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RGB color imaging technique for grading of dates

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ABSTRACT

Hardness is one of the major factors in determining the quality of dried fruits. It increases the chewiness and toughness of the fruits. A robust quality assurance system is required for on-line grading of dried fruits as the present manual methods are inconsistent, inaccurate and laborious. The objective of this study was to determine the efficiency of a RGB color imaging technique to classify dates into three classes based on hardness: hard, semi-hard and soft dates. Dates from three common varieties in Oman (Fard, Khalas and Naghal) were used in this study (total 3300 samples). The RGB image of individual date sample was taken by a CCD camera and analyzed using Matlab software. Thirty nine features (13 features in each R, G and B channel) were extracted from each image and analyzed. Three classes (hard, semi-hard and soft) and two classes (hard and soft ("semi-hard and soft" together as "soft")) classification models were developed using linear discriminant analysis (LDA) with all features and stepwise discriminant analysis (SDA) with selected features (based on level of contribution to classification). In three classes approach, the overall classification accuracy was 69%, 87% and 82% for Fard, Khalas and Naghal varieties, respectively, using LDA. It was 68%, 86% and 81% for Fard, Khalas and Naghal varieties, respectively, using SDA. The classification accuracy was improved in two classes approach. It was 84% (LDA) and 83% (SDA) for Fard, 90% (LDA) and 91% (SDA) for Khalas, and 96% (both in LDA and SDA) for Naghal varieties. Imaging techniques have great potential to develop on-line quality monitoring systems for dates based on hardness. However, further studies are required using other image acquisition systems such as NIR cameras to improve the classification.

1. Introduction

Date palm (*Phoenix dactylifera*, L.) is considered to be one of the oldest trees in the world. Over thousands of years, dates have been consumed as a stable food by the people in the Middle East and North Africa (Ait-Oubahou and Yahia, 1999). Dates are popular in these regions because of their nutritional values and readily available energy (Al-Marshudi, 2002; Al-Shahib and Marshall, 2003; Kader and Hussein, 2009; Al-Rawahi et al., 2005). In general, dates are mostly consumed as a whole fruit without any processing. However, recently the government in many dates growing countries are promoting the processing and export of dates. In spite of massive efforts, the amount of export continued to be a challenge in Oman and many other countries. This may be due to the inconsistencies in the supply of quality dates in the international markets (Al-Marshudi, 2002). There are four major attributes in the grade standards of dates: color, size, absence of defects and physical properties (such as hardness) (Kader and Hussein, 2009).

Hardness is one of the major degrading factors of date's quality. According to USA standards for grade of dates, hardness receives the highest points (Kader and Hussein, 2009). Hard dates are tough and difficult to chew (Rahman and Al-Farsi, 2005). Admixture of hard dates with soft dates will reduce the consumer preferences. During processing, the hard dates can damage the machine components that are used in making the date paste or syrup. Therefore, a robust quality assurance system is required to identify hard dates in handling and processing facilities.

At present, in most of the dates growing countries, the hard dates are identified by visual inspection method. But this is a time consuming, inaccurate, inconsistent and subjective method (Brosnan and Sun, 2002; Jarimopas and Jaisin, 2008; Al-Janobi, 1998). Al-Ohali (2011) mentioned that visual inspection is the main source of delay in the grading and sorting of dates. The common instrumental method used to measure the hardness of agricultural and food product is texture profile analyzer (TPA). However this method follows sample-destructive approach, and therefore it cannot be implemented in date factories for online quality monitoring.

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Computer vision technology has been widely used for quality assessment of various food products. The principle of this technology relies on the extraction of information from the acquired image about the quality of object (Gunasekaran, 1996). It is considered to be an accurate, non-destructive, consistent, fast, cost effective and efficient emerging technology (Chen et al., 2002; Lu et al., 2000; Tao et al., 1995; Brosnan and Sun, 2002; Du and Sun, 2006; Venora et al., 2009; Miranda et al., 2007; Ercisli et al., 2012). In computer vision method, several types of camera such as NIR, X-ray, infrared, thermal, RGB color and so on are broadly used to acquire images based on application.

However, the RGB color camera has been commonly used in many food industries mainly due to the easiness in image analysis and lower price. Some of the successful application using color imaging are: sorting of apple (Shahin et al., 2002), sorting of sweet tamarind (Jarimopas and Jaisin, 2008), grading of apple (Leemans et al., 2002), grading of strawberry (Liming and Yanchao, 2010), defects in apple (Puchalski et al., 2008; Leemans et al., 1998) and defects in citrus (Blasco et al., 2007; Lopez-Garcia et al., 2010).

