IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676, p-ISSN: 2320-3331, Volume 17, Issue 1 Ser. I (Jan. – Feb. 2022), PP 15-23
www.iosrjournals.org

Medical Diagnosis Based On Pattern Recognition

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Abstract: *This paper is a response to the paper by De, Biswas, and Roy that was published in Fuzzy Sets and Systems, 2001, 209-213. They considered an application of intuitionistic fuzzy sets in medical diagnosis. We point out that their approach contains questionable results that may lead to false diagnoses of patients' symptoms. Consequently, we advise researchers and physicians not to apply their approach to avoid risk to human life. Based on the similarity of pattern recognition, we provide a new approach to recognize the pattern of patients that will help physicians to determine the preliminary check for further laboratory examination in medical diagnosis.*

Key words: *Pattern recognition; Fuzzy set; Intuitionistic fuzzy set (IFS); Medical diagnosis; Intuitionistic fuzzy relation (IFR)*

Date of Submission: 07-02-2022 Date of Acceptance: 21-02-2022

I. Introduction

Medical diagnostic investigations are very complex. The doctor is faced with a patient who has his personal experiences, knowledge from books, and mental endowment. The doctor notes the patient's signs and symptoms, combines these with the patient's medical history, physical examination, and laboratory findings, and then diagnoses the disease. In medical science, the diagnosis can be regarded as a label assigned by the physician to describe and synthesize the medical status of a patient. It is based on the information about the patient collected by the physician and his/her present knowledge of medical sciences. The physician generally gathers the information, so-called symptoms, of the patient from the history, the interview, and the physical examination. In the face of uncertainty concerning both the observed symptoms of the patients and the relations of the symptoms to a disease, the physician can not avoid imprecision and uncertainty to determine the diagnostic label that will entail the appropriate therapeutic decision. Moreover, if the physician collects qualitative information from the interview or the history, the diagnosis is more complex and imprecise. Nevertheless, the physician is still quite capable of concluding this information. Physicians take careful attention to the precise definition of what and how they are measuring and how to describe the diagnosis with a quantitative scale. The fuzzy set framework has been utilized in several different approaches to modeling the diagnostic process. In the approach formulated by Sanchez [5] in 1979, he adopted the compositional rule of inference by Zadeh [12] as an inference mechanism. It accepted fuzzy descriptions of the patient's symptoms and inferred fuzzy descriptions of the patient's diseases employing the fuzzy relationships.

Furthermore, based on the concepts of fuzzy sets theory, several fuzzy approaches to medical diagnosis have been reviewed by Steimann and Adlassnig [6] and shown to be effective in this domain. Yao and Yao [11] (based on the fuzzy number and compositional rule of inference to solve medical diagnosis problem), and Ahn et al. 0 have presented a medical diagnostic method by applying a fuzzy classification of solution sets and linear regression approach. Innocent and John [3] presented a new method for computing a diagnostic support index, which uses vague symptom and temporal information, in a clinical diagnosis context. Palma et al. [4] provided a general framework for temporal model-based diagnosis (TMBD) which can deal with the time-varying behavior found in the medical domain. Seising [7] has linked Zadeh's [12] work on system theory and made a review of how it relates to medical diagnosis; Zeshui [13] proposed a new method for deriving the correlation coefficients to the interval-valued IFS theory and described its application in medical diagnosis.

Besides, De et al. [2] have also addressed applying IFS in medical diagnosis. But their approach contains questionable results that may lead to false diagnoses. In addition, three papers that we know of, Szmidt and Kacprzyk [8], [9], Vlachos and Sergiadis [10] have cited De et al. [2] in their references. However, none of them pointed out that the work of De et al. [2] is questionable. In a decision-making problem, the choice between fuzzy alternatives requests a ranking of imprecise values. In the literature this problem has been treated by several authors: the lack of a "good choice" allows various methods of ranking. Different approaches lead to a confusing situation in which there is no procedure able to interpret any problem correctly. Indeed, some

