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An Enhanced Image Segmentation Approach for Detection of Diseases in Fruit

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ABSTRACT

The progress in the realm of image segmentation has helped farmers to use nominal inputs for higher production within limited time. Preliminary identification of diseases on fruits is limited to naked eyes since the majority of these symptoms can only be identified by microscopic visuals. Image segmentation plays a vital part in distinguishing their infected parts from the disinfected ones. In this paper, clustering is used as an approach in image segmentation to cautiously discover the affected parts of the fruits by segmenting the affected areas from the non-affected parts. Four clustering techniques—IS-KM, IS-FEKM, IS-MKM, and IS-FECA—were employed for this purpose. The quality of segmentation was evaluated using few performance measures like SC, RMSE, MSE, MAE, NAE, and PSNR. The result obtained using IS-FECA is more reasonable compared to the other methods. Roughly each value of performance parameters confers better results for IS-FECA-based image segmentation method, which means proper separation of diseased parts in fruits from their un-affected ones is attainable.

KEYWORDS

Fruit Diseases, Image Processing, Image Quality Analysis, IS-FECA, IS-FEKM, IS-KM, IS-MKM

1. INTRODUCTION

Now-a-days the present agricultural science and technology is intensely advanced. The worth of fruits and vegetables depends on their quality. It is an imperative concern how to evaluate the quality of fruits in agricultural / horticultural realm (Saxena, 2014), and (Balakrishna, *et al.*, 2019). The orthodox method of fruits quality judgment is made by the experts in those domains that is quite effective, but is very time-consuming. It becomes incredibly imperative to examine the fruit diseases very precisely within limited time. Study reveals that, approximately 50% of fruits like apples, oranges, lemons, grapes, bananas etc. are destroyed every year due to plant diseases which cannot be detected professionally at the early stage. Few diseases can be identified by human experts, but it is always not likely to get them on time at remote areas. Some fruit diseases are so complicated that they require powerful microscopes for their identification. Hence, the expansion of computer visualization system

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for identifying and categorizing disease in fruits will immensely evade human intervention and will lead to impartial decision making about disease detection in fruits and this will also help in quick and absolute recovery of the disease. With the advent of image segmentation (Masood, 2016), and (Singh, *et al.,* 2020) we are effortlessly able to identify the defected portion of the fruit.

Digital images are now regarded as a key factor of conveying information in this real world. Mining the information from images and studying them minutely in order to make the extorted information valuable for several applications is a vital quality of digital image processing. Image segmentation (Gonzales, *et al.*, 2008) plays a key role in extorting the required features from the images. The data pixels with familiar visual characteristics are grouped into the same region and are separated from those having different characteristics. At present, image processing forms the mainstay in the research area in almost all the disciplines. For instance, after minutely analyzing the segmented images the cancerous tissue (Altarawneh, 2012) and (Kahaki, S. M. M, *et al.* 2017) can be effortlessly distinguished from the non-cancerous ones. From the results obtained from segmentation, it is effortlessly feasible to discover the essential area of significance.

The cluster-based approach of image segmentation (Tichkule, 2016) is extensively used owing to its ease of understanding and producing more precise results. A simple method to resolve the difficulty of generality-based image segmentation (Kaur, 2012) is used in which the performance evaluations of diverse cluster-based image segmentation methods are done. This method has used quite a few measures to evaluate the quality of clustering. Awate *et al.* (2015) initiated an image processing technique to diagnose and categorize disease within fruits. The images are mapped to their own disease groups on basis of colour, morphology, texture and formation of hole on the fruit. The system uses two image databases, one for execution of query images and the second for training the existing disease images. They have used Artificial Neural Network for pattern matching and classification of diseases. Deshpande *et al.* (2014) proposed a scheme to rank the diseases on pomegranate plant leaves automatically. An image processing technique to deal with the issue of plant pathology that is disease grading was proposed by them. The model works efficiently to identify the presence of bacterial blight disease on pomegranate plant. Image segmentation is used to obtain any disease spots on the leaves and fruits. Dubey *et al.* (2013) suggested a defect segmentation of fruits based on their colour features with the help of K-means clustering algorithm. The method was carried out in two phases. In the first phase, the image pixels are clustered based on their colour and spatial features and then the clustered blocks are combined to a defined number of regions, and in the second phase, the computational efficiency was improved by evading feature extraction for every pixel in the image. Revathi *et al.* (2012) proposed a strategy using mobile captured symptoms of cotton leaf spot images and categorize the diseases using HPCCDD Algorithm. The classifier was trained for early identification of diseases in the groves, selective fungicide application, etc. This work uses image RGB feature ranging techniques for identifying the diseases. Danti *et al.* (2012) suggested a technique for organizing areca nut into two classes basing on their colour. This method uses segmentation, masking and classification. At first the RGB image is transformed into YCBCR colour space. Areca nut colour space is modelled using three sigma control limits. Classification is done based on the red and green colour components. Results were quite encouraging with this method. Pujari *et al.* (2015) proposed a model to remotely examine the crop for the presence of any probable diseases and identify them at an earliest using GSM and remote sensing. They focused on early detection of fungal diseases based on their symptoms. Vijayalaxmi *et al.* (2018) suggested a method for detection of leaf diseases in plants using an improved sparse representation classifier (ISRC) technique. They had used four parameters like classification accuracy, error rate, precision and recall value to analyze the performance of their method. An image processing method for identifying plant lesion features is described by Petrellis, 2015. The low complexity of this technique makes it competent enough to be implemented on mobile phones. The accomplished accurateness is higher than 90% as obtained from the experimental results. The approach of defect segmentation, feature extraction, and classification (Dubey *et al.,* 2014) is used for the identification of fruit diseases. This method uses an improved sum and difference histogram (ISADH) texture feature based on the intensity values of the neighbouring pixels. Experimental results hinted that the classification accuracy is more than 97% using ISADH and nearly 99.9% in conjunction with the gradient filters. Madgi *et al.* (2015) presented a method for classification of vegetables based on RGB colour and local binary pattern (LBP) texture features. They used 18 varieties of vegetables with nine leafy and nine non-leafy vegetables. A multi-layer neural network is used for the classification. The experimental results show an overall classification accuracy of 93.3% is achieved with different vegetables. A technique for colour enrichment of low resolution digital images was proposed by Gupta *et al.* (2016) and they basically focused on image enhancement. They used the clock algorithm in this work which is based on the operation of analogue clock. This algorithm provides better results as it works on getting information from user and also from surrounding region of image under processing. Muhammad *et al.* (2018) conducted a survey on the detection and classification of different diseases that occurred on the leaves of citrus plants. They studied on various image processing, feature extraction and deep learning methods implemented on this realm. Their survey result shows that implementation of mechanized detection and classification methods for disease detection in plants is very much in its early stages.

