GUFBD / *GUJS* (2022) 12(4): 1207-1215
DOI: 10.17714/gumusfenbil.1179414 Araştırma Makalesi / *Research Article*

A novel distance measure for simplified neutrosophic sets with its applications in pattern recognition

Örüntü tanımadaki uygulamalarıyla basitleştirilmiş nötrosofik kümeler için yeni bir mesafe ölçüsü

Mesut KARABACAK*,[1]
[1]*Atatürk University, Faculty of Science, Department of Mathematics, Erzurum, Türkiye*

• Geliş tarihi / *Received*: 23.09.2022 • Düzeltilerek geliş tarihi / *Received in revised form*: 10.10.2022 • Kabul tarihi / *Accepted*: 13.10.2022

Abstract
The simplified neutrosophic set (SNS) is an essential modelling technique for effectively modelling and expressing inconsistent and ambiguous information. A crucial tool often utilized in a number of contexts, from clustering approach to medical diagnostics, is the distance measure. Although there are several distance measures in neutrosophic literature, some of them have the drawback of not providing the general requirements of the distance measure for certain particular values. We introduce a brand-new distance measure in this paper to deal with the relationship between two SNSs. When compared to alternative distance measures that are already in use, it appears that the new distance measure produces better results. The suggested distance measure has been put to use in a number of numerical instance concerning pattern recognition that is medical diagnosis.

Keywords: Simplified neutrosophic set, Pattern recognition, Distance measure, Medical diagnosis

Öz
Basitleştirilmiş nötrosofik küme (BNK), tutarsız ve belirsiz bilgileri etkili bir şekilde ifade etmek ve işlemek için temel bir modelleme tekniğidir. Kümeleme analizinden tıbbi teşhise kadar birçok bağlamda sıklıkla kullanılan önemli bir araç, mesafe ölçümüdür. Nötrosofik literatüründe birkaç uzaklık ölçütü olmasına rağmen, bunlardan bazıları belirli değerler için mesafe ölçüsünün genel gereksinimlerini sağlamama dezavantajına sahiptir. Bu yazıda iki basitleştirilmiş nötrosofik küme arasındaki ilişkiyi ele almak için yepyeni bir mesafe ölçüsü sunuyoruz. Hâlihazırda kullanımda olan alternatif mesafe ölçüleri ile karşılaştırıldığında, yeni mesafe ölçüsünün daha iyi sonuçlar verdiği görülmektedir. Önerilen mesafe ölçüsü, tıbbi teşhis de olmak üzere örüntü tanıma ile ilgili sayısal bir örnekte kullanıma sunulmuştur.

***Anahtar kelimeler**: Basitleştirilmiş nötrosofik kümeler, Örüntü tanıma, Mesafe ölçüsü, Tıbbi teşhis*

*Mesut KARABACAK; mkarabacak@atauni.edu.tr, Tel: (0442) 231 15 57, orcid.org/0000-0002-0057-8115

1. Introduction
1. Giriş

In a world full of uncertainty, clustering approaches and pattern recognition are two of the most crucial scientific areas. The intricacy of the data or information pertaining to the issue area makes it impossible to handle the uncertain data with standard tools. Therefore, the necessity for new modelling tool development is unavoidable. First, in 1965, Zadeh (1965) introduced the fuzzy sets (FSs). The fact that each of its members has only one membership degree is its most obvious trait. Since the FSs definition, other scholars have attempted to glean various expansions of this idea. The FSs were extended by Atanassov (1986) to intuitionistic fuzzy sets (IFSs). Each of its members has a degree of membership and non-membership, which is one of its distinctive features. Then, two of the most important information metrics are the distance measure and its counterpart, the similarity measure. Many scholars have used the measures for clustering analysis and pattern recognition (Balopoulos, 2007; Hatzimichailidis et al., 2012; Khatibi & Montazer, 2009; Tian, 2013; Zhang et al., 2007; Wang et al., 2011). FSs, and IFSs in the methodologies discussed above can only manage uncertainty and partial information; inconsistent and ambiguous information, which frequently exists in the actual life, cannot be handled. The idea of neutrosophic sets (NSs), which is an extension of FSs and IFSs, was developed philosophically by Smarandache (1999) in order to more effectively handle inconsistent and uncertain information. Its distinguishing feature is that each of its members has separately earned degrees in truth-membership, indeterminate-membership, and falsity-membership. However, applying NSs to actual decision-making problems is challenging. The definitions of a single-valued neutrosophic set (SVNS) and a simplified neutrosophic set (SNS), which are the subclasses of a neutrosophic set, were derived by Wang et al. (2010) and Ye (2014), respectively to address this issue. Both SVNS and SNSs have been used widely for modelling ambiguous and inconsistent information that is occurred in clustering approaches, machine learning, medical diagnosis, and pattern recognition because evolving technology necessitates an increasing amount of information processing processes. Two crucial tools are utilized to assess the similarity or difference between items in an uncertain environment: the similarity and distance measures. Because of their capacity to handle ambiguity and the fact that they have accumulated numerous works the related with similarity or distance measurements in neutrosophic environment, increasing numbers of researchers have begun to explore SVNSs and SNSs (Mondal et al., 2018; Pramanik et al., 2017; Majumdar & Samanta, 2014; Ren et al., 2019; Ye and Fu, 2016; Shahzadi et al., 2017; Şahin & Liu, 2015; Şahin & Küçük, 2015; Şahin, 2019; Ye, 2014a, 2014b, 2014c, 2015, 2016, 2017a, 2017b; Luo & Zhao, 2018; Köseoğlu, 2022a, 2022b).

