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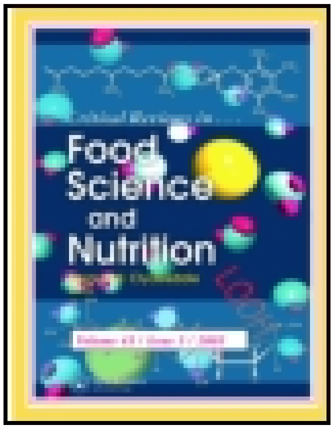

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A Comprehensive Survey of Fruit Grading Systems for Tropical Fruits of Maharashtra

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A Comprehensive Survey of Fruit Grading Systems for Tropical Fruits of Maharashtra

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Abstract:

It is said that the backbone of Indian economy is agriculture. The contribution of the agriculture sector to the national GDP (Gross Domestic Products) was 14.6% in the year 2010. To attain a growth rate equivalent to that of industry (viz. about 9%), it is highly mandatory for Indian agriculture to modernize and use automation at various stages of cultivation and post harvesting techniques. The use of computers in assessing the quality of fruits is one of the major activities in post harvesting technology. As of now, this assessment is majorly done manually, except for a few fruits.

Currently, the fruit quality assessment by machine vision in India is still at research level. Major research has been carried out in countries like China, Malaysia, UK, and Netherlands. To suit the Indian market and psychology of Indian farmers, it is necessary to develop indigenous technology. This paper is the first step towards evaluating the research carried out by the research community all over world for tropical fruits. For the purpose of survey, we have concentrated on the tropical fruits of the state of Maharashtra, while keeping in focus of the review image processing algorithms.

Keywords: Vision system, Food Grading, Image Processing.

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1. INTRODUCTION

India is the second largest producer of fruits after China, with a production of 44.04 million tonnes of fruits in an area of 3.72 million hectares. A large variety of fruits are grown in India, of which mango, banana, citrus, guava, grape, pineapple and apple are the major ones. Apart from these, fruits like papaya, jackfruit, ber, pomegranate in tropical and sub-tropical group and peach, pear, almond, walnut, apricot and strawberry in the temperate group are also grown in a sizeable area. Although fruit is grown throughout the country, the major fruit growing states are Maharashtra, Tamil Nadu, Karnataka, Andhra Pradesh, Bihar, Uttar Pradesh and Gujarat.

Maharashtra has diverse agro climatic conditions suitable for the cultivation of a wide range of crops, and a progressive farming community. The state has eight agro export zones for grapes and grape wine, mangoes, flowers, pomegranates, bananas and oranges. It also has five crop clusters for Cashew, Sapota, Sweet orange, Fig and Custard Apple. It is among the largest producers of seedless grapes (75.3%), pomegranates (67.7 %), Mandarin oranges (40%) and Sapotas (22.1%). Thus, Maharashtra has the highest gross value (16.8 %) contribution to food products in the country. This indicates that India has vast potential to export fruit, but meeting international quality standards and evaluating them quickly for exporting is a major issue. This calls for an automated system for objective quality assessment of fruits. Traditionally, assessment has been done manually by selecting one sample from batch and having it inspected by trained persons to detect defect and sort them according to quality. Thus, this paper reviews progress of computer vision in fruit quality assessment of tropical fruits which are specially grown in Maharashtra.

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2. FRUIT QUALITY ASSESSMENT

Methods to measure fruit quality can broadly be classified as destructive or non-destructive. Amongst instrumental measurements, the well-known and highly used conventional methods such as Firmness measurement by penetrometer test, Analysis of soluble solids by refract meter, and chemical methods are all destructive. Only the measurement of epidermal color by a colorimeter, and the evaluation of appearance by means of image analysis are non-destructive. Evidently, the major drawback of destructive methods is the resulting economic loss, apart from the fact that how a single sample can be thought to be representative of the entire batch.

Non-destructive methods overcome these problems, as they can be applied for selection and grading of every individual fruit, thus overcoming possible discrepancies between different batches and samples of fruit, and obviously without destroying a certain amount of sample fruit. According to the principle used to detect fruit properties, non-destructive methods can be classified as mechanical, acoustic, optical, and others.

A computer vision system offers the potential to automate manual grading practices, thus replacing tedious human inspection tasks. Computer vision has proven successful in objective, online measurement of several fruits with applications ranging from color inspection to the complex defect detection.

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Mango

Due to symmetry in its shape, Theekapun Charoenpong [1] et. al. (2004) proposed 2D ellipse model for volume measurement of mango. To calculate volume, the orthographic drawing method was applied. The top view and the side view photographs of the fruit were given as inputs to the system. Horizontal surface of the Nam-Dokmai mango was assumed to be an 'ellipse' and thus, its volume was estimated by multiplying slice area with slice thickness. The total volume was estimated by multiplying volume summation of all slices from tail to head of mango, as shown in the figure. 1. Estimated volume of mango was compared with water displacement method and it was been observed that its coefficient of determination was over 0.994 and the RMS error of volume in general size was 2.098%. It was concluded that the estimated value strongly agreed with the actual volume for symmetrical mangoes only.