Computer vision techniques have been used for measuring various internal and surface qualities of dates. The linear dimensions such as length, width and thickness of Mazafati cultivar was measured using RGB camera by Jahromi et al. (2008). From the basic measured units, projected area and sphericity were calculated. Shomer et al. (1998) studied the cellular damage in Madjhoul date variety after frozen storage for 10 months using an electron microscope. In another study, a computer vision based prototype mechatronic system was developed for grading of Saudi Arabian date varieties (Sukkari and Maneefi) (Al-Janobi, 2010). The average grading accuracy (three grades) for Sukkari variety was 88% and Maneefi variety was 93% while using feed forward multilayer perceptron neural network trained with back propagation algorithm. Lee et al. (2008b) developed an automatic date grading system using reflective near-infrared imaging to obtain reflectance images of the top surface of dates. The percentage of delamination was calculated and used in grade determination. The overall accuracy of the system was in the range of 79 to 95% for various grades. Al-Rahbi et al. (2013) detected surface cracks on dated using RGB camera with 58% to 78% classification accuracy in three classes model (no-crack, low-crack and high-crack) and 75% to 88% in two classes model (with-crack and without-crack) using statistical classifiers. The same color features were also used to determine the classification accuracy using back propagation neural network (BPNN) (Al-Rahbi et al., 2015). The classification accuracy was 77% for three classes model and 90% for two classes model. Thomas et al. (2012) classified three date varieties (Khalas, Fard and Madina) using a color camera and investigated the effect of motion blurring on classification. It was determined that motion blurring did not affect the classification results. Abdellahhalimi et al. (2013) developed a camera sensor system to sort date fruit bunches based on their maturity. Algorithm was developed to detect external defect and level of maturity based on HSV space color. Al-Ohali (2011) used color images to grade dates based on flabbiness, size, shape, intensity and defects (bruise and bird flicks) into three grades (grades 1, 2 and 3). Despite various studies on date quality using computer vision method, there is no published work on the evaluation of hardness using RGB color images.

Generally in handling facilities, the hardness of dates is identified by the graders based on visual surface appearance such as color, texture and waviness. While capturing the color image of the dates, and analyzing the surface qualities, it may be possible to identify the hardness of dates more accurately. Therefore, the objective of this study was to determine the potential of RGB color imaging technique to classify dates based on hardness.

2. Materials and methods

2.1. Samples collection

Three popular varieties of dates, Fard, Khalas and Nagal, were used in this study. Khalas and Naghal varieties were obtained from the Seeb Market, one of the biggest markets for dates in Oman. Different grades of these two varieties were purchased from different suppliers. In each variety, the samples were graded into three classes (hard, semi-hard and soft) from the conglomerate bulk, and class standard was confirmed by a date quality expert in Sultan Qaboos University. A representation of 750 dates (250 dates/class) in each variety were selected and used.

Fard variety is a commercial and one of the most processed varieties in Oman. Samples for this variety were collected from three main date producing regions (Al-Batinah, Al-Dakhliah and Al-Sharkiah). The dates were graded into three classes according to hardness (soft, semi-hard and hard) by an experienced grader and confirmed by the quality manager in Sun Bright Factory, Barka, Oman. A total of 1800 representative date samples were selected and used in this study (200 samples/class/region). Therefore, in total, 3300 dates (1800 Fardh + 750 Khalas + 750 Naghal) were imaged individually and analyzed.

2.2. Image acquisition

The image acquisition system used in this study consisted of three components: RGB color camera (model: EOS 550D, Canon Inc., Japan) at resolution of 5184 × 3456 pixel, two fluorescent lights for illumination (model: Dulux L, OSRAM, Italy), and a personal computer. The camera was calibrated by customizing the white balance using a gray card (model: Digital Gray Kard XL, DGK Color Tools, USA) with 18% reflectance (Valous et al., 2009; Pedreschi et al., 2006) before taking each batch of imaging.

A dark box was used to create an imaging chamber in order to avoid backscattering effects from other light sources. During imaging, each date sample was placed manually on a white background at 15 cm distance from the camera. The image was captured using an automatic remote shooting software in the computer linked with the camera. All the acquired images were stored in the computer and used for further analysis.

