

Research Article

Enhanced Decision Support Systems in Intensive Care Unit Based on Intuitionistic Fuzzy Sets

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In areas of medical diagnosis and decision-making, several uncertainty and ambiguity shrouded situations are most often imposed. In this regard, one may well assume that intuitionistic fuzzy sets (IFS) should stand as a potent technique useful for demystifying associated with the real healthcare decision-making situations. To this end, we are developing a prototype model helpful for detecting the patients risk degree in Intensive Care Unit (ICU). Based on the intuitionistic fuzzy sets, dubbed Medical Intuitionistic Fuzzy Expert Decision Support System (MIFEDSS), the shown work has its origins in the Modified Early Warning Score (MEWS) standard. It is worth noting that the proposed prototype effectiveness validation is associated through a real case study test at the Polyclinic ESSALEMA cited in Sfax, Tunisia. This paper does actually provide some practical initial results concerning the system as carried out in real life situations. Indeed, the proposed system turns out to prove that the MIFEDSS does actually display an imposing capability for an established handily ICU related uncertainty issues. The performance of the prototypes is compared with the MEWS standard which exposed that the IFS application appears to perform highly better in deferring accuracy than the expert MEWS score with higher degrees of sensitivity and specificity being recorded.

1. Introduction

Medical decision-making in Intensive Care Units (ICU) can be considered as a process, combining both logical cognition and perception. It undertakes analyzing, within complex models of multiple features, usually marked with vague, inaccurate, and inexact information. In a bid to provide an effective model of the ICU process, we design an expert decision support system for the ICU detection of deteriorating patients. This newly novel model is predominantly based on the intuitionistic fuzzy sets (IFS) and the Modified Early Warning Score (MEWS) standard [1].

The major reason for choosing the IFS as a major tool for the development of a decision-making system lies in the fact that IFS are improved better than effectively regarding the situations in which no overlap between the fuzzy sets is perceived. Indeed, imitating the expert's cognitive decision-making completeness the IFS attempt to achieve the convenient diagnosis, proceeded through maintaining the expert's detained knowledge as applied and safeguarded within an intelligent system.

Concerning the present paper, the Medical Intuitionistic Fuzzy Expert Decision Support System (MIFEDSS) has actually been implemented and tested within a real life context of Polyclinic ESSALEMA, Sfax, Tunisia. In this context, we focus on a detailed depiction of MIFEDSS based on the MEWS for the purpose of estimating the patient's risk degree.

This work is organized according to the following layout: following the introduction, Section 2 is devoted highlighting the IFS relevance and prevalence in the healthcare area. Section 3 presents theoretical background about IFS. Then, we reveal the MIFEDSS designed to ICU healthcare system. In Section 5, we present the implementation details of the prototype. Afterwards, we set forth a results and discussion section and then we wind up by a conclusion with further suggestions for additional advancement.

2. IFS in Healthcare Domain

In the literature there are several studies in fuzzy logic (FL) for medical care which were grouped into six area: (i) neuromedical filed [2], (ii) blood glucose monitoring [3–6],

(iii) neck and head cancer [7], (iv) breast cancer classification [2, 8], (v) brain tumor extraction and classification [9], and (vi) emergency decision system [10].

Since Atanassov instigated the concept of IFS [11], this technique has been utilized in different medical case research. The majority of these studies concern the use and the comparison of different IFS measures of similarity such as the distance between interval-valued IFS, the max–min–max composition rule, and Mold Cosine similarity measure. In fact, in [12] researchers use the max–min–max composition rule to detect the illness. This composition neglects extreme values. Similarly, Szmidi and Kacprzyk advance a new approach for medical care diagnosis process through application of the IFS based solution for useful for analyzing the optimally closest symptoms [13–15]. In these works, illness is depicted through several syndromes without aggregation of symptoms being involved. For this reason, to solve this issue, other studies present a new measure called interval-valued IFS based on the aggregation [16–18]. For instance, Chetia and Das apply an approach for medical care diagnosis based on interval-valued fuzzy soft sets and demonstrate the technique with a theoretical case study [18].

