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Arecanut Segregation System Using Local Binary Pattern and HOG Features

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***Abstract*— Agriculture is, doubtlessly, one of the most relevant fields that drive Indian economy. India produces diverse types of spices and seeds depending upon the different soil and climate conditions. India is also one among the cultivator of arecanut and much of its production happens in the coastal region. It is a tropical crop. There is a variation in the quality of arecanut that makes it classified into various types. The arecanut classification and segregation is necessary, basically segregation is done manually which consumes much time, more effort and more error prone. This paper proposes an automatized approach of classification and segregation using hardware and digital image processing.**

***Index Terms*— Arecanut, agriculture, image processing, local binary pattern, Respberry Pi**

I. INTRODUCTION

For a development of country Agriculture plays a important role in socioeconomic. It is a backbone of Indian economy contributing eighteen and half percent of the gross domestic product (GDP). Over sixty percent of India's land is suitable for agriculture, which makes India the second largest country for having vast agricultural land. About fifty percent of Indian population dwells home using agriculture as profession [1][2].Identifying the product and its quality is one of the most significant and challenging tasks for the machines. The classification and grading techniques used by the human for different fruits and vegetables fully rely on human efforts.

The classification and grading techniques that we do The manual grading and classification techniques that we do, for segregation of fruits and vegetables is fully depend upon human efforts. The manual techniques involves greater human intervention and also subjected to human errors, tiredness and require more man power. Hence the automated system is require to reduce the man power, process time and human errors system needs to be incorporated to minimize the work, reduce the errors. Hence we have proposed automatic segregation system for arecanut, which segregate different types of arecanuts and reduces the human effort, error and process time.

II. LITERATURE SURVEY

Arecanut popularly known as betel nut. It is believed that origin of the Areca nut was in Philippines or Malaysia. In Vietnam and Malaysia people use chewing the arecanut for 'stimulating' effect due to presence of the alkaloids. People in the other Asian countries started using it and now it is recognized as a cash crop [7].

There are many countries, which cultivate arecanut, among them are India, China, Burma, Indonesia, Myanmar and Bangladesh. India stand first in the production, where as China and Bangladesh takes the next place. In the year 2013-14 the production of Arecanut from an area of over nine and half lakh hectares in the world was over thirteen lakh tones. India's position is top in terms of area of cultivation of arecanut and its production. India produces fifty-four percent of the total arecanut production. China offers twenty percent of its total production and reserves five percent of its area for arecant. Bangladesh produces nine percentage of total production and the area it reserves is seventeen percentages. Indonesia produces fourteen percentage of total production and it reserves fourteen percentage in terms of area [8].

Machine vision applications of agriculture are briefly reviewed by Yud-Ren Chen et al [3]. To classify both raw and processed areca nuts the AjithDanthi & Suresha M proposed several techniques. Suresha M and AjithDanti [12] also proposed a technique Boiling and Non-boiling nuts classes. Here by converting RGB image the Arecanut YCBCR color space is obtained. For effective segmentation of Arecanuts the three sigma control limits on color features are obtained. SureshaM, AjithDanti and S K Narasimha Murthy [13] proposed a technique by using Haar wavelet to classify the Arecanuts. In this method feature extraction can be done using Wavelet decomposition.

Suresha M and AjithDanti[14] have also proposed a technique how to grade raw Arecanuts. Here for grading arecanut They used color as a main feature. Initially the threshold based segmentation algorithm is used for segmentation. To classify the Arecanuts Only red and green components are used In the segmented region, by suppressing the blue color components.

Suresha M and AjithDanti[15] have also proposed a technique based on texture features classification of Arecanut. Watershed segmentation is used to segment the Arecanut images. In the segmented regions GLCM features & Mean Around Features are extracted. Here for the

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classification of Arecanut used Decision tree classifier and the classification of six classes (Black Bette, Red Bette, Api, Chali, Gotu and Minne) is done.

Suresha M, AjithDanti and Narasimha Murthy S K[16] proposed a technique HSV images were obtained from respective RGB images for classification of Arecanut. Harish Naik T and SureshaM[17] proposed a technique which uses color features of components to classify raw Arecanut with husk in to various categories. At the stage of feature extraction here used HSV,RGB and YCbCr color spaces of Arecanut.

Kuo-Yi Huang[18] proposed a technique Bad, Good and Excellent 3 major categories are used to classify Arecanut. In his work defected Arecanuts with diseases or insects are segmented using detection line (DL) method. Siddesha S, S K Niranjan and V N Manjunath Aradya [19] proposed a differentiate color segmentation technique used for crop bunch in Arecanut. Thresholding Watershed segmentation, Fuzzy C Means (FCM), K-means clustering, Maximum Similarity based Region Merging and Fast Fuzzy C Means clustering (FFCM) color segmentation techniques are focused in their work.

