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Automatic segmentation of plant leaves disease using min-max hue histogram and k-mean clustering

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Abstract
Automatic segmentation of plant image's leaf diseases has recently become a popular area of study worldwide. The suggested approach automatically segments various areas of leaf disease from images of the plant, which can then be combined with machine learning or deep learning techniques to improve system accuracy. Our suggested method consists of three stages: Preprocessing is applied in the first stage where a rank order fuzzy (ROF) filter is proposed that reduces the background noise from the plant picture. In the next stage, disease spot detection is performed using proposed min-max hue histogram based techniques. Disease spot identification prior to segmentation helps in proper segmentation of k-mean clustering. The K-means clustering is then performed in the next stage to segment the leaf pictures into uniform regions. These segments are transformed into HSI color spaces and the segment with the largest hue value is extracted as the disease segment. The proposed methodology is implemented in Matlab 18a and studies are carried out on various plant images. The proposed ROF filter demonstrates superior results to the other state-of-the-art filters. The filter is also resistant to very large noise levels, and shows meaningful details at noise levels of 95%. Besides, our hue-based spot detection is compared with the existing method and it can be shown by the suggested approach, the diseases have been found mostly correctly. The segmentation accuracy of the proposed method is calculated using the Jaccard coefficient, Sensitivity and Positive Prediction Rate. Our proposed system achieved high Jaccard coefficient value of 0.7747.

Keywords Contrast stretching · Fuzzy filter · Hue histogram · HSI color model · K-mean clustering · Segmentation

Abbreviation

F_{ij}	2D Index matrix value at ith row and jth coloum. The value is either 0 or 1
ρ	The percentage of impulse noise prediction

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P_{ij}	Pixel value at location (i, j)
M	The total of rows in image
N	The total of columns in image
D'	First order absolute differences
W_{ij}	Window of size $(2M\times 1)$ $(2M\times 1)$ Centered at (i,j)
μ_{ij}	Fuzzy membership value
y_{ij}	Restoration term at location (i, j)
α	A non-negative integer constant
H	Hue component ranging from 0 to 360 degree
S	Saturation component ranging from 0 to1
I	Intensity component ranging from 0 to 1
θ	Hue degree
H_{ij}	Unmodified hue value of the image at coordinate (i,j)
H'_{ij}	Modified hue value of the image at coordinate (i,j)
η	Threshold to increase the hue value in the picture
$\tau 1$ and $\tau 2$	Threshold values in the hue histogram between 0 and 60 degree
C_k	Centroid of cluster k
$d_{i,\,k}$	the Euclidean distance between the center k and each data point i of an image
$E(x)$	The mean of the image x

1 Introduction

India is a country of agriculture. The crops would not necessarily be in good condition. In order to optimize crop yield and prevent disease, crop monitoring is important on a very frequent basis. Diseases in crops may decrease yields, which affects crop production. We must recognize the disease at the early stages so that we can allow farmers to keep crops away from the disease to maximize the yield [1]. Diseases such as bacterial blight, alternaria alternate (called fungal too), cercospora leaf spot, anthracnose, etc. may adversely affect crops. Crop disease can be practically detected by analyzing various trends in the parts of the crop, like leaves, fruit, and stems. Such types of diseases are most commonly present in rice, soyabean, and a number of other vegetables [5].

The monitoring of plant diseases is more challenging when done manually. The manual process necessitates longer processing time, a substantial quantity of labour, and knowledge of plant diseases [36]. Computer vision advancements have enabled the performance of visual detection tasks, and these visual detection approaches can be used to successfully identify plant diseases [31].In the last two decades, disease detection and diagnosis have increased, and informative and sophisticated research is being conducted [24]. Latest reviews show that image-based disease detection is constantly evolving [6, 7, 36]. Numerous methods for identifying and quantifying plant diseases are in use, and one of them is leaf image-based disease recognition [4, 15, 16, 22, 23, 25, 46].

The leaf image based disease recognition system comprises of image acquisition, pre-processing, image segmentation, feature extraction, and classification steps [9].Machine learning for disease identification and recognition/classification can give clues about how to identify and handle diseases in their early stages, thus improving the efficiency of agricultural production. Numerous machine learning methods for disease recognition have been suggested in the literature, but the effectiveness of the disease recognition is mostly dependent on how those leaves are segmented. The accuracy with which such leaves are classified is proportional to the quality of their segmentation. Certain researchers have used image segmentation techniques for segmenting plant diseases [2, 13, 14, 19, 21, 32, 34, 37, 38, 41, 44, 45, 47]. Despite the numerous segmentation techniques currently available, no general methods have been identified as the most effective approach for image segmentation. The motivation behind this study is to provide disease spot identification prior to segmentation using a hue histogram technique that helps in proper segmentation of k-mean clustering. Since K-means is the most popular image segmentation technique because it is quick and easy to use. The K-means algorithm produces results that are sensitive to two factors: cluster number and initial cluster centroids. As a result, the K-means algorithm provides a local optimal solution.

Apart from that, the most significant impediment to disease spot identification is noise introduced by camera light, changes in lighting, droning background, and the appearance of veins inside the plant leaf. As a result, a technique that eliminates noise and provides better disease spot segmentation is needed. To eliminate noise from the picture, our proposed method uses a rank-order fuzzy filter. The problem with median and other filters is that they smoothen the picture, resulting in blurring, but our method overcomes these issues.

The main objective of this research work is to develop a convenient and low-cost way to automatic segmentation of plant diseases without requirement of human intervention at any stage, with more accuracy using Min-Max Hue Histogram and k-mean clustering, which can then be further combined with any machine learning or deep learning techniques to increase disease detection accuracy.

The contribution of this study is summarized as follows.

- Apply preprocessing to the plant picture using the suggested rank order fuzzy filter to eliminate digitization noise.
- Find the disease spot using the min-max value of a hue histogram image in some predefined range.
- Segmentation of plant leaves into multiple regions using the K-means clustering algorithm applied on L*a*b* color model and identification of disease segments by computing the highest hue value over the other segments.
- Finally, the efficiency of the proposed algorithm is assessed and compared with the existing algorithms.

The following are the subsequent sections. Section 2 outlines the proposed image denoising method based on the rank order fuzzy (ROF) filter. Section 3 discusses a method for detecting disease spots dependent on color. Section 4 explains K-mean clustering. Section 5 describes how the proposed disease segmentation functions. Section 6 describes the evaluation criteria. Section 7 calculates the outcome of the suggested process. Conclusion is described in Section 8.

2 Literature review

There have been several algorithms developed for classifying plant leaf disease images in the recent years [2, 13, 14, 19, 21, 32, 34, 37, 38, 41, 44, 45, 47]. This section gives you a quick glance at a few important studies.

Authors who had conducted the research about disease spot segmentation in plant leaves [32] developed an algorithm that used image processing techniques to perform this task. Various colour models, such as HSI, CIELAB, and YCbCr, were used to test the ability to detect spots associated with disease. The median filter, which reduces the amount of noise in the image, was applied to cure their images. Using Otsu's colour component method, a disease threshold is calculated at the end. In experiments, background noise is removed using the CIELAB colour model.

Several authors in [37] have developed a way to recognize soybean frog eye disease. Infected areas are separated from healthy leaves using segmentation methods, as stated in the text. With statistical and spectral methods, they were able to extract particular shape, colour, and texture features. These features are fed into an SVM algorithm in the final classification.

In the article [38], Authors Attempt to Identify Infected Plant Leaves Using Two Different Infectious diseases. In their method, the image was first converted from RGB to HSV colour space, and afterwards image quality enhancement techniques were used. The thresholding technique was used to mask the image pixels. Following that, a genetic algorithm was used to divide the entities into segments. To identify specific features, the image containing the disease was first segmented and features are extracted using the colour co-occurrence method. The features were used in support vector machines (SVM) for classification.

The aim of the paper [21] was to aid in the identification of leaf diseases on plant images. To accomplish this, the authors proposed an OFA algorithm applied to an alternative active contour model (ACM) to give rise to a new segmentation option. They adopted Fruit fly algorithm to keep energy consumption to a minimum, while also employing a rectangular window approach for the local search window. The Jaccard index, the Dice index, and the Hausdorff distance are used to validate the strategy on real and synthetic images.

Authors in [14] developed an automatic disease detection algorithm for plant leaves. There are a number of different steps in their process, and they include median filter based preprocessing, Kapur's method based disease detection, and colour models like HSI, RGB, and YCrCb for segmentation. Their approach demonstrates that H component of HSI colour model disease spots are accurately and more favourably detected.

Using modern techniques, the detection of plant disease was proposed in [13]. They suggested five distinct steps to complete the process. Once the images were acquired, the process began. Next, they ran the image through some image processing. The images were segmented in the third step after being processed. Following this was finding the various features that were in the segmented regions. With the new features in place, disease classifications were employed.

A fuzzy clustering method (FCM) without supervision, was applied to prostate cancer MRIs images in [34]. To calculate the efficiency of their method, they conducted experiments on dice similarity, Jaccard index, and hausdor distance and the experiment results calculated the values to be 88.68, 81.26, and 4.1 respectively.

