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AUTOMATIC SEGMENTATION OF PLANT LEAF DISEASE USING IMPROVED FAST FUZZY C MEANS CLUSTERING AND ADAPTIVE OTSU THRESHOLDING (IFFCM-AO) ALGORITHM

M.Yogeshwari[1,*], and Dr.G.Thailambal[2]

[1] *School of Computer sciences, Department of computer science, Research Scholar, VISTAS, Pallavaram, Chennai, India. Email: yogisara777@gmail.com*

[2] *School of Computer sciences, Department of computer science, Associate Professor, VISTAS, Pallavaram, Chennai, India.*

ABSTRACT

Automatic segmentation of plant leaves is vital for the detection of plant leaf diseases. In this research, we propose a novel framework for segmentation of plant leaf images using Improved Fast Fuzzy C Means Clustering and Adaptive Otsu threshold (IFFCM-AO) algorithm. In the proposed framework, initially, the plant leaf images are preprocessed using filtering and enhancement techniques. Image filtering is done for the removal of noise. In our work, we have proposed 2D Adaptive Anisotropic Diffusion Filter (2D AADF) for noise removal. Using these de-noised images, enhancement is done using Adaptive Mean Adjustment (AMA) technique. This step helps to intensify the region of interest in the image. Using the enhanced image, segmentation is performed by means of clustering and threshold. Clustering is done using the proposed Improved Fast Fuzzy C Means Clustering (IFFCMC) Algorithm and image threshold is performed using the proposed Adaptive Otsu (AO) threshold algorithm. The materials are collected in real time images for processing on it. Experimental results show that the proposed framework is effective and achieves best segmentation results compared to the previous works proposed in the literature. In addition, to show the credibility of the proposed noise removal algorithm, we have compared the proposed 2D Adaptive Anisotropic Diffusion Filter with 2D Adaptive Median Filter. In addition, we have also compared the proposed IFFCMC Algorithm with the conventional K-means clustering algorithm. Quantitative results clearly show that the proposed algorithms perform better than the traditional ones and hence aid in achieving better segmentation results.

Keywords: Diffusion Filter, Otsu threshold, median filter, Fast Fuzzy C Means Clustering.

1. Introduction

In the field of agriculture, the quality of the produce is degraded due to the presence of a variety of leaf diseases. Hence, a system for automatically identifying such leaf diseases greatly enhances the quality of the produce and also eliminates the need for manual picking which is a time-consuming process. To achieve this, image processing techniques are widely being used to identify such diseased leaves. The identification of such leaves at early stage is very important[1]. Many machine learning techniques have been proposed in the literature for such disease image classification[2]. This classification is done based on the texture, shape and colour. etc[3][4][5]. Using these features many frameworks have been developed and presented so far[6][7]. The reliability of this identification mainly depends on the segmentation of such leaves[8][9][10].The accuracy of classification of such leaves in proportional to the quality of segmentation.

Hence, in our research we propose a novel scheme for automatic segmentation of images with plant leaf diseases.

The overall contributions of this paper are fourfold:

a) A novel image filtering algorithm using 2D Adaptive Anisotropic Diffusion Filter (2D AADF).
b) A new image enhancement scheme using Adaptive Mean Adjustment (AMA).
c) A novel image thresholding using Adaptive Otsu (AO) thresholding.
d) Anovel image clustering using Improved Fast Fuzzy C Means Clustering Algorithm (IFFCMC).

The rest of the paper is organized as follows. Section 2 includes a detailed literature survey of the previous works in the literature. Section 3 describes the proposed segmentation methodology. The results and discussion are performed in Section 4. Concludes of the paper is presented in Section 5.

2. Literature survey

Super pixel clustering technique was used in [11] for leaf image segmentation. Here, hybrid clustering technique was used for segmentation. The whole image is first segmented into various blocks comprising of a number of super pixels. This process aided in increasing the speed of segmentation algorithm.Classification of such pixels was performed using expectation maximization algorithm.

