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Detection of plant diseases using image-based similarity measures of Pythagorean fuzzy sets

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ABSTRACT

In image processing, data extraction from any image with deviation is difficult to pursue. Especially in identification of radiological images, many issues have been involved in the choosing of right image from the available images. In this paper, new similarity measure model for images is proposed that have application in the identification of the images of plant diseases. The application of the similarity measures is compared with existing models. The results reports that the proposed Pythagorean entropy measures have application in the detection of plant diseases. Even, the quality ofextraction of data from images is enhanced. Further, the study concludes that the proposed measures are better than the existing measures in case of image processing problems.

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1. INTRODUCTION

Agriculture is the backbone Indian economy and contributing almost 18% of the gross domestic product (GDP). In addition, more than 50% of the employment in India is only shared by the agriculture sector. This sector involves in catering the day-to-day food demand of around 15 billion population including export [1]. Plant leaves are the most sensitive part and show early signs of disease caused by agents such as fungi, bacteria, and viruses. In addition, change in climate also leads to occurrence of diseases in crops [2]. It is an exaggeration to say that each and every disease has unique and visible patterns. The literature reveals that diseases are occurring for the first time in the farms where they had never been seen before. Sometimes local disease experts are not familiar with the new types of pathogens, so they are unable to support farmers [3], [4]. In light of this, computation-based disease detection techniques are required to manage the accurate and early detection of disease in crops [5]. Many-a-time, farmers are using the un-ethical practices like use of fertilizers and pesticides etc. for the reason of fulfilling the demand of huge population and avoiding the diseases among the crops [6]. These fertilizers and pesticides are having an adverse effect on the human life in one way or other. So, it becomes prominent to utilize the adequate amount of the fertilizers and pesticides to meet the expectations of human beings and keep them healthy [7]. For such reasons, it is important to monitor the growth cycle of the crops from the very beginning. The signs of these infectious agents are visible on the leaves of plants. To deal with such conditions, the advanced reforms in terms of farm mechanization result in the development of high-yielding crops and reduction of unnecessary utility of chemicals in farms. Even, it helps in accelerating the crops maturity [8]. The adoption of innovative farming technologies in the agriculture sector becomes of great importance. It contributes through several ways i.e. utilizing the adequate amount of fertilizers/pesticides, lowering the production cost, space utilization, and most importantly responding to environmental conditions [9], [10]. These techniques also support the farmer through detection of various diseases at the early stage that can impact both physically and chemically to the crops [11].

The information technology (IT) secto revolution also revolutionized the agriculture sector [12]. The use of image sensing techniques is a common technique and mainly applied to understand the nurturing behaviors of the plants/crops without any pitfalls (diseases or early-stage failure) [13], [14]. This helps in identifying the diseases based on information in terms of capturing the images. The images of plants reveal the signs of infectious agents on the leaves of plants through the visible marks or lesions on the leaves, stems, flowers, and or fruits of the crops. This information is further used by the farmers to apply the adequate and economical use of pesticides that further lowers the cost of production [15]. Even, it helps in saving the environment and humans from harmful chemicals used in the form of pesticides and fertilizers [16]–[18].

The fuzzy sets introduced in 1965 and generalized in 1986 are used for extensive results [19], [20]. In fuzzy image sensing, the entropy-based fuzzy analysis on the images is promising the better results [21] It is a rule-based technique that acknowledges uncertain shapes, colours, textures, and other features of objects through images. The information is the back-bone for any decision-making process pertaining to either any business-related issues or for general issues [22]. The impact of the decision mostly forecast based on the preciseness and completeness of the information. Any vague or error in information may cause the negative impacts on the both side i.e. decision-maker and the humans associated with that decision process. In some situations where the degree of uncertainty is very high, it is difficult to pretend the implications of the decisions [23], [24]. While going through the literature available on agricultural context that it still strives to prevent the crops or plants from the diseases. In present day, the developed countries are looking for the healthy crops for their population [25]. This accelerates the researches on the disease detection of the crops and provide them the support to avoid/eliminate the impacts of the diseases on the crops at the final stage [26], [27]. The image sensing technique enable them to understand the disease briefly and acting on the solution part i.e. treatment to the crops well before the spread. These techniques are used as the support system that provides the image-based detection of diseases in plants and monitors the growth of plants without physical examination [28], [29]. The present work will address the following research questions:

- What is image sensing and its application in agriculture sector?
- How the fuzzy image sensing supports the agriculture sector to prevent from diseases and sustain for longer periods of time?
- The propositions and the implications of the current study?