The authors of [45] proposes a new method for detecting cucumber diseases that includes three steps: Disease leaf images are segmented using K-means clustering, colour and shape information is extracted from lesions, and disease leaf images are classified using sparse representation (SR). The improvement in recognition performance can be attributed to their use of SR space.

The paper [2] talks about how rice leaves are automatically segmented in a machine. Two major diseases, bacterial leaf blight and brown spot, were identified. Images of rice leaves were automatically segmented before feature extraction. Using a different colour channels, the algorithm separates leaf, sign, and illumination colours.. As a next step, the features that were extracted from the previous step were used for classification using a variety of algorithms. The use of various hybrid techniques and analyses are covered in this paper.

Several researchers in [47] proposed a hybrid clustering-based segmentation approach for disease detection from plant leaves. The authors use a hybrid clustering method to break up the entire colour leaf image into a number of smaller and nearly uniform superpixels, and these clustered pixels provide helpful classification cues to assist with image segmentation and speed up the expectation maximization (EM) algorithm's convergence speed.

To improve the K-means algorithms for segmenting tomato leaf images, the authors implemented an improved algorithm in [41]. They used the adaptive clustering number technique based on ìDaviesBouldin index to automatically initialization of number of clusters. To avoid a local optimum, the initial clustering center was provided.

Researchers of paper [19] created a novel hybrid histogram-based soft covering rough k-means clustering (HSCRKM) algorithm for leukaemia nucleus image segmentation. Combining the strengths of a soft-covering rough set and rough k-means clustering, their algorithm produces good results comparable to those of hard-covering classical rough set and k-means clustering. The histogram method was used to avoid random initialization. Colour, shape, and grey level co-occurrence matrices were obtained from the nucleus segmented image. The machine learning prediction algorithms were applied to the cell classification process.

In [44], the authors described a new segmentation approach they termed the Improved Fast Fuzzy C Means Clustering (IFFCMC) and the Adaptive Otsu threshold (AO) algorithm. The first step is to process the images using image enhancement and filtering techniques. Photographic image enhancement removes noise. For noise removal and enhancement, an adaptive anisotropic diffusion filter (2D AADF) and adaptive mean adjustment (AMA) are both employed. IFFCMC and AO threshold algorithms are employed to divide the enhanced image. Pictures are collected for processing in real time using their approach.

The literature listed above highlights a variety of image processing-based strategies for plant disease segmentation that have been used by a number of researchers in recent years. Otsu's approach, support vector machine, fuzzy c-means algorithm, K-means clustering, expectation maximisation (EM), Genetic Algorithm, and colour model based algorithms were the main strategies used. These methods are used to extract the desired leaf part from the images. However, due to the complexity of agricultural imagery, segmentation remains a difficult task. The automation of the segmentation system, complex images captured by outdoor lightning and destructive effects, the complexity of the image texture, noise introduced by camera light, changes in lighting, droning background, and the appearance of veins inside the plant leaf are all challenges in this process. As a result, there is still much that may be done to improve existing work in this sector. Limitation of existing work can be summarized as:

- In some circumstances, the implementation still lacks precision in the results. More work on optimization is required.
- No general methods have been considered as the efficient approach for image segmentation.
- Priori information is needed for segmentation.
- In order to achieve more accuracy, a database extension is required.
- Very few diseases have been covered. So, work needs to be extended to cover more diseases.

To remove these research gaps and take the advantages of some of the literatures, a new methodology for automatic segmentation of diseases area from plant leaves based on Min-Max Hue Histogram and k-mean clustering has been proposed. Our approach is a convenient and low-cost way to automatically separates various leaf disease regions from plant images. The suggested work focuses more on fully automatic segmentation of diseases with high accuracy. The advantages of proposed algorithm can be viewed as:

- Eliminates digital noises and provides better disease spot visualization than existing techniques.
- More accurate segmentation than other existing methodology.
- Provides the improved segmentation accuracy with proposed algorithm.
- Existing methods rely on the user to choose which part of the input image to segment while the proposed method is fully automatic.
- Provide disease spot identification prior to segmentation using hue histogram technique that helps in proper segmentation using k-mean clustering.

3 Image denoising using rank order fuzzy filter

The Rank Order Fuzzy (ROF) filter is used to improve the quality of impulse noisy images, especially in high corrupted noise. ROF is based on the ranking/density of noisy images [40, 43]. The step by step procedure of ROF is explained as follows:

3.1 Impulse noise detector & density predictor

Build a two-dimensional index matrix F_{ij} with element values of 0 or 1. The procedure for determining the value of index 0 or 1 in each index matrix F_{ij} is as follows:

Create a $(2M \times 1)(2M \times 1)$ neighborhood region with P_{ij} as the center for each pixel P_{ij} at position (i, j) in the picture.

If P_{ij} equals 0 or 255, then P_{ij} is a corrupted pixel, and the value of F_{ij} should be set to 1.

If P_{ij} is between 0 and 255, then P_{ij} could be an uncorrupted pixel. So, determine whether or not it is corrupted. To do so, first translate the window into a 1-D vector S and then sort the elements of S in ascending order.

If $S(\lfloor \alpha/2 \rfloor + 1) \leq P_{ij} \leq S(n - (\lfloor \alpha/2 \rfloor))$ where αan integer and $0 \leq \alpha \leq n$ then P_{ij} is an uncorrupted pixel, and the value of F_{ij} is set to 0. Otherwise, the pixel is mutated, and the value of F_{ij} is set to 1.

Calculate the percentage of impulse noise forecast using the following formula:

$$\rho = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} F_{ij} \times 100\% \tag{1}$$

Denoted:

ρ is the percentage of impulse noise prediction

F_{ij} is index matrix 2D at coordinate (i, j)

M is the total of rows and N is the total of columns.

3.2 Rank order fuzzy filter

Set the value of each noise element, where "salt or 255" by "0". So that P_{ij} only has one noise model that is "pepper or 0". If P_{ij} is an uncorrupted pixel then its value is left unchanged. Otherwise, follow the following step:

Select 2-D window of size$(2M \times 1)$ $(2M \times 1)$. Assume that the pixel being filtered isP_{ij}.

Matrix elements of the window should be sorted starting from the smallest value to the largest value. If the selected window contains all elements as 0's then increase the window size by one and again check the increased window. If increased window contains all 0's, then again increase window size by one. This process is repeated until we have a window with some element (except 0) on it or the maximum window size limit is reached.

Eliminate the 0 from the window and find the average and median of the remaining pixels. Suppose average and median is denoted by A_{ij} and M_{ij}.

Calculate first order absolute differences $D'(i + k, j + l)$ by:

$$D^{'}(i+k,j+l) = \left|p_{i+k,j+l}-p_{ij}\right| \ \boldsymbol{with} \ \ k,l\neq\boldsymbol{0} \tag{2}$$

Extract the local information D_{ij} from W_{ij} according to:

$$D_{ij} = max\left(D^{'}(m)\right)$$

Compute the fuzzy membership value μ_{ij} based on the local information D_{ij}

$$\mu_{ij} = \begin{cases} 0 & : D_{ij} < T1 \\ \dfrac{D_{ij}-T1}{T2-T1} & : T1\leq D_{ij} < T2 \\ 1 & : D_{ij}\geq T2 \end{cases} \tag{3}$$

Where, T1 and T2 are two predefined thresholds.

3.3 Pixel restoration

Pixelí restoration is done with the help of ROF filter which is based on rank/density of the noisy image. When the density of noise is less than 70% then the pixel is reconstructed based on its fuzzy membership value multiplied by the median value of noise free pixels under the window around the pixel observed. Meanwhile, when the density of noise is greater than 70%, then the pixel is reconstructed as given in Eq. 4.

Compute the restoration term y_{ij} as follows:

$$y_{ij} = \begin{cases} \mu^{*}A_{ij} + \left[1-\mu_{ij}\right]^{*}P_{ij} & \text{when}\rho > 0.7 \\ \mu^{*}M_{ij} & \text{when}\rho\leq 0.7 \end{cases} \tag{4}$$

4 Hue based disease spot identification

The steps of our proposed hue based disease spot identification are shown in Fig. 1 and elaborated in the following sub sections.

