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Emerging neutrosophic C means clustering based segmentation for rice plant leaf disease detection

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***Abstract*---**One of the main determinations of India is agriculture and the quantity of production is very essential in the field of cultivation. The rice crops are crucially admitted as one of the powerful energy streams for the production of resources. But rice plants suffer from various diseases due to infections that occur in leaf, fruit and stem. Hence, the production of rice plant is decreased and reflects severe issues in economic, agriculture and communal loss. The usage of image processing in leaf disease detection plays a vital role to diagnose and control it effectively. Though there are many existing works are done too detect rice plant leaf disease, still the presence of vagueness, impreciseness due to noise and outliers are primary challenges. The main aim of this paper is to optimize rice plant leaf disease detection by developing neutrosophic C-means clustering for segmentation. The features are extracted and their similarity is evaluated using neutrosophic Hausdorff distance. The degree of similarity is done based on truthiness, indeterminacy and falsity. The simulation results proved that enhance neutrosophic C-means clustering achieves highest rate of accuracy in rice plant leaf disease detection with less error rate compared to K-means, DBSCAN and FCM

***Keywords*---**rice plant leaf, disease detection, neutrosophic clustering, hausdorff distance, segmentation, vagueness, impreciseness.

Introduction

India ranks second in production of rice and it is the largest exporter in the world. It increases rice production from 53.6 to 120 million tons in 1980 – 2021

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respectively [1]. In India rice is one of the main and dominant grain that is cultivated in the largest area. Rise is grown in 30 districts of Tamilnadu states and top five districts are Villupuram, Nagapattinam, Tiruvarur, Thanjavur and Thiruvannamalai expect Chennai [1]. The cultivated rice plants will not be healthy always because they suffer from diseases like leaf smut, bacterial blight and brown spot. Hence it is very essential to monitor the occurrence of diseases at its earlier stage [2]. For successful cultivation and to increase good quality of rice plant production observation of plant diseases and it primary stage it is highly recommended to overcome heavy loss in cultivation. The occurrence of disease can be discovered by indications on the leaf of plant. The invention of image processing has tribally played vital role in agriculture field especially in case of crop disease recognition at its early stages [3]. To perform disease detection using leafs image it has to undergo removal of noise, image enhancement, removal of undesired distortion and applying smoothing filter to improve the contrast of image. Image segmentation is done to separate an image in various parts, the texture statistic are calculated for significant segments, the features extracted from them are used for clustering either as healthy or unhealthy.

Though there are many mining approaches are available to perform rice plant leaf disease classification the presence of outliers and noise pixels may affect the accuracy of the detection model. the vagueness and impreciseness are two major factors which impacts the performance of unsupervised leaf disease detection models. Thus, to overcome these difficulties and to empower the process of clustering this paper used neutrosophic C-means clustering for empowering accuracy rate of leaf disease categorization.

Related work

Harshadkumar et al [4] designed a prototype model for rice disease detection and classification on their infected areas of rice plant images. They used centroid based K-means clustering for disease portion segmentation from a least image. The features are extracted by feeding centroids and green pixels are removed from disease area of rice plant. Kawcher et al [5] in their work presented machine learning models which involves in rice leaf disease detection. They performed preprocessing and trained the model using J48, logistic regression, KNN and naive Bayes.Sladojevic et al [6] anticipated plant disease detection by adopting deep learning techniques. In this work they used Caffe deep learning architecture for training the model. They applied 10-fold cross validation to predict the presence of disease.

Maniyath et al [7] performed leaf disease detection by extracting the features using histogram of oriented gradient. With the extracted features an ensemble learning model is designed to classified diseased and healthy leaf. Prajapati et al [8] designed an unsupervised learning model for rice leaf disease detection. The K-means clustering is used to segment rice leaf image. The segmented area is consider for feature extraction and the model is trained using support vector machine. Yao et al [9] developed the classification model for rice plant disease detection. They performed denoising by applying 3*3 rectangular filter window. For segmentation Otsu method is used the extracted shape and color texture is given as input to support vector machine to classify healthy and disease leaf.