To answer the question, an exploratory attempt will be made on the literature available on image sensing and reported in section 2 of the paper. The current study will explore the contribution of image sensing applications in the agriculture sector and aims to provide insights into the importance of fuzzy image sensing based on the similarity measures of the images to acknowledge the uncertain images with accuracy. The section 3 of the work is providing an understanding on the research methodology that includes the prelimaniers and proposed model considerations. Section 4 of the paper is discussing the analytical comparision among the propsed model versus the existing model. Section 5 of the paper highlights the effectiveness of proposed model over the existing model. The present work reveals the proposed measures of the images are better than the existing measures. It also includes the limitation and future work.

2. PROPOSED METHOD

Each and every nation is on the way to developing its economy so-that it becomes a place to live a longer and healthier life. For such developments, each sector has to play the crucial role and contribute towards sustainability [30]. In general, agriculture sector sustainability is dependent on the growing the disease-free crops and the safer food supply chain [31], [32]. It is essential for the agriculture sector to implement the advance technologies in farming. Image sensing is one of the advance techniques used in farming process [14], [33]. The main application of image sensing in farming is the detection of diseases-based data regarding various characteristics of plants/crops collected through the captured images. Here it is an exaggeration to say that while discussing on image sensing in agricultural applications, the chances of uncertainties is higher. This can be handled through the application of fuzzy-based approach. The fuzzy based image sensing approach is also beneficial in the case where the texture of the diseases may vary from spots to bacterial infections that are mostly common in plant-based diseases. The fuzzy based image sensing has the applications in pattern recognition, image processing, and intelligent control. Here, it becomes prominent to deal with uncertainty while capturing the images. To deal with such concerns fuzzy sets proposed by Zadeh [19]. In the fuzzy-based approach, fuzzy sets are used to deal with the issues concerned with uncertainties. These fuzzy sets support the decisions by providing the precise information. The fuzzy set theory established the landmark in the decision-making approaches considering multi-criteria's. Later on, these sets were generalized for finding the solutions in special cases by Atanassov [20]. In general, the fuzzy sets applied under the intuitionistic fuzzy environment to analyse and measure the similarity among two images. The literature also reveals that if incase integrated file system (IFS) fails to solve the complex decision-making problems PFS-based measures is applied. Pythagorean fuzzy set, generalization of intuitionistic fuzzy set is defined as [1]:

$$Image\ (Im) = \{< x, \mu_{Im}(x), \nu_{Im}(x) > | x \in X\}$$

where, $\mu_{Im}(x)$ and $\nu_{Im}(x)$ are the degree of membership and non-membership such that $0 \le \mu_{Im}^2(x) + \nu_{Im}^2(x) \le 1$ with $\pi_{Im}^2(x) = 1 - [\mu_{Im}^2(x) + \nu_{Im}^2(x)]$ is the hesitancy/ uncertainty of Pythagorean fuzzy set.

3. METHOD

To overcome the issues with image sensing, the fuzzy interventions is applied that helps in exploring the plant diseases detected at the initial stages and also support the decision-maker to go with the correct decision to avoid/eliminate the chances of failures among the crops/plants. In the image sensing with fuzzy intervention, the diseases are detected automatically based on the images captured and analysed through using the fuzzy approaches. These techniques are beneficial for the farmers and cost-effective while applied for numerous of plants in large field area. With the help of a camera and computational techniques, the problem can also be handled remotely, which provides promising results [30], [31]. The present study includes the exploratory review on the applications of image sensing, its enablers and delimiters [34]. It is extended to include the application of Pythagorean fuzzy-based image sensing in detecting the diseases based on various parameters. The Pythagorean fuzzy set is an extension to intuitionistic fuzzy sets and is used for managing complex and uncertain decision problems [35], [36]. In the present study, the application of image sensing will be reviewed and compared. The existing fuzzy model output will be compared with the proposed potential field source surface (PFSS) model based on the similarity measures value among them.

3.1. Similarity measures based on PFSS

In this, the similarity among objects is measured based on the deviation in parameters. For the presents study, four different cosine similarity measures based on PFS along with the axioms have been proposed as:

Let $Image\ (Im\_1) = \{< x_i, \mu_{Im\_1}(x_i), \nu_{Im\_1}(x_i) > | x_i \in X\}$ and $Image\ (Im\_2) = \{< x_i, \mu_{Im\_2}(x_i), \nu_{Im\_2}(x_i) > | x_i \in X\}$ be the two Pythagorean fuzzy images sets in the universe set of images/discourse $X = \{x_1, x_2, \dots, x_n\}$ [37].