4.1 RGB to HSI conversion

The HSI color space is mostly used in image processing. In the HSI color space, H (hue) denotes the purity of the color, S (saturation) denotes the contribution of white to a particular color, and I (intensity) denote brightness [29]. The HSI paradigm is used in a variety of fields, including digital graphics, human visual í experience, image í processing, image manipulation, and computer vision [27]. The intensity component I, the saturation component S, and the hue

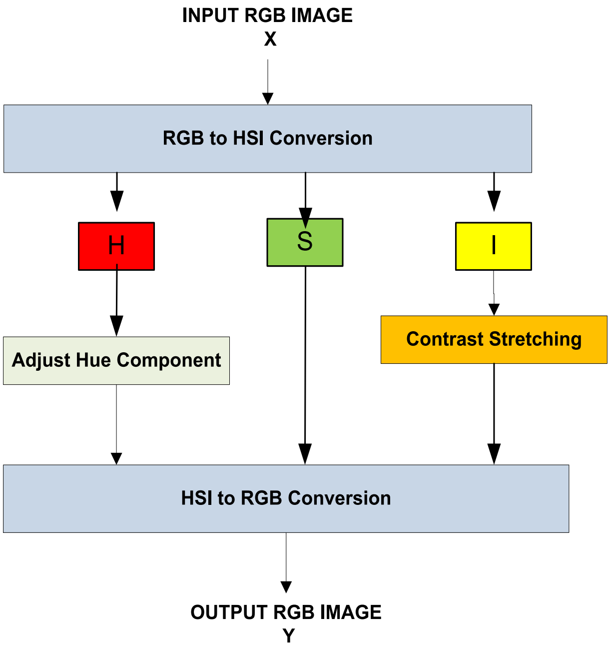


Fig. 1 Block diagram of the proposed hue based spot identification system

component H of an image X in RGB format are as follows [35]:

$$\mathrm{H} = \theta, \ \text{if} \ \mathrm{B} \leq \mathrm{G}$$
$$360\text{-}\theta, \ \text{if} \ \mathrm{B} > \mathrm{G}$$

$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-B)^2+(R-B)(G-B)^{1/2}\right]}\right\} \tag{5}$$

$$S = 1-\frac{3}{(R+G+B)}[MIN(R,G,B)] \tag{6}$$

$$I = \frac{1}{3}(R+G+B) \tag{7}$$

The range of intensity and hue are [0, 1] and [0,360], respectively and The range of saturation is from [0,1].

4.2 Contrast stretching on I component

Contrast stretching [26] is a straightforward strategy for enhancing the dynamic range of an image using point processing. It increases the image's contrast by darkening the dark pixels and brightening the most.

Contrast Stretching is added to I component after obtaining the HSI color model. This will result in a global increase in the intensity factor.

The first phase establishes upper and lower limits on the range of image intensity values that can be expanded. These lower and upper bounds will be denoted by the letters L and U, respectively. The following step calculates and examines the histogram of the original image in order to evaluate the value limits (lower = l, upper = u) of the unmodified image.

Finally, the function:

$$Y = (X - l)\left(\frac{U - L}{u - l}\right) + U \tag{8}$$

Equation 8 maps the original value X to the output value Y for each pixel.

4.3 H component based disease spot detection

Hue is the HSI color model's component, represented as a number between 0 and 360 degrees, corresponding to the color's location on a color wheel. The color changes from red to orange, yellow, green, cyan, blue, magenta, and eventually back to red as the hue value rises from 0 to 360 [33].

The hue adjustment is used to emphasize the color of the leaf disease. As a result, a procedure for detecting and isolating the disease location is essential. So, it is important to provide a cutoff value that distinguishes disease spots from plant leaves.

To do so, calculate the histogram of the hue component and identify the highest and lowest peak points between 0 and 60°(because most of the disease components lie between them and this range is selected on the basis of several trials) in the histogram where the disease color is located. These two points, designated $\tau 1$ and$\tau 2$, are used as thresholds.

The following step is used to change the hue value to optimize the amount of information available for detecting and isolating the disease spot inside the leaf picture.

$$H'_{ij} = \begin{cases} H_{ij} & : H_{ij} < \tau 1 \\ H_{ij} + \eta & : \tau 1 \leq H_{ij} < \tau 2 \\ H_{ij} & : H_{ij} \geq \tau 2 \end{cases} \tag{9}$$

Where, $H_{ij}$and H'_{ij} is unmodified and modified hue values of the image, respectively.

$\tau 1$ and $\tau 2$ are two threshold values in the hue histogram that identify the diseases in the picture and η is another threshold that increases the hue value in the picture with respect to separate the diseases.

4.4 HSI to RGB conversion

Combine the modified H, unmodified S and modified I component to get final enhanced HSI color image. Convert the final enhanced HSI color map back into the RGB color map [35] to obtain the enhanced image. After this process the conversion of HSI to RGB color space is done to exhibit the result of the enhancement. The inverse conversion algorithm can be given by,

$$\textbf{\textit{if}} \quad RG \quad \textbf{\textit{section}} \quad (\textbf{\textit{0}}^\circ \leq H < \textbf{\textit{120}}^\circ)$$

$$R = I\left[1 + \frac{ScosH}{cos(60^\circ - H)}\right] G = 1 - (R + G) B = I(1 - S) \tag{10}$$

$$\textbf{\textit{if}} \quad GB \quad \textbf{\textit{section}}(\textbf{\textit{120}}^\circ \leq H < \textbf{\textit{240}}^\circ)$$

$$R = I(1 - S)$$
$$G = I\left[1 + \frac{ScosH}{cos(60^\circ - H)}\right] B = 1 - (R + G) \tag{11}$$

$$\boldsymbol{if}\ BR\ \ \boldsymbol{section}(\boldsymbol{240^{\circ}} \leq H \leq \boldsymbol{360^{\circ}})$$
$$H = H - 240^{\circ}$$
$$R = 1 - (G + B)$$
$$G = I(1 - S)$$

$$B = I\left[1 + \frac{ScosH}{cos(60^{\circ} - H)}\right] \tag{12}$$

We describe the entire procedure in pseudo-code in Algorithm 1.

Algorithm 1 : Disease Spot Identification on HSI color model

```
procedure DiseaseDetectionByHSI(Image Y)
1. Convert the RGB Image Y into HSI image Z using eq.(5)(6) and (7)
      Z=rgb2hsi(Y);
2. Separate the each plane from Z
      H←Z(:, :, 1)
      S←Z(:, :, 2)
      I←Z(:, :, 3)
3. Hue Based disease spot detection
      Calculate Histogram of H
            G1=Histogram(H)
      Compute two Min-max thresholds τ1 and τ2 that belongs to disease
       spot
            for each element of H_ij in H do
                  if H_i,j between τ1 and τ2 then
                        H'_ij ← H_ij + η
                  end if
             end for
4. Intensity Based Contrast Stretching
      [L,U]←determine upper and lower limits for stretching
      Calculate Histogram of I
            G2←Histogram(I)
      [l,u]←determine upper and lower limits of plane I
      for each element I_i,j in I do
            original value I is mapped to updated output value I
            using eq. (8)
      end for
 5. Combine each plane to make a new HSI image W
      W(:, :, 1) ← H
      W(:, :, 2) ← S
      W(:, :, 3) ← I
 6. Convert the HSI Image W back into RGB image Z using
    eq.(10)(11)and (12);
      Z=rgb2HSI(W);
end procedure
```

5 K-means and hue based segmentation

The K-means [42] method has a good effect on the segmentation of plant leaves disease. In our proposed method, the image is split into multiple clusters by applying K-mean clustering on L*a*b* color model [8] because the RGB, or HSI color models do not provide a correct depiction of the allotment of color areas. In the CIE-Lab color model, plane a and b have a Euclidian distance directly proportional to the visual similarity of the color, so the clustering is performed only in "a" and "b" space. The "L" component stands for luminous and it is left unchanged [11]. After applying K-means clustering, we have multiple clusters in the image. The next step is to determine the appropriate cluster that contains the diseases. For doing so, we have adopted the HSI color model. Using this model, an object with a specific color can be easily identified and it can overcome the effect of light intensity from the exterior. Because of these advantages, all clusters are converted from RGB to HSI color model. We observed that the mean value of the disease cluster has a larger value than other clusters. So, a cluster that has a larger mean hue value will be segmented as a disease cluster.

Algorithm 2 : K-Mean Based Diseased Segmentation

procedure *DiseaseSegmentByKmean*(Image *Z*)

1. Convert the RGB Image *Z* into L*a*b color model *Lab*;
   Lab=rgb2lab(Z)
2. Decompose the image Lab into L, a and b color component;
   $L \leftarrow Lab(:, :, 1)$
   $a \leftarrow Lab(:, :, 2)$
   $b \leftarrow Lab(:, :, 3)$
3. Convert component a and b into 1D vector
   $a\_1D \leftarrow resize(1,a)$
   $b\_1D \leftarrow resize(1,b)$
4. Combine the color plane a and b into matrix
   $P = resize(2, a\_1D, b\_1D)$
5. Choose the number of clusters
   $K \leftarrow NumberofCluster$
6. Select at random K Points called Centroids
   for k=:1 to K **do**
   $C_k = rand();$
   end for
7. For each point of an image, calculate the Euclidean distance between the center and each point of an image
   for each centroids C_k **do**
   for each datapoint P_i in P **do**
   $d_{i,k} = \|P_i - c_k\|$
   end for
   end for
8. Assign all the pixels to the nearest centre based on distance d
   for each row i in d **do**
   $r_{i,k} = \arg\min_k(d_{i,k})$
   end for
9. After all pixels have been assigned, recalculate new position of the centre
   for each centroids C_k **do**
   for each datapoint P_i in P **do**
   $C_k = (r_{i,k} \times P_i) / \sum r_{i,k}$
   end for
   end for
10. Repeat step 7 to 9 until it satisfies the tolerance value or error value

end procedure

We describe the entire procedure in pseudo-code in Algorithm 2. In the algorithm there is a function called *resize()* that resize the dimension of the data. In this function first argument depicts the dimension in which the data is to be converted and the rest arguments shows dimension's data.

