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Detection of Mite Disease and Computation of Affected Area in Raw Coconut

S. Siddesha[1] and S. K. Niranjan[2]
[1]Assistant Professor, Department of Computer Applications,
JSS Science and Technology University, Mysuru, Karnataka, India.
[2]Professor, Department of Computer Applications,
JSS Science and Technology University, Mysuru, Karnataka, India.

(Corresponding author: S. Siddesha)
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ABSTRACT: Coconut is one of the versatile plantation crop of India. It has a very special role in Indian tradition and culture. Each and every part of coconut plant is useful for various purposes. The mite disease in one of the dangerous disease in coconut, it will reduce the yield and lead to poor quality of nuts. Early detection of mite attack will reduce the risk of low yield and avoid spreading of disease to other plants. Computation of affected area is a challenging task as it plays a major role in quality assessment. This work focused on detecting and computing the disease area of raw coconut. In this work we built a model to detect disease part on the raw coconut and compute the percentage of area affected. We used K-means clustering and Color Threshold algorithm to detect and extract the region of interest. Among these K -means gave good result. Computation of the area of affected region is carried out using pixel arithmetic operations on original image and the segmented images.

Keywords: Coconut, Disease detection, Segmentation, K-means clustering, performance measures, affected area computation.

Abbreviations: RoI, Region of Interest; JM, Jaccard Measure; DM, Dice Measure; RMSE, Root Mean Square Error; RI, Random Index, GCE, Global Consistency Error; VoI, Variation of Information.

I. INTRODUCTION

Coconut is the prime plantation crop of India. It plays an important role in every Indian's day to day life with different forms. Coconut is a part of the Indian culture and tradition. This is the prime source for various food recipes. Coconut is used in many forms like, tender coconut is very nutritious and used as a health drink, matured nuts are used in day to day food preparation and fully matured and seasoned nuts known as copra used for extraction of oil and in different sweets preparation. Other parts of the coconut plants are useful in different purposes like coir making, for shelter, as a fuel etc. In general, each and every part of the coconut is very useful. This provides employment in the rural and urban parts. These reasons make coconut as an in demand crop throughout the year. India ranks third among various countries of the world in producing of coconut crop.

Every crop suffers with different diseases in the nursery level or at the time of growth or in post harvest conditions. Crop affected with disease, reduces the quality of the crop in the market and it has bad impact on the socio economic condition of the small and medium level farmers [1].

The mite disease in coconut had a severe impact on the livelihood of farmers of Africa by incurring a loss of more than 30% of their regular income. This made the farmers to rely on other crops due to the negative impact of mite disease in coconut. Due to the diversification of other crops make the yield of coconut to fall down [2]. The disease affects because of various reasons like deficiency of nutrients in the soils, due to bacterial, fungal infection [3], because of insect and mite attacks. But the major loss of the crop is due to the mite attack on the nuts. There are seven species of mites which severely attack coconut fruit. Among these seven mite, the *Aceria guerreronis Keifer* mite is creating a major loss in many countries. The mites pierce the superficial nut and sucks the juices. This is having a very bad impact on the coconut when it matures. The impact of coconut mite is not specific any country, it's a global issue and these impacts were discussed in detail [28].

Detection of diseases at the early stage helps farmers in segregation of the disease crops from the healthy crops for avoidance of spreading of diseases. Manual disease detection when dealing with large amount of coconut suffers with wrong decision making and this will have an impact on quality maintenance.

II. EXISTING WORK

Few review works have been highlighted different image processing and machine learning approaches and their need for crop and food quality assessment [4-6]. Disease detection using machine vision and machine learning technologies provides a great support to farmers in maintenance of quality which helps in getting a good price for the crop in the market [7, 8]. The main features like color, shape and texture are extracted from the surface of the crop considered to carry out the disease detection, classification and these are the major tasks in agricultural inspection and quality assessment [9-11].