These innovative works suggested by researchers were the initiative factors for us to put our foot in the realm of image segmentation and thus imply an effective way which can help our farmers in identifying diseases in fruits (and can be extended to plant crops) easily thereby limiting their wastage of product, time and revenue. In this research, we are inclined towards working on the cluster-based image segmentation approach. Our objective is to employ clustering as a means to achieve image segmentation for identifying the presence of any rotten or diseased portion of fruits which generally is not visible to the naked eyes. In this method the pixels present in any fruit image are examined and any changes with their intensity are tracked, and depending upon the user's requirements those pixels with similar intensity are grouped into their respective segments. In this way one can identify the real fruit parts from the affected ones. This method of disease detection in fruits is quite straightforward and yields specific results, consequently limiting their wastage, cultivation time and revenue.

In this paper, we have evaluated few diverse cluster-based methods used for image segmentation *viz.*, Image Segmentation using K-Means (IS-KM), Image Segmentation by Far Enhanced Clustering Algorithm (IS-FECA), Image Segmentation using Modified K-Means (IS-MKM) and Image Segmentation Using Far Efficient K-Means (IS-FEKM). These are enforced on different input images of commonly available fruits. Then, experimentation was conducted to test the quality of output obtained. We have tracked the performances of these segmentation approaches by using some performance quality measures like SC, NAE, MSE, RMSE, PSNR, and MAE besides, we have also noted the time each segmentation algorithm takes for meeting their convergence. The main motto of choosing a few performance parameters and enforcing them on numerous fruit images is to obtain more accurate segmented images so that the presence of any diseases on the surface of a fruit can be easily and efficiently tracked as compared to the traditional approach of detection. Thereafter, we have calculated the accuracy of successful identified diseased portions by using Jaccard similarity index. Deciding the fine quality of segmented results, determining its accuracy and making a decision about the convergence period of segmentation algorithms are some important causes that influence the effect of segmentation. Hence, we have selected these parameters as our principal criteria for decision making and limited our current research within this scope, for accurately and clearly identifying the affected portions of the fruits and the period within which the detection is made. This research could be further improved for classification of the detected diseased portions of the fruits into various severity levels.

1.1 Approach

This research is carried out in the following manner: the images of various fruits are first obtained by using a digital camera or possibly by a mobile camera. In this work, most of them were captured at a closer proximity and some of them are raw images collected. Nevertheless, they can also be captured through aerial view. Then, they are then given as input to a computer which converts them into a 3-D matrix consisting of the RGB value of each pixel present in the image. Then, cluster-based image segmentation techniques are employed to the input matrix. These algorithms produce different segments of the fruit images from which the defected portions can be traced out from the actual ones. Since, there are varieties of fruits available which differ in their colour, sizes and appearances so, various colour groups may be formulated like gray scale, 3-coloured segment, 4-coloured segments etc. in order to easily identify the possible presence of diseases in them those are not recognizable by the naked eyes. From the obtained segmented form, the diseased part of the fruit is identified by comparing it with the disease data (colour) for that fruit. This process is illustrated in Figure 1.

2. PERFORMANCE MEASURES

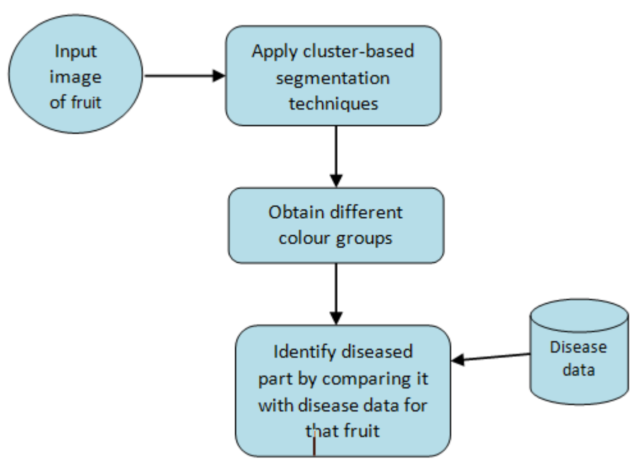
The performance measure is an important aspect in image segmentation. The quality of segmentation obtained by using different algorithms i.e. formation of well segmented groups, restraining of noise in the segmented image and obtaining the result of segmentation in the minimum time interval are some of the basic causes that influence the effect of segmentation. These factors determine how effectively the diseases are discovered in raw fruits by using system-based technologies. The techniques build for this reason should effectively consider these matters. The quality measure deals with judging these segmentation consequences. Now, we discuss in brief a variety of quality measures that is been used in this research that influence the result of segmentation.

2.1 Structural Content (SC)

SC value (Kaur *et al.,* 2012) immensely influences the class of segmented image. It approximates the similarity of configuration of two signals. It compares the entire weight of an original signal to that of a given one. SC measure is given by:

$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} in\left(i,j\right)^2}{\sum_{i=1}^{m}\sum_{j=1}^{n} seg\left(i,j\right)^2} \tag{1}$$

Figure 1. Basic flow diagram of the method used



where, *in(i, j)* is the input image, *seg(i, j)* is the target segmented image and *m* & *n* are image matrix rows and columns respectively.

A lesser value of SC implies the image is of superior quality and a larger value indicates that the segmented image obtained is of poor quality.