Even though the current distance measurement considers how elements interact, some situations frequently yield irrational findings (see Example 1). As a result, it is currently unclear how to produce a reliable distance measurement. We provide a unique distance between SNSs matching the axiomatic definition in Section 3 to address these circumstances.

In a broader sense, this study suggests a novel distance measure of SNSs and uses it to solve decision-making issues. Thus, the remainder of the study is put together as follows. We present a summary of several fundamental SNS ideas in Section 2. The Section 3 examines the shortcomings of the current SNS distance measures. Additionally, we construct a SNS distance measure and go through some of its characteristics. In Section 4, the established distance measure is employed to address a problem of pattern recognition concerning medical diagnosis to show their efficacy and validity. Final section provides conclusions.

2. Neutrosophic sets
2. Nötrosofik kümeler

To accomplish the objectives, we succinctly outline certain fundamental concepts pertaining to single-valued neutrosophic sets and associated distance measures from axiomatic qualities in this section.

Definition 1. (Smarandache, 1999) Let X be a space of points (objects) and $x \in X$. A neutrosophic set A in X is defined by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$. $T_A(x)$, $I_A(x)$ and $F_A(x)$ are real standard or real nonstandard subsets of $]0^-, 1^+[$. That is $T_A(x): X \to]0^-, 1^+[$, $I_A(x): X \to]0^-, 1^+[$ and $F_A(x): X \to]0^-, 1^+[$. There is not restriction on the sum of $T_A(x)$, $I_A(x)$ and $F_A(x)$, so $0^- \leq \sup T_A(x) \leq \sup I_A(x) \leq \sup F_A(x) \leq 3^+$.

Definition 2. (Ye, 2014) Let X be a discourse universe, then a simplified neutrosophic set (SNS) is defined as:

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in X\} \quad (1)$$

where, $T_A: X \to [0,1]$, $I_A: X \to [0,1]$ and $F_A: X \to [0,1]$ with $0 \le T_A(x) + I_A(x) + F_A(x) \le 3$ for all $x \in X$. The values $T_A(x), I_A(x)$ and $F_A(x)$ express the degree of truth-membership, the degree of indeterminacy-membership and the degree of falsity membership of x to A, respectively.

Definition 3. (Ye, 2014) The complement of simplified neutrosophic set A is denoted by A^c and is defined as $T_A^c(x) = F_A(x)$, $I_A^c(x) = 1 - I_A(x)$, and $F_A^c(x) = T_A(x)$ for all $x \in X$. That is,

$$A^c = \{\langle x, F_A(x), 1 - I_A(x), T_A(x)\rangle : x \in X\}. \quad (2)$$

Definition 4. (Ye, 2014) A simplified neutrosophic set A is contained in the other simplified neutrosophic set B, $A \subseteq B$, iff $T_A(x) \le T_B(x)$, $I_A(x) \ge I_B(x)$ and $F_A(x) \ge F_B(x)$ for each $x \in X$. The SNSs A and B are equal, denoted as $A = B$, iff $A \subseteq B$ and $B \subseteq A$.

The collection of all the SVNSs in X shall be referred to as $SNS(X)$.

3. A new distance measure of SNSs

3. BNK'lerin yeni bir mesafe ölçüsü

In this section, firstly, the existing distance measures for the SNSs are presented, and secondly, a new distance measure is defined.

3.1. The existing distance measure of SNSs

3.1. BNK'lerin varolan mesafe ölçüleri

Suppose that $U = \{x_1, x_2, \dots x_n\}$ is a discussion universe, and A and B are two SNSs in U. Then the some current distance measures between SNSs A and B can be presented as follows:

For $\Delta T(x_i) = |T_A(x_i) - T_B(x_i)|$, $\Delta I(x_i) = |I_A(x_i) - I_B(x_i)|$, and $\Delta F(x_i) = |F_A(x_i) - F_B(x_i)|$,

(1) The extended Hausdorff distance (Şahin and Küçük, 2014):

$$D_H(A,B) = \frac{1}{n}\sum_{i=1}^{n} \max\big(\Delta T(x_i), \Delta I(x_i), \Delta F(x_i)\big)$$

(2) The normalized-Hamming distance (Majumdar and Samanta, 2014):

$$D_{NH}(A,B) = \frac{1}{3n}\sum_{i=1}^{n}\big(\Delta T(x_i) + \Delta I(x_i) + \Delta F(x_i)\big)$$

