Automatic Date Fruit Classification By Using Local Texture Descriptors And Shape-Size Features

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***Abstract*— In this paper, we propose a system of automatically classifying different types of dates from their images. Different dates have various distinguished features that can be useful to recognize a particular date. These features include color, texture, and shape. In the proposed system, a color image of a date is decomposed into its color components. Then, local texture descriptor in the form of local binary pattern (LBP) or Weber local descriptor (WLD) histogram is applied to each of the components to encode the texture pattern of the date. The texture patterns from all the components are fused to describe the image. Fisher discrimination ratio (FDR) based feature selection is utilized to reduce the dimensionality of the feature set. Size and shape features are appended to the texture descriptors to fully describe the date. As a classifier, we use support vector machines. The proposed system achieves more than 99% accuracy to classify the dates and outperforms previous method of dates classification.**

Keywords- dates classification; local binary pattern; Weber local descriptor; support vector machine

I. INTRODUCTION

According to the Food & Agricultural Organization (FAO), the Middle-East and the North African countries are currently the largest dates producer countries in the world [1]. Fig. 1 shows the production amount in tons of dates for the top fifteen countries.

Dates of the Arab region are well known for their taste. Dates are delicious and rich in nutrition. Fresh date is a very good source of vitamin C, though it disappears once it is dried. It is also a good source of sugar, carbohydrate, fiber, calcium, iron, and potassium. However, it does not have significant amount of fat or cholesterol.

The scientific research on dates in an automated way is not very old. It started roughly around 15 years back; however, many things are still in questions. Al-Janobi proposed two methods, one with co-occurrence matrix and the other with color machine vision technique, to grade the date fruits in late '90s and early of this century [2, 3]. Defect dates were sorted out by image analysis in a method proposed by Wulfsohn *et al.* [4]; however it was a binary classifier that classified the dates as either defected or of good quality.

The maturity inspection of the dates by near infrared spectrometry was investigated by Schmilovitch *et al.* [5]. Shape and size based date grading system was introduced by Hobani *et al.* using neural network classifier [6]. A similar approach but by using probabilistic neural networks was proposed in [7].

One of the major researches on dates grading was conducted by Y. Alohali by using computer vision techniques [8]. Size, shape, intensity features were extracted in RGB color space and back-propagation neural network was used to classify the dates according to the grades. In another research, the three color information, perimeter, length, width, and length-to-width ratio features together with multilayer neural network classifier were used to grade the dates [9]. Some other recent automatic dates grading systems are proposed in [10, 12]. These systems either use fuzzy inference, computer vision techniques, or distinguished camera sensors. A list of recent date research can be found in the Date Palm Research Group portal of King Saud University [13].

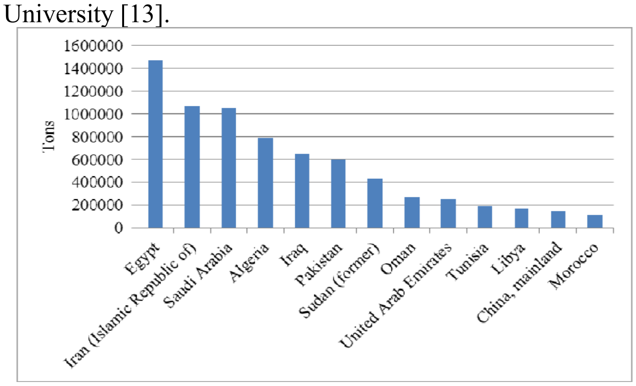

Figure 1. Top fifteen date producer countries in 2012 published by FAO.

Though some advances of date research have been made over the decades, much more are still needed. For example, there is no or little research in date recognition/classification (what kind of date). Almost all the previous works (except [11]) are to classify the dates based on the grades. We would like to mention that there are many works in the literature to classify other fruits, such as apples [14, 15], berries [16], etc. Comparing to the amount of this research, date fruit research is less; however, it is very important to this part of the world. Alohali reported in 2010 that the date sorting is performed completely manually and it is the main reason of delay in date production cycle [8]. Therefore, an automated computer vision based system can significantly reduce the delay in date industry.

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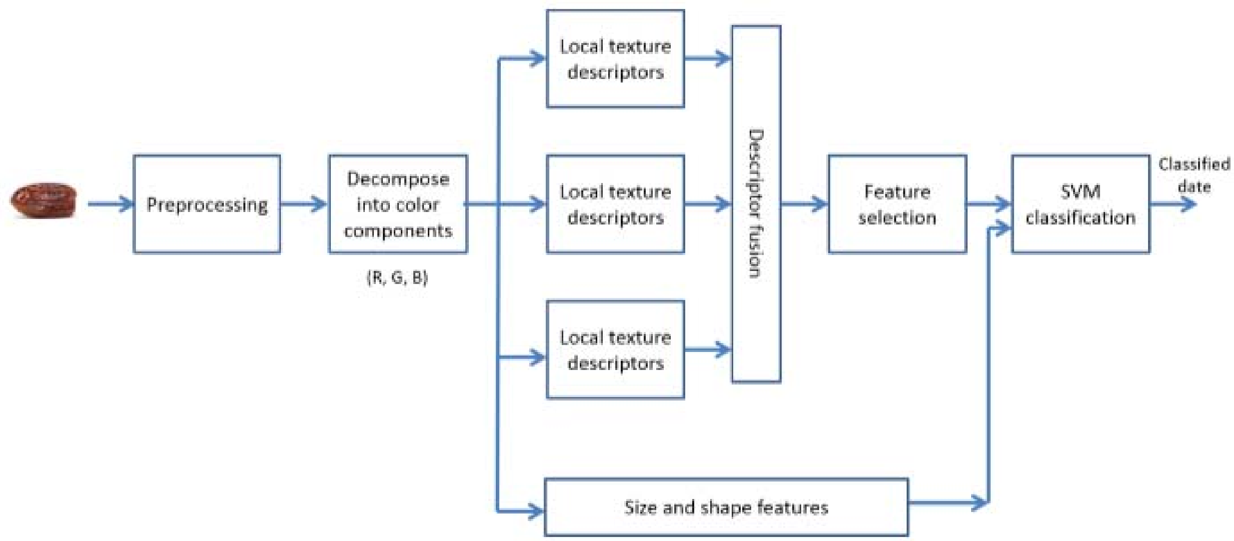

