Automated Cashew Kernel Grading Using Machine Vision

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***Abstract*—Quality of food and agricultural products is vital for farmers and consumers. Quality based classification of these products is being carried out manually in the industry which is tedious and expensive. Computer Vision systems can be used to automate the classification process. Automation can reduce the production cost and improve the overall quality. A computer vision system captures the image of the underlying object and transmits it to an image processor. The processor, after processing the image, presents it to a pattern recognizer. The recognizer performs the quality assessments and classifies the underlying object into pre-specified quality classes. Previous studies in this regard used minimal features to perform classification which reduces the accuracy. In the proposed approach more features are used which significantly improves the automation process. Automation process faces several challenges like identifying appropriate features and the best classifier. This study tries to grade cashew nuts based on external features like color, texture, shape and size. The effect of various pre-processing operations on the grading process is also studied. Five different classifiers were used and their performance in terms of accuracy is observed. Among the classifiers, Back Propagation Neural Network proved to be the most optimal.**

Keywords—Automation, Machine Learning, Image Processing

I. Introduction

Cashew is one of the most popular and important commercial crop in India. India is one of the leading producer, processor and exporter of cashew kernels in the world. Commercial cultivation of cashews began in the early 1960s and, over the years, cashew has become a crop of high economy and attained the status of an export-oriented commodity, earning considerable foreign exchange for the country. Major portion of the cashew industry still depends on expert employees for grading and sorting. Manual grading is inefficient, expensive, unreliable, labor intensive and time-consuming. The use of computer vision for automation of grading and evaluation of various attributes related to cashew kernel quality can lower production costs and increase quality.

A basic computer vision based quality assessment system consists of four phases; namely image acquisition, pre-processing, feature extraction, and classification phases. The computer vision system captures the image of the object and transmits it to an image processor. The processor, after processing the image, presents it to a pattern recognizer. The recognizer performs the quality assessments and classifies the object into pre-specified quality classes.

Great deal of research is being carried out in the area of machine vision based quality inspection, grading and sorting of agro-food products. A real-time prototypical date grading and sorting system was designed by Ohali [1], in which different external features such as color, size, shape and defects were extracted from the images to feed to the classifier for the grading purpose. Razmjooya et al [2] developed a real-time system for sorting potatoes according to their size and to identify defective potatoes based on their color. In order to determine the size, maximum diameter, minimum diameter and Length/width diameter ratio was calculated. To recognize the defects of potatoes, color features were used. Szczypinski et al [3] performed a detailed study on the identification of barley varieties, in which morphological features, statistical texture features and Color component histograms were used to extract shape, texture and color features respectively. Araújo et al [4] proposed a method for Beans quality inspection using correlation-based granulometry. In granulometry, the captured image was compared with kernels that represent all the shapes, eccentricities, orientations and sizes of the grains and the correlation was computed. To filter out the false detections, the peaks with low correlation and peaks that have large intersections with other peaks are discarded. Cross correlation was efficiently computed using FFT (Fast Fourier Transform). Huang [5] developed a method for determining the quality of areca nuts using machine vision based on color and texture features

As the result of the rapid growth of technology and engineering, mechanization has been introduced in various stages of cashew processing. Nevertheless, mechanization is confined to mainly roasting, cooling, shelling, drying, peeling, and packing .Manual labor continues to be in used in kernel grading due to lack of efficient and economical machines. The objective of the study is to understand the effect of various features in grading the cashew kernels and to find the best supervised learning model. The effect of various pre-processing operations on the grading process is also studied. The rest of the paper is organized as follows. Section 2 presents a general idea of the proposed system including a brief description of the system architecture. Section 3 deals with the experimental results and Section 4 concludes the paper.