2.2 Root Mean Square Error (RMSE)

RMSE (Poobal *et al.,* 2011) and (Willmott *et al*. 2005) is frequently used to measure the class of segmented images. It find out the difference in the values expected by a model with those actually present in that model. It is equivalent to the quantity of deviation present in the segmented image in contrast to that present in the input image. RMSE is specified by:

$$RMSE = \sqrt{1 / M * N \sum_{i=1}^{M} \sum_{j=1}^{N} ((x(i,j) - y(i,j))^2} \quad (2)$$

A smaller value obtained for RMSE implies the image is of premium quality.

2.3 Peak Signal-to-Noise Ratio (PSNR)

PSNR (Poobal *et al.,* 2011) is a widely used measure for accessing the image quality. The vital quality of PSNR is that a negligible spatial change of an image may produce a large numerical alteration but no visual deformation. A small value of PSNR implies the image is of poor quality. PSNR is defined by the equation:

$$PSNR = 20log_{10}\left(\frac{N}{RMSE}\right) dB \quad (3)$$

where, the maximum intensity of pixel is denoted by N.

2.4 Mean Square Error (MSE)

MSE works well when the image deformation is caused by the presence of noise. It determines the difference between the filtered image and the noisy image (Rajkumar, *et. al*, 2016). If MSE value is too larger, the resulting image obtained after segmentation is imperfect. MSE is defined as:

$$MSE = 1 / M * N \sum_{i=1}^{M} \sum_{j=1}^{N} ((x(i,j) - y(i,j))^2 \quad (4)$$

where, *M* is the number of pixels present in parallel, *N* is the number of pixels present perpendicularly, *x(i, j)* is the filtered and *y(i, j)* is the noisy image respectively.

2.5 Mean Absolute Error (MAE)

MAE is usually engaged in situations where it is necessary to detect the presence of any distortion in images which may occur mainly due to poor camera quality, atmospheric haziness etc. MAE is given by the equation:

$$MAE = 1 / M * N \sum_{i=1}^{M} \sum_{j=1}^{N} |(x(i,j) - y(i,j)| \quad (5)$$

A smaller value of MAE specifies that image is of better quality.

2.6 Normalised Absolute Error (NAE)

NAE gives an idea about how far the decompressed image is from the original image. NAE with a larger value indicates poor quality of the image. NAE can be calculated by sing the equation:

$$NAE = \sum_{i=1}^{M}\sum_{j=1}^{N}(|\,(x\left(i,j\right) - y\left(i,j\right)|) \,/\, \sum_{i=1}^{M}\sum_{j=1}^{N}(|\,(x\left(i,j\right)|) \tag{6}$$

2.7 Jaccard Similarity Measure (JSM)

Jaccard measure is used to evaluate the similarity measure for binary data. It abstractly determines a percentage of number of objects two sets have in common out of the total number of objects. The Jaccard similarity measure of two sets A and B is given by:

JSM = (no. of common objects) / (total no. of objects) i.e. jaccard (A, B)
= | intersection (A, B) | / | union (A, B) | (7)

JSM obtains a numeric scalar or vector value in the range between [0, 1]. If the similarity value obtained is closer towards 1, it implies the segmentation of two images is ideally matched.

3. METHOD

For the purpose of this research, we analyze few image segmentation methods where, we segregate the colour image pixels of the fruit from one another and thus discriminate the portion of fruit which may have affected from any diseases from the rest part. In this way we identify the ailing part of a fruit. This severance is done by means of clustering. Clustering in image segmentation separates a given input image into separate colour groups so that the pixels present in one group shares common characteristics to those present in other groups. We captured different fruit images and segment it to gray scale and other colour groups using different clustering approaches. Diverse colour groups were framed because fruits vary in their colour, dimension, surface and variety. Detecting an affected part using gray scale in one fruit may be more precise than its colour groupings whereas, more accurate results may be seen with more than two colored-group formation in another fruit than its gray scale segmented image. A few varieties of cluster-based image segmentation methods used in this paper are discussed below.

3.1 Method – I

3.1.1 Image Segmentation Using K-Means (IS-KM)

The K-Means algorithm proposed by J. Mac Queen (1967) is a simplest unsupervised algorithm used for any clustering problems. In every pass, each pixel is consigned to the nearest partition based on some similarity constraint (such as Euclidean distance measure). The image is initially decided to be segmented into a defined number of groups. The initial cluster centers are selected randomly. Every image pixel possess their own RGB values. Every pixel is matched with the previously selected cluster centers and its nearest center is recorded. The pixel that is nearest to a cluster center is assigned to that cluster. After that, in a cluster the RGB mean value of all pixels is found out. This mean is regarded as the new cluster center. This is repeated until the pixels do not change their corresponding clusters. The Euclidean distance measure is used for calculating the distance between each pixel and the cluster centers which is given by:

$$D_{ij} = \left(\sum_{l=1}^{d}\left|x_{il} - x_{jl}\right|^{2}\right)^{1/2} \tag{8}$$

The principal constraint in this method is that, since the initial centers are randomly chosen it may happen sometimes that a wrongly selected initial center may result in malicious segmentation thereby detecting the wrong portion of the fruit image which may not be affected by any diseases.

3.2 Method – II

3.2.1 Image Segmentation Using Modified K-Means (IS-MKM)

IS-MKM can effectively deal with the constraints faced by IS-KM. The random selection of cluster centers can be avoided and so-called near optimal centers can be obtained to some aspect. This method can be successfully applied to image segmentation applications where the image resolution is not so high. In such cases, this can produce good segmentation results both for gray scale as well as colour image partitioning in less computation time. Hence, we have used this method in our work to detect efficiently the rot or diseased portions of different kinds of fruits. The pseudo-code of this method is presented below:

```
Pseudo-code:
      IS-MKM (fruit_img_data, k):
1.    add fruit_img_data[1] to center[ ]
      // Record the intensity difference from fruit_img_data[1]
      to the remaining  pixels present in image matrix
2.    for every pixel in fruit_img _data:
          add eucldist_dif (fruit_img _data[1], pixel) to inten_dif [ ]
3.        sort fruit_img _data in ascending order according to inten_dif [ ]
4.        split fruit_img _data into k number of clusters
5.        add mean pixel value of each cluster to center[ ]
6.    return center
7.    After K number of centers are obtained, run K-Means for
      cluster formation
8.    end
```

In the beginning, the user decides the number of segments to be framed for the input image of the fruit. The very initial pixel present in the image matrix is picked and the Euclidean distance is measured from it to all other pixels present in the image matrix. This distance calculated is stored in *inten_dif [ ]* as shown in step 2. Those distances are then sorted in ascending order of their values, as presented in step 3. Now in step 4, we split the fruit image matrix into *K* number of segments as initially decided by the user. In step 5, the centers of each segment are updated by taking their mean. After *K* numbers of centers are obtained, K-Means algorithm is invoked for the formation of cluster and is repeated until convergence is reached.