Thanarat Chalidabhongse [2] et. al. (2006) analyzed 2D/3D visual properties of mango such as size, area and volume to sort them accordingly. Based on multiple silhouette images, 3D visualization of mango was constructed using volumetric caving. Initially, a large bounding box was modelled to enclose the 3D volume. The whole volume was then divided into cubical voxels. Voxel space containing n^3 voxels was generated. Each voxel in voxel space was projected using corresponding camera parameters. If the projected voxel fell outside the silhouette in at least one view, it was discarded from the volume which was set to be transparent. Otherwise, it was kept in the object voxel space. Figure 2 illustrates this method of 3D volume reconstruction. Two experiments were performed; one to show the accuracy of proposed vision-based measurement over instruments based measurement, and the other to show the sorting accuracy by comparing to human sorting. Experimental results showed that proposed method outperforms the manual sorting method.

Panitnat Yimyam et. al.[3] described the image processing techniques to extract physical properties of mango. First, hue model was constructed to segment the mango image. After removing noise using morphological operations, spline interpolation was used to fit mango boundary. Mango was peeled and with calibration parameters as shown in the figure 3, surface area was computed. Sixty “Nam Dokmai” mango samples in three various sizes ware graded using proposed methods and results were compared to those graded by experienced farmers. The results showed that the technique could be a good alternative and more feasible method for grading mango.

An accurate image analysis method to detect spot-like lesions on fruit was developed by G. Corkidi et. al. [4] . The technique was applied to evaluate the progression of fungal mango diseases. The hardware design of this method used stepper motor to rotate fruit so that a sequence of 360 images could be acquired. This image set was used to create pseudo cylindrical ‘equal-area’ projection of the fruit in a two-dimensional map. Using image analysis procedures, lesion area was computed. Percentage of affected area was considered as scale of disease measurement. The average error of the method was -0·1%, standard deviation 0·44. This technique may be adapted for use with most commercial image analyzers and for other diseases with spot-like symptoms.

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Pomegranate

Ali I. Hobani and A. Al. Janobi [5] developed a machine vision system for estimating shape and size of pomegranates. Two images of pomegranate were acquired from top view and side view. The prediction equations were developed from relationships between projected area, shape and size to estimate volume, surface area and weight. A power law equation was obtained to describe the relationship between volume surface area and the projected areas. Experiment was conducted on 'Banati' and 'Manfaluti' cultivators of pomegranate. This study found that the average values of pomegranate shape features for both cultivators were greater than zero, confirming the elliptical form. Measurement average error for prediction equation was less than 2% for 'Banati' and was less than 4% for 'Manfaluti' pomegranate.

B. Majidi et. Al[6] investigated computer vision system to classify pomegranate, pear and apple based on fused visual features. Researchers inspected the fruits' whole surface using two images of fruit which were acquired using two cameras. Because of time constraints in real time applications, simpler algorithms such as averaging and minimum-maximum selection were used to fuse images. To estimate volume from fused image, it was registered using point mapping. RGB image was converted into HSI domain to extract color features. 32x32 sampling window was used for sampling mean and variance of RGB and HSI color variables. Based on standard values of theses color features and blob detection, neural network was trained to classify the fruits according to defect and color. Author concluded that method is acceptable from execution point of view but to detect defects accurately, it must be merged with other sensors.

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Orange

Oranges were assessed according to surface characteristic by Michael Recce [7] et. al. (1996). Histograms of the normalized pixel values were constructed for two color planes (red and green). Frequency distribution of pixels was fitted into Gaussian. Data which was not fit well to a Gaussian were considered as defect free sample. Defects were classified using Zernike moments and neural network.

Yaowarat Sirisathitkul [8] et. Al. (2006) reported an automated 'Chokun' orange maturity sorting system by color grading. The image was transformed into HSI domain and color classifier was built using bimodal hue histogram. Finally, decision rules were derived from the hue histogram. Ninety 'Chokun' oranges in three degrees (raw, ripe and overripe) were used in the training step and 50 'Chokun' oranges were evaluated in the testing step. The experimental results showed that technique gives acceptable results but could further be improved by analyzing all sides of orange fruit for grading.

M. Khojastehnazhand et. Al. [9](2009) proposed an image processing algorithm for accurate computation of volume and surface area of oranges based on machine vision. The proposed image acquisition system was constructed using two right angled cameras to acquire images of two perpendicular views. Orange images in 3D representation were divided into frustums of right cylindrical cone as shown in figure 4. The volume and surface area of a conical frustum was calculated using mathematical equations. Now, the total volume of the orange could

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easily be calculated by adding the individual ones. The actual volume and surface area of orange was measured using water displacement method and tape method respectively. The paired *t-test* was used to compare the volume and surface area determined by the image processing techniques and the actual values. Experimental results showed that the aforesaid algorithm is rotationally invariant and may be applied for axi-symmetrical fruits such as melon, pear, kiwifruit and pomegranate.

Reza Fellegari et. al· [10] investigated another image processing method to estimate the volume of an orange. Author approximated spherical 2D image of orange as circle and area and volume were estimated using mathematical expressions applied for circular objects. Initially, this experiment was carried out for a known sample. Then calibration was performed to find ratio of real volume from water displacement method to the volume calculated by image processing method. This ratio was used to relate pixel area to actual volume estimation. Results showed that volume is more accurate if more number of known samples is used to find calibration ratio.