Zhang et al [10] performed leaf disease prediction using hybrid clustering for segmentation they divide image in to different blocks consisting of super pixels the classification of super pixels is achieved by expectation maximization model. Singh [11] devised a soft computing model for plant leaf image classification. Genetic algorithm is used for segmenting leaf image. They performed quantitative analysis on different soft learning algorithms. Tian et al [12] applied K-means clustering for leaf image segmentation. To improve its quality of segmentation adaptive model is used. The number of clusters is defined using Davis Bouldin index. Archana et al [13] in their work performed automatic rice leaf segmentation to identify two significant diseases Bacterial Leaf Blight and Brown Spot. Automatic segmentation is done and features are extracted from that portion. They used different classification models for classifying healthy and diseases rice leaf

Methodology: Enriched Neutrosophic Clustering based Rice leaf Disease Detection

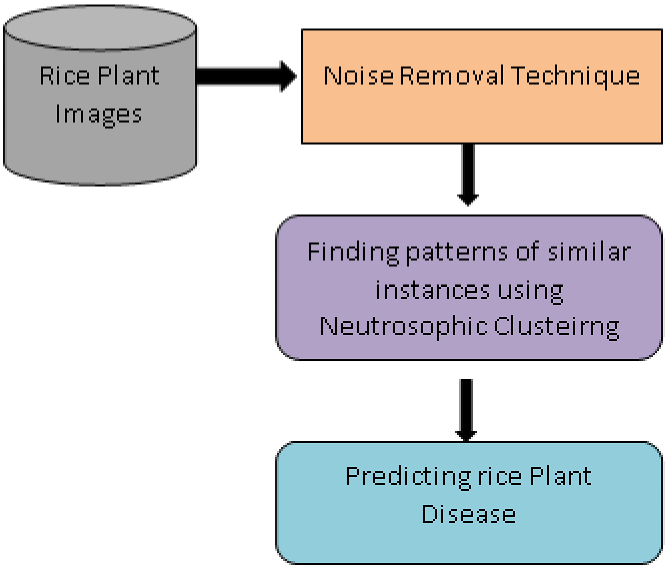

Figure 1 : Overall Framework of the Enriched Neutrosophic Clustering for Rice leaf disease detection

This research work developed an uncertainty handling clustering process to overcome the problem of outliers and inconsistencies to predict the rice leaves. This work uses the Kaggle rice plant leaf dataset [16] with 120 images for detecting disease leaf with its concern type and healthy rice leaves. Initially, the input raw image is preprocessed by applying adaptive anisotropic diffusion noise filtering model to improve the quality of the rice plant image. The significant features of the rice plant are extracted based on color, shape and texture. Clustering the rice plant images based on neutrosophic c means approach which handles the outlier and the inconsistencies to improve the accuracy of disease detection The overall architecture of the proposed model is shown in the figure 1.

Noise Removal

In this work three types of rice leaf disease is used they are leaf blast, brown spot and rice hispa. During image preprocessing the quality of image is enhanced by removing presence of noisy in rice image. The impulse noise in rice image is filtered using adaptive anisotropic diffusion filter. In this method the quality of pixel at position (i, j) is determined by its surrounding pixels in 3*3 matrix window. If the pixel is noiseless and its surrounding is either noise or noiseless consider the pixel value and retain it. If the pixel is noisy while its surrounding pixels are noiseless find the median value of surrounding pixels and replace it with pixel at position (i, j). In case of both pixel at (i, j) and its neighboring pixels are also noisy then apply convolutional filters.

Neutrosophic Knowledge and its Representation

The real time representation of objects or facts cannot be expressed in terms of crisp value, because it can be well explained in terms of linguistic form. Thus, in this work a theory of multivalued neutrosophic logic is adapted which represents the real time objects or images in terms of membership degree of truthiness, falsity and indeterminacy. The Neutrosophic paradigm is introduced by Smarandache [14] which aims to overcome the problem of ambiguity, impreciseness, inconsistencies and uncertainty to perform plant leaf disease detection using clustering model. The neutrosophic logic is a triplet representation of Truthiness (TS), Indeterminacy (IY), and Falsity (FL) as

$$\langle TS, IY, FL \rangle \quad \textbf{eq (1)}$$

The neutrosophic logic inherits both the classical and fuzzy theory by making the membership degree of TS+IY+FL = 1. When the neutrosophic membership grades are TS+FL <1 then it characterizes the feature of Intuitionistic fuzzy**.** The Paraconsistent Logic can also be denoted when the condition of factors is TS+IY+FL > 1 [15].

