An application of hybrid weighted similarity measure of neutrosophic set in medical diagnosis

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Abstract. The study introduces a hybrid weighted similarity measure (HWSM) for the analysis of symptoms and diseases in patients using a neutrosophic set (NS). NS proves valuable for modeling uncertainty by accommodating contradictory and ambiguous information. The development of a similarity measure for NS information is crucial in various applications, particularly in medical diagnostics, to quantify similarity between sets. While existing literature provides various similarity measures for NS, only a limited number incorporates hybrid techniques. This study proposes a hybrid similarity measure that combines existing measures and integrates them with an entropy weight measure. To elaborate, distance-based similarity measures for NS are initially considered. Subsequently, an entropy weight measure is employed to calculate the attributes' weight of the attributes. The work includes formulating the properties of the proposed HWSM and its practical application in medical diagnosis, focusing on assessing the possibility of medical diagnoses in a patient. The study examines five symptoms which are fever, headache, stomach pain, cough, and chest pain. The HWSM is applied to analyze these symptoms across five different diseases, resulting in consistent and reliable outcomes. This research contributes to the ongoing enhancement of diagnostic tools for medical practitioners, addressing challenges associated with uncertainty in patient information.

1 Introduction

In 1965, Zadeh introduced the notion of a fuzzy set [1], extending the idea of a crisp set to effectively handle fuzziness distinct from randomness in probability. Following this, various

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extensions to the fuzzy set emerged, including intuitionistic fuzzy set [2], fuzzy multiset [3], hesitant fuzzy sets [4], fuzzy soft set [5], and fuzzy rough set [6]. These extensions have found applications in diverse areas, including multi-criteria decision-making (MCDM), as demonstrated in [7].

In 2005, Smarandache [8] introduced the neutrosophic set (NS) as a conceptual tool designed to address challenges involving uncertain, indeterminate, and contradictory information. The NS contains truth membership value, indeterminacy membership value, and falsity membership value. This concept holds significance across various applications, particularly due to its unique evaluation of indeterminacy and the independence of truth membership, indeterminacy membership, and falsity values. Then, [9] presented a specific instance of the neutrosophic set called a single value neutrosophic set (SVNS), which serves as a generalization of the classic set, fuzzy set, interval-valued fuzzy set, intuitionistic fuzzy set, and inconsistent set. The SVNS holds significant relevance in modeling theory, making it applicable in practical scientific and technical scenarios. Many applications of NS and its extensions are discussed in the literature, some of them are [10-14].

In the realm of multiple criteria decision-making, the application of NS similarity measures proves valuable for perceiving similarities between criteria [11-14]. As highlighted in [15], similarity measures play a vital role in a variety of applications across diverse fields of decision-making, including pattern recognition, image thresholding, and multicriteria decision-making. A hybrid similarity measure is a metric that combines two or more similarity measures to produce a unified similarity value. In the domain of NSs, a generalized hybrid similarity measure covers various sides of uncertainty, indeterminacy, and vagueness intrinsic to a neutrosophic set. It integrates these components to yield a unified similarity value. Researchers, including [16] and [17], have explored novel hybrid distance-based similarity measures. [16] introduced a hybrid binary logarithm similarity measure explicitly crafted to handle indeterminacy in decision-making scenarios. Simultaneously, [17] presented an inventive hybrid distance-based similarity measure tailored for refined rough neutrosophic sets, demonstrating its application in medical diagnosis for specific diseases.

In contemporary research, there is an increasing recognition of the importance of combining entropy with similarity measures to tackle real-world challenges. Prior investigations [18, 19] have presented entropy concepts integrated with distance-based similarity measures for SVNS and interval-valued neutrosophic sets (IVNS), respectively. Nevertheless, certain entropy measures for SVNS are deemed overly intricate and lack intuitive appeal. To overcome this drawback, [20-21] explored applications in multi-attribute decision-making using SVNS similarity and entropy measures. [20] introduced axiomatic definitions of similarity and entropy for single-valued neutrosophic values (SVNV) based on an innovative inclusion relation between SVNV.