Banana

F. Mendoza [11] et. al. (2005) developed a computer vision algorithm to predict the seven ripening stages of banana. The color of the banana peel was considered as dominant factor in determining ripeness. Typically, the R'G'B' signals generated by a Color Digital Camera are device-dependent and not identical to the RGB intensities of the CIE system, so color calibration was performed. The images were segmented by thresholding method. Brown spots on peel of

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bananas were detected using combination of *a** and *b** color bands of the CIELAB color space as shown in figure 5. Color analysis was done by converting RGB image into HIS, CIELAB or *L*a*b** color spaces. Color feature was extracted from three regions of interest of the banana image (full banana image, background and brown spots). Best features were selected by simple statistical analysis. Discriminate analysis was used as selection criterion for classification of banana. Their findings indicated that three sets of color features were sufficient to predict banana ripeness with accuracy more than 94%.

Size and ripeness of banana fruit were evaluated using machine vision system by Nur Badariah Ahmad Mustafa [12] (2008). The Canny edge detection method with Gaussian filter was used to filter out the image. After obtaining the boundary of the selected region, properties such as area, perimeter and major and minor axis length were determined. A reference object as shown in Figure 6 was needed to translate the pixel count to area, perimeter, length and thickness, which lead to size estimation. As ripeness is directly related to yellow color percentage in the image, L*a*b* color space was analyzed to estimate ripeness.

Hasnida Saadl[13] et. al (2009) proposed a histogram based ripeness detection. After image acquisition, RGB color intensities were categorized into 3 groups, namely 0-120 pixel values as group 0, 121-190 grouped as group 122 and 191-255 as group 255. Thus each image had three values of intensities for each component of R, G, and B. The same data was used to train an Artificial Neural Network using back propagation method. Lastly, a GUI was designed

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to classify bananas according to their ripeness stage. Once the neural network was trained, new banana samples with various ripeness stages were tested. Results showed that the system performs the best when there are 7 hidden nodes, with learning rate fixed at 0.1 and momentum at 0.9. But, background & luminance effect was found to be prominent in recognizing the ripeness of bananas.

Yizhong Wang [14] et. Al. (2010) reported a novel nondestructive fruit quality inspection method based on fruits' surface color. First, the image was converted from the RGB color model to the HSI color model, and was segmented based on hue value to separate the fruit from its background. White balancing was used to remove luminance defects. Next, the simplified histograms of hue H and saturation S of fruit's surface color were calculated, which were used as the inputs of a designed back propagation (BP) network. The output of the BP network was the quality description of the inspected fruits. After training, the quality of fruits was inspected by the BP network according to the simplified histograms of H and S of fruit's surface color. Experiments were conducted for the quality inspection of bananas with satisfied results as shown in Figure 7.

Volume of a banana was estimated by Mahmoud Soltani[15] et. al. (2010) using mathematical approximation. The actual projected area and surface area were measured by image processing technique. The banana fruits were divided into six planes of cut along the longitudinal axis of the fruit. At each plane of cut, the perpendicular diameters (Di, di) were measured to 0.01 mm accuracy by a digital caliper (Figure 8). The external and internal length of banana (Lo, Li) was measured by a flexible ruler (Figure 9).

Expressions were developed for computing the banana's volume, surface area and projected area. It was presumed that the cross section of banana is elliptical. And to calculate the volume of each plane, elliptical area is rotated about the center of curvature (O_i), as shown in Figure 10. The volume of each cushion was computed and finally summed to obtain the total volume of banana. The total surface area was obtained by adding the perimeter of elliptical section of each element. The banana was divided into seven sections and it was assumed that each section was part of a ring. Mean value of the ring thickness and area of the sectoral frustum was computed. The actual volume of bananas was measured using the water displacement method (WDM). The paired t-test and the mean difference confidence interval approach were used to compare the volume, projected area and surface area of banana determined from mathematical approximation with the actual values of them that were calculated with water displacement method (volume) and image processing (projected area and surface area). The Bland - Altman (1999) approach was used to plot the agreement between measured parameters with the mathematical approximation.

Author concluded that, the size of banana has no effect on the estimation of its parameters such as volume, surface area and projected area using image processing.

Further, Mahmoud Soltani [16] et. al. (2011) investigated equation modeling of banana mass, surface area and projected area as a function of physical properties. The external and

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internal lengths of the bananas (Lo, Li) were measured by a flexible ruler (Figure 11). The perpendicular diameters (W, T) were measured to 0.01 mm accuracy by a digital caliper (Figure 12). The mass of each sample was measured by a digital balance with an accuracy of 0.01 g. The value of mean length of fruit (L) was then calculated using equation (1)

$$L = \frac{L_i + L_0}{2} \qquad (1)$$

Geometric mean diameter (Dg) and sphericity (Φ) values were determined using equations (2) and (3). The actual projected area and surface area were measured by image processing technique.

$$D_g = \sqrt[3]{LWT} \qquad (2)$$

$$\Phi = \frac{D_g}{L} \qquad (3)$$

Different models were considered based on single and multiple regressions of banana fruit mass. Through experimentation, advantages and flaws of each modeling technique were investigated, and then the most suitable modeling was selected. It was concluded that –

- For mass modeling, the appropriate modeling was based on one dimension (length) of the fruit.
- For surface area modeling, the appropriate modeling was based on one dimension (length) of the fruit, but the mass predicted the surface area better than the length of the fruit.

