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Research paper

# Mathematical modeling and AI based decision making for COVID-19 suspects backed by novel distance and similarity measures on plithogenic hypersoft sets

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ABSTRACT

It goes without saying that coronavirus (COVID-19) is an infectious disease and many countries are coping with its different variants. Owing to the limited medical facilities, vaccine and medical experts, need of the hour is to intelligently tackle its spread by making artificial intelligence (AI) based smart decisions for COVID-19 suspects who develop different symptoms and they are kept under observation and monitored to see the severity of the symptoms. The target of this study is to analyze COVID-19 suspects data and detect whether a suspect is a COVID-19 patient or not, and if yes, then to what extent, so that a suitable decision can be made. The decision can be categorized such that an infected person can be isolated or quarantined at home or at a facilitation center or the person can be sent to the hospital for the treatment. This target is achieved by designing a mathematical model of COVID-19 suspects in the form of a multi-criteria decision making (MCDM) model and a novel AI based technique is devised and implemented with the help of newly developed plithogenic distance and similarity measures in fuzzy environment. All findings are depicted graphically for a clear understanding and to provide an insight of the necessity and effectiveness of the proposed method. The concept and results of the proposed technique make it suitable for implementation in machine learning, deep learning, pattern recognition etc.

## 1. Introduction

There is no gainsaying the fact that the 21st century has been a century of different challenges for the mankind. On the top of all is the emergence of COVID-19 in the city of Wuhan, China in December 2019. Owing to the uncertainty, limited information and resources, it became a challenging task to tackle the pandemic in terms of its spread, vaccine and treatment. A reasonable amount of literature has been written on the topic by the mathematicians and statisticians to develop emergency support systems for COVID-19 [1–5]. In this article, a very important question has been addressed about the COVID-19 suspects who develop mild, moderate or severe symptoms and a smart decision is required for their treatment. The target is achieved by developing distance and similarity measures on plithogenic hypersoft sets and implemented to the MCDM model of COVID-19 suspects in fuzzy environment.

In order to deal with uncertainty, fuzzy set was introduced in 1965 by Zadeh [6], as an extension of the notion of classical set in which an element is either a member of the set or not. There is no third possibility. In fuzzy set, a membership value is allocated to all the elements in the interval $[0, 1]$. An extension of the fuzzy set, called intuitionistic fuzzy set (IFS), was presented by Atanassov [7–9], in which a membership grade as well as a non-membership grade is assigned to each element of the set. IFSs have numerous applications in logic programming [10], pattern recognition [11–15], decision making and medical diagnosis [16,17] etc. Fuzzy set and intuitionistic fuzzy set are unable to handle indeterminacy in the data. This gap was fulfilled by Smarandache who presented the idea of neutrosophic set [18]. A generalization of these concepts was proposed by Smarandache, and termed as plithogenic set [19,20]. It was noted that, in all these concepts, there is an insufficiency of parametrization tool. In 1999, Molodtsov [21], defined soft set as a parameterized family of the subsets of the universe. Soft set has been widely studied and applied in different fields [22–25]. In 2018, Smarandache [26] proposed the idea of hypersoft set, as a generalization of soft set. A lot of research work has been written on hypersoft set, its hybrids and applications [27–30]. Smarandache introduced plithogenic hypersoft set and its mathematical definition was given by Rayees et al. [31].

Distance and similarity measures play a key role in medical diagnosis and decision making. Beg et al. [32] and Chen et al. [33] presented

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the similarity measures for fuzzy sets and their hybrids. A number of researchers proposed the distance and similarity measures on IFSs along with their applications [12–14,34–36]. A ground breaking work was performed by Majumdar and Samanta [37,38] who proposed the similarity measures on soft sets and fuzzy soft sets, based on the distance between them. Kharal [39] presented a modified version of the distance and similarity measures on soft sets given by Samanta et al. Similarity measures have extensive applications in psychology [40], decision making [41] etc.

The contributions made in this article are two fold. First of all, distance and similarity measures are defined on plithogenic hypersoft sets. The necessity of defining these measures arises due to the fact that plithogenic hypersoft set is a generalization of all the previously defined structures. Moreover, it takes into account all the necessary information as well the shortcomings in the process of mathematical modeling of an MCDM problem. Therefore, the problems involving decisions on COVID-19 suspects must be intelligently handled on a broad spectrum. Thus, a mathematical model of COVID-19 suspects is structured into an MCDM problem in the context of plithogenic hypersoft set. Secondly, the proposed plithogenic distance and similarity measures are implemented on the problem to make smart decisions on the infected ones depending on the severity of the infection. Last but not the least, the algorithm of the proposed AI based method not only detects the infection in the suspects [42], but also talks about its severity. It is capable of reading the input, processing it according to the proposed algorithm steps and concluding with useful output. It makes the proposed method applicable to a variety of medical diagnosis problems. The algorithm is tested on COVID-19 suspects data due to the ongoing situation in the world facing the pandemic.

Mathematically, the proposed plithogenic distance and similarity measures satisfy the basic properties of distance and similarity measures and obey the results of relevant theorems. For the validation of the proposed algorithm, the results are calculated with the corresponding Euclidean and Hamming distance and similarity measures and a comparative analysis is performed. The obtained results prove the validity of the proposed algorithm and its efficiency in producing AI based decision making. The scope of the study can be extended to pattern recognition, image processing, picture science, in different environments like pythagorean fuzzy environment [43], $q$-rung orthopair fuzzy environment, spherical fuzzy environment, etc.

The remainder of the article is arranged such that, in Section 2, some basic concepts are given for a better understanding of the proposed work. In Section 3, plithogenic distance measure is defined, relevant theorems with proofs are given, types of plithogenic distance measures are given, and plithogenic similarity measure is defined. In Section 4, mathematical modeling and AI based decision making for COVID-19 suspects is given. In Section 5, the COVID-19 model is employed on COVID-19 suspects. Conclusion is given in Section 6 along with future directions of the study.