(3) The normalized-Euclidean distance (Majumdar and Samanta, 2014):

$$D_{NE}(A,B) = \left\{\frac{1}{3n}\sum_{i=1}^{n}\left(\Delta T(x_i)^2 + \big(\Delta I(x_i)\big)^2 + \big(\Delta F(x_i)\big)^2\right)\right\}^{\frac{1}{2}}$$

(4) The similarities of cosine (Ye, 2015):

$$S_{Cos1}(A,B) = \frac{1}{n}\sum_{i=1}^{n} \cos\left\{\frac{\pi\big(\Delta T(x_i) + \Delta I(x_i) + \Delta F(x_i)\big)}{6}\right\}$$

$$S_{Cos2}(A,B) = \frac{1}{n}\sum_{i=1}^{n} \cos\left\{\pi\frac{\max\big(\Delta T(x_i), \Delta I(x_i), \Delta F(x_i)\big)}{2}\right\}$$

and the distances between them are shown by $D_{C1}(A,B) = 1 - S_{C1}(A,B)$ and $D_{C2}(A,B) = 1 - S_{C2}(A,B)$.

(5) The cotangent similarities (Ye, 2017a):

$$S_{Cot1}(A,B) = \frac{1}{n}\sum_{i=1}^{n} \cot\left\{\frac{\pi}{4} + \frac{\pi}{12}\big(\Delta T(x_i) + \Delta I(x_i) + \Delta F(x_i)\big)\right\},$$

$$S_{Cot2}(A,B) = \frac{1}{n}\sum_{i=1}^{n} \cot\left\{\frac{\pi}{4} + \frac{\pi}{4}\big(\max(\Delta T(x_i), \Delta I(x_i), \Delta F(x_i))\big)\right\},$$

and the distances between them are shown by $D_{Co}(A,B) = 1 - S_{Co}(A,B)$ and $D_{Co2}(A,B) = 1 - S_{Co2}(A,B)$.

(6) The tangent similarities (Ye and Fu, 2016):

$$S_{Tan1}(A,B) = 1 - \frac{1}{n}\sum_{i=1}^{n} \tan\left\{\frac{\pi\big(\Delta T(x_i) + \Delta I(x_i) + \Delta F(x_i)\big)}{12}\right\},$$

$$S_{Tan2}(A,B) = 1 - \frac{1}{n}\sum_{i=1}^{n} \tan\left\{\pi\frac{\max\big(\Delta T(x_i), \Delta I(x_i), \Delta F(x_i)\big)}{4}\right\},$$

and the distances between them are shown by $D_{Tan1}(A,B) = 1 - S_{Tan1}(A,B)$ and $D_{Tan2}(A,B) = 1 - S_{Tan2}(A,B)$.

(7) The logarithmic similarities (Mondal et al., 2018):

$$S_{L1}(A,B) = \frac{1}{n}\sum_{i=1}^{n} \log_2\left\{2 - \left(\frac{1}{3}\big(\Delta T(x_i) + \Delta I(x_i) + \Delta F(x_i)\big)\right)\right\}$$

$S_{L2}(A,B) = \frac{1}{n}\left(\lambda\left[\sum_{i=1}^{n}\log_2\left\{2-\left(\frac{1}{3}(\Delta T(x_i)+\Delta I(x_i)+\Delta F(x_i))\right)\right\}\right]+(1-\lambda)\left[\sum_{i=1}^{n}\log_2\left\{2-\max\left(\frac{1}{3}(\Delta T(x_i),\Delta I(x_i),\Delta F(x_i))\right)\right\}\right]\right.$

and distances between them are shown by $D_{L1}(A,B) = 1 - S_{L1}(A,B)$ and $D_{L2}(A,B) = 1 - S_{L2}(A,B)$.

The aforementioned measures have been widely employed, but they also have some disadvantages, which are demonstrated with the help of the next numerical example.

Example 1. Let A, B, C and D be four SNSs on X, given by $A = \{\langle 0.5,0,0\rangle, \langle 0,0.6,0\rangle\}$, $B = \{\langle 0,0.3,0\rangle, \langle 0.4,0,0\rangle\}$, $C = \{\langle 0,0,0.3\rangle, \langle 0.4,0,0\rangle\}$. If we apply the existing measures (Şahin and Küçük, 2014; Majumdar and Samanta, 2014; Majumdar and Samanta, 2014; Ye, 2015; Ye, 2017a; Ye and Fu, 2016; Mondal et al., 2018) defined above, then we obtain the following:

Table 1. Computed values of distances regarding Example 1.
Tablo 1. *Örnek 1 ile ilgili hesaplanan mesafe değerleri*

Pair	D_H	D_{NH}	D_{NE}	D_{Cos1}	D_{Cos2}	D_{Tan1}	D_{Tan2}	D_{L1}	D_{L2}	D_{Cot1}	D_{Cot2}
(A,B)	0.550	0.300	0.379	0.110	0.353	0.240	0.717	0.235	0.327	0.387	0.630
(A,C)	0.550	0.300	0.379	0.110	0.353	0.240	0.717	0.235	0.327	0.387	0.630

According to Table 1, for the simplified neutrosophic sets A, B and C, if the distance measures between sets A and B, and A and C are equal, it is expected that sets B and C will be equal, but none of the distance measures discussed above can meet this expectation. Thus, we conclude that these measures are unable and inconsistent to perform the information measure between SNSs. Then, we can say that the distance measures defined above are not accurate and useful in actual decision-making circumstances.