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- For projected area modeling, the length of the fruit was appropriate to predict the projected area.

Mahmoud Soltani[17] (2011) extended his research to investigate physical and mechanical properties of banana at different stages of ripeness. The color of the fruit can be described by several color coordinate systems such as RGB or CIELAB. In CIELAB color space, the L* coordinate indicates lightness intensity (0-black to 100-white), the a* coordinate represents the position of the object's color on a pure green and pure red scale (where -127 represents pure green and +127 represents pure red), and the *b** coordinate represents the position of the object's color on a pure blue and pure yellow scale (where -127 represents pure blue and +127 represents pure yellow). Color index was then calculated using equation (4)

$$CI = 1000\frac{a^*}{L^* B^*} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Chroma (saturation) indicates strength of hue.

$$C = \sqrt{a^{*2} + b^{*2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

The hue angle (H) between the color vector and the negative a^* axis was used to characterize the color changes during developmental changes. Mechanical properties of specimens were measured by an Instron Universal Testing Machine (Model SANTAM ST 5) controlled by a *PC*-based data acquisition card in a personal computer. A randomized complete block experiment design was carried out on experiments. For each treatment, three samples were randomly selected and the average values of three experiments were reported. Experimental data were

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analyzed using analysis of variance (*ANOVA*). Duncan's multiple range test was employed for mean separation with the level of significance at 5%.

Mean values and standard deviations of chromatic properties of banana fruit were calculated. At different levels of ripeness, the relationship of these properties with stages of ripeness and coefficient of determination were found. The a^* and *CI* had a good correlation with the ripeness level of banana, so did firmness and hardness, so these properties could predict the ripeness level of banana fruit during ripening treatment. But extraction of mechanical properties would result in the destruction of samples. It could only be a good practice in laboratory and not for quality inspection in warehouses. Thus, the best method for predicting the level of ripeness is to measure chromatic properties (a^* and *CI*); since this method does not destroy the fruits.

Papaya:-

H. Saad [18] (2006) classified papaya ripeness by applying threshold rule and artificial neural network. Masking of original image and gray scale image that were morphologically processed was preferred before classification process. The findings indicated that classification by neural network was more effective than threshold rule method, although the processing time was larger.

Slamet Riyadi [19] et. al. (2007) investigated the unique shape characteristic for papaya size grading using combinations of area, mean diameter and perimeter. Pre-processing was done using automatic thresholding (Otsu) segmentation and morphological noise removal techniques. General descriptors of shape such as area mean diameter and perimeter were extracted from Papaya images and combination of these features was trained separately using an MLP model.

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Finally papaya images were classified into four grades using a neural network with more than 94% accuracy. Table I shows the result of papaya classification using four combinations of shape characteristic features.

The sorting of deformed papaya fruits from well formed fruits was performed based on fused pairs of wavelet transformed features by Asnor Juraiza Ishak and Slamet Riyadi [20] et. al. (2008). Papaya shape was determined by detecting its boundary which was defined as the contour signature. Contour signature which represents the boundary pixel coordinates was decomposed in terms of both row and column components. Graphical displays of the contour signature components in which both plots of the row and column signatures for both well-formed and deformed papayas, are as shown in Figure 13(a) and 13(b), respectively. Discrete Wavelet Transform (DWT) was applied to the signature contour of papaya image. The extracted detail coefficients of both row and column signatures were processed further in which three basic statistical properties (sum, mean, standard deviations) are computed. Finally, LDA was used to perform the shape classification task. All three derived feature sets were a good basis for sorting with accuracy of 98%.

D. I. Amarasinghe and D. U. J. Sonnadara [21] (2009) studied the surface color variation of Papaya fruits with maturity. RGB and OHTA color spaces based image segmentation algorithms were developed to detect yellow regions in papaya. Preliminary results showed that normalizing technique reduces the systematic bias due to lightening effect.

Lemon and Citrus Fruit:

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Fuzzy based color classification of lemons was studied by Wen-Hung Chan [22] et. al.(1994). Initially minimization of fuzziness was measured for optical threshold and then for sorting process membership function of criteria was established. Results showed that fuzzy method was superior to the traditional statistical methods, and a better accuracy of 93.3 % for combined sorting was reported.

As there is a difference in reflectance of the normal surface from the defective one, defect and diseases are characterized by different textures. Efficiency of wavelet transform for texture analysis was reported by K.Vijayarekha and R.Govindaraj [23] et. al. (2006). Wavelet transform decomposes image into several frequency sub bands at different scale. Difference in texture was identified by finding edges which were separating textures. Results showed that Wavelet packets were more efficient than discrete wavelet packet for texture analysis. Mean and standard deviation were estimated as features from wavelet coefficient. Finally artificial neural network was adopted for classification. ANN classification results of mandarin images using WPT features are shown in Table II.