In [17], author proposes a new method for medical care diagnosis: the distance between interval-valued IFS. This approach makes a diagnosis by aggregating several symptoms, using the distance of interval data in order to decrease the loss of data. In the same way, in 2014, authors [16] introduce a new method to sickness diagnosis, using interval-valued intuitionistic fuzzy set with logical operators.

In proposed works in [19], the study of Sanchez's [20] method of medical diagnosis approach is provided using the IFS theory notion. The idea of intuitionistic medical diagnosis methodology relies heavily on intuitionistic fuzzy relations. For a deeper investigation of the method the authors have provided hypothetical case study described by means of an illustrative flowchart.

In study conducted by Çuvalcıoğlu and Mercan [21] in 2004, the authors have made appeal to a clear definition of weak intuitionistic fuzzy sets along with several diagnosis algorithms through application of a tough method.

In a paper elaborated by [22] various classification methods have been applied to 17 different features, namely, stepwise logistic regression, stepwise discriminant analysis, and nonpulmonary weaning index as well as intuitionistic fuzzy Voronoi diagrams. The proposed algorithm has been applied to solve the classification problem fit for weaning initiation from long-term mechanical ventilation.

In 2011, Hung proposed an entropy measure based on intuitionistic fuzzy sets. An instructive scenario related to medical pattern recognition has revealed the convenience of such a study. Still, in a bid to make easier ranking results, a system interface has been developed to support doctors in constricting and reaching the most efficient decisions [23].

In 2011, Ye set up a cosine similarity measure along with a weighted cosine similarity among IFS. For the purpose of highlighting the proposed measure's efficiency, the existing similarity measures amid IFS have been assessed by means of cosine similarity measure initiated between IFS through

numerical examples applied to pattern recognition and medical diagnosis [24].

Similarly, another Mold Cosine similarity based measure projection formula to medical pattern recognition and intuitionistic fuzzy decision-making has been proposed in 2015 which involves a four pattern mode pertaining to Atanassov's intuitionistic fuzzy values [25].

In 2013, the authors in [26] survey other distance relating measures (Hamming distance, Euclidean distance, Normalized Hamming distance, and Normalized Euclidean distance) as pattern detection tools for IFS.

Overall, most tools of these researches display some of IFS associated similarity measures with exposing measures application technique with a hypothetic medical case study. In practical medical cases, at date only Khatibi and Montazer [27] and Chaira [28–30] seem to put forward a real solution. In [27], for instance, the authors introduce a useful for solving the bacteria classification problem through application of IFS to examine their abilities in coping work of the medical pattern detection related ambiguity.

In 2010 Chaira [28] proposed a new IFS applying framework useful for segmenting poor contrasted blood vessels as well as blood cells in pathological images. Thus, an intuitionistic fuzzy image turns out to be constructed by means of intuitionistic fuzzy Sugeno generator which has been used to retrieve the optimum threshold values. Additionally, Chaira presents an IFS approach relevant to color region extraction [29], in another context providing a novel approach to intuitionistic fuzzy C means clustering method using IFS theory. For the sake of testing and ensuring its efficiency, the devised algorithm has been tested on different regions of the CT scan brain images likely useful for application for brain abnormalities identification purposes [30].

Thus, it can be inferred from the above cited literature that the IFL are successfully applied in several medical applications, as helpful tools useful for monitoring and detecting wide range of disease. So the present work can be considered as the pioneering study whereby a hybrid approach simultaneously combining multiagent system (MAS) and IFS [31–33] is deployed in a real application context and environment. Indeed, our system provides a model that combines both the benefits of MAS and IFS. The architecture is composed of a set of autonomous agents adapted to the interaction: the expert agents with IFS based software learning in order to assist agent doctor. In this paper, we propose the modeling, the realization, and the evaluation of the intuitionistic fuzzy inference technique in medical decision (expert agents learning processes in the MAS). Here, we put forward the MIFEDSS based MEWS (Table 5) in ICU deployed in Polyclinic ESSALEMA, Sfax. In the next section we define the theoretical background of the IFS theory.