In the field of medical diagnosis, the rising volume of information obtained from modern medical equipment often needs to deal with incomplete, uncertain, imprecise, and inconsistent data, which is a critical aspect in addressing medical diagnosis challenges [22]. Symptoms, vital indicators in medical diagnosis, typically incorporate incomplete, ambiguous, and inconsistent information related to a disease. [23] highlighted that in medical diagnosis issues, symptoms and data examination of diseases may vary over different time intervals, raising the question of whether relying on a single inspection period is sufficient to determine a specific patient's condition. In some instances, individuals undergoing treatment may exhibit symptoms of various illnesses [24-26]. Researchers, such as those mentioned in [26], have applied the theory of SVNS and the theory of rough neutrosophic sets to enhance medical diagnosis. These theories contribute to a more precise and realistic assessment of a patient's condition, recognizing the dynamic nature of symptoms and data in medical scenarios.

This study aims to accomplish dual objectives. Firstly, advancing the development of a HWSM for SVNS, extended from [24]. Secondly, the goal is to apply the HWSM to real-world issues, enhancing the precision of similarity computations by integrating several established similarity measures. Given the key role of similarity and entropy measures in evaluating the relationships and uncertainties within an NS, the scientific community has made substantial contributions to this field. Motivation from the advantages of entropy measures in various neutrosophic set extensions, our paper incorporates an entropy measure from [21], into four hybrid similarity measures for SVNSs. The proposed methodology to integrate a hybrid approach into the distance-based similarity measure from Mustapha et al [24] with four other distance-based similarity measures from Euclidean distance, Hamming distance, Hausdorff distance [12] and Ren et al [14]. To underscore the practicality and efficacy of this approach, we employ it to address a medical problem in the conclusive phase of our study.

This generalized HWSM will find practical application in solving medical diagnosis problems. The subsequent sections of the paper are organized as follows. Section 2 provides preliminary definitions for key terms, while section 3 introduces new definitions for the HWSM. Section 4 delves into an empirical example illustrating the application of the measures in medical diagnosis. Finally, Section 5 concludes the present study.

2 Preliminaries

This section consists of some basic definitions that will be helpful in the rest of the article.

Definition 1[1] (Neutrosophic set (NS)):
Let a set of points or objects, represented by X, where each distinct element x belongs to X. In this framework, the $NS\ A$ can be conceptualized as an entity assuming a particular form

$$A = \left[\left(x, T_A(x), I_A(x), F_A(x)\right) : x \in X\right],$$

where the functions $T, I, F : X \to]^{-}0, 1^{+}[$ express the truth-membership function, an indeterminacy membership function, and a falsity-membership function for the given element $x \in X$, defining each function respectively to the set A with the condition :

$$^{-}0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3^{+}.$$

The function $T_A(x), I_A(x)$ and $F_A(x)$ are real standard or nonstandard subsets of $]^{-}0, 1^{+}[$. Since it is difficult to apply the neutrosophic set setting to practical problems.

Definition 2[9] (Single value neutrosophic set(SVNS)):
Imagine a set of points (objects) designated as X, with a generic element represented by x. An SVNS A in X is characterized by three membership functions: a truth membership function, $T_A(x)$, an indeterminacy membership function, $I_A(x)$ and a falsity membership function, $F_A(x)$. These functions, $T_A(x), I_A(x), F_A(x)$, are real subsets of the interval [0,1].

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

Definition 3[21] (Entropy weight measurement):
Let $A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle | x \in X\}$ be a SVNS set on *X*. Then, the entropy for SVNS, E_n defined as follows

$$E_n = \frac{\min\left(T_A(x), F_A(x)), I_A(x), I_A^c(x)\right)}{(T_A(x)+F_A(x))(|I_A(x)-I_A^c(x)|+2)}, \quad (1)$$

where $I_A^c(x) = \left(1 - I_A(x)\right)$. It is also noticed that $E_n \in [0,1]$ and the entropy weight of the j[th] attribute w_j is stated as follows:

$$w_j = \frac{1-E_n}{\sum_{j=1}^{n} 1-E_n}. \quad (2)$$

The entropy weight of the distance-based similarity measures is shown in Section 3.