Dae Gwan Kim[24] et. al (2009) investigated use of color texture features for detecting citrus peel diseases. A total of 39 image texture features were determined from the transformed HSI image. Region-of-interest from image was identified by color co-occurrence method for each fruit sample. Algorithms for selecting useful texture features were developed based on a stepwise discriminate analysis, and 14, 9, and 11 texture features were selected for three color combinations of HSI, HS, and I, respectively. Classification models were constructed using the reduced texture feature sets through a discriminate function based on a measure of the generalized squared distance. Results showed that the model using 14 selected HSI texture features achieved the best classification accuracy (96.7%).

A sorting system for grading lemon based on color and size was developed by M. Khojastehna zhand [25] et. al.(2010). The color of the fruit was determined by calculating average Hue (H) value from the fruit. By dividing the fruit image into a number of distinct sectors, the volume of lemon fruit was estimated. Comparing the information during sorting phase with the available information in the database, the final grade of passing fruits was determined. Author reported that the paired t-test results showed that the volume computed with IP (image processing) method was not significantly different from the volume measured with WDM (water displacement method).

Zhi-yuan Wen [26] et. al. (2010) developed a citrus fruit grading system based on machine vision with fractal dimensions. Initially, image was transformed into HIS color space. Then box counting method of fractal dimension was applied to find shape character value and color eigen values. To calculate color eigen values, for the H color space, the histograms of the four grades were obtained (Figure 14). But the histograms showed only the cumulative information of various hues, and the distribution information of the above hues was lost. So, fractal was necessary for the analysis.

Finally, classifier who integrates wavelet transform and neural network was tested to classify citrus fruit and found that a fractal dimension of the fruit describes its shape more

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accurately. Author concluded that fractal dimensions used to describe citrus shape is more accurate than those of geometry method.

Watermelon:

Fruit shape is one of the most important quality parameters for evaluation by consumer preferences. Also misshapen fruits are usually rejected according to grading standards of fruit such as watermelons. This study was carried out by Hassan Sadrnia[27] et. al.(2009) to develop "detection algorithm" for misshapen watermelons. Physical characteristics of watermelon such as mass, volume, dimensions, density, spherical coefficient and geometric mean diameter were measured. Relations and correlations coefficient obtained between above characteristics for normal and non-standard fruit shape. It was found that weight of normal watermelon could be determined by image analysis with error 2.42%. In addition fruit shape of long type watermelon in front view was well-described by an ellipsoid model with R2 = 0.97. Finally, the results indicated that length to width ratio and fruit area (2D) to background area ratio can be used to determine misshapen fruit.

Farah Yasmin Abdul Rahman[28] et. al.(2009) monitored watermelon ripeness based on image processing technique. The RGB color technique with mean values was utilized as the extracted features for the watermelon's rind. The extracted feature was classified using fuzzy logic system to determine the ripeness level of the watermelon. Experimental results reported that the average results attained was 98.45% of the watermelons were correctly classified into the ripeness level.

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Reviewed image processing techniques for fruit grading has been summarized in table III.

3. CONCLUDING REMARKS

This paper reviews computer vision systems developed for fruit quality assessment. The major focus of review is restricted to tropical fruits grown especially in Maharashtra. There are numerous instruments like Vernier caliper, Planimeter etc. available to measure physical properties of fruits, but vision based method proves that to be a better alternative.

Most of the researchers have proposed/developed a computer vision system to assess quality factors of fruits such as volume, shape, size, surface defect detection and evaluation of ripeness level. Background and luminance effect was found to be of prime concern in recognizing the ripeness of fruits. Normalization can be used to reduce the systematic bias which occurs due to lightening effect.

While measuring volume, image processing algorithms give accurate results only for symmetrical shapes, so mathematical modeling is needed. For color analysis, the projected area of fruit is taken into consideration and researchers reported that spatial information used as color feature is not related to the size of mango fruit. Evaluation of individual spots on mango fruit over time was done by G. Corkidi et. al. and found that there is no relation between initial size or position of spot and rate at which they enlarge in diameter.

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Image processing algorithms are developed by researchers to compute the volume and surface area of oranges. These algorithms are rotation invariant and it is shown that show that size has no effect on estimation of volume and surface area of orange.

Ripeness level of banana is estimated by analyzing banana in CILAB color space. As a* feature and CI (color index) have a good correlation with the ripeness level of banana, so do firmness and hardness. So these properties can predict the ripeness level of banana fruit during ripening treatment. But extraction of mechanical properties of banana resulted in the destruction of samples, and it could thus only be a good practice in laboratory and not for quality inspection in warehouses. The best method for predicting the level of ripeness is to measure chromatic properties (*a** and *CI*) using image processing since this method does not destroy the fruits.

Classification of papaya fruit using neural network is more effective than threshold rule, though the processing time is larger. The combination of the area and mean diameter features provide a unique shape characteristic for papaya size grading and it is reported that the accuracy is more than 94%.

Fractal dimension based method outperforms the geometry method for describing the shape of citrus fruits. Wavelet packets and HSI based texture features reported for defect detection accuracy up to 97% for citrus fruits. Fuzzy methods are superior to traditional statistical methods to classify lemon fruits. Image processing analysis of watermelon shows that length to width ratio and fruit area to background area ratio can be used to determine misshapen fruit.

Note: We searched for literature for other fruits grown in Maharashtra such as guava, bor and jamun. But no such literature was found.