Definition: Let us consider R be the set of images of the rice plant leaf and each leaf is denoted as Y then the neutrosophic triplet is defined as

$$R = \{\langle y; [TS_R(y), IY_R(y), FL_R(y)]\rangle \vdots\ y \in Y\} \quad \textbf{eq (2)}$$

where $TS_R(y)$ is signified as membership grade of confidence which is referred as truth value. $IY_R(y)$ is characterized as membership of indeterminacy also termed as inconsistent or uncertainty and $FL_R(y)$ symbolize the false membership degree and coined as skepticism. The value of all the three factors lies between 0 and 3 as it is represented in the equation

$$0 \le TS_R(y) + IY_R(y) + FL_R(y) \le 3 \quad \textbf{eq (3)}$$

Hausdorff distance

To measure how far two different images of a metric space are from each other by finding each pixel of either image is close to some pixel of the other image. Let us assume that I = ={$i1_1$,....., i_p} and J {j_1,....., j_q}, are two different images, the distance between them is calculated using Hausdorff as follows

$$\text{HD (I, J)} = \max \{h(I, J), h(J,I)\} \quad \textbf{eq (4)}$$

Where HD (I, J) = max-min dt(i, j) i∈I j∈J
i and j are pixels of images I and J respectively, dt(i, j) is any metric among these two pixels. The two distances ht(I, J) and ht(I, J) are termed as Hausdorff distance.

Let M = $\{M_1, M_2, \ldots, M_n\}$ be a discrete finite set. Let a neutrosophic set B in M is characterized as $\mathrm{TS}_{\mathrm{B(Mi)}}, \mathrm{IY}_{\mathrm{B(Mi)}}, \mathrm{FL}_{\mathrm{B(Mi)}} \in [0, 1]$, for every $M_i \in M$ signifies its membership degree of Truthiness, Indeterminacy, and Falsity values correspondingly signified by

$$B = \{< M, \mathrm{TS}_{\mathrm{A(xi)}}, \mathrm{IY}_{\mathrm{B(Mi)}}, \mathrm{FL}_{\mathrm{B(Mi)}} >\} \quad \textbf{eq (5)}$$

To determine the distance among the two Neutrosophic set I ∈ NS and J ∈ NS well-defined by

$$dt_{Hd}(\mathrm{I,J}) = \frac{1}{n}\sum_{i=1}^{n} \max\{|\mathrm{TS_I}(M_i) - \mathrm{TS}_J(M_i)|, |\mathrm{IY_I}(M_i) - \mathrm{IY_J}(M_i)|, |\mathrm{FL}_I(M_i) - \mathrm{FL_J}(M_i)|\} \quad \textbf{eq (6)}$$

Where $dt_{Hd}(\mathrm{I,J}) = \mathrm{Hd(I,J)}$ signifies the extended Hausdorff distance among two neutrosophic images I and J.
Consider I, J and K, be three neutrosophic sets for all $M_i \in M$ Then their distance are measure as follows:

$$dt_{Hd}(\mathrm{I,J}) = \mathrm{Hd(I,J)} = \max\{|\mathrm{TS_I}(M_i) - \mathrm{TS}_J(M_i)|, |\mathrm{IY_I}(M_i) - \mathrm{IY_J}(M_i)|, |\mathrm{FL}_I(M_i) - \mathrm{FL_J}(M_i)|\} \quad \textbf{eq (7)}$$

