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Exploring the Utilization of Cosine Similarity in Intuitionistic Fuzzy Soft Sets for Addressing the Chikungunya Problem through an Evidence-Based Model

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ABSTRACT:

This study explores the application of the cosine similarity measure within the structure of intuitionistic fuzzy soft sets, with the goal of developing an evidence-based model to address the complicated dynamics of the Chikungunya problem. The proposed model offers a nuanced understanding of the uncertainties present in Chikungunya data by combining intuitionistic fuzzy soft sets with cosine similarity. The study first presents intuitionistic fuzzy soft sets and outlines their basic components and operations. This model offers a comprehensive mechanism to handle the uncertainties related to Chikungunya data by effortlessly combining the adapted cosine similarity measure and intuitionistic fuzzy soft sets.

1. Introduction

The concept of similarity measurement is fundamental across various fields of engineering and science. It is customary to devise similarity measures to assess the authenticity of objects or documents, serving as a crucial tool for gauging the likeness between two entities. These measures draw upon fuzzy sets, intuitionistic fuzzy sets, and vague sets, extensively applied in domains like pattern recognition, image processing, signal detection, security systems, machine learning, and medical diagnosis. In psychological theories and experiments, similarity plays a pivotal role. Participants often rate the similarity between objects, employing various experimental approaches. Predominantly, participants are asked to rate the similarity or dissimilarity between objects on a scale, reflecting their opinions. Similarity is significant, albeit to a lesser extent, in modelling several psychological tasks, particularly in theories concerning object recognition, identification, and classification. Numerous clustering and classification techniques rely on statistical similarity measures, enabling researchers to computationally assess the similarities or differences among studied objects. In text analysis, a common method involves representing texts as sets of word counts and determining their dissimilarity based on these counts. Typically, similarity measures are expressed as numerical values increasing with the similarity between data samples. Conversions often present these values between zero and one, where zero signifies low similarity and one denotes high similarity. In essence, "similarity" encompasses a broad spectrum of scores and metrics used to evaluate distinctions between different types of data.

Numerous academic fields study how people think and make decisions in real-world situations, including cognitive science, philosophy, psychology, and artificial intelligence. Generally, these processes are explained by a range of mathematical and statistical models. The issue of decision-making arises during this procedure. Decision-making (DM) is the process of selecting one or more of the behavioural options that are offered to a person or an organization in order to accomplish a specific goal. According to research, instinct is insufficient for making complicated and significant decisions, even though it works well for many everyday decisions. A group of analytical methods known as Multi-Criteria Decision Making (MCDM) assesses options based on a broad range of factors. When a group of alternatives with different attributes is presented, MCDM approaches are used to help the DM process by ranking or choosing one or more of the alternatives based on competing criteria. Put differently, by employing MCDM approaches, decision-makers assess options with different characteristics by comparing them to a range of standards. A set of tactics commonly used at all levels and in all facets of life is called MCDM. In the context of DM challenges, uncertainty is a crucial concept. Unpredictability is a premise of uncertainty. Routine decisions cannot be mentioned in unpredictable scenarios. Carefully considering the benefit and drawbacks of possible consequences in unknowable circumstances is necessary. It is imperative to look closely at the environmental components right now. When faced with uncertainty, making final decisions is certain and it is not always helpful to rely on past experiences and assessments.

Though American philosopher Max Black had put forth some of the same ideas nearly three decades earlier in 1937, Lotfi A. Zadeh's 13 seminal paper published in 1965 marked a significant advancement in the modern concept of uncertainty. In Zadeh's work, a novel theory based on "fuzzy sets," or sets with boundaries between 0 and 1, was presented. This theory allows for the representation of the imprecision and ambiguity present in uncertain situations. The basic idea of degrees of membership serves as the foundation for these fuzzy sets. By creating fuzzy sets, Zadeh made a significant advancement and provided a useful tool for dealing with ambiguity and vagueness. Numerous fields have successfully implemented the theory of fuzzy set Maji et al.9 Introduced the concept of fuzzy soft sets in 2001. Additionally, they established a few fundamental characteristics of complement, intersection, and fuzzy soft union operations. Using Intuitionistic fuzzy sets, 3 investigated Sanchez's method of medical diagnosis in 2001using IFSs that 1 first proposed, 10 developed the concept of IFSSs. In light of the research of Maji et al. 4 presented the notion of the IFSSs relation and examined some of its algebraic properties 11 established a similarity measure between two generalized fuzzy soft sets, which was applied to a medical diagnosis problem. 12 Proposes a weighted cosine similarity measure and a cosine similarity measure between IFSs. The cosine similarity measure for fuzzy sets, which considers the information carried by the membership degree and the nonmembership degree in IFSs as a vector representation with the two elements, is the foundation for these.