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Table 1: Result of papaya size grading

Feature Combination	% Classification Accuracy				
	Grade				
	S	M	L	XL	All
Area-mean diameter	66.7	97.4	95.8	100	94.6
Area-perimeter	83.3	97.4	93.8	93.8	93.8
Mean diameter-perimeter	91.7	97.4	89.6	87.5	91.5
Area-mean diameter-perimeter	91.7	97.4	87.5	100	93.8

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Table II: mandarin fruit images and classification results (K.Vijayarekha and R.Govindaraj [25])

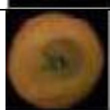
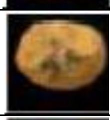
Image	Outputs Obtained			Classification
	P1	P2	P3	
	0.9996	-0.9993	-0.9988	Pitting
	0.9993	-0.9965	-0.9982	Pitting
	0.9995	-0.9997	-0.9983	Pitting
	-0.9687	-0.9983	0.9558	Stem-end rot
	-0.9813	-0.6173	0.8965	Stem-end rot
	-0.9768	-0.7844	0.5761	Stem-end rot
	-0.9930	0.9989	-1.000	Splitting
	-0.9259	0.9280	-0.9995	Splitting
	-0.9921	0.9920	-0.9999	Splitting

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Table III: Summary of fruit grading systems using image processing

Sr. No.	**Authors**	**Topic/Area of Work**			**Outcomes/Methodology used etc.**	
		Grading Parameters	**Image Acquisition technique**	**Image Features for grading**	**Image Processing Algorithms & Decision Criteria**	**Outcome/comments**
Class : Fruits Sub Class: Mango						
1	Theekapun Charoenpong et.al.	Volume	Orthographic View • Top view • Side view	2D elliptical model Slicing estimates volume.		Estimated volume strongly agreed with actual one for symmetrical mangoes only and for small sized mangoes results were not acceptable.
2	Thanarat Chalidabhongse et. al.	Size and volume	Multiple silhouettes images	2D/3D visual properties such as projected area (A), length (L), width (W), thickness (T),	Back propagation neural network	Results are more efficient in terms of speed and convenience as compared to instrument method.
3	Panitnat Yimyam	Physical properties		Sized parameters Mean value of R,G,B		color spatial distribution is not related to its size.
4	G. Corkidi et. al	Spot Detection	360 images of samples are taken by rotating stepper motor by 1^0	Pseudo cylindrical projections	Thresholding	There is no relation between initial size or position of spot and rate at which they enlarged in diameter.
Class : Fruits Sub Class: Pomegrante						
5	Ali I. Hobani	Shape and size	Top view and side	Surface area, projected area	Power Law equation and Regression	Average error reported is less than

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	and A. Al. Janobi [		view		equations are developed	4 %
6	B. Majidi et. Al	Visual features such as color , shape	Two camera images placed at right angled to each other	HIS color features	simpler algorithms such as averaging and minimum and graded using Neural network	To detect defects accurately, system must be merged with other sensors
Class : Fruits Sub Class: Orange						
7	Michael Recce	Surface characteristics		Color Histogram Data fitted into Gaussian	Defects are classified using Zernike moments and neural network, Fisher's linear discriminate analysis.	Close to meeting the requirements of a future commercial video grading machine.
8.	Yaowarat Sirisathitkul	Maturity		Bimodal Hus histogram Decision rules decides by hue color	Neural network	Gives acceptable results but can be improved by analyzing all sides of fruits
9	M. Khojastehnazhand	Volume and surface area	two right angled cameras gives perpendicular view of two images	Divided into conical frustum	Mathematical equations are used to calculate volume and surface area of conical frustum	Developed algorithm is rotationally invariant and may be applied for axi-symmetrical fruits such as melon, pear, kiwifruit, pomegranate.
10	Reza Fellegari et. al	Volume		Approximated 2D image of orange as circle	Calibrated with Mathematical formulas used to calculate circle are and volume	Accurate volume measurement can be possible by increasing calibration samples.
Class : Fruits Sub Class: Banana						
11.	F. Mendoza	Ripeness		Color features from L*a*b color space	Best features are selected by simple statistical analysis. Discriminate	Three evaluated sets of color features were able to correctly predict

					analysis is used as selection criterion for classification of banana	with more than 94% ripening stages
12.	Nur Badariah Ahmad	Size Ripeness		Physical features such as area, perimeter, length L*a*b Color features	Reference object is used to calibrate size of banana	Gives acceptable results.
13.	Hasnida Saadl	Ripeness		Color features	Histogram Artificial Neural network	The background of the images and luminance effect also played an important role in recognizing the ripeness of bananas.
14.	Yizhong Wang	Surface color		HIS color model	Hue and saturation histogram BPNN	Gives satisfactory results
15.	*Mahmoud Soltani*	Volume		Mathematical model approximation	paired t-test and the Bland-Altman approach	Results showed that the average error is 2.98%
16.	Mahmoud Soltani	Physical and mechanical properties of banana at ripeness stage		Color index ,chroma, hue angle is calculated form LAB color space		Color index shows good relations with ripeness and ripeness is directly related with mechanical properties. So, being a non destructive method it can be alternative to instrument based firmness and hardness detection
Class : Fruits Sub Class: Papaya						
17.	H. Saad	Ripeness		Morphological operations	Artificial Neural Network (ANN)	Classification by neural network is more effective than threshold rule even though the processing time is larger than

