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Segmentation of White Chali Arecanuts using Soft Computing Methods

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Abstract: Performance of computer vision based grading systems is remarkably affected by the efficiency of object segmentation. The automatic segmentation of low contrast objects is a challenging task in various fruit and nut grading systems. In this paper background elimination of white chali arecanut images is carried out using morphological segmentation. The fine-tuning of edge threshold for morphological segmentation is achieved by obtaining threshold values from multilevel thresholding of original grayscale image. The best figure ground segmentation is selected by a network trained using shape parameters of the ground truth masks. The performance of morphological segmentation is evaluated for the best figure ground segmentations using precision, recall and F-scores. Comparison of segmentation performance is done by employing multilevel thresholding based on Otsu, Fuzzy c-mean, Harmony search, Differential Evolution and Cuckoo Search algorithms. The experimental result shows that, multilevel thresholding using Differential Evolution and Cuckoo Search algorithms yield best results for the fine-tuning of edge thresholds and hence the better segmentation performance of the white chali arecanuts.

Keywords : Morphological Segmentation, Multilevel Thresholding, Soft computing method, White Chali Arecanut.

I. INTRODUCTION

The rapid technological advancement and complexity of consumer demands now impose new standards of quality on agricultural produce. Consumers expect more and more information on the goods they purchase to show strong preferences for high-quality, well-informed goods. Human beings are influential in the classification of the grades and the range of the arecanuts. There are many computer based technologies for other crops, but computer-based advanced technology does not suffice to classify the grade and variety of arecanuts. The potential for computer-based vision technology is rising to resolve the above problems for arecanuts producers. A system for the classification of white chali arecanuts is developed with machine learning algorithms [1]. In fruit or nut grading systems usually a white or black background is set in order to avoid diffusion of background color into the region of interest.

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However, in case of white chali arecanuts, both white and black backgrounds lead to the low contrast images as the white chali arecanut images are almost gray in color and vary from high light to high dark. The majority of white chali arecanuts exhibit good contrast with black background. However, there exits 10 to 20% of low contrast arecanut images, which depends upon the quality of the crop. Fig.1 shows white chali arecanut images with fixed background but the image contrast changes as the intensity of object changes. The rest of this section gives perspective of works related to segmentation of low contrast images for the fruit and nut grading systems.
The low contrast image normally exhibits a non-bimodal histogram. The segmentation of a non-bimodal histogram image is a challenging task. Considering the literature survey, there are several methods available for segmenting objects with low contrast and variable illumination in the scenario of food, fruit and seed grading. Ahmed A. Nashat and N. M. Hussain Hassan proposed a segmentation approach for extracting the olive fruit from the low contrast background using the discrete wavelets transform and k-means clustering [2]. The statistical textures were obtained to classify the olives between the healthy and unhealthy fruits. The segmentation results were compared with Local Binary Pattern (LBP) and found robust.

Fig.1. White Chali Arecanut images

The paper [3] focuses on the segmentation of natural light images. The authors suggested an improved natural image threshold segmentation (TsTN) technique and compared results with conventional approaches, such as Otsu and Fuzzy C Means (FCM). The Otsu approach divides the image into background and front depending on the value of the threshold. The binary images are black and white, with gray-level pixels greater than the threshold values set to white and the remaining pixels set to black. In comparison, FCM divided the image into many separate clusters. FCM is an unsupervised clustering technology and needs no named data but its sensitivity to the initial cluster centers is the main drawback of the FCM technique. The inaccurate initial centers can lead to poor segmentation. Both conventional approaches could not segment the image in the complex background, nor were the images captured with natural light uniformly illumined. All the Visual Evaluation and the Rand Index (RI) showed TsTN's dominance over conventional methods. A Pareto multi-objective optimization thresholding method has been presented [4] to perform the segmentation of synthetic images, well known test images and MRI images. In this paper, a new multilevel image thresholding technique, called Thresholding using Pareto Multi Objective (TPMO), was proposed, which combines the flexibility of multiobjective fitness functions with the power of an enhanced version of the most popular multiobjective genetic optimization algorithm NSGA-II for searching vast combinatorial state spaces. They had provided the improvement to the algorithm NSGA-II by suggesting the stopping iteration, initial population was selected from the algorithm automatically and number of generations. The performance of TPMO was better than the EM algorithm based method, Valley Emphasis (VE) based method, Otsu method, Kapur method and a method based on Tsallis Entropy (TE). Image segmentation by multilevel thresholding using genetic algorithm with fuzzy entropy cost functions [5] was used to segment the color and grayscale images. The authors employed triangular, trapezoidal and bell shaped membership functions. The optimum membership functions were determined by increasing the fuzzy entropy. The trapezoidal membership function exhibited better results over Otsu multilevel thresholding.