methods are counterintuitive or suffer from a lack of discrimination between alternatives. These methods make use of a preference function that expresses the degree to which every alternative is preferred to another. This information could be important, especially when the best alternative is hardly feasible. In Section 5, a combination of previous methods is shown, so that any decision-maker could customize his procedure to his features. The optimistic method is symmetrical to the pessimistic one; it considers only the best results that arise from a fuzzy number; therefore it is preferred by a decision-maker who presents a strong propensity for risk. The goal of this section is to give a general method of choice that could be used when the decision-maker prefers an intermediate situation between the pessimistic and optimistic points of view. We could simply link with a convex combination the optimistic and pessimistic functions of preference as follows. We give different orderings according to the value of the parameter λ : a risk-averse decision-maker prefers Z_2 , a gambler Z_1 , and a neutral party is indifferent between them, that is, our assigned weight according to the risk attitude of the decision-maker. Hence, the aim of this paper is fourfold. Firstly, we review their solution procedure and then revise it. Secondly, we point out that their procedure from an IFR to a crisp value cannot be preserved to be a non-negative number. Thirdly, using their example with a small modification, we point out their procedure contained questionable results. Fourthly, we propose a new approach to use similarity to consider pattern recognition to find the most possible disease for physician preliminary diagnosis then more laboratory results such as blood tests, X-rays, and ultrasonic will help physicians to determine the disease of a patient.

II. Review De et al.'s results

In De et al. [2], $P = \{P_1, ..., P_q\}$ is the set of patients, $S = \{S_1, ..., S_m\}$ is the set of symptoms, and $D = \{D_1, ..., D_n\}$ is the set of diseases. Q is the IFR between patients and symptoms that are the observed symptoms for each patient. R is the IFR between symptoms and diseases that is offered by the medical knowledge of doctors. $\mu_Q(p,s)$ and $\mu_R(s,d)$ are the membership functions. $\nu_Q(p,s)$ and $\nu_R(s,d)$ are the non-membership functions. De et al. [2] used the max-min operator to create the IFR, $T = Q \circ R$, between patients and diseases with the membership function, $\mu_T(p,d)$ and the non-membership function, $\nu_T(p,d)$

$$\mu_T(p,d) = \max_{s \in S}(\min\{\mu_Q(p,s), \mu_R(s,d)\}), \tag{1}$$

and

$$\nu_T(p,d) = \min_{s \in S}(\max\{\nu_Q(p,s), \nu_R(s,d)\}), \tag{2}$$

with $p \in P$ and $d \in D$.

For a patient, say p_k , De et al. [2] applied the following operation to convert IFS to a crisp value. It follows that

$$S_T(d) = \mu_T(p_k,d) - \nu_T(p_k,d)\pi_T(p_k,d) \tag{3}$$

where $\pi_T(p_k,d) = 1 - \mu_T(p_k,d) - \nu_T(p_k,d)$ is the hesitation.
De et al. [2] considered that if

$$S_T(d_j) = \max_{1 \le i \le n} S_T(d_i), \tag{4}$$

then the patient p_k will be diagnosed to have the disease d_j .

We recall their numerical example. There are four patients Paul, Jadu, Kundu, and Rohit in a hospital. Their symptoms are temperature, headache, stomach pain, cough, and chest pain, denoted as P = {Paul, Jadu, Kundu, Rohit} and S = {temperature, headache, stomach pain, cough, chest pain}. The IFR $Q(P \to S)$ is reproduced shown in Table 1.

Table 1. Reproduced from De et al. [2] for patients with symptoms.