3.3 Method – III

3.3.1 Image Segmentation Using Far Efficient K-Means (IS-FEKM)

Knowing from the shortcomings of K-Means, we suggested FEKM (Mishra *et al.,* 2012) for efficiently selecting the initial cluster centers. This algorithm too deals with avoiding the random selection of initial image centroids to achieve near optimal image cluster centers. The central idea of this algorithm is outlined below:

```
Algorithm:
1. From the fruit image, find two farthest pair of pixels and
treat them as two initial cluster centers (say d1 and d2).
2. Assign all pixels nearest to d1 to d1 cluster. Remove them from
image matrix.
```

```
3. Repeat step (2) till cluster segment d1 attains a threshold
value (50% of (N/K)). Recalculate new centroid c1 by taking the
mean of d1 .
4. Recur steps (2) and (3) for d2 to obtain its centroid c2.
5. For third center choose a pixel di such that,
max(min(distance({di, c1},{di, c2 })))
6. Assign pixels to this cluster till its capacity attains the
given threshold value. Remove the pixels of this cluster from
fruit image matrix.
7. Find mean of di to obtain its centroid ci.
8. Repeat steps (5) to (7) till number of clusters is less than K.
9. After K number of centers are obtained, run K-Means for cluster
formation
```

3.4 Method – IV

3.4.1 Image Segmentation by Far Enhanced Clustering Algorithm (IS-FECA)

This algorithm proposed by Mishra *et al.,* (2018) is an effort to improve the segmentation efficiency of FEKM, MKM and K-Means used for image segmentation. The idea is to achieve better segmentation of image pixels so that it is easier to identify the portions of fruits which are infected. The technique is discussed as follows:

Phase I - Discovering K cluster centers using FEKM

Initially, *K* is given by the user. Phase I begins with finding the near optimal *K* segment centers by using Method – III. The steps from *(5)* to *(7)* discussed above are repeated till number of segments are less than *K*. Then, second phase of the algorithm is used to perform the segmentation of image.

Phase II- Performing the segmentation

```
Pseudo-code:
1.     Initially, each pixel is assigned to its nearby centroids
2. (a) Frame two matrices Clust_cent[ ][ ] and Dist_matrix[ ][ ].
   (b) for (every pix[i][j] є Fruit_img) {
          Set Clust_cent [i][j] ← num    /* num is cluster index
          where pix[i][j] was prior allotted)  */
         Set Dist_matrix[i][j] ← distance of pix[i][j]  its nearby cluster
       }   /* for loop ends */
3.  Re-compute centres for all clusters by finding their mean.
4.  repeat
    {
       for (each pix[i][j] є Fruit_img)
       {
            find distance from pix[i][j] to its center to which it now belongs
             if (distance ≤ stored distance in Dist_matrix[ ][ ])
             then
                pix[i][j] remains in its original dispense cluster
             else
                {
                    for (each center  j)  {
```

```
                    find distance d_j between  j and pix[i][j]
                  }
                    d_m ← min_{1≤j≤K} {d_j}
                    Dist_matrix [i][j] ← d_m
                    Clust_cent [i][j] ← m
              }
       }         /* for loop ends */
     Recalculate the cluster center.
   }  until convergence is reached.
5.  end
```

After obtaining the required optimal pixel centers from Phase I, the method of segmentation of image begins in Phase II. In step *(2)* of Phase II, two matrices *Clust_cent[ ][ ]* and *Dist_matrix[ ][ ]* are formed to keep an index of the cluster number and distance from the cluster centre for a given pixel respectively. In step *(4),* an assessment is made whether a pixel will remain in its original cluster segment or a new segment. This procedure is repeated until convergence is reached.

Using all these above discussed methods we are able to get the segmented images of the input fruit image. The segmentation can be obtained for preferred values of initial decided cluster numbers. The quality of segmentation obtained for each values of *K* are further analyzed.

4. RESULTS AND DISCUSSION

To demonstrate our method we have created an image dataset consisting of a variety of fruit images. Most of those images were captured by 8 MP or 13 MP mobile cameras considering the fact that farmers generally use them for this purpose and also some of these images are raw fruit images collected. We have taken some of the fruits which are already infected by diseases. Knowingly they have been chosen as input to make an assessment that the methods selected for segmentation efficiently trace out the infected parts present in the fruits. Besides some other fruit images are considered in which the defected portions on their surfaces are clearly not visible to the naked eyes. Presence of a bunch of variations in the colour, size and texture makes the fruit dataset more sagacious. Different varieties of fruits are considered in order to test the effectiveness of the segmented results obtained. Further, the images were resized from their original ones and were converted into (200X200) pixel resolution for sensible computation speed. To test the effectiveness of the algorithms, experiment was conducted considering roughly about fifteen varieties of fruits and for each fruit no less than four or five images were considered. Experiment was carried out for obtaining different output segments of the original fruit image. However, in this paper, we have shown the segmentation results for gray scale and three-coloured segments only.

If closely viewed with a magnified glass, the diseases can be witnessed at various surfaces of the fruit by the presence of tiny dot like formation or existence of negligible dark spots on them. But, these facts are established once a good quality segmentation result confirms them. Hence, we have used quite a few standard performance measures to test the quality of segmentation. The performances of the discussed cluster-based segmentation algorithms are measured using SC, RMSE, MSE, MAE, NAE and PSNR quality measures.