The proposed cosine similarity measures are given as:

$$Sim\_1(Im\_1, Im\_2) = \frac{1}{2n} \sum_{i=1}^{n} \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| \end{bmatrix} \text{Without hesitancy} \quad (1)$$

$$Sim\_2(Im\_1, Im\_2) = \frac{1}{3n} \sum_{i=1}^{n} \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \pi_{Im\_1}^2(x_i) - \pi_{Im\_2}^2(x_i) \right| \end{bmatrix} \text{With hesitancy} \quad (2)$$

in many real-world situations, weights have been assigned to the measures and are defined as:

$$Sim\_3(Im\_1, Im\_2) = \frac{1}{2n} \sum_{i=1}^{n} W_i \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| \end{bmatrix} \text{Without hesitancy} \quad (3)$$

$$Sim\_4(Im\_1, Im\_2) = \frac{1}{3n} \sum_{i=1}^{n} W_i \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \pi_{Im\_1}^2(x_i) - \pi_{Im\_2}^2(x_i) \right| \end{bmatrix} \text{With hesitancy} \quad (4)$$

these candidate similarity measures (1)-(4) must satisfy the following axioms as:
- $0 \le Sim\_1(Im\_1, Im\_2) \le 1$.
- $Sim\_1(Im\_1, Im\_2) = 1 \Leftrightarrow [Im\_1, Im\_2]$.

- $Sim\_1(Im\_1, Im\_2) = Sim\_1(Im\_2, Im\_1)$.
- If $Image$ (Im_3) is a PFS in X and $[Im\_1 \subseteq Im\_2 \subseteq Im\_3)$ then,
- $Sim\_1(Im\_1, Im\_3) \leq Sim\_1(Im\_1, Im\_2)$ and,
- $Sim\_1(Im\_1, Im\_3) \leq Sim\_1(Im\_2, Im\_3)$ [7], [35].

The proofs of these axioms for the proposed measure have been given as:

Proof 1:
Since, $0 \leq \cos\theta \leq 1$,

Thus, $Sim\_1(Im\_1, Im\_2) = \frac{1}{2n} \sum_{i=1}^{n} \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| \end{bmatrix}$

$$0 \leq \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x) - \mu_{Im\_2}^2(x) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x) - \nu_{Im\_2}^2(x) \right| \end{bmatrix} \leq 2 \; 0 \leq \frac{1}{2} \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x) - \mu_{Im\_2}^2(x) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x) - \nu_{Im\_2}^2(x) \right| \end{bmatrix} \leq 1$$

$$0 \leq \frac{1}{2n} \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x) - \mu_{Im\_2}^2(x) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x) - \nu_{Im\_2}^2(x) \right| \end{bmatrix} \leq 1$$

Therefore, $0 \leq Sim\_1(Im\_1, Im\_2) \leq 1$.

Proof 2:

$$\Leftrightarrow \frac{1}{2n} \sum_{i=1}^{n} \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| \end{bmatrix} = 1$$

$$\Leftrightarrow \begin{bmatrix} cos\frac{\pi}{2} \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| + \\ cos\frac{\pi}{2} \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| \end{bmatrix} = 2$$

$\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| = 0$ and $\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| = 0$

$\Leftrightarrow \mu_{Im\_1}^2(x_i) = \mu_{Im\_2}^2(x_i)$ and $\nu_{Im\_1}^2(x_i) = \nu_{Im\_2}^2(x_i)$

$\Leftrightarrow Im\_1 = Im\_2$

Proof 3:
Since cosine function is symmetrical, the proof is obvious.
Proof 4:

Given that $Image$ (Im_3) is a PFS in X and $[Im\_1 \subseteq Im\_2 \subseteq Im\_3)$; $\forall\, x \in X$

$0 \leq \mu_{Im\_1}(x_i) \leq \mu_{Im\_2}(x_i) \leq \mu_{Im\_3}(x_i) \leq 1$ and $1 \geq \nu_{Im\_1}(x_i) \geq \nu_{Im\_2}(x_i) \geq \nu_{Im\_3}(x_i) \geq 0$

$\Leftrightarrow 0 \leq \mu_{Im\_1}^2(x_i) \leq \mu_{Im\_2}^2(x_i) \leq \mu_{Im\_3}^2(x_i) \leq 1$ and $1 \geq \nu_{Im\_1}^2(x_i) \geq \nu_{Im\_2}^2(x_i) \geq \nu_{Im\_3}^2(x_i) \geq 0$

$\Rightarrow \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| \leq \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|$

$\left| \mu_{Im\_2}^2(x_i) - \mu_{Im\_3}^2(x_i) \right| \leq \left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|$

and,

$\Rightarrow \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| \leq \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|$