As a result, it is necessary to create a new measure of distance in order to resolve the disadvantages of the current measures.

3.2. The proposed measure for SNSs
3.1. BNK'ler için amaçlanan mesafe ölçüsü

Definition 5. A mapping $D: SNS(X) \times SNS(X) \to [0,1]$ is a distance measure of the SNSs if it meets the following conditions:

(D1) $0 \le D(A,B) \le 1$ for all $A, B \in SNS(X)$,
(D2) $D(A,A) = 0$ for all $A \in SNS(X)$,
(D3) $D(A,B) = D(B,A)$ for all $A, B \in SNS(X)$.
(D4) For all $A, B, C \in SNS(X)$, if $A \subseteq B \subseteq C$, then $\max\{D(A,B), D(B,C)\} \le D(A,C)$.

There are a basic relation between distance and similarity measures
That is, for $A, B \in SNS(X)$, it follows that $S(A,B) = 1 - D(A,B)$.

Definition 6. Let $X = \{x_1, x_2, \ldots x_n\}$ be a discourse universe and A, B be two arbitrary SNSs in X. Then a distance measure between SNSs is define by

$$D_M(A,B) = \frac{1}{n}\sum_{i=1}^{n}\frac{D_i^T(A,B) + D_i^I(A,B) + D_i^F(A,B)}{3}, \quad (3)$$

where

$D_i^T(A,B) = 1 - \frac{e^{-|T_A(x_i)-T_B(x_i)|} - e^{-1}}{1-e^{-1}}$, $D_i^I(A,B) = |I_A(x_i) - I_B(x_i)|$, and $D_i^F(A,B) = \left|\sqrt{F_A(x_i)} - \sqrt{F_B(x_i)}\right|$ $(i = 1,2,\ldots,n)$.

Proposition 1. Let X be a discourse universe. Then $D_i^T(A,B)$, $D_i^I(A,B)$ and $D_i^F(A,B)$ $(i = 1,2,\ldots,n)$ meet the following requirements:

(1) $0 \le D_i^T(A,B), D_i^I(A,B), D_i^F(A,B) \le 1$ for all $A, B \in SNS(X)$,
(2) $D_i^T(A,A) = 0, D_i^I(A,A) = 0, D_i^F(A,A) = 0$ for all $A, B \in SNS(X)$,
(3) $D_i^T(A,B) = D_i^T(B,A)$, $D_i^I(A,B) = D_i^I(B,A)$ and $D_i^F(A,B) = D_i^F(B,A)$ for all $A, B \in SNS(X)$;
(4) For all A, B and $C \in SNS(X)$, if $A \subseteq B \subseteq C$ then
$\max\{D_i^T(A,B), D_i^T(B,C)\} \le D_i^T(A,C)$,
$\max\{D_i^I(A,B), D_i^I(B,C)\} \le D_i^I(A,C)$,
$\max\{D_i^F(A,B), D_i^F(B,C)\} \le D_i^F(A,C)$.

Proof. (1) For $A, B \in SNS(X)$, we have $0 \le |T_A(x_i) - T_B(x_i)| \le 1$, $0 \le |I_A(x_i) - I_B(x_i)| \le 1$,

$0 \leq \left|\sqrt{F_A(x_i)} - \sqrt{F_B(x_i)}\right| \leq 1$ and $e^{-1} \leq e^{-|T_A(x_i)-T_B(x_i)|} \leq 1$.

(2) For $A, B \in SNS(X)$ and $A = B$, we have $T_A(x_i) = T_B(x_i)$, $I_A(x_i) = I_B(x_i)$, and $F_A(x_i) = F_B(x_i)$. Then it means that $D_i^T(A,B) = 0, D_i^I(A,B) = 0, D_i^F(A,B) = 0$.

(3) It is obvious.

(4) For all $A, B, C \in SNS(X)$ and $A \subseteq B \subseteq C$, we have $T_A(x_i) \leq T_B(x_i) \leq T_C(x_i)$, $I_C(x_i) \leq I_B(x_i) \leq I_A(x_i)$, and $F_C(x_i) \leq F_B(x_i) \leq F_A(x_i)$. Then, it follows that $|T_A(x_i) - T_B(x_i)| \leq |T_A(x_i) - T_C(x_i)|$ and $|T_B(x_i) - T_C(x_i)| \leq |T_A(x_i) - T_C(x_i)|$ for all $i = i, 2, \ldots, n$ and so we have $e^{-|T_A(x_i)-T_C(x_i)|} \leq e^{-|T_A(x_i)-T_B(x_i)|}$ and $e^{-|T_A(x_i)-T_C(x_i)|} \leq e^{-|T_B(x_i)-T_C(x_i)|}$ and thus

(5)

$1 - \frac{e^{-|T_A(x_i)-T_B(x_i)|} - e^{-1}}{1-e^{-1}} \leq 1 - \frac{e^{-|T_A(x_i)-T_C(x_i)|} - e^{-1}}{1-e^{-1}}$ and $1 - \frac{e^{-|T_B(x_i)-T_C(x_i)|} - e^{-1}}{1-e^{-1}} \leq 1 - \frac{e^{-|T_A(x_i)-T_C(x_i)|} - e^{-1}}{1-e^{-1}}$.