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						threshold.
18.	Slamet Riyadi	Shape		Area, mean, perimeter	Artificial Neural Network (ANN)	The combination of the area and mean diameter features provided a unique shape characteristic for papaya size grading as with it classified papayas with more than 94% accuracy.
19.	Slamet Riyadi	Shape		Discrete Wavelet Transform Statistical properties	linear discriminate analysis(LDA)	All three derived feature sets gives an almost perfect classification of more than 98%.
20.	D. I. Amarasinghe	Maturity (Color)			RGB and Ohta color based segmentation algorithms	Preliminary results showed that normalizing technique reduces the systematic bias due to lightening effect.
Class : Fruits Sub Class: Lemon and citrus fruit						
21.	Wen-Hung Chan	color		Fuzzy set colors	Fuzzy membership function	Fuzzy method was superior to the traditional statistical methods, and accuracy of 93.3 % for combined sorting was reported
22.	K.Vijayarekha and R.Govindaraj	Defective texture		Texture analysis mean and std deviation from wavelet coefficients	Artificial neural Network	Wavelet packets were more efficient than discrete wavelet packet for texture analysis.
23.	Dae Gwan Kim	Citrus peel disease		Color texture features from HSI space	Discriminate function based model	14 selected HSI texture features achieved the best classification accuracy (96.7%)

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24.	Khojastehnazhand	on color and size		Average color values from HIS space, sector wise volume estimation		No significant different is observed between actual and estimated volume using image processing method.
25.	Zhi-yuan Wen	Color and shape		HIS color space	Box counting method of fractal theory Wavelet Neural Network	Fractal dimensions used to describe citrus shape is more accurate than those of geometry method.
Class : Fruits Sub Class: Watermelon						
26.	Hassan Sadrnia	Shape		Physical characteristics geometric mean diameter	ellipsoid model	Length to width ratio and fruit area (2D) to background area ratio can be used to determine misshapen fruit.
27.	Farah Yasmin et.Al.	Ripeness		Color features	Fuzzy logic	The application of soft computing techniques such as fuzzy logic should be opted as classifier.

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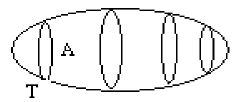

Fig.1 Volume of slice. (Source:- Theekapun Charoenpong [1])

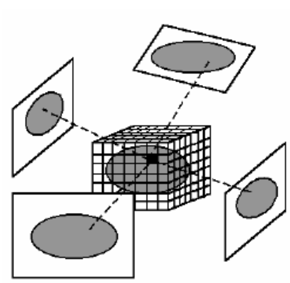

Fig. 2 3D volume reconstruction from multiple images. (Source:-Thanarat Chalidabhongse [2])

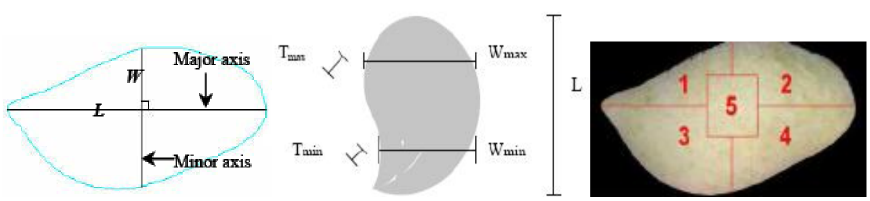

Fig. 3   The proposed mango sized parameters.(Source:- Panitnat Yimyam[3])

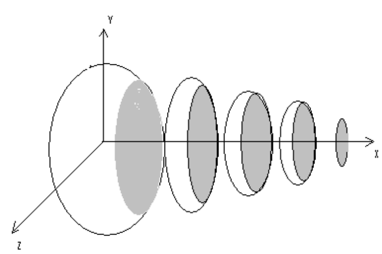

Fig. 4   segmentation of orange into a number of frustums of right elliptical cone (Source: M. Khojastehnazhand [9])

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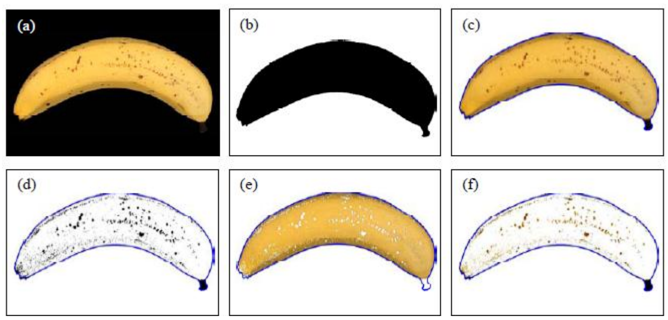


Fig. 5. Selected images of the segmentation process: (a) Original image, (b) Detection of full banana (using a threshold value of 50), (c) Segmented color image (full), (d) Detection of brown spots from a and b* color bands (threshold values of 140 and 156, respectively), (e) Segmented color background free of spots (back), (f) Segmented color spots (spot). .(Source:- F. Mendoza[11])*