Q	Temperature	Headache	Stomach pain	Cough	Chest pain
Paul	(0.8, 0.1)	(0.6, 0.1)	(0.2, 0.8)	(0.6, 0.1)	(0.1, 0.6)
Jadu	(0.0, 0.8)	(0.4, 0.4)	(0.6, 0.1)	(0.1, 0.7)	(0.1, 0.8)
Kundu	(0.8, 0.1)	(0.8, 0.1)	(0.0, 0.6)	(0.2, 0.7)	(0.0, 0.5)
Rohit	(0.6, 0.1)	(0.5, 0.4)	(0.3, 0.4)	(0.7, 0.2)	(0.3, 0.4)

Let the set of diseases be $D = \{$viral fever, malaria, typhoid, stomach pain, chest pain$\}$. The IFR $R(S \to D)$ is (hypothetically) given and then reproduced as Table 2.

Table 2. Reproduced from De et al. [2] for symptoms with diseases.

R	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Temperature	(0.4, 0.0)	(0.7, 0.0)	(0.3, 0.3)	(0.1, 0.7)	(0.1, 0.8)
Headache	(0.3, 0.5)	(0.2, 0.6)	(0.6, 0.1)	(0.2, 0.4)	(0.0, 0.8)
Stomach pain	(0.1, 0.7)	(0.0, 0.9)	(0.2, 0.7)	(0.8, 0.0)	(0.2, 0.8)
Cough	(0.4, 0.3)	(0.7, 0.0)	(0.2, 0.6)	(0.2, 0.7)	(0.2, 0.8)
Chest pain	(0.1, 0.7)	(0.1, 0.8)	(0.1, 0.9)	(0.2, 0.7)	(0.8, 0.1)

The composition $T = R \circ Q$ is reproduced shown in Table 3.

Table 3. Reproduced from De et al. [2] for $T = R \circ Q$.

T	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Paul	(0.4, 0.1)	(0.7, 0.1)	(0.6, 0.1)	(0.2, 0.4)	(0.2, 0.6)
Jadu	(0.3, 0.5)	(0.2, 0.6)	(0.4, 0.4)	(0.6, 0.1)	(0.1, 0.7)
Kundu	(0.4, 0.1)	(0.7, 0.1)	(0.6, 0.1)	(0.2, 0.4)	(0.2, 0.5)
Rohit	(0.4, 0.1)	(0.7, 0.1)	(0.5, 0.3)	(0.3, 0.4)	(0.3, 0.4)

Their calculation of S_R (should be revised as S_T) is reproduced in Table 4. From Table 4, De et al. [2] mentioned that it is obvious that, if the doctor agrees, then Paul, Kundu, and Rohit suffer from malaria whereas Jadu faces a stomach pain problem.

Table 4. Reproduced from De et al. [2] for S_R .

S_T	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Paul	0.35	0.68	0.57	0.04	0.08
Jadu	0.20	0.08	0.32	0.57	0.04
Kundu	0.35	0.68	0.57	0.04	0.05
Rohit	0.32	0.68	0.44	0.18	0.18

III. The computation results in their defuzzification

In this section, we will discuss their results for their operation from an IFR to a crisp value, $S_T = \mu_T - \nu_T \pi_T$. From Table 4, all crisp values from IFRs are positive. However, there are two computation errors in Table 4. The IFR of Rohit with Viral fever is $(0.4, 0.1)$, then

$$S_T = \mu_T - \nu_T \pi_T = 0.4 - 0.1(1 - 0.4 - 0.1) = 0.35 . \quad (5)$$

Moreover, the IFR of Jadu with Chest problem is $(0.1, 0.7)$, then

$$S_T = \mu_T - \nu_T \pi_T = 0.1 - 0.7(1 - 0.1 - 0.7) = -0.04 . \quad (6)$$

Fortunately, these two computation problems did not influence the medical diagnosis for patients, Jadu and Rohit.

IV. An inherent problem in their procedure

We will slightly change their example to reveal their procedure contained a severe problem that is beyond repair. We replace the disease, malaria, with another disease, chin cough (pertussis), and then replace the patient, Kundu with another patient, Smith, with two changes in IFR where modifications form (0.2, 0.7) to (0.0, 1.0), and form $(0.7, 0.0)$ to $(1.0, 0.0)$ so that changes are shown in Table 5 and Table 6, marked by boldface, respectively.