3 Several weighted distance-based similarity measures for SVNS

3.1 Existing distance-based similarity measures of SVNS with entropy weight

Several distance measures integrated with the weight operator in equation (2) have been chosen in this study to apply for two SNVS *A* and *B* with $\boldsymbol{X} = \left\{\boldsymbol{x_1}, \boldsymbol{x_2}, \boldsymbol{x_3}, \dots, \boldsymbol{x_n}\right\}$.

Definition 4 [24] (Distance-based similarity):

$$\boldsymbol{S_M(A,B) = 1 - \frac{2}{n}\sum_{i=1}^{n} w_i \frac{sin\left\{\frac{\pi}{10}|T_A(x_i)-T_B(x_i)|\right\}+sin\left\{\frac{\pi}{10}|I_A(x_i)-I_B(x_i)|\right\}+sin\left\{\frac{\pi}{10}|F_A(x_i)-F_B(x_i)|\right\}}{1+sin\left\{\frac{\pi}{10}|T_A(x_i)-T_B(x_i)|\right\}+sin\left\{\frac{\pi}{10}|I_A(x_i)-I_B(x_i)|\right\}+sin\left\{\frac{\pi}{10}|F_A(x_i)-F_B(x_i)|\right\}}} \quad (3)$$

Definition 5 [12](Normalized Hamming distance-based similarity measure):

$$\boldsymbol{S_{HM}(A,B) = 1 - \frac{1}{3n}\sum_{i=1}^{n} w_i(|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|)} \quad (4)$$

Definition 6 [12] (Normalized Euclidean distance-based similarity measure):

$$\boldsymbol{S_E(A,B) = 1 - \sqrt{\frac{1}{3n}\sum_{i=1}^{n} w_i((T_A(x_i) - T_B(x_i))^2 + (I_A(x_i) - I_B(x_i))^2 + (F_A(x_i) - F_B(x_i))^2)}} \quad (5)$$

Definition 7 [12] (The Extended Hausdroff distance-based similarity measure):

$$\boldsymbol{S_{HS}(A,B) = 1 - \frac{1}{n}\sum_{i=1}^{n} w_i max(|T_A(x_i) - T_B(x_i)|, |I_A(x_i) - I_B(x_i)|, |F_A(x_i) - F_B(x_i)|)} \quad (6)$$

Definition 8 [14] (Distance-based similarity)

$$\boldsymbol{S_{Ren}(A,B) = 1 - \frac{1}{2n}\sum_{i=1}^{n} w_i \left(\frac{(T_A(x_i)-T_B(x_i))^2}{2+T_A(x_i)+T_B(x_i)} + \frac{(I_A(x_i)-I_B(x_i))^2}{2+I_A(x_i)+I_B(x_i)} + \frac{(F_A(x_i)-F_B(x_i))^2}{2+F_A(x_i)+F_B(x_i)} + |m_A(x_i) - m_B(x_i)|\right)}, \quad (7)$$

where $\boldsymbol{m_j(x_i)} = \frac{\boldsymbol{1+T_j(x_i)-F_j(x_i)}}{\boldsymbol{2}}, \boldsymbol{j = A, B.}$

The measures in equations (3)-(7) have already proved to satisfy the properties of similarity measures of NS in [24], [12] and [14].

3.2 Hybrid distance-based similarity measures of SVNS

Hybrid formulas incorporate several approaches or strategies, frequently originating from several fields or specializations. When combined with the advantages of each technique, hybrid techniques yield findings that are more accurate than when one technique is used alone. Integrating various similarity measures into a hybrid formula should result in more accurate evaluations of persistent similarities. Furthermore, hybrid formulas are frequently more reliable and flexible to different datasets or contexts. They are appropriate for a variety of applications since they can handle a greater range of input data kinds and features.

Definition 9: (Hybrid vector distance measures of SVNS)
Let $A = [T_A(x_i), I_A(x_i), F_A(x_i)]$ and $B = [T_B(x_i), I_B(x_i), F_B(x_i)]$ be two SVNSs in a universe of discourse $X = \{x_1, x_2, \ldots, x_n\}$. Then, the HWSM of SVNSs in the vector space is defined as follows:

$$hw(A,B) = \varphi\big(S_*(A,B)\big) + (1-\varphi)S_M(A,B)) \qquad (8)$$

where $0 \leq \varphi \leq 1$ and $S_*(A,B)$ will be replaced with $S_{HM}, S_E, S_{HS},$ and S_{Ren} in equations (4-7) for various hybrid distance measures and $S_M(A,B)$ is a distance-based similarity measure as in equation (3).