Then we have $\max\{D_i^T(A,B), D_i^T(B,C)\} \leq D_i^T(A,C)$. Moreover, since$|T_A(x_i) - T_B(x_i)| \leq |T_A(x_i) - T_C(x_i)|$ and $|T_B(x_i) - T_C(x_i)| \leq |T_A(x_i) - T_C(x_i)|$, this implies that $\max\{|T_A(x_i) - T_B(x_i)|, |T_B(x_i) - T_C(x_i)|\} \leq |T_A(x_i) - T_C(x_i)|$ for all $i = i, 2, \ldots, n$. Then $\max\{D_i^T(A,B), D_i^T(B,C)\} \leq D_i^T(A,C)$. Finally, the other can be shown similarly.

Theorem 1. For $A, B \in SNS(X)$, the expression $D_M(A,B)$ meets the following conditions:

(1) $0 \leq D_M(A,B) \leq 1$ for all $A, B \in SNS(X)$,
(2) $D_M(A,\mathrm{A}) = 0$ for all $A \in SNS(X)$,
(3) $D_M(A,\mathrm{B}) = D_M(B,\mathrm{A})$ for all $A, B \in SNS(X)$.
(4) For all $A, B, C \in SNS(X)$, if $A \subseteq B \subseteq C$, then $\max\{D_M(A,\mathrm{B}), D_M(B,\mathrm{C})\} \leq D_M(A,\mathrm{C})$.

Proof. It is easy to prove this proof from Proposition 1.

The benefits of the proposed distance measure above all other distance measures, which are based on a number of counterintuitive instances, are presented in the subsection through a comparative analysis.

Example 2. If we apply the proposed distance measure D on the data considered in Example 1, then we obtain $D(A,B) = 0.341$ and $D(A,C) = 0.382$. With this result, we can easily see that the distance measure developed meets the expectation $B \neq C$. Above all, we might easily hope that the created distance measure may resolve the circumstances when the conventional distance measurements lead to counterintuitive results. As a result, the established distance measure is the most logical one.

4. Applications
4. Uygulamalar

Pattern recognition is a well-known application area in the field of medicine, and its numerous uses are supplied based on neutrosophic data (Broumi and Smarandache, 2015; Mondal et al., 2018; Shahzadi et al., 2017; Ye, 2015; Ye and Fu, 2016). We provide a different approach to address the issue of medical diagnosis in light of the recently created distance measure. Then, we can create a useful pattern recognition method for SNSs as follows:

Let $X = \{x_1, x_2, \ldots, x_n\}$ be a discourse universe. Suppose that there exist m patterns which are characterized by the form of SNSs, denoted by $K_j = \left\{\langle x_i, T_{K_j}(x_i), I_{K_j}(x_i), F_{K_j}(x_i)\rangle : x_i \in X\right\}$ $(j = 1,2,\ldots,m)$ in X and assume there is a sample pattern presented by an SNS $S = \{\langle x_i, T_S(x_i), I_S(x_i), F_S(x_i)\rangle : x_i \in X\}$. The recognition technical is as follows:

Step 1. Obtain the distance measure $D(K_j, P)$ between K_j $(j = 1,2,\ldots,m)$ and P.
Step 2. Determine the minimum one $D(K_{j0}, P)$ from $D(K_j, P)$ $(j = 1,2,\ldots,m)$, that is, $D(K_{j0}, P) = \min_{1\leq j\leq m}\{D(K_j, P)\}$. Thus, the sample pattern P belongs to the category of pattern K_{j_0}.

Example 3. (Medical diagnosis) Let us consider the medical diagnosis problem adapted from (Ye, 2015). Assume that a set of diagnoses is

$$K = \left\{\begin{array}{c} K_1 \text{ (viral fever)}, K_2 \text{ (malaria)}, \\ K_3 \text{ (typhoid)}, K_4 \text{ (gastritis)}, K_5 \text{ (stenocardia)} \end{array}\right\}$$

and a set of symptoms is

$$S = \left\{ \begin{matrix} s_1 \text{ (fever)}, s_2 \text{ (headache)}, s_3 \text{ (stomach pain)}, \\ s_4 \text{ (cough)}, s_5 \text{ (chest pain)} \end{matrix} \right\}.$$

The characteristics of the disorders under consideration are shown in Table 2, together with the neutrosophic symptom levels (represented by SNSs) for each. The truth-membership, indeterminacy-membership, and falsity-membership values are used to describe the neutrosophic symptom values as a triple of numbers.