## 2. Preliminaries

Let $U$ be an initial universe, $P(U)$ be its power set, and $\mathcal{P} \subseteq U$ be a finite set of alternatives under consideration. Let $\mathcal{A} = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$, $n \geq 1$ be a finite set of parameters or attributes, whose attribute values are members of the sets $A_1, A_2, \dots, A_n$ respectively, such that these sets are disjoint, i.e., $A_i \cap A_j = \phi$, with $i \neq j$ and $i, j = 1, 2, \dots, n$. Let $C = A_1 \times A_2 \times \cdots \times A_n$, and $B$ be a collection of selected attributes, i.e., $B \subseteq \mathcal{A}$.

### 2.1. Soft set [21]

A soft set $(F, B)$ is defined by the mapping $F : B \rightarrow P(U)$. Mathematically, it can be written as

$$(F, B) = \{\langle x, F_B(x)\rangle, x \in U, F_B(x) \in P(U)\}$$

### 2.2. Hypersoft set [26]

Let $C$ represents the cartesian product of $A_1, A_2, \dots, A_n$ having elements of the form $\delta = (\delta_1, \delta_2, \dots, \delta_n)$, where $\delta_i \in A_i$ for $i = 1, 2, \dots, n$. Then, a hypersoft set $(H, C)$ is defined by the mapping $H : C \rightarrow P(U)$, and given by

$$(H, C) = \{\langle \delta, H(\delta)\rangle, \delta \in C, H(\delta) \in P(U)\}$$

### 2.3. Plithogenic set [19]

If all members of the set $\mathcal{P}$ are characterized by attributes such that the attributes may have been further divided into attribute values, along with a contradiction degree defined between each attribute value and its corresponding dominant attribute value, then the set $\mathcal{P}$ is called a plithogenic set.

Mathematically, it is represented by the notation $(\mathcal{P}, \alpha, A, d, c)$, where $\mathcal{P}$ is a subset of $U$, $\alpha$ is an attribute, $A$ is the set of attribute values of $\alpha$, $d$ is the degree of appurtenance function, and $c$ is the contradiction degree function.

### 2.4. Plithogenic hypersoft set [31]

The set $(\mathcal{P}, \mathcal{A}, C, d, c)$ is called a plithogenic hypersoft set (PHSS), if an appurtenance degree function $d$ and a contradiction degree function $c$ between two attribute values are defined as follows:

$$d : \mathcal{P} \times C \rightarrow P([0, 1]^j), \forall\, p \in \mathcal{P}, j = 1, 2, 3.$$

$$c : A_i \times A_i \rightarrow P([0, 1]^j), 1 \leq i \leq n, j = 1, 2, 3.$$

where $j = 1, 2, 3$ gives the fuzzy, intuitionistic fuzzy, and neutrosophic degree of appurtenance respectively, such that for the attribute values $\delta_1$ and $\delta_2$ of the same attribute satisfy the following constraints:

$$c(\delta_1, \delta_1) = 0,$$

$$c(\delta_1, \delta_2) = c(\delta_2, \delta_1).$$

For $n$-tuple $(\delta_1, \delta_2, \dots, \delta_n) \in C$, PHSS $\mathcal{F}_P : C \rightarrow P(U)$ can be mathematically represented as

$$\mathcal{F}_P(\delta_1, \delta_2, \dots, \delta_n) = \{p(d_p(\delta_1), d_p(\delta_2), \dots, d_p(\delta_n)), p \in \mathcal{P}\}$$

### 2.5. Distance measure between fuzzy sets [32]

There are different measures in literature for distance which is calculated between the fuzzy sets under consideration. The most commonly used distances between fuzzy sets, were categorized as hamming distance measure $d_H$, normalized hamming distance measure $d_{NH}$, Euclidean distance measure $d_E$, and normalized Euclidean distance measure $d_{NE}$. For any two fuzzy sets $F_1$ and $F_2$, over a finite universe $U$, with truth membership functions $T_{F_1}(p_i)$ and $T_{F_2}(p_i)$, respectively for $i = 1, 2, 3, \dots, n$ such that $p_i \in U$, the said distances are

$$d_H(F_1, F_2) = \sum_{i=1}^{n} |T_{F_1}(p_i) - T_{F_2}(p_i)|$$

$$d_{NH}(F_1, F_2) = \frac{1}{n} \sum_{i=1}^{n} |T_{F_1}(p_i) - T_{F_2}(p_i)|$$

$$d_E(F_1, F_2) = \left[\sum_{i=1}^{n} [T_{F_1}(p_i) - T_{F_2}(p_i)]^2\right]^{\frac{1}{2}}$$

$$d_{NE}(F_1, F_2) = \left[\frac{1}{n} \sum_{i=1}^{n} [T_{F_1}(p_i) - T_{F_2}(p_i)]^2\right]^{\frac{1}{2}}$$

### 2.6. Distance measure between soft sets [39]

Let $U$ be finite universe, $\alpha_i$ be the attributes, such that $i = 1, 2, 3, \dots, m$, and $p_j \in U$ such that $j = 1, 2, 3, \dots, n$, then the commonly used distances between two soft sets $S_1$ and $S_2$, over $U$, are given as

$$d_H(S_1, S_2) = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n}|S_1(\alpha_i)(p_j) - S_2(\alpha_i)(p_j)|$$

$$d_{NH}(S_1, S_2) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}|S_1(\alpha_i)(p_j) - S_2(\alpha_i)(p_j)|$$

$$d_E(S_1, S_2) = \left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n}[S_1(\alpha_i)(p_j) - S_2(\alpha_i)(p_j)]^2\right]^{\frac{1}{2}}$$

$$d_{NE}(S_1, S_2) = \left[\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}[S_1(\alpha_i)(p_j) - S_2(\alpha_i)(p_j)]^2\right]^{\frac{1}{2}}$$

## 3. Plithogenic distance and similarity measures

In almost every field of science including pattern recognition, image processing, machine learning, artificial intelligence and related fields, whenever we need to distinguished two objects, the concept of distance and their similarity is required. There are different measures in literature for distance and similarity in which distance is calculated between the sets under consideration and the degree of similarity is calculated based on their associated distance. There are multiple applications in which the contradiction degree $C_F(\delta, \delta_d)$ need to be defined. So the effectiveness of our method can be seen there. The proposed distance formulas accommodated the contradiction degree $C_F(\delta, \delta_d)$ by maintaining the structure of original formula and also its conditions,