Sparse representation theory was used for the classification of disease images in [12].K-means clustering algorithm was used for the segmentation of cucumber leaf images. Reduction of computational cost was the major advantage of this technique. This system achieved an overall classification accuracy of about 85.7% for classification of seven varieties of diseases.

The authors of [8] used soft computing techniques for the leaf image classification. In addition, this paper also presented a detailed review of various algorithms used for disease image classification. This paper utilized genetic algorithm for the segmentation of leaf images. The effects of using various soft computing techniques were analyzed using quantitative analysis in this paper.

Detection of diseased leaf of sunflower images was proposed in [13]. This paper represented a detained survey of various techniques for the classification of diseased sun flower images. An algorithm called particle swarm optimization was utilized in this paper for the classification of diseased leaves in the sunflower images. This scheme achieved an overall classification accuracy of about 98%.

Segmentation of tomato leaves using K-means clustering algorithm was proposed in[14]. K-means clustering algorithm aided in improving the quality of segmentation process. In this paper, adaptive clustering was used to find the segmentation regions. In addition, the number of clusters used for segmentation was identified using DavisBouldin index in this paper.

Automatic segmentation of rice leaves was presented in [15].Here, two important diseases were identified namely the Bacterial Leaf Blight and Brown Spot. Automatic segmentation of rice leaf images was employed prior to feature extraction. The extracted features were then classified using various machine learning algorithms. A number of hybrid techniques were employed and analyzed in this paper.

Deep convolutional neural network was used for the segmentation of cucumber leaves in [16].In this paper, four different cucumber leaf images were considered and classified. This system achieved an overall accuracy of about 93.40% for the classification of the four diseases. Experimental analysis was performed using a number of classification algorithm like support vector machine (SVM) and random forest.

Weighted segmentation was used in [7]. This technique was used for the classification of citrus diseases. The overall classification algorithm was performed in two steps. In the first step,lesion spots were identified in the images. In the second step, classification was performed. The final classification was performed using multi-class support vector machinelearning technique.

Plant disease detection using a modern approach was proposed in [17]. This process involved five steps. In the first step, the images were acquired. In the second step, they were pre-processed. In the third step, the pre-processed images were segmented. Then in the fourth step, features were extracted from the segmented regions. Finally using the acquired features, diseases were classified.

A technique for detection of potato diseases using SVM was proposed in [18]. Around 300 images were considered for classification in this paper. An overall classification accuracy of around 95% was achieved in this paper.

3. Materials and Methods

The materials such as different types of leaf are collected for further processing. The materials are subjected to filtering, enhancement, segmentation, feature extraction and classification of disease. Based on the region growing technique, the algorithm is developed to estimate the whole leaf materials without the background. The Selection of a suitable threshold value according material is mandatory for segmenting it into a binary image. Super-pixel grouping, as a data preprocessing, can give a reliable estimation of an initial colored condition leaf materials in condition leaf segmentation. Super-pixels of the infection leaf material hold more data than pixel values, which, due to various values of pixels, have major advantages in processing performance, processing time and memory cost. This novel segmentation algorithm is implemented in this paper.

3.1. Image Preprocessing

Image preprocessing was performed using two steps namely, image filtering and image enhancement.

3.1.1. Image Filtering using 2D Adaptive Anisotropic Diffusion Filter (2D AADF)

Anisotropic diffusion technique was proposed in[19] by Perona and Malik. This technique cannot be used for the elimination of impulse noise from images. Hence in our work, we have proposed Adaptive Anisotropic Diffusion Filter that can be used for the elimination of impulse noise.