Veska M. Georgieva and Stephan G. Vassilev [6] proposed a method to segment poor SNR valued and boundary misplaced ultra sound images. These images were pre-processed using Contrast Limited Adaptive Histogram Equalization (CLAHE) method and homomorphic filter for contrast enhancement based on wavelet decomposition. The active contour was the method employed for segmenting the image without considering the edges. A new image binarization method based on edge information analysis [7] involves three steps; Firstly, the edges of an image are detected using the Canny method. Secondly, the gray level transition range of each edge point is calculated and then a new histogram of cumulative edge gray level transition range is obtained. Finally, the peak of the new histogram is set as the optimal threshold for image binarization. An image data field-based frame work for image thresholding was proposed in [8], and improved four thresholding methods under the proposed framework. It involved generating the image data field, implementing image transformation with potential-weighted sum, and then determining the binary threshold for the transformed image by applying the conventional approaches. The performances of the algorithms were tested on a variety of synthetic and real images, with and without noise and found to be accurate, noise-robust, efficient and scalable. Review of literature reflects that the thresholding based segmentation gives a promising result for the segmentation of low contrast images. Determination of threshold value for binarization plays an important role in segmentation. An unsupervised segmentation can be achieved by selecting the threshold value automatically. The following section gives details of the methods used to extract ROI from the white chali arecanut images using automatic morphological segmentation.

II. PROPOSED SYSTEM

The morphological segmentation has been proven as an efficient tool for contour segmentation or segmenting the ROI with entirety. The first step in morphological segmentation is the selection of proper threshold value to identify the edges of the object. This can be accomplished by finding the threshold using edge detector and then fine-tuning it to account for the ROI [9]. The automatic fine-tuning of this threshold value will enhance the segmentation process and lead to unsupervised work flow. P.Shanmugavadivu and Visalakshi Sivakumar [10] have used fractal bound gamma transformation to obtain the threshold and segmenting of masses in digital mammograms using morphological segmentation. Berthe and Vinoy [11] have fine-tuned this threshold value by exploiting the synergy between fractal dimension and lacunarity of the image. In this work, the edge threshold is obtained by using Sobel edge detector and then fine-tuned by the threshold values obtained using multilevel thresholding algorithms. Fig.2 illustrates the procedure followed in this work. The morphological segmentation of original grayscale image is carried out for each fine-tuned threshold. Later the shape features of each segmented mask are extracted. The ground truth masks of white chali arecanuts exhibit a consistent shape features. An unsupervised or automatic segmentation is achieved by the automatic selection of best suitable threshold value for edge detection. This is done by comparing the shape features of the segmented masks with the shape features of the standard masks stored in the database.