2.3. Feature extraction

The RGB components of all images were analyzed using an algorithm developed in Matlab software (Version 7.6.0, The Mathworks Inc., Natick, MA, USA). In each image, the date sample was segmented from the background using simple thresholding method combined with morphological operations (Fig. 1). The morphological operations such as dilation and filling of holes were performed on images to improve the segmentation process. After segmenting the date sample from the background, 13 features in each R, G and B channels (total 39 features) were extracted from the region pertaining to date in each image. The description for all features is explained in Table 1.

2.4. Statistical analysis

All extracted features were used in the development of classification models using SPSS software (Version 20, IBM Corporation, New York, USA). The classification accuracies were determined in three classes model (hard, semi-hard and soft) using linear discriminant analysis (LDA). Similarly, in two classes model, the images of semi-hard dates and soft dates were mixed together and treated as soft dates (soft vs. hard). In both approaches, the classification accuracy of stepwise discriminant analysis (SDA) with selected features

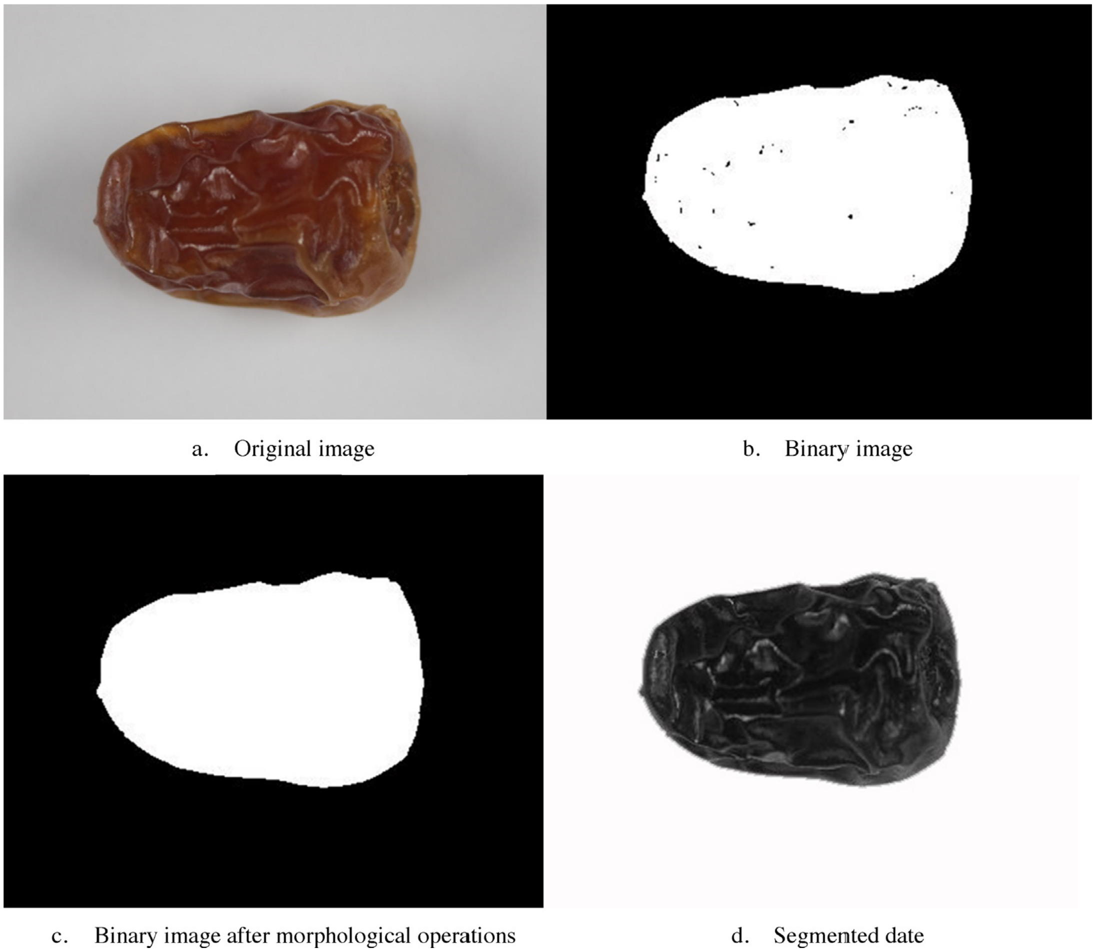

Fig. 1. Steps involved in the segmentation of dates from the background.

Table 1
Details of features extracted from color images of dates in each R, G and B channel.