Table 1(a) to 6(a) represents the performance measures which judge the gray scale segmentation consequences and Table1 (b) to 6(b) verifies the same for three colored segmentation outputs. Performance measures determine the resemblance of two images by using a co-relation function. They determine the variations of results expected by a model than those which is really present. This function makes it feasible to determine the closeness between two images which the naked eyes fail to discriminate. For example, two images with SC values 0.5 and 0.6 will appear similar to naked eyes but in reality these two images do not acquire that much of similarity. In fact, lower these values obtained using these similarity measures, better is the segmentation result. However, this is opposite for PSNR which is calculated by taking the inverse of RMSE, as can be seen from equation (3). So, a larger value of PSNR means the obtained segmented result is of better quality. If we consider Table 1(a), SC values are calculated for different images of fruits using different cluster-based image segmentation techniques for obtaining gray scale segmentation results. These values are obtained by using equation (1) for all algorithms. Similar cases for other tables mentioned.

Research was done considering different values of segments formation, K. Keeping K as 2 it was observed that, almost all values of SC obtained for each input fruit images for IS-FECA are smaller as compared to those obtained from IS-KM, IS-MKM and IS-FEKM. This fact is also true when K was initialized to 3.This implies good quality segmentation for IS-FECA. Table 1(a) and (b) shows these facts. In the same way, majority values of RMSE for IS-FECA are lesser in contrast to other three segmentation methods for both K=2 and 3, as shown in Table 2(a) and (b) respectively. That implies clear visibility of any sort of diseases can be discriminated from the unaffected portion by using IS-FECA. Next, when PSNR was considered as the next quality check for image evaluation,

Table 1a. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using SC (with K=2)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	0.631	0.805	0.612	0.564
pomegranate.jpg	3.790	2.817	1.933	0.682
orange.jpg	3.041	2.394	1.768	0.741
lemon.jpg	1.711	1.967	0.986	0.614
grape.jpg	1.854	0.624	0.781	0.667
banana.jpg	0.838	1.092	0.654	0.699
guava.jpg	2.017	2.303	1.752	1.224
papaya.jpg	0.996	0.875	0.606	0.723
watermelon.jpg	0.772	1.644	1.208	0.905
cucumber.jpg	2.325	2.042	1.670	1.313

Table 1b. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using SC (with K=3)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	1.160	1.501	1.105	1.044
pomegranate.jpg	1.285	1.334	1.187	1.035
orange.jpg	2.049	1.963	1.727	1.092
lemon.jpg	0.613	1.509	1.326	0.804
grape.jpg	3.015	2.752	1.785	1.996
banana.jpg	1.863	1.642	0.954	0.661
guava.jpg	2.736	1.913	1.605	0.913
papaya.jpg	2.024	2.348	1.948	0.892
watermelon.jpg	1.235	0.851	0.909	0.679
cucumber.jpg	0.983	0.602	0.851	0.766

Table 2a. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using RMSE (with K=2)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	5.835	5.701	4.629	4.010
pomegranate.jpg	5.164	3.105	2.575	2.946
orange.jpg	4.842	3.920	3.601	3.136
lemon.jpg	3.102	3.358	2.006	1.579
grape.jpg	3.395	3.193	2.956	2.251
banana.jpg	2.411	2.691	2.144	2.352
guava.jpg	1.907	1.774	1.842	1.830
papaya.jpg	2.624	2.438	2.212	2.021
watermelon.jpg	2.707	3.586	3.952	3.605
cucumber.jpg	4.639	3.271	3.018	2.629

Table 2b. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using RMSE (with K=3)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	5.035	4.881	4.650	3.998
pomegranate.jpg	4.003	4.396	4.211	4.148
orange.jpg	5.568	3.845	3.642	3.060
lemon.jpg	3.919	3.703	3.251	3.410
grape.jpg	4.015	4.206	2.983	2.466
banana.jpg	3.092	2.819	2.405	2.011
guava.jpg	2.641	2.593	2.429	1.904
papaya.jpg	3.014	2.743	2.551	2.124
watermelon.jpg	2.924	1.633	1.219	2.153
cucumber.jpg	4.644	4.027	3.878	3.270

we obtained bigger values for IM-FECA than IM-KM, IM-MKM and IM-FEKM for more than 60% of fruit images keeping K=2 and 3 respectively. Table 3(a) and (b) reveals this fact. Considering for both gray scale and three-colored segmentation result by keeping K=2 and 3 respectively with MSE, we obtain less values of IM-FECA for around 70% fruit images. This result is relatively acceptable for MSE. The results can be seen from Table 4(a) and (b) in that order. Last but not the least, the computed values of both MAE and NAE are smaller for majority fruit images with IS-FECA for both values of K as 2 and 3. This fact is shown in Table 5(a), (b) and Table 6(a), (b) respectively. All these facts confirm that, almost all values of disparate performance quality parameters show better outcome for IS-FECA as per our anticipation. Therefore, the possibility of detecting any kind of diseases on the surfaces of fruits using IS-FECA is better than the traditional and other cluster-based methods. But, its only drawback is it's slightly larger convergence time.

All algorithms were implemented using 5th generation Intel core i3 processor with frequency 1.90 Ghz. and 4 GB RAM. The computation time of each method were recorded for achieving different segmentation results as can be witnessed from Table 7(a) and (b). It was observed that, both IS-KM and IS-MKM reach their stopping criteria slightly early as compared to IS-FEKM and IS-FECA

Table 3a. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using PSNR (with K=2)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	42.431	40.023	44.971	46.812
pomegranate.jpg	39.958	40.414	41.497	44.226
orange.jpg	39.162	36.046	37.441	38.925
lemon.jpg	40.234	42.490	45.523	44.347
grape.jpg	37.911	38.347	38.442	41.524
banana.jpg	41.143	40.032	40.986	42.327
guava.jpg	43.174	43.119	44.591	45.209
papaya.jpg	40.485	43.013	42.147	42.816
watermelon.jpg	33.644	32.370	36.244	35.982
cucumber.jpg	30.565	30.095	30.864	32.112