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II. DESIGN OF THE PROPOSED SYSTEM

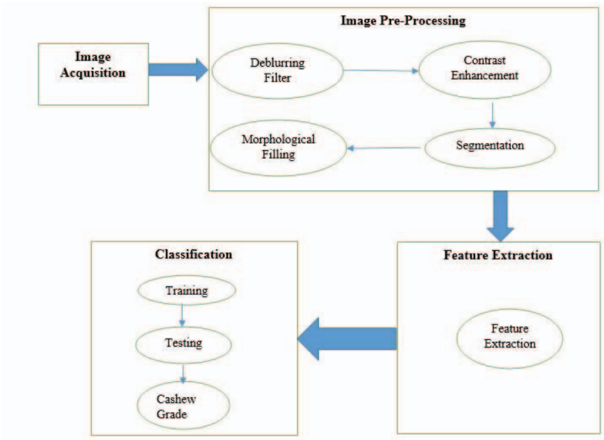

Fig. 1. System Design

The proposed system consists of four phases namely image acquisition, pre-processing, feature extraction and classification

A. Image Acquisition

Image acquisition is the first step for a computer vision application. Illumination is critical for the image acquisition. Proper illumination helps to acquire high quality images. Charge Coupled Device(CCD) camera is placed on an artificially illuminated chamber to highlight the features of the cashew kernels. The experimental setup consists of illumination chamber with Watts 8 watt T5 Fluorescent Lamp lighting and a Basler scA1390-17g GigE camera with the Sony ICX267 CCD sensor that delivers 17 frames per second at 1.4 MP resolution. The camera was placed on Kaiser RS 2 XA Camera Stand, at a height of 30 cm above the base where the object was placed. Cashew kernel images were acquired using Image acquisition toolbox of Matlab 2015 software. The image frames were transported to the computer via D-Link Cat-6 1000Base-T Ethernet cable[7].

B. Image Preprocessing

The captured image needs to be preprocessed so as to make the subsequent steps easier and error free. Contrast enhancement by dynamic stretching was applied to highlight the object whilst leaving the unimportant background region intact [2]. Certain samples were blurred and hence Lucy filter was applied to eliminate the blurring effect. Lucy filter was preferred to Weiner Filter as it has lower Signal to Noise Ratio(SNR) and higher Peak Signal to Noise Ratio (PSNR). Image segmentation techniques were applied to split the pixels of the image in to two subsets: object area, and the background. A black-gray background was used which ensured that maximal contrast between the white/ivory cashew kernel and the background was achieved. Genetic algorithm was used for segmentation as it provided the best performance and also the time taken is much lesser than other algorithms [8]. After segmentation, morphological processing was applied to improve the background subtraction in which the unwanted small holes on the background region were identified and removed [3].

C. Feature Extraction

The various features extracted for subsequent classification were color, texture, shape and size.

Among the different methods for color feature extraction, color moments are the most prominent one they are rotation and scale invariant [9]. As the captured cashew images were in RGB color mode, the RGB color moments could be directly extracted. Since RGB is a poor choice for color analysis, HSV (Hue, Saturation, Value) color moments were also used. RGB images were first converted into HSV color space. The first three color moments (mean, standard deviation and skewness) of the color distribution were extracted as most of the color information is contained in these three moments.

For the colored image of size M x N, mean (μ), standard deviation (σ), and skewness (γ) can be evaluated as follows :

$$\mu_i = \frac{\sum_{j=1}^{M.N} x_{ij}}{M.N} \quad (1)$$

$$\sigma_i = \sqrt{\frac{1}{M.N}\sum_{j=1}^{M.N}(x_{ij} - \mu_i)^2} \quad (2)$$

$$\Upsilon_i = \sqrt[3]{\frac{1}{M.N}\sum_{j=1}^{M.N}(x_{ij} - \mu_i)^3} \quad (3)$$

where x_{ij} represents the value of the pixel j of color channel i (i Є {R, G, B} in case of RGB color channel and i Є {H, S, V}in case of HSV color channel).

Gray Level Co-occurrence Matrix(GLCM) [11] functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image. GLCM matrix was created from the gray scale equivalent of the captured RGB image and the textural features were derived from the GLCM matrix. The measures extracted from GLCM were

- Contrast: Measures the local variations in the gray-level co-occurrence matrix.
- Correlation: Measures the joint probability occurrence of the specified pixel pairs.
- Energy: Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.
- Homogeneity: Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal
- Entropy: measure of randomness in the gray scale image

These five features were used as it includes both first order and second order properties which are sufficient to classify the images based on texture.