Algorithm 1: Proposed 2D Adaptive Anisotropic Diffusion Filter (2D AADF)

Input:

Input image $I \in R^{M \times N}$

Output:

Filtered image $I^F \in R^{M\times N}$

Steps:

for $i = 1:M,\ j = 1:N$

1. Check the quality of pixel at (i, j) and the surrounding pixels in 3×3 window.
2. ifpixel at (i, j) is noiseless and surrounding pixels are also noiseless, then, retain the pixel value.
3. if pixel at (i, j) is noiseless and surrounding pixels are noise,then, retain the pixel value.
4. if pixel at (i, j) is noisy and surrounding pixels are noiseless, then, replace the pixel with median value of the pixels in the surrounding 3×3 window.
5. if pixel at (i, j) is noisy and surrounding pixels are also noisy, then, use the convolution filters shown in Figure 1.

end

$$\begin{bmatrix} 0 & 1 & 0 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 1 & -1 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \\ 0 & -1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Figure 1. Convolution mask for adaptive anisotropic diffusion

3.1.2. Image Enhancement using Proposed Adaptive Mean Adjustment (AMA)

The filtered images are enhanced using adaptive mean adjustment technique. This is done to improve the contract of the images. Here, the filtered image I^F is used as input to produce the enhanced image I^E. The input image is divided into 3×3 non-overlapping blocks and the mean is computed for each block. The maximum among all the mean values are represented as $M_{\max}$ and the minimum is represented as $M_{\min}$. If the difference between $M_{\max}$ and $M_{\min}$ is too low, it indicates that the image has a poor contrast. This can be improved using the following transformation function.

$$I^E(i, j) = T(I^F(i, j)) \tag{1}$$

where

$$T(g) = \frac{g \times h}{M_{\max} - M_{\min}} - \frac{M_{\min} \times h}{M_{\max} - M_{\min}} \tag{2}$$

Here g represents the grey scale value at $I^F(i, j)$ and h is the highest grey scale value in the image.

Input:

Filtered image $I^F \in R^{M\times N}$

Output:

Enhanced image $I^E \in R^{M\times N}$

Steps:

1. Divide image into3×3 non-overlapping blocks and find mean of each block.
2. Find maximum mean $M_{\max}$ and minimum mean $M_{\min}$.
3. for $i=1:M,\ j=1:N$

   Transform each pixel using $I^E(i,j)=T(I^F(i,j))$.

   where $T(g)=\dfrac{g\times h}{M_{\max}-M_{\min}}-\dfrac{M_{\min}\times h}{M_{\max}-M_{\min}}$
4. end

4.1. Image Segmentation

The segmentation of image is performed using clustering and thresholding. In our work, clustering is performed using Improved Fast Fuzzy C Means Clustering Algorithm and thresholding is performed using Adaptive Otsu (AO) thresholding.

4.1.1. Clustering using Improved Fast Fuzzy C Means Clustering Algorithm (IFFCMC)

Fuzzy C Means Clustering is a popularly used technique for segmentation of images since the efficiency of this algorithm is better than other machine learning techniques. However, the main drawback of this technique was the speed. To improve the speed of this algorithm, Fast Fuzzy C Means Clustering algorithm was used. In this algorithm, the main difference was that, image histogram was used instead of raw image pixels. Here, the objective function of Fast Fuzzy C Means Clustering algorithm is given by,

$$J=\sum_{i=0}^{255}\sum_{q=1}^{C}h_i f_{iq} d(i,\theta_q) \tag{3}$$

Here, h_i refers to the histogram,

f_{iq} refers to the fuzzy membership between pixel x_i and histogram of cluster with center θ_q,

$d(i,\theta_q)$ refers to the distance between pixel x_i and histogram of cluster with center θ_q.

In our work, a fourth term is added to the objective function. Let $q=1,2,\ldots C$ represent each centroid. Then, the mean of the pixelsin each centroid is given as M_q. The Euclidean distance between the data point x_i with each M_q is then computed. This term is added to the objective function in the proposed IFFCMC scheme. Thus, the new objective function is given as

$$J = \sum_{i=0}^{255} \sum_{q=1}^{C} h_i f_{iq} d(i, \theta_q) e(i, q) \quad (4)$$

where $e(i,q) = EucDist\{x_i, M_q\}$ (5)

Algorithm 2: Proposed Improved Fast Fuzzy C Means Clustering Algorithm (IFFCMC)

Input:

Enhanced image $I^E \in R^{M \times N}$

Output:

Clustered image $I^C \in R^{M \times N}$

Steps:

1. Compute the maximum intensity $I_{\max}$ and minimum intensity $I_{\min}$.
2. Compute the histogram of the image.
3. Divide into two clusters with one having high frequency pixels and other having low.
4. Update the centroid of the cluster and membership function using the new objective function
   $$J = \sum_{i=0}^{255} \sum_{q=1}^{C} h_i f_{iq} d(i, \theta_q) e(i, q)$$
5. Compute the distance d_c between current and previous centroid.
6. if $d_c > \lambda$

   for $i = 1 : M$, $j = 1 : N$

   Compute the distance to centroid

   Compute the fuzzy membership value

   end
7. end
8. Update the centroid.

4.1.2. Thresholding using Adaptive Otsu (AO)thresholding

Otsu threshold is widely used technique forimage segmentation. It identifies a global threshold for segmenting an image into two categories namely, the foreground and the background.Every pixel value in an image is compared with the threshold. If the value of the pixel is greater than the threshold, then it is classified as foreground, else it is classified as background pixel. The efficiency of Otsu algorithm depends on the selection of initial threshold. Hence, in our work we propose adaptive Otsu thresholding algorithm that adaptively identifies optimum initial threshold value.

Algorithm 3: Proposed Adaptive Otsu (AO) thresholding

Input:

Clustered image $I^C \in R^{M \times N}$

Output:

Segmented image $I^S \in R^{M \times N}$

Steps:

1. Compute the initial threshold T_i as the median value of all pixels in $I^C \in R^{M \times N}$.
2. Using T_i form two clusters.
3. For each cluster j find standard deviation value of each 3×3 non-overlapping block i.e., $\sigma_1, \sigma_2, \ldots \sigma_{B_j}$.
4. Combine and sort the standard deviation values of both the clusters to form vector S_d.
5. Normalize the vector S_d using l_2 normalization.
6. Split the vector S_d into two groups with a cut off value of 0.5.
7. Identify the corresponding 3×3 non-overlapping blocks of each group and find the mean value of each cluster as MC_1 and MC_2.
8. The new threshold is computed as

$$T_{i+1} = \frac{MC_1 + MC_2}{2}.$$

9. Repeat steps 2 to 8 until the difference between two successive thresholds is less than τ.
10. Using the acquired threshold value perform the conventional Otsu algorithm for further segmentation.

5. Results and Discussion

5.1. Parameter Settings

The proposed system was simulated using MATLB software running on windows intel i3 core processor with 6GB RAM. The value of λ in Algorithm 2 was set as 0.1. The value of τ used in Algorithm 3 was set as 0.01.

5.2. Simulation Results

Figure 2 shows some sample disease leaf images used in our work for evaluation.

Figure 2. Sample leaf disease images used in this work

Figure 3 represents the output images obtained after each step for healthy leaf images. Figure 3. (a) shows the Input Image. Figure 3. (b) represents the Filtered Image using 2D Adaptive Anisotropic Diffusion Filter. Figure 3. (c) illustrates the Adaptive Mean Adjustment output and Figure 3. (d) depicts the Improved Fast Fuzzy C Means Clustering Algorithm output. Figure 4.shows the final segmentation result of normal leaf.

(a) **(b)** **(c)** **(d)**

Figure 3. (a) Input Image (b) Filtered Image using 2D Adaptive Anisotropic Diffusion Filter (c) Adaptive Mean Adjustment output (d) Improved Fast Fuzzy C Means Clustering Algorithm result