Feature	Description
Mean intensity	Measure of average intensity of all pixels in an image
Standard deviation	Measure standard deviation of all pixels in an image
Variance	Measure of variance of all pixels in an image
Eccentricity	Ratio of distance between the foci of the ellipse and its major axis length
Solidity	Proportion of the pixels in the convex hull that are also in the region
Extent	Proportion of the pixels in the bounding box that are also in the region
Variance-GLCM*	Measure of intensity heterogeneity from of all pixels in an image
Contrast-GLCM	Measure of the intensity contrast between a pixel and its neighbors over the entire image of red intensities
Correlation-GLCM	Measure of how correlated a pixel is to its neighbor over the entire image
Energy-GLCM	Measure of the sum of squared elements in GLCM
Homogeneity-GLCM	Measure of closeness of distribution of elements in the GLCM to the GLCM diagonal
Maximum probability-GLCM	Measure of the strongest response of GLCM
Entropy-GLCM	Measure of the randomness of intensity image

(Gonzalez et al., 2011).
* GLCM—gray level co-occurrence matrix.

was also determined. In SDA, the model selected most contributing features automatically and used in the classification. The mean intensity of R, G and B components in different varieties and classes of dates were tested using student *T*-test ($\alpha = 0.05$).

3. Results and discussion

3.1. RGB images of dates

Fig. 2 shows the typical color images of dates from different varieties. In general, the hard dates in all varieties had wavier or wrinkle skin compared to other classes. This may be due to the lower moisture content in hard dates. The R, G and B intensities of date images are given in Table 2. In all varieties, R component was greater than the G and B components. This was in alignment with the findings of Al-Janobi (2000) who demonstrated that the red color band contributed more than other bands in grading of dates. In Fard variety, there was no difference in G component among three classes. There were no differences in R and B components between hard and semi-hard dates of Khalas variety. But in Naghal variety, the R, G and B components were significantly different for each class.

The contribution of different color bands was based on application. For example, Fadel et al. (2006) measured the color properties of five date varieties (Lolo, Khalas, Berhi, Fard and Bomaan) from UAE to develop the classification protocols. It was reported that R component was suitable for discrimination of Berhi from Bomaan and Berhi from Fard, the G component was good for the classification of Fard and Berhi, and Fard and Bomaan. Similarly the B

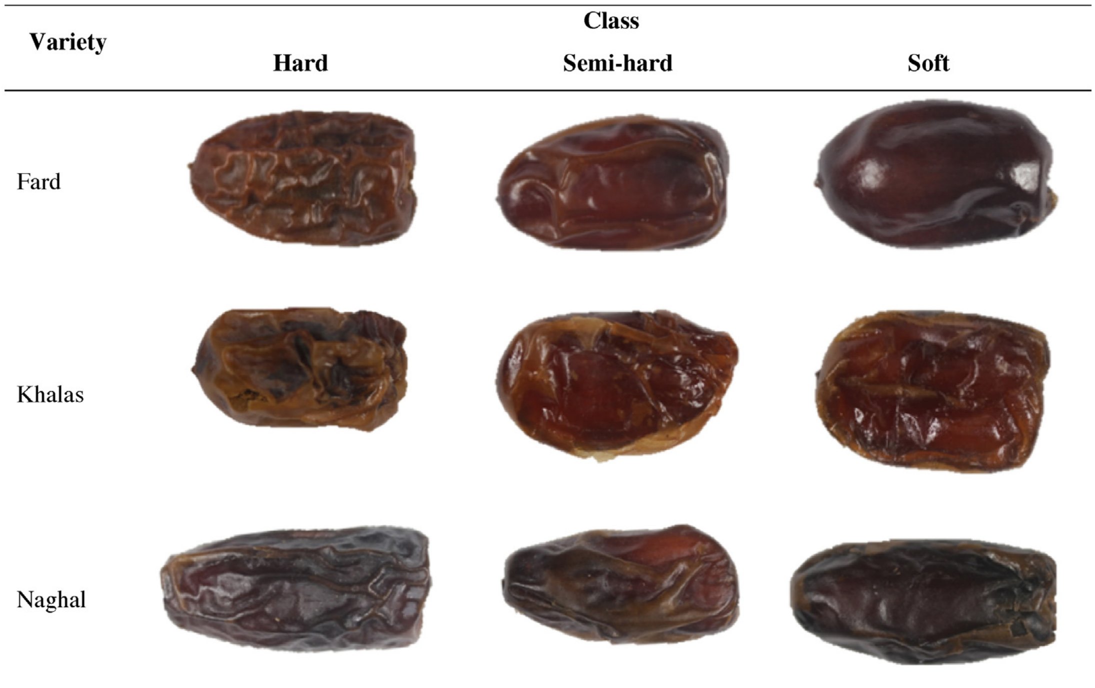

Fig. 2. Typical color images of date samples from different varieties.

component was suitable for differentiating Fard and Berhi, Fard and Bomaan, Lolo and Berhi, and Khalas and Berhi.