By fusing the extended ordinal weighted average operator with the heuristic fuzzy ordered weighted cosine similarity measure, 14 created the heuristic fuzzy ordered weighted cosine similarity measure. A refined cosine similarity measure designed specifically for differentiating between two Intuitionistic Fuzzy Sets (IFSs) is presented in 20186. This method takes into consideration the degree of ambiguity that exists between membership function pairs as they interact. Consequently, enhanced cosine and weighted cosine similarity measures are suggested for effective application within the IFS framework. Additionally, in 2023 Kirisci 7 introduces innovative measures for cosine similarity and distance specifically designed for Fermatean fuzzy sets. The research delves into the attributes of these novel measures, furnishing definitions grounded in Fermatean fuzzy sets.

Our work aims at proposing a cosine similarity measure for intuitionistic fuzzy soft sets. We also talked about a few fundamental properties of cosine similarity for intuitionistic fuzzy soft sets.This paper was motivated by our introduction of cosine similarity for fuzzy soft sets that are intuitionistic. To aid in making decisions based on cosine similarity measure even more, we present the Chikungunya problem.

Preliminaries

2.1 An intuitionistic fuzzy set $\mathfrak{A}$ exists in a finite universe of discourse $\mathfrak{U}$ $=\{\mathfrak{u}_1, \mathfrak{u}_2, \mathfrak{u}_3 \dots \mathfrak{u}_n$. It is defined as $\mathfrak{A} = \{\mathfrak{u}, \mu_{\mathfrak{A}}(\mathfrak{u}), \nu_{\mathfrak{A}}(\mathfrak{u}) | \mathfrak{u} \in \mathfrak{U}\ \}$ where $\mu_{\mathfrak{A}}(\mathfrak{u}), \nu_{\mathfrak{A}}(\mathfrak{u})$ respectively, represent the degrees of membership and non-membership of the element $\mathfrak{u} \in \mathfrak{U}$ to the set $\mathfrak{A}$, such that their sum is at most one. Term $\pi_{\mathfrak{A}} = 1 - \mu_{\mathfrak{A}}(\mathfrak{u}) - \nu_{\mathfrak{A}}(\mathfrak{u})$ represents the degree of hesitation of$\mathfrak{u}$. For a given $\mathfrak{u}$, the intuitionistic fuzzy value (IFV) or intuitionistic fuzzy number (IFN) is a pair $\mathfrak{A} = (\mu_{\mathfrak{A}}, \nu_{\mathfrak{A}})$, where $\mu_{\mathfrak{A}} \in [0, 1]$, $\nu_{\mathfrak{A}} \in [0, 1]$, $\mu_{\mathfrak{A}} + \nu_{\mathfrak{A}} \leq 1$.

2.2 Assume that the original universe set is $\mathfrak{V}$ and let $\mathfrak{G}$ be a subset of $\mathfrak{K}$. $\mathfrak{K}$ comprises the set of parameters. The representation of an intuitionistic fuzzy soft set over $\mathfrak{V}$ is a pair $(\mathfrak{F}, \mathfrak{G})$, where $\mathfrak{F}$ is a mapping indicated as$\mathfrak{F}: \mathfrak{G} \to \mathfrak{I}^{\mathfrak{V}}$. Here, the set of all intuitionistic fuzzy subsets of $\mathfrak{V}$ is denoted by $\mathfrak{I}^{\mathfrak{V}}$.

2.3 Let $\mathfrak{U} = \{\mathfrak{u}_1, \mathfrak{u}_2, \mathfrak{u}_3 \cdots \mathfrak{u}_n\}$ be a finite fixed set, $\mathfrak{A} = \{\mathfrak{u}, \mu_{\mathfrak{A}}(\mathfrak{u}), \nu_{\mathfrak{A}}(\mathfrak{u}) | \mathfrak{u} \in \mathfrak{U}\}$ and $\mathfrak{B} = \{\mathfrak{u}, \mu_{\mathfrak{B}}(\mathfrak{u}), \nu_{\mathfrak{B}}(\mathfrak{u}) | \mathfrak{u} \in \mathfrak{U}\}$ be two intuitionistic fuzzy soft sets. If

$$K(\mathfrak{A}, \mathfrak{B}) = \frac{\mathfrak{C}(\mathfrak{A}, \mathfrak{B})}{\sqrt{\mathfrak{T}(\mathfrak{A})\mathfrak{T}(\mathfrak{B})}}$$

