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A machine vision based approach to Cashew Kernel grading for efficient industry grade application

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ABSTRACT

An algorithm for automated, image-based segregation of cashew kernels into different categories is the need of the hour to drive up the productivity of the Indian cashew industry. The aim of this study is to find a supervised learning model that will accurately recognize and classify the cashew kernel into different grades. Various image processing techniques are used to preprocess the cashew image dataset. K-means clustering is used to perform colour image segmentation. Feature selection is performed first using neighbourhood component analysis, followed by stepwise regression. Two multi-class classification methods are implemented. Support Vector Machines (SVM) with 'one-vs-one' classification and Adaptive Directed Acyclic Graph (ADAG) learning model showed satisfactory results. However, even higher accuracy is obtained by using the Random Forest classification model. Random Forests are easy to train, which makes them good for high dimensional data, with a large number of training examples. The main contribution of this work is developing a robust and efficient computer vision system that can grade cashew kernels on the industrial scale with high accuracy and without compromising much on the speed of computation.

Keywords— *Computer vision, Machine learning, Random forest, SVM, Automation, Image Processing*

1. INTRODUCTION

The cashew crop (Anacardium occidentale) was first introduced to India by the Portuguese settlers who migrated to Goa in the 16th Century. It quickly spread to other parts of the country primarily for the purpose of afforestation and checking soil erosion, but by the 20th Century, it had become an important commercial crop and a top foreign exchange earner for India. As of 2018, India is the largest single-producer of Raw Cashew Nut (RCN) in the world [1]. Apart from large-scale production units, Cashews kernels are also widely produced in small and marginal holdings all over India [2].

The production and processing of cashews is a highly labour-intensive process in India. The cashew nut shells are steamed under pressure so that they become soft and the kernels inside loosen and become easily extractable. This also increases their moisture content, which in turn reduces the risk of them getting scorched when roasted. The shell is split longitudinally and the kernel is taken out. This is a largely manual operation. The cashew kernels are then dried in an oven at low temperatures to loosen the skin, which is later peeled off. They are graded based on visual inspection, into 26 categories, most of which are export quality, and are priced accordingly. Grading of RCN in India is done adhering to the standards set by the Cashew Export Promotion Council (CEPC) of India in the Cashew Export Act of 1963. The various grades are given in Table 1.

Presently, the grading and sorting of cashews are done by manual inspection, which makes it a tedious process, subject to a lot of errors and inconsistencies. To automate this process, optical sorting machines have been invented that can sort cashews into 3-5 categories. However, these machines have a very high initial cost. This has drastically increased the cost of production of cashews nuts and has made it difficult for Indian cashews to compete in the international market. For small-scale Indian industries, affording these machines is not viable. The industry needs an economical, yet accurate means to categorize cashew kernels so that cashew growers can achieve an optimal yield and enjoy profitable returns. The objective of this study is to develop an accurate, efficient and intelligent computer vision system to support automatic grading of cashews. As of now, there is no existing image database for cashew kernels in India. For our study, a sizable database was obtained through various small-scale industries, consisting of images of eight grades of cashews: WW-450, WW-320, WW-180, SW-240, Splits, Black Spots, Discoloration, and Mixed Defects. The dataset was studied and the salient features required for classifying cashew kernels were identified.
Different supervised learning approaches were applied to find the most optimal model for the classifier.

2. LITERATURE REVIEW

A lot of work has been done in the grading and sorting of agricultural products. In research paper [3] a system to classify 5 grades of cashews using shape, size, colour and texture features and Back Propagation Neural Networks (BPNN) was proposed, which worked with an accuracy of 96.8%. Another study,[4] concluded that there was a linear relationship between cashew length and height. This lead to cashew length replacing cashew height in feature selection for learning algorithms. A groundbreaking paper [5] on extracting textural features for image classification using grey-tone spatial dependence matrices opened new doors for image analysis.

In [6] an accuracy of 90.9% was achieved using machine vision to grade the quality of areca nuts. Another research paper,[7] made a comparative study of various supervised learning models for an intelligent cashew grading system. In [8], it was found that SVM gave better accuracy rates than BPNN for cashew grading applications. Till date, there has been no satisfactory classification model using Random Forests, which are robust, easy to train and suited for large, high dimensional data sets. In this research paper, an efficient Random Forest tree ensemble has been proposed, that will perform well for industry level applications.