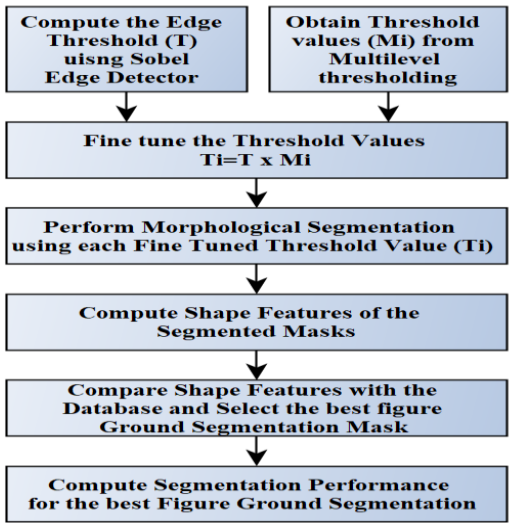

Fig. 2. Work Flow of Proposed Method

The subsequent section illustrates the algorithms employed in morphological segmentation and multilevel thresholding of the given image. Later, the performance of morphological segmentation with different multilevel thresholding algorithms are compared.

III. MORPHOLOGICAL SEGMENTATION

The selection of threshold value for the binarization affects the result of morphological segmentation. Normally, this is determined in two steps; first, roughly computing the edge threshold using edge detector such as Sobel edge detector, and then fine-tuning it before actually binarizing the grayscale image. This process is followed by dilation of the gradient mask, filling the interior gaps of dilated mask, removing the connected objects on the boarder and finally smoothing the of the mask as shown in Fig. 3. In this work, the fine-tuning of threshold is done by obtaining the threshold values from multilevel thresholding of the given grayscale image.

The experimental result shows that a minimum of five level multilevel thresholding (four threshold values) is required to effectively capture a favorable threshold value for fine-tuning. The following section illustrates the methods used for multilevel thresholding of the given grayscale image.

IV. SOFT COMPUTING METHODS FOR MULTILEVEL THRESHOLDING

Multilevel thresholding is a process of splitting a grayscale image into specified number of distinct regions.

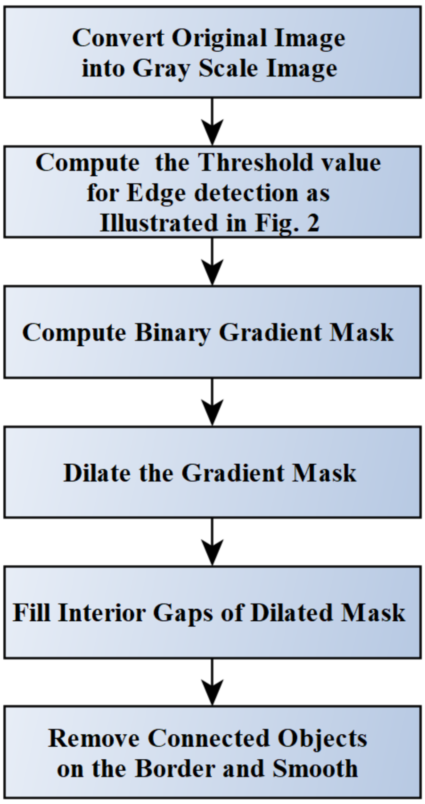

Fig. 3. Morphological Segmentation

The Otsu method is commonly used to measure the threshold value for grayscale image binarization. This approach involves iterating the threshold values and evaluating the distribution of each threshold side for the pixel levels, i.e. the pixels which are either in the foreground or in the background. The objective is to define the threshold value where the sum of the front and background is at a minimum. Even though the Otsu method is easy, fast and widely used, its main limitation is its assumption of binary classes. Hence this method does not give better result when the histograms are non-bimodal. This is overcome by adapting soft computing methods for multilevel thresholding, but they are slower when compared to Otsu method. The following section illustrates the soft computing methods used to compute the multi thresholds.