Where $\mathfrak{C}(\mathfrak{A}, \mathfrak{B}) = \sum_{i=1}^{n}(\mu_{\mathfrak{A}}(\mathfrak{u}_i)\, \mu_{\mathfrak{B}}(\mathfrak{u}_i) + \nu_{\mathfrak{A}}(\mathfrak{u}_i)\nu_{\mathfrak{B}}(\mathfrak{u}_i))$ be the covariance between $\mathfrak{A}$ and $\mathfrak{B}$; $\mathfrak{T}(\mathfrak{A}) = \sum_{i=1}^{n}(\mu_{\mathfrak{A}}^2(\mathfrak{u}_i) + \nu_{\mathfrak{A}}^2(\mathfrak{u}_i))$ and $\mathfrak{T}(\mathfrak{B}) = \sum_{i=1}^{n}(\mu_{\mathfrak{B}}^2(\mathfrak{u}_i) + \nu_{\mathfrak{B}}^2(\mathfrak{u}_i))$ be the intuitionistic values of $\mathfrak{A}$ and $\mathfrak{B}$ respectively, then $K(\mathfrak{A}, \mathfrak{B})$ is called the co relation coefficient of intuitionistic fuzzy sets $\mathfrak{A}$ and $\mathfrak{B}$.

2.4 Cosine similarity measure among two intuitionistic fuzzy sets $\mathfrak{A}$ and $\mathfrak{B}$ is defined as

$$C_{IFS}(\mathfrak{A},\mathfrak{B})=\frac{1}{n}\sum_{i=1}^{n}\frac{\mu_{\mathfrak{A}}(\mathrm{u}_i)\mu_{\mathfrak{B}}(\mathrm{u}_i)+\nu_{\mathfrak{A}}(\mathrm{u}_i)\nu_{\mathfrak{B}}(\mathrm{u}_i)}{\sqrt{\sum_{i=1}^{n}(\mu_{\mathfrak{A}}^2(\mathrm{u}_i)+\nu_{\mathfrak{A}}^2(\mathrm{u}_i))}\sqrt{\sum_{i=1}^{n}(\mu_{\mathfrak{B}}^2(\mathrm{u}_i)+\nu_{\mathfrak{B}}^2(\mathrm{u}_i))}}$$

Where $0\le C_{IFS}(\mathfrak{A},\mathfrak{B})\le 1$.

1.Proposed Cosine similarity measure for intuitionistic fuzzy soft sets and intuitionistic fuzzy soft points

The similarity index between the two intuitionistic fuzzy soft points defined over a fixed set can be calculated using the cosine similarity measures that we have presented in this section.

3.1 Let $\mathrm{e}_i(\mathfrak{F}_E),(\mathrm{e}_j\ (\mathfrak{G}_W)$ be two intuitionistic fuzzy soft points. Then the cosine similarity measure between them, denoted by $S^-(\mathrm{e}_i(\mathfrak{F}_E),(\mathrm{e}_j\ (\mathfrak{G}_W))$ is defined as

$$S^-(\mathrm{e}_i(\mathfrak{F}_E),\mathrm{e}_j\ (\mathfrak{G}_W))=\frac{\sum_{t=1}^{n}\ \mu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\nu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)}{\sqrt{\sum_{i=1}^{n}(\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2\ (h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2(h_t))}\sqrt{\sum_{i=1}^{n}(\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}^2\ (h_t)+\nu_{\mathfrak{G}_{(j)}}^2(h_t)}}$$

Where $i=1\ or\ 2\ or\cdots or\ m,\ \ j=1 or\ 2\ or\ 3\ or\cdots or\ n$

Proposition: Let $\mathrm{e}_i(\mathfrak{F}_E)$and $\mathrm{e}_j\ (\mathfrak{G}_W)$ are two intuitionistic fuzzy soft points. Then

i. $S^-(\mathrm{e}_i(\mathfrak{F}_E),\mathrm{e}_j\ (\mathfrak{G}_W))=S^-(\mathrm{e}_j\ (\mathfrak{G}_W),\mathrm{e}_i(\mathfrak{F}_E)$

ii. $0\le S^-(\mathrm{e}_i(\mathfrak{F}_E),\mathrm{e}_j\ (\mathfrak{G}_W))\le 1$

iii. $S^-(\mathrm{e}_i(\mathfrak{F}_E),\mathrm{e}_j\ (\mathfrak{G}_W))=1 \quad if \quad \mathrm{e}_i(\mathfrak{F}_E)=\mathrm{e}_j\ (\mathfrak{G}_W)$

Proof: (i) For $i=1\ or\ 2\ or\cdots or\ m$. We get

$$S^-(\mathrm{e}_i(\mathfrak{F}_E),\mathrm{e}_j\ (\mathfrak{G}_W))=\frac{\sum_{t=1}^{n}\ \{\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\nu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2\ (h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2(h_t))}\sqrt{\sum_{t=1}^{n}(\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}^2\ (h_t)+\nu_{\mathfrak{G}_{(j)}}^2(h_t)}}$$

$$=\frac{\sum_{t=1}^{n}\{\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)+\nu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}^2\ (h_t)+\nu_{\mathfrak{G}_{(j)}}^2(h_t))}\ \sqrt{\sum_{t=1}^{n}(\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2\ (h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2(h_t))}}$$

$$=S^-(\mathrm{e}_j\ (\mathfrak{G}_W),\mathrm{e}_i(\mathfrak{F}_E)$$

ii. It is obvious.