3. Preliminaries

The intuitionistic fuzzy sets (IFS) were introduced by Atanassov [34] as a generalization of fuzzy sets of Zadeh [35] “which look more accurate to uncertainty quantification and provide the opportunity to precisely model the problem based on the existing knowledge and observations,” where,

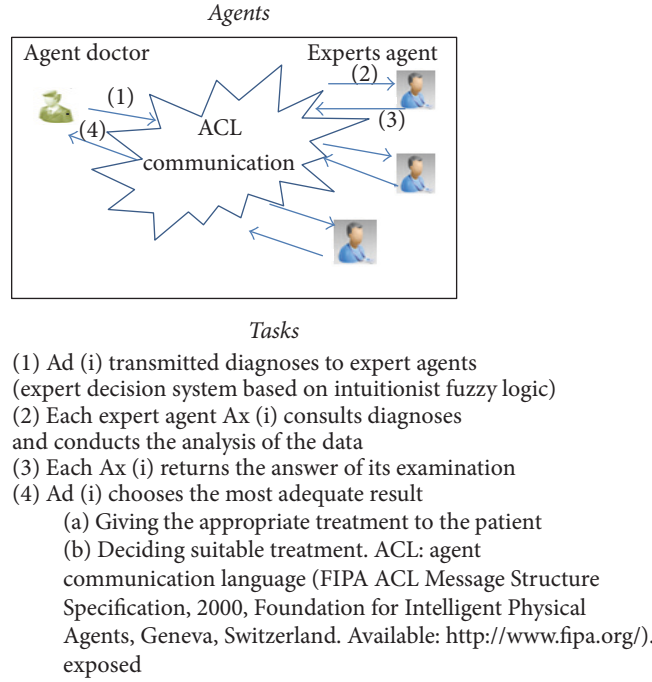


FIGURE 1: Agent (doctor and expert) tasks.

besides the degree of membership $\mu A(x) \in [0, 1]$ of each one element $x \in X$ to a set A , the degree of nonmembership $\gamma A(x) \in [0, 1]$ was also measured.

Let X is a nonempty fixed set. An intuitionistic fuzzy set (IFS) A is an object of the form

$$A = \{x, \mu A(x), \gamma A(x) \mid x \in X\}, \quad (1)$$

where μ and γ are degrees of membership and nonmembership (“falsity degree” or “degree of nonvalidity” [11]) of each $x \in X$, respectively, and $0 \leq \mu(x) + \gamma(x) \leq 1$ for each $x \in X$. A class of all the IFS in X is denoted as $\text{IFS}(X)$. The pair $\mu A(x), \gamma A(x)$ is called “Intuitionistic Fuzzy Pair” [11].

In addition to membership and nonmembership functions, a function of hesitancy or uncertainty of x to A denoted by $\pi A(x)$ must be taken into consideration. $\pi A(x)$ is computed as

$$\pi A(x) = 1 - \mu A(x) - \gamma A(x) \quad \text{with } 0 \leq \pi A(x) \leq 1. \quad (2)$$

In real world tasks, we recurrently deal with vague information. Accessible information is occasionally vague, inexact, or inadequate. “There are situations where, due to insufficiency in the information available, the evaluation of membership values is not possible up to our satisfaction. Due to the some reason, evaluation of nonmembership values is not also always possible and consequently there remains a part in determinism on which hesitation survives. Certainly fuzzy sets theory is not appropriate to deal with such problem; rather IFS theory is more suitable” [36].

Indeed, we assume that IFS have been found to be practical to deal with ambiguity.

4. The Proposed MIFEDSS

In this study, we propose the modeling, implementation, and validation of the MIFEDSS; in the previous work [31, 32, 37] we present a multiagent system (MAS) for healthcare interaction in Mobile Cloud Computing Applications; in the MAS system they are different expert agent with intuitionistic fuzzy sets based software learning in order to assist doctor agent and assess patients.