Table 5. Our hypothetical IFR for patients with symptoms.

Q	Temperature	Headache	Stomach pain	Cough	Chest pain
Paul	(0.8, 0.1)	(0.6, 0.1)	(0.2, 0.8)	(0.6, 0.1)	(0.1, 0.6)
Jadu	(0.0, 0.8)	(0.4, 0.4)	(0.6, 0.1)	(0.1, 0.7)	(0.1, 0.8)
Smith	(0.8, 0.1)	(0.8, 0.1)	(0.0, 0.6)	**(0.0, 1.0)**	(0.0, 0.5)
Rohit	(0.6, 0.1)	(0.5, 0.4)	(0.3, 0.4)	(0.7, 0.2)	(0.3, 0.4)

Table 6. Our artificial IFR for symptoms with diseases.

R	Viral fever	Pertussis	Typhoid	Stomach pain	Chest pain
Temperature	(0.4, 0.0)	(0.7, 0.0)	(0.3, 0.3)	(0.1, 0.7)	(0.1, 0.8)
Headache	(0.3, 0.5)	(0.2, 0.6)	(0.6, 0.1)	(0.2, 0.4)	(0.0, 0.8)
Stomach pain	(0.1, 0.7)	(0.0, 0.9)	(0.2, 0.7)	(0.8, 0.0)	(0.2, 0.8)
Cough	(0.4, 0.3)	**(1.0, 0.0)**	(0.2, 0.6)	(0.2, 0.7)	(0.2, 0.8)
Chest pain	(0.1, 0.7)	(0.1, 0.8)	(0.1, 0.9)	(0.2, 0.7)	(0.8, 0.1)

Therefore, according to the max-min operator, we derive the composition of IFRs R and Q as following Table 7.

Table 7. The composition $T = R \circ Q$.

T	Viral fever	Pertussis	Typhoid	Stomach pain	Chest pain
Paul	(0.4, 0.1)	(0.7, 0.1)	(0.6, 0.1)	(0.2, 0.4)	(0.2, 0.6)
Jadu	(0.3, 0.5)	(0.2, 0.6)	(0.4, 0.4)	(0.6, 0.1)	(0.2, 0.8)
Smith	(0.4, 0.1)	(0.7, 0.1)	(0.6, 0.1)	(0.2, 0.4)	(0.1, 0.5)
Rohit	(0.4, 0.1)	(0.7, 0.1)	(0.5, 0.3)	(0.3, 0.4)	(0.3, 0.4)

And through the result of Table 7, we can derive the next table between patients and diseases that are derived by Equation (3) of De et al.'s approach.

Table 8. The crisp value among patients and diseases.

S_T	Viral fever	Pertussis	Typhoid	Stomach pain	Chest pain
Paul	0.35	0.68	0.57	0.04	0.08
Jadu	0.20	0.08	0.32	0.57	0.20
Smith	0.35	0.68	0.57	0.04	–0.10
Rohit	0.35	0.68	0.44	0.18	0.18

According to Equations (4) and Table 8, we can conclude that De et al. [2] will still imply that Paul, Smith, and Rohit suffer from pertussis whereas Jadu faces a stomach pain problem.

However, after our modification, the IFR of Smith and cough is (0.0, 1.0), and the IFR of cough and pertussis, is (1.0, 0.0). Under our hypothetical IFR, pertussis will certainly have a symptom of cough, and Smith is definitely without a symptom of cough. Hence, Smith cannot have pertussis. It points out that applying the max-min operator to handle the diagnoses problem may derive questionable results.

V. The positive estimation in their defuzzification

In this section, we will discuss the sign of their results for their operation from an IFR to a crisp value, $S_T = \mu_T - \nu_T \pi_T$. From Table 4, all crisp values from IFRs are positive. However, there are two computation errors in Table 4.

