Detection Of Affected Regions Of Disease Arecanut Using K-Means And Otsu Method

S Siddesha, S K Niranjan

Abstract: This work presents a disease detection model to detect and identify affected Arecanut using K-Means and Otsu method. This approach has two steps; preprocessing and disease detection. In preprocessing the arecanut image is segmented from the background to remove shadow effects using color K-means clustering. In disease detection, RGB image is converted to monochrome using Otsu thresholding. Then the affected regions on the Arecanut is marked using connected components approach. We used our own dataset of 50 disease affected arecanut images to carry out the experimentation.

Index Terms: Detection, Disease, Arecanut, Segmentation, K-Means, Threshold, Otsu method.

1 INTRODUCTION

Agriculture is the most important occupation of the human kind as it provides food for the livelihood. To provide the quality food is of very much essential in the current scenario. Maintenance of crops quality in the post harvest condition is challenging process. Storing crops for some time is crucial for farmers to get appropriate price in the market. In this process there might be a chance of disease attack due to different weather and environmental conditions. Detection of disease affected crop in the early stage can avoid the spreading of disease due to fungal infection or mite attack, otherwise this leads to poor quality and loses its value in the market. Manual detection of affected crops is very laborious and cumbersome and may sometimes end up with wrong decision. To overcome this there is a need of machine vision techniques in food industry. There have been several works reported on machine vision techniques for crop quality inspection. A review work was reported on enhancing the food product quality using image processing methods for different products like cereal grains, vegetables and fruits. The factors considered here are shape, size, color and the blemishes on the surface [1]. Another review work reported on importance of image features like color, shape, size and texture in the quality assessment of different variety of vegetables and fruits along with meat and dairy products [2]. In another work, the critical need of machine vision system for quality of food and crops and the full advantage of machine vision with the challenges in detection and recognition were reported [3]. The other review highlights the need of machine vision techniques for contamination detection in food like meat, cereal, fruit and vegetables using different technique viz., preprocessing, segmentation, data reduction and classification [4]. A work which reviews the different advancement in computer vision and applications of it in outer part inspection of vegetables and fruits, they discussed about the hardware set to capture the external surface defects in fruits and vegetables [5].

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A work on recent approaches of machine learning is reported, which concentrates on the model for disease detection and classification of agriculture products with basic steps from image acquisition to disease recognition [6]. Disease detection in crop is a major setback in attaining quality, there are several work reported on different plant, vegetable and fruits diseases. In one of the review work, advanced imaging techniques of electronics like fluorescence, hyper spectral, infrared and x-ray for plant disease detection was reported [7]. There are many works reported which mainly used machine vision techniques for disease detection, few important works are, A work was reported for identification of diseases in apple fruit, the model consists of three steps, segmentation using K-means, feature extraction and classified apples with disease from normal using multi class SVM classifier [8]. Another approach was reported for detecting disease in pomegranate using color, external surface as features and K-Means for segmenting the disease parts, finally infected fruits were classified from non infected one using SVM [9]. A SVM based disease detection in tomato leaves reported using color, shape and texture features for differentiating the infected leaves from normal [10]. A system for detecting the fungal disease in cereals, fruits, vegetables and commercial crops was built applying different image processing methods [11]. A computer vision method was formulated to detect the maturity of fruit and disease in leaf of tomato using thresholding, k-means techniques[12] . Also on works on disease detection in cucumber using artificial neural networks [13], pomegranate using k-means, SVM [14], apple using color k-means segmentation method[15] , papaya using k-means and SVM [16] was reported. A review work on disease detection of leaf, root and stem of different crops was reported[17]. Only very few works were reported on arecanut disease detection. A work reported on detection and classification of diseased arecanut with normal one, different texture features like wavelets, GLCM, LBP and Gabor filters used on HSI and YCbCr color models of arecanut image with K-NN for classification [18]. Another work was done for classifying and detecting arecanut disease using HSV color model, the work focused on classifying the infected arecanut considering boiled and non boiled classes [25]. All the above work focused on detection and classifying the disease affected from the healthy nuts, no work has been reported on affected regions of the disease arecanut. In our work, we employed pure detection of affected regions of disease arecanut image.

