NSS

A new method of measuring similarity between two neutrosophic soft sets and its application in pattern recognition problems

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Abstract. Smarandache in 1995 introduced the concept of neutrosophic set and in 2013 Maji introduced the notion of neutrosophic soft set, which is a hybridization of neutrosophic set and soft set. After its introduction neutrosophic soft sets become most efficient tools to deals with problems that contain uncertainty such as problem in social, economic system, medical diagnosis, pattern recognition, game theory, coding theory and so on. In this work a new method of measuring similarity measure and weighted similarity measure between two neutrosophic soft sets (NSSs) are proposed. A comparative study with existing similarity measures for neutrosophic soft sets also studied. A decision making method is established for neutrosophic soft set setting using similarity measures. Lastly a numerical example is given to demonstrate the possible application of similarity measures in pattern recognition problems.

Keywords: Fuzzy sets, soft sets, neutrosophic sets, neutrosophic soft sets, similarity measure, pattern recognition.

1 Introduction

The concept of fuzzy set theory was initiated by Prof. L. A. Zadeh in1965[20]. After its introduction several researchers have extended this concept in many directions. The traditional fuzzy set is characterized by the membership value or the grade of membership value. Sometimes it may be very difficult to assign the membership value for a fuzzy set. To overcome this difficulty the concept of interval valued fuzzy sets was proposed by L.A. Zadeh in1975[21]. In some real life problems in expert system, belief system, information fusion and so on, we must consider the truth-membership as well as the falsity-membership for proper description of an object in uncertain, ambiguous environment. Neither the fuzzy sets nor the interval valued fuzzy sets is appropriate for such a situation. Intuitionistic fuzzy setsintroduced by K. Atanassov[1] in 1986 and interval valued intuitionistic fuzzy setsintroduced by K. Atanassov and G. Gargov in 1989[2] are appropriate for such a situation.But these do not handle the indeterminate and inconsistent information which exists in belief system. F. Smarandache in 1995[16,17], introduced the concept of neutrosophicset,which is a mathematical tool for handling problems involving imprecise, indeterminacy and inconsistent data. Soft set theory[7, 11] has enriched its potentiality since its introduction by Molodtsov in 1999. Using the concept of soft set theory P. K. Maji in 2013[12] introduced neutrosophic soft set**.** Neutrosophic sets and neutrosophic soft sets now become the most useful mathematical tools to deal with the problems which involve the indeterminate and inconsistent information.

Similarity measure is an important topic in the fuzzy set theory. The similarity measure indicates the degree of similarity between two fuzzy sets. P. Z. Wang[18] first introduced the concept of similarity measure of fuzzy sets and gave a computational formula. Science then, similarity measure of fuzzy sets has attracted several researchers' interest and has been investigated more. Domain of application of similarity measure of fuzzy sets are fuzzy clustering, image processing, fuzzy reasoning, fuzzy neural network, pattern recognition, medical diagnosis, game theory, coding theory and several problems that contain uncertainties. S. M. Chen[5, 6] proposedsimilarity between vague sets, similarity measure of soft sets was studied by P. Majumderet al.[8, 9, 10] and W.K. Min[13], NaimCagman and Irfan Deli[4] introduced similarity measure for intuitionistic fuzzy soft sets, severalsimilarity measures for interval-valued fuzzy soft sets were studied by A. Mukherjee and S. Sarkar[14]. Said Broumi and FlorentinSmarandache[3] introduced the concept of several similarity measures of neutrosophic sets and Jun Ye[19] introduced the concept of similarity measures between interval neutrosophic sets. Recently A. Mukherjee and S. Sarkar[15] introduced several methods of similarity measure for neutrosophic soft sets

Pattern recognition problem has been one of the fastest growing areas during the last two decades because of its usefulness and fascination. The main objective of pattern recognition problems is supervised or unsupervised classification of unknown patterns. Among the various frameworks in which pattern recognition problem has been traditionally formulated the statistical approach has been most intensively studied and used in practice.

In this paper a new method of measuring degree of similarity and weighted similarity measure between two neutrosophic soft set is proposed and some basic properties of similarity measure also are studied. A decision making method is established based on the proposed similarity measure. An illustrative numerical example is given to demonstrate the application of proposed decision making method in a supervised pattern recognition problem that is on the basis of the knowledge of the known pattern our aim is to classify the unknown pattern.