Same formula is used for finding distance among I and K such that, For all $M_i \in M$

$$\text{Hd (I, K)} = \max\{|\mathrm{TS_I}(M_i) - \mathrm{TS}_K(M_i)|, |\mathrm{IY_I}(M_i) - \mathrm{IY_k}(M_i)|, |\mathrm{FL}_I(M_i) - \mathrm{FL_k}(M_i)|\} \quad \textbf{eq (8)}$$

And distance among J and K is characterized as, For all $M_i \in M$

$$\text{Hd(J, K)} = \max\{|\mathrm{TS_J}(M_i) - \mathrm{TS}_K(M_i)|, |\mathrm{IY_J}(M_i) - \mathrm{IY_k}(M_i)|, |\mathrm{FL}_J(M_i) - \mathrm{FL_k}(M_i)|\} \quad \textbf{eq (9)}$$

Definition : Consider I, J be two neutrosophic represented images in M = $\{\mathrm{M}_1, M_2, \ldots, \mathrm{M}_n\}$, if I = $\{< M, \mathrm{TS}_{\mathrm{I(Mi)}}, \mathrm{IY}_{\mathrm{I(Mi)}}, \mathrm{FL}_{\mathrm{I(Mi)}} >\}$ and J = $\{< M, \mathrm{TS}_{\mathrm{J(Mi)}}, \mathrm{IY}_{\mathrm{B(Mi)}}, \mathrm{FL}_{\mathrm{J(Mi)}} >\}$ are neutrosophic values of M in I and J correspondingly, then the similarity measure among the neutrosophic sets I and J can be assessed by the mathematical modelling as follows:

For all M_i in M

$$\mathrm{SM_{TS}}(I, J) = \left(\sum_1^N \left|\frac{\min(\mathrm{TS_I}(M_i), \mathrm{TS_J}(M_i))}{\mathrm{Max}(\mathrm{TS}_I(M_i), \mathrm{TS}_J(M_i))}\right|\right)/n \quad \textbf{eq (10)}$$

$$\mathrm{SM_{IY}}(I,J) = 1 - (\textstyle\sum_1^N |\frac{\min(\mathrm{IY_I}(M_i),\mathrm{I_J}(M_i))}{\mathrm{Max}(\mathrm{IY_I}(M_i),\mathrm{I_J}(M_i))}|)/n \qquad \textbf{eq (11)}$$

$$\mathrm{SM_{FL}}(I,J) = 1 - (\textstyle\sum_1^N |\frac{\min(\mathrm{FL_I}(M_i),\mathrm{FL}_J(M_i))}{\mathrm{Max}(\mathrm{FL}_I(M_i),\mathrm{FL}_J(M_i))}|)/n \qquad \textbf{eq (12)}$$

Thus, the similarity among the two images I and J is determined as

$$\mathrm{SM}\ (\mathrm{I},\mathrm{J}) = (\mathrm{SM_{TS}}(I,J), \mathrm{SM_{IY}}(I,J), \mathrm{S_F}(I,J)) \qquad \textbf{eq (13)}$$

Where
$\mathrm{SM_{TS}}(\mathrm{I},\mathrm{J})$ Signifies the degree of similarity (where we take only the Truthiness's).
$\mathrm{SM_{IY}}(\mathrm{I},\mathrm{J})$ Means the degree of indeterminate similarity
(where we take only the Indeterminacies').
$\mathrm{SM_{FL}}(\mathrm{I},\mathrm{J})$ Represents the degree of non-similarity (where we take only the Falsity's).
Max signifies the maximum among each pixel of I and J.
Min signifies the minimum among each pixel of I and J.

Neutrosophic Clustering based Segmentation for Rice Leaf Disease Detection

The Neutrosophic C -Means clustering is adapted in this work for finding similar group of rice leaf and clustering them based on the type of disease affected leaf as well as healthy leaf. Each image is computed with the degree of belongingness towards the determinant and indeterminate clusters in a parallel manner. The determinant clusters are denoted by the Degree of Truthiness of each image and the indeterminate clusters are further subcategorized into ambiguity and outlier cluster which are represented by membership grade of Indeterminacy and Falsity.
To discover the similarity among each leaf image with centroids, the neutrosophic Hausdorff distance measure is introduced in this work instead of performing Euclidean distance to handle the uncertainty ang impreciseness due to the outliers and border lying images.