Several works have been reported in the literature on disease detection on various crops. A web based tool was proposed for identifying diseases in Pomegranate fruit, the infected part was extracted using features like CCV color, boundary, the infected part is segmented using K-mean clustering and then the fruits were classified into infected and non infected using SVM classifier [12]. A similar work reported on pomegranate disease detection by segmenting the fruit surface using K-means and threshold technique. The wavelet features of the segmented part was extracted and SVM classifier is used to classify different diseases [13].
A approach was reported to disease infected leaves of tomato. The texture feature of leaf image was extracted using GLCM features, then it was classified for leaf state health or un healthy using support vector classifier [14]. In another work, maturity of tomato fruit and fungal infection of its leaves are determined. The maturity of the fruit was detected using thresholding technique then the fungal disease on the leaf was segmented using K-means segmentation algorithm. As a final step the area of infection was analyzed [15]. A grading system was proposed to grade tomato into infected and non infected based on the fruit calyx and stalk. Histogram features were extracted using mean green and red values of a RGB image. The extracted features were used for classification using SVM with RBF kernel function [16].
A system was proposed, for the disease diagnosis in case of cucumber leaves, GLCM and color moments features were extracted and then neural network classifier is used for diagnosing healthy and disease leaves, based on the diagnosis, system suggests respective treatment [17]. In another work, color of the apple image is used for segmentation of disease part. Then median filter was applied to enhance the disease part [18].
An online system was proposed that will capture the papaya fruit image from handheld device and K means clustering was applied to segment disease part from the image. GLCM Texture feature and color feature moments features were extracted from the segmented image and these features were used for classifying different disease of papaya using SVM [19].
Most of the work reported used classification techniques. Only few works are on pure disease detection and disease area computation.
Only fragmentary works have been found in the literature on the coconut crop. A study was done to classify the land cover area of coconut crop in Kasaragod district of Kerala state. Spectral Mixture Analysis technique was used for the experimentation [20]. Only very few work are reported on the disease detection of coconut crop, which classifies the leaf rot disease affected coconut leaves using neural network [21]. A expert system was developed for diagnosis of different coconut diseases in leaf, stem, bud and root part of coconut tree [22].
No work was reported in disease detection on the surface of the nut.
In this work we propose a model which extracts the disease part from the coconut fruit and computes the percentage of disease affected area. Computation of the disease area is important in quality assessment of the coconut in the market. Base on the percentage of infected area, coconuts are used for different purposes. If the disease area is moderate, the coconuts are rejected for its primary uses like, as a drink, food preparation and these nut are used for oil extraction after drying for 8 to 10 months.

III. MATERIALS AND METHODS

The proposed work mainly has two steps, in the first step, the disease affected part from the coconut is extracted using segmentation methods and the second step computes the percentage of disease affected on the coconut. The model is shown is Fig. 1.

Input disease Coconut image
↓
Extraction of disease part
↓
Calculate area of full image
↓
Calculate the disease area
↓
Compute the percentage of affected area

Fig. 1. Proposed model.

For extraction of the disease part from the coconut, we used color k-means and color threshold segmentation technique. Three clusters are used for addressing the background, foreground and the region of interest (RoI). Here the disease affected part is the RoI and color is used as the feature for creation of cluster. The disease part will have entirely different color compared to the surface color of the coconut.
Any computer vision experiment is performed with image or video data. Without image data none of the CV model can be built. There are no disease image data available for coconut crop. To perform the experiments we created our own dataset of 100 disease coconut image. The sample images are shown in Fig. 2.

Fig. 2. Sample disease coconut images.

A. Segmentation
Segmentation is the process of portioning the image into sub parts for further processing [23]. This is one of the challenging task of image processing. Color image

segmentation is carried out using differentiation of colors present in the image. Generally it groups the pixels which are of similar color intensities [24].

K-Means Clustering: Is a well known unsupervised clustering technique divides the sample observations in to different number of parts known as clusters [25]. Each observation is a part of cluster having similar or nearly similar mean value [26].