6 Proposed methodology

This section describes the details of our proposed method for disease spot identification and segmentation of different leaf disease regions from the crop images. The proposed method is partitioned into the following segments:

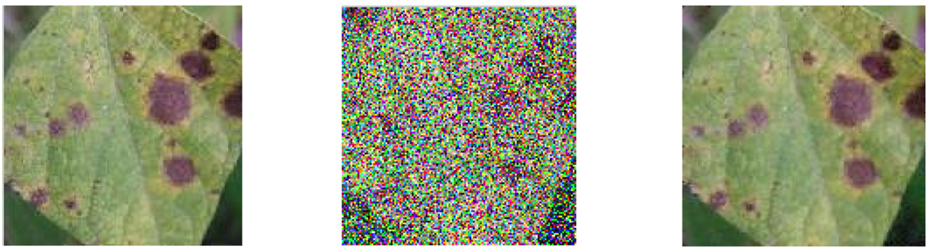
a. Fuzzy Rank Order Filter
b. Disease spot identification on HSI model
c. K-means and Hue based Segmentation

6.1 Fuzzy rank order filter

The proposed color image filtering system consists of impulse noise prediction & noise detector, ROF filter, and pixel reconstruction steps. Since color images consist of three color channels-Red, Green, and Blue. So we apply it to the three color channels-Red, Green and Blue separately, and then combine the results for each of the channels to acquire the final denoised image. Figure 2 shows the alternaria alternate disease image corrupted using impulse noise density of 50% and image reconstruction from impulse noise using a proposed fuzzy technique.

6.2 Disease spot identification on HSI model

A method for detecting and isolating the disease spot is needed, which can be accomplished easily using the hue part of the image, since it indicates the color purity, allowing us to more clearly recognize the leaf disease color.



(i) (ii) (iii)

Fig. 2 The alternaria alternate disease image (**i**) corrupted using impulse noise density of 50% (**ii**) and image reconstruction from impulse noise (**iii**)

This is accomplished by converting the RGB color picture obtained in the previous process to an HSI color model and then separating the components of the HSI color model.

On the hue part, we quantify the histogram of hue and identify the two points in the histogram where the disease color is located. All pixels that fall between these two thresholds are adjusted to highlight the leaf disease color.

Apart from this, the intensity component is also enhanced by using contrast stretching that increases the intensity contrast by darkening the dark pixels and brightening the bright pixels.

Figure 3 shows the output of the hue based disease spot identification with a hue histogram. From the histogram, it is clear that some portions of the histogram are shifted toward the right side that belong between the threshold value $\tau 1$ and$\tau 2$. This is due to an addition in hue value with a threshold that separates the disease from the leaf. In our experiments we have chosen the threshold value of $\eta = 0.75$.

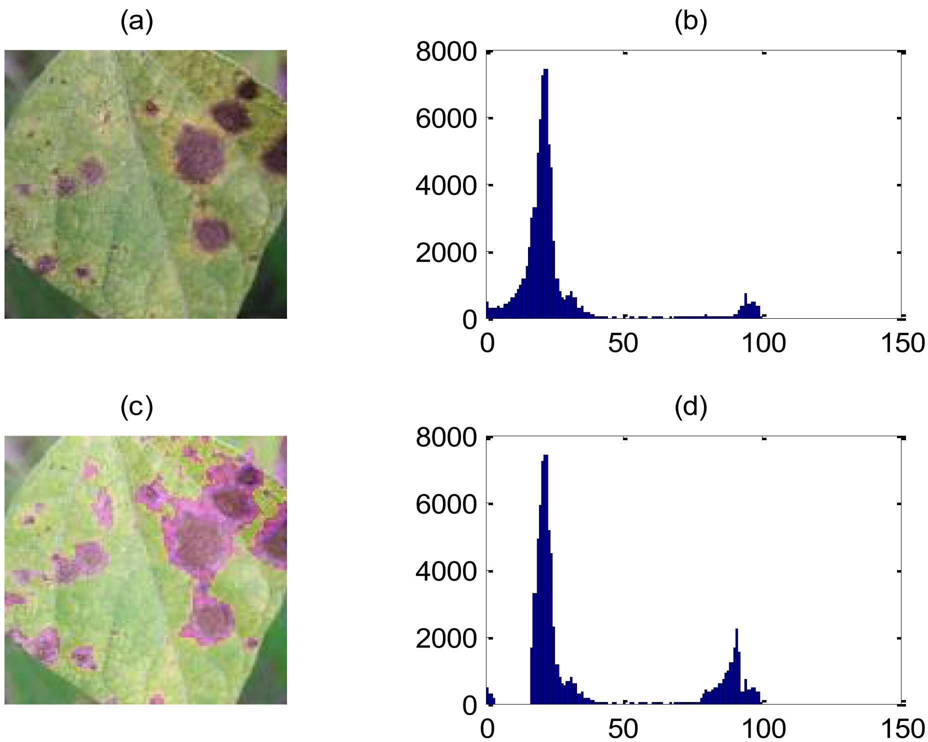


Fig. 3 The alternaria alternate disease image in (**a**) with their hue histogram in (**b**) image with disease spot identified in (**c**) with modified hue histogram in (**d**)

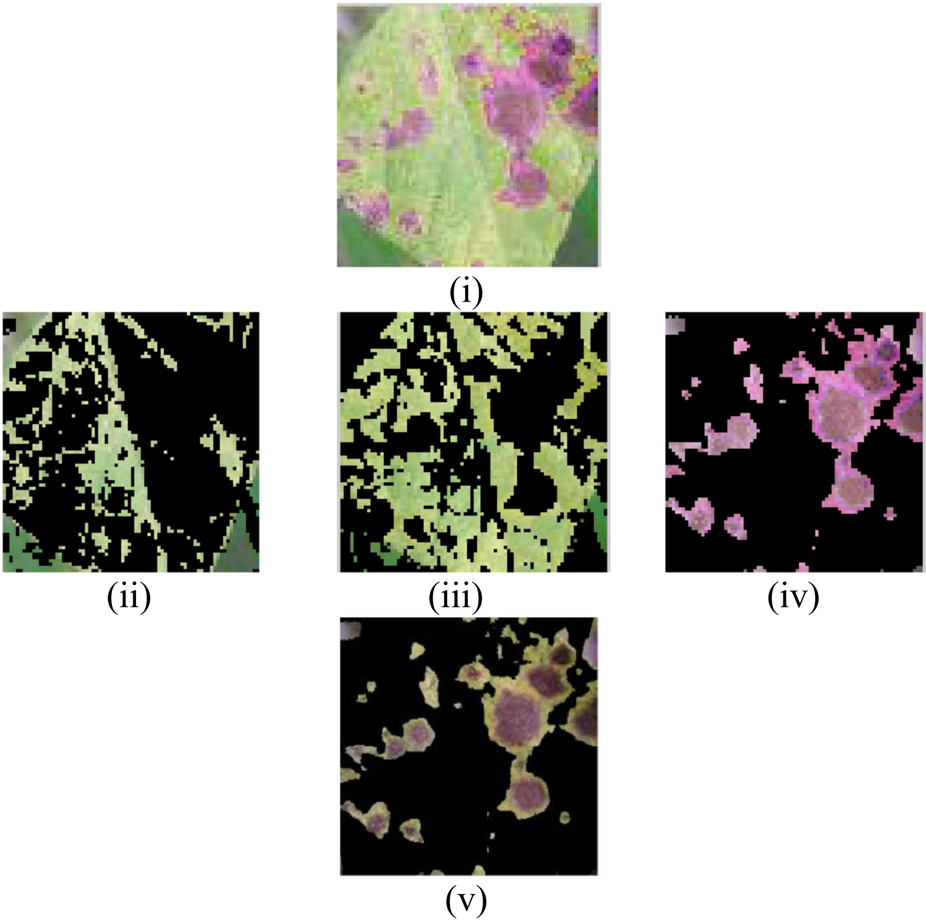


Fig. 4 process of k-mean clustering ((**i**) original image (**ii**) (**iii**), (**iv**) clusters using k-mean clustering, (**v**) cluster that belongs to the disease that has high hue values among all

6.3 K-means and hue based segmentation

In the third phase, the image is split into multiple clusters by applying K-mean clustering on L*a*b* and the result will be multiple clusters. The next step is to determine the appropriate cluster that contains the diseases. To do so, we have adopted the HSI color model. Using this model, an object with a specific color can be easily identified and it can overcome the effect of light intensity from the exterior. Because of these advantages, all clusters are converted from RGB to HSI color model. We observed that the mean value of the disease cluster has a larger value than other clusters. So, a cluster that has a larger mean hue value will be treated as a disease cluster and from this cluster, a mask is generated and based on the mask, disease spot is segmented from the original plant image. The whole process is visualized in Fig. 4.