A. Fuzzy C Mean Clustering (FCM)

For briefing of algorithm let us consider $Y = \{y_1, y_2 \ldots. y_k\}$ as the sample of N observations in R_n (Euclidean space); considering the y_k as the kth feature vector. Let us assume the number of clusters *C* as the partition for *Y* and it is the integer ranging from 2 to n. The sample of ROI i.e. *Y* should satisfy the below three equations [12].

$$Y_i \neq \emptyset \quad 1 \leq i \leq C \tag{1a}$$

$$Y_i \cap Y_j = \emptyset, i \neq j \tag{1b}$$

$$\cup_{i=1}^{C} Y_i = Y \tag{1c}$$

In these equations the $\emptyset$ is the empty set. $\cap$ *and* $\cup$ meaning remains same as intersection and union. These are the basic equations can be used for FCM by extending the *C* to matrix-theoretic terms. The matrix $\cup$ is the product of *C* and N matrix, the $\cup$ is the two dimension of *Y* (it can be image), the below equation formulizes this concept,

$$u_i(y_k) = u_{ik} = \begin{cases} 1; & y_k \in Y_i \\ 0; & otherwise \end{cases} \tag{2a}$$

$$\sum_{i=1}^{N} u_{ik} > 0 \; for \; all \; i; \tag{2b}$$

$$\sum_{i=1}^{N} u_{ik} = 1 \; for \; all \; k \tag{2c}$$

The Fuzzy C Means Clustering gives better results than the Otsu method for determining the threshold value. The FCM attempts to partition the finite collection *Y* into a collection of *C* fuzzy clusters with respect to some given objective function.

B. Harmony Search Optimization Algorithm

The Harmony search optimization algorithm (HSA) provides the solution called as harmony and it is represented as n dimensional vector. The algorithm has following steps [13];

Initializing the algorithm parameters using the equation

$$f(x), \; x = (x(1), x(2), \ldots x(n)) \in R^n \tag{3}$$

subject to: x (f) ∈ [l(f), u(f)] f= 1, 2, . . . , n, where $f(x)$ is the objective function, x = (x(1), x(2), . . . , x(n)) is the set of design variables, n is the number of design variables, and l(f) and u(f) are the lower and upper bounds for the design variable x(f), respectively. The parameters for HSA are harmony memory size (HMS) which holds the solutions in vector format and harmony memory consideration rate (HMCR). Harmony memory initialization*:* The HMS are considered in this stage. The HMS are the randomly generated harmony vector as shown below,

$$\text{HM} = \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ x_{HMS} \end{bmatrix} \tag{4}$$

Improvisation of New Harmony vectors: The improvisation of the vectors is done by considering three operators; they are memory consideration, random re-initialization and pitch adjustment. These improvements are modelled shown below,

$$x_{new}(f) = \begin{cases} x_i(f) \in \{x_1(f), x_2(f) \dots . x_{HMS}(f)\}, probability\ of\ HMCR \\ l(f) + (u(f) - l(f)).rand(0,1), probability\ of\ 1 - HMCR \end{cases} \quad (5)$$

Updating the harmony memory: Once the x_{new} is obtained based on the size of the x_{new} the harmony memory is updated and the fitness value is calculated for x_{new}.

Computational procedure: This procedure is implemented for minimization purpose. The computational procedure of the basic HSA can be summarized as in Algorithm 1 in paper [14].

C.Differential Evolution Algorithm

The normalized histogram of the image is considered while implementing the multilevel thresholding of the image.

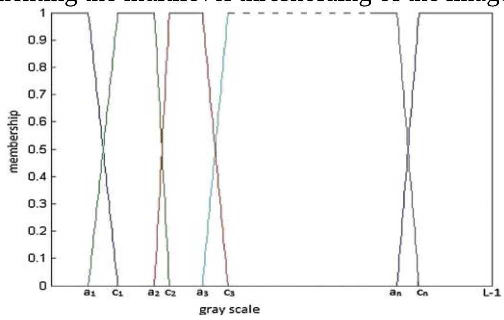

Fig.4. Membership Function for n level multi thresholding

Fig.4 shows membership function for n level multi thresholding [15]. For simplicity trapezoidal membership function is used to estimate the membership of n segmented regions, μ_1, μ_2, … μ_n by using 2×(n-1) unknown fuzzy parameters, namely a_1, c_1… a_{n-1}, c_{n-1} where $0 \le a_1 \le c_1 \le \dots \le a_{n-1} \le c_{n-1} \le L-1$.