2 PROPOSED MODEL

In our work, we employed only detection of diseases from the arecanut image. The proposed model is shown in Fig. 1.

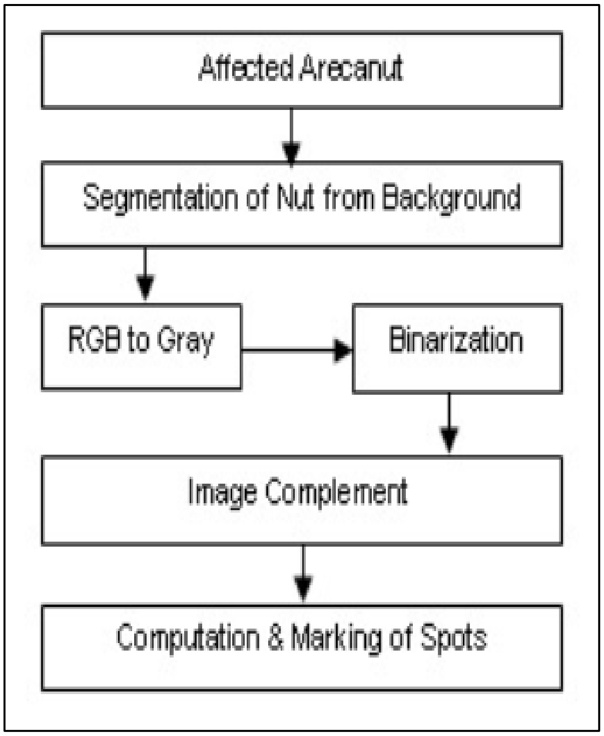

Fig.1. *Proposed model for affected arecanut detection*

2.1 Segmentation

A image has to be divided to sub images or parts to capture vital information for further work. This process is known as segmentation and is one of the challenging task of image processing. This is carried considering two basic things of image pixel intensities similarity and disconnection [19]. Here, segmentation is carried out to extract the foreground, the arecanut image from the background. We used K-Means clustering method for foreground extraction.

K-Means Clustering

Is a low level image segmentation techniques unsupervised in nature and is most widely used technique. This creates a given number of partitions which suites to global partitions that are non hierarchical. This algorithm works without intervention and focuses in clubbing the partitions using the clusters created initially by the user [20]. This separates the images based on their complex color texture [21].

2.2 Thresholding

Thresholding is a partitioning technique for dividing an image into sub parts by considering the intensity values. If T is a threshold for a partition of an image, all pixels whose value is greater than T the that pixel is added to the foreground part else it will be added to a background [22].

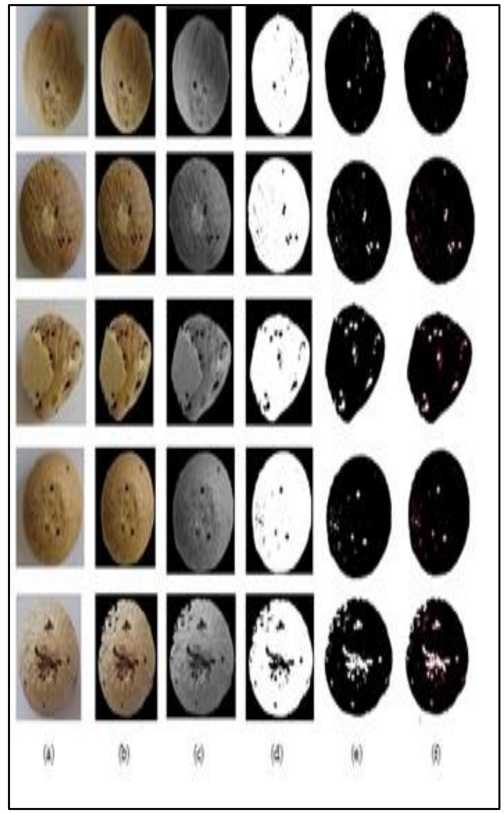

Fig. 2*. Different operations on defective arecanut images*
(a) RGB image (b) Segmented image (K-Means) (c) Gray image
(d) Binary image (Otsu) (e) Complemented image (f) affected region