The rest of the paper is organized as --- section 2: some preliminary basic definitions are given in this section. In section 3 similarity measures, weighted similarity measure between two NSSs is defined with examples and some basic properties are studied. In section 4 a decision making method is established with an example in a pattern recognition problem. In Section 5 a comparative study of similarity measures between existing and proposed method is given. Finally in section 6 some remarks of the proposed similarity measure between NSSs and the proposed decision making method are given.

2 Preliminaries and related works

In this section we briefly review some basic definitions related to neutrosophic soft sets which will be used in the rest of the paper.

2.1 Definition[20] Let X be a non empty collection of objects denoted by x. Then a *fuzzy set* (*FS for short*) α in X is a set of ordered pairs having the form $\alpha = \{(x, \mu_\alpha(x)) : x \in X\}$,

where the function $\mu_\alpha : X \to [0,1]$ is called the membership function or grade of membership (also degree of compatibility or degree of truth) of x in α .The interval M = $[0,1]$ is called membership space.

2.2 Definition[21] Let D[0, 1] be the set of closed sub-intervals of the interval [0, 1]. An *interval-valued fuzzy set* in X, $X \neq \phi$ and Card(X) = n, is an expression A given by $A = \{(x, M_A(x)) : x \in X\}$, where $M_A : X \to D[0,1]$.

2.3 Definition[1] Let X be a non empty set. Then an *intuitionistic fuzzy set (IFS for short)* A is a set having the form A={(x, $\mu_A(x)$, $\gamma_A(x)$): x∈X} where the functions μ_A: X→[0,1] and γ_A: X→[0,1] represents the degree ofmembership and the degree of non-membership respectively of each element x∈X and $0 \le \mu_A(x)+\gamma_A(x) \le 1$ for each x∈X.

2.4 Definition[7,11] Let U be an initial universe and E be a set of parameters. Let P(U) denotes the power set of U and A⊆ E. Then the pair (F,A) is called a *soft set* over U, where F is a mapping given byF:A→P(U).

2.5 Definition[16,17] A neutrosophic set A on the universe of discourse X is defined as $A = \{(x, T_A(x), I_A(x), F_A(x)), x \in X\}$ where *T, I, F* : $X \to]^-0,1^+[$ and

$^-0 \le T_A(x) + I_A(x) + F_A(x) \le 3^+$.

From philosophical point of view, the neutrosophic set takes the value from real standard or non-standard subsets of $]^-0,1^+[$. But in real life application in scientific and engineering problems it is difficult to use neutrosophic set with value from real standard or non-standard subset of $]^-0,1^+[$. Hence we consider the neutrosophic set which takes the value from the subset of [0,1] that is

$$0 \le T_A(x) + I_A(x) + F_A(x) \le 3 .$$

2.6 Definition[12] Let U be the universe set and E be the set of parameters. Also let A ⊆ E and P(U) be the set of all neutrosophic sets of U. Then the collection (F, A) is called neutrosophic soft set over U, where F is a mapping given by F: A →P(U).

2.7 Definition[12] Let (F,E_1) and (G,E_2) be two neutrosophic soft sets over the common universe U , where E_1, E_2 are two sets of parameters. Then (F,E_1) is said to be neutrosophic soft subset of (G,E_2) if $E_1 \subseteq E_2$ and $T_{F(e)}(x) \le T_{G(e)}(x)$, $I_{F(e)}(x) \le I_{G(e)}(x)$, $F_{F(e)}(x) \ge F_{G(e)}(x)$, $\forall e \in E_1, x \in U$. If (F,E_1) be neutrosophic soft subset of (G,E_2) then it is denoted by $(F, E_1) \subseteq (G, E_2)$.

2.8 Definition[12]

Let E = {e_1, e_2, e_3, ... ,e_m} be the set of parameters, then the set denoted by ˥E and defined by ˥E = {┐e_1, ┐e_2, ┐e_3, ... , ┐e_m}, where ┐e_i = not e_i , $\forall i$ is called NOT set of the set of parameters E. Where ˥ and ┐different operators.

2.9 Definition[12] The complement of a neutrosophic soft set (F,E) denoted by $(F,E)^c$ is defined as $(F,E)^c$ = (F^c ,˥E), where F^c : ˥E→ $P(U)$ is amapping given by

$F^c(\alpha)$ = neutrosophic soft complement with

$T_{F^c(x)} = F_{F(x)}$, $I_{F^c(x)} = I_{F(x)}$ and $F_{F^c(x)} = T_{F(x)}$.

