IMAGE SEGMENTATION USING EFCM FOR BANANA STEM DISEASE IDENTIFICATION

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ABSTRACT -Image Segmentation is the interaction by which an advanced image is divided into different subgroups (of pixels) called Image Objects, which can diminish the intricacy of the image, and accordingly examining the image gets less difficult. This paper portrays another automatic image segmentation methodology for segmenting plants. This paper presents straightforward methodology towards plant growth analysis Enhanced Fuzzy C- Means clustering algorithm is utilized to segment the region of interest, morphological shape analysis is applied to the Image Segmentation for Banana Plant. The strategy is highly promising nearby accuracy agriculture when we have large area to monitor.
Keywords: [Image Segmentation; Enhanced Fuzzy C- Means clustering algorithm; Plant Monitoring System.]

1. INTRODUCTION

Image segmentation is one of the critical and fundamental stages of image handling. Image Segmentation is quite possibly the most fundamental interaction in PC vision applied in plant growth monitoring. The exactness of recognizable proof of the plant growth relies upon the proficiency of the segregation of plant to the foundation climate. Various computer vision algorithms for plant growth monitoring were accentuated on the works about plant parts segmentation, infection discovery, highlight extraction, which remain challenging for plant imaging area. Image segmentation segments an information image into non-overlapping, homogeneous and associated regions to such an extent that "association of any two spatially nearby regions isn't homogenous". A district is homogeneous if all pixels in that locale "fulfil homogeneity conditions characterized per at least one-pixel attributes, like intensity, shading, texture, and so on and if an associated way between any two pixels exists inside the region"

After the image is upgraded utilizing brightness protecting dynamic fuzzy histogram equalization, it is segmented to get the ideal ROI, by partitioning the image into different segments, which is additionally used for features extraction. Image segmentation is a plan where the areas and features relating to the same features are recognized and together assembled. In this work, the district-based segmentation is utilized that segments the ROI dependent on textures or examples that are outstanding to each and every kind of region. Diverse segmentation methods have been utilized in the past work for ROI extraction, by taking leaves having dark foundation however in this examination, ailing leaves are taken with live backgrounds. A couple of computer vision algorithms for plant growth monitoring were stressed on the works about plant parts segmentation, infection location, feature extraction, which stay pursuing for plant imaging area.

Figure 1. Image Segmentation for Banana plant

Image Segmentation is to partition a digital image into multiple segments (sets of pixels, otherwise called super pixels) for finding objects and boundaries (lines, curves, etc.) in images and its objective is to rearrange and additionally change the representation of an image into significant representation, which is simpler to analyse. The technique utilized Fuzzy C-means clustering and GA to automatically portion a picture into its constituent parts. "Segmentation doles out a label to each pixel in an image to such an extent that pixels with a similar label share certain visual characteristics", such as colour, intensity, or texture.

Plant growth can be characterized as growth status, growth tendency and the level of plant advancement, which incorporates singular characteristics (plant height, leaf area) and gathering characteristics (plant spacing, row spacing, tiller number) of plants. Plant growth conditions have been generally seen by farmers instead of automatic monitoring and the executives of plant production. Practice ignores plants' particular necessities that must be unequivocally cantered on in greenhouse production. Today, an ever-increasing number of new innovations are utilized for monitoring plant growth; it makes farming production more exact and intelligent. Right now, there are basically two various types of sensors monitoring plant growth.

Image segmentation is a significant component in many image understanding algorithms and reasonable vision frameworks. In any case, the assessment of segmentation algorithms hitherto has been largely abstract, leaving a framework planner to pass judgment on the effectiveness of a technique dependent on intuition and results as a couple of model segmented images.

In this paperEFCM clustering algorithm is utilized to segment the region of interest, morphological shape analysis is applied to investigate the Plant Growth Monitoring for Image.

2. EXISTING METHOD

2.1 Fast and Robust Fuzzy C-Means clustering algorithm

Tao Lei et al. proposed Fast and Robust Fuzzy C-Means clustering algorithm for image segmentation to improve the segmentation quality and reduce the effect of image noise. FRFCM algorithm utilizes MR to supplant mean or median filters because of its robustness to noise. It is easier and essentially faster for computing the distance between pixels inside local spatial neighbours and clustering focuses.

2.2 Edge detection and blend of a round fitting algorithm

H N Patel, et al has worked on effective area of fruit on the tree is one of the significant prerequisites for the fruit collecting system and carries out the fruit detection utilizing shape analysis. The algorithm was made out of edge detection, region marking and circle fitting based detection. The Edge detection and mix of a round fitting algorithm is applied for the programmed segmentation of natural product in the image. The results showed that the work can precisely segment the blocked fruits with the productivity of 98% and the normal yield estimation mistake was found as 31.4 %.It was designed to take care of the issues of shifting enlightenment and fruit impediment through segmentation and shape-based detection.