Table 3b. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using PSNR (with K=3)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	37.819	37.043	40.771	38.166
pomegranate.jpg	43.020	40.932	43.204	45.112
orange.jpg	37.167	37.092	39.841	40.802
lemon.jpg	46.895	44.128	45.782	45.084
grape.jpg	39.870	41.256	42.992	42.011
banana.jpg	40.321	42.287	44.007	44.880
guava.jpg	40.129	40.572	43.016	47.256
papaya.jpg	40.954	46.001	44.202	44.215
watermelon.jpg	38.628	36.017	36.145	37.022
cucumber.jpg	32.456	34.903	35.021	35.935

Table 4a. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using MSE (with K=2)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	10.308	7.621	7.305	5.851
pomegranate.jpg	9.997	9.162	8.566	8.012
orange.jpg	13.078	13.905	10.131	11.009
lemon.jpg	7.290	6.410	6.858	4.120
grape.jpg	10.353	9.751	8.233	7.066
banana.jpg	12.453	10.394	10.151	8.282
guava.jpg	3.018	2.615	3.423	3.094
papaya.jpg	7.137	7.889	6.227	7.230
watermelon.jpg	13.690	13.991	13.010	12.063
cucumber.jpg	9.563	10.124	8.546	6.023

Table 4b. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using MSE (with K=3)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	16.740	17.141	15.071	14.329
pomegranate.jpg	12.130	12.908	10.739	8.902
orange.jpg	17.546	13.374	12.570	10.495
lemon.jpg	7.571	6.185	5.099	6.042
grape.jpg	6.115	4.172	3.086	3.909
banana.jpg	5.085	7.340	6.986	6.127
guava.jpg	6.870	6.583	5.126	4.024
papaya.jpg	11.112	10.480	8.163	6.404
watermelon.jpg	11.623	12.057	10.239	8.045
cucumber.jpg	12.508	9.996	9.014	7.564

Table 5a. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using MAE (with K=2)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	134.431	131.578	126.803	120.129
pomegranate.jpg	73.567	68.238	70.509	65.896
orange.jpg	127.007	119.142	113.275	110.106
lemon.jpg	61.063	54.926	60.735	58.080
grape.jpg	68.981	68.236	66.768	62.045
banana.jpg	60.629	59.112	57.417	55.692
guava.jpg	49.868	48.458	48.753	47.687
papaya.jpg	53.405	50.211	47.384	44.466
watermelon.jpg	124.614	113.764	106.832	110.193
cucumber.jpg	111.547	105.141	107.715	102.188

Table 5b. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using MAE (with K=3)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	124.554	127.423	124.056	122.112
pomegranate.jpg	80.405	68.832	75.236	71.281
orange.jpg	121.657	105.112	91.409	86.761
lemon.jpg	84.645	93.011	62.002	67.323
grape.jpg	107.631	68.932	66.112	56.392
banana.jpg	88.075	86.810	77.536	65.008
guava.jpg	49.369	33.316	28.212	30.789
papaya.jpg	86.682	78.119	74.173	53.919
watermelon.jpg	112.640	110.034	98.721	97.909
cucumber.jpg	54.623	80.915	68.092	61.364

Table 6a. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using NAE (with K=2)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	0.974	0.932	0.789	0.813
pomegranate.jpg	1.045	1.709	0.443	0.337
orange.jpg	1.732	0.890	0.924	0.770
lemon.jpg	0.801	0.699	0.682	0.544
grape.jpg	0.532	0.603	0.560	0.491
banana.jpg	1.634	1.429	0.984	0.701
guava.jpg	0.518	0.587	0.429	0.312
papaya.jpg	1.542	0.974	0.730	0.681
watermelon.jpg	0.891	0.778	0.567	0.342
cucumber.jpg	0.812	0.456	0.731	0.602

Table 6b. Analysis of IS-KM, IS-MKM, IS-FEKM and IS-FECA using NAE (with K=3)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	0.989	0.931	0.871	0.671
pomegranate.jpg	0.756	0.599	0.406	0.375
orange.jpg	0.810	0.589	0.498	0.422
lemon.jpg	0.489	0.297	0.505	0.337
grape.jpg	0.883	0.764	0.804	0.799
banana.jpg	0.590	0.554	0.303	0.493
guava.jpg	0.493	0.442	0.397	0.204
papaya.jpg	1.124	0.832	0.608	0.385
watermelon.jpg	0.873	0.986	0.995	0.899
cucumber.jpg	0.778	0.904	0.891	0.808

Table 7a. Running time (in sec.) of IS-KM, IS-MKM, IS-FEKM and IS-FECA (with K=2)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	3.812	4.124	4.311	5.601
pomegranate.jpg	3.005	3.247	4.860	5.826
orange.jpg	4.055	3.671	4.445	5.617
lemon.jpg	2.661	2.324	3.099	3.554
grape.jpg	2.256	2.948	3.938	4.015
banana.jpg	3.915	3.104	2.449	4.634
guava.jpg	3.008	3.631	4.089	4.412
papaya.jpg	2.820	3.664	3.972	4.236
watermelon.jpg	3.426	3.990	4.551	5.023
cucumber.jpg	3.011	2.871	3.556	3.982

Table 7b. Running time (in sec.) of IS-KM, IS-MKM, IS-FEKM and IS-FECA (with K=3)

Fruit Images	IS-KM	IS-MKM	IS-FEKM	IS-FECA
apple.jpg	4.031	4.689	5.268	5.917
pomegranate.jpg	4.042	4.316	4.846	5.772
orange.jpg	4.523	4.873	4.904	5.223
lemon.jpg	3.990	3.112	4.002	4.668
grape.jpg	3.428	2.234	3.716	4.347
banana.jpg	4.453	4.720	5.001	5.342
guava.jpg	3.066	3.889	4.356	5.562
papaya.jpg	4.125	4.868	5.442	5.796
watermelon.jpg	4.541	4.924	5.344	5.558
cucumber.jpg	4.257	3.919	4.428	4.862

for almost all images of fruits which are the latter two methods drawback. IS-KM executes faster because the segment centers are selected randomly however in most cases may produce malicious results if wrong and haphazard centers are selected. However, IS-MKM, IS-FEKM and IS-FECA takes slightly more time for meeting their convergence because they efficiently computes their near optimal segment centers then proceed for grouping of pixels to the respective segments.