The expert agents and agent doctor role are described in Figure 1.

In this study, the IFS is founded on the Modified Early Warning Score (MEWS), defined as a clear guide for caregivers in the emergency unit to find the level of sickness of a patient [1]. This MEWS was evaluated in 206 surgical patients over 9 months in 1999. The purpose of the MEWS is to facilitate communication between nursing [38].

The Modified Early Warning Score (MEWS) is a physiological score for estimation and is based on five physiological parameters. The observations included in this scoring are exposed in Table 1: respiratory rate, systolic blood pressure, heart rate, temperature, and Glasgow score or AVPU score.

A limitation of current MEWS is that they are not capable of modeling the hesitancy introduced into a complex system due to inadequate facts, loss of information, and uncertainty. To handle this issue, we propose a novel extension of the MEWS model which is based on the theory of intuitionistic fuzzy sets (Table 2).

The vital signs monitored that help the medical diagnosis are systolic blood pressure (SBP), heart rate (HR), blood glucose (BG), patient temperature (TEMP), oxygen saturation (O2S), and Kalmy (KAM). A human expert knowledge, from

TABLE 1: MEWS standard.

Categories	Scores						
	3	2	1	0	1	2	3
Respiratory rate (breaths/min)		<9		9–14	15–20	21–29	≥30
Heart rate (beats/min)		≤40	41–50	51–100	101–110	111–129	≥130
Systolic blood pressure (mmHg)	≤70	71–80	81–100	101–199		≥200	
Temperature (°C)		<35		35–38.4		≥38.5	
AVPU score				Alert	Reacting to voice	Reacting to pain	Unresponsive

TABLE 2: Intuitionistic fuzzy MEWS system.

Risk	Modified Early Warning Score						
	Low 3	Low 2	Low 1	Level of risk Normal 0	High 1	High 2	High 3
sbp	SBP < 75	70 < SBP < 85	80 < SBP < 100	95 < SBP < 199		SBP > 185	
HR		HR < 40	45 < HR < 60	53 < HR < 100	95 < HR < 110	105 < HR < 130	HR > 125
O2S	O2S < 85	83 < O2S < 90	87 < O2S < 92	O2S > 92			
TEMP		T < 36.5		36 < T < 38.5		T > 38	
BG	BS < 66	63 < BS < 72	—	70 < BS < 110	—	106 < BS < 150	BS > 140
Kalmy		KLM < 3.7		3.6 < KLM < 5		KLM > 4.9	

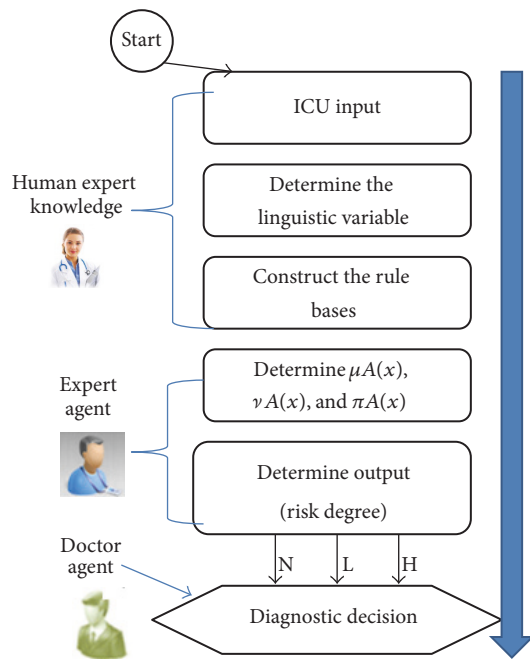


FIGURE 2: The flowchart for MIFEDSS diagnosis process [39].

Polyclinic ESSALEMA, was used for the determination of the input fields. Three experts in ICU department were asked to be involved in this study. For that, in order to calculate the complete score, we add Kalmy input to the original MEWS. We assign score for each parameter from 0 to 3 presented in Table 2.