For this, let $U$ be the finite universe, $\mathcal{A} = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$ be the set of attributes, and $A = \{A_1, A_2, \dots, A_n\}$ be the set of corresponding attribute values sets of the attributes $\alpha_1, \alpha_2, \dots, \alpha_n$ such that $m$ represents the number of chosen attributes and $l$ represents the equal number of attribute values of each attributes. Let $C$ be the cartesian product of attribute values $A_1, A_2, \dots, A_n$ such that $(\delta_1, \delta_2, \dots, \delta_n) \in C$ be $n$-tuple of the attribute values and $c_F(\delta, \delta_d)$ represents the fuzzy contradiction degree between the attribute value $\delta$ and their corresponding dominant attribute value $\delta_d$. Let $\mathcal{P}_1$ and $\mathcal{P}_2$ be two PHSSs such that $d_{\mathcal{P}_1}(p_j)$ and $d_{\mathcal{P}_2}(p_j)$, be their corresponding degree of appurtenance, respectively, where $j = 1, 2, 3 \dots, l$, then the following plithogenic distance and similarity measures are proposed as follows:

### 3.1. Plithogenic distance measures

The proposed plithogenic distance measures (PDM) are named as plithogenic hamming distance measure $d_H^{\mathcal{P}}$, normalized plithogenic hamming distance measure $d_{NH}^{\mathcal{P}}$, plithogenic Euclidean distance measure $d_E^{\mathcal{P}}$, and normalized plithogenic Euclidean distance measure $d_{NE}^{\mathcal{P}}$. For any two PHSSs $\mathcal{P}_1$ and $\mathcal{P}_2$, the said distances are proposed as follows:

$$d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}|d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)| \times \max(c_F^i(\delta_j, \delta_d)) \tag{3.1}$$

$$d_{NH}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{l}|d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)| \times \max(c_F^i(\delta_j, \delta_d)) \tag{3.2}$$

$$d_E^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = \left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}(d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j))^2 \times \max(c_F^i(\delta_j, \delta_d))\right]^{\frac{1}{2}} \tag{3.3}$$

$$d_{NE}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = \frac{1}{n}\left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}(d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j))^2 \times \max(c_F^i(\delta_j, \delta_d))\right]^{\frac{1}{2}} \tag{3.4}$$

#### 3.1.1. Theorem 1

The distance measures between plithogenic hypersoft sets $\mathcal{P}_1$ and $\mathcal{P}_2$ satisfies the following inequalities.

(1) $d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) \le n$
(2) $d_{NH}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) \le 1$
(3) $d_E^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) \le \sqrt{n}$
(4) $d_{NE}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) \le 1$

It is obvious from the definitions described in the Eqs. (3.1), (3.2), (3.3), and (3.4), that the proposed plithogenic distance measures obey these laws.

#### 3.1.2. Theorem 2

The distance functions $d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2), d_{NH}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2), d_E^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2), d_{NE}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$ defined from $P(U) \to R^+$ are metric.

**Proof.**

Let $\mathcal{P}_1, \mathcal{P}_2$ and $\mathcal{P}_3$ be three plithogenic hypersoft sets over the universe $U$. then

(1) $d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) \ge 0$
(2) Suppose $d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = 0$,

$$\Leftrightarrow \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}|d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)| \times \max(c_F^i(\delta_j, \delta_d)) = 0$$

$$\Leftrightarrow \sum_{i=1}^{m}\sum_{j=1}^{l}|d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)| = 0$$

$$\Leftrightarrow |d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)| = 0$$

$$\Leftrightarrow d_{\mathcal{P}_1}^i(\delta_j) = d_{\mathcal{P}_2}^i(\delta_j)$$

$$\Leftrightarrow \mathcal{P}_1 = \mathcal{P}_2$$

(3) $d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = d_H^{\mathcal{P}}(\mathcal{P}_2, \mathcal{P}_1)$
(4) For any three plithogenic hypersoft sets $\mathcal{P}_1, \mathcal{P}_2$ and $\mathcal{P}_3$, consider $d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$

$$\begin{aligned} d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) &= \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}|d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)| \times \max(c_F^i(\delta_j, \delta_d)) \\ &= \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}|d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_3}^i(\delta_j) + d_{\mathcal{P}_3}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)| \\ &\quad \times \max(c_F^i(\delta_j, \delta_d)) \\ &= \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}|\ [d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_3}^i(\delta_j)] + [d_{\mathcal{P}_3}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)]\ | \\ &\quad \times \max(c_F^i(\delta_j, \delta_d)) \\ &\le \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}|d_{\mathcal{P}_1}^i(\delta_j) - d_{\mathcal{P}_3}^i(\delta_j)| \times \max(c_F^i(\delta_j, \delta_d)) \\ &\quad + \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}|d_{\mathcal{P}_3}^i(\delta_j) - d_{\mathcal{P}_2}^i(\delta_j)| \times \max(c_F^i(\delta_j, \delta_d)) \end{aligned}$$

This implies that

$$d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) \le d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_3) + d_H^{\mathcal{P}}(\mathcal{P}_3, \mathcal{P}_2)$$

In similar way, we can prove the results for $d_{NH}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2), d_E^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$ and $d_{NE}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$.

### 3.2. Categories of plithogenic distance measures

It is evident that PHSS is the generalization of crisp, fuzzy, intuitionistic fuzzy and neutrosophic set. On the basis of the degree of appurtenance, these distance measures are categorized as:

- Plithogenic crisp distance measure

- Plithogenic fuzzy distance measure
- Plithogenic intuitionistic fuzzy distance measure
- Plithogenic neutrosophic distance measure