3 Similarity measure for neutrosophic soft sets(NSSs)

In this section we have proposed a new method for measuring similarity measure and weighted similarity measure for NSSs and some basic properties are also studied.

3.1 Similarity measure

U = {x_1, x_2, x_3, ...,x_n} be the universe of discourse and E = {e_1, e_2, e_3, ... ,e_m} be the set of parameters and (N_1,E), (N_2,E) be two neutrosophic soft sets over U(E). Then the similarity measure between NSSs (N_1,E) and (N_2,E) is denoted by $Sim(N_1, N_2)$ and is defined as follows :

$$Sim(N_1, N_1) = \frac{1}{3mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\Big(3-\left|T_{N_1}(x_i)(e_j)-T_{N_2}(x_i)(e_j)\right|-\left|I_{N_1}(x_i)(e_j)-I_{N_2}(x_i)(e_j)\right|-\left|F_{N_1}(x_i)(e_j)-F_{N_2}(x_i)(e_j)\right|\Big) \quad \text{.................................... (1)}$$

3.2 Theorem If $Sim(N_1, N_2)$ be the similarity measure between two NSSs (N_1,E) and (N_2,E) then

(i) $0 \le Sim(N_1, N_2) \le 1$

(ii) $Sim(N_1, N_2) = Sim(N_2, N_1)$

(iii) $Sim(N_1, N_1) = 1$

(iv) $If\ (N_1, E) \subseteq (N_2, E) \subseteq (N_3, E)\ then\ Sim(N_1, N_3) \le Sim(N_2, N_3)$

Proof:

(i) Obvious from definition 3.1 .

(ii) Obvious from definition 3.1 .

(iii) Obvious from definition 3.1

(iv) Let U = {x_1, x_2, x_3, ..., x_n} be the universe of discourse and E = {e_1, e_2, e_3, ... ,e_m} be the set of parameters and (N_1,E), (N_2,E), (N_3,E) be three neutrosophic soft sets over U(E), such that $(N_1, E) \subseteq (N_2, E) \subseteq (N_3, E)$ .Now by definition of neutrosophic soft sub sets (Maji, 2013) we have

$$T_{N_1}(x_i)(e_j) \le T_{N_2}(x_i)(e_j) \le T_{N_3}(x_i)(e_j)$$
$$I_{N_1}(x_i)(e_j) \le I_{N_2}(x_i)(e_j) \le I_{N_3}(x_i)(e_j)$$
$$F_{N_1}(x_i)(e_j) \ge F_{N_2}(x_i)(e_j) \ge F_{N_3}(x_i)(e_j)$$

$$\Rightarrow \left|T_{N_1}(x_i)(e_j)-T_{N_3}(x_i)(e_j)\right| \ge \left|T_{N_2}(x_i)(e_j)-T_{N_3}(x_i)(e_j)\right|,$$
$$\left|I_{N_1}(x_i)(e_j)-I_{N_3}(x_i)(e_j)\right| \ge \left|I_{N_2}(x_i)(e_j)-I_{N_3}(x_i)(e_j)\right|,$$
$$\left|F_{N_1}(x_i)(e_j)-F_{N_3}(x_i)(e_j)\right| \ge \left|F_{N_2}(x_i)(e_j)-F_{N_3}(x_i)(e_j)\right|$$

$$\Rightarrow \Big(\left|T_{N_1}(x_i)(e_j)-T_{N_3}(x_i)(e_j)\right|+\left|I_{N_1}(x_i)(e_j)-I_{N_3}(x_i)(e_j)\right|+\left|F_{N_1}(x_i)(e_j)-F_{N_3}(x_i)(e_j)\right|\Big) \ge \Big(\left|T_{N_2}(x_i)(e_j)-T_{N_3}(x_i)(e_j)\right|+\left|I_{N_2}(x_i)(e_j)-I_{N_3}(x_i)(e_j)\right|+\left|F_{N_2}(x_i)(e_j)-F_{N_3}(x_i)(e_j)\right|\Big)$$