The process of the MIFEDSS (Figure 2) starts with the determination of the linguistic variables afforded by the medical experts' caregivers of ICU. Then, the building of the

rules base, with regard to the cited above steps, is realized by the assist of medical expert knowledge. Thereafter, the expert agent calculates membership degree, nonmembership degree, and hesitation margin to determine the degree of risk. Finally, the expert agent transmits the output variable (normal, large, and high) to the doctor agent to provide the suitable treatments to the patient.

5. Implementation

In this study we define six input variables performed on a fuzzy logic model by employing MATLAB 2013b software package developed by math works and deployed in the mobile applications [37, 39, 40] by using JFUZZY, a Java-based version of FuzzyLogic; it implements fuzzy control language specification [41].

Figure 3 demonstrates a full number of input variables taken during diagnosis of ICU. A total number of input attributes are a temperature (TEMP), O2S, blood glucose (BG), Kalmy (KAM), systolic blood pressure (SBP), and heart rate (HR). Every input consists of two or three triangular or trapezoidal membership functions. Mamdani system is adopted during analysis due to its capability to describe expertise knowledge in more intuitive and similar to a human like operator. Also, Mamdani type “systems are capable of handling substantial burden” [5]. The output, that is, risk, consists of three triangular membership functions. A total quantity of constructed fuzzy rules is 5400 rules that classify each parameter according to the explanation consulted by a physician.

This number of rules is calculated using

$$N = p_1 \times p_2 \times \dots \times p_n. \quad (3)$$

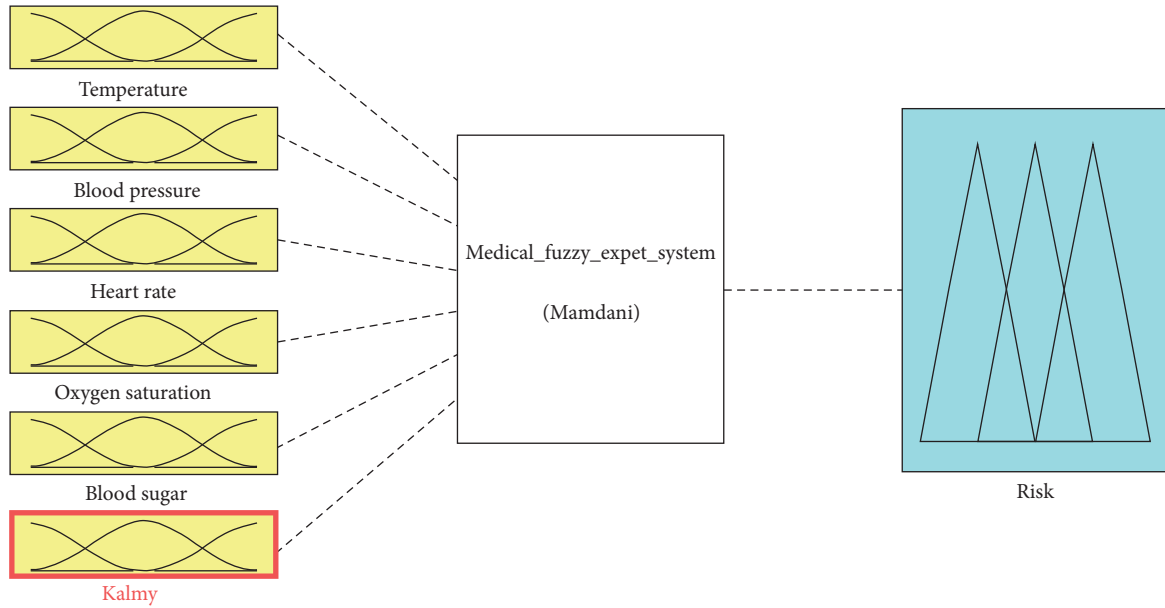


FIGURE 3: The IFS inference system (input and output).

N presents the total number of possible rules and p_n presents the number of linguistic parameters for the input fuzzy sets N .