### 3.2.1. Plithogenic crisp distance measure

For any two plithogenic crisp hypersoft sets $\mathcal{P}_1$ and $\mathcal{P}_2$ over a finite universe $U$, the proposed distance measures are as follows:

$$d_H^C(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} |\Gamma^i_{\mathcal{P}_1}(\delta_j) - \Gamma^i_{\mathcal{P}_2}(\delta_j)| \times \max(c^i_F(\delta_j,\delta_d)) \tag{3.5}$$

$$d_{NH}^C(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{l} |\Gamma^i_{\mathcal{P}_1}(\delta_j) - \Gamma^i_{\mathcal{P}_2}(\delta_j)| \times \max(c^i_F(\delta_j,\delta_d)) \tag{3.6}$$

$$d_E^C(\mathcal{P}_1,\mathcal{P}_2) = \left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} (\Gamma^i_{\mathcal{P}_1}(\delta_j) - \Gamma^i_{\mathcal{P}_2}(\delta_j))^2 \times \max(c^i_F(\delta_j,\delta_d))\right]^{\frac{1}{2}} \tag{3.7}$$

$$d_{NE}^C(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{n}\left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} (\Gamma^i_{\mathcal{P}_1}(\delta_j) - \Gamma^i_{\mathcal{P}_2}(\delta_j))^2 \times \max(c^i_F(\delta_j,\delta_d))\right]^{\frac{1}{2}} \tag{3.8}$$

where $\Gamma_{\mathcal{P}_1}(\delta_j)$ and $\Gamma_{\mathcal{P}_2}(\delta_j)$ represents the crisp value which are either 0 or 1.

### 3.2.2. Plithogenic fuzzy distance measure

For any two plithogenic fuzzy hypersoft sets $\mathcal{P}_1$ and $\mathcal{P}_2$ over a finite universe $U$, the proposed distances are:

$$d_H^F(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} |T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j)| \times \max(c^i_F(\delta_j,\delta_d)) \tag{3.9}$$

$$d_{NH}^F(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{l} |T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j)| \times \max(c^i_F(\delta_j,\delta_d)) \tag{3.10}$$

$$d_E^F(\mathcal{P}_1,\mathcal{P}_2) = \left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} (T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j))^2 \times \max(c^i_F(\delta_j,\delta_d))\right]^{\frac{1}{2}} \tag{3.11}$$

$$d_{NE}^F(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{n}\left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} (T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j))^2 \times \max(c^i_F(\delta_j,\delta_d))\right]^{\frac{1}{2}} \tag{3.12}$$

where $T_{\mathcal{P}_1}(\delta_j)$ and $T_{\mathcal{P}_2}(\delta_j)$ represents the truth membership values from the interval $[0,1]$.

### 3.2.3. Plithogenic intuitionistic fuzzy distance measure

For any two plithogenic intuitionistic fuzzy hypersoft sets $\mathcal{P}_1$ and $\mathcal{P}_2$ over a finite universe $U$, the proposed distances are:

$$d_H^{IF}(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} (|T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j)| + |F^i_{\mathcal{P}_1}(\delta_j) - F^i_{\mathcal{P}_2}(\delta_j)|) \times \max(c^i_F(\delta_j,\delta_d)) \tag{3.13}$$

$$d_{NH}^{IF}(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{l} (|T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j)| + |F^i_{\mathcal{P}_1}(\delta_j) - F^i_{\mathcal{P}_2}(\delta_j)|) \times \max(c^i_F(\delta_j,\delta_d)) \tag{3.14}$$

$$d_E^{IF}(\mathcal{P}_1,\mathcal{P}_2) = \left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} ((T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j))^2 + (F^i_{\mathcal{P}_1}(\delta_j) - F^i_{\mathcal{P}_2}(\delta_j))^2) \times \max(c^i_F(\delta_j,\delta_d))\right]^{\frac{1}{2}} \tag{3.15}$$

$$d_{NE}^{IF}(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{n}\left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} ((T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j))^2 + (F^i_{\mathcal{P}_1}(\delta_j) - F^i_{\mathcal{P}_2}(\delta_j))^2) \times \max(c^i_F(\delta_j,\delta_d))\right]^{\frac{1}{2}} \tag{3.16}$$

where $T_{\mathcal{P}_1}(\delta_j), T_{\mathcal{P}_2}(\delta_j)$ and $F_{\mathcal{P}_1}(\delta_j), F_{\mathcal{P}_2}(\delta_j)$ represent the truth memberships and false memberships of the sets $\mathcal{P}_1$ and $\mathcal{P}_2$ respectively from the interval $[0,1]$ with the defined constraints $0 \le T_{\mathcal{P}}(\delta_j) + F_{\mathcal{P}}(\delta_j) \le 1$.

### 3.2.4. Plithogenic neutrosophic distance measure

For any two plithogenic neutrosophic hypersoft sets $\mathcal{P}_1$ and $\mathcal{P}_2$ over a finite universe $U$, the proposed distances are:

$$d_H^N(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} (|T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j)| + |I^i_{\mathcal{P}_1}(\delta_j) - I^i_{\mathcal{P}_2}(\delta_j)| + |F^i_{\mathcal{P}_1}(\delta_j) - F^i_{\mathcal{P}_2}(\delta_j)|) \times \max(c^i_F(\delta_j,\delta_d)) \tag{3.17}$$

$$d_{NH}^N(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{l} (|T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j)| + |I^i_{\mathcal{P}_1}(\delta_j) - I^i_{\mathcal{P}_2}(\delta_j)| + |F^i_{\mathcal{P}_1}(\delta_j) - F^i_{\mathcal{P}_2}(\delta_j)|) \times \max(c^i_F(\delta_j,\delta_d)) \tag{3.18}$$

$$d_E^N(\mathcal{P}_1,\mathcal{P}_2) = \left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} ((T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j))^2 + (I^i_{\mathcal{P}_1}(\delta_j) - I^i_{\mathcal{P}_2}(\delta_j))^2 + (F^i_{\mathcal{P}_1}(\delta_j) - F^i_{\mathcal{P}_2}(\delta_j))^2) \times \max(c^i_F(\delta_j,\delta_d))\right]^{\frac{1}{2}} \tag{3.19}$$

$$d_{NE}^N(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{n}\left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l} ((T^i_{\mathcal{P}_1}(\delta_j) - T^i_{\mathcal{P}_2}(\delta_j))^2 + (I^i_{\mathcal{P}_1}(\delta_j) - I^i_{\mathcal{P}_2}(\delta_j))^2 + (F^i_{\mathcal{P}_1}(\delta_j) - F^i_{\mathcal{P}_2}(\delta_j))^2) \times \max(c^i_F(\delta_j,\delta_d))\right]^{\frac{1}{2}} \tag{3.20}$$

where $T_{\mathcal{P}_1}(\delta_j), T_{\mathcal{P}_2}(\delta_j)$ represents the truth memberships, $I_{\mathcal{P}_1}(\delta_j), I_{\mathcal{P}_2}(\delta_j)$ represents the indeterminacy memberships and $F_{\mathcal{P}_1}(\delta_j), F_{\mathcal{P}_2}(\delta_j)$ represents the false memberships of the sets $\mathcal{P}_1$ and $\mathcal{P}_2$ from the interval $[0,1]$ with the defined constraints $0 \le T_{\mathcal{P}}(\delta_j) + I_{\mathcal{P}}(\delta_j) + F_{\mathcal{P}}(\delta_j) \le 3$.