$\left| \nu_{Im\_2}^2(x_i) - \nu_{Im\_3}^2(x_i) \right| \leq \left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|$

$$\Rightarrow \frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right| \leq \frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|$$

$$\frac{\pi}{2}\left| \mu_{Im\_2}^2(x_i) - \mu_{Im\_3}^2(x_i) \right| \leq \frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|$$

and,

$$\Rightarrow \frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right| \leq \frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|$$

$$\frac{\pi}{2}\left| \nu_{Im\_2}^2(x_i) - \nu_{Im\_3}^2(x_i) \right| \leq \frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|$$

$$\Rightarrow cos\left(\frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right|\right) \leq cos\left(\frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|\right)$$

$$cos\left(\frac{\pi}{2}\left| \mu_{Im\_2}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|\right) \leq cos\left(\frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|\right)$$

and,

$$\Rightarrow cos\left(\frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right|\right) \leq cos\left(\frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|\right)$$

$$cos\left(\frac{\pi}{2}\left| \nu_{Im\_2}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|\right) \leq cos\left(\frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|\right)$$

adding the above equations,

$$\Rightarrow \left[cos\left(\frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right|\right) + cos\left(\frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right|\right)\right] \leq$$

$$\left[cos\left(\frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|\right) + cos\left(\frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|\right)\right]$$

$$\Rightarrow \frac{1}{2n}\sum_{i=1}^{n}\left[cos\left(\frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_2}^2(x_i) \right|\right) + cos\left(\frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_2}^2(x_i) \right|\right)\right] \leq$$

$$\frac{1}{2n}\sum_{i=1}^{n}\left[cos\left(\frac{\pi}{2}\left| \mu_{Im\_1}^2(x_i) - \mu_{Im\_3}^2(x_i) \right|\right) + cos\left(\frac{\pi}{2}\left| \nu_{Im\_1}^2(x_i) - \nu_{Im\_3}^2(x_i) \right|\right)\right]$$

$$\therefore\ Sim\_1(Im\_1, Im\_3) \leq\ Sim\_1(Im\_1, Im\_2)$$

Similarly, $Sim\_1(Im\_1, Im\_3) \leq\ Sim\_1(Im\_2, Im\_3)$

3.2. Numerical validation of the proposed measures

The proposed similarity measures have been verified by means of properties given by Wei and Wei [10]. The Image (I*m*_1), Image (I*m*_2) and Image (I*m*_3) be the Pythagorean fuzzy image sets in the universe set of images/discourse $X = \{x_1, x_2, ,,,,,, x_n\}$:

- Image (I*m*_1) = {(x_1, 0.6, 0.2), (x_2, 0.4, 0.6), (x_3, 0.5, 0.3)}.
- Image (I*m*_1) = {(x_1, 0.8, 0.1), (x_2, 0.7, 0.3), (x_3, 0.6, 0.1)}.
- Image (I*m*_1) = {(x_1, 0.9, 0.2), (x_2, 0.8, 0.2), (x_3, 0.7, 0.3).

The values mentioned above are further used for finding the similarity measures. The similarity measure is represented in Table 1. The mesures represented in the Table 1 reveals the factors for decision making about the disease of a plant.

3.3. Applications in detection of plant diseases

The model discussed earlier are now studied for the detection the plant diseases. For this, three plant images are selected randomly and the mathematical models applied. Let Image (I*m*_1), Image (I*m*_2) and Image (I*m*_3) be the three plant images of a plant caused by any known disease. Also, the $X = \{x_1, x_2, x_3\}$ be the universal set of plant disease images defined in PFS taking:

- Image (Im_1) = {(x1, 1.0, 0.0), (x2, 0.8, 0.0), (x3, 0.7, 0.1)}.
- Image (Im_1) = {(x1, 0.8, 0.1), (x2, 1.0, 0.0), (x3, 0.9, 0.1)}.
- Image (Im_1) = {(x1, 0.6, 0.2), (x2, 0.8, 0.0), (x3, 1.0, 0.0)}.

- X = {(x1, 0.5, 0.3), (x2, 0.6, 0.2), (x3, 0.8, 0.1)}

Also, taking weights as: 0.5, 0.3 and 0.2 respectively. The proposed similarity measures is calculated and shown in Table 2. In Table 2, the similarity measures is reported for all three images. The values of similarity measure for *Sim_1* reveals that *Im_3* is the better than the others two. In other words, the highest value of the similarity measure is the decision value. The proposed similarity measures are then compared with the existing measures and reported in Table 3.