3. METHODOLOGY AND IMPLEMENTATION

The system for classification consists of five stages (as shown in figure 2): Image Acquisition, Image Preprocessing, Image segmentation, Feature Extraction and Classification.

3.1 Image Acquisition

The Image acquisition step is the process by which the dataset for the learning problem is obtained. A 12 MP digital camera was used to capture images of cashews, in an artificially illuminated environment. The focus, aperture and lighting were kept the same for all the images. The dataset consists of well-lit images of the top-view of single cashew kernels, obtained in the JPG file format. Images were transferred to Intel I5 core Lenovo Laptop through a USB connection. Images were acquired using the Image Acquisition Toolbox of MATLAB 2018.

3.2 Image Preprocessing

Before segmenting the image and extracting its features, some preprocessing was done to ensure better classification results.

- Images were resized to 800 pixels along the larger dimension, but their aspect ratio was maintained.
- Lucy filter was applied for deblurring, as it has low PSNR. A Gaussian point spread function [2] was modelled for the filter.
- The resulting image was sharpened using a median filter.

3.3 Image Segmentation

To extract features of the cashew kernel, the kernel (object) must be recognized and labelled in the image. Colour image segmentation was performed using a K-means clustering algorithm as in [9] to separate the background from the cashew kernel. By experimental methods, it was found that the saturation and value dimensions of the HSV colour space gave better segmentation results than the RGB colour space. K-means clustering using Euclidean distance was applied on the image pixels, which held the saturation and value information. The number of clusters (two or three) was decided according to the decrease in the average sum of the distances between points and cluster centroids. If the ratio between the sum of distances of 2 clusters and sum of distances of 3 clusters was less than 1.7, then the algorithm worked with 2 clusters else, it worked with 3. Finally, the background cluster (largest number of pixels) was subtracted from the main image to obtain the segmented cashew kernel. Fig. 1 shows the results of segmentation with k-means clustering. It can be seen that in this case, clustering with three clusters gives more optimal results.

Table 1: Grades of Cashew Kernels (CEPC 2010)

No.	Cashew Kernel	Characteristics of Kernel
Whole Whites (WW)		
1	WW-180	Light Ash or Pale Ivory or white in colour with a characteristic shape. Size decreases from WW-180 to WW-500.
2	WW-210	
3	WW-240	
4	WW-320	
5	WW-450	
6	WW-500	
Scorched Wholes (SW)		
7	SW	Darkened slightly due to over-heating. Size decreases from SW-180 to SW-500.
8	SW-180	
9	SW-210	
10	SW-240	
11	SW-320	
12	SW-450	
13	SW-500	
Other Grades		
14	Scorched Small Wholes (SSW)	Underdeveloped, Over-scorched, Spattered, Wrinkled, Discolored Blue.
15	Dessert Wholes (DW)	Spattered, Deep Scorched or Blue or Brown, Discolored and Black Spotted

16	Butts (B)	Light Ash or Pale Ivory or white. Cross-wise evenly or unevenly broke.
17	Splits (S)	Light Ash or Pale Ivory or white. Natural split lengthwise.
18	Large White Pieces (LWP)	Light Ash or Pale Ivory or white.
19	Small White Pieces (SWP)	
20	Baby Bits (BB)	
21	Scorched Butts (SB)	Darkened slightly (due to overheating). Cross-wise broken kernel.
22	Scorched Splits (SS)	Darkened slightly (due to overheating). Kernel split lengthwise.
23	Scorched Pieces (SP)	Darkened slightly (due to overheating).
24	Scorched Small Pieces (SSP)	
25	Scorched Pieces Seconds (SPS)	Underdeveloped, Over-Scorched, Spattered, Wrinkled, Discolored Blue.
26	Dessert Pieces (DP)	Spattered, Deep-Scorched or Blue or Brown, Discolored and Black Spotted.