The proposed hue histogram based spot detection and k-means clustering based plant disease segmentation system is elaborated in algorithm 3.

```
Algorithm 3 : Proposed Plant leaf Disease Identification &
Segmentation
procedure: DiseaseIdentificationSegmentation(Image X)
Input: A plant leaf disease RGB image X
output: An output image W containing only leaf disease
Steps:
1.  Input the plant leaves image containing disease as X.
2.  On image X, Apply a fuzzy rank order filter as described in
    algorithm 1 on image X to remove various impulse noises from the
    image.
     Y=FuzzyRankOrderDenoising(X)
2. Apply Hue histogram based disease spot identification algorithm
   as described in algorithm 2 on noise free image Y obtained from
   the previous step.
     Z=DiseaseDetectionByHSI(Y)
3. Applying the K-mean Clustering technique to image Z to find out
desired segment W.
     W=DiseaseSegmentByKmean(Z)
end procedure
```

The proposed algorithm's flow chart (see Fig. 5) depicts the step-by-step procedure for segmentation of disease from crop images. The original image is fed into the system, where impulse noise is added, resulting in a noisy image. The noisy image is subjected to a fuzzy rank order filter, which removes the digitalized noise. This denoised image is passed into the RGB to HSI conversion step, which transforms the image into an HSI model and separates all three components, H, S, and I. On the H component, the proposed min-max hue histogram method is applied, which emphasizes the color of the leaf disease and isolates the disease spots from the plant leaf. Similarly, contrast stretching is used on the I component, resulting in a global increase in the intensity factor. The saturation component remains unchanged because varying the saturation in the image results in visual artifacts. Finally, combine the modified H, unmodified S, and modified I components to obtain the final enhanced HSI colour image, which is then converted back to the RGB model using the HSI to RGB step. Following this step, the disease spot can be easily visualized. This step helps k-means clustering for accurate disease segmentation from plant leaves. In the next step, the image is divided into multiple clusters using K-mean clustering on the L*a*b* colour model. In the segmentation and masking step, all clusters are converted from RGB to HSI color space, and the mean value of the hue of all clusters is calculated. A cluster with a larger mean hue value is treated as a disease cluster, and a mask is generated from that cluster, and a disease area is segmented from the original plant image based on the mask. The objective behind this study is to provide disease spot identification prior to segmentation using a hue histogram technique that helps in proper segmentation of k-mean clustering as well as remove the digitalize noise prior the spot disease identification using rank order fuzzy filter.

7 Parameter measurement

The above method is compared from a statistical point of view by using some standard quality measures.

7.1 Peak-signal-to-noise-ratio (PSNR)

In general, the PSNR value is íused to calculate the quality of the restored picture and it's significant. PSNR is expressed in decibels (dB) and is calculated as follows: [30]:

$$PSNR = 10\log 255^2 / MSE \tag{13}$$

Where MSE is a Mean square error and it is defined as an error between two images. The higher the PSNR value is, the better the constructed image [22].

7.2 Absolute mean brightness error (AMBE)

The Absolute Mean Brightness Error is used to determine the extent to which brightness is preserved. It can be done using the equation as [30]:

$$\boldsymbol{AMBE} = |E(x) - E(y)| \tag{14}$$

Where, E(x) is the mean of the input image, E(y) is the mean of the output image. A low value implies better brightness preservation.

7.3 Intersection over Union (IoU)

The IoU (Jaccard Index) [20] is a simple way to measure the percent overlap between our estimate and the goal mask.

Simply, the IoU metric is the number of pixels that are shared by estimate and the goal mask divided by the total number of pixels in both masks [39].

$$\frac{IoU = \boldsymbol{target} \cap \boldsymbol{prediction}}{\boldsymbol{target} \cup \boldsymbol{prediction}} \tag{15}$$

7.4 Volume-based metrics

Volume-based matrices [10] are another set of performance measures that performs object detection using area calculate. Suppose V_p and V_G represent the regions segmented by proposed method and the "ground true" boundary respectively, then, we can define the following matrices.

The True positive volume (V_{TP}) = $V_p \cap V_G$,
The false positive volume (V_{FP}) = V_p - V_G,
The false negative volume (V_{FN}) = V_G - V_p and
The true negative volume (V_{TN}) = SCENE − V_p - V_G.

Where SCENE is the region encompassing all possible segmented regions.

With these quantities, Sensitivity and Positive prediction rate metrics can be defined thus:

$$\text{Sensitivity} = \frac{V_{TP}}{V_G} V_{TP} / V_G \tag{16}$$

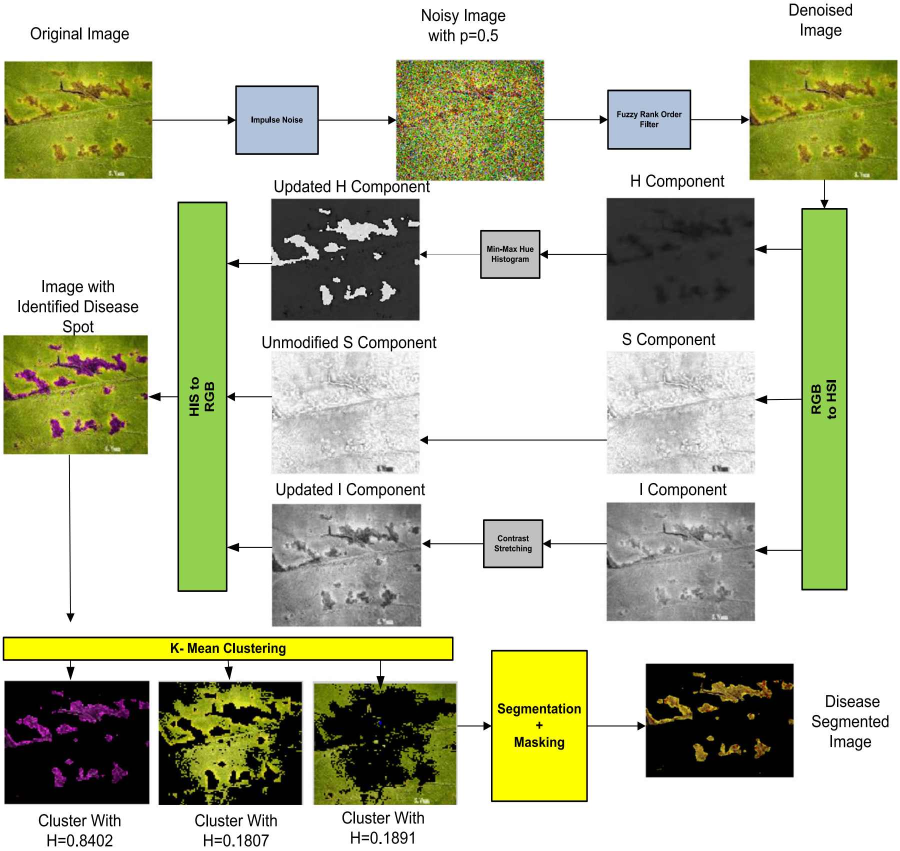


Fig. 5 Flow chart of proposed algorithm

$$\text{Positive Prediction Rate (PPR)} = \frac{V_{TP}}{V_{TP} + V_{FP}} \tag{17}$$

8 Results and discussions

8.1 Database

The datasets used for this work were downloaded from plant village dataset (https://www.forestryimages.org, https://plantvillage.org, http://www.image-net.org/challenges/LSVRC/2012/). From the dataset 75 different crop leaf images were selected in the experiments. 15 of these are healthy images and the rest are images containing the leaves disease. The unhealthy image goes into various classes, like bacterial blight, alternaria alternate (called fungal too), cercospora leaf spot, anthracnose (see Fig. 6).

8.2 Effect of varying impulse noise on proposed ROF filter

This section illustrates the result of our ROF filter. Different noise contents and different image samples were conducted to evaluate the performance of our proposed ROF filter. The

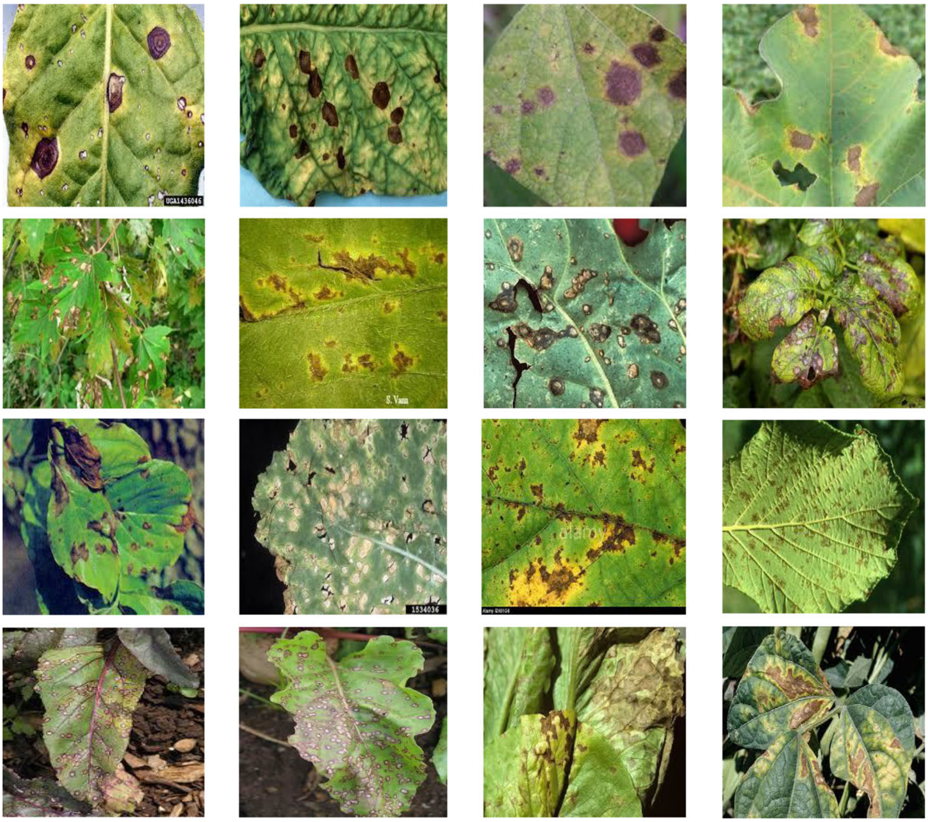


Fig. 6 Some of the experimental images

performance of the ROF filter is analyzed by qualitative and quantitative parameters. Qualitative parameters are conducted by visual observation. Meanwhile, quantitative parameters are conducted by PSNR (Peak Signal to Noise Ratio) calculation.

