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The notion of fuzzy soft sets in medical ailment diagnosis

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The notion of fuzzy soft sets in medical ailment diagnosis

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Abstract. People deal with the complexities of uncertain data; the most effective method for coping with uncertainty is the fuzzy set theory (Uncertain Sets) developed by Zadeh in 1965. This paper proposes a method to examine Sanchez's medical diagnosis approach using Fuzzy Soft Complement in addition to a matrix representation of Fuzzy Soft Collection. Medical data from a particular hospital in Lagos, Nigeria, were collected and tested for diarrhea, cholera, and dysentery.

Keywords: Fuzzy set, uncertainty, epidemiology

1. Introduction

Sometimes real-life issues typically require data that are not all smooth (crisp) and precise because of different uncertainties (fuzziness) linked with these issues [1-3]. These uncertainties usually are tackled using mathematical tools like Rough sets, Interval mathematics, and Probability theory. Nevertheless, all these noted theories have their difficulties and limitations, which is the lack of the parameterization tool. The most relevant theory for handling fuzziness or uncertainties (contingencies) is that of fuzzy sets (Uncertain Sets) developed by Zadeh in 1965 [4-6]. Let us define the notion of a fuzzy set.
In a fuzzy set, the value of the membership function is usually a real value which varies within the interval of 0 and 1.
For every set $D \subset Y$, define its indicator function (characteristic function) μ_D

$$\mu_D(x) = \begin{cases} 1, & if \quad x \in A \\ 0, & if \quad x \notin A \end{cases}$$

As of now, fuzzy sets are growing fast. Nevertheless, some difficulties and limitations exist due to insufficient parametrization tools [7-9].
Soft set theory is a mathematical tool used for tackling uncertainties; it employs a family of subsets linked with each parameter. Soft set theory can be applied in science, economics, medical science, and even decision making.
Hybrid models have, however, been found to be more useful than soft sets components. Maji *et al.* (2001) developed a theory called "Fuzzy Soft Set" in detail that is a hybrid model of fuzzy sets and soft sets and presented an application of soft set in the decision-making problems using the reduction of rough sets. It was also applied in operation research, probability, measurement theory and game theory.

It has been discovered that in real-life systems, the degree of membership functions within a fuzzy set cannot be verified. Thus, it is more suitable to provide interval-valued data to define membership degree; with that in mind Zadeh introduced interval-valued fuzzy set to be an extension of fuzzy set, and then interval-valued fuzzy soft set (IVFSS) was introduced by Yang *et al.* (2009). A lot of researchers have worked on fuzzy set, fuzzy soft sets, predictive diagnosis, neuro-fuzzy systems, diagnostic cases, and so on, likewise their various application and adoptable hints [10-14].
This study aims to apply a fuzzy soft set to the medical sector for some ailments. Thus, the objectives are to apply the fuzzy soft set technique for the diagnosis of cholera, dysentery; and diarrhea.

1.1 Preliminaries and basic terms [1-7]

Definition 1: Crisp sets are sets in which the membership function of any element, known as the characteristic function, is either 0 or 1. In other words, an element is either a member or not a member of the set.

Example 1: Let $U=\{b_1,b_2,b_3,b_4\}$ be a set of four basketball players and $A=\{speed(a_1), acceleration(a_2), strength(a_3), vertical(a_4)\}$ be a set of parameters that describes the player a coach want to recruit. We represent this in a crisp set as:

$$
\begin{aligned}
(C,S)=\{c(a_1)&=\{(b_1,b_2,b_3)\},\\
\{c(a_2)&=\{(b_1,b_2,b_3)\},\\
\{c(a_3)&=\{(b_2,b_3,b_4)\},\\
\{c(a_4)&=\{(b_1,b_3,b_4)\}.
\end{aligned}
$$

Definition 2: Fuzzy soft sets are extensions of crisp sets. In fuzzy sets, all elements have a degree of membership, known as membership function, whose value is usually a real value which varies within the interval of 0 and 1.