iii. Let $\mathrm{e}_i(\mathfrak{F}_E)=\mathrm{e}_j\ (\mathfrak{G}_W)$ and for $i=1,2,3,\cdots,m$ we have

$$S^-(\mathrm{e}_i(\mathfrak{F}_E),\mathrm{e}_j\ (\mathfrak{G}_W))=\frac{\sum_{t=1}^{n}\ \{\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\nu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2\ (h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2(h_t))}\sqrt{\sum_{t=1}^{n}(\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}^2\ (h_t)+\nu_{\mathfrak{G}_{(j)}}^2(h_t)}}$$

$$=\frac{\sum_{t=1}^{n}\{\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2\ (h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2(h_t)\}}{\sum_{t=1}^{n}\{\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2\ (h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2(h_t)\}}$$

$$=1$$

3.2 Two intuitionistic fuzzy soft sets are $\mathfrak{F}_E$ and $\mathfrak{G}_W$. Then $S^-(\mathfrak{F}_E,\ \mathfrak{G}_W)$ the cosine similarity between them, is defined by

$$S^-(\mathfrak{F}_E,\ \mathfrak{G}_W)=\frac{1}{n}\sum_{t=1}^{n}\frac{\sum_{t=1}^{n}\ \{\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}(h_t)\nu_{\mathfrak{G}_{(\mathrm{e}_j)}}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2\ (h_t)+\nu_{\mathfrak{F}_{(\mathrm{e}_i)}}^2(h_t))}\sqrt{\sum_{t=1}^{n}(\mu_{\mathfrak{G}_{(\mathrm{e}_j)}}^2\ (h_t)+\nu_{\mathfrak{G}_{(j)}}^2(h_t)}}$$

Proposition: Let $\mathfrak{F}_E$ and $\mathfrak{G}_W$ are two intuitionistic fuzzy soft sets. Then,

i. $S^-(\mathfrak{F}_E,\ \mathfrak{G}_W)=S^-(\mathfrak{G}_W,\ \mathfrak{F}_E)$

ii. $0\le S^-(\mathfrak{F}_E,\ \mathfrak{G}_W)\le 1$

iii. $S^-(\mathfrak{F}_E,\ \mathfrak{G}_W)=1\ if\ \mathfrak{F}_E=\mathfrak{G}_W$

Proof: It is obvious

2.Weighted Cosine similarity measure for intuitionistic fuzzy soft sets and intuitionistic fuzzy soft points

Definitions and illustrations of weighted measure of similarity between intuitionistic fuzzy soft sets and intuitionistic fuzzy soft points are examined in this section. Moreover, a few properties are introduced.

Let the set of parameters $\mathfrak{K} = \{\mathfrak{e}_1, \mathfrak{e}_2, \mathfrak{e}_3 \ldots \mathfrak{e}_m\}$ and $\mathfrak{W}_i$be the weight of $\mathfrak{e}_i$ and $\sum_{t=1}^{n}\mathfrak{W}_i = 1$ $\mathfrak{W}_i \in [0,1]$ but not all zero. Let $(\mathfrak{e}_i(\mathfrak{F}_E), \mathfrak{e}_j(\mathfrak{G}_W))$ be two intuitionistic fuzzy soft points. Then the weighted cosine similarity measure between them, denoted by $S^{-}(\mathfrak{e}_i(\mathfrak{F}_E), \mathfrak{e}_j(\mathfrak{G}_W))$ is defined as

$$\mathfrak{W}_i S^{-}(\mathfrak{e}_i(\mathfrak{F}_E), \mathfrak{e}_j(\mathfrak{G}_W) = \frac{\dfrac{\sum_{t=1}^{n}\mathfrak{W}_i\{\mu_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\mu_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)+\nu_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\nu_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)+\nu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t))}\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)+\nu^2_{\mathfrak{G}_{(j)}}(h_t)}}}{\sum_{t=1}^{n}\mathfrak{W}_i}$$

Where $i = 1$ or 2 $or \cdots or$ m, $j = 1 or$ 2 or 3 $or \cdots or$ n

Proposition: Let $\mathfrak{e}_i(\mathfrak{F}_E)$and $\mathfrak{e}_j(\mathfrak{G}_W)$ are two intuitionistic fuzzy soft points. Then

i. $\mathfrak{W}_i S^{-}(\mathfrak{e}_i(\mathfrak{F}_E), \mathfrak{e}_j(\mathfrak{G}_W)) = \mathfrak{W}_i S^{-}(\mathfrak{e}_j(\mathfrak{G}_W), \mathfrak{e}_i(\mathfrak{F}_E)$

ii. $0 \le \mathfrak{W}_i S^{-}(\mathfrak{e}_i(\mathfrak{F}_E), \mathfrak{e}_j(\mathfrak{G}_W)) \le 1$

iii. $S\mathfrak{W}_i^{-}(\mathfrak{e}_i(\mathfrak{F}_E), \mathfrak{e}_j(\mathfrak{G}_W)) = 1 \quad if \quad \mathfrak{e}_i(\mathfrak{F}_E) = \mathfrak{e}_j(\mathfrak{G}_W)$