2.3 Multilevel threshold of Grey-level & Gradient Magnitude (GLGM)

In 2015authors have used Multilevel threshold of Gray-level &Gradient Magnitude (GLGM) entropy dependent on GA for Image Segmentation. In any case, this technique is as yet not ready to recognize image edges and noise well overall. The phase presumes that GA can give amazing hunt abilities regardless of whether the inquiry space is not contiguous. The greatest benefit of GA is its adaptive search abilities and shirking of falling into nearby optima.

2.4 Genetic algorithm for Image Segmentation

Chun and Yang et.al, proposed a segmentation technique which depended on genetic algorithm, in which, fuzzy fitness function is utilized. Gong and Yang addressed by means of quad-trees, the images that are original and segmented. They have given an enhancement framework that depends on two pass genetic algorithm. Energy function is limited, in the primary pass, for which genetic algorithms is used. The segmentation strategy is tuned finely, in the subsequent pass.

2.5 Fuzzy Possibility c-means algorithm (FPCM)

M. Gomathi et.al, have proposed Fuzzy Possibility c-means algorithm (FPCM) by altering FCM for disposing of the restrictions of FCM. "The FPCM alters the distance estimation of the standard FCM algorithm to allow the labeling of a pixel to be impacted by different pixels and to limit the noise impact during segmentation. Rather than having one term in the objective function, a subsequent term is incorporated, compelling the participation to be pretty much as high as conceivable without a most extreme breaking point limitation of one". The authors have used the strategy for medical image segmentation.

3. PROPOSED SYSTEM

Image segmentation is one of the huge and basic stages of image processing.It is likewise an important advance which segments an image into homogeneous, non-overlapping and associated regions with the end goal that association of two neighboring regions yields a heterogeneous segment. Segments distinguished by this cycle are later on used in applications, for example, object recognition, include extraction, object detection and classification etc. In numerous fields like medical imaging, mineral imaging, bioinformatics, material science and agriculture etc. Numerous techniques are accessible for image segmentation has isolated the segmentation algorithms into three classes i.e., cluster based, region based and edge based.

SEGMENTATION USING ENHANCED FUZZY C-MEANS (EFCM)

Fuzzy C-means (FCM) is a technique for clustering which grants one piece of information to have a place at any rate of two clusters. Fuzzy logic is a multi-esteemed logic got from fuzzy set hypothesis. FCM is pervasively used for fine segmentations like brain tissue model. Also, FCM can give ideal outcomes over other clustering algorithms like KM, EM, and KNN. In this stage, we introduced the medical image segmentation techniques dependent on various kinds of FCM algorithms. The proposed segmentation FRFCM technique was attempted to distinguish the structure of plant images. The core idea is to combine the thoughts of Image segmentation techniques and Plant Growth Monitoring for Image Segmentation to get the required end product. The elements to examine are warmth and moistness that cause delicate changes in the strength of the plant. In the proposed system, work images are intensify using brightness conserving dynamic fuzzy histogram equalization algorithm. For the portraiture and processing of advanced images fuzzy statistics are used. It contains following working stages showed up in Figure 2.

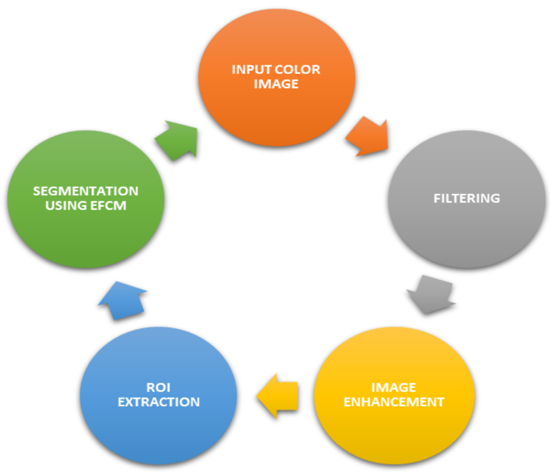


Figure 2. Overall Proposed Model

3.1 Filtering

Removal of Noise Using Gaussian Estimator - They should be considered and eliminated, else they will influence the edge detection process. In this way, to eliminate any noise, we should smoothen the image. Smoothening is finished with the assistance of Gaussian Blur. To carry out such, image convolution technique is applied with a Gaussian Kernel. Prior to proceeding towards region of interest (ROI)) segmentation, the image must be separated and upgraded to acquire improved outcomes. Images caught from camera mobile phones, contain different variables which may influence the consequence of the segmentation. Image preprocessing technique is subsequently performed by following certain stages which are image resizing, noise disposal and image upgrade.