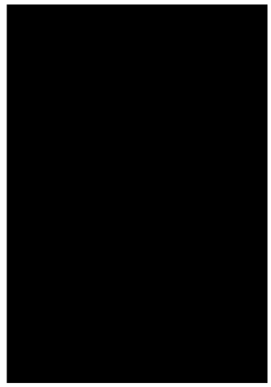
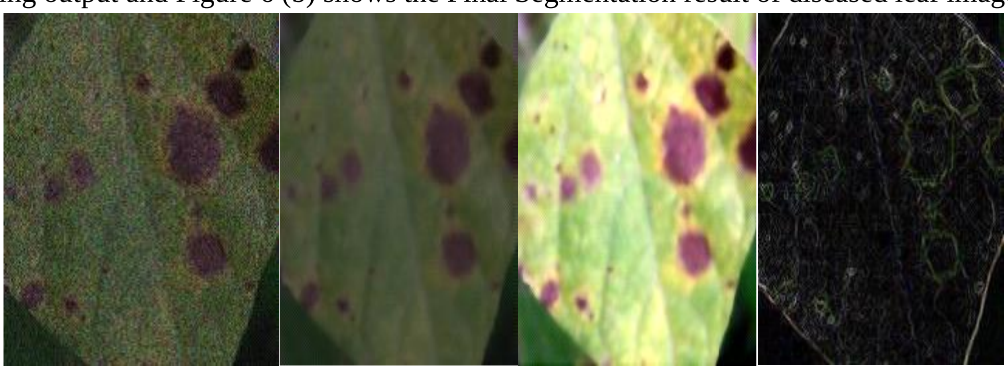


Figure 4.Final segmentation result of normal leaf

Figure 5 represents the output images obtained after each step for diseased leaf images. Figure 5. (a) shows the Input Image. Figure 5. (b) represents the Filtered Image using 2D Adaptive Anisotropic Diffusion Filter. Figure 5. (c) illustrates the Adaptive Mean Adjustment output and Figure 5. (d) depicts the Improved Fast Fuzzy C Means Clustering Algorithm output. Figure 6 (a) shows the Adaptive Otsu Thresholding output and Figure 6 (b) shows the Final Segmentation result of diseased leaf image.



(a) **(b)** **(c)** **(d)**

Figure 5 (a) Input Image(b) Filtered Image using 2D Adaptive Anisotropic Diffusion Filter (c) Adaptive Mean Adjustment (d) Improved Fast Fuzzy C Means Clustering Algorithm

(a) **(b)**

Figure 6 (a) Adaptive Otsu Thresholding result (b) Final Segmentation of disease leaf image

5.3. Evaluation of Filtering Algorithms

The proposed system was evaluated using metrics like mean square error and peak signal to noise ratio.

Mean Square Error (MSE):

MSE gives the average difference between the original image O and the denoised image D after applying the filter. It is given by

$$(1/N^2)\sum_{i=1}^{N}\sum_{j=1}^{N}[O(i,j)-D(i,j)]^2 \quad (1)$$

Peak Signal to Noise Ratio (PSNR):

PSNR gives the ratio of signal value to the error value. The PSNR value increases the quality of image increases. It is calculated as

$$PSNR = 10\log_{10}\frac{255^2}{(1/N^2)\sum_{i=1}^{N}\sum_{j=1}^{N}[O(i,j)-D(i,j)]^2} \quad (2)$$

Table 1 shows the performance evaluation using mean square error. From Table 1 we infer that, the average value of MSE for 2D median filter was 7.136. Similarly, the average value of MSE for 2D adaptive median filter[20]was 3.838. But, the proposed 2D adaptive anisotropic diffusion filter achieved a minimum MSE of 0.892. Thus, our proposed framework achieves best performance in terms of MSE.

Table 1. Performance evaluation using Mean Square Error

Image Number	**MSE**		
	2D Median Filter	2D Adaptive Median Filter	Proposed 2D Adaptive Anisotropic Diffusion Filter
1	7.83	3.95	0.83
2	7.12	3.23	0.89
3	7.62	3.43	0.97
4	6.82	4.32	0.79
5	6.29	4.26	0.98

Table 2 shows the performance evaluation using peak signal to noise ratio. From Table 2 we infer that, the average value of PSNR for 2D median filter was 22.34. Similarly, the average value of PSNR for

2D adaptive median filter was 28.12. But, the proposed 2D adaptive anisotropic diffusion filter achieved a maximum PSNR of 37.35. Thus, our proposed framework achieves best performance in terms of PSNR.