$$\Rightarrow \Big(3-\left|T_{N_1}(x_i)(e_j)-T_{N_3}(x_i)(e_j)\right|-\left|I_{N_1}(x_i)(e_j)-I_{N_3}(x_i)(e_j)\right|-\left|F_{N_1}(x_i)(e_j)-F_{N_3}(x_i)(e_j)\right|\Big) \le \Big(3-\left|T_{N_2}(x_i)(e_j)-T_{N_3}(x_i)(e_j)\right|-\left|I_{N_2}(x_i)(e_j)-I_{N_3}(x_i)(e_j)\right|-\left|F_{N_2}(x_i)(e_j)-F_{N_3}(x_i)(e_j)\right|\Big)$$

$$\Rightarrow \frac{1}{3mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\Big(3-\left|T_{N_1}(x_i)(e_j)-T_{N_3}(x_i)(e_j)\right|-\left|I_{N_1}(x_i)(e_j)-I_{N_3}(x_i)(e_j)\right|-\left|F_{N_1}(x_i)(e_j)-F_{N_3}(x_i)(e_j)\right|\Big) \le \frac{1}{3mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\Big(3-\left|T_{N_2}(x_i)(e_j)-T_{N_3}(x_i)(e_j)\right|-\left|I_{N_2}(x_i)(e_j)-I_{N_3}(x_i)(e_j)\right|-\left|F_{N_2}(x_i)(e_j)-F_{N_3}(x_i)(e_j)\right|\Big)$$

$\Rightarrow$ $Sim(N_1, N_3) \le Sim(N_2, N_3)$ [By equation (1)]

3.3 Weighted similarity measure

Let U = {x_1, x_2, x_3, ...,x_n} be the universe of discourse and E = {e_1, e_2, e_3, ... ,e_m} be the set of parameters and (N_1,E), (N_2,E) be two neutrosophic soft sets over U(E). Now if we consider weights w_i of x_i (i = 1,2,3,.....,n) then the weighted similarity measure between NSSs (N_1,E) and (N_2,E) is denoted by $WSim(N_1, N_2)$ is proposed as follows :

$$WSim(N_1, N_2) = \frac{1}{3m}\sum_{i=1}^{n}\sum_{j=1}^{m} w_i\Big(3-\left|T_{N_1}(x_i)(e_j)-T_{N_2}(x_i)(e_j)\right|-\left|I_{N_1}(x_i)(e_j)-I_{N_2}(x_i)(e_j)\right|-\left|F_{N_1}(x_i)(e_j)-F_{N_2}(x_i)(e_j)\right|\Big) \quad \text{.. (2)}$$

Where $w_i \in [0,1]$, i = 1,2,3,.......,n and $\sum_{i=1}^{n} w_i = 1$. In particular if we take $w_i = \frac{1}{n}$, i = 1,2,3,... ....,n then $WSim(N_1, N_2) = Sim(N_1, N_2)$.

3.4 Theorem Let If $WSim(N_1, N_2)$ be the similarity measure between two NSSs (N_1,E) and (N_2,E) then

(i) $0 \le WSim(N_1, N_2) \le 1$

(ii) $WSim(N_1, N_2) = WSim(N_2, N_1)$

(iii) $WSim(N_1, N_1) = 1$

(iv) $If\ (N_1, E) \subseteq (N_2, E) \subseteq (N_3, E)\ then$
$WSim(N_1, N_3) \le WSim(N_2, N_3)$

Proof:

(i) Obvious from definition 3.3 .

(ii) Obvious from definition 3.3 .

(iii) Obvious from definition 3.3 .

(iv) Similar to proof of (iv) of theorem 3.2.

3.5 Example Here we consider example 3.3 of [15]. Let U={x_1,x_2,x_3} be the universal set and E={e_1,e_2, e_3} be the set of parameters. Let (N_1,E) and (N_2,E) be two neutrosophic soft sets over U such that their tabular representations are as follows:

Table 1: tabular representation of (N_1,E)

(N_1,E)	e_1	e_2	e_3
x_1	(0.2,0.4,0.7)	(0.5,0.1,0.3)	(0.4,0.2,0.3)
x_2	(0.7,0.0,0.4)	(0.0,0.4,0.8)	(0.5,0.7,0.3)
x_3	(0.3,0.4,0.3)	(0.6,0.5,0.2)	(0.5,0.7,0.1)

Table 2: tabular representation of (N_2,E)