Here we present a sample of generated rules in JFUZZY:

- (i) RULE 64: IF temperature IS low2 AND blood_presure IS low3 AND heart_rate IS low AND o2s IS low3 AND blood_sugar IS low2 AND ka IS low THEN risk IS large;
- (ii) RULE 76: IF temperature IS low2 AND blood_presure IS low3 AND heart_rate IS low AND o2s IS low2 AND blood_sugar IS low3 AND ka IS low THEN risk IS large;
- (iii) RULE 91: IF temperature IS low2 AND blood_presure IS low3 AND heart_rate IS low AND o2s IS low1 AND blood_sugar IS low3 AND ka IS low THEN risk IS large;
- (iv) RULE 94: IF temperature IS low2 AND blood_presure IS low3 AND heart_rate IS low AND o2s IS low1 AND blood_sugar IS low2 AND ka IS low THEN risk IS large;
- (v) RULE 3053: IF temperature IS normal AND blood_presure IS normal AND heart_rate IS normal AND o2s IS normal AND blood_sugar IS normal AND ka IS normal THEN risk IS normal;
- (vi) RULE 5232: IF temperature IS high2 AND blood_presure IS high2 AND heart_rate IS high1 AND blood_sugar IS high2 AND ka IS high THEN risk IS high;
- (vii) RULE 5235: IF temperature IS high2 AND blood_presure IS high2 AND heart_rate IS high1 AND blood_sugar IS high3 AND ka IS high THEN risk IS high;

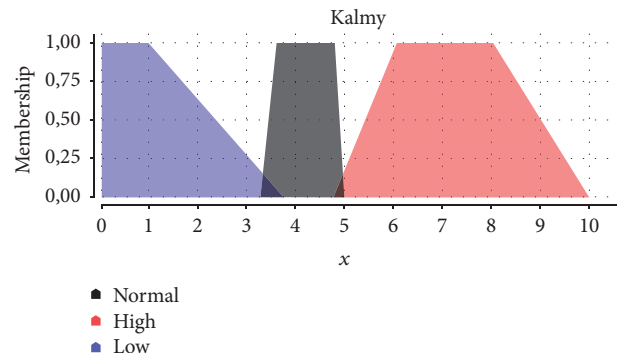


FIGURE 4: The range of Kalmy parameter.

- (viii) RULE 5247: IF temperature IS high2 AND blood_presure IS high2 AND heart_rate IS high1 AND blood_sugar IS high2 AND ka IS high THEN risk IS high;
- (ix) RULE 5262: IF temperature IS high2 AND blood_presure IS high2 AND heart_rate IS high1 AND blood_sugar IS high2 AND ka IS high THEN risk IS high.

Figure 4 illustrates membership plot for Kalmy (KAM) consisting of three membership function values (Hypokalmy, Normal, and Hyperkalmy, Table 3).

In temperature (TEMP) input variable, we allocate 3 linguist variables (low 2, normal, and high 2) and for O₂S input that presents the oxygen saturation. In this parameter, we have four fuzz sets.

For heart rate (HR) based on the MEWS this parameter presents six fuzzy sets (bradycardy, low, normal, high 1, high 2, and tackcardy) (Table 4 and Figure 5).

TABLE 3: The range of Kalmy input parameter.

Input parameter	Collection	Fuzzy Sets
Kalmy (KA)	<3.7	Hypokalmy
	3,6–4,8	Normal
	>4,7	Hyperkalmy

TABLE 4: The range of heart rate input parameter.

Input parameter	Collection	Fuzzy sets
Heart rate(HR)	<40	Bradycardy
	45–60	Low
	53–100	Normal
	95–110	High 1
	105–130	High 2
	>125	Tackcardy

TABLE 5: The output variable (risk) ranges.

Output parameter	Arrange	linguistic variables
Risk	$0 < R < 0.5$	Normal
	$0.5 < R < 4.5$	Large
	$4.5 < R < 14$	High

The output stage degree of risk is expressed by fuzzy linguistic values such as normal, large, and high as shown in Figure 6. It consists of three triangular membership functions which varies from 0 to 15.

