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Computer Revelation System Based Classification Of Intact Cashew Grading System

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Abstract

Computer vision provides one alternative for an automated, non-destructive and cost-effective technique to accomplish these requirements. This inspection approach based on image analysis and processing has found a variety of different applications in the food industry. The aim of this study is to investigate the performance of different multiclass classification techniques against whole cashew data set and to find the most appropriate technique for cashew grading system. The purpose of this study is to develop the computer vision based cashew grading system in conjunction with most accurate classification technique. The performance of different classification techniques including Multi-Layer Perceptron, Naive Bayes, K-Nearest Neighbor, Decision tree, Support Vector Machine are evaluated using WEKA toolbox to have most suitable classification technique for the cashew grading system. Subsequently, the classification technique that has the potential to significantly improve the performance of the system is suggested to be utilized in cashew grading system.

Keywords

Computer vision; Image processing; Image analysis ,Cashew grading system, Decision tree, k-Nearest Neighbors, Multi-Layer Perceptron (MLP), Naïve Bayes, Support Vector Machine (SVM).

Introduction

The increased awareness and sophistication of consumers have created the expectation for improved quality in consumer food products. This in turn has increased the need for enhanced quality monitoring. Quality itself is defined as the sum of all those attributes which can lead to the production of products acceptable to the consumer when they are combined. Quality has been the subject of a large number of studies (Shewfelt & Bruckner, 2000). The basis of quality assessment is often subjective with attributes such as appearance, smell, texture, and flavour, frequently examined by human inspectors. Consequently Francis (1980) found that human perception could be easily fooled. Together with the high labour costs, inconsistency and variability as-sociated with human inspection accentuates the need for objective measurements systems. Recently automatic inspection systems, mainly based on camera—computer technology have been investigated for the sensory analysis of agricultural and food products. This system known as computer vision has proven to be successful for objective measurement of various agricultural (He, Yang, Xue, & Geng, 1998; Li & Wang, 1999) and food products (Sun, 2000; Wang & Sun, 2001).

Computer vision includes the capturing, processing and analysing images, facilitating the objective and non-destructive assessment of visual quality characteristics in food products (Timmermans, 1998). The potential of computer vision in the food industry has long been recognised (Tillett, 1990) and the food industry is now ranked among the top 10 industries using this technology (Gunasekaran, 1996). Recent advances in hardware and software have aided in this expansion by providing low cost powerful solutions, leading to more studies on the development of computer vision systems in the food industry (Locht, Thomsen, & Mikkelsen, 1997; Sun, 2000). As a result automated visual inspection is under going substantial growth in the food industry because of its cost e ectiveness, consistency, superior speed and accuracy. Traditional visual quality inspection performed by human inspectors has the potential to be replaced by computer vision systems for many tasks. There is increasing evidence that machine vision is being adopted at commercial level (Locht et al., 1997). This paper presents the latest developments and recent advances of computer vision in the food industry. The fundamental elements of the systems and technologies involved are also examined.

Computer vision is the construction of explicit and meaningful descriptions of physical objects from images (Ballard & Brown, 1982). The term which is synonymous with machine vision embodies several processes. Images are acquired with a physical image sensor and dedicated computing hardware and software are used to analyse the images with the objective of performing a predefined visual task. Machine vision is also recognised as the in-tegrated use of devices for non-contact optical sensing and computing and decision

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processes to receive and interpret an image of a real scene automatically. The technology aims to duplicate the e ect of human vision by electronically perceiving and understanding an image (Sonka, Hlavac, & Boyle, 1999). Table 1 illustrates the benefits and drawbacks associated with this technology.