The formulation of properties for the new hybrid distance measure of SVNS is as follows. The HWSM, denoted as $hw(A,B)$ for NSs A, and B satisfies the following properties.

For proving purposes, let $S_M(A, B)$ represent equation (3) taken from [24] and only let $S_*(A,B)$ be the distance-based similarity measures of Hausdroff equation (4) becoming:

$$hw(A,B) = \varphi\big(S_{HS}(A,B)\big) + (1-\varphi)S_M(A,B)) \qquad (9)$$

with $0 \leq \varphi \leq 1$.

Proposition 1: The similarity measure, $hw(A,B)$ satisfies the following properties:
$(C1)$ $0 \leq hw(A,B) \leq 1$
$(C2)$ $hw(A,B) = hw(B,A)$
$(C3)$ $hw(A,B) = 0$ if and only if $A = B$
$(C4)$ For $A \subseteq B \subseteq C$, then $hw(A,C) \geq hw(A,B)$ and $hw(A,C) \geq hw(B,C)$

Proof $(C1)$*:* Suppose $S_{HS}(A,B)$ and $S_M(A,B) \in [0,1]$, thus, we have

$$0 \leq S_{HS}(A,B) + S_M(A,B) \leq 2;$$

with $0 \leq \varphi \leq 1$,

$$0 \leq \varphi(S_{HS}(A,B) + (1-\varphi)S_M(A,B)) \leq 1;$$

with $\varphi = 0$,

$$0 \leq S_M(A,B) \leq 1;$$

with $\varphi = 1$,

$$0 \leq S_{HS}(A,B) \leq 1.$$

Hence, $hw(A,B)$ within [0,1]. Thus $0 \leq hw(A,B) \leq 1$
Proof $(C2)$*:* $hw(A,B) = hw(B,A)$ is obvious.

Proof (C3): If A and B are identical $(A = B)$, the distances $S_{HS}(A,B)$ and $S_M(A,B)$ lead to $S_{HS}(A,A)$ and $S_M(A,A)$, as demonstrated in the proof of $S_M(A,B)$ outlined in [24] and the proof of $S_{HS}(A,B)$ in [12]. Thus, we have

$$S_{HS}(A,A) = 0 \text{ and } S_M(A,A) = 0,$$

with $0 \leq \varphi \leq 1$,

$$\varphi(S_{HS}(A,A) + (1-\varphi)S_M(A,A)) = 0 + 0 = 0$$

Likewise, if $B = A$.
Hence, $hw(A,B) = 0$ if and only if $A = B$

Proof $(C4)$: According to the proof of $S_M(A,B)$ shown in [24], for $A \subseteq B \subseteq C$, and the proof of $S_{HS}(A,B)$ in [12], we have $S_M(A,C) \geq S_M(A,B)$, $S_M(A,C) \geq S_M(B,C)$, $S_{HS}(A,C) \geq S_{HS}(A,B)$ and $S_{HS}(A,C) \geq S_{HS}(B,C)$. Then, it becomes

$$S_{HS}(A,C) + S_M(A,C) \geq S_{HS}(A,B) + S_M(A,B)$$

with $0 \leq \varphi \leq 1$,

$$\varphi S_{HS}(A,C) + (1-\varphi)\, S_M(A,C)) \geq \varphi S_{HS}(A,B) + (1-\varphi) S_M(A,B)$$

Therefore, we obtain $hw(A,C) \geq hw(A,B)$.
Likewise, we have $hw(A,C) \geq hw(B,C)$.
The theorem has been proved completely. The other three HWMSs can be proven similarly.

4 Application using the proposed hybrid weighted similarity method

In this section, we apply the proposed HWSM to the medical diagnosis. This research relies on secondary data, as documented in [10]. From this source, we have specifically chosen a dataset that is specific to one patient. This dataset is considered adequate for our case study, which examines five distance-based similarity measures and hybrid approaches. Let's consider a scenario in medical diagnosis decision-making. Suppose there is a set of a patient for our case study, denoted as ρ. Patient ρ is presenting with multiple symptoms, denoted as ξ= {Temperature (ξ_1), Headache (ξ_2), Body pain (ξ_3), Cough (ξ_4), Sneezing (ξ_5)}. Using neutrosophic data, we aim to determine the type of disease affecting each person from a set of common prevalent diseases, denoted as δ = {Viral fever (VF), Malaria (ML), Typhoid (TY), Chickugunya (CG), Coronavirus (CV)}.

