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Research paper

White whole (WW) grades cashew kernel's classification using artificial neural network (ANN)

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Abstract

In this paper, we introduce an algorithm for the fitting of bounding rectangle to a closed region of cashew kernel in a given image. We propose an algorithm to automatically compute the coordinates of the vertices closed form solution. Which is based on coordinate geometry and uses the boundary points of regions. The algorithm also computes directions of major and minor axis using least-square approach to compute the orientation of the given cashew kernel. More promising results were obtained by extracting shape features of a cashew kernel, it is proved that these features may predominantly use to make the better distinction of cashew kernels of different grades. The intelligent model was designed using Artificial Neural Network (ANN). The model was trained and tested using Back-Propagation learning algorithm and obtained classification accuracy of 89.74%.

Keywords: *Cashew kernel; Bounding rectangle; Shape features; Artificial Neural Network.*

1. Introduction

Cashew tree (Anacardium Occidentale) is a native of southern America and was brought to India by the Portuguese. The tree produces nuts in a kernel, which is of more commercial value in the market with greater economic importance. The major cashew producing countries are Mozambique, Sri Lanka, Kenya, Tanzania, India Madagascar, Thailand, Malaysia, Indonesia, Nigeria, Malawi Senegal and Angola [1]. In India, cashew farms are located in Maharastra, Goa, Andhra Pradesh, Orissa, West Bengal, Karnataka, Kerala, Tamilnadu, Madhya Pradesh and Eastern regions [2]. India being one of the significant contributors of cashew kernel in the global market, has an important role play in cashew processing. About 132 thousand metric tons of cashew kernels were exported during the year 2011-12, earning foreign exchange at the level of around 44,000 million Rupees [2].

Cashew nut is very nutritious with a high amount of energy as it contains minerals, fats, carbohydrate, vitamins protein, and fiber, all of which contribute enormously to good health from its consumption. Cashew nut kernel can be eaten fried, raw and sometimes pre-treated with salt or sugar. Other useful products made from cashew are juice, jam, syrup, beverage, and chutney [1].

Physical properties of biological materials such as cashew nut and kernels have unique characteristics which set them apart from other engineering materials. The irregular shape of most biological materials complicates the analysis of their behavior. Physical properties of cashew nut and kernel like other cereals, fruits and vegetables are needed for the design of processing equipment [1].

The automated grading and sorting systems that use image processing techniques to determine geometrically and shape parameters, such as size, shape, color, ripeness, mass, bruising, disease, and rot, are being developed in many countries [10–13]. Also, an automated grading system would free up labor, which is already in short supply and expensive, to more critical farming or horticultural operations – thereby made available for crop production.

A concerted effort in the area of machine vision will enable the production of high-quality. Modern technologies have enabled broad application of machine vision techniques for quality analysis elsewhere, but a more straightforward technique would be a good start for regions that have not seen any mechanization. Algorithms for detecting fruit size [9], [14], color, shape or ripeness [15–17], defects [8], [18–22], sugar content [23], and mass [24], were successfully applied in those machine vision based grading systems.

The grading process needs to be given primary importance, because, it is the last opportunity to segregate and control the quality aspects of the food. So far the quality control is being done with more of manual intervention, where it is likely to be of human errors in grading mechanism. Therefore it is of our greater concern that, such human errors must be corrected to compete in the international marketplace. To the longer extent possible, our concern is to make it more of automatic and avoid human intervention in the grading process. This will enable our product to be graded accurately to fulfill the international standards and exports to other parts of the world. We are the largest exporter & distributor of Cashew Nuts in the world, our cashew nuts are of the highest quality, and this has helped us in gaining repute amongst all in the international market.

In the present scenario, the grading of cashew nuts is based on manual inspection of physically perceived quality attributes such as color, shape, and size. Using these attributes, a trained person tries to separate and put into different bins and classify. Table I, illustrates the designated Grades and definitions of quality of kernels(white wholes) [7].

Today, most of the customer are paying primary importance to quality aspects of food items; their purchase decisions depend critically on items geometric features like size, shape, color, etc., [7]. Keeping these aspects mind, we are trying to build an intelligent model, which can able to understand and analyze the significance of these morphological features (i.e., Shape), and do the classification. There are many such applications; they do analyze such features are realized in the literature. Along with these applications, many methods have been developed to characterize product shape, including two major categories- Size-dependent measurements and Size independent measurements [6].