The performance of the ROF filter is tested on various random samples with several impulse noise densities on the corrupted image, starting from a noise density of $p = 20\%$ to $p = 90\%$. The performance comparison with other filters with respect to PSNR is summarized in Table 1. From the table, the testing results show our proposed method always has a consistent PSNR value greater than the several comparison methods. It is applicable to all variations of impulse noise density that range from $p = 10\%$ up to $p = 90\%$. If we look table carefully, fuzzy based filter [28] has higher PSNR when density is 20%. However, when the density is high ($p > 20\%$), our method has superiority in terms of PSNR and visual quality which shows that the proposed method has a higher accuracy than other state and art methods.

The quantitative analysis presented in Table 1 can be supported by the qualitative analysis presented in Fig. 7. Figure 7 shows the PSNR of the proposed method with other existing methods.

Figure 8 presents visual simulation results for various impulse noise densities on anthracnose selected leaf images. Here, the average filtering result has a very rough texture that makes it difficult to see the important information in the image. While, the median and wiener filters still have spread impulse noise on the filtered image. Meanwhile, the quality of the adaptive median filter and the proposed ROF filter are almost the same (both have smooth qualities). If we look carefully, both of them have a little bit of a rough texture, especially in the edge region. However, when the density is high (p70%), our method has superiority in terms of PSNR and visual quality.

8.3 Analysis of hue based disease spot detection

The proposed algorithm is made to run for each individual image. In our solution we have covered four different types of diseases, which are *Alternaria Alternata*, Anthracnose, Bacterial blight, and Cercospora leaf spot.

To improve spot detection, further experiments were done. In the second step, the RGB image is initially transformed into an HSI color model by using the color transform formula previously described. Then contrast stretching is employed on the component for contrast enhancement. Disease spots are detected by applying a proposed threshold technique to the H component of the filtered HSI color image. Experimental results are shown in Fig. 9. Diseases were detected more successfully in the case of the proposed model when compared to the detection in the RGB model. When the HSI model is used, detection of the spots is quite correctly recognized as actual diseases.

Table 2 shows PSNR and AMBE results before and after the hue based spot disease identification process. We have tested the proposed step with randomly selected ten images. It is clear from the table that PSNR values are low after this step due to changes in hue values in the image as well as enhancement in the V component, but still the value is large enough to allow visual quality identification. The values of AMBE are extremely changed due to the addition of threshold value in the pixels that belong to color or disease spot. So we can say that the output images have more brightness than the last ones.

The proposed method is compared with M. E. Sghair et.al [14]. The RGB image in their experiment has been changed to the HSI model, and by applying the Kapur's threshold on H components in the filtered HSI color region, disease spots were recognized. Detections of plant diseases on two different disease images by their method and our proposed method are shown in Fig. 10. As it can be seen, diseases were mostly discovered correctly by the proposed method when compared to the sghair et.al method. In their method, some not infected parts are still marked as a disease, which is visible in the second test example, but our proposed method covers almost completely infected parts.

Table 1 Comparison result of PSNR value for 20 standard images (average values)

Method	Noise density			
	20%	50%	70%	90%
Average Filter [17]	32.8647	31.4420	30.7282	30.1704
Median Filter [12]	34.4441	29.2229	26.8183	25.2008
Wiener Filter [18]	32.2868	31.1091	30.5545	30.1082
Max Filter [17]	24.9493	24.7941	24.7914	24.7913
Adaptive Median Filter [18]	32.7185	32.2079	29.7877	26.1779
Fuzzy Based Filter [28]	42.8862	20.5274	20.5927	18.8372
2D Adaptive Anisotropic Diffusion Filter [44]	34.4420	33.2150	32.8105	30.1025
Proposed Fuzzy Rank Order Filter	38.4584	35.9148	34.5647	32.5824

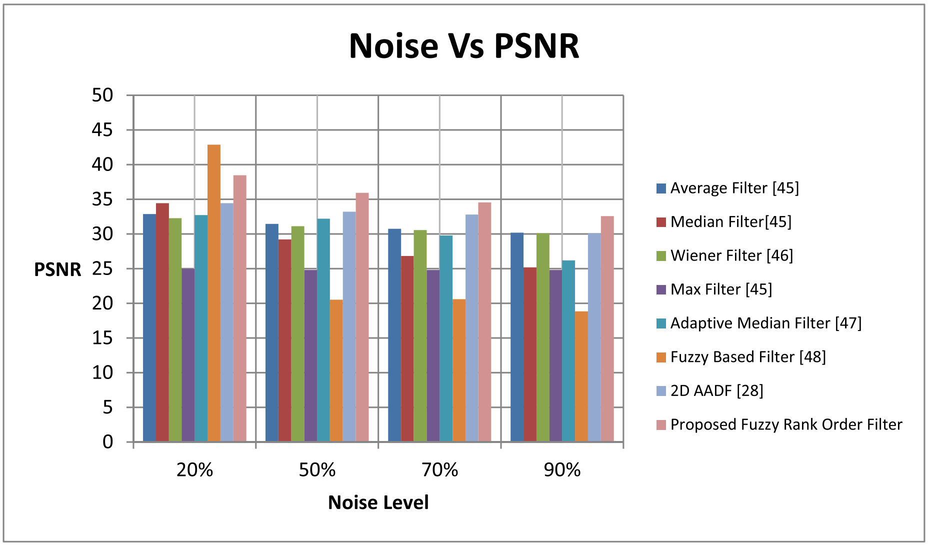


Fig. 7 Show PSNR Comparison graph of proposed method with other existing method on different noise density for 20 random selected images

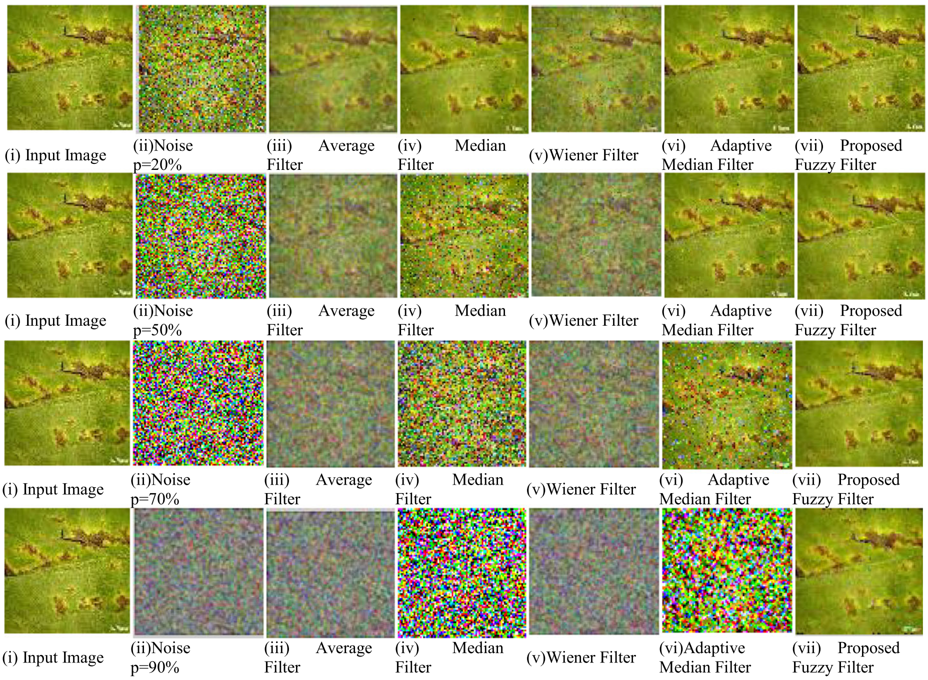


Fig. 8 Some example of the output of different filters for a leaf that is infected with early crop disease (**i**) Input test image. (**ii**) Impulse Noise Density (**iii**) Average Filter (**iv**) Median Filter (**v**) Wiener Filter (**vi**) Adaptive Median Filter (**vii**) Proposed Fuzzy filter