(N_2,E)	e_1	e_2	e_3
x_1	(0.3,0.5,0.4)	(0.4,0.3,0.4)	(0.5,0.1,0.2)
x_2	(0.7,0.1,0.5)	(0.2,0.4,0.7)	(0.5,0.6,0.3)
x_3	(0.3,0.3,0.4)	(0.7,0.5,0.2)	(0.6,0.6,0.2)

Now by definition 3.1 similarity measure between (N_1,E) and (N_2,E) is given by *Sim*(N_1,N_2) = 0.91

3.6 Example

Let U={x_1,x_2,x_3} be the universal set and E={e_1,e_2, e_3} be the set of parameters. Let (A_1,E) and (A_2,E) be two neutrosophic soft sets over U such that their tabular representations are as follows:

Table 3: tabular representation of (A_1,E)

(A_1,E)	e_1	e_2	e_3
x_1	(0.1,0.2,0.1)	(0.2,0.1,0.1)	(0.1,0.1,0.2)
x_2	(0.3,0.1,0.2)	(0.2,0.2,0.3)	(0.7,0.2,0.2)
x_3	(0.9,0.3,0.1)	(0.1,0.1,0.2)	(0.2,0.3,0.8)

Table 4: tabular representation of (A_2,E)

(A_2,E)	e_1	e_2	e_3
x_1	(0.9,0.9,0.8)	(0.8,0.7,0.9)	(0.9,0.8,0.9)
x_2	(0.9,0.8,0.8)	(0.8,0.8,0.9)	(0.1,0.9,0.9)
x_3	(0.1,0.9,0.9)	(0.8,0.8,0.9)	(0.8,0.9,0.2)

Now by definition 3.1 similarity measure between (A_1,E) and (A_2,E) is given by *Sim*(A_1,A_2) = 0.32 .

3.7 Definition Let (N_1,E) and (N_2,E) be twoNSSsover the universe U. Then (N_1,E) and (N_2,E) are said be α - similar , denoted by $(N_1, E)\overset{\alpha}{\simeq}(N_2, E)$ if and only if *Sim*(N_1,N_2) > α for α ∈ (0,1). We call the two NSSs significantly similar if *Sim*(N_1,N_2) > 0.5 .

3.8 Definition Let (N_1,E) and (N_2,E) be twoNSSs over the universe U. Then (N_1,E) and (N_2,E) are said be substantially-similar if *Sim*(N_1,N_2) > 0.95 and is denoted by (N_1,E) ≡ (N_2,E) .

3.9 Definition In example 3.5 Sim(N_1,N_2) = 0.91> 0.5 , therefore (N_1,E) and (N_2,E) are significantly similar. Again in example 3.6 Sim(A_1,A_2) = 0.32 < 0.5 , therefore (A_1,E) and (A_2, E) are not significantly similar.

3.10 Theorem

Let (N_1,E) and (N_2,E) be two neutrosophic soft sets over the universe U and $\left(N_1^c, E\right)$ and $\left(N_2^c, E\right)$ be their complements respectively. Then

i. if $Sim(N_1, N_2) = \mu$ then $Sim(N_1^c, N_2^c) = \mu$, ($0 \le \mu \le 1$) .

ii. if $WSim(N_1, N_2) = \lambda$ then $WSim(N_1^c, N_2^c) = \lambda$, $0 \le \lambda \le 1$.

Proof : Straight forward from definition **2.7**, **3.1** and **3.3** .

4 Application of similarity measure of NSSs in pattern recognition problem

In this section we developed an algorithm for pattern recognition problem in neutrosophic soft set setting using similarity measure. A numerical example is given to demonstrate the effectiveness of the proposed method.
Steps of algorithm are as follows:

Step1: construct NSS(s) $\hat{N}_i$ (i = 1,2,3........,n)as ideal pattern(s).

Step2: construct NSS(s) $\hat{M}_j$ (j = 1,2,3........,m)for sample pattern(s) which is/are to be recognized.

Step3: calculate similarity measure between NSS(s) for ideal pattern(s) and sample pattern(s).

Step4: recognize sample pattern(s) under certain predefined conditions.

4.1 Example In order to demonstrate the application of the proposed method of measuring similarity between NSSs, we consider the medical diagnosis problem discussed in example 5.1 [15] as a supervised pattern recognition problem . In this example our proposed method is applied to determine whether an ill person having some visible symptoms is suffering from cancer or not suffering from cancer. We first construct an ideal NSS (known pattern) for cancer disease and NSS(sample pattern) for the ill person(s) and we also assume that if the similarity measure between these two NSSs is greater than or equal to **0.75** then the ill person is possibly suffering from the diseases.