Hardware

A computer vision system generally consists of five basic components: illumination, a camera, an image

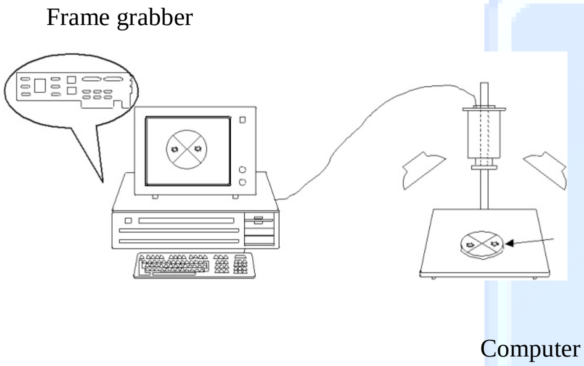

Fig. 1. Components of a computer vision system (Wang & Sun, 2002a).

capture board (frame grabber or digitizer), computer hardware and software as shown in Fig. 1 (Wang & Sun, 2002a).

As with the human eye, vision systems are affected by the level and quality of illumination. Sarkar (1991) found that by adjustment of the lighting, the appearance of an object can be radically changed with the feature of interest clarified or blurred. Therefore the performance of the illumination system can greatly influence the quality of image and plays an important role in the overall efficiency and accuracy of the system (Novini, 1995). In agreement Gunasegaram (1996) noted that a well-designed illumination system can help to improve the success of the image analysis by enhancing image contrast. Good lighting can reduce reflection, shadow and some noise giving decreased processing time. Various aspects of illumination including location, lamp type and color quality, need to be considered when de-signing an illumination system for applications in the food industry (Bachelor, 1985). Gunasegaram (2001) found that most lighting arrangements can be grouped as either front or back lighting. Front lighting (electron projection lithography or reflective illumination) is used in situations where surface feature extraction is required such as defect detection in apples (Yang, 1994). In contrast back lighting (transmitted illumination) is employed for the production of a silhouette image for critical edge dimensioning or for sub-surface feature analysis as in the size inspection of chicken pieces (So-Borski, 1995). Light sources also differ but may include incandescent, fluorescent, lasers, X-ray tubes and infrared lamps. The choice of lamp affects quality and image analysis performance (Bachelor, 1985). The elimination of natural light effects from the image col-election process is considered of importance with most modern systems having built in compensatory circuitry.

Cashew is one of the most popular tree nuts. It is an expensive agricultural product and the prices depend on its quality. Today, various kinds of cashews are available in the market with different qualities. To ascertain the quality, grade standard have been designed by considering the color and the size (weight) of the cashew kernel as important characteristic as shown in Table 1 and Table 2.

Several attempts have been made to mechanize the grading of the kernels, with limited success. Power driven rotary sieves are one mechanical method, another being the use of two outwardly rotating rubber rollers aligned at a diverging angle. Because of direct contact, which can cause the damage to the cashew kernel, mechanical grading system is not appropriate for the cashew kernel grading.

With exception of few mechanical methods, grading of the cashew kernel is still labor intensive manual process. Cashew kernels are mostly graded manually by skilled labor, employed only for grading, but the quality decisions may vary among the graders and are inconsistent. This way of grading presents many quality problems and grading is the last opportunity for the quality control.

Computer vision system has proven successful for the objective, online measurement of several agricultural products [2]. Computer vision based cashew grading system is an alternative to the manual, mechanical and optical methods. This method offers automated, high speed, non-destructive and cost effective technique for classification.

Designing such system without taking the physical properties of cashew kernel into consideration may yield poor results. In [1], the physical properties of the raw cashew nut and cashew kernel have been evaluated. Length (L), Width (W) and Thickness (T) of the cashew kernel plays vital role in deciding the grade of the cashew kernel which are measured as shown in Figure. 1.

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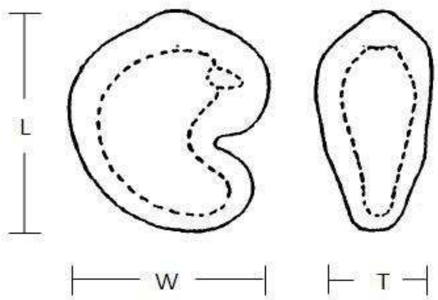

Figure 1: Length (L), Width (W) and Thickness (T) of the cashew kernel.

