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Research Article

Comparative study of fermatean fuzzy soft sets with normalized distances and its application in diagnose infectious diseases

Saika SHEWALI[1], Borah Manash JYOTI[2], Mahanta Dimpal JYOTI[1,*]

[1]Department of Mathematics, The Assam Kaziranga University, Assam, 785006, India
[2]Department of Mathematics, Bahona College, Assam, 785101, India

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ABSTRACT

The employment of Fermatean fuzzy soft sets with normalized distances in the perspective of diagnosis in medical treatment are observed in this research. The effectiveness of normalized distances—such as Fermatean, Hamming, and Euclidean measures—in handling the inherent uncertainty in medical data is evaluated. Through a comparative analysis, we assess their performance in medical diagnosis tasks, aiming to demonstrate how these methods can enhance the accuracy and reliability of diagnostic systems. The goal of the research is to shed light on how Fermatean fuzzy soft sets with normalized distances might enhance the precision and dependability of medical diagnostic systems. This illustrative example of Chikungunya highlights the benefits of combining normalized distances into Fermatean fuzzy soft set frameworks, contributing to advancements in medical decision support systems.

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INTRODUCTION

An essential concept for decision-making issues is uncertainty. Because of inconsistencies and unreliable data, individuals making decisions are frequently finding it challenging to provide their evaluation of an object in clear values. Theory of fuzzy sets (FS), in his groundbreaking work, in 1965 Zadeh [1] proposed a membership function that is a powerful instrument for resolving issues with imprecision, vagueness, and uncertainty. The function's value fell between 0 and 1. Though there was no membership function—that is, only acceptances—in real life, FS theory resolved a great deal of practical issues. In real life, rejection is precisely as important as acceptance. After providing clarification on the issue, Atanassov [2] in 1986 proposed the intuitionistic fuzzy set (IFS) theory, which uses the membership and non-membership functions, the sum of the membership and non-membership grades, which equals 1. This criterion also limits the resolution of inaccurate, ambiguous, and vague problems.

In 2013 Yager [3] has offered Pythagorean fuzzy sets (PFS) as a solution to this problem. Because PFS uses the criterion that the sum of the squares of the membership and non-membership grades must be equal to or less than one, it is more extensive than IFS. PFs is also a particular case

***Corresponding author.**
*E-mail address: dimpaljmahanta@gmail.com

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of Neutrosophic Set initiated by Smrandache [4] in 2019.In the literature there are many studies on FS, IFS and PFS theories [5-10]. These theories have restrictions in spite of all potential solutions. Limitations include things like not taking the parameterization tool into consideration and how to set the membership function in each specific object. These restrictions make it more difficult for decision-makers to reach the right conclusion throughout the analysis.

A solution to the stated limitations was found when Molodtsov [11] in 1999 presented a novel technique called Soft Set, in which the preferences for each alternative were expressed in separate parameters. According to Molodtsov, there is a lot of room for application of soft set theory in different mathematical fields. Soft set theory is expanding quickly in all directions and finding applications in many mathematical fields. [12,13]. Maji et al. [14], [15,16] defined fuzzy soft sets u (FSS) and intuitionistic fuzzy soft sets (IFSS) in 2001 and 2004 respectively and assessed their various properties. Peng et al. [17] defined the Pythagorean fuzzy soft set (PFSS) in 2015 by fusing PFS and IFSS. In [18] and [19] the key components of PFSS were investigated and applied to a variety of domains, including medical diagnosis and team selection for business investment issues with stocks, etc.

Senapati and Yager [20]implemented the Fermatean fuzzy set in 2020, wherein the membership and non-membership degrees satisfy the condition $0 \leq m_H^3 + n_G^3 \leq 1$. This was a novel concept introduced in the literature that produced superior results in defining uncertainties when compared to the intuitionistic fuzzy set and Pythagorean fuzzy set. In cases where IFS and PFS are unable to support data containing uncertainty, FFS provides decision makers with additional flexibility. By extending the spatial scope of membership and non-membership, the FFS enhances its abilities to describe uncertain information when compared to IFS and PFS.Various FFS attributes, including score and accuracy, are provided by Senapati and Yager [20]. The TOPSIS method, which is often used to handle MCDM problems, has been used to tackle the FFS problem. Furthermore, according to Senapati and Yager, the TOPSIS approach—which is commonly used to address MCDM problems—was used to conduct the FFS. The TOPSIS method, which is commonly used in MCDM issues, has also been applied to FFS, as mentioned by Senapati and Yager [20].