For segmentation of any image, it is imperative to identify the foreground and background of the image. It very well may be effectively done once the active and inactive pixels are recognized. Gaussian Estimator is one of the devices through which we can uniformly distribute among these pixels. Recurrence of each edge can be reduced once the classification is finished. As indicated by Rahman Farnoosh et.al, image can be visualized as a matrix in which every component addresses a pixel. The estimation of the pixel is a number that shows intensity or color of the image. For a probability model assurance, the combination of Gaussian circulation is as given in equation1.

$$\mathbf{f(x)} = \frac{\mathbf{1}}{\mathbf{n_i}}\sum_{\mathbf{i=1}}^{\mathbf{k}} \mathbf{p_i N}\ (\mathbf{x} \mid \boldsymbol{\mu}_\mathbf{i}, \boldsymbol{\sigma}_\mathbf{i}{}^{\mathbf{2}}(1)$$

Where x is a random variable and k is the number of components or regions and $p_i > 1$ are weights such that, $\sum_{\mathbf{i=1}}^{\mathbf{k}} \mathbf{p_i} = \mathbf{1}$and

$$\mathbf{N}(\boldsymbol{\mu}_\mathbf{i}, \boldsymbol{\sigma}_\mathbf{i}{}^{\mathbf{2}}) = \frac{\mathbf{1}}{\boldsymbol{\sigma}_{\mathbf{i}\sqrt{\mathbf{2\pi}}}} \mathbf{exp}(-(\mathbf{x} - \boldsymbol{\mu}_\mathbf{i})^{\mathbf{2}}/\mathbf{2}\boldsymbol{\sigma}_\mathbf{i}{}^{\mathbf{2}} \quad (2)$$

Where μ_i and $\sigma_i{}^2$ are mean and standard deviation respectively, of class i.

3.2 Image Enhancement

Later the image has been filtered, image upgrade is done which improves the impression of data or interpretability in images for natural eye and furthermore offers additionally improved image processing methods. In the proposed work, binary preserved dynamic fuzzy histogram equalization (BPDFHE) improvement strategy is proposed for contrast upgrade of the filtered banana image. At that point assessment of index is done to contrast the proposed method and as of now existing upgrade procedures. The accompanying section gives a point-by-point perspective on the proposed procedure alongside a concise perspective on the all-around existing methods.

Histogram Equalization (HE)

Histogram, Equalization improves the contrast of the image by passing on the power estimation of pixels in input image, so the yield image includes steady force strength and at the yield a consistent histogram is acquired. This strategy routinely builds the widespread contrast of images, for the most part when the functional information in the image is described by close contrast esteems. By this procedure, the forces can be equitably appropriated on the histogram. This encourages for lower neighborhood contrast territories to acquire a more prominent contrast. Histogram equalization finishes this by viably dispersing out the most rehashed force esteems. The apple leaf images improved by HE.

Fuzzy histogram z(v) is the pace of the occurrence of gray levels around grayscale value v. In the proposed technique, at first fuzzy histogram is processed as given in Equation (3), for an image S with pixel gray value S(i, j) at location (i, j).

$$\mathbf{z(v)} \leftarrow \mathbf{h(v)} + \sum_{\mathbf{i}} \sum_{\mathbf{k}} \boldsymbol{\xi}_{\mathbf{s(i,j),v}} \ (3)$$

Where V ϵ {0, 1 …L-1} and $\boldsymbol{\xi}_{\mathbf{s(i,j),v}}$is the fuzzy membership function defining membership of S (i, j) to the set of pixels with grayscale value v given in Equation 4.

$$\boldsymbol{\xi}_{\mathbf{s(i,j),v}} = \mathbf{max}\ (\mathbf{0}, \mathbf{1} - \frac{|\mathbf{s(i,j)-v}|}{\boldsymbol{\alpha}})(4)$$

After that, to attain numerous sub histograms, histogram segregation dependent on the local maxima is finished. A segment is intended for every valley portion that is located among two successive maxima local. For this at first local maximum is detected and afterward partitions are made which are explained below.
The fuzzy histogram's first and second derivative is used for locating the local maxima. For approximating a discrete derivative, the focal distinction administrator is used expressed in Equation (5).

$$\mathbf{z^o(v)} = \frac{\mathbf{d^2 z(v)}}{\mathbf{dv^2}} \mathbf{\Delta z(v+1) - 2(v) + z(v-1)} (5)$$

Where Z^{oo} (v) represents the fuzzy histograms second order derivative.

3.3 ROI Extraction using K-means Clustering

K-means clustering partitions various understandings in k clusters where each and every perception connects to cluster with the close by mean, helping as an example of the cluster. The objective of the algorithm is to localize group in the data with all out of the groups addressed by the variable k. It uses squared Euclidean distances to compute the nearest data points. The algorithm iteratively attempts to administer every data point to a single k group developed on the features that are delivered. Data points are clustered grounded on the element similarity. Here K means clustering measure is applied on BPDFHE upgraded apple leaf images to segment the ROI part for additional processing of highlight extraction and classification.