Suppose that we have a sample from patient P in the field of medical diagnosis who has all symptoms, which are characterized by the SNS data:

$$\text{P(patient)} = \left\{ \begin{matrix} \langle s_1, 0.8,0.2,0.1 \rangle, \langle s_2, 0.6,0.3,0.1 \rangle, \langle s_3, 0.2,0.1,0.8 \rangle, \\ \langle s_4, 0.6,0.5,0.1 \rangle, \langle s_5, 0.1,0.4,0.6 \rangle \end{matrix} \right\}.$$

Table 2. Characteristics of the illnesses that SNSs represent
Tablo 2. *BNK'ler tarafından temsil edilen hastalıkların karakteristik değerleri.*

	s_1 (fever)	s_2 (headache)	s_3 (stomach p.)	s_4 (cough)	s_5 (chest pain)
K_1	$\langle s_1, 0.4,0.6,0.0 \rangle$	$\langle s_2, 0.3,0.5,0.5 \rangle$	$\langle s_3, 0.1,0.3,0.7 \rangle$	$\langle s_4, 0.4,0.3,0.3 \rangle$	$\langle s_5, 0.1,0.2,0.7 \rangle$
K_2	$\langle s_1, 0.7,0.3,0.0 \rangle$	$\langle s_2, 0.2,0.2,0.6 \rangle$	$\langle s_3, 0.0,0.1,0.9 \rangle$	$\langle s_4, 0.7,0.3,0.0 \rangle$	$\langle s_5, 0.1,0.1,0.8 \rangle$
K_3	$\langle s_1, 0.3,0.4,0.3 \rangle$	$\langle s_2, 0.6,0.3,0.1 \rangle$	$\langle s_3, 0.2,0.1,0.7 \rangle$	$\langle s_4, 0.2,0.2,0.6 \rangle$	$\langle s_5, 0.0,0.0,0.9 \rangle$
K_4	$\langle s_1, 0.1,0.2,0.7 \rangle$	$\langle s_2, 0.2,0.4,0.4 \rangle$	$\langle s_3, 0.8,0.2,0.0 \rangle$	$\langle s_4, 0.2,0.1,0.7 \rangle$	$\langle s_5, 0.2,0.1,0.7 \rangle$
K_5	$\langle s_1, 0.1,0.1,0.8 \rangle$	$\langle s_2, 0.0,0.2,0.8 \rangle$	$\langle s_3, 0.2,0.0,0.8 \rangle$	$\langle s_4, 0.2,0.0,0.8 \rangle$	$\langle s_5, 0.8,0.1,0.1 \rangle$

We now use the algorithm to address the aforementioned diagnosis problem.

Step1. Using Eq.(3), we calculate the distance measures $D(K_j, P)$ between K_j $(j = 1,2, \dots, m)$ and P. The obtain results are given in Table 3.

Table 3. Distance measure values for SNS information
Tablo 3. *BNK bilgileri için mesafe ölçüm değerleri*

	K_1 (viral fever)	K_2 (malaria)	K_3 (typhoid)	K_4 (gastritis)	K_5 (stenocardia)
$D(K_i, P)$	0.241	**0.205**	0.208	0.394	0.408
$D(K_i, P)$ (Ye, 2015)	0.687	**0.681**	0.692	0.726	0.745
$D(K_i, P)$ (Ye, 2015)	0.704	**0.702**	0.719	0.796	0.813

We are able to provide the patient P with the appropriate diagnosis by taking into account the distance measure presented in Eq. (3). The highest distance measure suggests the correct diagnosis, according to the theory of minimum distance degree. Table 4 contains the acquired results. By examining the facts in Table 4, we may conclude that the patient P has K_2 (malaria). The end result is same with Ye's approach (2015) yielded.

4.1. Comparison and discussion of results
4.1. Sonuçların tartışılması ve karşılaştırması

We demonstrate a general comparison study using the provided example to show benefits of the developed distance measure over the current distance measures.

According to Table 4, all of results under different distance measures is same for the related pattern recognition problem. As it was already indicated above, there are significant limitations to the current distance measures in particular situations, and they sometimes cannot account for ludicrous or illogical facts. As a result, the developed distance measure of SNSs is better than the current distance measures of SNSs in that it solves the counter-intuitive cases of the existing distance measures under the simplified neutrosophic information.

Table 4. The outcomes of additional distance measurements now in use for the pattern identification issue addressed in Example 1
Tablo 4. *Örnek 1'de tartışılan örüntü tanıma problemi için mevcut diğer mesafe ölçümlerinden elde edilen sonuçlar*

Distance Measure	K_1 (viral fever)	K_2 (malaria)	K_3 (typhoid)	K_4 (gastritis)	K_5 (stenocardia)	Results
D_H	0.280	**0.260**	0.300	0.560	0.580	K_2- malaria
D_{NH}	0.207	**0.167**	0.200	0.367	0.407	K_2- malaria
D_{NE}	0.238	**0.214**	0.271	0.440	0.489	K_2- malaria
D_{Cos1}	0.687	**0.681**	0.692	0.726	0.745	K_2- malaria
D_{Cos2}	0.702	**0.701**	0.719	0.796	0.813	K_2- malaria
D_{Tan1}	0.055	**0.044**	0.054	0.100	0.112	K_2- malaria
D_{Tan2}	0.075	**0.070**	0.082	0.161	0.169	K_2- malaria
D_{Cot1}	0.277	**0.227**	0.256	0.449	0.479	K_2- malaria
D_{Cot2}	0.055	**0.033**	0.362	0.631	0.637	K_2- malaria
D_{L1}	0.159	**0.127**	0.157	0.297	0.337	K_2- malaria
D_{L2} ($\lambda = 0.5$)	0.347	**0.269**	0.365	0.779	0.981	K_2- malaria

In addition, in Figure 1, we can easily see that the sample has the diagnosis of malaria according to all the discussed distance measures.