Example 2: Let $U=\{b_1,b_2,b_3,b_4\}$ be a set of four basketball players and $A=\{speed(a_1), acceleration(a_2), strength(a_3), vertical(a_4)\}$ be a set of parameters that describes the player a coach wants to recruit. We represent this in a fuzzy soft set as:

$$
\begin{aligned}
(G,D)=\{g(a_1)&=\{(b_1,.80),(b_2,.70),(b_3,.65),(b_4,0.20)\}\\
\{g(a_2)&=\{(b_1,.75),(b_2,.65),(b_3,.55),(b_4,.20)\},\\
\{g(a_3)&=\{(b_1,.20),(b_2,.45),(b_3,.40),(b_4,.85)\},\\
\{g(a_4)&=\{(b_1,.50),(b_2,.65),(b_3,.70),(b_4,.85)\}.
\end{aligned}
$$

Definition 3: Medical diagnosis is a method of understanding which illness or disorder describes the symptoms and signs of an individual. It is most generally referred to as diagnosis, though the medical meaning is implied.

Definition 4: Uncertainty applies to epistemic circumstances in which the knowledge is incomplete or uncertain. It refers to the prediction of future events or the unknown.

Definition 5: A pair (F, G) is said to be a soft set ($over U$) if and only if F is a mapping of G into the set of all subsets of the set U.

Definition 6: Let $N, M \in f(u)$

- the *union* of N and M expressed as $(N \cup M)$ is

  $\mu_m \cup_n(x)$ = sup [$\mu_m(x)$, $\mu_n(x)$] = [sup $(\mu^L_m(x), \mu^L_n(x))$, sup ($\mu^U_m(x), \mu^U_n(x)$)];

- the *intersection* of N and M is

  $\mu_m \cap_n(x)$ = inf [$\mu_m(x)$, $\mu_n(x)$] = [inf $(\mu^L_m(x), \mu^L_n(x))$, inf ($\mu^U_m(x), \mu^U_n(x)$)];

- the *complement* of M, (M') ') is

  $\mu_m c(x) = 1 - \mu_m(x)$ = [1 - $\mu^u_m(x), 1-\mu^L_n(x)$]

Definition 7: Let U be a universal set, G a set of parameters and $A \subset G$. Then a pair (F, D) is called soft set over U, where F is a mapping from D to 2^U , the power set of U.

2. Review on fuzzy soft set and Fuzzy Soft Set in Matrix Form

The degree of membership in a fuzzy set cannot be checked in real-life application, so it is more appropriate to provide interval-valued data to define membership degree from that standpoint interval-valued fuzzy set was introduced by Zadeh to be an extension of fuzzy set. Fuzyy Soft Set in Matrix Form is considered as follows.

Let $U = \{d_1, d_2, d_{3,\cdots,} d_x\}$ be a universal set and let S be the set of parameters that is $S = \{s_1, s_2, \cdots, s_y\}$. Then a fuzzy soft set (F, S), can be expressed as $B = [b_{mn}]_{x \times y}$ or $[b_{mn}], where\ m = 1, 2, 3, \ldots, x\, and\ n = 1, 2, 3, \ldots, y$ and $b_{ij} = (\mu_{n1}(d_m), \mu_{n2}(d_m))$; where $\mu_{n1}(d_m)$, and $\mu_{n2}(d_m)$ stands for membership and reference function of d_m in $F(s_n)$ so that $\delta_{mn} d_m = \mu_{n1}(d_m) - \mu_{n2}(d_m)$ provides the membership value of d_m . A fuzzy soft matrix defines a fuzzy soft set. All fuzzy soft matrices over U will be interpreted as a set of $FSM_{x \times y}$.

Example 3: Suppose $U = \{f_1, f_2, f_3, f_4\}$ is the universal set and S a set of parameters that is $S = \{s_1, s_2, s_3\}$.

Then,

$$(G, S) = \{G(s_1) = \{(f_1, .65, 0), (f_2, .30, 0), (f_3, .70, 0), (f_4, .75, 0)\},$$

$$\{G(s_2) = \{(f_1, .75, 0), (f_2, .90, 0), (f_3, .20, 0), (f_4, .50, 0)\},$$

$$\{G(s_3) = \{(f_1, .35, 0), (f_2, .45, 0), (f_3, .90, 0), (f_4, .20, 0)\}\}$$

This will give us:

$$\left[b_{xy}\right]_{4\times3} = \begin{bmatrix} (0.65,0) & (0.75,0) & (0.35,0) \\ (0.30,0) & (0.90,0) & (0.45,0) \\ (0.70,0) & (0.20,0) & (0.90,0) \\ (0.75,0) & (0.50,0) & (0.20,0) \end{bmatrix}_{4\times3}$$