Proof: (i) For $i = 1$ or 2 $or \cdots or$ m. We get

$$\mathfrak{W}_i S^{-}(\mathfrak{e}_i(\mathfrak{F}_E), \mathfrak{e}_j(\mathfrak{G}_W)) = \frac{\dfrac{\sum_{t=1}^{n}\mathfrak{W}_i\{\mu_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\mu_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)+\nu_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\nu_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)+\nu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t))}\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)+\nu^2_{\mathfrak{G}_{(j)}}(h_t)}}}{\sum_{i=1}^{n}\mathfrak{W}_i}$$

$$= \frac{\dfrac{\sum_{t=1}^{n}\mathfrak{W}_i\{\mu_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)\,\mu_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)+\nu_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)\nu_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)+\nu^2_{\mathfrak{G}_{(j)}}(h_t)}\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)+\nu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t))}}}{\sum_{i=1}^{n}\mathfrak{W}_i}$$

$$= \mathfrak{W}_i S^{-}(\mathfrak{e}_j(\mathfrak{G}_W)\mathfrak{e}_i(\mathfrak{F}_E))$$

ii. It is obvious

iii. Let $\mathfrak{e}_i(\mathfrak{F}_E) = \mathfrak{e}_j(\mathfrak{G}_W)$ and for $i = 1, 2, 3, \cdots, m$ we have

$$\mathfrak{W}_i S^{-}(\mathfrak{e}_i(\mathfrak{F}_E), \mathfrak{e}_j(\mathfrak{G}_W)) = \frac{\dfrac{\sum_{t=1}^{n}\mathfrak{W}_i\{\mu_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\mu_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)+\nu_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\nu_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)+\nu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t))}\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{G}_{(\mathfrak{e}_j)}}(h_t)+\nu^2_{\mathfrak{G}_{(j)}}(h_t)}}}{\sum_{i=1}^{n}\mathfrak{W}_i}$$

$$= \frac{\dfrac{\sum_{t=1}^{n}\mathfrak{W}_i\{\mu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)+\nu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\}}{\sum_{t=1}^{n}\{\mu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)+\nu^2_{\mathfrak{F}_{(\mathfrak{e}_i)}}(h_t)\}}}{\sum_{i=1}^{n}\mathfrak{W}_i}$$

$$= 1$$

Two intuitionistic fuzzy soft sets are $\mathfrak{F}_E$ and $\mathfrak{G}_W$. Then $\mathfrak{W}_i S^{-}(\mathfrak{F}_E, \mathfrak{G}_W)$, the weighted cosine similarity between them, is defined by

$$\mathfrak{W}_i S^-(\mathfrak{F}_E, \mathfrak{G}_W) = \frac{1}{n}\sum_{t=1}^{n} \frac{\frac{\sum_{t=1}^{n} \mathfrak{W}_i \{ \mu_{\mathfrak{F}(\mathrm{e}_i)}(h_t)\mu_{\mathfrak{G}(\mathrm{e}_j)}(h_t)+\nu_{\mathfrak{F}(\mathrm{e}_i)}(h_t)\nu_{\mathfrak{G}(\mathrm{e}_j)}(h_t)\}}{\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{F}(\mathrm{e}_i)}(h_t)+\nu^2_{\mathfrak{F}(\mathrm{e}_i)}(h_t))}\sqrt{\sum_{t=1}^{n}(\mu^2_{\mathfrak{G}(\mathrm{e}_j)}(h_t)+\nu^2_{\mathfrak{G}(j)}(h_t)}}}{\sum_{i=1}^{n}\mathfrak{W}_i}$$

Proposition: Let $\mathfrak{F}_E$ and $\mathfrak{G}_W$ are two intuitionistic fuzzy soft sets. Then,

i. $\mathfrak{W}_i S^-(\mathfrak{F}_E, \mathfrak{G}_W) = \mathfrak{W}_i S^-(\mathfrak{G}_W, \mathfrak{F}_E)$
ii. $0 \leq \mathfrak{W}_i S^-(\mathfrak{F}_E, \mathfrak{G}_W) \leq 1$
iii. $\mathfrak{W}_i S^-(\mathfrak{F}_E, \mathfrak{G}_W) = 1 \; if \; \mathfrak{F}_E = \mathfrak{G}_W$