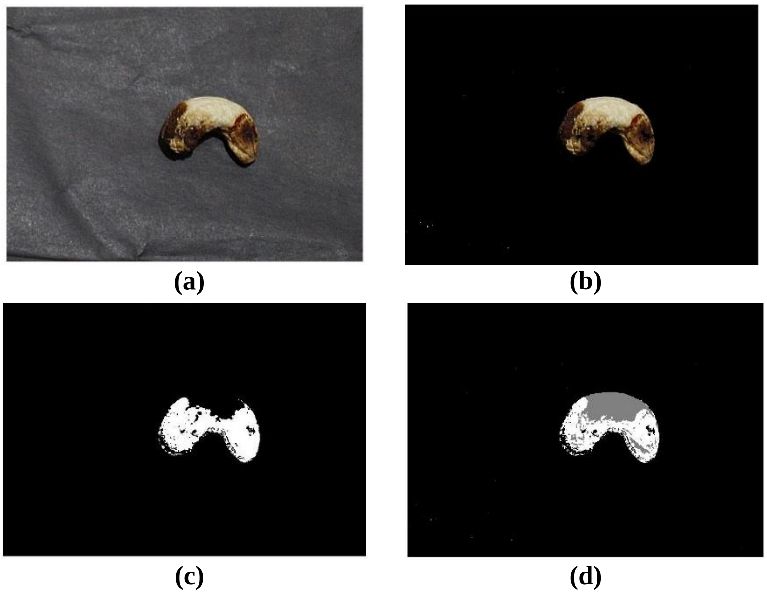

Fig. 1: Image Segmentation using K-means Clustering (Clockwise) (a) Cashew with Black Spots (b) Image after background subtraction (c) Segmentation with two clusters (d) Segmentation with three clusters

3.4 Feature Extraction

3.4.1 Morphological (Shape and Size) features: Shape and size of the cashew kernel were identified using the morphological feature method [10]. The segmented colour image is converted into a binary image. The object segment is identified as the largest connected component in the image. Before extracting the shape and size features, the binary images were rotated such that the major axis of the circumscribed ellipse (i.e., the ellipse that has the same second-moments as the object segment) was aligned with the horizontal axes (or x-axis) of the image. The following morphological features were extracted.

- **Area (A):** The actual number of pixels contained within the boundary of the region.
- **Major axis length and Minor axis length of the circumscribed ellipse:** The major axis length was considered the actual length (L) and the minor axis length of considered the actual width (W) and thickness (T) [11].
- **Aspect Ratio:** Ratio of major axis length to minor axis length.
- **Perimeter (P)**: the contour length of the boundary.
- **Equivalent Diameter:** Diameter of the circle having the same area as the region.
- **Convex area (Co):** It is the number of pixels in the smallest convex polygon that can contain the cashew kernel region.
- **Eccentricity:** The eccentricity is the ratio of the distance between the foci of the circumscribing ellipse and its major axis length.
- **Extent:** Ratio of the area of the region to the area of the smallest rectangular bounding box that encloses the region.
- **Solidity:** Ratio of the area of the region to the area of the smallest convex polygon that encloses the region.
- **Roundness:** Roundness(R) [7] is calculated by equation (1).

$$R = \frac{4 * \pi * A}{p^2} \tag{1}$$

- Compactness: Compactness(C) [7] is calculated by the equation (2).

$$c = \frac{\sqrt{\frac{4 * A}{\pi}}}{L} \tag{2}$$

- Certain Shape factor, proposed in [12] were also calculated by (3)
- Shape Factor =

$$Shape\ Factor = \frac{Major\ Axis\ Length\ (L)}{Area\ (A)} \tag{3}$$

- In order to extract the shape features, Fourier coefficient method [8,13] has been employed. This method involves the following steps to estimate the shape feature.
  - Estimate the outermost boundary points of the cashew kernel region.
  - Determine the centroid (xc , yc) of the kernel region.
  - Find Euclidean distance R(k) from each boundary point(xk , yk) to the centroid.
  - Discrete Fourier Transform is applied to R(k), resulting one-dimensional feature vector of the cashew kernel. Only the first term is used as a shape feature.