To achieve this, two types of observations are required:

1. For the patient, we need to identify the multiple symptoms present.
2. For each disease, under normal circumstances, we need to identify the specific symptoms associated with it.

Both sets of observations are documented in an NS format, offering specifics like the percentage of membership function (T), the percentage of indeterminacy function (I), and the percentage of non-membership function (F), among other details, as outlined in Tables 1 and 2. Table 1 defines the characteristic symptoms observed in a patient, while Table 2 illustrates the symptom-disease relationships. Employing the data from Tables 1 and 2, the computation of four HWSMs discussed in Section 2 is performed. The outcomes are presented in Tables 3-6.

Table 1. The characteristic symptoms observed in every patient [10].

	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5
ρ	(0.1,0.6,0.4)	(0.4,0.6,0.3)	(0.3,0.5,0.4)	(0.3,0.5,0.4)	(0.3,0.6,0.7)

Based on the information provided in Table 1, the truth membership degree for the five symptoms among patients varies from 0.1 to 0.4. Likewise, the indeterminacy membership degree for a patient is within the range of 0.5 to 0.6, while the falsity membership degree spans from 0.3 to 0.7. Notably, in the case of this specific patient, the symptom of sneezing is classified as causing less distress, with a falsity membership degree of 0.7. Upon examination, the temperature dataset (0.1, 0.6, 0.4) indicates a low temperature for this patient.

Table 2. The relationship between diseases and symptoms [10].

Symptoms	VF	ML	TY	CG	CV
ξ_1	(0.6,0.3,0.3)	(0.2,0.5,0.3)	(0.2.0.6,0.4)	(0.1,0.6,0.6)	(0.1,0.6,0.4)
ξ_2	(0.4,0.5,0.3)	(0.2,0.6,0.4)	(0.1,0.5,0.4)	(0.2,0.4,0.6)	(0.1,0.6,0.4)
ξ_3	(0.1,0.6,0.3)	(0.0,0.6,0,4)	(0.2,0.5,0.5)	(0.8,0.2,0.2)	(0.1,0.7,0.1)
ξ_4	(0.4,0.4,0.4)	(0.4,0.1,0.5)	(0.2,0.5,0.5)	(0.1,0.7,0.4)	(0.4,0.5,0.4)
ξ_5	(0.1,0.7,0.4)	(0.1,0.6,0.3)	(0.1,0.6,0.4)	(0.1,0.7,0.4)	(0.8,0.2,0.2)

Table 3. The entropy weight measurements.

Symptoms	Entropy Measure	Weight Measure
ξ_1	0.045455	0.208659
ξ_2	0.097403	0.197303
ξ_3	0.107143	0.195174
ξ_4	0.107143	0.195174
ξ_5	0.068182	0.203691

Table 3 shows the entropy weight values, assigning specific weights to each symptom. The entropy weight measure is used to calculate the weights of attributes (symptoms). This means that attributes with higher entropy (more uncertainty) will be assigned lower weights and attributes with lower entropy (less uncertainty) will be assigned higher weights. This weighting process helps give more importance to attributes that contribute more information and are more reliable in the context of medical diagnostics. As indicated in Table 1, Temperature (ξ_1) carries the highest weight, followed by Sneezing (ξ_5) and other symptoms.

The HWSM is defined according to different values of φ as stated below:

1. If φ = 0, the weighted distance-based similarity measure is the distance from [24];
2. If φ =1, the weighted distance-based similarity measure is generalized to either the distance from Hamming [12], Hausdroff [12], Euclidean [12], or Ren et al [14] measure;
3. If φ =0.1, 0.2, 0.5, 0.7 and 0.9, the HWSM.

In Table 4, we present the outcomes of five distance-based similarity measures computed without entropy weight. These computations follow the formulas outlined in section 3.

Table 4. The similarity measure values for patient ρ without entropy weight.