3.3.1 Excess Green Part Removal

For ROI extraction, the background with the green territory is removed for the leaf picture overwhelming part of green pixels. For this 3 components of an improved RGB picture (I) are extracted for example the red green and blue part with assistance of the accompanying algorithm is shown below.

```
Ired = I (:, :,1);

Igreen = I (:, :, 2);

Iblue = I (:,:, 3);
```

For green background removal, the implemented algorithm is shown below.

```
Algorithm for green background removal

Loop1 j=1: rows

Loop2 k=1: columns

If Ired (j, k)<Igreen (j, k)and Iblue

(j, k)<Igreen (j,k)

Ired (j,k) =0

Igreen (j,k) =0

Iblue (j,k) =0

End if

End Loop1

End Loop2
```

3.3.2 Black/White Background Removal

For white or black background removal, the algorithm is shown in below:

Algorithm for white or black background removal

Loop1 for j=1 : rows

Loop2 for k=1 : Columns

diff1 = Ired (j,k) – Igreen (j,k);

diff2 = Ired(j,k) – Iblue (j,k);

If diff1<threshold &&

diff2,threshold

Ired (j,k) =0

Igreen (j,k) =0

Iblue (j,k) =0

End if

End Loop1

End Loop2

Here the lines and columns are the sizes of the first dark level image. The edge esteem utilized here is 10 which is picked by the hit and preliminary method. Utilizing these two algorithms, the green, white and dark background of the image is removed so that consequences of K means clustering can be greater.

After the removal of the background, the k means clustering technique is carried out on the background eliminated images further to order them into various clusters. The proposed algorithm gives better results that can't compute utilizing the k-means algorithm alone. For this, background eliminated RGB picture is right off the bat changed over to L*a*b space picture, where L is a brilliant layer, a will be a chromatic layer and b is another chromatic layer which will assist with isolating various parts of a picture. Presently k means clustering is applied to cluster the various parts of the picture into two unique clusters, one being the diseased part and the other the non-diseased part.

3.4 Enhanced Fuzzy C-Means clustering algorithm

Image segmentation is the process of partitioning an image into various portions to discover the object of interest. In this work segmentation is completed with Enhanced Fuzzy C-Means clustering algorithm (EFCM) system and it uses the Morphological Reconstruction (MR). To improve the image quality without using any channel is done by using EFCM technique.

Fuzzy C-means (FCM) is a methodology for clustering which grants one piece of data to have a place with in any event two clusters. Fuzzy logic is a multi-regarded logic got from fuzzy set speculation. FCM is noticeably used for delicate divisions like brain tissue model. And additionally, FCM can give preferable outcomes over other clustering algorithms like KM, EM, and KNN. In this paper we introduced the Banana plant image segmentation techniques dependent on different sorts of FCM algorithms.
Conventional clustering algorithm finds "hard partition" of a given dataset dependent on certain criteria that assess the integrity of partition. By "hard partition" we imply that each datum has a place with exactly one cluster of the partition. While the soft clustering algorithm finds "soft partition" of a given dataset. In "soft partition" datum can incompletely have a place with numerous clusters. A soft partition isn't necessarily a fuzzy partition, since the information space can be bigger than the dataset. Notwithstanding, most soft clustering algorithms do create a soft partition that likewise frames fuzzy partition. A sort of soft clustering of special interest is one that guarantees enrollment level of point x on the whole clusters amounting to one, i.e.,

$$\sum_j \mu_{c_j}(x_i) = 1 \forall x_i \in X \quad (1)$$

$$J_w(P,V) = \sum_{i=1}^{k} \sum_{\in X} \mu_{C_i}(x_k))^m \parallel x_k - x_k \parallel^2 \quad (2)$$

$$\mu_{c_j}(x) = \frac{1}{\sum_{J=1}^{k}\left(\frac{\|x-v_i\|^2}{\|x-v_j\|^2}\right)^{\frac{1}{m-1}}} \quad (3)$$

$$1 \leq i \geq k, x \in X v_i = \frac{\sum_{x\in X} \mu_{C_i}(x)^m x}{\sum_{x\in X}^{n} \mu_{C_i}(x)^m} \quad (4)$$

Not many significant focuses with respect to the FCM algorithm: It ensures meet form> 1. It discovers local minimum of the target work Jm. The consequence of applying FCM to a given dataset depends not just upon the decision of boundary m and c, yet additionally on the decision of starting model.

Proposed Algorithm

Step 1: Set the cluster prototype value c, fuzzification boundary m, the size of filtering window w and the negligible error threshold ὴ.

Step 2: Figure the new picture € by utilizing following condition and register the histogram of €.

$$\in = R^c(f) \quad (5)$$

Where R^c denotes morphological closing reconstruction and f represents an original image.

Step 3: Introduce arbitrarily the participation partition matrix U (0).

Step 4: Set the loop counter t = 0.