Fadel (2008) developed algorithms to determine the sugar content of date varieties (Lolo and Bamoon) based on color analysis. The R, G and B components of the images were correlated with actual values of fructose and glucose. A minimum accuracy of 86% was achieved while determining the sugar content using RGB components.

3.1.1. *Effect of region in Fard dates*

Visually, there were some overlaps in the color of semi-hard and soft dates of Al-Batinah and Al-Dakhliah regions (Fig. 3). The dates from Al-Sharqiah region were brighter than other regions. The R component was in the range of 74 to 91 for different classes (Table 3). In all regions, the R value increased with the level of hardness. The R value of hard and semi-hard dates was higher in Al-Sharqiah region than that of its counterparts. But the R value of soft dates from Al-Sharqiah region was lower than that of other two regions. The G component of tested dates ranged between 61 and 66. In all regions, there were no differences between semi-hard and soft dates. In Al-Batinah and Al-Dakhliah regions, the G value of hard dates was lower than that of other grades. Whereas in Al-Sharqiah region, it was higher for hard dates than soft and semi-hard dates. Similarly, the B component of dates varied from 61 to 67. In general, the B value decreased with the level of hardness of dates. However, there were several overlaps between classes and regions.

The variations in the color of dates belonging to same variety but grown in different regions might be due to various reasons such as changes in microclimate, agronomic practices, fertilization, irrigation and so on. The exact reason for the color pattern of dates from Al-Sharquiah region is not clear.

3.2. *Classification*

3.2.1. *Three classes model*

Table 4 explains the classification accuracies of Fard variety (irrespective of regions) in linear discriminant analysis (LDA) and stepwise discriminant analysis (SDA) methods. In both methods, the soft dates were classified with the highest accuracies and semi-hard dates were classified with the lowest accuracies. Semi-hard dates were misclassified mostly as soft dates.

Table 2
Mean intensity of RGB components in different varieties of dates.

Variety	Class	R	G	B
Fardh	Hard	$89.2^{*a¥} \pm 8.8^{**}$	$64.1^{a} \pm 5.3$	$62.4^{a} \pm 6.3$
	Semi-hard	$82.1^{b} \pm 7.6$	$64.1^{a} \pm 4.8$	$65.2^{b} \pm 5.3$
	Soft	$75.6^{c} \pm 6.6$	$64.3^{a} \pm 5.1$	$66.2^{c} \pm 5.5$
Khalas	Hard	$95.0^{a} \pm 9.3$	$62.3^{a} \pm 4.3$	$48.7^{a} \pm 4.6$
	Semi-hard	$95.6^{a} \pm 21.7$	$58.3^{b} \pm 7.5$	$49.2^{a} \pm 7.8$
	Soft	$82.7^{b} \pm 10.3$	$55.9^{c} \pm 3.9$	$51.1^{b} \pm 4.5$
Naghal	Hard	$93.2^{a} \pm 26.3$	$71.1^{a} \pm 20.8$	$85.2^{a} \pm 52.8$
	Semi-hard	$67.2^{b} \pm 20.0$	$53.1^{b} \pm 14.4$	$50.0^{b} \pm 15.3$
	Soft	$72.2^{c} \pm 13.0$	$58.9^{c} \pm 4.3$	$55.3^{c} \pm 4.5$

* Mean.
¥ Values with same letters in a column of each grade are not significantly different ($\alpha = 0.05$).
** Standard deviation.