The IFR of Rohit with Viral fever is $(0.4, 0.1)$, then

$$S_T = \mu_T - \nu_T \pi_T = 0.4 - 0.1(1 - 0.4 - 0.1) = 0.35 . \tag{7}$$

Moreover, the IFR of Jadu with Chest problem is $(0.1, 0.7)$, then

$$S_T = \mu_T - \nu_T \pi_T = 0.1 - 0.7(1 - 0.1 - 0.7) = -0.04 . \tag{8}$$

It points out that sometimes the values of S_T are negative. Therefore, we consider the problem to find the criterion to insure the positive of S_T . To simplify the expression, we assume that $a = \mu_R$ and $b = \nu_R$ then

$$S_T = \mu_T - \nu_T \pi_T = a - b(1 - a - b) . \tag{9}$$

Under the condition that $0 \le a + b \le 1$. Hence, we face the following problem: to find the criterion of a so that

$$f(b) = b^2 + ab + a - b \ge 0 , \tag{10}$$

for $0 \le b \le 1 - a$. We rewrite equation (10) as follows

$$f(b) = \left(b - \frac{1 - a}{2} \right)^2 - \frac{a^2 - 6a + 1}{4} . \tag{11}$$

Based on equation (11), if $a^2 - 6a + 1 \le 0$, then $f(b) \ge 0$ holds.

If $a^2 - 6a + 1 > 0$, $f(b)$ has minimum point $b = \dfrac{1-a}{2}$ with the minimum value

$$f\left(\frac{1-a}{2}\right) = -\frac{a^2 - 6a + 1}{4} < 0. \tag{12}$$

We assume an auxiliary function, say

$$g(a) = a^2 - 6a + 1, \tag{13}$$

for $0 \le a \le 1$.

We rewrite $g(a)$ as

$$g(a) = (a-3)^2 - 8, \tag{14}$$

to imply that $g(a)$ is a decreasing and convex function, with the minimum value at $a = 1$, and maximum value at $a = 0$.

When $a = 3 - 2\sqrt{2}$, it yields that $a^2 - 6a + 1 = 0$.

We know that when $0 \le a < 3 - 2\sqrt{2} \approx 0.172$, then $a^2 - 6a + 1 > 0$.

When $0 \le a < 3 - 2\sqrt{2} \approx 0.172$, if

$$\frac{1-a-\sqrt{a^2-6a+1}}{2} < b < \frac{1-a+\sqrt{a^2-6a+1}}{2}, \tag{15}$$

then $f(b) < 0$. It means that we find the lower and upper bound to imply the negative of $f(b)$. To check these two bounds satisfying the condition, $0 \le b \le 1-a$, we find that, since $4a \ge 0$, then

$$0 \le \frac{1-a-\sqrt{a^2-6a+1}}{2}, \tag{16}$$

and

$$\frac{1-a+\sqrt{a^2-6a+1}}{2} \le 1-a, \tag{17}$$

both hold. In the following, we list the lower and upper bounds of b to imply that $f(b) < 0$.

Table 9. The lower and upper bounds of b to imply $f(b) < 0$

	$a = 0$	$a = 0.04$	$a = 0.08$	$a = 0.12$	$a = 3 - 2\sqrt{2}$
Lower bound of b	0	0.044	0.097	0.169	$\sqrt{2} - 1 \approx 0.414$
Upper bound of b	1	0.916	0.823	0.711	$\sqrt{2} - 1 \approx 0.414$

From Table 9, when μ_T is smaller than $3 - 2\sqrt{2} \approx 0.172$, where ν_T is between our lower bound and upper bound, then $S_T = \mu_T - \nu_T \pi_T < 0$ to derive a negative result.

VI. Our further argument from the probability viewpoint

Our previous discussion is based on some very strong assumptions. For example, the degree of membership between cough and pertussis is 1 and the degree of non-membership between a cough and a patient (Smith) is 1. To claim something is 100% related to medicine that may result in our previous discussion cannot happen in realistic situations. Hence, we revise our previous discussion in the following three cases with patients, Albert, Berry, and Candy and diseases, paragonimiasis, pulmonary tuberculosis (phthisis), and bronchitis that will be listed in the next table, where the value of x in Table 10 is represented by a very small positive number.