Local Binary Patterns(LBP) computes a local representation of texture[10]. This local representation is constructed by comparing each pixel with its surrounding neighborhood of pixels. The LBP code for the center pixel is computed as follows

$$LBP_{P,R} = \sum_{i=0}^{P-1} s(g_i - g_c).2^i \tag{4}$$

Where g_c is the gray scale value of the center pixel, g_i is the value of its i^{th} neighbor, P is the number of neighbors, R is the radius of the circular neighborhood that is the Euclidean distance between the center pixel and its neighbors, and s(x)is a binarisation function that is defined as follows:

$$s(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & else \end{cases} \tag{5}$$

LBP labels the pixels of an image by thresholding the neighborhood of each pixel with the value of the center pixel and considers the result as a binary number. Here 8 neighborhood was considered. Then, compute the histogram over the cell, based on the frequency of each "number". Concatenate histograms of all cells. This gives a feature vector for the entire window.

The size feature was calculated by counting the number of non-zero pixels in the segmented image and then normalizing it with the total number of pixels

In order to extract the shape features, the images were first converted to transform domain using Discrete Wavelet Transform(DWT). DWT decomposes a signal into a set of basis functions called wavelets. Four bands are generated upon applying DWT which are approximation, horizontal, vertical and diagonal. Shape features of the cashew kernels were extracted using Morphological features method [3]. Due to the asymmetric and irregular shape of the cashews, the most effective shape features needed to be extracted. Five features were extracted:

- Major axis length and Minor axis length of the circumscribed ellipse: The minimum area covering ellipse that encloses the cashew kernel region was determined and extracted the length of the major axis and minor axis
- Aspect ratio: Ratio of the length of major axis to the length of minor axis
- Eccentricity: This is the ratio of the distance between the foci of the surrounded ellipse and its major axis length
- Perimeter: Distance around the boundary of the cashew kernel region.
- Equivalent Diameter: This specifies the diameter of the circle with the same area as that of the kernel region.

D. *Classification*

Classification is the final stage in the cashew grading process. Classification is a two-step process. In the first step, a classifier is built describing a predetermined set of data classes or concepts. In the second step the model is used for classification. Various classifiers such as Random Forest, Multi-Layer Perceptron, Multi Class classifier, Regression and Back Propagation Neural Network were used. To determine the accuracy of the classifier k-fold cross validation was performed with k=10. Performance of these classifiers in terms of accuracy was analyzed. Classification was performed using Weka tool and Matlab 2015

III. EXPERIMENTAL RESULTS

A. *Data Collection*

Out of 26 export quality cashew grades, 5 grades were used in this study. A total of 500 samples (100 samples from each grade) were obtained. 330 samples were used for training and 170 samples for testing. General characteristics of these 5 grades are shown in Table 1.

B. *Choice Of Filter*

Lucy Filter was used for deblurring as it has a high PSNR value and low MSE. These values are shown in Table 2.

C. *Effect of Features On Classification*

The effect of features on the classification accuracy is studied. Tables 3-5 covers the comparison of classification accuracy using one, two and three features respectively. When single feature is used, color is most prominent one. When two features are used together, color and texture are the most significant. Using combination of three features further improves accuracy.

TABLE I. Specifications of the Cashew Grades used in this Study

Grade	Trade Name	Color/ Characteristics	Number of Kernels per 454 grams
W180	White Wholes	White/pale ivory/light ash. Characteristic shape	170-180
W320	White Wholes	White/pale ivory/light ash. Characteristic shape	300-320
SW320	Scorched Wholes	Light brown, light ivory, light ash or deep ivory in color due to scorching as a result of over-heating	300-320
SSW	Scorched Wholes Seconds	Kernels may be over-scorched, immature, shriveled, speckled discolored and light blue	Not Applicable
B	Butts	White/pale ivory or light ash. Kernels broken cross-wise (evenly or unevenly) naturally Attached	Not Applicable

TABLE II. Comparison of Different Filters for Preprocessing

Filter Used	Average PSNR(dB)	Average MSE
Weiner Filter	34.70	22.07
Lucy Filter	41.58	4.62
Regular Filter	35.57	18.02

TABLE III. Performance evaluation of classifier using single feature

Feature	Average Classification Accuracy
Color	85.48%
Texture(LBP)	73.65%
Texture(GLCM)	68.26%
Shape (Transform Domain)	70.24%
Shape (spatial domain)	64.41%
Size	44.42%