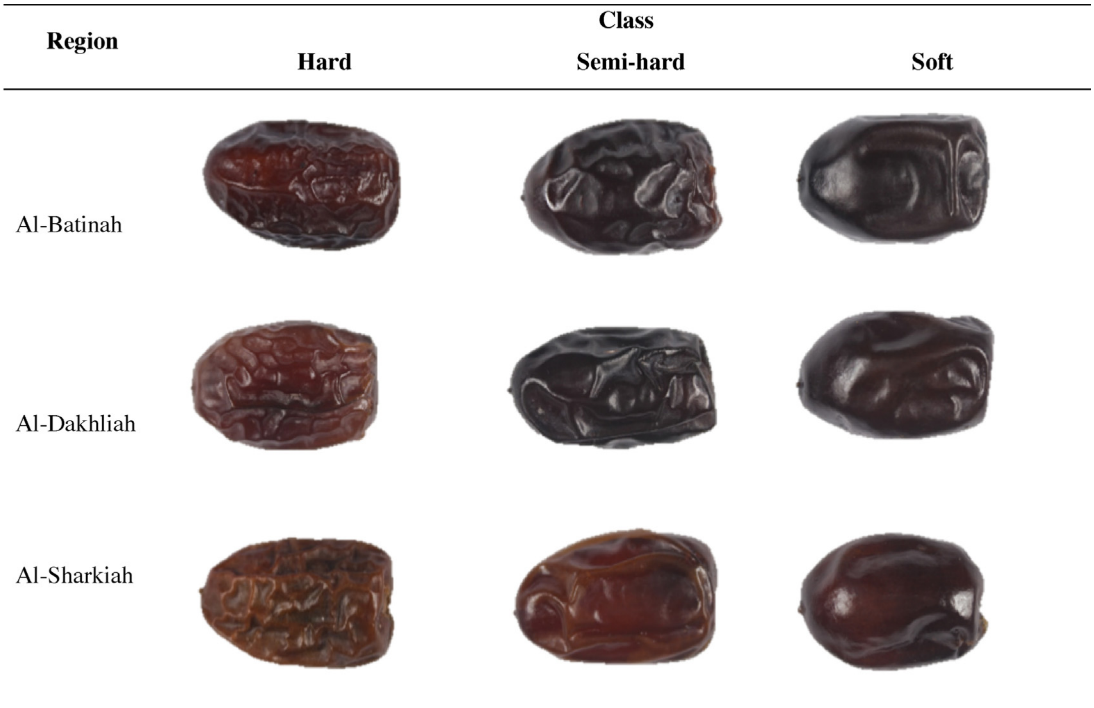

Fig. 3. Typical color images of date samples in Fard variety from different regions.

Table 3
Mean intensity of RGB components in different grades of dates in Fard variety.

Region	Class	R	G	B
Al-Batinah	Hard	$87.8^{*a¥} \pm 9.3^{**}$	$63.9^{a} \pm 4.6$	$62.5^{ad} \pm 6.1$
	Semi-hard	$80.5^{b} \pm 8.0$	$65.1^{b} \pm 5.1$	$66.2^{b} \pm 5.7$
	Soft	$76.5^{c} \pm 7.7$	$65.6^{b} \pm 5.7$	$67.4^{c} \pm 6.1$
Al-Dakhliah	Hard	$88.4^{a} \pm 8.3$	$64.0^{a} \pm 4.1$	$63.1^{ae} \pm 5.1$
	Semi-hard	$80.3^{b} \pm 7.0$	$65.5^{b} \pm 4.4$	$67.0^{bc} \pm 4.8$
	Soft	$75.8^{c} \pm 5.8$	$65.1^{b} \pm 4.7$	$67.1^{bc} \pm 5.1$
Al-Sharqiah	Hard	$91.3^{d} \pm 8.6$	$64.4^{ab} \pm 6.7$	$61.7^{d} \pm 7.4$
	Semi-hard	$85.4^{e} \pm 6.8$	$61.6^{c} \pm 3.9$	$62.5^{ad} \pm 4.3$
	Soft	$74.5^{f} \pm 6.2$	$62.1^{c} \pm 4.3$	$64.0^{e} \pm 4.6$

* Mean.
¥ Values with same letters in a column are not significantly different ($\alpha = 0.05$).
** Standard deviation.

Table 4
Classification accuracy (%) of three classes model for Fard variety.

From class	To class				Overall accuracy
	Hard	Semi-hard	Soft	Classification method/selected features	
Hard	67.0	24.2	8.8	LDA (all features)	68.8
Semi-hard	13.0	64.2	22.8		
Soft	2.0	22.7	75.3		
Hard	66.2	24.7	9.1	SDA (variance-R, mean intensity-R, variance-G, standard deviation-G, mean intensity-B, mean intensity-G, correlation-GLCM-R)	67.7
Semi-hard	13.5	62.2	24.3		
Soft	3.0	22.3	74.7		

Table 5
Classification accuracy (%) of three classes model for Khalas variety.

From class	To class				Overall accuracy
	Hard	Semi-hard	Soft	Classification method/selected features	
Hard	83.2	12.0	4.8	LDA (all features)	86.5
Semi-hard	5.6	84.0	10.4		
Soft	0.8	6.8	92.4		
Hard	82.0	12.8	5.2	SDA (entropy-GLCM-B, variance-G, mean intensity-G, mean intensity-B, eccentricity-G, standard deviation-B, variance-R, entropy-GLCM-R, correlation-GLCM-G, eccentricity-R)	86.0
Semi-hard	5.6	84.0	10.4		
Soft	1.2	6.8	92.0		

Table 6
Classification accuracy (%) of three classes model for Naghal variety.