Otsu method

This method has used frequently in defect detection tasks. This methods is mainly working on the concept of thresholding. A 2D gray image is a function $f(x,y)$ having the gray level varies from $0 \; to \; L-1$ with L number of unique gray levels. Let n_i be the number of pixels with i gray levels and n is the total pixels of the image, the probability of gray level occurrence i is given by,

$$prob_i = \frac{n_i}{n} \tag{1}$$

Average gray level of the image is calculated as,

$M_T = \sum_{i=0}^{L-1} iprob_i$, For a single thresholding the image pixels are of two classes $P_1 = \{0,1,....,t\} \; and \; P_2 = \{t+1, t+2, ..., L-1\}$, t is the threshold value. P_1 and P_2 represents the foreground and background. The probability of these two are,

$$C_1(t) = \sum_{t=0}^{t} prob_i \; and \; \mathrm{C}_2(\mathrm{t}) = \sum_{i=t+1}^{L-1} prob_i \tag{2}$$

Mean gray value of the above classes is given by,

$$M_1(t) = \sum_{i=0}^{t} iprob_i \,/\, C_1(t) \; and \; M_2(t) = \sum iprob_i \,/\, C_2(t)$$

(3)

Optimal threshold is given by[23],

$$t^{op} = \underset{0 \le t < L}{Arg\ Max} \left\{ \sigma_B^2(t) \right\}$$

(4)

The variance between classes σ_B is given as,

$$\sigma_B^2(t) = C_1(t)(M_1(t) - M_T)^2 + C_2(t)(M_2(t) - M_T)^2$$

(5)

Multilevel thresholding for $K-1$ of a image with K classes, i.e., $P_1 \cdots P_M$, the optimal thresholds $\{t_1^{op}, t_2^{op}, t_3^{op}, \ldots\ldots t_{K-1}^{op}\}$ are selected to maximize the variance between the classes is [23],

$$\{t_1^{op}, t_2^{op}, t_3^{op}, \ldots\ldots t_{K-1}^{op}\} = \underset{0 \le t_1 < \ldots\ldots < t_{K-1} < L}{Arg\ Max} \left\{ \sum_{j=1}^{K} C_j M_j^2 \right\}$$

(6)

For defect detection applications, Otsu method will work fine when defects are from small to large [24].

3 DATASET AND EXPERIMENTATION

For detecting the arecanut disease, we created our own disease arecanut image dataset by capturing pictures using Nikon cool pix digital camera with half meter distance. The disease arecanut images were collected from the place Sagar and Chennagiri of Shimoga district, Karnataka state in India. These images were captured under the supervision of expert arecanut stockiest. The arecanut which are infected from mites were considered for preparing the dataset. The dataset contains 50 disease affected arecanut images to conduct this experiment. The captured RGB images were kept in a folder and Color K-Means clustering algorithm with k=3 executed on these images and the output is stored in another folder, then all these images were converted to gray. These gray images were fed to Otsu threshold method and the output binary images were stored and then it gets complemented to highlight the affected spots from the arecanut images. Finally the affected sports were marked using connected component technique. The performance of this model is evaluated by counting the number of spots in the RGB image and then counting the number of spots detected in the marked images. With these information precision, recall and f-measure for this model is computed using,

$$PRECISION = \frac{Truely\ Detected\ spots}{Truely\ Detected\ spots + Non\ True\ Detected\ as\ True}$$

(7)

$$RECALL = \frac{Truely\ Detected\ spots}{Truely\ Detected\ spots + True\ Detected\ as\ Non\ True}$$

(8)

$$f - measure = \frac{2 * (PRECISION * RECALL)}{PRECISION + RECALL}$$

(9)

and the results are tabulated in the Table 1.