Fig. 6 Original Image of single banana with coin as reference .(Source:- Nur Badarish Mustafa[12])

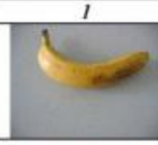
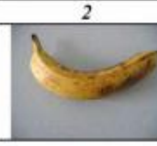
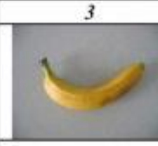
No.	1	2	3
Image			
BP Network output	0 0.001 0.9137 0 0.0061	0 0 0.0016 0.9910 0.0182	0.9998 0 0 0 0.0047
Actual activity	5	3	9
Measured activity	5	3	9

Fig. 7 Experimental results. (Source:- Yizhong Wang [14])

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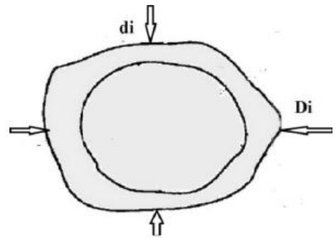

Fig. 8 Plane of the cut along longitudinal axis(Source:- Mahmoud Soltani[15])

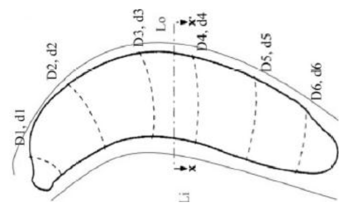

Fig. 9 Longitudinal section of banana fruit(Source:- Mahmoud Soltani[15])

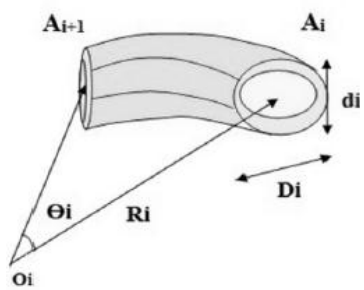

Fig.10. Clavicle shape of each banana section (Source: Mahmoud Soltani[15])

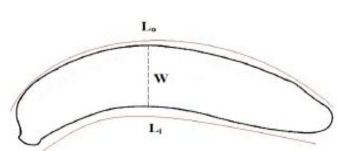

Fig 11 Major dimensions of banana fruits (Source:- Mahmoud Soltani[16])

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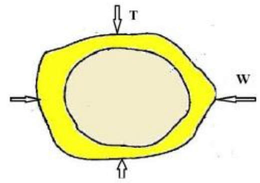
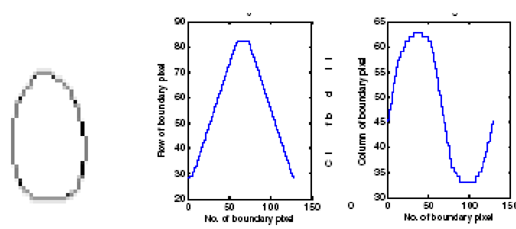
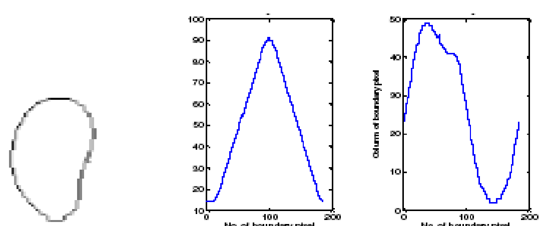


Fig 12 The perpendicular diameters of banana fruit (Source: Mahmoud Soltani[16])



(a) Well-formed Papaya Contour *i) Row signature* *ii) Column Signature*



(b) De-formed Papaya Contour *i) Row signature* *ii) Column Signature*

Fig. 13 Contour and row, column signature of Papaya (Source: - Asnor Juraiza Ishak and Slamet Riyadi [22])

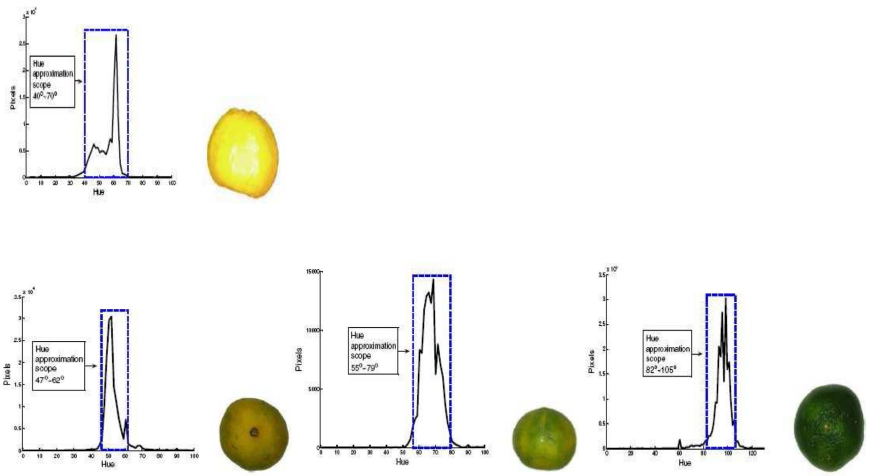


Figure 14 Hue component histogram (a) Golden yellow fruit (b) Orange yellow fruit (c) Yellow green fruit (d) Green fruit

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