From class	To class				Overall accuracy
	Hard	Semi-hard	Soft	Classification method/selected features	
Hard	69.2	28.4	2.4	LDA (all features)	81.6
Semi-hard	13.6	83.2	3.2		
Soft	0.0	7.6	92.4		
Hard	66.4	30.4	3.2	SDA (variance-GLCM-R, mean intensity-R, variance-R, eccentricity-B,	80.5
Semi-hard	13.2	82.8	4.0	mean intensity-G, standard deviation-B, maximum	
Soft	0.0	7.6	92.4	probability-GLCM-B, eccentricity-G, variance-G, solidity-B)	

Table 7
Classification accuracy (%) of LDA in three classes model (region wise) for Fard variety.

Region	From class	To class			Regional accuracy	Overall accuracy
		Hard	Semi-hard	Soft		
	Hard	64.5	27.5	8.0		
Al-Batinah	Semi-hard	17.5	46.5	36.0	58.7	
	Soft	3.0	32.0	65.0		
	Hard	78.5	11.0	10.5		
Al-Dakhliah	Semi-hard	15.0	56.5	28.5	68.7	70.3
	Soft	3.5	25.5	71.0		
	Hard	78.5	18.0	3.5		
Al-Sharqiah	Semi-hard	6.5	85.5	8.0	83.5	
	Soft	0.5	13.0	86.5		

Table 8
Classification accuracy (%) of SDA in three classes model (region wise) for Fard variety.

Region	From class	To class			Selected features	Regional accuracy	Overall accuracy
		Hard	Semi-hard	Soft			
	Hard	64.0	26.5	9.5	Mean intensity-R, mean intensity-B,		
Al-Batinah	Semi-hard	16.0	48.0	35.5	homogeneity-GLCM-G, standard deviation-R, extent-B,	59.7	
	Soft	3.5	30.0	66.5	extent-R, homogeneity-GLCM-B		
	Hard	77.5	14.0	8.5	Mean intensity-R, homogeneity-GLCM-G,		
Al-Dakhliah	Semi-hard	17.0	57.5	25.5	variance-GlCM-G, contrast-GLCM-G, contrast-GLCM-R,	68.0	70.0
	Soft	4.5	26.5	69.0	variance-R, solidity-B, standard deviation-G		
	Hard	73.5	22.5	4.0	Variance-R, mean intensity-R, variance-G, standard		
Al-Sharqiah	Semi-hard	5.5	86.0	8.5	deviation-G, mean intensity-B, mean intensity-G,	82.2	
	Soft	1.0	12.0	87.0	correlation-GLCM-R		

In Khalas variety, all classes were classified with more than 80% accuracy (Table 5). Although the soft dates in Naghal variety was classified with 92% efficiency (both LDA and SDA), the hard dates were classified with lower than 70% accuracy (Table 6). Most of the hard dates were misclassified as semi-hard dates.

In general, for all varieties, the accuracy of SDA with around 10 features was closure to LDA with all features. This indicates that it may not be necessary to use all extracted 39 features for classification. However the selection of features was different for each model.

Lee et al. (2008a) developed a color space conversion model for the automated evaluation of date maturity. An overall accuracy of 90% was obtained while identifying seven grades based on maturity level. Al-Ohali (2011) developed a computer vision based grading system for dates to classify into three grades and obtained 80% accuracy.

3.2.1.1. Effect of region in classification of Fard dates. Table 7 shows the classification accuracies of LDA while analyzing each region separately (region wise classification model) in Fard variety. The overall accuracy obtained in this method was 70%. However, the accuracies varied widely from 47% to 87% for various classes and regions. In Al-Batinah and Al-Dakhlia regions, the semi-hard dates yielded the lowest accuracies as several dates were misclassified as hard and soft dates. However the misclassification of semi-hard dates was higher into soft dates in these regions. In Al-Sharqiah region, the hard dates were classified with the lowest accuracy mainly misclassified as semi-hard dates. The highest classification was obtained for Al-Sharikiah region dates, and the lowest accuracy for Al-Batinah region. Similarly, in each region, soft dates were classified with higher accuracy than other two classes. The accuracies and selected features in region wise models in SDA (Table 8) were similar to that that of LDA.