Step 5: Revamp the clustering centers using following equation.

$$u_{ki} = \frac{\|\in_l - v_k\|^{-2/(m-1)}}{\sum_{j=1}^{c}\|\in_l - v_j\|^{-2/(m-1)}} \quad (6)$$

$$u_{ki} = \frac{\sum_{i=1}^{q} \gamma\iota\mu_{kl}^{m} \in_l}{\sum_{i=1}^{q} \gamma\iota\mu_{kl}^{m}} \quad (7)$$

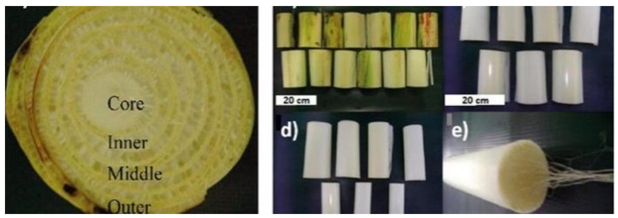
Where represents the fuzzy membership of Gray value with l respect to cluster k and,

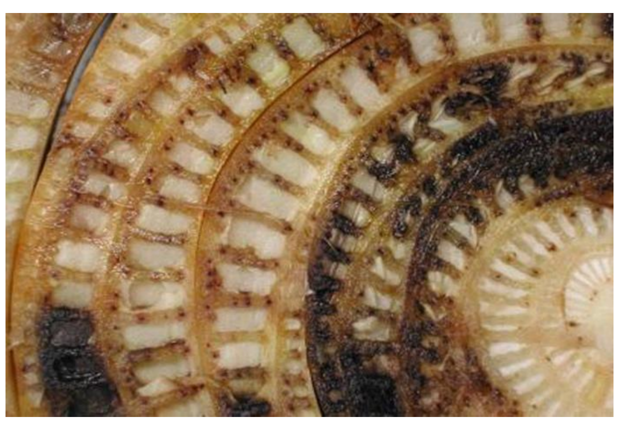
$$\sum_{i=1}^{q} \gamma\iota = N \quad (8)$$

Step 6: Upgrade the membership partition matrix U (t+1) using (2),
Step 7: If max $\{U^{(t)} - U^{(t+1)}\} < \eta$ then stop, otherwise, set t = t + 1 and go to Step 5.
Step8: Implement median filtering on membership partition matrix U' using following equation,

$$U'' = med\{U'\} \qquad (9)$$

4. EXPERIMENTAL RESULT





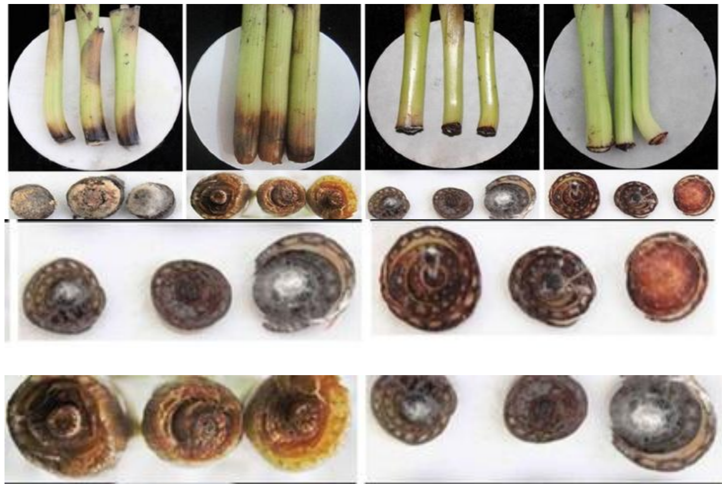


Figure 3: Three different stem data are taken and Experimented with Novel Image Segmentation method