Let V be the new image which is represented as the union of determinant cluster and indeterminate clusters noisy and border lying images. They are mathematically expressed as

$$V = D_i \cup N \cup B,\ i = 1\ldots \qquad \textbf{eq (14)}$$

where D_i represents determinate cluster, N is associated with noisy pixel, B indicates as pixels in boundary regions and $\cup$ refers union operation. To handle indeterminacy by clustering its objective function is represented as

$$\mathrm{OJ}(\mathrm{TS},\mathrm{IY},\mathrm{FL},\mathrm{C}) = \textstyle\sum_{i=1}^{N}\sum_{j=1}^{C}(\delta_1 TS_{ij})^z\left\|y_i - c_j\right\|^2 + \sum_{i=1}^{N}(\delta_2\mathrm{IY}_i)^z\left\|y_i - \bar{c}_{imax}\right\|^2 + \sum_{i=1}^{N}\varphi^2(\delta_3\mathrm{FL}_i)^z \qquad \textbf{eq (15)}$$

$$\bar{c}_{imax} = \frac{C_{r_i}+C_{s_i}}{2}\ ;\ r_i = \underset{j=1,2\ldots C}{\mathrm{argmax}}(TS_{ij}); \qquad s_i = \underset{j\neq r_i\cap\, j=1,2\ldots C}{\mathrm{argmax}}(TS_{ij}) \qquad \textbf{eq (16)}$$

Where z is the constant, r_i and s_i are the biggest and second biggest clusters number with highest membership degree of Truthiness (TS), $\bar{c}_{imax}$ is calculated using the r_i and s_i and it is treated as constant value will not be changed anymore. The distance measure of image and the centroid image $|y_i - c_j|$ is computed using neutrosophic Hausdorff distance measure. The deterministic, boundary and noisy pixels of an image satisfies the following condition

$$\sum_{i=1}^{N} TS_{ij} + \mathrm{IY}_i + \mathrm{FL}_i = 1 \qquad \textbf{eq (17)}$$

The clustering of leaf image dataset is done in an iterative way with membership of $TS_{ij}, \mathrm{IY}_i, \mathrm{FL}_i$. The centroid C_j is computed by equation [22] during each iteration.

$$TS_{ij} = \frac{F}{\delta_1}\left(y_i - c_j\right)^{-\frac{2}{z-1}} \qquad \textbf{eq (18)}$$

$$\mathrm{IY}_i = \frac{F}{\delta_2}(y_i - \bar{c}_{imax})^{-\frac{2}{z-1}} \; \textbf{eq (19)}$$

$$\mathrm{FL}_i = \frac{F}{\delta_3}\varphi^{-\frac{2}{z-1}} \; \textbf{eq (20)}$$

$$\mathrm{F} = \left[\frac{1}{\delta_1}\sum_{j=1}^{c}\left(y_i - c_j\right)^{-\frac{2}{z-1}} + \frac{1}{\delta_2}(y_i - \bar{c}_{imax})^{-\frac{2}{z-1}} + \frac{1}{\delta_3}\varphi^{-\frac{2}{z-1}}\right]^{-1} \qquad \textbf{eq (21)}$$

$$\mathrm{C_j} = \frac{\sum_{i=1}^{N}(\delta_2 TS_{ij})^z y_i}{\sum_{i=1}^{N}(\delta_2 TS_{ij})^z} \text{ eq (22)}$$

During each iteration $\bar{c}_{imax}$ is calculated relevant to largest and second largest value of TS_{ij}. A is the constant value. The process of iteration will continuous until the condition $|TS_{ij}^{(t+1)} - TS_{ij}^{(t)}| < \varepsilon$, ε is the termination condition lies among 0 and 1, t denotes iteration stage.