### 3.3. Plithogenic similarity measure

It is a very emerging concept in every field of science to distinguished any two objects when they are closely similar to each other. A novel concept of PSM is proposed based on the newly developed PDM, given as

$$S^{\mathcal{P}}(\mathcal{P}_1,\mathcal{P}_2) = \frac{1}{1 + d^{\mathcal{P}}(\mathcal{P}_1,\mathcal{P}_2)} \tag{3.21}$$

where the distance $d^{\mathcal{P}}(\mathcal{P}_1,\mathcal{P}_2)$ represents the plithogenic distance, which may be plithogenic hamming distance $d_H^{\mathcal{P}}(\mathcal{P}_1,\mathcal{P}_2)$, normalized plithogenic hamming distance $d_{NH}^{\mathcal{P}}(\mathcal{P}_1,\mathcal{P}_2)$, plithogenic Euclidean distance $d_E^{\mathcal{P}}(\mathcal{P}_1,\mathcal{P}_2)$, or normalized plithogenic Euclidean distance $d_{NE}^{\mathcal{P}}(\mathcal{P}_1,\mathcal{P}_2)$. In addition, PSM is termed as plithogenic crisp similarity measure, plithogenic fuzzy similarity measure, plithogenic intuitionistic fuzzy similarity measure, or plithogenic neutrosophic similarity measure, if the degree of appurtenance between the sets under consideration with their associated distances is crisp, fuzzy, intuitionistic fuzzy, or neutrosophic respectively.

## 4. Mathematical modeling and AI based decision making for COVID-19 suspects

In this section, an algorithm is developed based on the newly developed plithogenic distance and similarity measures between PHSSs. Furthermore, the algorithm is implemented in a specific scenario to see the results.

### 4.1. Algorithm of the proposed method

Let $U$ be a universe of COVID-19 suspects such that $\mathcal{P} = \{s_1, s_2, \dots, s_k\} \subseteq U$ be the set of alternatives or suspects under consideration, $\mathcal{A} = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$, $n \geq 1$, be a finite set of attributes or symptoms, and $B = \{\alpha_1, \alpha_2, \dots, \alpha_m\}$, $m \leq n$ be the set of chosen symptoms, i.e., $B \subseteq \mathcal{A}$. Let $C = A_1 \times A_2 \times \cdots \times A_n$ be the cartesian product of the sets $A_1, A_2, \dots, A_n$ containing the attribute values of the attributes $\alpha_1, \alpha_2, \dots, \alpha_n$ respectively, such that these sets are disjoint, i.e., $A_i \cap A_j = \phi$, with $i, j = \{1, 2, \dots, n\}$. Each alternative $s \in \mathcal{P}$ is allocated a degree of appurtenance $d(s, \delta)$ w.r.t. each attribute value $\delta$, and $d(s, \delta)$ can be fuzzy, intuitionistic fuzzy or neutrosophic degree of appurtenance. The aim of the specialist (doctor) is to examine the chosen suspects whether they are infected from the COVID-19 or not, and if they are infected, then what is severity of the disease in order to draw a suitable conclusion on each suspect. For this purpose, an efficient AI based method is proposed. The construction steps of the proposed algorithm are as follows:

Step 1: Specialist allocates a fuzzy degree of appurtenance to each suspect w.r.t. each symptom, represented by PHSS $\mathcal{P}_1$.

Step 2: Construct a set of established values of the symptoms of disease under study according to the sub-symptoms based on their severity, represented by PHSS $\mathcal{P}_2$.

Step 3: Measure the distance between PHSSs $\mathcal{P}_1$ and $\mathcal{P}_2$, using the proposed novel distance measures, i.e., plithogenic hamming distance and plithogenic Euclidean distance measures given as follows:

$$d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = \frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{l} |d^i_{\mathcal{P}_1}(\delta_j) - d^i_{\mathcal{P}_2}(\delta_j)| \times \max(c^i_F(\delta_j, \delta_d)) \tag{4.1}$$

$$d_E^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = \left[\frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{l} (d^i_{\mathcal{P}_1}(\delta_j) - d^i_{\mathcal{P}_2}(\delta_j))^2 \times \max(c^i_F(\delta_j, \delta_d))\right]^{\frac{1}{2}} \tag{4.2}$$

where $m$ represents the number of chosen attributes and $l$ represents the number of attribute values of each attribute.

Step 4: To check how much they are similar, calculate the plithogenic similarity based on plithogenic distance measures between the specialist allocated values and their corresponding established values.

$$\mathcal{S}^{\mathcal{P}} = \mathcal{S}^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2) = \frac{1}{1 + d^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)}$$

where $d^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$ may be any plithogenic distance from the proposed PDM. The PSM between any two PHSSs $\mathcal{P}_1$ and $\mathcal{P}_2$ are plithogenic-similar if and only if $\mathcal{S}^{\mathcal{P}} \geq 0.5$, where 0.5 is threshold value, keeping in mind that this value may be different in normalized plithogenic distances.

Step 5: If $\mathcal{S}^{\mathcal{P}} < 0.5$, it implies that the suspect is not infected.

Step 6: If $\mathcal{S}^{\mathcal{P}} \geq 0.5$, the suspect is infected and the decision will be made based on the severity of the infection by following the cases mentioned below:

- If $0.5 \leq \mathcal{S}^{\mathcal{P}} < 0.7$, the suspect needs to be quarantined at home with proper isolation.
- If $0.7 \leq \mathcal{S}^{\mathcal{P}} < 0.9$, the suspect needs to be quarantined at a facilitation center.
- If $0.9 \leq \mathcal{S}^{\mathcal{P}} \leq 1$, the suspect must be sent to the hospital for proper treatment.