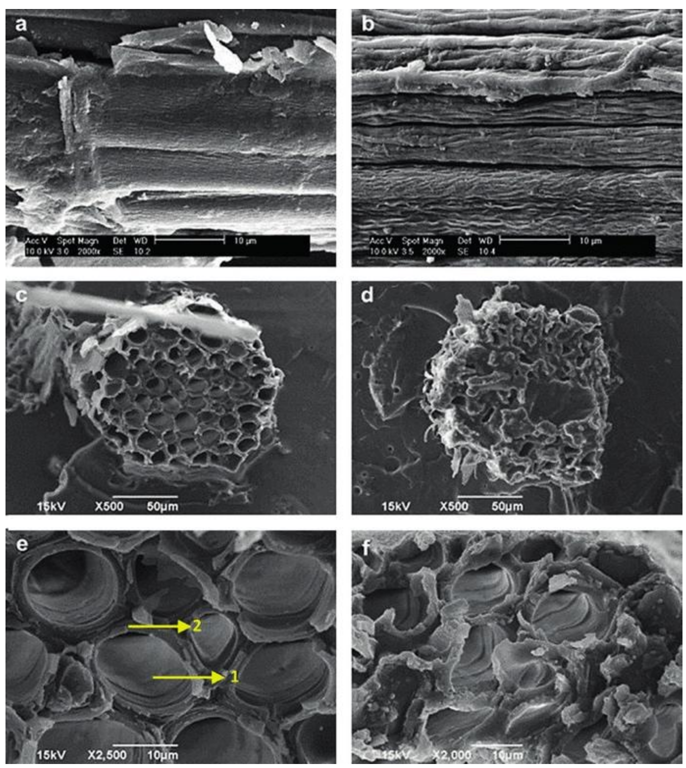


Figure 4: Image after Processing

4.1 Mean Square Error

Mean square error has been calculated by taking average of squares of error. Measurement unit of mean square error is same as that of quantity being evaluated. Mean square error is calculated by

$$\boldsymbol{MSE(A,B)} = \frac{\mathbf{1}}{\boldsymbol{XY}}\sum_{\boldsymbol{m=1}}^{\boldsymbol{X}}\sum_{\boldsymbol{n=1}}^{\boldsymbol{Y}}(\boldsymbol{A_{mn}} - \boldsymbol{B_{mn}})^{\mathbf{2}} \quad (1)$$

Where 'A' is the original image and 'B' is the segmented image with similar image size X × Y, 'm' and 'n' as their particular lines and segments. The MSE is less for the lesser distorted image and high for distorted images.

IMAGE	THRESHOLD SEGMENTATION	COLOR IMAGE SEGMENTATION	PROPOSED EFCM SEGMENTATION
1	0.2754	0.2939	0.1922
2	0.4243	0.3963	0.1398
3	0.2780	0.1271	0.0901
4	0.2791	0.2055	0.1291
5	0.3004	0.2682	0.1640

Table 1: Comparison table of MSE

The Comparison table 1 of MSE Values explains the different values of existing algorithms (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation. While comparing the Existing algorithm (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation, provides the better results. The existing algorithm values start from 0.2754 to 0.4243, 0.1271 to 0.3963 and proposed EFCM Segmentation values starts from 0.0901 to 0.1922. Provides the great results.

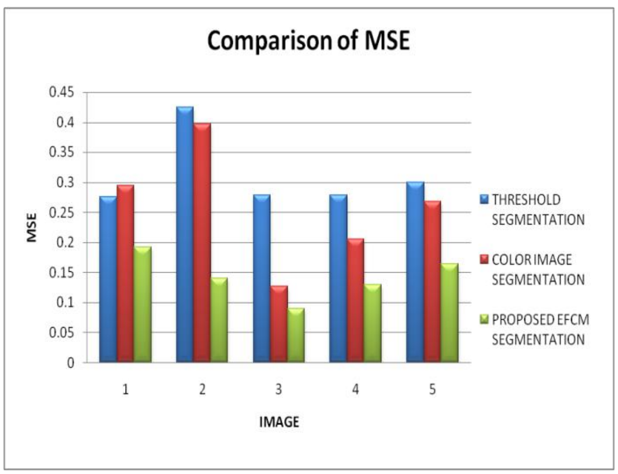


Figure 5: Comparison chart of MSE

The Figure 3 Shows the comparison chart of MSE demonstrates the existing1, existing 2 (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation. X axis denote the image and y axis denotes the MSE values. The proposed EFCM Segmentation values are better than the existing algorithm. The existing algorithm values start from 0.2754 to 0.4243, 0.1271 to 0.3963 and proposed EFCM Segmentation values starts from 0.0901 to 0.1922. Provides the great results.

4.2 Peak Signal-to-Noise Ratio

Peak signal-to-noise ratio is an conventional image quality assessment metric used to measure the error sensitivity between the original and the segmented images. It has been calculated from mean square error to measure the quality of the segmented image as follows:

$$PSNR(A,B) = 10\,log_{10}\left(\frac{255^2}{MSE(A,B)}\right) \quad (2)$$

Image quality is excellent for segmented images which have higher value of PSNR and is poor for images which have lower value of PSNR.

IMAGE	THRESHOLD SEGMENTATION	COLOR IMAGE SEGMENTATION	PROPOSED EFCM SEGMENTATION
1	19.4299	13.6499	23.0431
2	14.8720	14.7952	23.0263
3	15.7503	12.7541	22.7403
4	17.8947	15.8572	22.3772
5	16.4886	15.9745	20.6744

Table 2: Comparison table of PSNR

The Comparison table 2 of Peak Signal-to-Noise Ratio Values explains the different values of existing algorithms (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation. While comparing the Existing algorithm (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation, provides the better results. The existing algorithm values start from 14.872 to 19.4299, 12.7541 to 15.9745 and proposed EFCM Segmentation values starts from 20.6744 to 23.0431. Provides the great results.