3.2.2. *Two classes model*

In factories, under some circumstances, hard dates alone are removed from the processing line. Therefore in the two classes approach, the images of semi-hard and soft dates were mixed together and treated as soft, then compared with hard dates (soft vs. hard).

The classification accuracy was greatly improved for all three varieties in two classes approach (Tables 9–11). The accuracy of hard and soft dates was varying in each grade. For example, the accuracy of classification for hard date was around 74% in Fard variety, whereas it was around 97% in Naghal variety.

3.2.2.1. Effect of region in classification of Fard dates. Table 12 shows the classification accuracy of two classes model obtained using LDA. The overall accuracy was 87%. In two classes approach also the accuracy was the highest for Al-Sharqiah region and the lowest for Al-Batinah region. Similarly, soft dates were classified with

Table 9
Classification accuracy (%) of two classes model for Fard variety.

From class	To class		Classification method/selected features	Overall accuracy
	Hard	Soft		
Hard	74.3	25.7	LDA (all features)	83.8
Soft	11.4	88.6		
Hard	73.3	26.7	SDA (mean intensity-R, mean intensity-B, mean intensity-G, maximum probability-GLCM-B,	83.1
Soft	12.0	88.0	extent-B, energy-GLCM-R, variance-G, standard deviation-G, extent-R)	

Table 10
Classification accuracy (%) of two classes model for Khalas variety.

From class	To class		Classification method/selected features	Overall accuracy
	Hard	Soft		
Hard	89.6	10.4	LDA (all features)	90.1
Soft	8.8	91.2		
Hard	90.2	9.8	SDA (correlation-GLCM-B, variance-B, correlation-GLCM-R, mean intensity-G, mean intensity-B,	90.8
Soft	8.0	92.0	standard deviation-G, energy-GLCM-B, energy-R, variance-B, eccentricity-B, correlation-GLCM-G)	

Table 11
Classification accuracy (%) of two classes model for Naghal variety.

From class	To class		Classification method/selected features	Overall accuracy
	Hard	Soft		
Hard	97.0	3.0	LDA (all features)	96.0
Soft	6.0	94.0		
Hard	96.8	3.2	SDA (energy-GLCM-R, variance-B, mean intensity-G, standard deviation-B, mean intensity-B, standard deviation-G,	96.4
Soft	4.4	95.6	eccentricity-G, correlation-GLCM-B, correlation-G, maximum probability-GLCM-R, homogeneity-GLCM-R)	

Table 12
Classification accuracy (%) of LDA in two classes model (region wise) for Fard variety.

Region	From class	To class		Regional accuracy	Overall accuracy
		Hard	Soft		
Al-Batinah	Hard	69.5	30.5	80.8	86.6
	Soft	13.5	86.5		
Al-Dakhliah	Hard	82.5	17.5	88.2	
	Soft	9.0	91.0		
Al-Sharqiah	Hard	82.0	18.0	90.8	
	Soft	4.8	95.3		

Table 13
Classification accuracy (%) of SDA in two classes model (region wise) for Fard variety.

Region	From class	To class		Selected features	Regional accuracy	Overall accuracy
		Hard	Soft			
Al-Batinah	Hard	71.5	28.5	Mean intensity-R, standard deviation-R, maximum	81.3	86.1
	Soft	13.8	86.3	probability-GLCM-G, eccentricity-B, entropy-GLCM-G, solidity-R		
Al-Dakhliah	Hard	82.5	17.5	Mean intensity-R, mean intensity-B, homogeneity-GLCM-G, standard	86.8	
	Soft	11.0	89.0	deviation-R, extent-B, extent-R, homogeneity-GLCM-B		
Al-Sharqiah	Hard	82.5	17.5	Mean intensity-R, variance-G, standard deviation-R, mean intensity-B,	90.3	
	Soft	5.8	94.3	mean intensity-G, extent-B variance-B, standard deviation-G, maximum probability-GLCM-B, energy-GLCM-R		

the highest accuracy in all regions. The mean classification of Fard variety in two classes model was 86% using SDA (Table 13).

4. Conclusion

A simple imaging system was developed with a color camera and pair of illuminations. The developed computer vision system was tested on three popular date varieties for its performance. The mean classification accuracy was 68% to 86% in three classes model and 83% to 96% in two classes model for three varieties of dates. Although 39 features were extracted from the date images, around 10 features were sufficient to obtain similar classification results in both approaches. This method has great potential to be utilized for online quality monitoring of dates. However, the performance must be studied for bulk samples and samples in motion.

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