Proof: It is obvious

Application of Cosine Similarity Measure for Intuitionistic Fuzzy Soft Sets in Chickungunya Problem

The bite of an Aedes mosquito, especially Aedes aegypti, is the pathogen that causes chikungunya. Mosquitoes are believed to carry the chikungunya virus primarily from humans, or from reservoirs. As a result, the mosquito typically bites someone who is ill before biting someone else to spread the illness. An infected individual cannot directly infect other people. In India, outbreaks of chikungunya frequently occur during the monsoon and early post-monsoon seasons. There is a correlation between the risk of chikungunya in India and higher average temperatures. Chikungunya can induce excruciating joint pain, swelling, and discomfort. Using intuitionistic fuzzy soft sets, we attempted to determine the cosine similarity between two regions of India in this section. Six Indian states are examined: Maharashtra, Goa, and Gujarat in the west, and Bihar, Jharkhand, and West Bengal in the east. The National Centre for Vector Borne Diseases Control, Directorate General of Health Services, Ministry of Health and Family Welfare, Government of India 5 provided data on which six state details, including suspected cases, confirmed cases, and negative cases, were created. The only years for which data were gathered were 2018; 2020; and 2022.

In our model the universal set contain three elements i.e $\mathfrak{U} = \{\mathfrak{h}_1, \mathfrak{h}_2, \mathfrak{h}_3\}$, where $\mathfrak{h}_1 = 2018$, $\mathfrak{h}_2 = 2020$, $\mathfrak{h}_3 = 2022$. Different states of regions of India is considered as a parameter set $E = \{\mathrm{e}_1, \mathrm{e}_2, \mathrm{e}_3, \mathrm{e}_4, \mathrm{e}_5, \mathrm{e}_6\}$ where $\mathrm{e}_1 = \text{Bihar}, \mathrm{e}_2 = \text{Jharkhond}, \mathrm{e}_3 = \text{West Bengal}, \mathrm{e}_4 = \text{Maharashtra}, \mathrm{e}_5 = \text{Goa}, \mathrm{e}_6 = \text{Gujarat}.$ here we applied the following algorithm.

Algorithm:

1. To compile information from the National Centre for Vector Borne Diseases Control, Directorate General of Health Services, Ministry of Health and Family Welfare, Government of India.
2. Using suspected cases to assist in the conversion of data to decimal form.
3. To represent data in tabular form using intuitionistic fuzzy soft sets $\mathfrak{F}_E$ and $\mathfrak{G}_W$.
4. Determine cosine similarity measure $S^-(\mathfrak{F}_E, \mathfrak{G}_W)$between $\mathfrak{F}_E$ and $\mathfrak{G}_W$.
5. If cosine similarity measure is higher than 0.5, we are able to infer that the regions and states are possibly the spread of Chikungunya similar.

Table 1: Chickungunya data

Year	Region	State	Suspected cases	Confirmed cases	Negative Cases
2018	East	Bihar	156	156	0
2018	East	Jharkhand	3405	851	2554
2018	East	West Bengal	52	23	29
2018	West	Maharashtra	9884	1009	8875
2018	West	Goa	455	77	378

2018	West	Gujarat	10601	1290	9311
2020	East	Bihar	38	38	0
2020	East	Jharkhand	627	157	470
2020	East	West Bengal	391	82	309
2020	West	Maharashtra	4258	782	3476
2020	West	Goa	64	15	49
2020	West	Gujarat	8120	1061	7059
2022	East	Bihar	40	38	0
2022	East	Jharkhand	2113	249	1864
2022	East	West Bengal	1533	148	1385
2022	West	Maharashtra	14785	1087	13698
2022	West	Goa	868	106	762
2022	West	Gujarat	20855	1046	19809

We express suspected cases in bar diagram from Table 1 in Figure 1.

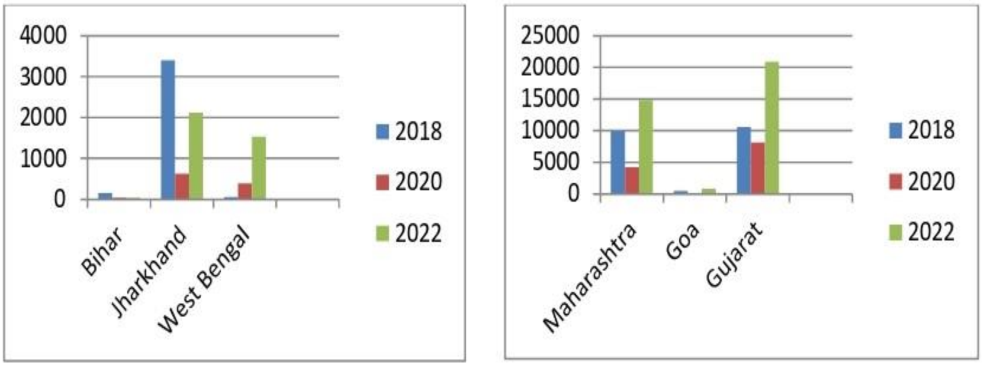

Figure 1: Suspected cases of East and West region States

Again we have presented the year wise converted data in table 2.