Methods And Material

The samples of whole cashews of different grades, used in this study were collected from Orbitta Exports, one of the cashew production companies of Gujarat. Initially the different samples of the each grade are taken and weight of each cashew kernel is measured individually with accuracy of 0.001 gm.

A Computer Vision System is developed which consists of two digital cameras placed in front and top of cashew sample under investigation at distance of 15 cm from the sample position as well as perpendicular to each other, an image capturing box, fluorescent lamp and computer system. Image processing toolbox in the MATLAB is used as image analysis and processing software to extract the features from the image. Fig. 2 shows the general operations for the cashew grading system.

Table 1. Color characteristic of the whole cashew kernel

Cashew Kernel Type	Color Characteristic
White Whole (W)	Cashew kernels are white and free from damage.
Scorched Whole (SW)	Cashew kernels are light brown and free from damage.
Dessert Whole (DW)	Cashew kernels are dark brown, it may show deep black spot and free from

Table 2. Weight characteristic of the whole cashew kernel

<table>
<tr><th>White Whole</th><th>Number of Kernels</th><th>Scorched Whole</th><th>Number of Kernels</th><th>Dessert Whole</th><th>Number of Kernels</th></tr>
<tr><td>W180</td><td>170-180</td><td>SW180</td><td>170-180</td><td rowspan="8">DW</td><td rowspan="8">No sepcification</td></tr>
<tr><td>W210</td><td>200-210</td><td>SW210</td><td>200-210</td></tr>
<tr><td>W240</td><td>220-240</td><td>SW240</td><td>220-240</td></tr>
<tr><td>W280</td><td>260-280</td><td>SW280</td><td>260-280</td></tr>
<tr><td>W320</td><td>300-320</td><td>SW320</td><td>300-320</td></tr>
<tr><td>W400</td><td>350-400</td><td>SW400</td><td>350-400</td></tr>
<tr><td>W450</td><td>400-450</td><td>SW450</td><td>400-450</td></tr>
<tr><td>W500</td><td>450-450</td><td>SW500</td><td>450-450</td></tr>
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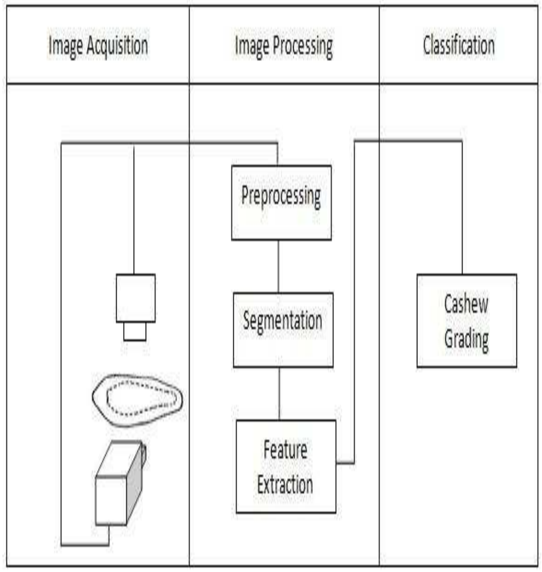
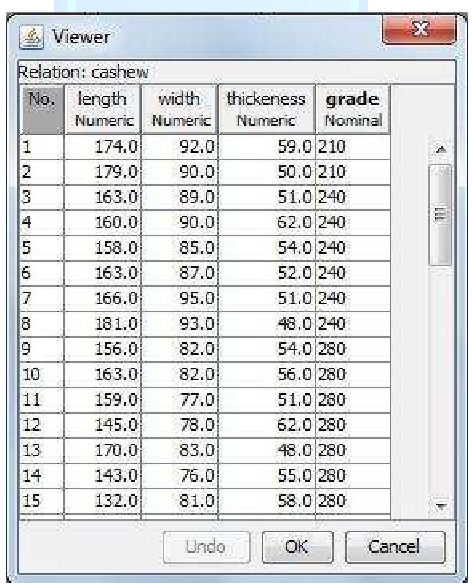