A systematic procedure of the proposed algorithm is given in Fig. 4.1.

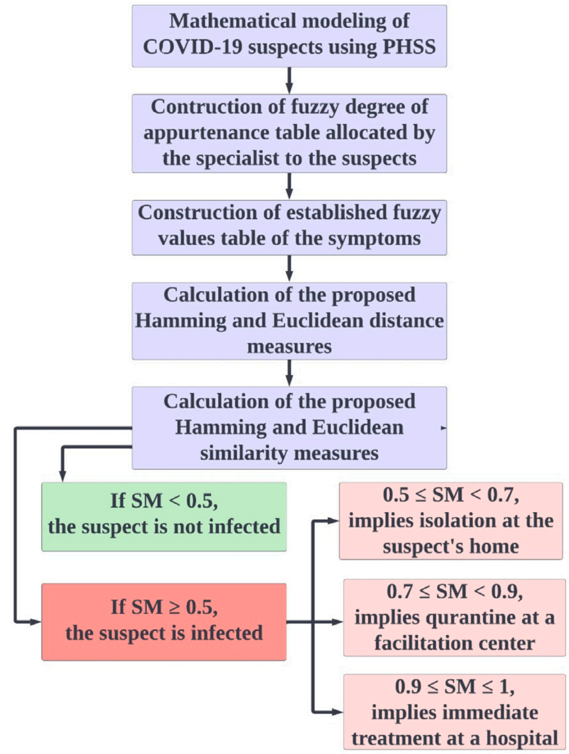


**Fig. 4.1.** Proposed COVID-19 model flowchart.

### 4.2. Implementation of the proposed method

Let $U$ be the universe of discourse, such that $\mathcal{P} = \{s_1, s_2, \dots, s_5\} \subseteq U$ be a set of COVID-19 suspects. In order to monitor the suspects, the attributes or symptoms are as follows:

$\alpha_1$ = Fever
$\alpha_2$ = Dry cough
$\alpha_3$ = Tiredness
$\alpha_4$ = Difficulty breathing or shortness of breath
$\alpha_5$ = Chest pain or pressure
$\alpha_6$ = Loss of speech or movement
$\alpha_7$ = Aches and pain
$\alpha_8$ = Sore throat
$\alpha_9$ = Diarrhea
$\alpha_{10}$ = Conjuctivitis
$\alpha_{11}$ = Headache
$\alpha_{12}$ = Loss of taste or smell
$\alpha_{13}$ = Rash on skin, or discoloration of fingers

Each symptom is further categorized to low $(L)$, medium $(M)$ and high $(H)$, which have mild symptoms, moderate symptoms, and severe symptoms, respectively, to analyze the severity of the disease in terms of their attribute values correspondingly for better diagnoses. That is,

$\delta(i, 1) = L$,
$\delta(i, 2) = M$,
$\delta(i, 3) = H$,

where $1 \leq i \leq 13$. The suspects under observations recorded by the symptoms lies in the specific region where these suspects come from are as $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \alpha_9, \alpha_{11}$. Each suspect under observation is allocated a hypothetical fuzzy degree of appurtenance correspondingly to each chosen attribute w.r.t some constraints designed by the specialist to check the validity of the method, is given in Table 1.

Each symptom has a dominant attribute value $\delta_d$ from the chosen symptom, and the fuzzy contradiction degree $c_F$ of each chosen attribute between the attribute value and the dominant attribute value is given in Table 2.

A PHSS $\mathcal{P}_1$ is constructed and represented the data in tabular form with the opinion of the specialist field expert doctor, given in Table 3.

The established values of chosen symptoms by the experts are mentioned in Table 4.

**Table 1**
Fuzzy degree of appurtenance of each alternative w.r.t. each attribute value.

| Symptoms | Severity | Suspects | | | | |
|---|---|---|---|---|---|---|
| | | $s_1$ | $s_2$ | $s_3$ | $s_4$ | $s_5$ |
| $\alpha_1$ | L | 0.58 | 0.52 | 0.20 | 0.50 | 0.15 |
| | M | 0.75 | 0.68 | 0.29 | 0.55 | 0.32 |
| | H | 0.93 | 0.86 | 0.19 | 0.72 | 0.22 |
| $\alpha_2$ | L | 0.60 | 0.58 | 0.10 | 0.42 | 0.20 |
| | M | 0.69 | 0.62 | 0.25 | 0.51 | 0.29 |
| | H | 0.83 | 0.76 | 0.30 | 0.64 | 0.36 |
| $\alpha_3$ | L | 0.64 | 0.58 | 0.19 | 0.46 | 0.12 |
| | M | 0.79 | 0.60 | 0.29 | 0.57 | 0.31 |
| | H | 0.77 | 0.72 | 0.20 | 0.65 | 0.20 |
| $\alpha_4$ | L | 0.71 | 0.65 | 0.27 | 0.50 | 0.29 |
| | M | 0.88 | 0.80 | 0.35 | 0.68 | 0.33 |
| | H | 0.97 | 0.90 | 0.40 | 0.65 | 0.50 |
| $\alpha_5$ | L | 0.70 | 0.59 | 0.17 | 0.52 | 0.26 |
| | M | 0.82 | 0.71 | 0.24 | 0.64 | 0.30 |
| | H | 0.96 | 0.85 | 0.30 | 0.79 | 0.42 |
| $\alpha_6$ | L | 0.70 | 0.61 | 0.21 | 0.59 | 0.29 |
| | M | 0.95 | 0.75 | 0.40 | 0.80 | 0.20 |
| | H | 0.97 | 0.92 | 0.28 | 0.70 | 0.17 |
| $\alpha_7$ | L | 0.20 | 0.11 | 0.13 | 0.10 | 0.20 |
| | M | 0.31 | 0.14 | 0.26 | 0.28 | 0.30 |
| | H | 0.60 | 0.24 | 0.35 | 0.39 | 0.40 |
| $\alpha_8$ | L | 0.25 | 0.30 | 0.22 | 0.21 | 0.22 |
| | M | 0.29 | 0.40 | 0.35 | 0.44 | 0.35 |
| | H | 0.32 | 0.51 | 0.44 | 0.30 | 0.40 |
| $\alpha_9$ | L | 0.45 | 0.46 | 0.50 | 0.62 | 0.10 |
| | M | 0.49 | 0.45 | 0.10 | 0.53 | 0.19 |
| | H | 0.60 | 0.59 | 0.12 | 0.60 | 0.18 |
| $\alpha_{10}$ | L | 0.11 | 0.41 | 0.20 | 0.22 | 0.33 |
| | M | 0.19 | 0.15 | 0.34 | 0.40 | 0.27 |
| | H | 0.32 | 0.38 | 0.51 | 0.35 | 0.43 |
| $\alpha_{11}$ | L | 0.70 | 0.61 | 0.13 | 0.33 | 0.16 |
| | M | 0.60 | 0.50 | 0.10 | 0.55 | 0.14 |
| | H | 0.34 | 0.62 | 0.18 | 0.60 | 0.10 |
| $\alpha_{12}$ | L | 0.19 | 0.41 | 0.20 | 0.50 | 0.20 |
| | M | 0.26 | 0.30 | 0.36 | 0.40 | 0.45 |
| | H | 0.35 | 0.45 | 0.60 | 0.46 | 0.52 |
| $\alpha_{13}$ | L | 0.10 | 0.22 | 0.40 | 0.38 | 0.40 |
| | M | 0.32 | 0.31 | 0.21 | 0.50 | 0.49 |
| | H | 0.40 | 0.60 | 0.43 | 0.60 | 0.58 |