Diseases	Hamming [12] $\varphi=1$	Hausdorff [12], $\varphi=1$	Euclidean [12], $\varphi=1$	Ren et al [14], $\varphi=1$	Mustapha et al [24], $\varphi=0$
VF	0.853333	0.760000	0.803362	0.933997	0.768174
ML	0.853333	0.720000	0.806782	0.928859	0.759830
TY	**0.882000**	**0.800000**	**0.850579**	**0.937730**	**0.802570**
CG	0.806667	0.700000	0.767621	0.886966	0.700873
CV	0.826667	0.760000	0.749667	0.886743	0.749287

Table 5. The similarity measures values with entropy for patient ρ

Diseases	Hamming [12] $\varphi=1$	Hausdorff [12], $\varphi=1$	Euclidean [12], $\varphi=1$	Ren et al [14], $\varphi=1$	Mustapha et al [24], $\varphi=0$
VF	0.970211	0.951256	0.857866	0.986457	0.953001
ML	0.970722	0.944315	0.913779	0.985784	0.952048
TY	**0.976282**	**0.959787**	**0.932945**	**0.98762**	**0.960328**
CG	0.961647	0.94027	0.896661	0.977636	0.940606
CV	0.965318	0.952179	0.887662	0.977228	0.949934

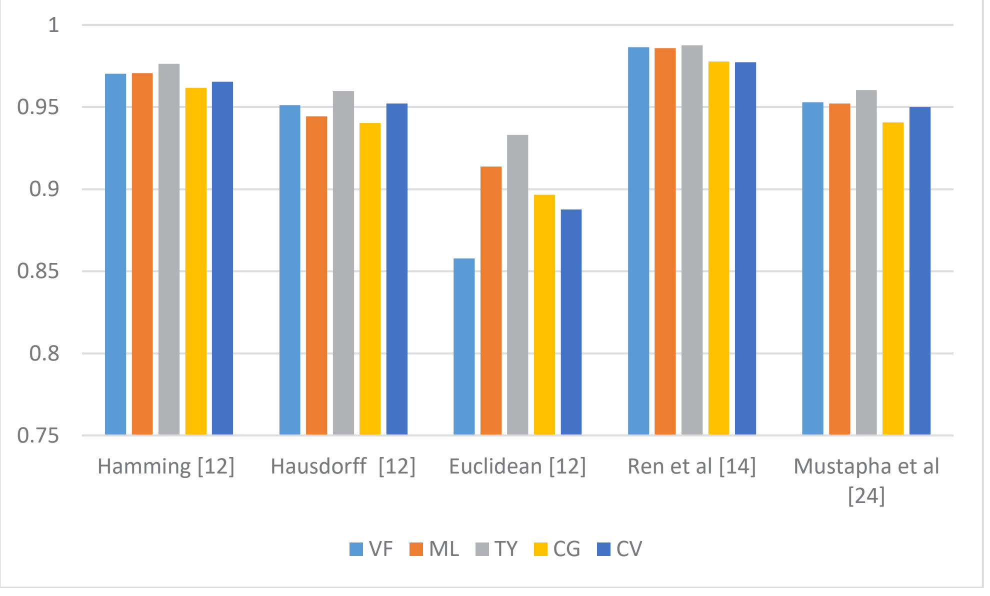

Fig. 1. The similarity measures values with entropy for patient ρ.