Example 4: Let $U = \{b_1, b_2, b_3, b_4\}$ be a set of four basketball players and $A = \{speed(a_1), acceleration(a_2), strength(a_3), vertical(a_4)\}$ be a set of parameters that describes the player a coach want to recruit. We represent this in a fuzzy soft set as:

$$\begin{aligned}(G,D) = \{&g(a_1) = \{(b_1,.80),(b_2,.70),(b_3,.65),(b_4,0.20)\}\\ &\{g(a_2) = \{(b_1,.75),(b_2,.65),(b_3,.55),(b_4,.20)\},\\ &\{g(a_3) = \{(b_1,.20),(b_2,.45),(b_3,.40),(b_4,.85)\},\\ &\{g(a_4) = \{(b_1,.50),(b_2,.65),(b_3,.70),(b_4,.85)\}.\end{aligned}$$

We will represent Example 4 in matrix form

$$(G,D) = \begin{pmatrix} p_1 & p_2 & p_3 & p_4 \\ (a_1,0.80) & (a_1,0.70) & (a_1,0.65) & (a_1,0.20) \\ (a_2,0.75) & (a_2,0.65) & (a_2,0.55) & (a_2,0.20) \\ (a_3,0.20) & (a_3,0.45) & (a_3,0.40) & (a_3,0.85) \\ (a_4,0.50) & (a_4,0.65) & (a_4,0.70) & (a_4,0.85) \end{pmatrix}$$

Studying the use of fuzzy soft set in medical diagnosis illustrates the utility of fuzziness as it has progressed over the years from Zadeh's time to the present. It has led to the development of more efficient tools for dealing with real-life uncertainties. Applying fuzzy soft set to medical diagnosis may also be a gateway to other applications involving fuzzy soft set and can lead to other undiscovered medical problems in medical history in one way or another.

In this work will implement a fuzzy soft set in matrix form, and then expand the medical diagnostic approach of Sanchez using the notion of a fuzzy soft complement.

3. Hints on Fuzzy Soft Sets and Medical Diagnosis

Suppose $Symptom(S)$ is a set of symptoms of certain diseases, a set of diseases called $Diseases(D)$ which is linked to those symptoms in $Symptom(S)$ then let $Patient(PA)$ be a set of patients displaying symptoms in $Symptom(S)$. Then create a Fuzzy soft set (F,D) over S. Then we acquire a matrix M_1 from (F,D) We will call this "*symptom disease matrix*". Then $(F,D)^C$ which is the complement of (F,D) acquires a matrix M_2, We'll call this matrix "*non-symptom diseases matrix*". We construct two Fuzzy soft set (F_1,S) over PA and its complement $(F_1,S)^C$ then we acquire a matrix Q_1 from (F_1,S) and we call it the "*patient symptom matrix*" and then $(F_1,S)^C$ gives us the second matrix Q_2, We'll call this matrix the "*patient non-symptom matrix*".

Then, we obtain two matrices $P_1 = Q_1M_1$ and $P_2 = Q_1M_2$ we'll call it the "*patient disease symptom matrix*" and "*patient disease non symptom matrix*". also, we introduce the matrices $P_3 = Q_2M_1$ We will

call this matrix the patient non symptom disease matrix and $P_4 = Q_2 M_2$ We'll call this patient non symptom non disease matrix.
So,
$P_1 = Q_1 M_1,\ P_2 = Q_1 M_2,\ P_3 = Q_2 M_1, p_4 = Q_2 M_2$
we get the membership value matrices
$MV(P_1), MV(P_2), MV(P_3)\, and\, MV(P_4)$.
Then we calculate S_{p_1} and S_{p_2} (diagnosis score) for and against the disease (D)
$S_{p_1} = MV(p_1) - MV(p_3),\ S_{p_2} = MV(p_2) - MV(p_4)$
Then if $\max\left(S_{p_1}(pa_i, d_j) - S_{p_2}(pa_i, d_j)\right)$ occurs for exactly (pa_i, d_k), then the diagnosis for patient pa_i is disease d_k. repeat the process for by reassessing the symptoms if there is a tie. References are made to Tables 1 to 6 for some cases and details.