The optimum value of parameters can be obtained by maximizing the total entropy given by

$$\varphi(t_1, t_2, \dots t_n) = Arg\ ma\,x([H_1(t) + H_2(t) + \cdots\ \ H_n(t)]) \quad (6)$$

Where H_1, H_2, … H_n are maximum fuzzy entropy for each segment. The Differential Evolution (DE) is a population-based global optimization algorithm, used to optimize Eq. (6). In this DE, the i[th] individual (parameter vector) of the population at generation (time) t is a *D* dimensional vector containing a set of D optimization parameters;

$$Z_i(t) = Z_{i,1}(t) + Z_{i,2}(t) + \cdots Z_{i,D}(t) \quad (7)$$

For each target vector $Z_i(t)$, a trial vector $R_i(t)$is created in the following fashion:

$$R_{i,j}(t) = \begin{cases} Y_{i,j}(t)\ if\ r\ and\ j\ (0,1) \le Cr\ or\ j = rn(i) \\ Z_{i,j}(t);\ otherwise \end{cases} \quad (8)$$

Finally, 'selection' is performed in order to determine which one between the target vector and trial vector will survive in the next generation i.e. at time *t=t+1*. If the trial vector yields a better value of the fitness function, it replaces its target vector in the next generation; otherwise the parent is retained in the population.

D.Cuckoo Search Algorithm

This is the algorithm Cuckoo Search (CS) used for multilevel thresholds which is given below[16];

Step 1: The CS algorithm produces a randomly distributed initial population of N solutions (nests) $xi\ \ (i = 1,2, \dots N)$with K dimensions denoted by matrix X, (Generate initial solution population).

$$X = [x_1, x_2, \dots x_N] \text{ and } x_i = [x_{i1}, x_{i2}, \dots x_{iK}] \quad (9)$$

where x_{ij} is the j[th] component value that is restricted into $[0, \dots L-1]$ and the $x_{ij} < x_{ij}$+1 for all j.

Objective function values of all solutions are evaluated and period = 1 is set. The CS algorithm detects the most efficient solution prior to beginning an iterative search process.

Step 2: (Calculate the new population)

Calculate matrix of new solutions V for each solution in the search population X using the Eq. (9). For each solution $v_i\ \ i = (1, 2, \dots N)$ evaluate the objective function values. If the objective function value of the new one (v_i) is higher than that of the previous one (x_i), memorize the new solution and forget about the old solution. If not, it preserves the old solution.

Step 3: (Record the best solution)

Memorize the best solution so far (x_{best}), i.e. the solution vector with the highest objective function value.

Step 4. (Fraction p_α of worse nests are abandoned and new nests are being built) Apply the crossover operator on each solution xi in the search population by;

$$vi = \begin{cases} x_i + rand.(x_{ip1} - x_{ip2}), if\ rand_i > p_\alpha \\ x_i, \quad Otherwise \end{cases} \quad (10)$$

where rand is random number in [0,1] range, p_1 and p_2 are different rows permutation functions applied on nests matrix.

Step 5. (Record the best solution) memorize the new solution so far (x_{best}), and forget about the old solution, and add the cycle one by one.

Step 6. (Check the termination criterion) When the process is equal to the maximum number of iterations, the algorithm execution is completed, else jump to the Step 2.

The above algorithms are employed in multilevel thresholding of the original grayscale image. The following section gives the results of multilevel thresholding and morphological segmentation.

V. RESULTS AND DISCUSSION

For evaluating the proposed method of segmentation, 160 white chali arecanut images are selected from the database consisting of 5862 images.

The images are selected with more emphasis on low contrast, and are manually segmented for the purpose of evaluating the segmentation performance. The shape features such as major axis, area, equidiameter , minor axis, Eccentricity, Extent, Solidity, Convex Area, Perimeter, Roundness and Complexity are extracted from the ground truth masks and are stored in the database.