3.4.2 Texture Features: Gray Level Co-occurrence Matrix (GLCM) functions, proposed in [5] characterize the texture of an image by calculating how often pairs of the pixel with specific values and in a specified spatial relationship occur in an image. Five statistical features are extracted from the GLCM of the given image:

- **Energy/Uniformity:** Sum of the squared elements of the GLCM.
- **Entropy:** Measure of randomness in the grey-scale image. Calculated using equation (4).
- **Contrast:** Measures the local variations in the grey-level co-occurrence matrix.
- **Correlation:** Measures the joint probability occurrence of the specified pixel pairs.
- **Homogeneity:** Measures closeness of distribution of elements in the GLCM to GLCM diagonal. (Large if diagonal values are large). It is calculated by the formula in equation (5).

$$Entropy = -\sum_i \sum_j C_{ij} log C_{ij} \tag{4}$$

$$Homogeneity = -\sum_i \sum_j \frac{C_{ij}}{1 + |i - j|} \tag{5}$$

Local Binary Patterns (LBP) computes a local representation of texture [3]. It is constructed by comparing each pixel with its surrounding neighbourhood of pixels. The LBP code for the centre pixel is computed as follows in (6).

$$LPB_{P.R} = \sum_{i=0}^{P-1} s(g_i - g_c).s^i \tag{6}$$

Where g_c is the gray scale value of the centre pixel, g_i is the value of its ith neighbour, P is the number of neighbours, R is the radius of the circular neighbourhood that is the Euclidean distance between the centre pixel and its neighbours, and s(x) is a binarization function that is defined as follows.

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{7}$$

Arun et al. (2016) wrote in his study [3] that "LBP labels the pixels of an image by thresholding the neighbourhood of each pixel with the value of the centre pixel and considers the result as a binary number." The 8 neighbourhoods were considered and histograms were computed over each cell of these binary numbers. Concatenating the histograms gave a feature vector for the window.

3.4.3 Colour Features: The Hue, Saturation and Value (HSV) colour space is considered more informative than the Red, Blue, Green (RGB) colour space for colour analysis of images [3]. Hue describes the colour (or tint), Saturation describes the shade, or amount of gray and Value gives the brightness value. Thus, all images were first converted from the RGB colour space to the HSV colour space. The first, second and third colour moments (mean, standard deviation, and skewness) were extracted from the images and used as features for analysis.

$$Mean\ (\mu_i) = \frac{\sum_{j=1}^{M.N} x_{ij}}{M.N} \tag{8}$$

$$Std.Dev.(\sigma_i) = \sqrt{\frac{1}{M.N}\sum_{j=1}^{M.N}(x_{ij} - \mu_i)^2} \tag{9}$$

$$Skewness\ (\gamma_i) = \sqrt[3]{\frac{1}{M.N}\sum_{j=1}^{M.N}(x_{ij} - \mu_i)^2} \tag{10}$$

Where x_{ij} represents the value of the pixel j of colour dimension i *s* {H, S, V}. The mean intensity and maximum intensity of the gray-scale image was recorded. The weighted centroid of the gray-scale image was calculated and the distance between the actual centroid and the weighted centroid was taken as a feature for analysis.

3.4.4 Features obtained by clustering: Clustering by K-means is an unsupervised learning technique, which has been used for image segmentation in Step 3 of the algorithm. The ratio between the sum of distances of 2 clusters and the sum of distances of 3 clusters was also taken as a feature for classification.

3.5 Feature Extraction
Feature selection is an important step in any machine learning problem, especially while dealing with high dimension data and a limited number of observations. It leads to dimensionality reduction which reduces storage and computation time and makes results easier to understand. Feature selection was performed using two techniques: stepwise regression and neighbourhood component analysis. Every feature was inspected and irrelevant features were removed. Then Neighborhood Component Analysis (NCA) -proposed in [14] was performed. NCA is a non-parametric and embedded method for selecting features with the goal of maximizing prediction accuracy of regression and classification algorithms. NCA used with regularization is used to find a set of feature weights that minimize an objective function that measures the average leave-one-out classification loss over the data. All the features with NCA weights greater than 0.2 were considered for further analysis. On these, Stepwise Regression was performed which involves sequentially adding or removing features until there is no change in accuracy rate.