3.1 *Medical Data*

Table 1: Case of Diarrhea

Date	**Diagnosis**	**Gender**	**Temperature (°c)**	**Symptoms**
23/1/2020	Diarrhea	F/6 years old	37.2	1. Frequent stooling. 2. Stomach pain.
24/1/2020	Diarrhea	M/2 years old	37.8	1. Vomiting and fever. 2. frequent stooling. 3. Stomach ache.
13/2/2020	Diarrhea	M/Adult	37.6	1. Frequent stooling. 2. Stomach ache.
2/3/2020	Diarrhea	F/Adult	37.5	1. Vomiting. 2. frequent stooling. 3. Stomach ache.
13/3/2020	Diarrhea	M/2 years old	37.7	1. Fever and Vomiting. 2. Stomach ache. 3. frequent stooling.
14/3/2020	Diarrhea	M/3 years old	36.8	1. frequent stooling. 2. Stomach ache.
14/3/2020	Diarrhea	F/Adult	37.2	1. Vomiting and fever. 2. frequent stooling.
17/3/2020	Diarrhea	M/Adult	37.8	1. fever. 2. frequent stooling. 3. General body weakening.

Table 2: Case of Cholera.

date	**diagnosis**	**gender**	**temperature (°c)**	**symptoms**
1/1/2020	Cholera	F/4 years old	37.5	1. Stomach pain. 2. Vomiting. 3. frequent stooling. 4. Dehydration.
5/1/2020	Cholera	M/5 years old	37.8	1. Dehydration.

				2. Fever. 3. Stomach ache. 4. Vomiting 5. Watery stool.
13/2/2020	Cholera	F/3 years old	37.9	1. General body weakening. 2. Dehydration. 3. Fever. 4. Stomach pain. 5. Vomiting and stooling.
15/2/2020	Cholera	M/6 years old	37.7	1. Loss of appetite. 2. Dehydration. 3. Fever. 4. Vomiting. 5. Watery stool.
8/3/2020	Cholera	F/3 years old	38.0	1. Fever and Vomiting 2.Watery stool. 3. Dehydration. 4. Stomach pain.
18/3/2020	Cholera	M/4 years old	37.9	1. Fever. 2. Dehydration. 3. Loss of appetite. 4. Watery stool. 5. Vomiting.

Table 3: Case of Dysentery

date	**diagnosis**	**gender**	**temperature (°c)**	**symptoms**
27/1/2020	Dysentery	M/Adult	37.9	1. Fatigue. 2. Blood stained watery stool. 3. Stomach pain.
28/2/2020	Dysentery	F/Adult	38.1	1. Fever. 2. Fatigue. 3. Blood stained watery stool. 4. Stomach pain.
10/3/2020	Dysentery	F/Adult	37.6	1. Blood stained watery stool. 2.Stomach pain. 3. Fever.
16/3/2020	Dysentery	F/Adult	37.7	1. Blood stained watery stool. 2.Stomach pain. 3. Vomiting
21/3/2020	Dysentery	M/Adult	37.6	1. Blood stained watery stool. 2.Stomach pain. 3. Fever.

3.2 Statistics for the symptoms of each diseases (General)

Table 4: Scale Rating I (Ranging from 1 – 10)

Rare	Medium	Neutral	High	Extremely high
1 – 2.4	2.5 – 4.9	5 – 7.4	7.5 – 9.9	10

- Cholera (P1)

Fever – 2.5, Stomach ache – 5, Vomiting – 7.5, Stooling – 6

- Diarrhea (P2)

Fever – 7.5

Stomach ache – 8, Vomiting – 2.5, Stooling – 7.5

- Dysentery (P3)

Fever – 5, Stomach ache – 9, Vomiting – 7, Stooling – 2

3.3 Statistics for the symptoms (for some patients)

Table 5: Scale Rating II (Ranging from 1 – 10)