The algorithm for Neutrosophic C Means Clustering for Rice Plant leaf disease detection is as follows:

Algorithm: Enriched Neutrosophic C Means Clustering based Segmentation for Rice Plant Leaf Disease Detection

1. Input : Rice leaf images
2. Set TS^0, IF^0, FL^0 , C, z, $\delta_1, \delta_2, \delta_3$
3. Set t = 0; {iteration step}
4. Calculate centroid of each cluster's C_i using Hausdorff Distance measure at iteration t
5. Compute $\bar{c}_{imax}$ reliant to the largest and second largest TS value by a performing comparison using the formula
   $\bar{c}_{imax} = \frac{C_{r_i} + C_{s_i}}{2}$; $r_i = \underset{j=1,2\ldots C}{\operatorname{argmax}}(TS_{ij})$; $s_i = \underset{j \neq r_i \cap j=1,2\ldots C}{\operatorname{argmax}}(TS_{ij})$
6. Update $\mathrm{TS}^{(t)}$ to $\mathrm{TS}^{(t+1)}$, $\mathrm{IY}^{(t)}$ to $\mathrm{IY}^{(t+1)}$ FL $\mathrm{FL}^{(t)}$ to $\mathrm{FL}^{(t+1)}$
7. If $|TS_{ij}^{(t+1)} - TS_{ij}^{(t)}|$ < ε then terminate the process, else go to step 4
8. Allocate each image into the class (healthy or unhealthy) which has the biggest TSM = [TS, IY, FL]

Where y(i)∈ clth class if cl = $\underset{j=1,2\ldots C+2}{\operatorname{argmax}}(TSM_{ij})$

Output: Clustered Rice Leaf image {Healthy, Unhealthy}

Results and Discussion

In this section the performance of the enriched neutrosophic clustering (ENCM) based rice plant leaf disease detection is discussed in detail. The proposed model ENCM is implemented using python software. The rice plant leaf dataset is collected from Kaggle repository. In this work 120 images are used to cluster whether the rice leaf is healthy or diseased due to brown spot or Hispa or leaf blast is determined

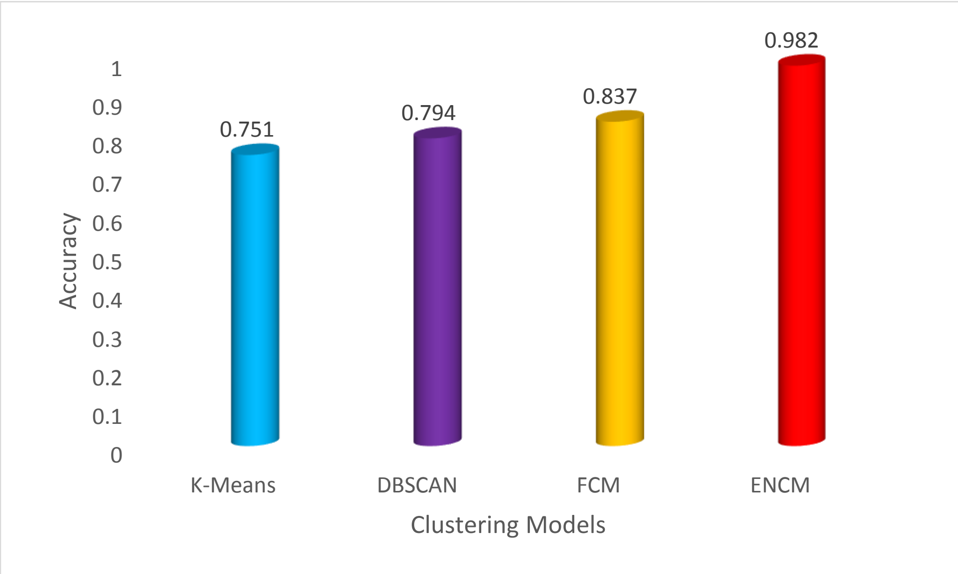

Figure 2 Performance Comparison based on Accuracy

The figure 2 shows the performance comparison of four different clustering models involved in rice plant leaf disease detection. The region of affected area is segmented and the features which describes the presence of disease is accomplished by the proposed Neutrosophic C-means Clustering with highest accuracy of 0.982%, while K-means produced 0.751%, DBSCAN produced 0.794% and FCM produced 0.837. this is because ENCM with its ability of truthiness, falsity and indeterminacy it handles the impreciseness in determining type of plant leaf disease with highest accuracy.