Table 1. Results for similarity measures

Similarity measures	(Im_1, Im_2)	(Im_2, Im_3)	(Im_1, Im_3)
Sim_1	0.9434	0.9840	0.8825
Sim_2	0.9532	0.9781	0.8869
Sim_3	0.3135	0.3278	0.2912
Sim_4	0.3157	0.3261	0.2909

Table 2. Proposed similarity measures

Similarity measures	(Im_1, *X*)	(Im_2, *X*)	(Im_3, *X*)
Sim_1	0.8746	0.8847	0.9548
Sim_2	0.8510	0.8605	0.9452
Sim_3	0.2752	0.2930	0.3217
Sim_4	0.2644	0.2854	0.3197

Table 3. Comparison of proposed measures with the existing measures

Similarity measures	(Im_1, *X*)	(Im_2, *X*)	(Im_3, *X*)
Peng et al. 2017 [5]	0.6066	0.6	0.7116
Wei &Wei, 2018 [10]	0.6573	0.7627	0.9329
Wei &Wei, 2018 [10]	0.8843	0.9228	0.9782
Wei &Wei, 2018 [10]	0.6573	0.7627	0.9329
Wei &Wei, 2018 [10]	0.6573	0.7627	0.9329
Zhang et al., 2019 [12]	0.5462	0.5291	0.686
Ejegwa, 2020 [34]	0.8261	0.7995	0.8614
Verma & Merigo, 2019 [15]	0.7532	0.7801	0.8545
Sim_1	0.8746	0.8847	0.9548
Sim_2	0.8510	0.8605	0.9452
Sim_3	0.2752	0.2930	0.3217
Sim_4	0.2644	0.2854	0.3197

4. RESULTS AND DISCUSSION

This paper offers new cosine similarity measures on PFSs. These candidate measures satisfy the axoims (1-4), that shows the validity of the proposed measures. Further, numerical computations have been resented to acknowledge the reliability of the proposed measures. Figure 1 shows the output of similarity measure by the propsed model in the study. The proposed measures are implemented in the given image processing problem of disease detection in plants and compare the results with the existing similarity measures given by [5], [10], [12], [15], [35] on PFS, given in Figure 2.

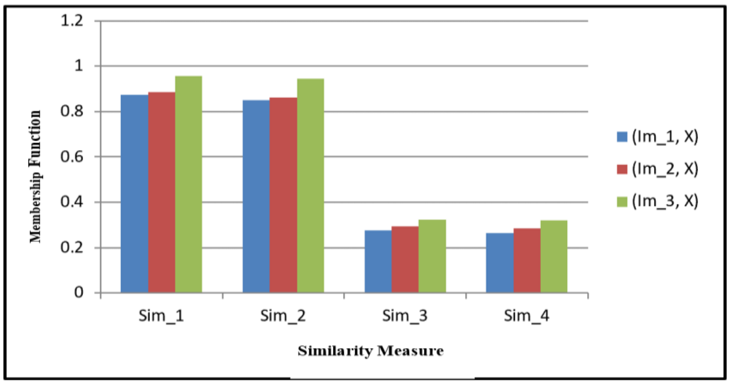

Figure 1. Proposed similarity measures with respect to the given images

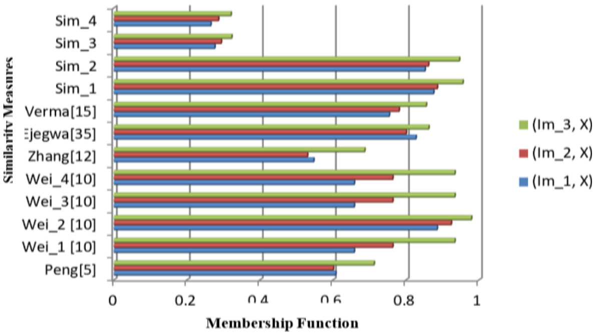

Figure 2. Comparison of proposed similarity measures with the existing measures

5. CONCLUSION

The agricultural sector is also critical to the development and growth of nations and has a direct impact on the living standards and economic status of a country. The use of image processing techniques in farming for the detection of diseases is very fruitful. The present study explores the critical facets of detection of diseases among the crops/plants using the Pythagorean fuzzy-based image sensing system. Four entropy measures have been proposed that highlights the applications of similarity measures in getting the perfect and precision information while using multiple parameters of an image. From the results it is concluded that the proposed entropy measures are better than the existing measures for image processing problems. Despite of the useful insights provided by the present study; it has certain limitations that need to be acknowledged. Firstly, the study only focused on the applications of fuzzy-based image sensing in detecting the diseases. In the future, more research should be conducted to address the limitations of the present study. The study could be expanded to include the factors that impact managing the precise information regarding the growth acceleration rate of disease and the impacts pertaining to the kind of disease on the crops.

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