The sample observations are given by,

$$x_1,\ x_2,\ldots\ldots\ x_m \qquad (1)$$

After grouping the above observation into k sets given by,

$$N = (N_1,\ N_2,\ldots\ldots\ldots N_k) \qquad (2)$$

these sets must satisfy the minimum of sum of errors given by,

$$\arg\min_{N} \sum_{i=1}^{k} \sum_{x_j \in N_i} \left\| x_j - v_i \right\|$$

(3) v_i - is the mean of value of N_j. N_j .

K-means technique is iterative in nature and it has two steps [22],

Step 1: Initialization - here each and every observation is put into the cluster based on the nearest mean value and is given by,

$$N_i^t = \left\{ x_j : \left\| x_j - m_i^t \right\| \le \left\| x_j - m_{i^*}^t \right\| \forall i^* = 1, 2, \ldots k \right\} \qquad (4)$$

for a given initial state of K-means $m_1^1, m_2^1, \ldots.. m_k^1$.

Step 2: Updation: In this step, a new mean is calculate and this will be a centroid for the observation of the cluster given by,

$$m_i^{t+1} = \frac{1}{\left| N_i^t \right|} \sum_{x_j \in N_i^t} x_j \qquad (5)$$

The initialization and updation steps are repeated till the pre-specified threshold is reached.

Color Thresholding: Color thresholding is a simple but effective segmentation technique. It divides an image in to a number of parts based on the high similarity and high contrast color pixels between parts. For a RGB color image, three color histograms will be created with minimum and maximum threshold values of Red, Green and Blue color. Segmentation is done based on variations in the color with the threshold values of different parts in the image [29].

B. Computation of affected area

After the segmentation, next step is to compute the affected area of the coconut. This is computed as follows. The color image in RGB color space before segmentation is given by I_{bef}, the size of this image is computed by,

$$[m, n, o] = \text{size of}(I_{bef}) \qquad (6)$$

Total area (pixels) of image I_{bef}, are calculate by

$$P_{Tbef} = m \times n \times o \qquad (7)$$

Total background area (pixels white) of I_{bef} is calculated by

$$P_{Wbef} = \text{Sum}(I_{bef}(:) = 255) \qquad (8)$$

Total fore ground area (pixels) of I_{bef} is computed by

$$P_{Bforg} = P_{Tbef} - P_{Wbef} \qquad (9)$$

Now we have to find the area of disease affected part or segmented image I_{aft}, Total area (pixels) of image I_{aft}, the size of this image is computed by

$$[p, q, r] = \text{size of}(I_{aft}) \qquad (10)$$

Total area (pixels) of image I_{aft}, are calculate by

$$P_{Taft} = p \times q \times r \qquad (11)$$

Total background area (pixels white) of I_{aft} is calculated by

$$P_{Waft} = \text{Sum}\ (I_{aft}\ (:) = 255) \qquad (12)$$

Total fore ground area (pixels) of I_{aft} is computed by,

$$P_{Aforg} = P_{Taft} - P_{Waft} \qquad (13)$$

Total percentage area of affected region of the coconut is computed using,

$$P_{dis} = \left(\frac{P_{Aforg}}{P_{Bforg}} \right) \times 100 \qquad (14)$$

IV. RESULTS AND DISCUSSION

The disease affected coconut image is segmented using K-means clustering and color threshold techniques, the segmentation is carried out to extract the disease affected region from the coconut image. We created 3 clusters, each cluster for background, foreground and region of interest. Here foreground is healthy area, and disease area is the region of interest.

The performance of the K-means and Color Threshold technique is validated in comparison with manual segmentation i.e. the ground truth image. Using different statistical measures, correlation, Jaccard measure (JM), Dice measure (DC), Root mean square error (RMSE), Random index (RI), Global consistency error (GCE) and Variation of Information (VoI) [27].