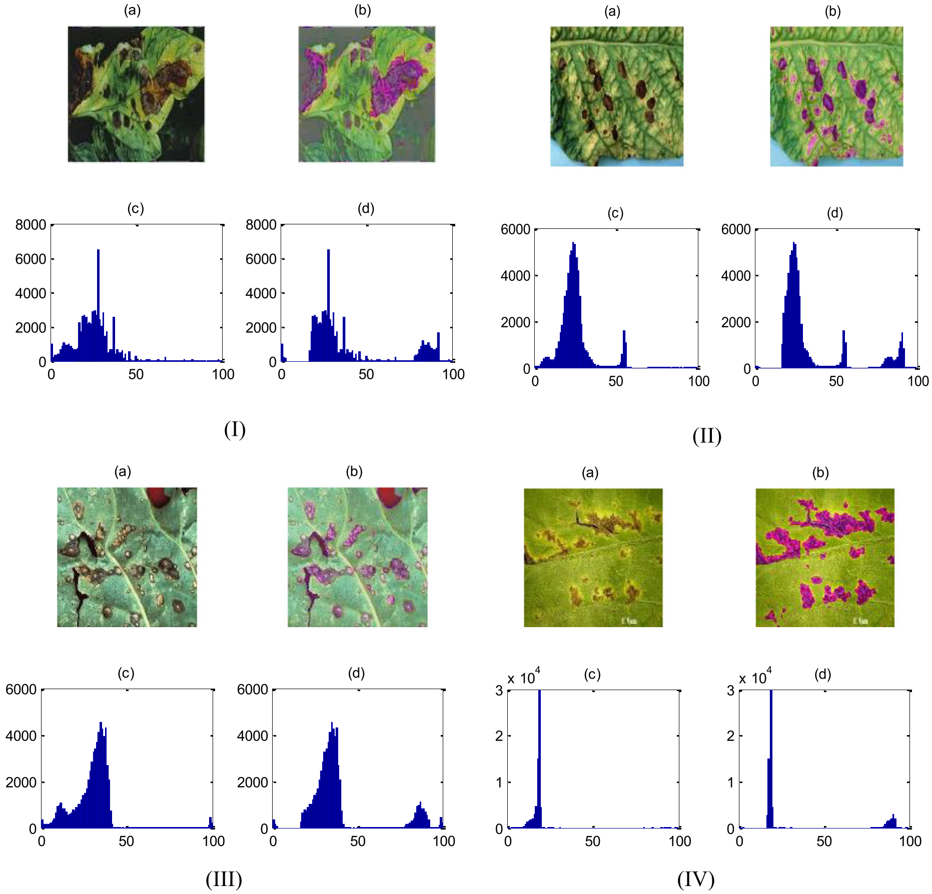


Fig. 9 Four random experiments is shown in (**I**) to (**IV**) in which (a) test image and its histogram in (c), spot detection in image by proposed method in (b) with its histogram in (d)

8.4 Efficiency of K-mean clustering

The proposed algorithm is applied to a given image dataset where disease spots are computed on HSI color model to find the best cluster using K-mean clustering. Clusters which return high hue values are considered further.

The K-mean clustering algorithm gives the disease cluster of the leaf and the results are computed against various disease leaf images.

Table 3 shows the different number of random samples taken and the area of the affected regions in percentage for each individual image. It also shows the absolute error between the ground truth image and the image achieved by the proposed method. The average absolute error is 0.0129, which shows the effectiveness of the proposed method. Figure 11 shows an example of the visual difference between Otsu's [3] and the proposed method. Figure 11a shows the mask generated by the ground truth image and Fig. 11b, c show the mask of segmented image using global thresholding and proposed k-mean clustering. From the figure, it is clear that the proposed method is more visual similar to Otsu's thresholding method.

Table 2 Comparison of evaluation matrices before and after hue based spot detection

Test images	Before		After	
	PSNR	AMBE	PSNR	AMBE
Test image 1	39.5065	0.1207	35.3236	7.2517
Test image 2	42.0758	0.0502	31.4079	23.0650
Test image 3	50.2572	0.0045	36.4153	5.9176
Test image 4	44.7824	0.0021	34.0763	4.2643
Test image 5	50.8343	0.0171	34.1808	10.1668
Test image 6	49.8529	0.0276	30.9846	25.6461
Test image 7	37.5372	0.2274	28.7982	43.4010
Test image 8	43.4793	0.0155	31.3326	21.4520
Test image 9	49.5645	0.0150	29.5323	27.6747
Test image 10	30.5448	0.2818	28.0761	40.0108

Table 4 shows the performance evaluation using the Jaccard Coefficient, Sensitivity and Positive Prediction Rate (PPR). From Table 4, we infer that the average value of the Jaccard Coefficient for Otsu's method was 0.5901. But, the proposed method based on k-mean achieved a maximum Jaccard coefficient of 0.7414. Similarly, the average value of the sensitivity and PPR for Otsu's method was 0.6821 and 0.8438. But, the proposed method achieved a maximum sensitivity and PPR of 0.8062 and 0.9420, respectively. Thus, our proposed framework achieves the best performance in terms of the Jaccard Coefficient, sensitivity and PPR.

Table 5 shows the segmentation accuracy of the proposed method using the Jaccard Coefficient against different existing methods. The experiments were done on the same set of images. The average value of the Jaccard Coefficient for Otsu's global thresholding was

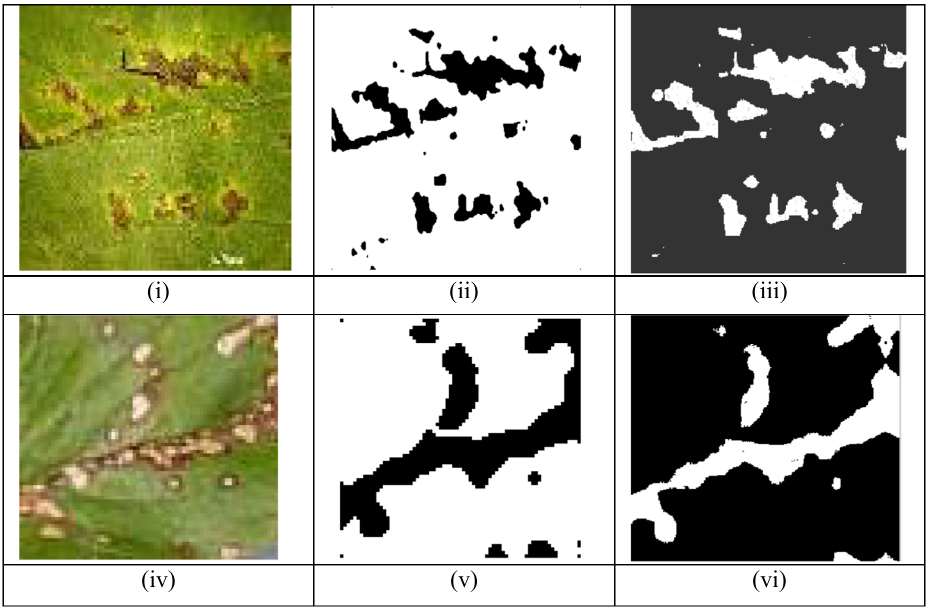


Fig. 10 (**i**) and (**iv**) original image, (**ii**) and (**v**) segmentation using Sghair. et. al., (**iii**) and (**vi**) segmentation using proposed methodology

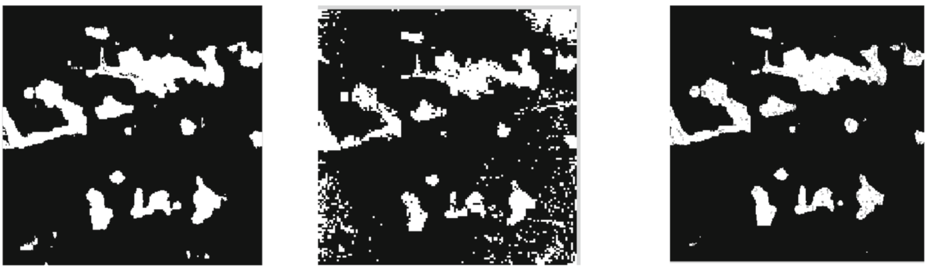
Table 3 Comparison of proposed method with ground truth images

Test images	Area of the disease region (%)		Absolute error
	Calculated by proposed method	Ground truth image (approx.)	
Test image 1	0.1766	0.1650	0.0116
Test image 2	0.0505	0.0628	0.0123
Test image 3	0.0697	0.0916	0.0219
Test image 4	0.3525	0.3428	0.0097
Test image 5	0.1227	0.1451	0.0224
Test image 6	0.0869	0.0774	0.0095
Test image 7	0.1379	0.1422	0.0043
Test image 8	0.1339	0.1584	0.0245
Test image 9	0.1974	0.2016	0.0042
Test image 10	0.0785	0.0695	0.0090
Average Absolute Error			0.0129

0.5427 and the average value of the Jaccard Coefficient for K means clustering was 0.5684.Similarily; the average value of the Jaccard Coefficient for Fast Fuzzy C Means Clustering and improved Fast Fuzzy C Means Clustering was 0.6550 and 0.7491, respectively whereas the proposed method has an average value of Jaccard Coefficient of 0.7747. From the table, it is clear that our proposed framework achieves the best segmentation accuracy in terms of the Jaccard Coefficient.

The results in Fig. 12 demonstrate the proposed method's effectiveness against various existing methods.

The results of segmentation using Hue based Spot detection and K-means clustering on different leaf diseased images are shown in Fig. 13. In each of the figures, the first column is a given input image, the second column shows the preprocessed image, the third column shows the diseased portion detection using Hue based spot detection and the last column shows the diseased portion segmentation using K-means clustering algorithm.