Subsequently, we extend our experimentation for finding out the accuracy of the obtained segmented fruit images. The Jaccard similarity measure which is a simplest approach for finding the solution is used for this purpose. Initially, the defected portions of the fruits were marked manually which gave the ground truth for Jaccard measure. The pixels present in the defected marked portions were grouped into one cluster and the remaining pixels into another cluster considering K=2. The segmented gray scale images obtained by applying different algorithms formed the predicted parameter for JSM. Once these two sets were obtained (ground truth and predicted values), the percentage of similarities among them were calculated by comparing each pixels of ground truth set with those of predicted set. Similar procedure was followed for K=3, 4 etc. Table 8 (a) provides the results obtained for evaluating the accuracy of similarity using JSM for gray scale segmentation and Table 8 (b) evaluates those for three-coloured segmentation. As discussed earlier, value of JSM closer towards 1 is good and towards 0 is bad, we find that baring a few fruit images a majority of values for IS-FECA are nearer to 1 as compared to other segmentation methods. This confers higher percentage of clustering accuracy for IS-FECA. JSM obtained for IS-KM is not satisfactory for most images. This may be one of its pitfalls.

When K = 2, we can observe the gray scale image of the original one where one cluster shows the non-infected part and the other one the defect part. And with K as 3, the defected part is clearly separated from the original surface and the background. The defected portions are marked both in the original as well as segmented images. A few segmented results of fruit images using IS-FECA are shown in Figure 2(a), (b) and (c). Figure 2 (a) shows the original fruit image, 2 (b) shows the segmentation result when K=3 and 2 (c) shows the segmentation result when K=2.

As mentioned earlier, most fruit images shown in Figure 2 (a) have a clear presence of defectiveness on their surfaces. They are knowingly considered as input in order to assess the efficacy of the segmentation methods in tracing them out. Consequently, experimentation was also conducted on the images of fruits which have lesser visibility of the defective portions to the naked eyes. Figure 3 (a) shows few of them. Figure 3 (b) illustrates its three-colored and (c) its gray scale segmentation using IS-FECA respectively. It is quite evident from the

Table 8a. Similarity calculation using Jaccard index for IS-KM, IS-MKM, IS-FEKM and IS-FECA (with K=2)

Fruit Images	IS-KM	IS-FEKM	IS-MKM	IS-FECA
apple1	0.619	0.699	0.656	0.718
pomegranate	0.685	0.731	0.772	0.752
orange	0.645	0.654	0.623	0.613
mango1	0.704	0.788	0.801	0.799
apple2	0.682	0.894	0.858	0.905
banana	0.748	0.899	0.832	0.921
mango2	0.807	0.885	0.79	0.867
lemon	0.596	0.668	0.601	0.695
watermelon	0.732	0.855	0.791	0.886
grape	0.459	0.549	0.493	0.582
papaya	0.953	0.917	0.869	0.907
guava	0.744	0.802	0.813	0.844

Table 8b. Similarity calculation using Jaccard index for IS-KM, IS-MKM, IS-FEKM and IS-FECA (with K=3)

Fruit Images	IS-KM	IS-FEKM	IS-MKM	IS-FECA
apple1	0.512	0.593	0.559	0.601
pomegranate	0.613	0.682	0.753	0.711
orange	0.497	0.551	0.576	0.595
mango1	0.832	0.896	0.805	0.876
apple2	0.657	0.887	0.852	0.921
banana	0.702	0.922	0.871	0.962
mango2	0.689	0.784	0.722	0.823
lemon	0.508	0.676	0.685	0.716
watermelon	0.727	0.867	0.916	0.879
grape	0.642	0.801	0.714	0.755
papaya	0.783	0.861	0.844	0.918
Guava	0.809	0.815	0.899	0.864

segmentation results that the defected portions on the fruit surface shown in Figure 3 (a) which was not remarkably visible are now clearly distinguishable from the real ones emphasizing the significance of the segmentation method.

The segmentation accuracy was determined using JSM for citrus, guava and peach images for K=2 and 3. The results achieved are shown in Table 9 (a) and (b) respectively. The segmentation accuracy of IS-FECA for the three images is relatively higher. This was a challenging aspect of the work to discover any damaged or diseased portions from the fruit surface which is not clearly apparent to the naked eyes. However, IS-FECA came up with a better solution to this dilemma. Besides, IS-FEKM and IS-MKM are not too far behind considering both segmentation quality and accuracy.

Figure 2. (a) Original fruit image (b) Segmentation result when K=3 (c) Segmentation result when K=2 using IS-FECA