Rare	Medium	Neutral	High	Extremely high
1 – 2.4	2.5 – 4.9	5 – 7.4	7.5 – 9.9	10

- Fever

  P1 (M/2 years old, diarrhea, 37.7°C) - 5

  P2 (M/5 years old, cholera, 37.8°C) – 6

  P3 (M/Adult, dysentery, 37.6°C) – 7.5

- Stomach pain

  P1 (F/6 years old, diarrhea, 37.2°C) - 6

  P2 (F/4 years old, cholera, 37.5°C) – 7.5

  P3 (F/Adult, dysentery, 38.1°C) – 9

- Stooling

  P1 (M/2 years old, diarrhea, 37.7°C) – 8.5

  P2 (M/5 years old, cholera, 37.8°C) – 4.5

  P3 (F/Adult, dysentery, 37.6°C) – 8.5

- Vomiting

  P1 (F/Adult, diarrhea, 37.2°C) - 9

  P2 (F/4 years old, cholera, 37.5°C) – 5

  P3 (F/Adult, dysentery, 37.7°C) – 2

4. Result and Discussion

Suppose there are three patients $\boldsymbol{pa}_{*1}, \boldsymbol{pa}_2, \boldsymbol{pa}_3$ with symptoms fever, stomach pain, stooling and vomiting. Let cholera, diarrhea and dysentery be the diseases associated with these symptoms.

We consider a set $Symptom\ (S) = \{s_1, s_2, s_3, s_4\}$ as universal set with $\boldsymbol{s}_1, \boldsymbol{s}_2, \boldsymbol{s}_3$ ***and*** $\boldsymbol{s}_4$ representing the symptoms fever, stomach pain, stooling and vomiting respectively, as well as a set $Diseases(D) = \{d_1, d_2, d_3\}$, where $\boldsymbol{d}_1, \boldsymbol{d}_2$ ***and*** $\boldsymbol{d}_3$ represent the cholera, diarrhea and dysentery.

Suppose (F,D) a Fuzzy soft set over S, where $F:D\to\tilde{F}(S)$, where D is Diseases and S is Symptom. Then

$$(F,D)=\{F(d_1)=\{(s_1,.25,0),(s_2,.50,0),(s_3,.60,0),(s_4,.75,0)\},$$
$$\{F(d_2)=\{(s_1,.75,0),(s_2,.80,0),(s_3,.75,0),(s_4,.25,0)\}$$
$$\{F(d_3)=\{(s_1,.50,0),(s_2,.90,0),(s_3,.20,0),(s_4,.70,0)\}\}$$

Then the Complement of (F,D) is

$$(F,D)^c=\{F^c(d_1)=\{(s_1,1,0.25),(s_2,1,0.50),(s_3,1,0.60),(s_4,1,0.75)\}$$
$$\{F^c(d_2)=\{(s_1,1,0.75),(s_2,1,0.80),(s_3,1,0.75),(s_4,1,0.25)\},$$
$$\{F^c(d_3)=\{(s_1,1,0.50),(s_2,1,0.90),(s_3,1,0.20),(s_4,1,0.70)\}$$

We represent (F,D) and $(F,D)^c$, with matrices M_1 and M_2

$$M_1=\begin{array}{c}\\ s_1\\ s_2\\ s_3\\ s_4\end{array}\begin{bmatrix} d_1 & d_2 & d_3\\ (0.25,0) & (0.75,0) & (0.50,0)\\ (0.50,0) & (0.80,0) & (0.90,0)\\ (0.60,0) & (0.75,0) & (0.20,0)\\ (0.75,0) & (0.25,0) & (0.70,0)\end{bmatrix} \text{ and } M_2=\begin{array}{c}\\ s_1\\ s_2\\ s_3\\ s_4\end{array}\begin{bmatrix} d_1 & d_2 & d_3\\ (1,0.25) & (1,0.75) & (1,0.50)\\ (1,0.50) & (1,0.80) & (1,0.90)\\ (1,0.60) & (1,0.75) & (1,0.20)\\ (1,0.75) & (1,0.25) & (1,0.70)\end{bmatrix}$$