Senapati and Yager [21] carried out this work by delving into a number of new operations, such as the division, subtraction, and Fermatean arithmetic mean operations on FFSs. They also employed the Fermatean fuzzy weighted product model to address MCDM problems. Senapati and Yager [21]in 2019 have defined novel aggregation operators that are a component of the FFS and have examined the attributes that go along with them.

Kirisci [22] introduced the concept of Fermatean fuzzy soft sets (FFSS) along with an entropy measure derived from it. Shahzadi and Akram [23] present a decision support method based on the FFSS notion to increase the efficacy of anti-virus masks.

Whether two sets are sharp, fuzzy, or vague, comparing them is the primary issue in real-world situations. The relevant tools for comparing the similarity of two sets are matching function-based similarity measures and distance measures. Measures of similarity and distance indicate how similar and different something is from another. First, fuzzy set similarity measures were introduced by Wang in 1997 [24]. Researchers have proposed a variety of similarity measures for fuzzy sets, including interval-valued fuzzy sets, intuitionistic fuzzy sets. In 2008 Majumdar and Samanta [25] defined similarity measure for soft set and in 2011 [26] for fuzzy soft sets. Later on it has been extended to IFSS [27], IVFSS [28], PFSS [29]. Among the various structures discussed so far, FFSS [30] being the most generalized one.

As the Fermatean fuzzy soft set is a great tool for handling more than PFSS and IFSS, it is also important to determine the distance similarity. Machine learning, pattern recognition, and distributed memory problems can all be resolved with the help of distance measures. The two most widely used distance measurements are Euclidean and Hamming distances. This article discusses new distance measures based on FFSSs that are employed to quantify uncertain information. These include normalized Euclidean distance, normalized Hamming distance, Fermatean distance, and cosine distance. A comprehensive theoretical background of these distance measures along with a decision-making algorithm has been provided. Examples of validated techniques for medical decision making are offered.

Preliminaries

Here are essential definitions that lay the groundwork for the upcoming discussion.

Soft set

Let $\mathcal{E}$ represents a collection of parameters and let $\mathcal{U}$ denote the universal set. Defined as a pair $(\mathcal{A}, \mathcal{E})$, a soft set (SS) is characterized over $\mathcal{U}$, where $\mathcal{A}$ is a function $\mathcal{A} : \mathcal{E} \to P_{SS}(\mathcal{U})$ In essence, the SS can be described as a parameterized assortment of subsets of the set $\mathcal{U}$ [18].

Fuzzy soft set

A pair $(\mathcal{A}, \mathcal{E})$ is denoted as a fuzzy soft set over the universal set $\mathcal{U}$ provided that the mapping $\mathcal{A} : \mathcal{E} \to f(\mathcal{U})$ represents a correspondence from $\mathcal{A}$ to the collection of all fuzzy sets in $\mathcal{U}$, where $f(\mathcal{U})$ denotes the set encompassing all fuzzy subsets of $\mathcal{U}$. [18]

Intuitionistic fuzzy soft set

The notation $If(\mathcal{U})$ is used to represent the intuitionistic fuzzy power set of $\mathcal{U}$, where $\mathcal{A} \subset \mathcal{E}$ An ordered pair $(\mathcal{F}, \mathcal{A})$ is defined as an intuitionistic fuzzy soft set over $\mathcal{U}$ if the function $\mathcal{A} : \mathcal{E} \to If(\mathcal{U})$ holds [18].

Pythagorean fuzzy soft set

The Pythagorean fuzzy soft set is defined as a pair $(\mathcal{A}, \mathcal{E})$ where $\mathcal{A} : \mathcal{E} \to P_{PFS}(\mathcal{U})$ represents the collection of Pythagorean fuzzy subsets of $\mathcal{U}$. Within the context of

Pythagorean fuzzy soft sets, it holds that $\mathcal{T}_{\mathcal{P}}^2(a) + \mathcal{I}_{\mathcal{P}}^2(a) \leq 1$ and in cases where $\mathcal{T}_{\mathcal{P}}(a) + \mathcal{I}_{\mathcal{P}}(a) \leq 1$, Pythagorean fuzzy soft sets transition into intuitionistic fuzzy soft sets.[18]