TABLE IV. Performance evaluation of classifier using two features

Feature	Average Classification Accuracy
Color & Texture	87.66%
Color & Shape	86.70%
Color& Size	85.77%
Texture& Shape	80.89%
Texture & Size	79.05%
Size & Shape	69.60%

TABLE V. Performance evaluation of classifier using three features

Feature	Average Classification Accuracy
Color, Texture, Shape	87.40%
Color, Texture, Size	87.40%
Color, Shape, Size	87.71%
Texture, Size, Shape	81.64%

D. Variation of Cashew Grades towards Different Features

Figures 2-4 depicts the variation of different cashew grades towards the features extracted. From the graphs it can be verified that the features like color, texture, size, and shape can be distinguished from one another and hence they can be very well employed for automatic grading of the cashew kernels. Different conclusions that can be drawn by analyzing these graphs are as follows:

- Grades W180, W320, and Butts have comparable color and texture features, while their size and shape feature varied intensely
- Grades W320, and SW320 have analogous size, shape, and texture features, hence color features are mandatory to categorize these two grades.
- For categorizing SSW, texture features are the best fit.
- SSW, and Butts are showing high variation in size and shape features when compared to W320 and SW320.

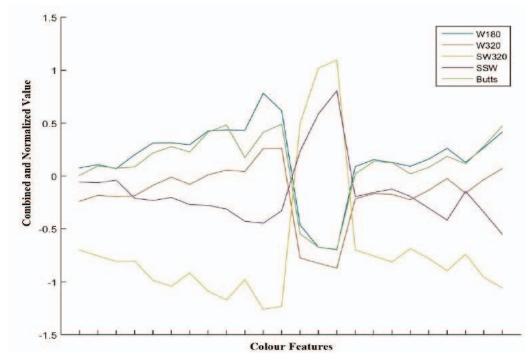

Fig. 2. Variation of different cashew grades towards color features

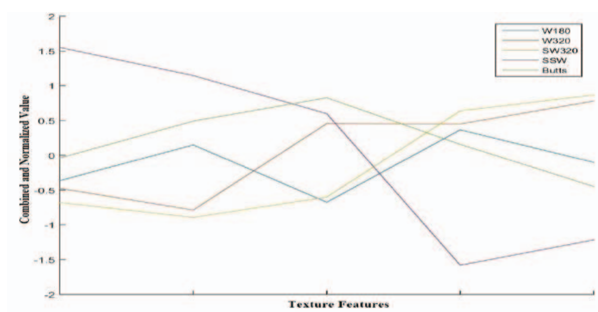

Fig. 3. Variation of different cashew grades towards texture features

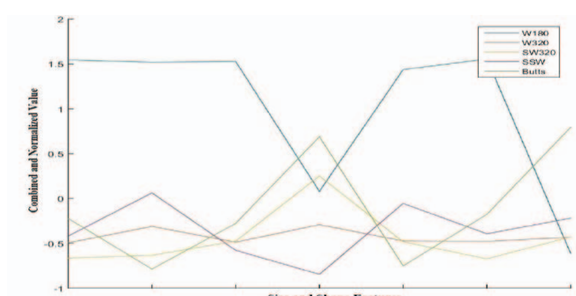

Fig. 4. Variation of different cashew grades towards size and shape features

E. Classification Results

Five different classifiers were used and their accuracy was obtained under different conditions. Color, texture, shape and size features were considered. It can be seen that the use of preprocessing operations such as contrast enhancement and Lucy filter improves the accuracy. It is found that extracting shape features from transform domain and combining it with the feature set from spatial domain gives the best results. Among classifiers, BPNN gives optimal results.