Table 10. Further discussion for our modification

			Further modification		
	Original data	Our previous data	Case 1	Case 2	Case 3
IFS of patient and cough	Kundu (0.1, 0.7)	Smith (0.0, 1.0)	Albert (0.1, 0.9)	Berry (0.01, 0.99)	Candy (x, 1–x)
IFS of cough and disease	malaria (0.7, 0.0)	pertussis (1.0, 0.0)	paragonimiasis (0.9, 0.1)	phthisis (0.99, 0.01)	bronchitis (1–x, x)

If we apply De's approach with the max-min operator, then the same results, as Table 8 will be derived. From the probability point of view, for Case 1, the probability of patients suffering from a disease can be computed as follows. First, we compute Albert with cough, then

(Albert with cough) (paragonimiasis with cough) +
(Albert without cough) (paragonimiasis without cough)

$$= (0.1)(0.9) + (0.9)(0.1) = 0.18 . \tag{18}$$

Similarly, for Case 2, the probability of Berry suffering phthisis is 0.0108, since

(Berry with cough) (paragonimiasis with cough) +
(Berry without cough) (paragonimiasis without cough)

$$= (0.01)(0.99) + (0.99)(0.01) = 0.0108. \tag{19}$$

For the general condition of case 3, the probability of Candy suffering bronchitis is $2x(1-x) \approx 2x$, since

(Candy with cough) (paragonimiasis with cough) +
(Candy without cough) (paragonimiasis without cough)

$$= (\mathrm{x})(1-\mathrm{x}) + (1-\mathrm{x})(\mathrm{x}) = 2\,\mathrm{x}\,(1-\mathrm{x}). \tag{20}$$

when x is a very small positive number.

When the value of x decreases the possible correspondence between patient and disease should also decrease. It indicates that De's approach based on the max-min operator cannot reflect the above situation.

Based on the above discussion, we may predict that they selected an inappropriate operator. In the following, we will consider the above examples to further explain why we claim that the max-min operator is unsuitable for medical diagnosis.

The connection between a patient (Kundu) and a disease (malaria) can be attached by five routes: temperature, headache, stomach pain, cough, and chest pain. Among the five routes, if we only need to find one route with the maximum throughput then the max-min operator is a suitable operator from the viewpoint of traffic transportation. According to our example, Kundu definitely has no cough and malaria absolutely has cough such that Kundu will not have malaria. A path from Kundu, to cough, then to malaria is blocked with zero traffic capacity. However, using the max-min operator, De et al. [2] select another route, from Kundu to temperature, then to malaria with IFS (0.7, 0.1) and then applied Equation (3) to find that

$$0.7 - 0.1(1 - 0.7 - 0.1) = 0.68 . \tag{21}$$

The above discussion reveals that the connection between a patient (Kundu) and malaria, a doctor has to consider all five routes. It indicates that De et al. [2] overlooked the basic rule of health checks by misusing the max-min operator. In the next section, we will prepare our improvement to repair the questionable approach in De et al. [2].

VII. Our proposed approach

Here, we begin to discuss our proposed method to consider a new method for the medical diagnosis that is based on pattern recognition by similarity measure. For example, we try to find the distance between a patient, Juda, and a disease, viral fever.

From the third row of Table 1, and the second column of Table 2, we quote the results in the next table.