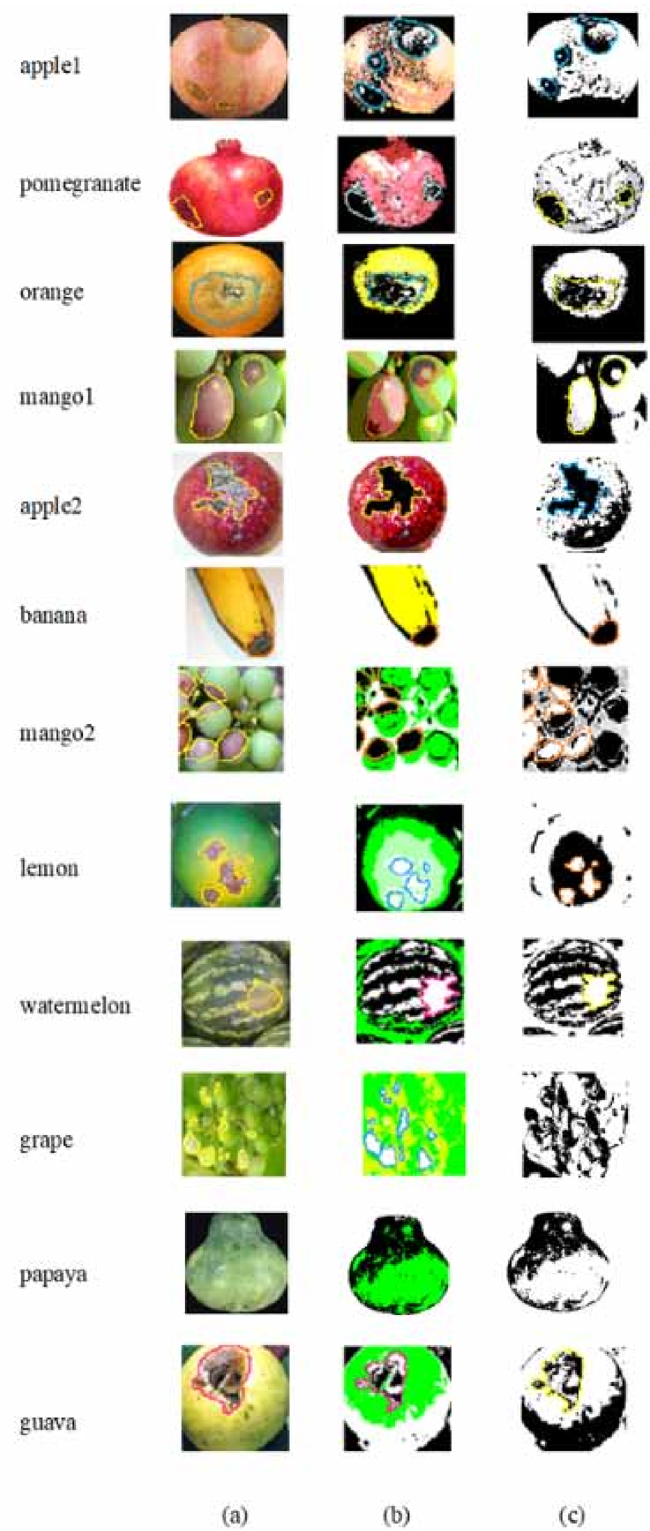


Figure 3. (a) Original fruit image (b) Segmentation result when K=3 (c) Segmentation result when K=2 using IS-FECA

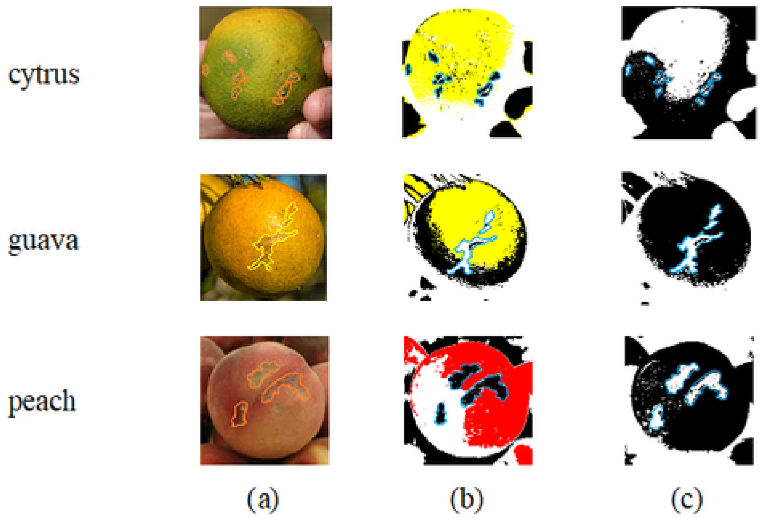


Table 9a. JSM for IS-KM, IS-MKM, IS-FEKM and IS-FECA on images of fruits (with K=2)

Fruit Images	IS-KM	IS-FEKM	IS-MKM	IS-FECA
citrus	0.728	0.819	0.836	0.817
guava	0.705	0.839	0.844	0.923
peach	0.764	0.879	0.871	0.909

Table 9b. JSM for IS-KM, IS-MKM, IS-FEKM and IS-FECA on images of fruits (with K=3)

Fruit Images	IS-KM	IS-FEKM	IS-MKM	IS-FECA
citrus	0.584	0.726	0.698	0.792
guava	0.751	0.812	0.843	0.887
peach	0.806	0.739	0.794	0.863

5. CONCLUSION

Considering today's requirements of effortlessly, timely, accurately and cost effectively detecting the diseases in various fruits, we came up with image segmentation approach for the purpose. At the outset the images were taken by mobile cameras and were reduced to 200x200 pixel resolutions for speeding up the computation. Different cluster-based image segmentation techniques were employed and analyzed to efficiently trace the disease defected regions in different varieties of fruits.

In this paper, we have observed four varieties of clustering-based image segmentation algorithms applied on numerous defected fruit images. The effectiveness of the segmented results obtained was evaluated by using few well known performance quality measures like SC, RMSE, PSNR, MSE, MAE and NAE. When the results of segmentation were analyzed comparing IS-KM, IS-MKM, IS-FEKM and IS-FECA based image segmentation techniques it was found that, the quality of segmentation obtained by IS-FECA is better than the others used for this purpose. Almost all values of quality measures used showed satisfactory outcome for IS-FECA. Subsequently, the accuracy of obtained segmentation measured by Jaccard similarity index suggested that IS-FECA achieved higher scale of precision for majority fruit images compared to other techniques used. Even the fruit images with lesser visibility of defected portions on their surfaces can now clearly traced out. These facts imply that IS-FECA image segmentation method for detecting diseases in fruits is robust for the reason that it can precisely segment the defected parts present in several fruit region from the un-defected parts. However, its only limitation is its slight larger computation time. On the other hand, IS-KM executes faster since the segment centers are chosen randomly and not much time is spent in that part of the algorithm, but in most cases the centers selected may not be optimal and results in ineffective segmentation outcome.

In this work, the main focus revolves around efficient detection of any kind of disease on the surface of varieties of fruits, which is achieved to a large extent. Subsequently, we have it in mind to improve the methods to achieve the result much faster and also to detect the diseases at different severity levels. We have further thought of expanding this work and utilize it in other domains of agriculture and society. This is to improve our farming and help our farmers to achieve quality crops in a smart way. In order to get more effective results, we will also look at the other prospect of removal of noisy pixels from the clustered images.

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CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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