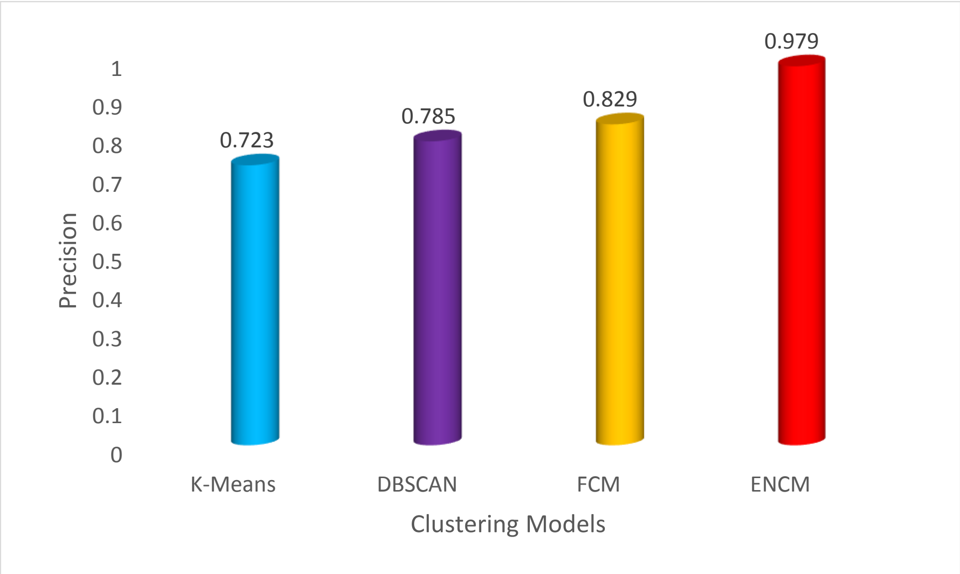

Figure 3 Performance Comparison based on Precision

The figure 3 explores precision rate of three different clustering models-based feature extraction and effective rice plant leaf disease detection. The Neutrosophic C-means with memetic based centroid selection improves the rice plant leaf detection by finding similarity among leaf images and categorizing them as Leaf blast, Brown spot, Hispa and Healthy leaf. The precision rate of ENCM is higher then, other three clustering models. The ENCM precision rate is 0.979%, K-means generates 0.829%, DBSCAN and FCM obtains 0.785%, 0.829% respectively.