(a) (b) (c)

Fig. 11 Mask Comparison of Plant diseases detection using ousu's and proposed method. **a** mask of ground truth image. **b** mask of segmented image using global thresholding. **c** mask of segmented image using proposed K-man technique

Table 4 Comparison of proposed method with Otsu's method

Test images	Otsu's method			Proposed method		
	Jaccard coefficient	Sensitivity	PPR	Jaccard coefficient	Sensitivity	PPR
Test image 1	0.5175	0.6854	0.8241	0.5540	0.6956	0.8340
Test image 2	0.4787	0.5982	0.7825	0.5216	0.6654	0.7934
Test image 3	0.5813	0.6254	0.8152	0.7594	0.7602	0.9987
Test image 4	0.6557	0.7058	0.8814	0.7838	0.7876	0.9947
Test image 5	0.6893	0.7251	0.9103	0.8257	0.8451	0.9881
Test image 6	0.6325	0.7157	0.8746	0.7743	0.9367	0.8359
Test image 7	0.5416	0.6754	0.7947	0.8034	0.8451	0.9881
Test image 8	0.5650	0.6876	0.8124	0.7379	0.7742	0.9980
Test image 9	0.5504	0.6774	0.8218	0.7788	0.8465	0.9932
Test image 10	0.6890	0.7251	0.9214	0.8754	0.9051	0.9958
Average	**0.5901**	**0.6821**	**0.8438**	**0.7414**	**0.8062**	**0.9420**

Table 5 Performance evaluation of proposed method against existing methods using Jaccard Coefficient

Test images	Otsu's method	K-Means clustering	Fast Fuzzy C-mean clustering	Improved fast Fuzzy C-mean clustering [44]	Proposed method
Test image 1	0.4870	0.5789	0.6759	0.7329	0.7785
Test image 2	0.5487	0.5832	0.6380	0.7239	0.7120
Test image 3	0.5479	0.4928	0.6938	0.7819	0.7958
Test image 4	0.5827	0.5933	0.6381	0.7139	0.7621
Test image 5	0.5473	0.5938	0.6292	0.7929	0.8249
Average	**0.5427**	**0.5684**	**0.6550**	**0.7491**	**0.7747**

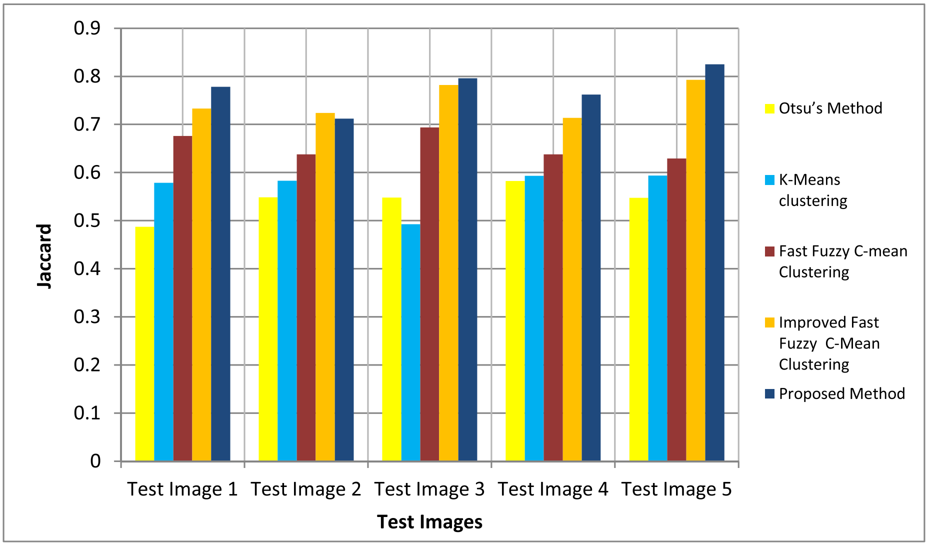


Fig. 12 Comparison of proposed method with existing methods

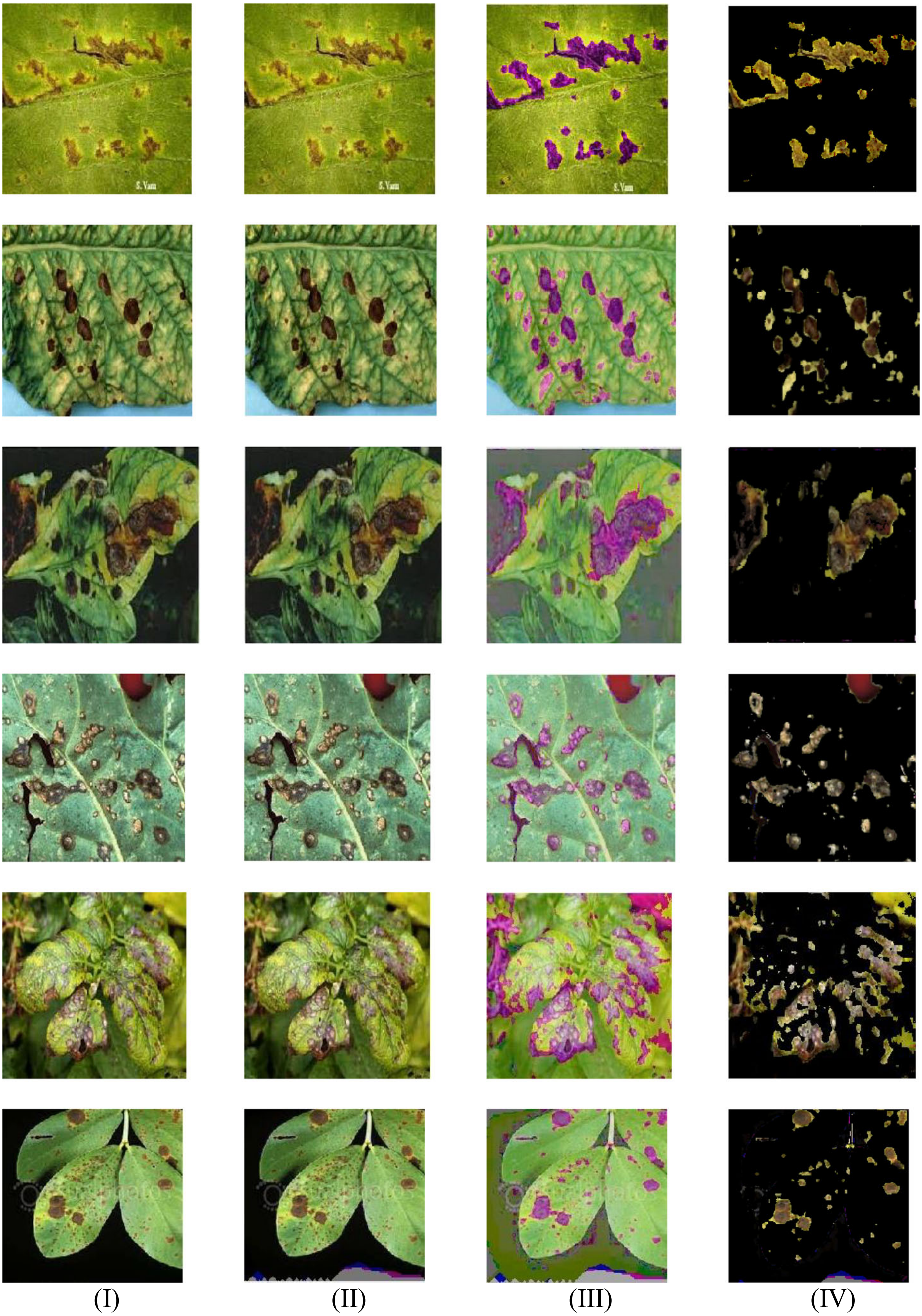


Fig. 13 System Process (**I**) Input test image (**II**) denoised image (**III**) hue based spot detection (**IV**) segmentation using k-mean clustering

9 Conclusion

The effectiveness of the disease recognition system is mostly dependent on the segmentation techniques used for extracting disease leaves from the plant images. The accuracy of the classification system is proportional to the quality of the segmentation. Certain researchers have used image segmentation techniques for segmenting plant diseases. But still, no general methods have been identified as the most effective approach for image segmentation. In our proposed system, we provide a disease spot identification step before the segmentation using a min-max hue histogram technique that helps in proper segmentation of k-mean clustering. Our system automatically segments leaf disease regions from the crop images. We also apply preprocessing to the crop images in order to remove the digitization noise. Proposed techniques are implemented on Matlab 18a and experiments are carried out on various plant images downloaded from the plant-village dataset. The proposed ROF filter demonstrates superior results to the other state-of-the-art filters. The filter is also resistant to very large noise levels, and shows meaningful details at noise levels of 95%. Apart from that, our hue-based spot detection is compared with the existing method and it can be shown that by the suggested approach, the diseases have been found mostly correctly. The segmentation accuracy of the proposed method is calculated using the Jaccard Coefficient, Sensitivity and PPR. Our system achieved a high Jaccard Coefficient value of 0.77547. We will try to establish our technique in the future by using multiple machine learning approaches for disease prediction.

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