Fermatean fuzzy set

The Fermatean fuzzy set (FS) denoted by $\mathcal{F}$ in the universal set $\mathcal{U}$ can be described as a structured entity defined as $\mathcal{F} = \{< a, \mathcal{T}_{\mathcal{F}(a)} + \mathcal{I}_{\mathcal{F}(a)} >: a \in \mathcal{U}\}$, where the functions $\mathcal{T}_{\mathcal{F}}: \mathcal{U} \to [0,1]$ and $\mathcal{I}_{\mathcal{F}}: \mathcal{U} \to [0,1]$ and adhere to the constraint $0 \leq \mathcal{T}_{\mathcal{F}(a)}^3 + \mathcal{I}_{\mathcal{F}(a)}^3 \leq 1$ [18].

Fermarean fuzzy soft set

Let $\mathcal{U}$ be a set, $\mathcal{E}$ be the set of parameter. $P_{FS}(\mathcal{U})$ the whole of all FSs on $\mathcal{U}$. Let $\mathcal{A} \subset \mathcal{E}$ A pair $(\mathcal{F}, \mathcal{A})$ is called Fermarean fuzzy soft set (FFSS) over $\mathcal{U}$ where $\mathcal{F} : \mathcal{A} \to P_{FS}(\mathcal{U})$. A FSS on $\mathcal{U}$ is a family of parameters formed by some Fermatean fuzzy sub sets on $\mathcal{U}$. For any parameter $\mathcal{E} \in \mathcal{A}. \mathcal{F}(\mathcal{E})$ is a FFSS associate with $\mathcal{E}$ of $\mathcal{U}$, then it is called Fermatean fuzzy value set of parameter $\mathcal{E}. \mathcal{F}(\mathcal{E})$ can be written as $\mathcal{F}(\mathcal{E}) = \{< a, \mathcal{T}_{\mathcal{F}(\mathcal{E})}(a) + \mathcal{I}_{\mathcal{F}(\mathcal{E})}(a) >: a \in \mathcal{U}\}$

Where $\mathcal{T}_{\mathcal{F}(\mathcal{E})}(a)$ and $\mathcal{I}_{\mathcal{F}(\mathcal{E})}(a)$ are membership and nonmembership functions respectively. The conditions $0 \leq \mathcal{T}_{\mathcal{F}(\mathcal{E})}^3(a) + \mathcal{I}_{\mathcal{F}(\mathcal{E})}^3(a) \leq 1$ holds [18].

Measure of Similarity Based on Distance for Fermatean Fuzzy Soft Sets

The definitions of hamming, Euclidean, Fermatean, and cosine distances between two Fermatean fuzzy soft sets are given in this section. Based on these distances, similarity measures are suggested. Chikungunya is an infectious viral disease that is transmitted to humans through the bites of infected mosquitoes. It manifests with symptoms including fever, joint pain, muscle pain, headache, fatigue, and rash. We construct a Fermatean fuzzy soft set utilizing the observed symptoms. By defining a distance function, we can assess whether a patient is afflicted with chikungunya or not. In this situation, we employ typical Chikungunya patent information to compute the dissimilarity between two typical patents. If the calculated distance approaches zero, the patent is classified as positive for chikungunya. Conversely, if the distance exceeds 0.5, it suggests that the patients may be affected by other conditions.

Definition Let $\mathcal{U} = \{u_1, u_2, u_3 \ldots u_n\}$ be an initial inverse and $\mathcal{E} = \{e_1, e_2, e_3, \ldots, e_m\}$ be the set of parameters. Let $FFS(\mathcal{U})$ denotes the set of all Fermatean fuzzy subsets of $\mathcal{U}$. Also let $(\mathcal{A}, \mathcal{E})$ and $(\mathcal{B}, \mathcal{E})$ be two FFSSs over $\mathcal{U}$, where $\mathcal{A}$ and $\mathcal{B}$ are mappings given by $\mathcal{A}, \mathcal{B}: \to FFS(\mathcal{U})$. Define the following distances between $(\mathcal{A}, \mathcal{E})$ and $(\mathcal{B}, \mathcal{E})$ as follows:

Hamming Distance:

$$HD\,\{(\mathcal{A},\mathcal{E}),(\mathcal{B},\mathcal{E})\} = \sum_{i=1}^{n}\sum_{j=1}^{m}\Big\{\big|\mathcal{T}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{T}_{\mathcal{B}(e_j)}^3(x_i)\big| + \big|\mathcal{F}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{F}_{\mathcal{B}(e_j)}^3(x_i)\big|\Big\} \tag{1}$$

Normalized Hamming Distance:

$$NHD\,\{(\mathcal{A},\mathcal{E}),(\mathcal{B},\mathcal{E})\} = \frac{1}{2mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\Big\{\big|\mathcal{T}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{T}_{\mathcal{B}(e_j)}^3(x_i)\big| + \big|\mathcal{F}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{F}_{\mathcal{B}(e_j)}^3(x_i)\big|\Big\} \tag{2}$$

Euclidean Distance:

$$ED\,\{(\mathcal{A},\mathcal{E}),(\mathcal{B},\mathcal{E})\} = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{m}|\mathcal{T}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{T}_{\mathcal{B}(e_j)}^3(x_i)|^2 + |\mathcal{F}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{F}_{\mathcal{B}(e_j)}^3(x_i)|^2} \tag{3}$$

Normalized Euclidean Distance:

$$NED\,\{(\mathcal{A},\mathcal{E}),(\mathcal{B},\mathcal{E})\} = \frac{1}{2mn}\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{m}|\mathcal{T}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{T}_{\mathcal{B}(e_j)}^3(x_i)|^2 + |\mathcal{F}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{F}_{\mathcal{B}(e_j)}^3(x_i)|^2} \tag{4}$$

Fermatean Distance:

$$FD\{(\mathcal{A},\mathcal{E}),(\mathcal{B},\mathcal{E})\} = \left\{\sum_{i=1}^{n}\sum_{j=1}^{m}|\mathcal{T}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{T}_{\mathcal{B}(e_j)}^3(x_i)|^2,\ \sum_{i=1}^{n}\sum_{j=1}^{m}|\mathcal{F}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{F}_{\mathcal{B}(e_j)}^3(x_i)|^2\right\} \tag{5}$$

Normalized Fermatean Distance:

$$NFD\{(\mathcal{A},\mathcal{E}),(\mathcal{B},\mathcal{E})\} = \left\{\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{1}{mn}|\mathcal{T}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{T}_{\mathcal{B}(e_j)}^3(x_i)|^2,\ \frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}|\mathcal{F}_{\mathcal{A}(e_j)}^3(x_i) - \mathcal{F}_{\mathcal{B}(e_j)}^3(x_i)|^2\right\} \tag{6}$$

$$= \{\mathcal{T}^-(x_i), \mathcal{F}^-(x_i)\}$$

$$< \mathcal{T}, \mathcal{F} > = \frac{\mathcal{T}^-(x_i)}{\mathcal{T}^-(x_i) + \mathcal{F}^-(x_i)}, \frac{\mathcal{F}^-(x_i)}{\mathcal{T}^-(x_i) + \mathcal{F}^-(x_i)}$$

Cosine Distance:

$$CD\,\{(\mathcal{A},\mathcal{E}),(\mathcal{B},\mathcal{E})\} = 1 - \text{cosine similatity} \tag{7}$$

Where Cosine similarity

$$= \frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{\mathcal{T}_{\mathcal{A}(e_j)}^3(x_i)\mathcal{T}_{\mathcal{B}(e_j)}^3 + \mathcal{F}_{\mathcal{A}(e_j)}^3(x_i)\mathcal{F}_{\mathcal{B}(e_j)}^3}{\sqrt{\mathcal{T}_{\mathcal{A}(e_j)}^6(x_i) + \mathcal{F}_{\mathcal{A}(e_j)}^6(x_i)}\sqrt{\mathcal{T}_{\mathcal{A}(e_j)}^6 + (x_i)\mathcal{F}_{\mathcal{B}(e_j)}^6(x_i)}}$$

We have established three distance functions to gauge the dissimilarity between two patients with chikungunya. If the calculated distances fall below 0.5, we conclude both have a similar condition; otherwise, if distances exceed 0.5, their conditions may differ. For Fermatean distance, when $\mathcal{T} > \mathcal{F}$, the decision favors the true membership value.