Table 11. Data recorded from Table 1 and Table 2

	Temperature	Headache	Stomach pain	Cough	Chest pain
Jadu	$(a_1, b_1) = (0,0.8)$	$(a_2, b_2) = (0.4,0.4)$	$(a_3, b_3) = (0.6,0.1)$	$(a_4, b_4) = (0.1,0.7)$	$(a_5, b_5) = (0.1,0.8)$
Viral fever	$(c_1, d_1) = (0.4,0)$	$(c_2, d_2) = (0.3,0.5)$	$(c_3, d_3) = (0.1,0.7)$	$(c_4, d_4) = (0.4,0.3)$	$(c_5, d_5) = (0.1,0.7)$

First, we compute the weighted p-norm distance for the membership relation between Juda and viral fever as follows

$$\sum_{k=1}^{5} w_k \left| a_k - c_k \right|^p , \tag{22}$$

where $w_k = c_k \Big/ \sum_{j=1}^{5} c_j$, for $k = 1,\ldots,5$ is the weight of viral fever corresponding to five symptoms based on membership function, where a_k and c_k are membership functions of Juda and viral fever, respectively.

For example, for $p = 2$, the distance between Jadu and viral fever is computed as follows,

$$\frac{4}{13}\left(0 - \frac{2}{5}\right)^2 + \frac{3}{13}\left(\frac{2}{5} - \frac{3}{10}\right)^2 + \frac{1}{13}\left(\frac{1}{10} - \frac{4}{10}\right)^2 + \frac{4}{13}\left(\frac{1}{10} - \frac{4}{10}\right)^2 + \frac{1}{13}\left(\frac{1}{10} - \frac{1}{10}\right)^2$$

$$= \frac{32}{325} = 0.098 . \tag{23}$$

Therefore, the similarity measure between Jadu and viral fever for the membership functions is denoted as follows

$$SMM = 1 - \sum_{k=1}^{5} w_k \left| a_k - c_k \right|^p , \tag{24}$$

where *SMN* means similarity-measure-membership.

Similarly, the weighted p-norm distance for the non-membership relation between Juda and viral fever is expressed as

$$\sum_{k=1}^{5} \theta_k \left| b_k - d_k \right|^p , \tag{25}$$

where $\theta_k = d_k \Big/ \sum_{j=1}^{5} d_j$, for $k = 1,\ldots,5$ is the weight of viral fever corresponding to five symptoms based on non-membership function, where b_k and d_k are non-membership functions of Juda and viral fever, respectively. Hence, the similarity measure between Juda and viral fever for the non-membership functions is denoted as follows

$$SMNM = 1 - \sum_{k=1}^{5} \theta_k \left| b_k - d_k \right|^p , \tag{26}$$

where *SMNM* means similarity-measure-non-membership.

We summarize our computation results for the similarity measure for membership functions in Table 12 and that of non-membership functions in Table 13.

Table 12. For $p = 2$, the similarity measure for membership functions, SMM

T	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Paul	0.917	0.973	0.924	0.731	0.636
Jadu	0.902	0.645	0.939	0.970	0.672
Kundu	0.879	0.850	0.923	0.573	0.562
Rohit	0.945	0.983	0.936	0.803	0.787

Table 13. For $p = 2$, the similarity measure for non-membership functions, $SMNM$

T	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Paul	0.952	0.917	0.904	0.781	0.636
Jadu	0.858	0.739	0.865	0.994	0.825
Kundu	0.826	0.868	0.835	0.874	0.745
Rohit	0.939	0.836	0.844	0.904	0.714

Now, we try to synthesize the similarity measures for membership functions and non-membership functions. We will apply a convex combination of two previous results so that any decision-maker could customize his procedure to his features. The similarity measure of a patient to a disease, SM, is denoted as

$$SM = \alpha SMM + (1 - \alpha) SMNM , \tag{27}$$

where α expresses the preference attitude of the decision-maker.

When $\alpha = 1$, a doctor only concerns about the results from the membership function. On the other hand, when $\alpha = 0$, a doctor only pays attention to the results from the non-membership function.

When $p = 2$, we compute the synthesized results for $\alpha = 1$, $\alpha = 0.5$, and $\alpha = 0$, since $\alpha = 1$, the results are the same as Table 11, and when $\alpha = 0$, the results are the same as Table 12. Hence, we only list the results for $\alpha = 0.5$ shown in Table 14.