The procedure followed in this work is illustrated by considering an example as follows. Fig. 5 (a) shows an original image and the corresponding five level thresholded image is shown in Fig.5(b). In this example, the multilevel thresholding is performed using CS algorithm.

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Fig. 6 shows the histogram of original grayscale image with four threshold values obtained by using five level thresholding of image shown in Fig. 5(a). The performance of morphological segmentation depends upon the proper selection of the threshold for binarization. The image shown in Fig. 5(a) is converted grayscale and edge threshold is determined using Sobel edge detector. Now this threshold value is fine-tuned using four threshold values obtained from multilevel thresholding of the original grayscale image. This results in four distinct thresholds. Now

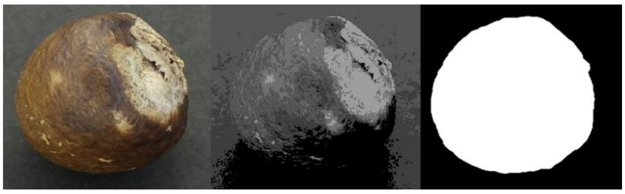


Fig. 5 (a) Original Image (Left) (b) Five Level Thresholded Image (Middle) (c) Ground Truth Image (Right)

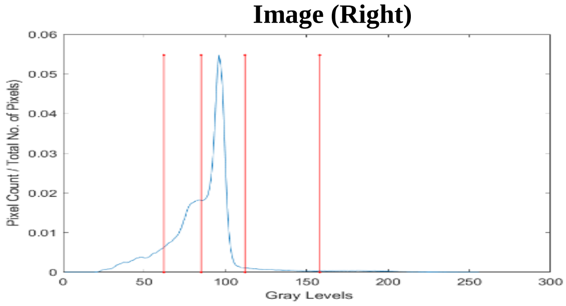


Fig.6. Image Histogram and Multi thresholds using CS Algorithm with N=5

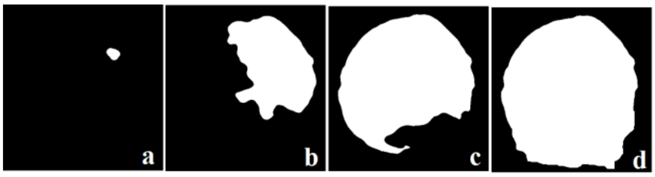


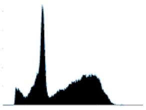
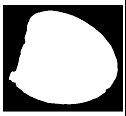
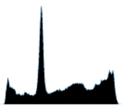
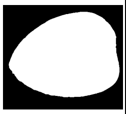
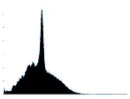
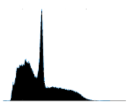
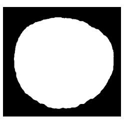
Fig.7. Segmented Mask with (a) Th=0.2431 (b) Th=0.3333 (c) Th=0.4392 (d) Th=0.6196

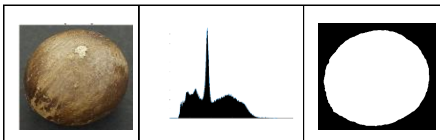
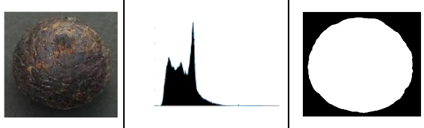
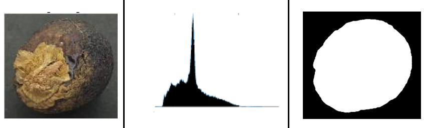
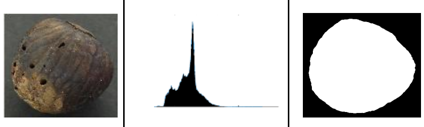
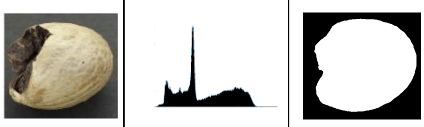
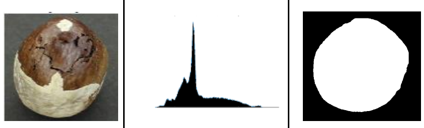
the morphological segmentation of original image is done separately with these four threshold values. The resulting masks are as shown in Fig.7.