Then we take $Patient(PA)=\{pa_{*1},pa_2,pa_3\}$ as the universal set where $pa_1,pa_2\ and\ pa_3$ represent three patients respectively and $Symptom(S)=\{s_1,s_2,s_3,s_4\}$ as the set of parameters, where $s_1,s_2,s_3\ and\ s_4$ represent the symptoms fever, stomach pain, stooling and vomiting respectively.
Let (F_1,S) be a fuzzy soft set, where $F_1:S\to\tilde{F}(PA)$, which represents the patient and symptoms.
Let

$$(F_1,S)=\{F_1(s_1)=\{(pa_{*1},0.50,0),(pa_2,0.60,0),(pa_3,0.75,0)\}$$
$$\{F_1(s_2)=\{(pa_{*1},0.60,0),(pa_2,0.75,0),(pa_3,0.90,0)\},$$
$$\{F_1(s_3)=\{(pa_{*1},0.85,0),(pa_2,0.45,0),(pa_3,0.85,0)\},$$
$$\{F_1(s_4)=\{(pa_{*1},0.90,0),(pa_2,0.50,0),(pa_3,0.20,0)\}\}$$

we represent (F_1,S) with matrix Q_1 and call it *patient-symptom matrix.*

$$Q_1=\begin{array}{c}\\ pa_{*1}\\ pa_2\\ pa_3\\ \\ \end{array}\begin{bmatrix} s_1 & s_2 & s_3 & s_4\\ (.50,0) & (.60,0) & (.85,0) & (.90,0)\\ (.60,0) & (.75,0) & (.45,0) & (.50,0)\\ (.75,0) & (.90,0) & (.85,0) & (.20,0)\\ & & & \end{bmatrix}$$

Complement of (F_1, S) is given by

$$
\begin{aligned}
(F_1,S)^c = \{ & F_1^c(s_1) = \{(pa_{*1},1,.50),(pa_2,1,.60),(pa_3,1,.75)\}, \\
& \{F_1^c(s_2) = \{(pa_{*1},1,.60),(pa_2,1,.75),(pa_3,1,.90)\}, \\
& \{F_1^c(s_3) = \{(pa_{*1},1,.85),(pa_2,1,.45),(pa_3,1,.85)\}, \\
& \{F_1^c(s_4) = \{(pa_{*1},1,.90),(pa_2,1,.50),(pa_3,1,.20)\}\}
\end{aligned}
$$

we represent $(F_1, S)^c$ with matrix Q_2 we'll call it the *patient non-symptom matrix*

$$
Q_2 = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array}
\left[\begin{array}{cccc}
s_1 & s_2 & s_3 & s_4 \\
(1,0.50) & (1,0.60) & (1,0.85) & (1,0.90) \\
(1,0.60) & (1,0.75) & (1,0.45) & (1,0.50) \\
(1,0.75) & (1,0.90) & (1,0.85) & (1,0.20)
\end{array}\right]
$$

Then, we find the product of fuzzy soft matrices

$$
P_1 = Q_{*1}M_{*1} = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array}
\left[\begin{array}{ccc}
d_1 & d_2 & d_3 \\
(0.75,0) & (0.75,0) & (0.70,0) \\
(0.50,0) & (0.75,0) & (0.75,0) \\
(0.60,0) & (0.80,0) & (0.90,0)
\end{array}\right],
\quad
p_2 = Q_1M_2 = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array}
\left[\begin{array}{ccc}
d_1 & d_2 & d_3 \\
(0.90,0.25) & (0.90,0.25) & (0.90,0.20) \\
(0.75,0.25) & (0.80,0.25) & (0.90,0.20) \\
(0.90,0.20) & (0.90,0.20) & (0.90,0.20)
\end{array}\right]
$$

The membership value matrices $MV(p_1)$ and $MV(p_2)$ is given as

$$
MV(p_1) = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array}
\left[\begin{array}{ccc}
d_1 & d_2 & d_3 \\
0.75 & 0.75 & 0.70 \\
0.50 & 0.75 & 0.75 \\
0.60 & 0.75 & 0.90
\end{array}\right],
MV(p_2) = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array}
\left[\begin{array}{ccc}
d_1 & d_2 & d_3 \\
0.65 & 0.65 & 0.70 \\
0.50 & 0.50 & 0.70 \\
0.65 & 0.65 & 0.70
\end{array}\right]
$$

then

$$
p_3 = Q_2M_1 = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array}
\left[\begin{array}{ccc}
d_1 & d_2 & d_3 \\
(0.90,0.25) & (0.90,0.25) & (0.90,0.20) \\
0.75,0.25) & (0.80,0.25) & (0.90,0.20) \\
(0.90,0.20) & (0.90,0.20) & (0.90,0.20)
\end{array}\right],
p_4 = Q_2M_2 = \begin{array}{c} \\ pa_1 \\ pa_2 \\ pa_3 \end{array}
\left[\begin{array}{ccc}
d_1 & d_2 & d_3 \\
(1,0.50) & (1,0.75) & (1,0.50) \\
(1,0.60) & (1,0.50) & (1,0.45) \\
(1,0.75) & (1,0.25) & (1,0.70)
\end{array}\right]
$$