Table 1: White Wholes Cashew Kernels

Grade	Count per 454 gms size description	General Characteristic
W-180	170-180	Cashew kernels shall have been obtained through shelling and peel cashew nuts. Shall have the characteristic shape; shall be white, pale ivory or light ash in color reasonably dry and free from insect damage, damaged kernels, and black or brown spots. The kernels shall be completely free from testa.
W-210	200-210	
W-240	220-240	
W-320	300-320	

2. Proposed system

The proposed system acquires images of the cashew kernel and uses that image as an input for further processing. The captured image is pre-processed, and image features are extracted to support decision making in the next level. The complete block diagram is shown in Fig. 1. The system consisting of ANN, which is trained with extracted features using a supervised learning algorithm to understand the geometry of the kernel [7].

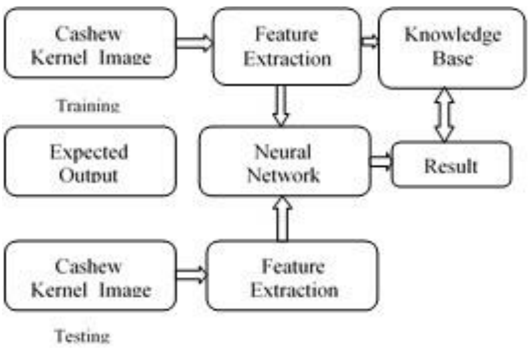

Fig. 1: Block Diagram of the System for Classification of Cashew Kernels.

3. Materials and methods

3.1. Experiment samples

Cashew kernel samples were obtained from the Achal Industry, Mangalore, Karnataka, and Balaji Exports Jarkal Karkal Tq. Udupi, Karnataka. The samples include of various classes of kernels as mentioned in Table I. Generally these samples were categorized manually by a trained person. Some of the digitized samples of the cashew kernels of different categories are shown in Fig. 2. These sample images were captured using image acquisition system shown in Fig. 3.

3.2. Collection of sample image of cashew kernels

We set up the image acquisition system; the specification is as follows.

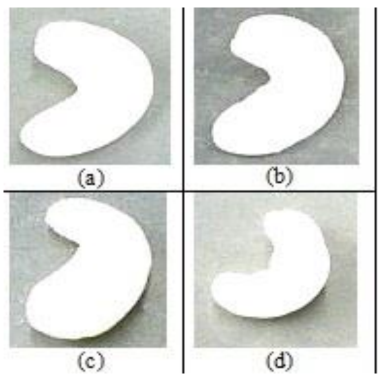

Fig. 2: Images of Cashew Kernels (A) White Wholes-180 (B) White Wholes-210 (C) White Wholes-240 (D) White Wholes-320.

i) Color Matching Cabinet is used for color matching under different lighting sources. The equipment is fitted with FIVE light sources as per CIE international Standards. The lighting sources and color temperature are as follows (Refer Table II)

Table 2: Specifications of Color Matching Cabinet

Sl. No.	Light Sources	Color Temp.	Quantity	Wattage
01	Artificial Daylight Fluorescent Lamps (D-65)	6500° K	02 Nos	18 W
02	Cool White Fluorescent Lamps (CWF)	6500° K	02 Nos	18 W
03	Tungsten Filament Lamps (FL)	4000° K	04 Nos	40 W
04	Triphosphor Fluorescent Lamp (TL-84)	2850° K	02 Nos	18 W
05	Ultra Violet Black Lamp (UV)	Ultra Violet	01 Nos	18 W

The Standard booths are made for connection to an electrical supply 210-250 Volts, 50 Hz, single phase AC Supply (Refer Fig. 3).

Fig. 3: Image Acquisition System.

ii) Image acquisition system was setup, to capture an image of size 640x480 added to the database by using two webcams (iBall and SmartPC, each of 12 megapixels still image resolution), in a color matching cabinet with proper control of lighting intensity under different lighting sources. Distances and heights between webcams and object (i.e., cashew kernel) were fixed for all the samples with moisture content in the range of 3.5 - 5%. Figure 3 shows a schematic representation of the setup used for data acquisition. The captured images were obtained as JPEG image files.

iii) Image acquisition system was setup, to capture an image of size 640x480 added to the database by using two webcams (iBall and SmartPC, each of 12 megapixels still image resolution), in a color matching cabinet with proper control of lighting intensity under different lighting sources. Distances and heights between webcams and object (i.e., cashew kernel) were fixed for all the samples with moisture content in the range of 3.5 - 5%. The Fig. 3 shows a schematic representation of the setup used for data acquisition. The captured images were obtained as JPEG image files.