In the next step, the shape parameters of these segmented mask are determined and fed to a network trained by using shape parameters of the ground truth masks. This trained network outputs the best possible figure ground mask as the result of segmentation. In the selected example Fig.7 (c) is the best figure ground mask with threshold Th=0.4392.

Now for the purpose of evaluating multilevel thresholding algorithms used for fine-tuning the edge threshold, segmentation performances such as precision, recall and F score are evaluated using corresponding ground truth masks. The experimental result reveals that the multilevel thresholding using Differential Evolution and Cuckoo Search algorithms yield most favorable results for fine-tuning the edge threshold. Table I shows the results obtained for some of candidates of the dataset.

Table- I: Comparison of Segmentation Results

Image	Histogram	Ground Truth	Performance Metrics	Performance for the Best Threshold Value of each Algorithm				
				Otsu	FCM	HS	DE	CS
			Precision	0.9006	1	1	1	1
			Recall	0.9807	1	1	1	1
			F-Score	0.9389	1	1	1	1
			Precision	0.7172	0.7192	0.8087	0.8202	**0.8449**
			Recall	0.7218	0.7504	0.7976	0.8133	**0.8441**
			F-Score	0.7195	0.7345	0.8031	0.8168	**0.8445**
			Precision	0.4677	0.9265	0.9345	**1**	**1**
			Recall	0.5724	0.9689	0.9697	**1**	**1**
			F-Score	0.5148	0.9472	0.9517	**1**	**1**
			Precision	0.6449	0.5692	0.6449	**0.7640**	0.7149
			Recall	0.6341	0.5696	0.6350	**0.7521**	0.7037
			F-Score	0.6395	0.5694	0.6399	**0.7580**	0.7093

	Precision	0.6279	0.5152	0.6449	**0.7755**	**0.7755**
	Recall	0.6184	0.5080	0.6276	**0.7824**	**0.7824**
	F-Score	0.6231	0.5115	0.6361	**0.7789**	**0.7789**
	Precision	0.5428	0.6188	0.8987	**0.9925**	0.9875
	Recall	0.6102	0.6628	0.9124	**0.9958**	0.9917
	F-Score	0.5745	0.6400	0.9055	**0.9942**	0.9896
	Precision	0.6070	0.5150	0.6095	0.8210	**0.8328**
	Recall	0.6713	0.5458	0.6713	0.8128	**0.8406**
	F-Score	0.6376	0.5299	0.6389	0.8168	**0.8367**
	Precision	0.4877	0.5151	0.6057	0.9937	**1**
	Recall	0.6352	0.6765	0.7439	1	**1**
	F-Score	0.5517	0.5849	0.6677	0.9969	**1**
	Precision	0.8360	0.9303	0.8553	**0.9448**	0.9320
	Recall	0.9024	0.9480	0.9165	**0.9551**	0.9504
	F-Score	0.8679	0.9391	0.8849	**0.9500**	0.9411
	Precision	0.5456	0.8818	0.7691	0.9160	**0.9593**
	Recall	0.6798	0.8967	0.7848	0.9231	**0.9650**
	F-Score	0.6054	0.8892	0.7769	0.9196	**0.9622**

VI. CONCLUSION

In this paper, the automatic segmentation of low contrasts white chali arecanut images is carried out using morphological segmentation. The determination of threshold for edge detection in morphological segmentation is a key point in enhancing segmentation performance. This threshold value is computed by using Sobel edge detector and multilevel thresholding of original grayscale image. Making use of Differential Evolution and Cuckoo Search algorithms for multilevel thresholding gives better results for automatic morphological segmentation of white chali arecanut images. By the inference of the results, this method can be extended for the segmentation of low contrast images of similar species.

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