Siddesha S, S K Niranjan and V N Manjunath Aradya[20] proposed the texture based grading of Arecanut. By using Gabor, Wavelet, LBP, Gray GLDM and GLCM features the different texture features are extracted for arecanut. Similar to Arecanut to grade and classify fruits, vegetables and seeds there are several technologies developed based on Color, Shape and Texture. Some of the important works are: R. Dinesh et al.[21] proposed a techniques for grading and sorting of fruits which used HSI model. Yousef Al Ohali [22] has proposed using computer vision based system for grading of dates. Hassan Sadrnia et al [23] proposed a technique to classify watermelon based on the shapes.

A. Classification of arecanut

India is the major producer of arecanut in global scenario. Tamil Nadu, Karnataka, Kerala, Assam, West Bengal and Meghalaya states are major contributor of arecanut in india.

Depending on different regions and countries arecanut are classified into various categories. According to their usage and needs several individual industries differentiate arecanut in different types. To determine types, class and grade used different features of arecanut such as color, Maturity, moisture content, texture, glossy appearance, size, weight, shape etc. Basically Arecanut is classified in to two main categories, that are, processed Arecanut(without husk) and raw Arecanut(with husk. Further raw arecanut is classified into 4 categories that is, Chali, Hasa, Bette and Gorabalu [2] as shown in figure 1. Chali is typical raw Arecanut which is dried and used after removing its outer shell. Hasa is costliest, less weighs and is a premature state of Arecanut. Bette is a transition state of nut between immature to mature Arecanut. Using color, hardness etc Gorabalu can be easily identified it is matured Arecanut [11]. Based on application the Processed Arecanut is classified into many types that is Hasa, Rash iIdi, Bette, Gorabalu and Chali. Further Gorabalu is classified in to 4 different categories, Rashi and Idi are classified in to 3 different categories and Hasa, Bette and Chali are again classified in to 7 of its categories [11].

Fig. 1. Classification of arecanut

III. ARECANUT SEGREGATION MACHINE

A. Operational Working

Arecanuts enter the machine in a queue and a plate properly designed collects them, one by one, with help of a servo motor. The motor rotates the plate in a way that areca nuts are carried to a position in which a sensor, that is a digital camera, is used to capture the arecanuts images and sends it to controlling and processing unit. Controlling and processing unit is the brain of our machine, it is a microcontroller that processes the image, compares it with those stored in the memory to classify the different types of arecanuts. After identifying the type of the nut being processed, controlling and processing will, then perform the segregation operation which is to control a motor attached to a structure in which the arecanut being processed is driven to the particular container assigned to its specific type. It is illustrated in block diagram of Fig, 2.

IV. Arecanut Recognition

The crucial part in the working of this project is the recognition of different types of arecanuts by the microcontroller. This process was designed using Open Source Computer Vision, shortly known as OpenCV, to enable our microcontroller to perform such operation and the code is written in Python. The process is summarized in the Fig 3, and, as can been seen it consists of three tasks, namely: data gathering, train the recognizer and recognition. In data gathering, the features of different arecanuts are captured by a camera to assign the identification of each type arecanuts. On the second phase, we must take all user data from our dataset and "train" the OpenCV Recognizer. This is done directly by a specific OpenCV function. The result will be a yml file that will be saved on a "trainer/" directory. In the last phase we capture a fresh nut on the camera and if this nut has its features captured and trained before, our recognizer will make a "prediction" returning its id and an index. This operation is done by using LBPH algorithm.

V. Local Binary Pattern

Local Binary Pattern (LBP) is a simple and efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. The LBP first introduced in 1994 and it is powerful feature for texture classification. When LBP is combined with histogram of oriented gradients (HOG) descriptor, which improves the detection performance considerably in some dataset and can be referred as LBPH.

Using the LBP combined with histograms we can represent the face images with a simple data vector. As LBP is a visual descriptor it can also be used for face recognition tasks, as can be seen in the following step-by-step explanation.

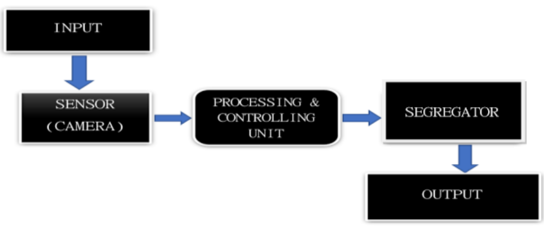

Fig. 2 Block Diagram.