3.3. Pre-Processing

Images captured using webcams subject to different types of noise, such as the electronic noise while digitizing video signals, the wiring noise while transferring video signals from cameras to computers, and the read-out noise while reading information from cameras. All these lead to degradation of the quality of the images when they are subsequently processed [6]. To enhance the data sample of cashew kernel image and get valuable information from region interest. Because of this, an image pre-processing stage is a primary step in the cashew kernel quality evaluation.

In the image pre-processing stage, we have experimented median by adding some of the known noise like Salt and pepper noise, Gaussian noise, Poisson noise and Speckle noise, with noise reduction filtering techniques such as Arithmetic mean, Geometric mean, Harmonic mean, Median, and Wiener. Among all noise reduction filtering techniques, the median filtering technique is outperformed.

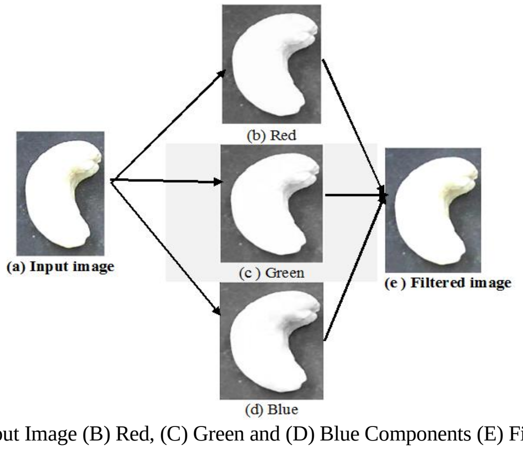

Fig. 4: (A) Input Image (B) Red, (C) Green and (D) Blue Components (E) Filtered Image.

The median filter [6] has been applied to the acquired data sample of kernel image to eliminate noise, which has crept during in the digitization or acquisition process. The median filter replaces the value of a pixel by the median value of the data sample's space, which consists of a 5×5 centered kernel on the considered pixel. The use of median filter facilitates the identification of an optimal threshold for the image during segmentation. The program for pre-processing of cashew kernel image has been written in MATLAB, using Image processing Toolbox available in MATLAB 2012a and results as shown in Fig. 4.

After the preprocessing step, critical information is being extracted and proceeded to the next step for segmentation. In the segmentation, step image is carefully subdivided into a meaningful non-overlapping region used for further analysis. Image representation involves representing the segmented image as a boundary or a region. Boundary representation is suitable for analysis of morphological (i.e., size and shape) features. In this context, segmenting an image consists of separating the cashew kernel from a background of the image.
In this research, we are investigated Uniform and Adaptive Thresholding, and Optimal Thresholding for segmenting cashew kernel image. Among image above segmentation techniques, an Optimal Thresholding is outperformed.
An Optimal Thresholding is an advanced technique. This usually seeks to select a value for the threshold that separates an object from its background. Otsu's method is one of the most popular techniques of Optimal Thresholding. The Otsu's (N Otsu, 1979) algorithm maximizes the variance between the foreground and background pixels. Pixels that have the values less than the global threshold (i.e.0.7) are classified as cashew kernel, and the others are classified as background. The program for segmentation of cashew kernel image has been written in MATLAB, using Image processing Toolbox available in MATLAB 2012a and results as shown in Fig. 5.

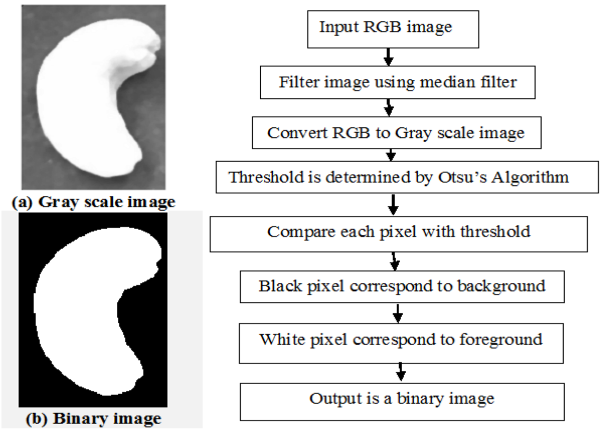

Fig. 5: Shows Segmentation Steps and Output.