Table 2. Performance evaluation using Peak Signal to Noise Ratio

Image Number	**PSNR (in dB)**		
	2D Median Filter	2D Adaptive Median Filter	Proposed 2D Adaptive Anisotropic Diffusion Filter
1	21.32	27.82	36.12
2	22.53	27.81	37.97
3	23.89	26.91	38.98
4	21.22	28.10	37.89
5	22.78	29.97	35.81

5.4. Evaluation of Thresholding Techniques

Table 3 shows the average value of threshold obtained using different thresholding technique. We see that, using basic morphological operation an average threshold of 128 was obtained. For Otsu thresholding, average threshold of 120 was obtained. However, the proposed adaptive Otsuthresholding produced an adaptive threshold in the range of 120 to 130 based on the input data.

Table 3. Average threshold value for different thresholding techniques

S. No	**Thresholding Techniques**	**Average Threshold Value**
1	Morphological Operation	128
2	Otsu	120
3	Adaptive Otsu	120 to 130

5.5. Evaluation of Clustering Algorithms

Jaccard coefficient is commonly used for evaluating the performance of clustering algorithms. It is given by

$$J(O_a) = \frac{B \cap G}{B \cup G} \tag{3}$$

where O_a is the overlap area, B is the binary image and G is the ground truth image.

The Dice coefficient is computed as

$$D(B,G) = \frac{2|B \cap G|}{|B| + |G|} \tag{4}$$

Its value ranges between 0 to 1. 0 represents no overlap and 1 represents complete overlap.

Table 4 shows the performance evaluation using Jaccard Coefficient. From Table 4 we infer that, the average value of Jaccard Coefficient for K means clustering was 0.5684. Similarly, the average value of Jaccard CoefficientforFast Fuzzy C Means Clustering was 0.6514. But the proposed Improved Fast Fuzzy C Means Clustering achieved a maximum Jaccard Coefficient of 0.749. Thus, our proposed framework achieves best performance in terms of Jaccard Coefficient.

Table 4. Performance evaluation using Jaccard Coefficient

Image Number	**Jaccard Coefficient**		
	K means clustering	Fast Fuzzy C Means Clustering	Proposed Improved Fast Fuzzy C Means Clustering
1	0.5789	0.6579	0.7329
2	0.5832	0.6380	0.7239
3	0.4928	0.6938	0.7819
4	0.5933	0.6381	0.7139
5	0.5938	0.6292	0.7927

Table 5 shows the performance evaluation using Dice Coefficient. From Table 5 we infer that, the average value of Dice Coefficient for K means clustering was 0.6262. Similarly, the average value of Dice Coefficient for Fast Fuzzy C Means Clustering was 0.6758. But the Proposed Improved Fast Fuzzy C Means Clustering achieved a maximum Dice Coefficient of 0.7754. Thus, our proposed framework achieves best performance in terms of Dice Coefficient.

Table 5. Performance evaluation using Dice Coefficient

Image Number	Dice Coefficient		
	K means clustering	Fast Fuzzy C Means Clustering	Proposed Improved Fast Fuzzy C Means Clustering
1	0.6282	0.6928	0.7923
2	0.6199	0.6721	0.8352
3	0.6129	0.6821	0.7923
4	0.6381	0.7112	0.7381
5	0.6319	0.6211	0.7193