TABLE VI. Classification Accuracy without using Preprocessing Operations

Classifier Used	Cross Validation	Classification Accuracy
Random Forest	81.2%	79%
Multi Class Classifier	83.6%	80.8%
Classification via regression	81%	78%
Multi-Layer Perceptron	84.4%	81.18%
BPNN	86%	89.6%

TABLE VII. Classification Accuracy after applying Contrast Enhancement

Classifier Used	Cross Validation	Classification Accuracy
Random Forest	85.4%	82%
Multi Class Classifier	90%	87.2%
Classification via regression	85.8%	84.8%
Multi-Layer Perceptron	89%	88.24%
BPNN	94.4%	94.4%

TABLE VIII. Classification Accuracy after applying Contrast Enhancement and Filtering

Classifier Used	Cross Validation	Classification Accuracy
Random Forest	90.4%	88.83%
Multi Class Classifier	91%	87.65%
Classification via regression	90.2%	90.59%
Multi-Layer Perceptron	90.4%	89.41%
BPNN	95%	96%

TABLE X. Classification Accuracy by Combining features from spatial and transform domain

Classifier Used	Cross Validation	Classification Accuracy
Random Forest	89.4%	88.82%
Multi Class Classifier	91.6%	90%
Classification via regression	90.6%	88.26%
Multi-Layer perceptron	91.8%	90%
BPNN	94.4%	96.8%

IV. CONCLUSIONS

This study shows that using the most relevant features and appropriate classifier can significantly improve automation of cashew grading process. Use of preprocessing operations provides further improvement. All the external features including color, texture, size, and shape are necessary to grade the various cashew kernels efficiently. A single feature may be good for discriminating two varieties, and another feature may be good for some other pair. But considering the grading process as a system, all these features are needed together. Amongst the classifiers used, Back Propagation Neural Network provided the most optimal result with an accuracy of 96.8%. These results proved that computer vision and image processing techniques can be employed as a fine alternative for the existing manual grading system.

The proposed system will not be able to efficiently grade splits, which are a kind of grade in which the kernels split naturally lengthwise. This can be achieved by two-sided imaging techniques. Future work includes incorporating techniques for identifying damaged cashews based on their color so that such cashews can be eliminated from the grading process.

References

[1] Y. A. Ohali, “Computer vision based date fruit grading system: Design and implementation," J. of King Saud University Computer and Information Sciences, vol. 23, pp. 29-36, 2011.

[2] Navid Razmjooya, B. Somayeh Mousavib, F. Soleymani “A real-time mathematical computer method for potato inspection using machine vision”, Computers and Mathematics with Applications 63,pp. 268–279,2012

[3] Piotr M. Szczypinski, Artur Klepaczko, Piotr Zapotoczny,” Identifying barley varieties by computer vision”, Computers and Electronics in Agriculture 110 , pp.1–8,2015

[4] Sidnei Alvesde Araújo, Jorge Henrique Pessota, HaeYong Kim,” Beans quality inspection using correlation-based granulometry”, Engineering Applications of Artificial Intelligence 40,pp.84–94,2015

[5] Kuo-Yi Huang,” Detection and classification of areca nuts with machine vision”, Computers and Mathematics with Applications 64,pp.739–746,2012

[6] H. Zhang and D. Li, “Applications of computer vision techniques to cotton foreign matter inspection: A review," Computer and Electronics in Agriculture, vol. 109, pp. 59-70, 2014.

[7] C. S. Nandi, B. Tudu, and C. Koley, “A machine vision-based maturity prediction system for sorting of harvested mangoes," IEEE Trans. On Instrumentation and Measurement, vol. 63, July 2014.

[8] M. Omid, M., Abbasgolipour, A., Keyhani and S.S. Mohtasebi, “Implementation of an Efficient Image Processing Algorithm for Grading Raisins”, International Journal of Signal and Image Processing (Vol.1-/Iss.1), pp. 31-34,2010

[9] N. El-Bendary, E. El-Hariri, A. E. Hassanien, and A. Badr, “Using machine learning techniques for evaluating tomato ripeness," Expert Systems with Applications, vol. 42, pp. 1892-1905, 2015M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

[10] G. Muhammad, “Date fruits classification using texture descriptors and shape-size features," Engineering Applications of Artificial Intelligence, vol 37, pp. 361-367, 2015

[11] J. Hu, D. Li, Q. Duan, Yueqi Han, Guifen Chen, and Xiuli Si,” Fish species classification by color, texture and multi-class support vector machine using computer vision," Computers and Electronics in Agriculture, vol. 88, pp.133-140, Oct. 2012