4. Feature extraction

The ideal measurement of shape is that which can be used to discriminate one shape adequately from another. In other words, with this ideal measurement, every shape has a unique value. It is thus a matter of concern that size-dependent measurements (SDM) may be insufficient to characterize the shape of every food product because of the more considerable irregularities of shape. Size-independent measurements (SIM), including region-based and boundary-based methods, have consequently been developed [6].
In this, we are trying to extract morphological features such as shape, which will play an essential role in making a better distinction between multiple grades of cashew kernels.
Algorithm 01: To Compute the minimum-bounding rectangle (Height and Width) [5]
Step 1: Computing the centroid of an object: Consider an object A in an image, where (x_i,y_i), i=1,2,….n are the n boundary points of the object. Then centroid ($\bar{x}$, $\bar{y}$) of A is defined by

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \text{ and } \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1}$$

Step 2: Determination of principal axes: Let (x_i,y_i), i = 1,2,….n be the edge points of the object A. Let ɵ be the angle of the major and minor axis with the horizontal axis. The equation of the line passing through ($\bar{x}$, $\bar{y}$) at an angle ɵ is

$$x \tan\theta - y + \bar{y} - \bar{x} \tan\theta = 0 \tag{2}$$

The perpendicular distance of an edge point where (x_i,y_i), i=1,2,….n to the line in equation is $p_i = (x_i - \bar{x})\sin\theta - (y_i - \bar{y})\cos\theta$. (3)
Therefore, the sum of the square of the perpendicular distances is given by

$$P = \sum_{i=1}^{n} [(xi - \bar{x})\sin\theta - (yi - \bar{y})\cos\theta]^2 \tag{4}$$

To compute the angle ɵ, we minimize P concerning ɵ. Therefore, ∂P/∂Θ = 0 gives

$$\tan 2\Theta = \frac{2\sum_{i=1}^{n}(xi - \bar{x})(yi - \bar{y})}{\sum_{i=1}^{n}[(xi - \bar{x})^2 - (yi - \bar{y})]^2} \tag{5}$$

Step 3: Computing the upper and lower furthest edge points
Let (x_i,y_i), i = 1,2,….n be the edge points of the object A. The equation of the major axis is

$$(y - \bar{y}) - \tan\theta(X - \bar{x}) = 0 \tag{6}$$

Substituting the value x=xi and y = yi in eqn 7

$$V = (y - \bar{y}) - \tan\theta\,(X - \bar{x}) \tag{7}$$

If V>0 then (xi, yi) is an upper edge point concerning the major axis.
If V<0 then (xi, yi) is a lower edge point concerning the major axis.

If V = 0 then (xi, yi) lies on the major axis.

Similarly, we can find out all the upper and lower edge points of the object concerning the minor axis (y - $\bar{y}$) – cot ɵ(X - $\bar{x}$)= 0 (8)
Step 4: computing the vertices for the bounding rectangle
Let (x1, y1) and (x2, y2) be the upper and lower furthest edge points of A with respect to the major axis. Now the line passing through (x1, y1) and parallel to major axis is given by

$$(y - y1) - \tan\theta(x - x1) = 0 \tag{9}$$

This line represents one of the sides for the fitting of bounding rectangle or square.
Similarly, we can find the other side of the rectangle, which passes through (x2, y2) and parallel to major axis is

$$(y - y2) - \tan\theta(x - x2) = 0 \tag{10}$$

To find the other two sides, we use the upper and lower furthest edge points of A concerning the minor axis.
Let (x3,y3) and (x4,y4) be the upper and lower furthest edge points of A concerning the minor axis. The lines passing through these two points and parallel to the minor axis, are given by

$$(y - y3) + \cot\theta(x - x3) = 0 \tag{11}$$

$$(y - y4) + \cot\theta(x - x4) = 0 \tag{12}$$

From the above equations we can find the top left, top right, bottom left, and bottom right (x, y) coordinates for the fitting of bounding rectangle or square, respectively. Therefore from the bounding rectangle, we can find Height and Width of each cashew kernel in an image. The Fig. 6 illustrates the output of the algorithm 1. Using the algorithm 1 presented above, we have computed morphological (i.e., shape) features such as height and width of WW cashew kernel presented pictorially in Fig. 7.