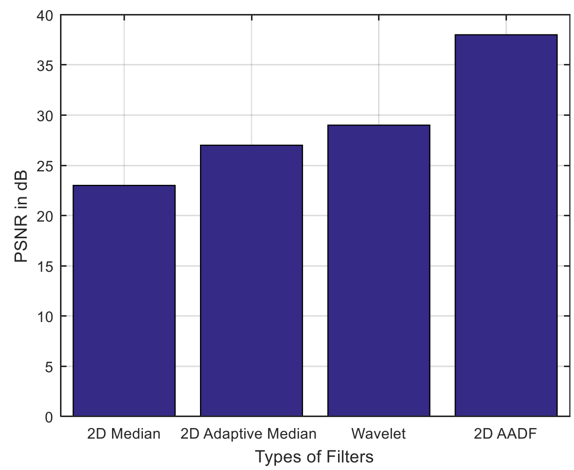


Figure 7 (a) PSNR Bar chart for different filtering techniques

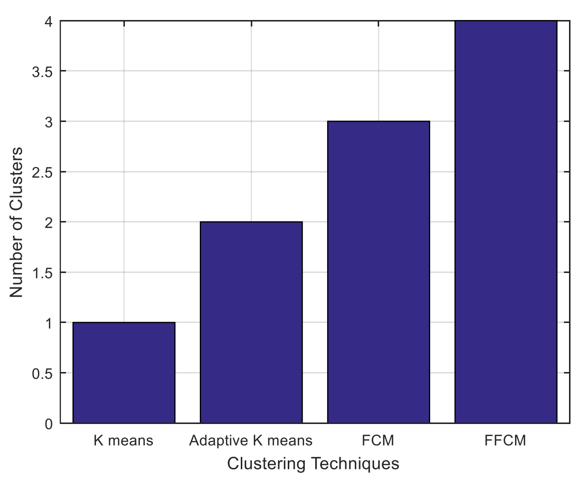


Figure (b) various clustering techniques Vs Number of clusters graph

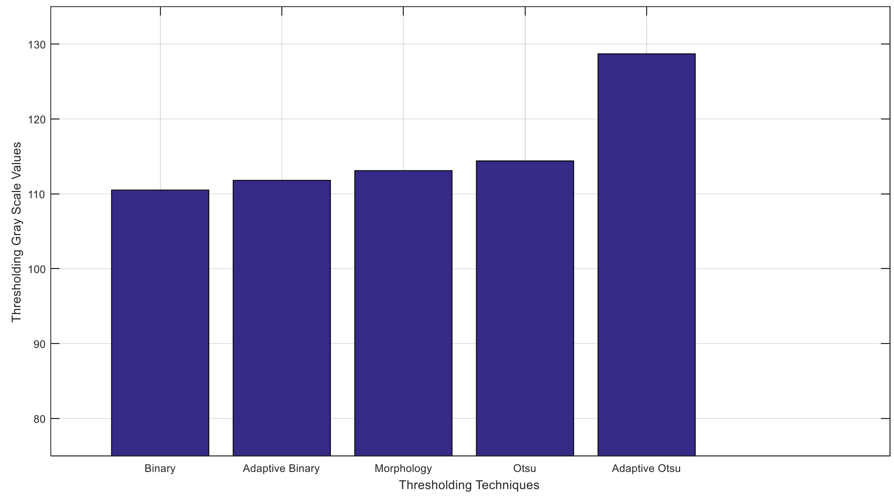


Figure 7 (c) Bar chart for Thresholding technique

In figure 7 (a), the various filtering techniques are compared with proposed methodology. The proposed filter has higher range of PSNR value. Figure 7 (b) shows comparison graph of various clustering techniques. The FFCM cluster is better than other techniques. Figure 7 (c) shows various thresholding techniques comparison.

6. Conclusion

In this research, we have proposed a novel framework for segmentation of plant leaf images using Improved Fast Fuzzy C Means Clustering and Adaptive Otsu thresholding algorithm. In our work, we have proposed and used 2D Adaptive Anisotropic Diffusion Filterfor noise removal. Image enhancement wasdone using Adaptive Mean Adjustment technique. Using the enhanced image, clustering was done using the proposed Improved Fast Fuzzy C Means Clustering Algorithm and finally image thresholding was performed using the proposed Adaptive Otsu (AO) thresholding algorithm. Our system achieved a minimum average MSE of 0.892. Similarly, our framework achieved a good PSNR of 37.35. Our system was also evaluated using Jaccard coefficient and we achieved a high value of 0.749. Finally, system was compared using Dice coefficient and our system achieved a high value of 0.7754. Thus, the credibility of the proposed system was proved using various evaluation metrics.

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