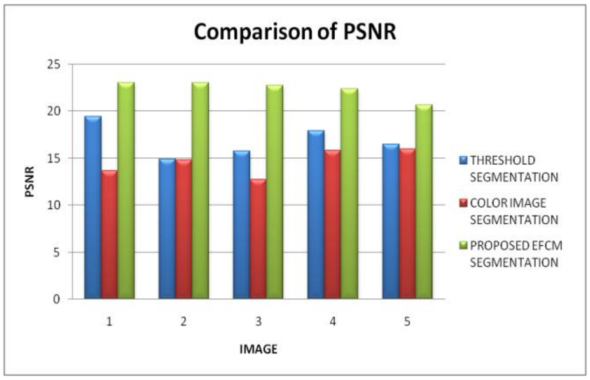


Figure 6:Comparison chart of PSNR

The Figure 4 Shows the comparison chart of PSNR demonstrates the existing1, existing 2 (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation. X axis denote the image and y axis denotes the PSNR values. The proposed EFCM Segmentation values are better than the existing algorithm. The existing algorithm values start from 14.872 to 19.4299, 12.7541 to 15.9745 and proposed EFCM Segmentation values starts from 20.6744 to 23.0431. Provides the great results.

4.3 Structural similarity index measure (SSIM)

It measures the image quality based on structural information in an image. This method is as an extension of Universal Image Quality Index. Luminance, contrast and structure are considered as important features to measure the similarity between two images. Main advantage of this method is its pixel by pixel quality analysis with easier, simpler and understandable mathematical knowledge. Structural similarity index between the original and segmented images is calculated using the formula,

$$\boldsymbol{SSIM} = \frac{(2\mu_a\mu_b + c1)(2\sigma_{ab} + c2)}{(\mu_a^2 + \mu_b^2 + c1)(\sigma_a^2 + \sigma_b^2 + c2)} \quad \textbf{(3)}$$

Where a and b are the original and segmented image, respectively μ_a and μ_b are mean values of the two images; σ_a and σ_b are standard deviations of the two images. σ_{ab} is the co-variance value for a and b; c1 and c2 are the constant values used stabilized the result. Similarity (SSIM) between two images lies within range of -1 to 1.

IMAGE	THRESHOLD SEGMENTATION	COLOR IMAGE SEGMENTATION	PROPOSED EFCM SEGMENTATION
1	0.07	0.05	0.18
2	0.15	0.12	0.17
3	0.23	0.22	0.25
4	0.11	0.07	0.15
5	0.21	0.18	0.23

Table 3: Comparison table of SSIM

The Comparison table 3 of Structural similarity index measure Values explains the different values of existing algorithms (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation. While comparing the Existing algorithm (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation, provides the better results. The existing algorithm values start from 0.07 to 0.21, 0.05 to 0.18 and proposed EFCM Segmentation values starts from 0.18 to 0.23. Provides the great results.

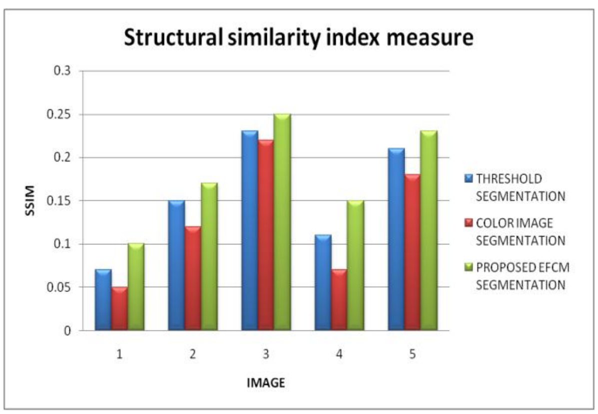


Figure 7: Comparison chart of SSIM

The Figure 5 Shows the comparison chart of SSIM demonstrates the existing1, existing 2 (Threshold Segmentation, Color Image Segmentation) and proposed EFCM Segmentation. X axis denote the image and y axis denotes the SSIM values. The proposed EFCM Segmentation values are better than the existing algorithm. The existing algorithm values start from 0.07 to 0.21, 0.05 to 0.18 and proposed EFCM Segmentation values starts from 0.18 to 0.23. Provides the great results.

4.4 Pixel Accuracy

An elective measurement to assess a semantic segmentation is to just report the percent of pixels in the image which were accurately grouped. The pixel accuracy is generally announced for each class independently just as all around the world across all classes.