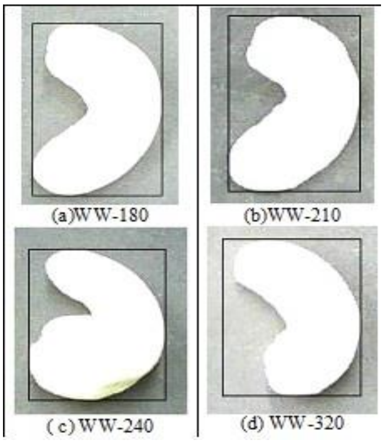

Fig. 6: Illustrate the Output Result of the Algorithm.

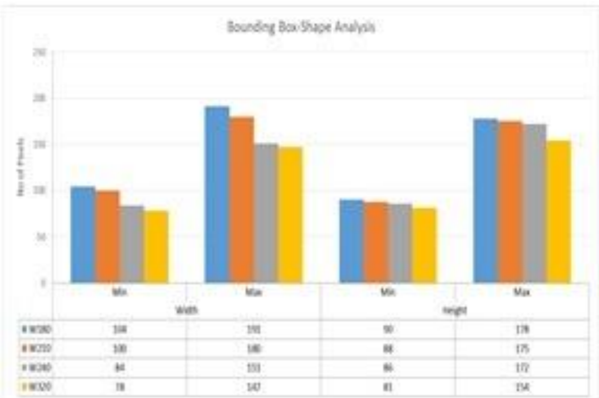

Fig. 7: Illustrates the Shape Features of WW Cashew Kernels.

5. Results & discussion

The network recognizes and classifies the given kernel as a pattern of vector P as belonging to class O^i if the i^{th} output of the network is "high" whereas all other outputs are "low." A feed-forward neural network was trained for classification of the cashew kernel samples into W-180, W-210, W-240 and W-320 grades. Inputs to the network were shape features computed, and four outputs formed a three–bit binary number representing the category of classification (000 to black, 001 to WW-180, 010 to WW-210, 011 to WW-240, 100 to WW-320 and 111 to white). Levenberg-Marquardt Back Propagation algorithm was used for training. Tan sigmoid function was used in the hidden layers. The log-sigmoid transfer function was selected because its output (0 to 1) was fit for classification. The network was trained to output a 1 in the correct variety of the output vector and to fill the rest of the output vector with 0. Different numbers of layers and nodes were tested for

the network structure. Hidden layers are required, as the patterns belonging to various classes are linearly non-separable. The mean squared error (MSE) of prediction for the validation data set was used to select an appropriate network structure without overfitting.
The function cashew_classify() performs this task. The classification of the cashew kernels of different grades was done by varying nodes in the hidden layer on trial and error basis and obtained the results empirically as shown in Table III.

Table 3: Classification Rate of Cashew-Kernel Grade

Sl. No.	Cashew Kernel Grade	Classification rate (%)
01	WW-180	90.00
02	WW-210	89.99
03	WW-240	90.00
04	WW-320	88.99

A sample set, which was not part of either the training or validation (i.e., 300 samples of each WW above cashew kernels), was used to test the trained neural network classifier. The test set included 300 randomly selected cashew kernels of each afore said WW grades. The test results of classification are summarized in Table III. Almost all (89.74%) of the cashew kernels were correctly classified.

6. Conclusions & future scope

The current work developed the software that includes image acquisition, processing and analysis techniques to grade cashew kernels using shape features of WW grades in a static setting. However, to implement the algorithm into an automated inspection system, there is a need to implement a conveyor system for acquiring images while kernels are in motion. It is also essential to integrate the grading software with the hardware that performs the mechanical action of grading the cashew kernels.
The work presented in this could be extended in many folds. In this research work, only four types of cashew kernel (WW grades) were used for classification. In future work, all kinds of cashew kernel grades would be incorporated. Classification of kernels is done only on external features (size, shape color, and textures). The size and volume of the cashew kernel could be determined by considering a data/feature set that contains depth information in 3D view.

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