Application on Chikungunya

We develop a decision-making approach utilizing the similarity measure of two Fermatean fuzzy soft sets. This measure is instrumental in assessing the likelihood of an individual with specific symptoms being ill. We employ various distance measures such as Normalized Hamming Distance, Normalized Euclidean Distance, and cosine distance for this estimation process. Determining whether someone has chikungunya involves creating Fermatean fuzzy soft sets for both the disease and the individual's symptoms. By assessing the similarity measure between these sets, if it's below 0.5, it indicates a likelihood of the individual having chikungunya. Conversely, a similarity measure equal to or greater than 0.5 suggests the person is unlikely to have the disease.

Proposed approach

1. A Fermatean fuzzy soft set is formulated to represent disease characteristics across the universal set $\mathcal{U}$, leveraging insights from medical experts.
2. A Fermatean fuzzy soft set is established across the universe $\mathcal{U}$ in the context of a patient application.
3. To assess the dissimilarity between a Fermatean fuzzy soft set for disease and a Fermatean fuzzy soft set for patients, compute the Hamming Distance, Euclidean Distance, Cosine Distance, and Fermatean Distance.
4. Determine similarity measure between them.
5. Assess the outcome by applying similarity measures.

The flowchart of the proposed approach is given in the following Figure 1.

Example 1 Here, we present an illustration of a decision-making approach within a Fermatean fuzzy soft set context employing a similarity measure.

We choose an exemplary case, such as a patient afflicted with Chikungunya. By comparing the similarity between suspected patients and this ideal case, doctors can swiftly diagnose the disease. This approach facilitates expedited medical decision-making and fosters a supportive environment for patient care.

Let us consider a patient who was suffering from Chikungunya. Using Chikungunya patient data we will decide for a set of new patients, $\mathcal{P}_1$, $\mathcal{P}_2$, $\mathcal{P}_3$ and universal set $\mathcal{U} = \{x_1, x_2, x_3\}$ and $\mathcal{E} = \{e_1, e_2, e_3, e_4\}$ be the set of parameters. Consider $(\mathcal{A}, \mathcal{E})$, $(\mathcal{A}, \mathcal{P}_1)$, $(\mathcal{A}, \mathcal{P}_2)$, $(\mathcal{A}, \mathcal{P}_3)$ are four Farmatean fuzzy soft sets over $\mathcal{U}$ Here $\mathcal{A}$ is known person. We have to calculate the distance of $\mathcal{P}_i$ from $\mathcal{A}$ Tabular represenions of $(\mathcal{A}, \mathcal{E})$, $(\mathcal{P}_1, \mathcal{E})$, $(\mathcal{P}_2, \mathcal{E})$ and $(\mathcal{P}_3, \mathcal{E})$ are presented in the Table 1, Table 2, Table 3 and Table 4 respectively.