Table 2: Year wise Converted data

Year	Region	State	Confirmed cases	Negative Cases
2018	East	Bihar	1	0
2018	East	Jharkhand	.25	.75
2018	East	West Bengal	.44	.56
2018	West	Maharashtra	.10	.89
2018	West	Goa	.17	.83
2018	West	Gujarat	.12	.87
2020	East	Bihar	1	0
2020	East	Jharkhand	.25	.75
2020	East	West Bengal	.21	.79
2020	West	Maharashtra	.18	.82
2020	West	Goa	.23	.76
2020	West	Gujarat	.13	.86
2022	East	Bihar	1	0
2022	East	Jharkhand	.12	.88
2022	East	West Bengal	.09	.90
2022	West	Maharashtra	.07	.93
2022	West	Goa	.12	.87

2022	West	Gujarat	.04	.96

Tabular form of intuitionistic fuzzy soft sets $\mathfrak{F}_E$ and $\mathfrak{G}_W$ in Table 4

Table 3: Tabular form of $\mathfrak{F}_E$ and $\mathfrak{G}_W$

$\mathfrak{F}_E$	$\mathfrak{e}_1$	$\mathfrak{e}_2$	$\mathfrak{e}_3$
$\mathfrak{h}_1$	(1, 0)	(0.25, 0.75)	(0.44, 0.56)
$\mathfrak{h}_2$	(1, 0)	(0.25, 0.75)	(0.21, 0.79)
$\mathfrak{h}_3$	(1, 0)	(0.12, 0.88)	(0.09, 0.90)
$\mathfrak{G}_W$	$\mathfrak{e}_4$	$\mathfrak{e}_5$	$\mathfrak{e}_6$
$\mathfrak{h}_1$	(0.10, 0.89)	(0.17, 0.83)	(0.12, 0.87)
$\mathfrak{h}_2$	(0.18, 0.82)	(0.23, 0.76)	(0.13, 0.86)
$\mathfrak{h}_3$	(0.07, 0.93)	(0.12, 0.87)	(0.04, 0.96)

Table 4: Cosine Similarity in tabular form

$S^{-}(\mathfrak{F}_E,\ \mathfrak{G}_W) = 0.69 \geq 0.5$	
$S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_4\ (\mathfrak{G}_W))$	0.131
$S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_5\ (\mathfrak{G}_W))$	0.2062
$S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_6\ (\mathfrak{G}_W))$	0.1069
$S^{-}(\mathfrak{e}_2(\mathfrak{F}_E), \mathfrak{e}_4\ (\mathfrak{G}_W))$	0.9252
$S^{-}(\mathfrak{e}_2(\mathfrak{F}_E), \mathfrak{e}_5\ (\mathfrak{G}_W))$	0.9969
$S^{-}(\mathfrak{e}_2(\mathfrak{F}_E), \mathfrak{e}_6\ (\mathfrak{G}_W))$	0.9890
$S^{-}(\mathfrak{e}_3(\mathfrak{F}_E), \mathfrak{e}_4\ (\mathfrak{G}_W))$	0.9515
$S^{-}(\mathfrak{e}_3(\mathfrak{F}_E), \mathfrak{e}_5\ (\mathfrak{G}_W))$	0.9971
$S^{-}(\mathfrak{e}_3(\mathfrak{F}_E), \mathfrak{e}_6\ (\mathfrak{G}_W))$	0.9565

From Table 4 It is evident that all values greater than 0.5 except $S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_4\ (\mathfrak{G}_W))$, $S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_5\ (\mathfrak{G}_W))$, $S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_6\ (\mathfrak{G}_W))$. Therefore both East and West region, and all the states spread similarly chikungunia except Bihar of East region.

Use of the weighted Cosine similarity measure in the Chikungunya problem for intuitionistic fuzzy soft sets.

Weighted Cosine similarity measure for intuitionistic fuzzy soft sets in Chikungunya have been applied in this section. According to the number of suspected cases of particular state, we have applied weight. Bihar, Jharkhand, West Bengal Maharashtra, Goa, and Gujarat have 40, 215, 20, 2526, 12 and 4044 confirmed cases in 2021. On the basis of this data we find the weight 0.0058, 0.0313, 0.0029, 0.3683, 0.0017 and 0.5897 of the given states. So the weight of

$\mathfrak{e}_1$(Bihar)=0.0058,$\mathfrak{e}_2$(Jharkhand)=0.0313,$\mathfrak{e}_3$(WestBengal)=0.0029, $\mathfrak{e}_4$(Maharashtra)=0.3683, $\mathfrak{e}_5$(Goa)=0.0017 and $\mathfrak{e}_6$(Gujarat)=0.5897.