Table 6. The similarity results for hybrid weighted similarity measures

φ	Diseases	Hamming [12]	Hausdorff [12]	Euclidean [12]	Ren et al [14]
$\boldsymbol{\varphi = 0.9}$	VF	0.968490	0.951431	0.867380	0.983111
	ML	0.968854	0.945088	0.917606	0.982411
	TY	**0.974687**	**0.959841**	**0.935683**	**0.984891**
	CG	0.959543	0.940303	0.901055	0.973933
	CV	0.963780	0.951954	0.893889	0.974498
$\boldsymbol{\varphi = 0.7}$	VF	0.965048	0.95178	0.886407	0.97642
	ML	0.965119	0.946635	0.925259	0.975663
	TY	**0.971496**	**0.959949**	**0.941160**	**0.979432**
	CG	0.955334	0.940371	0.909845	0.966527
	CV	0.960703	0.951506	0.906344	0.96904
$\boldsymbol{\varphi = 0.5}$	VF	0.961606	0.952129	0.905434	0.969729
	ML	0.961385	0.948181	0.932913	0.968916
	TY	**0.968305**	**0.960057**	**0.946636**	**0.973974**
	CG	0.951126	0.940438	0.918634	0.959121
	CV	0.957626	0.951057	0.918798	0.963581
$\boldsymbol{\varphi = 0.2}$	VF	0.956443	0.952652	0.933974	0.959693
	ML	0.955783	0.950501	0.944394	0.958795
	TY	**0.963519**	**0.960220**	**0.954851**	**0.965786**
	CG	0.944814	0.940539	0.931817	0.948012
	CV	0.953011	0.950383	0.937480	0.955393
$\boldsymbol{\varphi = 0.1}$	VF	0.954722	0.952827	0.943488	0.956347
	ML	0.953915	0.951275	0.948221	0.955421
	TY	**0.961923**	**0.960274**	**0.957589**	**0.963057**
	CG	0.942710	0.940573	0.936212	0.944309
	CV	0.951473	0.950159	0.943707	0.952664

Subsequently, Table 5 introduces an additional dimension by incorporating entropy weight into the previously mentioned five distance-based similarity measures. As we compare the results in Tables 4 and 5, we observe that the values of similarity measures for all types depict better results, as the values are closer to 1. These results highlight the increased importance of entropy weight measurements in supporting and differentiating between attributes. In the medical field, incorporating an entropy weight measure helps in refining the analysis and improving the accuracy of diagnostic outcomes. Attributes with more certainty or reliability contribute more to the overall similarity calculation, leading to more robust and dependable results. The graphical results for distance-based similarity measure values with entropy for patient ρ shown in Figure 1.

Furthermore, Table 6 displays the calculated results of five HWSMs depending on the values of φ, which are chosen to be 0.1, 0.2, 0.5, 0.7, and 0.9. Each similarity measure employed in this table has been previously validated to meet all essential properties.

The results in Tables 3 to 6 indicate a probability of diagnosing the patient with typhoid. This assertion remains consistent across diverse similarity measures utilized in our analysis, exhibiting remarkable coherence in the results. These findings support earlier research [10] where the patient was also diagnosed with typhoid using the Hausdroff distance measure. From our obtained findings, the results are consistent when we use various hybrid formulas. Reliability in results across multiple similarity measures increases the strength of diagnostic implications, further strengthening the indications of possible typhoid infection.

5 Conclusion

In conclusion, we consider the difficulties caused by ambiguity and uncertainty in patient data by introducing and applying the hybrid weighted similarity measure (HWSM) of the neutrosophic set (NS) in medical diagnosis. The applications of NS have proven beneficial when modeling uncertainty, as it accommodates conflicting and ambiguous data.

In the development of HWSM, the entropy weight is integrated with the present similarity measure. The entropy weight measure is essential because of its reliability and diagnostic value when assigning weights to quality. When analyzing the symptoms and diseases of this patient, the improvements have resulted in more reliable similarity measures.

The distance integration given by Mustapha et al. [24] with extended Hausdorff distance [12], normalized Hamming distance [12], normalized Euclidean distance [12], and Ren et al. [14], the consistency of similarity values observed in a patient across the four HWSM. The assessment of possible different medical diagnoses based on the five core symptoms is the main objective of the practical application of HWSM in medical diagnosis. The consistent and reliable results obtained from several HWSMs highlight the usefulness of the proposed strategy. This work contributes to the ongoing efforts to improve medical practitioners' diagnostic tools, especially when patient information uncertainty presents a significant difficulty.

As the medical field continues to progress, the applications of the HWSM display its potential to increase diagnostic accuracy and reliability. The hybrid nature of the proposed similarity measure, integrating existing techniques and entropy weight measures, positions it as a valuable tool for medical professionals struggling with complex and uncertain patient data. The findings contribute to the evolving landscape of medical diagnostics, emphasizing the potential of NS applications in enhancing reliability in healthcare decision-making. The insights gained from this study pave the way for further advancements in medical diagnostics, which benefit practitioners and patients alike.

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