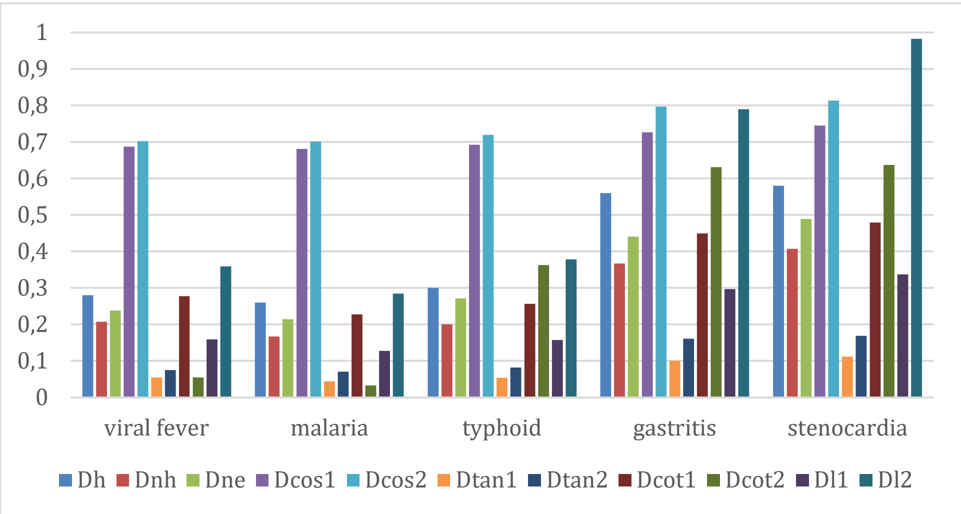

Figure 1. The results of Example 1 according to the distance measures
Şekil 1. *Örnek 1'in mesafe ölçülerine göre sonuçları*

5. Conclusion
5. Sonuç

A fundamental factor in establishing the link between things is the distance measure. Numerous distance measures have been put out in the neutrosophic literature from various viewpoints. However, the majority of them have a few situations that defy logic. This study was created a brand-new SNS distance measure that addresses the circumstances where it is counter-intuitive. The usefulness and benefits of our suggested distance measure were evaluated through comparison with other existing distance measures. Then, using it to resolve a decision-making issues in a streamlined neutrosophic environment, we applied it to real-world application including medical diagnosis. By examining the data, we can see that the developed distance measure can be used to manage simplified neutrosophic information as well as provide decision-makers. The new SNS distance measurement can be used in subsequent research in fields including cluster approaches, image processing, and decision-making.

Yazar katkısı
Author contribution

Bu makalede uygulanan metodoloji, kavramsallaştırma, veri toplama, hesaplama, yazma, görselleştirme ve inceleme işlemleri yazar Mesut KARABACAK tarafından yapılmıştır.

Etik beyanı
Declaration of ethical code

Bu çalışmada, "Yükseköğretim Kurumları Bilimsel Araştırma ve Yayın Etiği Yönergesi" kapsamında uyulması gerekli tüm kurallara uyulduğunu, bahsi geçen yönergenin "Bilimsel Araştırma ve Yayın Etiğine Aykırı Eylemler" başlığı altında belirtilen eylemlerden hiçbirinin gerçekleştirilmediğini taahhüt ederim. Ayrıca bu çalışmada kullanılan materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel izin gerektirmediğini beyan ederim.

Çıkar çatışması beyanı
Conflicts of interest

Yazar herhangi bir çıkar çatışması olmadığını beyan eder.

References
Kaynaklar

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *20*(1), 87–96.

Altun, F., Şahin, R., and Güler, C. (2020). Multi-criteria decision making approach based on PROMETHEE with probabilistic simplified neutrosophic sets. *Soft Computing*, 24(7), 4899-4915.

Balopoulos, V., Hatzimichailidis, A.G., Papadopoulos, B.K. (2007). Distance and similarity measures for fuzzy operators. *Inf Sci* , 177(11):2336–2348.

Broumi S, Smarandache F (2015) Extended Hausdorff distance and similarity measures for neutrosophic refined sets and their applications in medical diagnosis. *J New Theory* 7:64–78.

Hatzimichailidis, A.G., Papakostas, G.A. and Kaburlasos, V.G. (2012). A novel distance measure of intuitionistic fuzzy sets and its application to pattern recognition problems, *International Journal of Intelligent Systems* 27(4) 396-409.