The membership value matrices $MV(p_3)$ and $MV(p_4)$ is given as

$$MV(p_3) = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array} \begin{bmatrix} d_1 & d_2 & d_3 \\ 0.65 & 0.65 & 0.70 \\ 0.50 & 0.55 & 0.70 \\ 0.70 & 0.70 & 0.70 \end{bmatrix}, MV(p_4) = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array} \begin{bmatrix} d_1 & d_2 & d_3 \\ 0.50 & 0.25 & 0.50 \\ 0.40 & 0.50 & 0.55 \\ 0.25 & 0.75 & 0.30 \end{bmatrix}$$

then, the diagnosis scores S_{p_1} and S_{p_2} are calculated as follows:

$S_{p_1} = MV(p_1) - MV(p_3)$ and $S_{p_2} = MV(p_2) - MV(p_4)$

then

$$S_{p_1} = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array} \begin{bmatrix} d_1 & d_2 & d_3 \\ 0.10 & 0.10 & 0.00 \\ 0.00 & 0.20 & 0.05 \\ -0.10 & 0.05 & 0.20 \end{bmatrix} \text{ and } S_{p_2} = \begin{array}{c} \\ pa_{*1} \\ pa_2 \\ pa_3 \end{array} \begin{bmatrix} d_1 & d_2 & d_3 \\ 0.15 & 0.40 & 0.20 \\ 0.10 & 0.00 & 0.15 \\ 0.40 & -0.10 & 0.40 \end{bmatrix}$$

4.1 Results

Now, we have the difference for and against the diseases as in Table 6.

Table 6: Diseases differences

$S_{p_1} - S_{p_2}$	d_1	d_2	d_3
pa_{*1}	–0.05	–0.30	–0.20
pa_2	–0.10	0.20	–0.10
pa_3	–0.50	0.40	–0.20

Finally, we come to the conclusion that patient pa_{*1} may be suffering from the disease d_3 (Dysentery) and patients pa_2 may be suffering from the disease d_2 (Diarrhea) as well as pa_3 may be suffering from disease d_2 (Diarrhea). No patient is suffering from disease d_1 (Cholera).

4.2. Remarks and Recommendations

This work applied fuzzy soft set in medical diagnosis using the method of fuzzy soft compliment with matrix representation and the "product" operation on fuzzy soft sets. The steps used in obtaining the solution include the following:

i. Input the value of (F, D) and $(F, D)^c$. Use (F, D) to get M_1 and $(F, D)^c$ to get M_2.

ii. Input the value of (F_1, S) and $(F_{1,} S)^c$. Use to (F_1, S) get Q_1 and $(F_{1,} S)^c$ to get Q_2.

iii. Determine $P_1 = Q_1 M_1,\ P_2 = Q_1 M_2,\ P_3 = Q_2 M_1,\ P_4 = Q_2 M_2$

iv. Determine the corresponding membership value matrices $MV(P_1), MV(P_2), MV(P_3), MV(P_4)$.

v. Determine the diagnosis scores S_{T_1} and S_{T_2}.

vi. Find $S_k = \max\left(S_{p_1}(pa_i, d_j) - S_{p_2}(pa_i, d_j)\right)$, viii: Then patient p_i is suffering from the disease d_k.

5. Conclusion

In this work, we have studied the evolution of fuzzy set theory in general, which has led to Fuzzy Soft complements. The matrix representation and the "product" operation have been successfully applied on fuzzy soft sets, thereby describing the theory of fuzzy soft sets in the area of medical diagnosis. This approach is recommended for medical centers that need to diagnose certain diseases of their patients. There are different diseases with similar symptoms, so there is room for error in the diagnosis, but with this work, medical centers will be able to diagnose those patients' diseases with few errors (if any).

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