Algorithm:

1. To take into account all of the information gathered for section 5.
2. To multiply the data (Table 3) by the appropriate parameter weight.
3. Find the weighted Cosine similarity between intuitionistic fuzzy soft points of intuitionistic fuzzy soft set model $\mathfrak{F}_E$ and $\mathfrak{G}_W$.
4. Determine the weighted Cosine similarity between intuitionistic fuzzy soft set model $\mathfrak{F}_E$ and$\mathfrak{G}_W$.
5. If similarity values are less than 0.5 then we conclude that the states and the regions are similar to control of chikungunia.

We have consider the data from Section 5 and implement of weight of corresponding parameters, the Table 3 converted to Table 5 as

Table 5: Tabular form of $\mathfrak{F}_E$ and $\mathfrak{G}_W$

$\mathfrak{F}_E$	$\mathfrak{e}_1$(.0058)	$\mathfrak{e}_2$(.0313)	$\mathfrak{e}_3$(.0029)
$\mathfrak{h}_1$	(.0058, 0)	(0.0078, 0.0234)	(0.0012, 0.0016)
$\mathfrak{h}_2$	(.0058, 0)	(0.0078, 0.0234)	(0.0006, 0.0022)
$\mathfrak{h}_3$	(.0058, 0)	(0.0037, 0.0275)	(0.0003, 0.0026)
$\mathfrak{G}_W$	$\mathfrak{e}_4$(.3683)	$\mathfrak{e}_5$(.0017)	$\mathfrak{e}_6$(.5897)
$\mathfrak{h}_1$	(0.0368, 0.3277)	(0.0003, 0.0014)	(0.0707, 0.5130)
$\mathfrak{h}_2$	(0.0662, 0.3020)	(0.0004, 0.0013)	(0.0767, 0.5071)
$\mathfrak{h}_3$	(0.0257, 0.3425)	(0.0002, 0.0014)	(0.0235, 0.5661)

Table 6: Weighted Cosine Similarity in tabular form

$\mathfrak{W}S^{-}(\mathfrak{F}_E,\ \mathfrak{G}_W) = 0.067$	
Similarity between States	Values
$\mathfrak{W}S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_4\ (\mathfrak{G}_W))$	0.008
$\mathfrak{W}S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_5\ (\mathfrak{G}_W))$	0.024
$\mathfrak{W}S^{-}(\mathfrak{e}_1(\mathfrak{F}_E), \mathfrak{e}_6\ (\mathfrak{G}_W))$	0.012
$\mathfrak{W}S^{-}(\mathfrak{e}_2(\mathfrak{F}_E), \mathfrak{e}_4\ (\mathfrak{G}_W))$	0..110
$\mathfrak{W}S^{-}(\mathfrak{e}_2(\mathfrak{F}_E), \mathfrak{e}_5\ (\mathfrak{G}_W))$	0.112
$\mathfrak{W}S^{-}(\mathfrak{e}_2(\mathfrak{F}_E), \mathfrak{e}_6\ (\mathfrak{G}_W))$	0.111
$\mathfrak{W}S^{-}(\mathfrak{e}_3(\mathfrak{F}_E), \mathfrak{e}_4\ (\mathfrak{G}_W))$	0.106
$\mathfrak{W}S^{-}(\mathfrak{e}_3(\mathfrak{F}_E), \mathfrak{e}_5\ (\mathfrak{G}_W))$	0.012
$\mathfrak{W}S^{-}(\mathfrak{e}_3(\mathfrak{F}_E), \mathfrak{e}_6\ (\mathfrak{G}_W))$	0.107

3. Conclusion

In this paper, a cosine similarity measure for intuitionistic fuzzy soft sets is presented, and some of its basic properties are discussed. Furthermore, we offer a Chikungunya problem application for intuitionistic fuzzy soft sets. In order to forecast the quantity of confirmed cases of chikungunya in Indian States, we have put forth deep learning models. We have developed the algorithm based on the quantity of chikungunya cases in the Indian States that are both confirmed and negative. An epidemiological model to determine within two regions and six states, the cosine similarity in India are developed using a control theoretic approach. Result depict that there is a rapid decrease in the number of cases in the states in near future. It is crucial to remember that the projected future is based on certain system parameters and could vary based on outside outputs like when indoors, wear insect repellents on skin and clothing, stay in areas with good screening, and use bed nets. When working outside, wear long sleeves and long pants to safeguard from mosquito bites during the day. Also never keep water in storage for more than a week. This approach will prove beneficial for a wide range of practical uncertainty problems, such as those pertaining to pattern recognition, image processing, coding theory, and economic systems.

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