While considering the per-class pixel accuracy we're basically assessing a twofold cover; a genuine positive addresses a pixel that is accurately anticipated to have a place with the given class (as indicated by the objective veil) though a genuine negative addresses a pixel that is effectively recognized as not having a place with the given class.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

IMAGE	THRESHOLD SEGMENTATION	COLOR IMAGE SEGMENTATION	PROPOSED EFCM SEGMENTATION
1	85.425	85.302	86.452
2	86.649	86.714	86.999
3	83.154	84.231	84.745
4	90.267	90.498	91.406
5	92.623	93.606	93.910

Table 4: Comparison table of Pixel Accuracy

Table 4 shows that Comparison table of Various Segmentation Techniques with Accuracy, comparison between existing threshold, color image segmentation and proposed EFCM method regarding accuracy. In Image 1 the accuracy value of EFCM segmentation has 86.452% and the accuracy of existing threshold, color image segmentation has 85.425% and 85.302% respectively. Also, in Image 5 the accuracy value of EFCM segmentation has 93.910% and the accuracy of existing watershed, threshold, color image segmentation has 92.623% and 93.606% respectively which is lower than the proposed EFCM segmentation method. The performance of the proposed FCM method is better compared with other existing methods as far as accuracy.

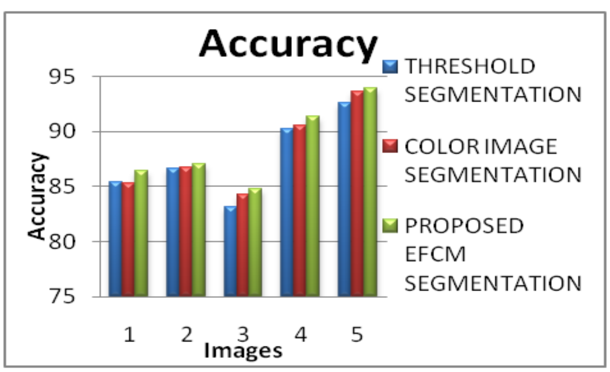


Figure 7: Comparison chart of Pixel Accuracy

Figure 7 shows that Comparison Chart of Various Segmentation Techniques with Accuracy,comparison between existing threshold, color image segmentation and proposed EFCM method regarding accuracy. In Image 1 the accuracy value of EFCM segmentation has 86.452% and the accuracy of existing threshold, color image segmentation has 85.425% and 85.302% respectively.The performance of the proposed FCM method is better compared with other existing methods as far as accuracy.

Experiments of Disease Identification

In general diseases are identified using the existing available symptoms and appearance in stem .based on that perception the below diseases are identified .

D1(Disease 1)Stem Rotting Disease

Figure 8: Rotting of Stem identification

In the above image the dark black patches represent the Rotten area. This disease is more pronounced on young suckers leading to rotting and emitting of foul odor

- Routing of collar region is a commonest symptom followed by epinasty of leaves, which dry out suddenly

- If affected plants are pulled out it comes out from the collar region leaving the corm with their roots in the soil
- In early stage of infection dark brown or yellow water soaked areas are more in the cortex area When affected plants are cut open at collar region yellowish to reddish ooze is seen.

Cause of Disease: Higher temperatures and high humidity are ideal growing conditions for the bacteria. Bacteria survive in crop debris and infect by water splash through damaged tissues.

D2 (Disease 2)Stem Chlorosis Disease

Figure 9: Stem chlorosis Disease

The disease manifests itself in all stages of crop growth.Due to repeated use of suckers from infected plants the disease spreads and resulting in the gradual decrease in yield and quality.The disease is known to occur in all banana-growing states.Light yellow streaks run parallel to leaf veins giving the leaf a striped appearance.The streaks run usually from mid rib to edge of the blade.

Cause of Disease: Virus is disseminated by suckers and Aphis gossy.

D3: Disease 3 – Mosaic Virus

The disease is characterized by the presence of spindle shaped pinkish to reddish streaks on pseudostem, midrib and peduncle.

Figure 10 Mosaic reddish spot

Typical mosaic and spindle shaped mild mosaic streaks on bracts, peduncle and fingers also observedSuckers exhibit unusual reddish-brown streaks at emergence and separation of leaf sheath from central axis. Clustering of leaves at crown with a travelers palm appearance, elongated peduncle and half filled hands are its characteristic symptom.The disease is caused by a virus belonging to potyvirus group. The virions are flexuous filamentous. The virus is transmitted through aphid vectors such as Aphis gosypii, Pentolonianigronervosa and Rhopalosiphummaidis. In field the disease spread mainly through suckers.

CONCLUSION

The yield of the plant growth monitoring system subject to image Segmentation method from images caught using multi-cameras. EFCM clustering algorithm is used to segment the region of interest, morphological shape analysis is applied to investigate the Banana Plant Growth Monitoring for Image Segmentation. It very well may be concluded by reviewing different methods that as the productivity of methods builds then the exactness of getting accurate results. The filtered image is then segmented and processed by image Segmentation technology to separate the information. The information gathered can be communicated to the farmers. The rovers can have the particular number of pesticides, fertilizers ready. finally 3 diseases are identified using the segmentation method , one bacterial infected disease and 2 virus infected diseases are identified , hence the segmentation model results in high degree of stem disease identification .

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