**Table 2**
Contradiction degrees with corresponding dominant value.

| Symptoms | Dominant | $L$ | $M$ | $H$ |
|---|---|---|---|---|
| $\alpha_1$ | H | 0.95 | 0.70 | 0.00 |
| $\alpha_2$ | H | 1.00 | 0.60 | 0.00 |
| $\alpha_3$ | M | 0.45 | 0.00 | 0.60 |
| $\alpha_4$ | H | 1.00 | 0.75 | 0.00 |
| $\alpha_5$ | H | 0.97 | 0.80 | 0.00 |
| $\alpha_6$ | M | 0.40 | 0.00 | 0.58 |
| $\alpha_9$ | L | 0.00 | 0.50 | 0.90 |
| $\alpha_{11}$ | L | 0.00 | 0.58 | 0.95 |

To measure the distance between the specialist recorded values and established values, plithogenic hamming and Euclidean distances are measured between them using the Eqs. (4.1) and (4.2), and the results are given in Table 5.

Now, plithogenic similarity based on plithogenic distance is evaluated to examine the severity of the infectedness of the suspects under observation to measure plithogenic-similarity is mentioned in Table 6.

From Table 6, the values of the hamming and euclidean similarity measures are obtained efficiently. From these values, a decision for the suspects are taken based on the obtained values which is represented in Table 7.

The graphical representation of these suspects is given in Fig. 4.2.

**Table 3**
Fuzzy degree of appurtenance allocated by the specialist to the suspects.

| Symptoms | Severity | Suspects | | | | |
|---|---|---|---|---|---|---|
| | | $s_1$ | $s_2$ | $s_3$ | $s_4$ | $s_5$ |
| $\alpha_1$ | L | 0.58 | 0.52 | 0.20 | 0.50 | 0.15 |
| | M | 0.75 | 0.68 | 0.29 | 0.55 | 0.32 |
| | H | 0.93 | 0.86 | 0.19 | 0.72 | 0.22 |
| $\alpha_2$ | L | 0.60 | 0.58 | 0.10 | 0.42 | 0.20 |
| | M | 0.69 | 0.62 | 0.25 | 0.51 | 0.29 |
| | H | 0.83 | 0.76 | 0.30 | 0.64 | 0.36 |
| $\alpha_3$ | L | 0.64 | 0.58 | 0.19 | 0.46 | 0.12 |
| | M | 0.79 | 0.60 | 0.29 | 0.57 | 0.31 |
| | H | 0.77 | 0.72 | 0.20 | 0.65 | 0.20 |
| $\alpha_4$ | L | 0.71 | 0.65 | 0.27 | 0.50 | 0.29 |
| | M | 0.88 | 0.80 | 0.35 | 0.68 | 0.33 |
| | H | 0.97 | 0.90 | 0.40 | 0.65 | 0.50 |
| $\alpha_5$ | L | 0.70 | 0.59 | 0.17 | 0.52 | 0.26 |
| | M | 0.82 | 0.71 | 0.24 | 0.64 | 0.30 |
| | H | 0.96 | 0.85 | 0.30 | 0.79 | 0.42 |
| $\alpha_6$ | L | 0.70 | 0.61 | 0.21 | 0.59 | 0.29 |
| | M | 0.95 | 0.75 | 0.40 | 0.80 | 0.20 |
| | H | 0.97 | 0.92 | 0.28 | 0.70 | 0.17 |
| $\alpha_9$ | L | 0.45 | 0.46 | 0.50 | 0.62 | 0.10 |
| | M | 0.49 | 0.45 | 0.10 | 0.53 | 0.19 |
| | H | 0.60 | 0.59 | 0.12 | 0.60 | 0.18 |
| $\alpha_{11}$ | L | 0.70 | 0.61 | 0.13 | 0.33 | 0.16 |
| | M | 0.60 | 0.50 | 0.10 | 0.55 | 0.14 |
| | H | 0.34 | 0.62 | 0.18 | 0.60 | 0.10 |

**Table 4**
Established values of chosen symptoms.

| Attributes | $L$ | $M$ | $H$ |
|---|---|---|---|
| $\alpha_1$ | 0.59 | 0.75 | 0.95 |
| $\alpha_2$ | 0.62 | 0.70 | 0.85 |
| $\alpha_3$ | 0.68 | 0.77 | 0.82 |
| $\alpha_4$ | 0.71 | 0.90 | 1.00 |
| $\alpha_5$ | 0.70 | 0.85 | 1.00 |
| $\alpha_6$ | 0.76 | 0.90 | 1.00 |
| $\alpha_9$ | 0.40 | 0.59 | 0.70 |
| $\alpha_{11}$ | 0.43 | 0.65 | 0.74 |