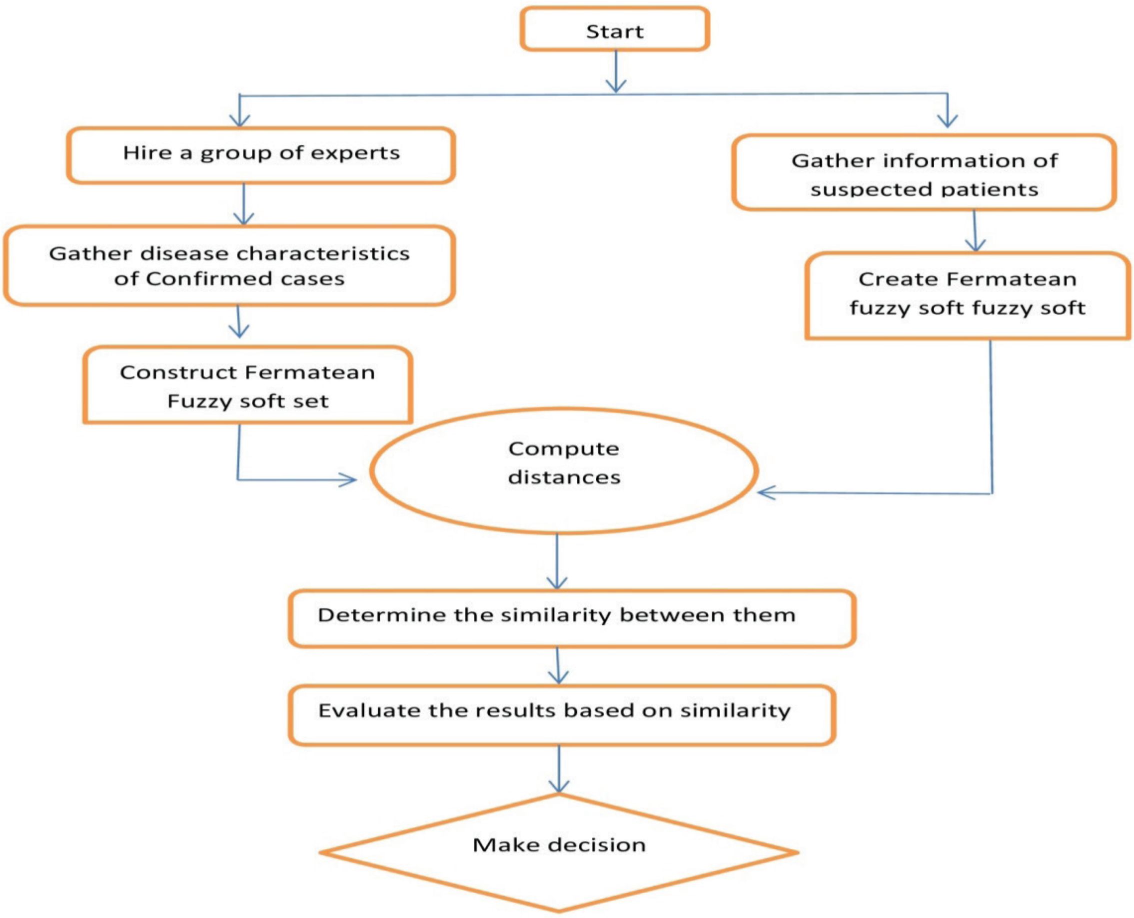

Figure 1. Flow chart of proposed approach

Table 1. Tabular representation of set ($\mathcal{A}$, $\mathcal{E}$)

($\mathcal{A}$, $\mathcal{E}$)	**Fever (e_1)**	**Headache (e_2)**	**Join pain (e_3)**	**Rash (e_4)**
x_1	(1, 0)	(1, 0)	(1, 0)	(1, 0)
x_2	(1, 0)	(1, 0)	(1, 0)	(1, 0)
x_3	(1, 0)	(1, 0)	(1, 0)	(1, 0)

Table 2. Tabular representation of set ($\mathcal{P}_1$, $\mathcal{E}$)

($\mathcal{P}_1$, $\mathcal{E}$)	**Fever (e_1)**	**Headache (e_2)**	**Join pain (e_3)**	**Rash (e_4)**
x_1	(0.7, 0.5)	(0.6, 0.4)	(0.8, 0.6)	(0.4, 0.2)
x_2	(0.6, 0.6)	(0.5, 0.5)	(0.7, 0.7)	(0.3, 0.3)
x_3	(0.8, 0.4)	(0.7, 0.3)	(0.9, 0.5)	(0.5, 0.1)

NHD = 0.408, *NED* = 0.107, *CD* = 0.121, *NFD* = (0.86,0.137), *NFD* = (0.86,0.137)

Table 3. Tabular representation of set ($\mathcal{P}_2$, $\mathcal{E}$)

($\mathcal{P}_2$, $\mathcal{E}$)	**Fever (e_1)**	**Headache (e_2)**	**Join pain (e_3)**	**Rash (e_4)**
x_1	(0.8, 0.6)	(0.7, 0.5)	(0.6, 0.4)	(0.5, 0.3)
x_2	(0.8, 0.7)	(0.7, 0.6)	(0.6, 0.5)	(0.5, 0.4)
x_3	(0.9, 0.5)	(0.8, 0.4)	(0.7, 0.3)	(0.6, 0.2)

NHD = 0.383, *NED* = 0.100, *CD* = 0.074, *NFD* = (0.846,0.153)

Table 4. Tabular representation of set ($\mathcal{P}_3$, $\mathcal{E}$)

($\mathcal{P}_3$, $\mathcal{E}$)	**Fever (e_1)**	**Headache (e_2)**	**Join pain (e_3)**	**Rash (e_4)**
x_1	(0.9, 0.6)	(0.8, 0.5)	(0.7, 0.4)	(0.6, 0.3)
x_2	(0.8, 0.7)	(0.7, 0.6)	(0.6, 0.5)	(0.5, 0.4)
x_3	(0.8, 0.6)	(0.7, 0.5)	(0.6, 0.4)	(0.5, 0.3)

NHD = 0.396, *NED* = 0.100, *CD* = 0.085, *NFD* = (0.821,0.178)

Calculation of Normalized Hamming Distances

By (2) Normalized Hamming Distances between $\mathcal{A}$ and $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are as

$$NHD(\mathcal{A}, \mathcal{P}_1) = 0.408,\ NHD(\mathcal{A}, \mathcal{P}_2) = 0.383,\ NHD(\mathcal{A}, \mathcal{P}_3) = 0.396$$

According to equation (2) the decision by the above distance the patients $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are Chikungunia positive.