Let U be the universal set, which contains only two elements x_1 = severe and x_2 = mild i.e. U={x_1,x_2}. Here the set of parameters E is a set of certain visible symptoms. Let E = {e_1,e_2,e_3,e_4,e_5}, where e_1 = headache, e_2 = fatigue, e_3 = nausea and vomiting , e_4 = skin changes, e_5 = weakness.

Step 1: construct an ideal NSS ($\hat{N}$,E) for illness (cancer) which can be done with the help of medical expert.

Table 5: tabular representation of NSS ($\hat{N}$,E) for cancer.

($\hat{N}$,E)	e_1	e_2	e_3	e_4	e_5
x_1	(0.6,0.2,0.3)	(0.7,0.3,0.4)	(0.4,0.3,0.6)	(0.8,0.2,0.3)	(0.5,0.3,0.2)
x_2	(0.4,0.1,0.2)	(0.3,0.1,0.2)	(0.2,0.2,0.4)	(0.3,0.1,0.4)	(0.2,0.1,0.3)

Step 2: construct NSSs for ill persons (patients) X and Y.

Table 6: tabular representation of NSS ($\hat{M}_1$,E) for patient X.

($\hat{M}_1$,E)	e_1	e_2	e_3	e_4	e_5
x_1	(0.7,0.3,0.4)	(0.8,0.2,0.5)	(0.4,0.2,0.5)	(0.8,0.1,0.2)	(0.5,0.3,0.2)
x_2	(0.3,0.2,0.3)	(0.2,0.2,0.3)	(0.3,0.1,0.3)	(0.3,0.2,0.3)	(0.1,0.2,0.2)

Table 7: tabular representation of NSS ($\hat{M}_2$, E) for patient Y.

($\hat{M}_2$,E)	e_1	e_2	e_3	e_4	e_5
x_1	(0.2,0.5,0.8)	(0.1,0.0,0.8)	(0.8,0.6,0.1)	(0.1,0.5,0.8)	(0.9,0.6,0.8)
x_2	(0.9,0.6,0.7)	(0.7,0.5,0.6)	(0.7,0.6,0.1)	(0.8,0.7,0.9)	(0.8,0.7,0.7)

Step 3: By definition 3.1 similarity measure between ($\hat{N}$,E) and ($\hat{M}_1$,E) is given by $Sim(\hat{N},\hat{M}_1) = 0.91$ and similarity measure between ($\hat{N}$,E) and ($\hat{M}_2$,E) is given by $Sim(\hat{N},\hat{M}_2) = 0.54$.

Step 4: Since $Sim(\hat{N},\hat{M}_1) = 0.91 >$ **0.75** therefore patient X is possibly suffering from cancer. Again since $Sim(\hat{N},\hat{M}_2) = 0.54 <$ **0.75** therefore patient Y is possibly not suffering from cancer.

The result obtained here is same as the result obtained in [15].

5 Comparison of different similarity measures for NSSs

In this section effectiveness of the proposed method is demonstrated by the comparison between the proposed similarity measure and existing similarity measures in NSS setting. Here we consider NSSs of examples 3.5, 3.6 and 4.1 for comparison of similarity measures as given in table 8.

Table 8: comparison of different similarity measures

NSSs→ / Similarity measure based on ↓	**(N_1,N_2)**	**(A_1,A_2)**	$(\hat{N}, \hat{M}_1)$	$(\hat{N}, \hat{M}_2)$
Hamming distance	0.71	0.24	0.69	0.31
Set theoretic approach	0.80	0.20	0.75	0.33
Proposed method	**0.91**	**0.32**	**0.92**	**0.54**

Table 8 shows that each method has its own measuring but the results of similarity measures by proposed method are emphatic over the other.

Conclusions

In this paper we proposed a new method of measuring degree of similarity and weighted similarity between two neutrosophic soft sets and studied some properties of similarity measure. Based on the comparison between the proposed method and existing methods introduced by Mukherjee and Sarkar[15], proposed method has been found to give strong similarity measure. A decision making method is developed based on similarity measure. Finally a fictitious numerical example is given to demonstrate the application of similarity measure of NSSs in a supervised pattern recognition problem. Next research work is to develop the application in other fields.

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