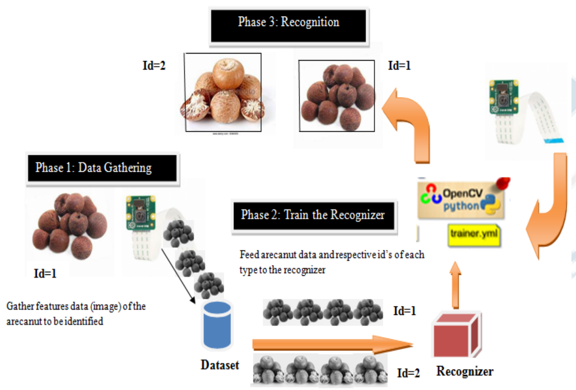

Fig. 3 Arecanut recognition operation.

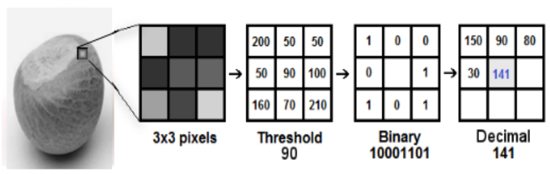

Fig. 4 Feature extraction

1. Parameters: the LBPH uses 4 parameters:

- **Neighbors**: the number of sample points to build the circular local binary pattern. Keep in mind: the more sample you include, the higher the computational cost. It is usually set to 8.
- **Radius**: the radius is used to build the circular local binary pattern and represents the radius around the central pixel. It is usually set to 1.
- **Grid X**: the number of cells in the horizontal direction. The more cells, the finer the grid, the higher the dimensionality of the resulting feature vector. It is usually set to 8.
- **Grid Y**: the number of cells in the vertical direction. The more cells, the finer the grid, the higher the dimensionality of the resulting feature vector. It is usually set to 8.

2. Training the Algorithm: First, we need to train the algorithm. To do so, we need to use a dataset with the images of the arecanut we want to recognize. We need to also set an ID for each image, so the algorithm will use this information to recognize an input image and give you an output. Images of the same arecanut type must have the same ID. With the training set already constructed, let's see the LBPH computational steps

3. Applying the LBP operation: Initially the LBPH is to By highlighting the nut characteristics it create an intermediate image to describes the original image in a better way,. To do so, the algorithm uses a concept of a sliding window, based on the parameters radius **and** neighbors. The procedure of LBPH given in following steps Based on the image shown in figure 3.

- Assuming gray scale image of arecanut.
- Get the windows of 3x3 pixels of this image.
- Then same window can be represented into 3x3 matrix with intensity of each pixels from 0 to 255.
- Then, find the central value of the matrix to be used as the threshold.
- This value will be used to define the new values for the 8 neighbors will be defined by this central value of matrix.
- For each neighbor of the central value (threshold), we set a new binary value. We set 1 for values equal or higher than the threshold and 0 for values lower than the threshold.
- Now, the matrix will contain only binary values (ignoring the central value). We need to concatenate each binary value from each position from the matrix line by line into a new binary value (e.g. 10001101). **Note:** some authors use other approaches to concatenate the binary values (e.g. clockwise direction), but the final result will be the same.
- Then, we convert this binary value to a decimal value and set it to the central value of the matrix, which is actually a pixel from the original image.
- At the end of this procedure, we have a new image which represents better the characteristics of the original image.

Based on the image above, we can extract the histogram of

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each region as follows:

- As we have an image in grayscale, each histogram (from each grid) will contain only 256 positions (0~255) representing the occurrences of each pixel intensity.
- Then, we need to concatenate each histogram to create a new and bigger histogram. Supposing we have 8x8 grids, we will have 8x8x256=16.384 positions in the final histogram. The final histogram represents the characteristics of the original image.

5. Performing the arecanut recognition: The already trained algorithm is used in this step. Each image from the training dataset represented is created by each histogram. So, we repeat steps again for this given an input image and create a histogram which represents the image.

- We need to compare two histograms to find the image which matches the input image.
- We can use various approaches to compare the histograms, for example: **euclidean distance**, **chi-square**, **absolute value**, etc. Here we are using the Euclidean distance using the following formula:

$$D = \sqrt{\sum_{i=1}^{n}(hist1_i - hist2_i)^2}$$

- We will get ID from the image with the closest histogram as algorithm output. The calculated distance is also return from algorithm which can be used as a '**confidence**' measurement.
- If the algorithm correctly recognized the image. We can then use a threshold and the 'confidence' to automatically estimate.
- if the confidence is lower than the threshold. We can assume that the algorithm has successfully recognized.

