar) algorithm, such as in the ARDS Advisor application [2], could enhance the user-friendliness of the application. This is particularly relevant when considering the potential improvement of the ARDS Advisor application by incorporating additional symptoms for determining the ARDS phase in patients.

VI Conclusions

The utilization of fuzzy systems provides a formal foundation for modeling and constructing decision-making systems based on soft computing. These systems have the ability to incorporate verbally expressed experiences in the relevant field. This article discusses the practical implementation of fuzzy systems, specifically the Bellman-Zadeh approach for independent and equally important information, as well as the Choquet integral for interacting and not equally important information. The potential application of these approaches in telemedicine is also explored, which may be of interest for considering other aggregation functions. By including interaction among criteria, a more flexible model of ARDS can be achieved, allowing physicians to express their preferences in relation to the complex phenomena of criteria and subsets of criteria interaction. The ARDS Advisor can be further enhanced by expanding the number of parameters considered and applying it to a larger number of cases. Additional improvements can be made by incorporating interaction indices and identifying fuzzy measures. The integration of intelligent medical computer aid in the case of ARDS is highly beneficial in clinical practice. It can alert physicians, remind them of the

possibility of patients developing ARDS, and indicate the level of respiratory distress. However, the final decision still rests with the physician. To make the application more applicable to clinical practice, pattern recognition systems for breathing and chest radiograph images should be implemented. The application of fuzzy systems provides a mathematical foundation for developing medical systems that align with human cognitive processes, allowing for the utilization of verbally expressed medical experience in the field

REFERENCES

- [1] D. M. Velašević, D. Z. Šaletić, S.Z. Šaletić, “A fuzzy sets theory application in determining the severity of respiratory failure”, *International Journal of Medical Informatics*, 63, 2001, pp. 101-107.
- [2] D.Z.Šaletić, M.Savić, Software Implementation of Fuzzy Decision-Making in Determining the Severity of Respiratory Distress, Ed. Aniko Szakal Proceedings of the 6th Symposium on Intelligent Systems and Informatics, SISY 2008, September 26-27, 2008, Subotica, Serbia, 27- sisy2008-submission.pdf
- [3] M. Grabisch: Fuzzy integral in multicriteria decisionmaking, *Fuzzy Sets and Systems*, 69, 1995. pp. 279-298.
- [4] Mendez-Vazquez A., P. Gader, J. M. Keller, K. Chamberlin Minimum Classification Error Training for Choquet Integrals With Applications to Landmine Detection, *IEEE Trans. Fuzzy Systems*, 16(1), February 2008, 225 – 238
- [5] Dujmović, J.J. Evaluation of Disease Severity and Patient Disability Using LSP Method, L. Magdalena, L. OjedaAciego, J.L. Verdegay (eds.) Proceedings of IPMU 2008, pp. 1398-1405
- [6] Bellman, R. E., L.A. Zadeh: Decision-making in a fuzzy environment, *Management Sciences*, Ser.B 17(1970), 141- 164
- [7] M.Grabish, J.L. Marishal, R. Mesiar, E. Pap, *Aggregation Functions*, Cambridge University Press, 2009
- [8] Grabisch, M., A new algorithm for identifying fuzzy measures and its application to pattern recognition. In: Proc. Joint Conf. 4th IEEE Internat. Conf. on Fuzzy Systems and 2nd Internat. Fuzzy Engineering Symposium, pp. 145-150.
- [9] Murofushi, T. and S.Soneda. Techniques for reading fuzzy measures (iii): interaction index. In Proc. 9th Fuzzy System Symposium, pages 693-696, Sapporo, Japan, May 1993. In Japanese.
- [10] Grabisch, M., k-order additive discrete fuzzy measures and their representation, *Fuzzy Sets and Systems*, 92, 1997., 165-
- [11] Grabisch, M., Alternative representation of discrete fuzzy measures for decision making. *Int. J. of Uncertainty, Fuzziness, and Knowledge Based Systems*, pages 587-607, 1997.
- [12] Mori, T. , T. Murofushi, An analysis of evaluation model using fuzzy measure and the Choquet integral, 5th Fuzzy System Symposium, Kobe, Japan, June 2-3 1989 (in Japanese)
- [13] Ganesh, E.N., Bettyjane, J. Simulation and synthesis of TS fuzzy system using parallel distribution Compensation technique *International journal of information technology* 12,1443-1449(2020).
<https://doi.org/10.1007/s41870-020-00456-2>
- [14] Betty Jane, J., Ganesh, E.N. (2020). Big Data and Internet of Things for Smart Data Analytics Using Machine Learning Techniques. In: Pandian, A., Palanisamy, R., Ntalianis, K. (eds) *Proceeding of the International Conference on Computer Networks, Big Data and IoT (ICCBI - 2019)*. ICCBI 2019. *Lecture Notes on Data Engineering and Communications Technologies*, vol 49. Springer, Cham. https://doi.org/10.1007/978-3-030-43192-1_24.
- [15] J.Betty Jane, E.N.Ganesh “A Feature Selection Prediction Technique for Healthcare using Naive Bayes Algorithm” in *International Journal of Recent Technology and Engineering (IJRTE)* ISSN: 2277-3878 (Online), Volume-8, Issue-1, May 2019 page 1467-1472.
- [16] B. Sathyasri, E.N. Ganesh and P. Senthil Kumar, 2016. Fauna Inspired Probabilistic and Randomly Computed Channel Assignment and Multipath Routing for Multi-Channel Multi- Radio Mesh Networks.
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