3.6 Training the Learning Model and Classification
The dataset was normalized by subtracting the mean and dividing each value by the standard deviation. To get rid of outliers or corrupted data, all data with normalized absolute values greater than 3σ was removed.

The first model was trained using Support Vector Machines with Gaussian kernel function [8]. To begin with, the "One v/s All" classification technique was employed. As this did not give good accuracy, the "One v/s One" Classification, using Adaptive Directive Acyclic Graphs as in [15] was used, which presented a much higher accuracy. Regularization parameter and sigma of the Gaussian kernel was calculated on cross-validation data, using the 10-fold cross-validation process.

To perform a comparative study of two supervised learning techniques, a second model was trained using Random Forest. Random forest classifier is an ensemble learning algorithm that creates a set of decision trees from a randomly selected subset of the training set. It then aggregates the votes from different decision trees to decide the final class of the test object. The Bagged Ensemble for this study was trained with the hyper-parameters of 80 decision trees, maximum of 6 predictors for a decision tree and a minimum of 2 leafs, and an Out of Bag fraction of 0.2.

4. EXPERIMENTAL RESULTS
4.1 Data Collection
A data-set of 468 training examples and 107 testing examples was obtained from Isha Cashews, Kumbalgodi Industrial Estate, Bangalore. Samples collected belonged to eight different categories and were labelled correctly under the supervision of trained experts from the Isha Cashews manufacturing plant. A total of 5 grades of cashews were used, namely, Whole Whites (WW) – 450, WW-320, WW-180, Splits, Scorched Wholes (SW) – 240. Additionally, 3 types of defective cashews were identified, namely, Black Spots, Discoloration and Mixed Defects.

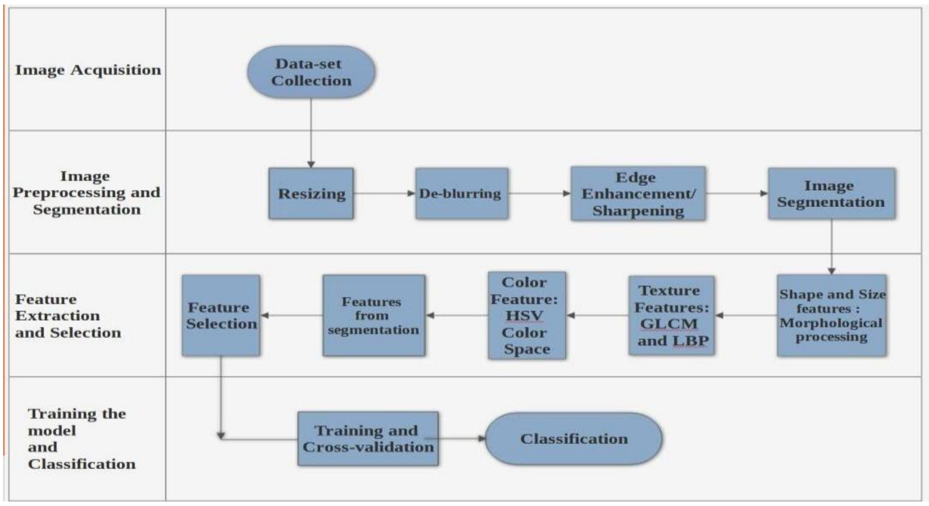

Fig. 2: Process flow diagram

4.2 Image Processing
The Image Processing Toolbox of MATLAB2018 was used for all image preprocessing, segmentation and feature extraction. After deblurring by the Lucy filter and sharpening by the median filter, the average Peak Signal to Noise Ratio (PSNR) was found to be around 36.05. Image segmentation by K-means was able to successfully demarcate the object region, with most images giving optimal results with two clusters. However, images coming under the category of black spots and mixed defects gave better results when three clusters were chosen for clustering.

By trial and error, it was found that a combination of morphological, texture and colour features are required to get the best classification results. We observed the following:
- WW-450, WW-320 and WW-180 show distinct colour properties when compared to the other classes. Among the Whole Whites, four morphological features made it easy to clearly distinguish between the three classes: Perimeter, Minor Axis Length, Equivalent Diameter and Convex Area.
- The colour features that were important for classification were skewness of Hue and Saturation, and standard deviation of Hue, Value and Red colour dimension.