TABLE 1

Precision, Recall and F-measure of 50 images

Images	Total Spots	TP	FP	FN	Precision	Recall	F-Measure
1	9	10	1	0	0.91	1.00	0.95
2	10	13	2	1	0.87	0.93	0.90
3	7	18	8	1	0.69	0.95	0.80
4	11	19	8	1	0.70	0.95	0.81
5	19	24	5	1	0.83	0.96	0.89
6	20	23	3	0	0.88	1.00	0.94
7	13	14	1	1	0.93	0.93	0.93
8	15	15	0	0	1.00	1.00	1.00
9	8	10	2	1	0.83	0.91	0.87
10	10	13	2	1	0.87	0.93	0.90
11	20	22	2	0	0.92	1.00	0.96
12	12	14	2	1	0.88	0.93	0.90
13	34	36	2	0	0.95	1.00	0.97
14	8	9	1	0	0.90	1.00	0.95
15	9	10	1	0	0.91	1.00	0.95
16	12	14	2	0	0.88	1.00	0.93
17	20	25	4	1	0.86	0.96	0.91
18	13	11	0	2	1.00	0.85	0.92
19	12	13	1	0	0.93	1.00	0.96
20	13	9	0	4	1.00	0.69	0.82
21	31	37	5	1	0.88	0.97	0.93
22	8	14	4	2	0.78	0.88	0.82
23	14	19	5	0	0.79	1.00	0.88
24	9	12	3	0	0.80	1.00	0.89
25	9	14	5	0	0.74	1.00	0.85
26	8	7	1	1	0.88	0.88	0.88
27	17	19	2	0	0.90	1.00	0.95
28	11	16	5	0	0.76	1.00	0.86
29	12	14	2	0	0.88	1.00	0.93
30	21	26	5	0	0.84	1.00	0.91
31	18	23	5	0	0.82	1.00	0.90
32	19	22	3	0	0.88	1.00	0.94
33	19	23	4	0	0.85	1.00	0.92
34	7	7	0	0	1.00	1.00	1.00
35	10	11	1	0	0.92	1.00	0.96
36	18	25	7	0	0.78	1.00	0.88
37	13	15	2	0	0.88	1.00	0.94
38	29	30	1	0	0.97	1.00	0.98
39	14	19	5	0	0.79	1.00	0.88
40	10	14	3	1	0.82	0.93	0.88
41	11	14	3	0	0.82	1.00	0.90
42	16	22	5	1	0.81	0.96	0.88
43	10	8	1	1	0.89	0.89	0.89
44	8	9	1	0	0.90	1.00	0.95
45	8	10	2	0	0.83	1.00	0.91
46	7	9	2	0	0.82	1.00	0.90
47	32	37	5	0	0.88	1.00	0.94
48	8	11	3	0	0.79	1.00	0.88
49	7	12	5	0	0.71	1.00	0.83
50	10	13	3	0	0.81	1.00	0.90
Average					0.86	0.97	0.91

The average precision, recall and f-measure obtained for the model is 0.86, 0.99 and 0.91 respectively and results are shown and the graphical representation of corresponding average results for 10 images are for are shown in Fig. 3.

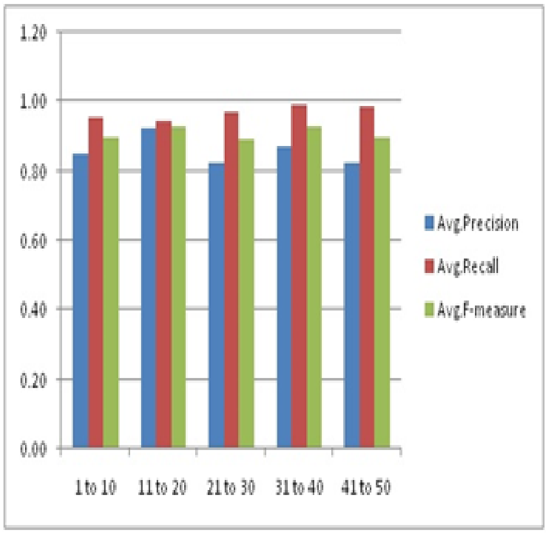

Fig.3. *Average Precision, Recall and F-measure for 10 images.*

4. CONCLUSION

This work focus on detection of affected region from a infected arecanut image. Experimentation is conducted on a infected arecanut image dataset of 50 images. K-means clustering is used for segmentation of foreground from background. Otsu method is employed to detect the affected region of the arecanut image. Further this work could be enhanced with other segmentation techniques using different features. The performance of the proposed model is quote good with the theoretical approach. Further the same can be tested for a real time scenario with live disease detection of arecanut in different environment.

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