Table 14. For $p = 2$, the similarity measure, SM with $\alpha = 0.5$

T	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Paul	0.935	0.945	0.914	0.756	0.636
Jadu	0.880	0.692	0.902	0.982	0.749
Kundu	0.856	0.859	0.879	0.724	0.645
Rohit	0.942	0.910	0.890	0.854	0.751

We may combine the results of medical diagnosis from similarity measures concerning different α and the results from De et al. [2], in the next table.

Table 15. The summary of medical diagnosis, when $p = 2$

	De et al. [2]	Our proposed approach		
		SM		
		$\alpha = 1$	$\alpha = 0.5$	$\alpha = 0$
Paul	Malaria	Malaria	Malaria	Viral fever
Jadu	Stomach pain	Stomach pain	Stomach pain	Stomach pain
Kundu	Malaria	Typhoid	Typhoid	Typhoid
Rohit	Malaria	Malaria	Viral fever	Viral fever

It reveals that De et al. [2] applied the max-min operator and the defuzzification method of Equation (3), then their results are close to the results of $\alpha = 1$.

From table 15, we may claim that Jadu had a stomach pain problem. According to our proposed method, based on similarity measure that Kundu suffers typhoid so that our approach avoids the shortcomings of the max-min operator.

For Paul and Rohit, if the doctor preferred the membership function, then the patient is seen being sick with malaria. On the other hand, if the doctor preferred the non-membership function, and the patient is seen as having a viral fever.

For a more complete picture, we also consider the case with $p = 1$ to list the results in the following tables.

Table 16. For $p = 1$, the similarity measure for membership functions, SMM

T	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Paul	0.738	0.871	0.836	0.513	0.454
Jadu	0.723	0.441	0.779	0.833	0.485
Kundu	0.685	0.676	0.771	0.420	0.473
Rohit	0.769	0.912	0.793	0.580	0.562

Table 17. For $p = 1$, the similarity measure for non-membership functions, $SMNM$

T	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Paul	0.818	0.761	0.731	0.588	0.476
Jadu	0.700	0.635	0.712	0.944	0.688
Kundu	0.759	0.648	0.788	0.728	0.576
Rohit	0.773	0.613	0.619	0.608	0.482

Table 18. For $p = 1$, the similarity measure, SM with $\alpha = 0.5$

T	Viral fever	Malaria	Typhoid	Stomach pain	Chest pain
Paul	0.778	0.816	0.784	0.551	0.465
Jadu	0.712	0.538	0.746	0.889	0.587
Kundu	0.722	0.662	0.780	0.574	0.525
Rohit	0.771	0.763	0.706	0.594	0.522

We discover that when we apply the SM operator with $\alpha = 0.5$, and then the medical diagnosis for $p = 2$ and $p = 1$ are the same in Tables 14 and 18. It demonstrates that our approaches are consistent with each other with different norms.

VIII. Conclusion

In this paper, we have pointed out that De's procedure is too complicated and, consequently, their computation contains questionable results. Based on De et al.'s [2] examples, we slightly modify their example to demonstrate that their procedure contains severe problems that may imply questionable judgment, which may endanger the health of patients. Moreover, we point out that their misusing of the max-min operator may lead to false judgments about the symptoms of patients. We provide a new approach that is based on similarity measures for pattern recognition. The weight for a disease to symptoms according to medical knowledge is incorporated in our method. Our results are consistent with 2-norm and 1-norm. It may indicate that our approach based on pattern recognition is better than the previous max-min operator for medical diagnosis. The symptoms and course of malaria are often atypical and, consequently, positive diagnosis depends on microscopic identification and examination of the parasites in blood smears. We conclude that our proposed method may provide doctors with a more accurate operator available in making an initial evaluation of clinical diseases of patients.

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Yenmeng Chen, et. al. "Medical Diagnosis Based On Pattern Recognition." *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, 17(1), (2022): pp. 15-23.