Calculation of Normalized Euclidean Distances

By (4) Normalized Euclidean Distances between $\mathcal{A}$ and $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are as

$$NED(\mathcal{A}, \mathcal{P}_1) = 0.107,\ NED(\mathcal{A}, \mathcal{P}_2) = 0.100,\ NED(\mathcal{A}, \mathcal{P}_3) = 0.100$$

According to equation (4) the decision by the above distance the patients $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are Chikungunia positive.

Calculation of Cosine Distances

By (7) Cosine Distances between $\mathcal{A}$ and $\mathcal{P}_1$, P_2, P_3 are as

$$NED(\mathcal{A}, \mathcal{P}_1) = 0.121,\ NED(\mathcal{A}, \mathcal{P}_2) = 00.074,\ NED(\mathcal{A}, \mathcal{P}_3) = 0.085$$

According to equation (7) the decision by the above distance the patients $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are Chikungunia positive.

Calculation of Normalized Fermatean Distances

By (6) Normalized Fermatean Distances between $\mathcal{A}$ and $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are as

$$NFD(\mathcal{A}, \mathcal{P}_1) = (0.86, 0.137),\ NFD(\mathcal{A}, \mathcal{P}_2) = (0.846, 0.153),$$
$$NFD(\mathcal{A}, \mathcal{P}_3) = (0.821, 0.178)$$

According to equation (6) the decision by the above distance the patients $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are Chikungunia positive.

After the calculation of Normalized Hamming Distances, Normalized Euclidean Distances, Cosine Distances and Normalized Fermatean Distances we find that the patients $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are all Chikungunia positive.

RESULTS AND DISCUSSION

This research focuses on using Fermatean fuzzy soft sets, along with several normalized distance methods, to help diagnose infectious diseases, especially chikungunya. The study looks at different distance measures—such as Fermatean, Hamming, and Euclidean—to find out which one works best for diagnosing diseases, especially when the data isn't completely clear or consistent. Compared with earlier fuzzy set models like intuitionistic and Pythagorean sets, the Fermatean fuzzy approach gives researchers and doctors more flexibility in making judgments that reflect real situations. New distance function can effectively group patients based on their symptoms, improving how diagnoses are made is one of the key outcome of this study. Specifically, a distance close to zero suggests a positive chikungunya diagnosis, while a distance greater than 0.5 indicates alternative conditions. After determination of Normalized Hamming Distances, Normalized Euclidean Distances, Cosine Distances and Normalized Fermatean Distances we find that the patients $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ are all Chikungunia positive. When normalized distance measures are applied within the Fermatean fuzzy soft set (FFS) framework, medical diagnosis systems tend to become more accurate and dependable, according to the study's comparison. The results also show that including FFS in medical decision-making tools could help improve how infectious diseases are identified. These findings support the view that pairing Fermatean fuzzy soft sets with the right distance methods can help doctors and researchers make better decisions in uncertain medical conditions, while also giving space for more work to be done in this area.

CONCLUSION

When different distance measures were applied within the FFSS framework, the study found noticeable improvements in how precisely and consistently diagnoses were made. This combination not only raised the level of accuracy but also made the medical diagnostic process more dependable overall. In short, integrating these distance measures helped the system perform better and increased confidence in its diagnostic results.The case of Chikungunya illustrated how this approach can be used effectively in real healthcare situations, showing its practical value.

The results indicate that FFSS could be a useful tool in medical decision-support systems, particularly when the available data is uncertain or incomplete. This opens up space for more research into how FFSS can be applied to other medical areas and decision-making problems. Overall, the work shows that combining Fermatean fuzzy soft sets with normalized distance measures can make diagnostic processes more efficient and help improve patient outcomes.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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