VI. Hardware Implementation

To design segregation machine we used Respberry Pi 3 and arduino uno. The Respberry Pi 3 is used for design the recognising the type of arecanut and give the output to Arduino uno which then handle the motors to separate the recognised type of arecanut from other types. The Respberry Pi 3 which has built in Broadcom BCM2837B0, Cortex-A53 (ARMv8) 64-bit, 1GB of SDRAM, USB 2.0, Extended 40-pin GPIO,CSI camera port for connecting a Raspberry Pi camera, DSI display port for connecting a Raspberry Pi touch screen display, 4-pole stereo output and composite video port, Micro SD port for loading your operating system and storing data, it require 5V/2.5A DC input power supply. The Arduino uno has built in ATmega328, 32Kb of flash memory and it required 5v power supply for operation. The experimental setup is shown in figure 6.

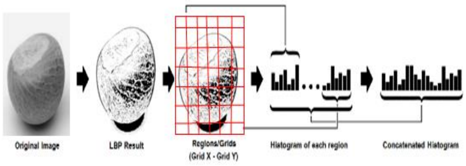

Fig. 5 Histogram extraction

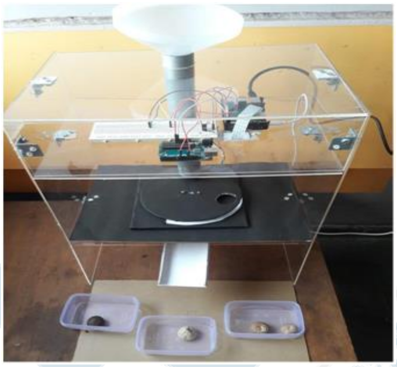

Fig. 6 Experimental setup for segregation machine

VII. RESULTS

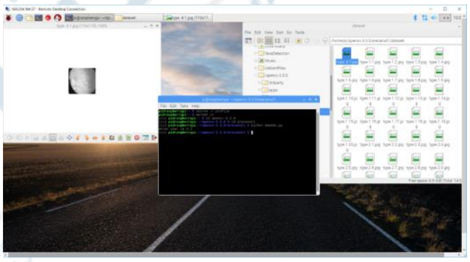

Fig. 7. Creating dataset

We designed the setup of arecanuts segregation machine for segregation of 3 kind of arecanuts which is shown in figure 6. The created data set for arecanut is given in snapshot of figure 7. Using a dataset with the images of the arecanut we want to recognize we set an ID for each image, using this information the algorithm recognizes an input image and gives an output. Images of the same arecanut type must have the same ID. Different types of arecanut are recognized and those whose information are not stored in the dataset are labeled as unknown. The trainer and recognizing process of arecanut is shown in figure 8 and 9.

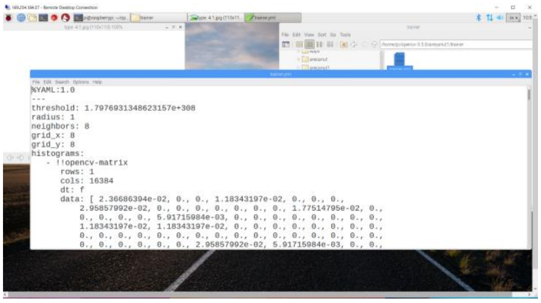

Fig. 8 Trainer

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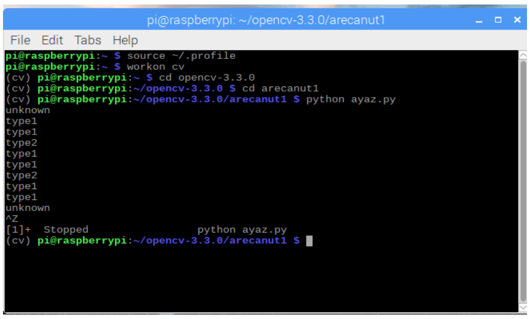

Fig. 9 Recognition of arecanut.

VIII. CONCLUSION

While researching for to start working in this project, we had a hard time trying to find related paper to the topic we present. Arecanut plantation is a rural activity and did not bring much attention of academics to create solutions that facilitates the farmers dealing with this tropical crop despite its relevant impact in India economy. With successful completion of this project we see that it may help a lot in the industries and even in the independent farmers' activities by improving the speed and precision of segregation as well as by reduce human effort.

This project can be further improved by adding a new operation: quality checking. At beginning of this work, we intended to perform the segregation based on type and also based on the quality of each type. But the second operation was left aside due to technical complexity which was unfeasible to solve by now.

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