Figure 2: Schematic representation of cashew grading system

Image acquisition involves capturing of RGB front and top view images of each cashew kernel under study. During Preprocessing phase image is smoothed using 3x3 average filter. In this study, black color background is utilized to have bimodal histogram. Threshold segmentation technique differentiates the cashew kernel region from background and converts the gray-scale image into the binary image. To estimate the grade of the cashew kernel, Length, Width, Thickness and Color of the cashew kernel are considered as important features. These Features are extracted using image analysis and image processing algorithms.

The dataset for the cashew is designed from the extracted features as shown in Fig. 3, with a total data of 6800 and a dimension of 1700 rows, each row contains the data of single cashew and 4 columns, each column contains data for one of the extracted features value of color, length, width, thickness. Waikato Environment for Knowledge Analysis (WEKA) toolbox is used to evaluate and find most suitable classification techniques for the cashew grading system among various multi-class classification techniques including Multi-Layer Perceptron (MLP), Decision Tree, k-Nearest Neighbors, Naïve bayes and Support Vector Machine.



No.	length Numeric	width Numeric	thickeness Numeric	grade Nominal
1	174.0	92.0	59.0	210
2	179.0	90.0	50.0	210
3	163.0	89.0	51.0	240
4	160.0	90.0	62.0	240
5	158.0	85.0	54.0	240
6	163.0	87.0	52.0	240
7	166.0	95.0	51.0	240
8	181.0	93.0	48.0	240
9	156.0	82.0	54.0	280
10	163.0	82.0	56.0	280
11	159.0	77.0	51.0	280
12	145.0	78.0	62.0	280
13	170.0	83.0	48.0	280
14	143.0	76.0	55.0	280
15	132.0	81.0	58.0	280

Figure 3: Data set of cashew kernels

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Classification Techniques

Multi-Layer Perception

Multilayer Feed forward Neural Networks [5] provide a natural extension to the multiclass problem. Instead of just having one neuron in the output layer, with binary output, we could have N binary neurons. The output codeword corresponding to each class can be chosen as either one-per- class coding or distributed output coding:

• <u>One-per-class coding:</u> Each output neuron is designated the task of identifying a given class. The output code for that class should be 1 at this neuron, and 0 for the others. Therefore, we will need N = K neurons in the output layer, where K is the number of classes. When testing an unknown example, the neuron providing the maximum output is considered the class label for that example.

• <u>Distributed output coding</u>: Each class is assigned a unique binary codeword from 0 to 2N − 1, where N is the number of output neurons. When testing an unknown example, the output codeword is compared to the codeword for the K classes, and the nearest codeword, according to some distance measure, is considered the winning class. Usually the Hamming distance is used in that case, which is the number of different bits between the two codeword. For instance, for a 4 class problem, and using N = 5 bit codeword, the coding can be as shown in table 2. The hamming distance between each pair of classes is equal to 3 i.e. each two codes differ in three bits. If we got a codeword for an unknown example as 11101, we compute its distance from the four codeword shown above. The nearest codeword is that for class 3 with a distance of 1, so class label assigned to that example will be class 3.

Decision Tree

Decision trees are a powerful classification technique. Two widely known algorithms for building decision trees are Classification and Regression Trees [6] and ID3/C4.5 [7]. The tree tries to infer a split of the training data based on the values of the available features to produce a good generalization. The split at each node is based on the feature that gives the maximum information gain. Each leaf node corresponds to a class label. A new example is classified by following a path from the root node to a leaf node, where at each node a test is performed on some feature of that example. The leaf node reached is considered the class label for that example. The algorithm can naturally handle binary or multiclass classification problems. The leaf nodes can refer to either of the K classes concerned.