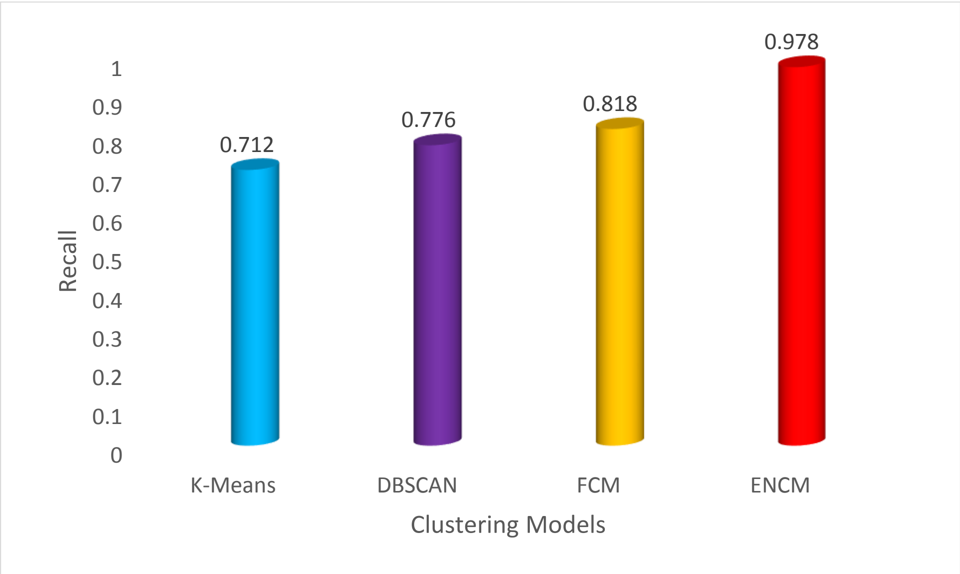

Figure 4 Performance Comparison based on Recall

The figure 4 shows the results of recall obtained by four different clustering models K-means, DBSCAN, FCM and NCM to categorize types of plant leaf disease by determining similarity among them. The neutrosophic C-means determines the similarity by finding membership of truthness, falsity and indeterminacy to discover feature extraction. By handling uncertainty and indeterminacy the proposed ENCM produced highest recall value compared to other three clustering models. The recall rate of NCM is higher then, other three clustering models. The ENCM precision rate is 0.978%, K-means generates 0.712%, DBSCAN and FCM obtains 0.776%, 0.818% respectively.

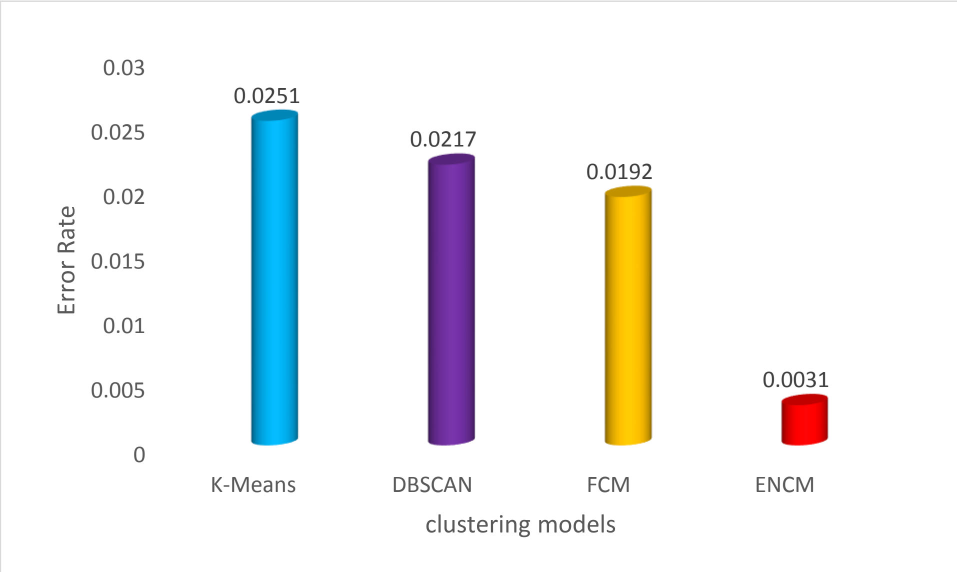

Figure 5 Performance Comparison based on Error Rate

The figure 5 demonstrates that proposed ENCM produced least error rate 0.0031% compared to other three models K-means, DBSCAN and FCM with 0.0251%, 0.0217% and 0.0192% respectively. The reason is enhanced NCM handles outliers and border lying images using the degree of indeterminacy it performs accurate detection. The rice plant leaf image is enhanced by performing noise removal, contrast enhancement, feature extraction with the concept of neutrosophic logic and clustering them by finding similarity using neutrosophic Hausdorff distance.

Conclusion

This paper focuses on effective rice leaf disease identification by developing an emerging unsupervised learning model neutrosophic C-means clustering. The issue of vagueness and impreciseness in clustering of rice plant as healthy or unhealthy is overcome by representing them as asset of membership degree towards truthiness, indeterminacy and falsity. It handles uncertainty due to presence of noise in an image and indeterminacy during segmentation is also well treated by neutrosophic clustering. The simulation results also explore effectiveness of rice plant leaf disease detection more accurately using neutrosophic clustering at its earlier stages with least error rate compared to K-means, DBSCAN and FCM.

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