6. Results and Discussion

The validation of the prototype is based on the comparison between the risk calculated by MIFEDSS and the risk presented by the MEWS score. The experimentation presented here (Figure 7) includes 16 patients’ data obtained from the ICU in Polyclinic ESSALEMA, Sfax. Out of the 16 cases, 4 were normal cases, who had normal values, 7 were patients suffering from moderate risk, and the remaining were having severe risk.

In ICU we obtained a satisfactory result, with 100% accuracy in risk linguistic variable values. The results obtained match with the expert’s opinion.

This IFS did perform better than the MEWS method; nevertheless the evaluation performed has led to substantial improvement of the prototype by adding new input parameter like age and annury input in order to increase the chances of successful treatment.

Derived from the experimental results, the proposed method is robust compared to usual MEWS methods in terms of sensitivity, specificity, and accuracy. IFS has shown remarkable improvements in decision-making abilities over typical MEWS score and typical FL, by adding $\mu A(x)$, $\nu A(x)$, and $\pi A(x)$.

This study was undertaken with an aim to design an agent expert system for the diagnosis of risk level in ICU. The results obtained from the prototype disclose that the diagnostic system is giving expected results and its efficiency

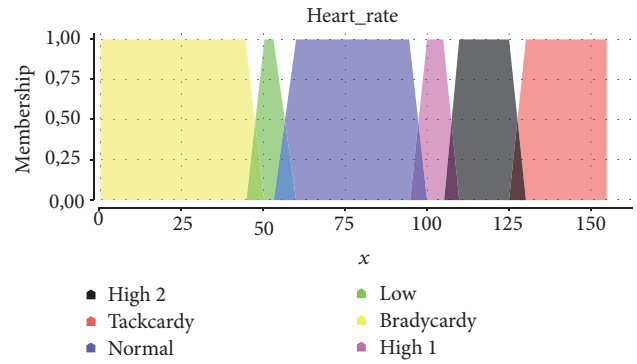


FIGURE 5: The range of heart rate parameter.

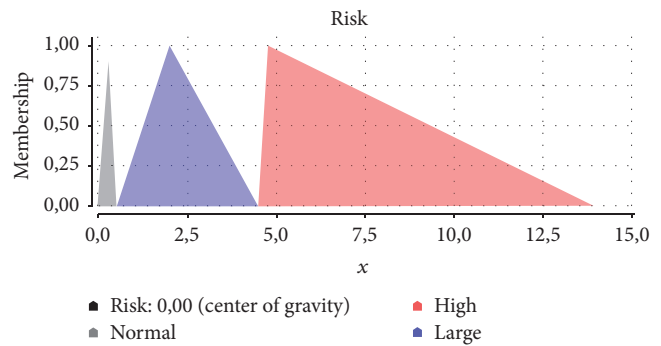


FIGURE 6: The triangular risk membership functions.

has been approved by three specialist doctors in Polyclinic ESSALEMA, Sfax. The developed prototype was not intended to replace the expert doctor; however it can be used to support and help the specialist in diagnosing and forecasting patient’s health status. Thus we conclude that studies involving the use of IFS in medical diagnostic are highly assuring for the future according to the existing system.

To date, the results are very encouraging. The generality of the proposed approach presented in Figure 2 suggests its suitability for a diversity of medical decision system in order to assist inexperienced physicians in arriving at final diagnosis of other illnesses more proficiently and competently.

To evaluate our solution, we have proposed to 15 participants a questionnaire-based survey after a training session; the summary of usability/readability approval evaluation results is presented in [37]. In terms of usability, 65% of the interviewees judged that the system was “good.” As for readability assessment, 62% of the interviewees considered that the system was “good.” The evaluation results are suitable and induce us to keep applying the IFS system in other healthcare domain. The evaluation is based on subjective options: good, average, and poor. Yet it is useful to build hybrid evaluation system (objective and subjective measures). Even though we are only on beginning stage, we assume that the combination of the above measures evaluation can ensures a useful model for the analysis of the prototype.