K-Nearest Neighbors

K-Nearest Neighbors [8] is considered among the oldest non- parametric classification algorithms. To classify an unknown example, the distance (using some distance measure e.g. Euclidean) from that example to every other training example is measured. The k smallest distances are identified, and the most represented class in these k classes is considered the output class label. The value of k is normally determined using a validation set or using cross-validation.

Naive Bayes

Naive Bayes [9] is a successful classifier based upon the principle of Maximum A Posteriori (MAP). Given a problem with K classes {C1, . . . ,CK} with so-called prior probabilities P(C1), . . . , P(CK), we can assign the class label c to an unknown example with features x = (x1, . . . , xN) such that c = argmaxcP(C = ckx1, . . . , xN), that is choose the class with the maximum a posterior probability given the observed data. This aposterior probability can be formulated, using Bayes theorem, as follows: P(C = ckx1, . . . , xN) = P(C=c)P(x1,...,xNkC=c) P(x1,...,xN). As the denominator is the same for all classes, it can be dropped from the comparison.

Now, we should compute the so-called class conditional probabilities of the features given the available classes. This can be quite difficult taking into account the dependencies between features. The naive bayes approach is to assume class conditional independence i.e. x1, . . . , xN are independent given the class. This simplifies the numerator to be P(C = c)P(x1kC = c) . . . P(xNkC = c), and then choosing the class c that maximizes this value over all the classes c = 1, . . . ,K. Clearly this approach is naturally extensible to the case of having more than two classes, and was shown to perform well in spite of the underlying simplifying assumption of conditional independence.

Support Vector Machine

Support Vector Machines are among the most robust and successful classification algorithms [10,11]. They are based upon the idea of maximizing the margin i.e. maximizing the minimum distance from the separating hyper plane to the nearest example. The basic SVM supports only binary

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classification, but extensions have been proposed to handle the multiclass classification case as well. In these extensions, additional parameters and constraints are added to the optimization problem to handle the separation of the different classes. The formulation can result in a large optimization problem, which may be impractical for a large number of classes.

Experimental Results

The performance of the different classification techniques are evaluated with respect to whole cashew kernel data set. The experimental results are as per Table 3.

Table 3. Performance evaluation of different Classification techniques

Sr. No.	Classification Techniques	Classification
1	ML-Perceptron	86%
2	Decision tree	79%
3	k-Nearest Neighbors	76%
4	Naive Bayes	81%
5	SVM	77%

Conclusion

Computer vision has the potential to become a vital component of automated food processing operations as increased computer capabilities and greater processing speed of algorithms are continually developing to meet the necessary online speeds. Thus continued development of computer vision techniques such as X-ray, 3-D and colour vision will ensue higher implementation and uptake of this technology to meet the ever expanding requirements of the food industry. The aim of this study is to investigate the performance of different multiclass classification techniques against whole cashew data set and to find the most appropriate technique for cashew grading system. Performance of the various classifiers including Multi-Layer Perceptron (MLP), Decision Trees, k- Nearest Neighbors, Naive Bayes, Support Vector Machine are evaluated and it is observed that Multi-Layer Perceptron classification technique is more feasible to be used in cashew grading system as it possesses comparatively higher classification accuracy of 86% than other classifiers.

Future Work

In this study we evaluate the performance of the several classifier techniques to identify the efficient classifier for the automatic cashew grading system. In cashew kernel grading specification, there is presence of imprecision in weight based characteristic. If number of white cashew kernels per pound (454 gms) are in between 170 to 180 then cashew kernel grade is W180 and if number of white cashew kernels per pound are in between 200 to 210 then cashew kernel grade is W210. But it is observed that there is no specification for in- between ranges (181-199 cashew kernels per pound). Because of this kind of the imprecision it is possible that the fuzzy logic can be more effective for the decision control. Therefore in the future work, for the same dataset of the whole cashew kernel, Fuzzy Inference System will be designed to improve the classification accuracy.

References

[1] Balasubramanian, D. 2001. Physical properties of raw cashew nut. Journal of agricultural Engineering Research, 78(3), pp. 291-297.

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