- Important features for distinguishing black spots, splits and discolouration defects were: Maximum Intensity and mean intensity of the gray-scale image, and the distance between the centroid of the image and the weighted centroid.
- Entropy and Uniformity were the textural features which had a large weightage during NCA feature selection.
- Some other important features for distinction were the Shape Factor 1 ((3)), Compactness ((1)), Roundness ((2)) and Ratio of the sum of clusters distances for two clusters and three clusters.

Table 2: Confusion Matrix for SVM Classifier: Accuracy: 90.6%

		Actual Classification								Precision
		WW-450	**WW-320**	**WW-180**	**SW-240**	**Splits**	**Black Spots**	**Discoloration**	**Mixed**	**(Class-Wise)**
Predicted classification	WW-450	15	0	0	0	0	0	0	0	1.00
	WW-320	0	11	0	0	0	0	0	0	0.84
	WW-180	0	2	11	0	0	0	0	0	1.00
	SW-240	0	0	0	32	1	0	0	0	0.97
	Splits	0	0	0	0	15	0	0	0	0.94
	Black Spots	0	0	0	0	0	4	1	1	1.00
	Discoloration	0	0	0	0	0	0	5	0	0.50
	Mixed	0	0	0	1	0	0	4	4	0.80
Recall (Class-Wise)		1.00	1.00	0.85	0.97	1.00	0.67	1.00	0.44	

Table 3: Confusion Matrix of Random Forest Classifier. Accuracy: 94.28%

		Actual Classification								Precision
		WW-450	**WW-320**	**WW-180**	**SW-240**	**Splits**	**Black Spots**	**Discoloration**	**Mixed**	**(Class-Wise)**
Predicted classification	WW-450	16	0	0	0	0	0	0	0	1.00
	WW-320	0	11	0	0	0	0	0	0	1.00
	WW-180	0	0	13	0	0	0	0	0	1.00
	SW-240	0	0	0	35	0	0	0	0	0.97
	Splits	0	0	0	1	14	0	0	0	1.00
	Black Spots	0	0	0	0	0	2	0	2	0.50
	Discoloration	0	0	0	0	0	0	4	0	0.8
	Mixed	0	0	0	0	0	2	1	4	0.67
Recall (Class-Wise)		1.00	1.00	1.00	1.00	0.93	0.50	1.00	0.57	

4.3 Classification

After feature normalization and scaling, a total of five outlying data points were removed. On the clean data, the SVM One-vs.-All algorithm worked with an efficiency of 85%. The model was not able to satisfactorily identify WW-180 kernels and misidentified them as WW-320 or WW-450. Black Spot defects and discolouration defects showed a low f-score because the system often got mixed up between these two classes. The SVM one-vs-one algorithm showed a much-improved accuracy of 90.6% but at the cost of approximately 1 second more of computation time. One-vs-one was implemented using the Adaptive Directed Acyclic Graph method, which showed a similar accuracy but with comparatively lesser computation time.

Random Forest classifiers were trained using a select set of most important features. This showed a maximum accuracy of 94.28%. The mixed defects and black spot defects classes showed low precision and recall. The discolouration class showed better recall, but it still suffered from a low f-score. However, Whole Whites and Scorched Wholes were categorized with high accuracy. On the whole, this indicated that the Random Forest Classifier served as a better classification model for classifying the five classes' cashew kernels and identifying defective kernels. The class-wise precision and recall for SVM and Random Forest are tabulated in Table 2 and 3.

5. CONCLUSION AND SCOPE FOR FUTURE WORK

This study brings us a step closer to automating the Indian cashew industry, which still relies heavily on manual labour for this task. From this study, we can conclude that a Random Forest Classification model can successfully sort cashews into different grades, with an accuracy of 94.28%. This can be adopted for industry-grade classification. Image preprocessing makes the classification task more efficiently. Clustering by K-means serves as a good segmentation algorithm. A combination of textural, morphological and colour features is important for training the classifier. While the distinction among the defective cashews still lacks accuracy, it is a problem that can be solved by gathering a larger dataset. Future scope lies in consolidating a comprehensive data set, with additional features such as the weight of the cashew, and the side-view of the kernel.

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