Khatibi, V. and Montazer, G.A. (2009). Intuitionistic fuzzy set vs. fuzzy set application in medical pattern recognition *Artificial Intelligence in Medicine*. 47, 43-52.

Köseoğlu, A. and Şahin, R. (2021). Correlation coefficients of simplified neutrosophic multiplicative sets and their applications in clustering analysis. *Journal of Ambient Intelligence and Humanized Computing*, 1-22.

Köseoğlu, A. (2022a). Subsethood measure for picture fuzzy sets and its applications on multicriteria decision making. *Gümüşhane Üniversitesi Fen Bilimleri Dergisi*, 12(2), 385-394.

Köseoğlu, A. (2022b). Intuitionistic multiplicative set approach for green supplier selection problem using TODIM method. *Journal of Universal Mathematics,* 5(2), 149-158.

Luo, M. and Zhao, R.A. (2018). Distance measure between intuitionistic fuzzy sets and its application in medical diagnosis, *Artificial Intelligence in Medicine* 89, (2018), 34-39.

Majumdar, P., and Samanta, S.K. (2014). On Similarity and Entropy of Neutrosophic Sets, *Journal of Intelligent and Fuzzy Systems*, 26(3): 1245–1252.

Mondal K, Pramanik S, Giri BC. (2018) Hybrid Binary Logarithm Similarity Measure for MAGDM Problems under SVNS Assessments, *Neutrosophic Sets and Systems*, 20:12-25.

Pramanik S., Biswas, P. and Giri, B.C. (2017). Hybrid vector similarity measures and their applications to multi-attribute decision making under neutrosophic environment. *Neural Computing & Applications*, 28(5): 1163-1176

Ren HP, Xiao SX, Zhou H (2019) A Chi-square distance-based similarity measure of single valued neutrosophic set and applications. *Int J Comput Commun control* 14:78–89.

Shahzadi, G., Akram, M., Borumand A. and Saeid, A.B. (2017). An Application of Single-Valued Neutrosophic Sets in Medical Diagnosis, *Neutrosophic Sets and Systems*, 18.

Şahin, R. and Liu, P.D. (2015). Maximizing deviation method for neutrosophic multiple attribute decision making with incomplete weight information, *Neural Computing and Applications*, https://doi.org/10.1007/s00521-015-1995-8.

Şahin, R. and Küçük, A. (2015). Subsethood measure for single valued neutrosophic sets. *J. Intell. Fuzzy Syst*., 29(2): 525–530.

Şahin, R. (2019). An approach to neutrosophic graph theory with applications. *Soft Comput.* 23(2), 569-581

Smarandache, F. (1999). A unifying field in logics. neutrosophy: Neutrosophic probability, set and logic, American Research Press, Rehoboth.

Tian, M.Y. (2013). A new fuzzy similarity based on cotangent function for medical diagnosis, *Adv. Model. Optim.* 15 (2) 151–156.

Wang, Z., Xu, Z., Liu, S. and Tang, J. (2011). A Netting Clustering Analysis Method under Intuitionistic Fuzzy Environment, *Applied Soft Computing*, 11, 5558–5564.

Wang, H., Smarandache, F., Zhang, Y.Q. and Sunderraman, R. (2010). Single valued neutrosophic sets, *Multispace and Multistructure* 4: 410–413.

Ye, J. (2014a) Single Valued Neutrosophic Minimum Spanning Tree and Its Clustering Method, *Journal of Intelligent Systems*, 23(3) 311–324.

Ye, J. (2014b). Vector similarity measures of simplified neutrosophic sets and their application in multicriteria decision making. *International Journal of Fuzzy Systems*, 16, 204–211.

Ye, J. (2014c). A multicriteria decision-making method using aggregation operators for simplified neutrosophic sets, *J. Intell. Fuzzy Syst.* 26 (5) 2459–2466.

Ye, J. (2015). Improved cosine similarity measures of simplified neutrosophic sets for medical diagnoses. *Artif Intell Med*. 63(3):171–179.

Ye, J. and Fu, J. (2016). Multi-period medical diagnosis method using a single valued neutrosophic similarity measure based on tangent function. *Computer Methods and Programs in Biomedicine* 123, 142-149.

Ye, J. (2016). Fault Diagnoses of Hydraulic Turbine Using the Dimension Root Similarity Measure of Single-valued Neutrosophic Sets. *Intelligent Automation & Soft Computing*. https://doi.org/10.1080/10798587.2016.1261955 .

Ye, J. (2017a). Single-valued neutrosophic similarity measures based on cotangent function and their application in the fault diagnosis of steam turbine. *Soft Computing* 21(3): 817-825.

Ye, J. (2017b). Single-Valued Neutrosophic Clustering Algorithms Based on Similarity Measures, *Journal of Classification* 34(1) 148-162.

Zadeh, L.A. (1965). *Fuzzy sets, Inf. Control* 8: 338–353.

Zhang, H., Xu, Z. and Chen, Q. (2007). Clustering Method of Intuitionistic Fuzzy Sets, *Control and Decision*, 22(8), 882–888.