**Table 5**
Distance measures.

| Suspects | $d_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$ | $d_E^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$ |
|---|---|---|
| $s_1$ | 0.0710 | 0.0905 |
| $s_2$ | 0.2219 | 0.2557 |
| $s_3$ | 1.3272 | 1.4428 |
| $s_4$ | 0.4397 | 0.5105 |
| $s_5$ | 1.3055 | 1.4131 |

**Table 6**
Similarity measures.

| Suspects | $S_H^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$ | $S_E^{\mathcal{P}}(\mathcal{P}_1, \mathcal{P}_2)$ |
|---|---|---|
| $s_1$ | 0.9338 | 0.9170 |
| $s_2$ | 0.8184 | 0.7963 |
| $s_3$ | 0.4297 | 0.4094 |
| $s_4$ | 0.6946 | 0.6620 |
| $s_5$ | 0.4337 | 0.4144 |

**Table 7**
Suspects decision.

| Similarity index | Decision | Suspects |
|---|---|---|
| $0 \leq S^{\mathcal{P}} < 0.5$ | Safe zone | $s_3, s_5$ |
| $0.5 \leq S^{\mathcal{P}} < 0.7$ | Home Isolation | $s_4$ |
| $0.7 \leq S^{\mathcal{P}} < 0.9$ | Quarantine center | $s_2$ |
| $0.9 \leq S^{\mathcal{P}} \leq 1$ | Hospital treatment | $s_1$ |

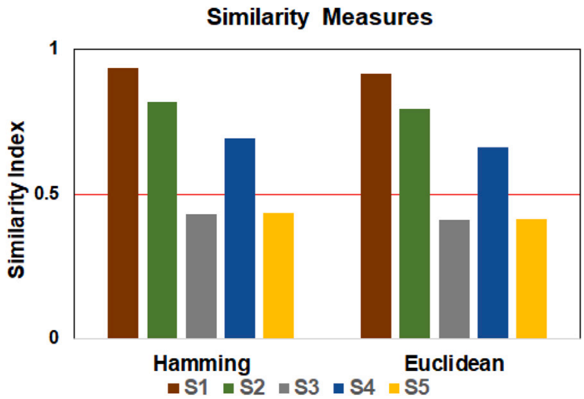


**Fig. 4.2.** Plithogenic-similarity of suspects.

**Table 8**
Comparative analysis of COVID-19 suspects using hamming similarity measure (HSM) and plithogenic hamming similarity measure (PHSM)

| Suspect | HSM | Decision | PHSM | Decision |
|---|---|---|---|---|
| $s_1$ | 0.9259 | Hospital treatment | 0.9338 | Hospital treatment |
| $s_2$ | 0.7897 | Quarantine center | 0.8184 | Quarantine center |
| $s_3$ | 0.3941 | Safe zone | 0.4297 | Safe zone |
| $s_4$ | 0.6633 | Home Isolation | 0.6946 | Home Isolation |
| $s_5$ | 0.3949 | Safe zone | 0.4337 | Safe zone |

**Table 9**
Comparative analysis of COVID-19 suspects using Euclidean similarity measure (ESM) and plithogenic Euclidean similarity measure (PESM)

| Suspect | ESM | Decision | PESM | Decision |
|---|---|---|---|---|
| $s_1$ | 0.9132 | Hospital treatment | 0.9170 | Hospital treatment |
| $s_2$ | 0.7782 | Quarantine center | 0.7963 | Quarantine center |
| $s_3$ | 0.3910 | Safe zone | 0.4094 | Safe zone |
| $s_4$ | 0.6465 | Home Isolation | 0.6620 | Home Isolation |
| $s_5$ | 0.3924 | Safe zone | 0.4144 | Safe zone |

It is obvious from the graph, there is a danger zone above the line 0.5, while below the line, there is a safe zone. Hence, the vertical bars of the suspects which are below the danger zone line, are safe, while those who are above this line, are in danger (see Fig. 4.2).

## 5. Comparative analysis

To authenticate the proposed plithogenic distances, we compare our results with the usual hamming and Euclidean distance measures given in the Eqs. (5.1) and (5.2) given below:

$$d_H(\mathcal{P}_1,\mathcal{P}_2)=\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}|d^i_{\mathcal{P}_1}(\delta_j)-d^i_{\mathcal{P}_2}(\delta_j)| \quad (5.1)$$

$$d_E(\mathcal{P}_1,\mathcal{P}_2)=\left[\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{l}(d^i_{\mathcal{P}_1}(\delta_j)-d^i_{\mathcal{P}_2}(\delta_j))^2\right]^{\frac{1}{2}} \quad (5.2)$$

where $m$ represents the number of chosen attributes and $l$ represents the equal number of attribute values of each attributes.

Now, plithogenic similarity based on plithogenic distance is compared with the usual similarity based on usual distances to examine the severity of the infection in the suspects. The comparative analysis of hamming similarity measure with plithogenic similarity measure is shown in Table 8.

The comparative analysis of Euclidean similarity measure with plithogenic similarity measure is shown in Table 9.

It can been seen that the proposed plithogenic distance and similarity measures are reliable and efficient in producing results.

## 6. Conclusion

In this article, plithogenic distance and similarity measures on plithogenic hypersoft sets are defined for making intelligent decisions on COVID-19 suspects. For this purpose, mathematical modeling of COVID-19 suspects is structured into an MCDM problem by using the concept of plithogenic hypersoft set in a fuzzy environment and a novel algorithm is implemented on the problem, based on newly developed plithogenic distance and similarity measures. The algorithm of the proposed method not only detects the infection in the suspects, but also explain its severity. Mathematically, the proposed plithogenic distance and similarity measures satisfy the basic properties of distance and similarity measures and obey the results of relevant theorems. For the validation of the proposed algorithm, the results are calculated with the corresponding Euclidean and Hamming distance and similarity measures and a comparative analysis is performed. The obtained results prove the validity of the proposed algorithm and its efficiency in producing AI based decision making. The scope of the study can be extended to pattern recognition, image processing, picture science, in different environments like pythagorean fuzzy environment, $q$-rung orthopair fuzzy environment, spherical fuzzy environment, etc.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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