Correlation is a effective measure for pattern matching between two images. The measure is in the range -1 to+1, the result approaches towards +1 for good quality of segmentation.

Fig. 3. Manual, K-Means and Threshold segmented images.

Jaccard measure (JM) is between 0 to 1, 1 means the images are identical, 0 means both sets are not identical. Dice measure (DM) also measures the quality of segmentation and its value also ranges from 0 to 1, 1 means the result is a perfect match with ground truth and 0 means not. Root Mean Square Error (RMSE) is a quality measure of the image, higher MSE value indicates the poor and lower MSE indicates the good quality of segmentation. Random index (RI) is measures the quality index between the clusters, this is also in range of 0 to 1, with 1 as full agreement and 0 for disagreement. Global Consistency Error (GCE) measures segmentation of one with other as refinement, if one segmented area is a subset of other leads the error as 0. Values towards 0 is the indication of best segmentation. Variation of Information (VoI) measures the randomness in one segment with the other. The images are converted to binary image and validated using the above measures. The results are tabulated in Table 1. In the second step, the segmented image of disease affected region of the coconut using K Means and Color Threshold is computed and the same is compared with the manual segmented disease affected area. The results of the five sample images are tabulated in Table 2.

From Table 1 and 2, it is evident that, K-Means segmentation performs well compared to Color Threshold method.

Table 1: Different Segmentation Performance measure for segmented sample images.

	K Means							Threshold						
Image	**Corr**	**JM**	**DM**	**RMSE**	**RI**	**GCE**	**VoI**	**Corr**	**JM**	**DM**	**RMSE**	**RI**	**GCE**	**VoI**
1	0.55	0.78	0.17	0.46	0.67	0.28	1.37	0 .53	0.71	0.12	0.53	0 .62	0.32	1.22
2	0.64	0.81	0.23	0.39	0.74	0.12	1.12	0.61	0.77	0.21	0.43	0.72	0.18	1.00
3	0.49	0.62	0.02	0.53	0.59	0.20	1.47	0.41	0.55	0.01	0.59	0.54	0.25	1.18
4	0.49	0.70	0.16	0.48	0.64	0.34	1.52	0.41	0.61	0.13	0.52	0.57	0.39	1.12
5	0.54	0.79	0.06	0.42	0.71	0.26	1.26	0.23	0.73	0.04	0.51	0.62	0.28	1.22

Table 2: Computation of percentage of affected regions of the coconut.

Image	**Total area of image with background**	**Total area of image only**	**Manual Segmentation**		**K Means Segmentation**		**Threshold Segmentation**	
			Disease area	**% of affected area**	**Disease area**	**% of affected area**	**Disease area**	**% of affected area**
1	486450	336011	232515	69.20	174567	51.95	166929	49.68
2	486450	374992	154673	41.25	210285	56.08	130215	34.72
3	486450	379697	278146	73.25	212571	55.98	206283	54.33
4	486450	389209	209870	53.92	231763	59.55	218070	56.03
5	486450	402327	170048	42.27	159890	39.74	103874	25.82

V. CONCLUSION

This work proposes a coconut mite disease detection and infected area computation model. The model has two parts segmentation of disease region and computation of infected. For segmentation, we used two methods K Mean clustering and Color Threshold. Among these two K Mean gave good result. This model is evaluated with a self created disease coconut image dataset of 100 images by comparing the manual segmented disease area with algorithmically segmented area. Even this model yields good result, same model need to be validated with a huge dataset of different disease infected coconut. Inspire of this, the model can be used in line at post harvest conditions like in quality inspection and marketing

VI. FUTURE SCOPE

From the result of this experimentation, even the model works fine for our dataset, still it can be improved with other segmentation techniques. Also the experiment can be conducted on a huge dataset of different disease coconuts using deep learning techniques. Current work is carried out on a theoretical set up, further this can be converted to portable using mobile technology on either Android or iOS platform.

Conflict of Interest. Nil.

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