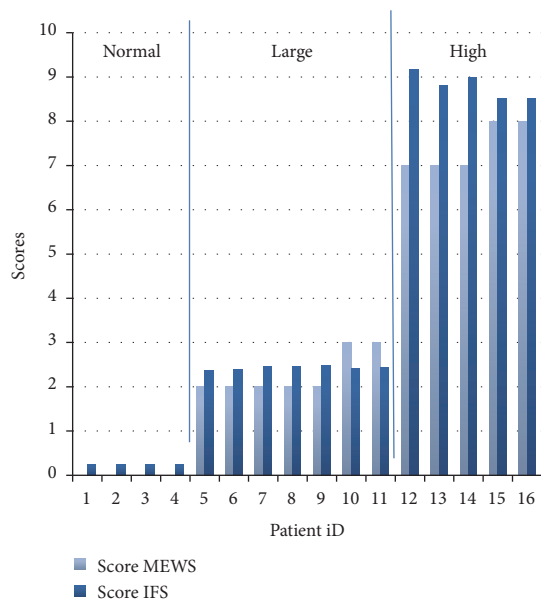


FIGURE 7: Column chart for MEWS score and the MIFEDSS.

7. Conclusion

Intensive Care Unit (ICU) is a complex healthcare environment especially in diagnostic tasks, when we recurrently deal with inaccurate information (accessible information is occasionally vague, inadequate, or incorrect). Therefore, IFS has been found to be practical to deal with ambiguity. In this regard, decision support system and artificial intelligence using IFS techniques can help us to handle this complexity in a harmless, successful, and proficient way. In this paper, we describe a system for detecting patient's degree of risk in Intensive Care Unit. The proof of concept prototype is based on intuitionistic fuzzy sets to model the natural uncertainty in making healthcare decisions, which is integrated into a multi-agent system. The system has been used as an implemented real life application, and some early results are described in the paper.

Accordingly, we assume that IFS is likely to be of great avail to healthcare domain. Indeed, in future research, we will reflect on other medical applications of this approach and deploy the prototype, not only in Polyclinic ESSALEMA, but also in other healthcare environments to evaluate tolerability and performance of the applications. The MIFEDSS prototype was designed and developed for ICU. Nevertheless, the obtained method may be simply matched and applied to further similar medical decision system. Also, we plan to make hybrid evaluation in order to evaluate the system by both subjective and objective features.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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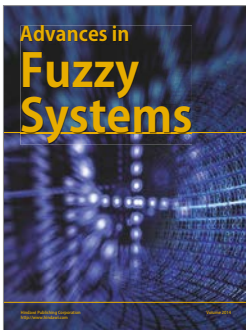
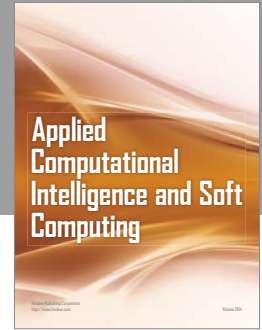
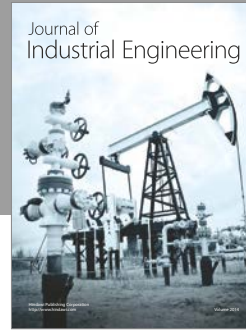
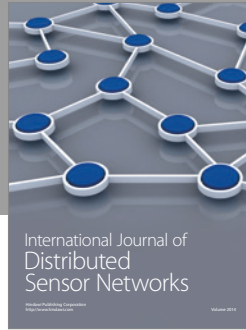
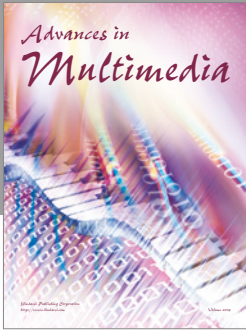
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