Figure 2. Block diagram of the proposed dates classification system.

In this paper, we propose a system to automatically classify the dates using shape, size features and texture descriptors. The major contribution of this system is the introduction of two well-known and powerful local texture descriptors in the form of local binary pattern (LBP) [17] and Weber local descriptor (WLD) [18]. We also use multi-class support vector machine (SVM) as a classifier. The proposed system does not require any physical instruments to measure the size or the shape, and thereby can operate fast and is inexpensive.

The rest of the paper is organized as follows. Section II describes the proposed method; Section III gives experimental results with discussion, and Section IV draws some conclusion.

II. PROPOSED METHOD

Fig. 2 shows a block diagram of the proposed date fruits classification system. In the following, we describe the steps in details.

The input of the system is a color image of a single date. The image can be taken with a uniform (non-texture) color background. There is no restriction on the size of the image. Once the image is input to the system, some pre-processing is applied. In the pre-processing step, first, a copy of the color image is converted into black and white image using the image histogram. The minimum and the maximum vertical and horizontal coordinates of the black image (corresponding to the date) are identified. Based on these coordinates, the original color image is cropped to produce the region of interest. Fig. 3 shows examples of four types of dates' images after cropping

The cropped color image of a date fruit is converted into three color channels, which are red (R), green (G), and blue (B). The logic behind these color spaces is that the dates vary in colors and therefore contain important information in different color spaces. LBP and WLD histograms are then extracted from these color components.

Figure 3. Cropped images (region of interest) of four types of dates.

A. LBP

The LBP is a simple but powerful texture descriptor [17]. The LBP labels the pixels of an image by decimal numbers called LBP codes. The local structure around the center pixel is encoded by thresholding the eight neighbors pixels' grayscale values in a 3× 3 neighborhood with the center value and considering the result as a binary number. The center pixel is subtracted from each of its eight neighbors. If the result of the subtraction is negative, it is encoded with 0, otherwise it is encoded with 1. The eight binary values are concatenated either clockwise or counter clockwise to form an 8-bit binary number. The corresponding decimal value of the generated binary number is then used as a label for the given center pixel. Fig. 4 shows an illustration of LBP calculation.

It has been realized that certain patterns contain more information than others, so it possible to use a small subset of the total number of patterns to describe any texture. This subset is called uniform and it includes at most two bitwise transitions from 0 to 1 or vice versa. In the proposed method, a uniform version of LBP ($LBP^{u2}_{(P,R)}$) is used. The neighboring 8 pixels are located on a circular position with radius 1. Fig. 5 shows examples of LBP histograms of green channel of the four types of dates, Ajwah, Sagai, Sellaj, and Sukkary. From the figure, it can be seen that the histograms are different than each other, which implies the discrimination capabilities of the LBP between different types of dates.

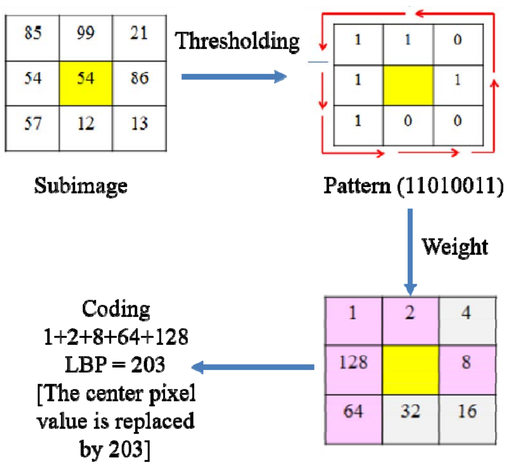

Figure 4. LBP calculation.

B. WLD

The WLD was based on psychological law called "Weber's Law" that states that the fact that human perception of a pattern depends not only on the change of a stimulus like sound, lighting, but also on the original intensity of the stimulus. WLD includes two components, which are differential excitation (DE) and gradient orientation (GO) [18]. The DE is a function of the ratio between two terms: one is the relative intensity differences of a current pixel against its neighbors; the other is the intensity of the current pixel. The orientation component is the GO of the current pixel. For details, the readers can go through [18].

There are three parameters (T, M, and S) associated with the WLD. T is the number of the dominant orientations used for quantizing the gradient orientation values, M is the number of segments used to divide each sub-histogram, and S is the number of bins in each segment. In the experiments, we investigated different combinations of the values of T, M, and S. We found (T = 6, M = 4, S = 5) combination to be the optimum. Fig. 6 shows examples of WLD histograms of green channel of the four types of dates.

C. Fisher discrimination ratio (FDR)

The dimension of LBP histogram or WLD histogram is relatively higher than that of other related studies. Not all the features (histogram bins) are equally important to a particular task. In the proposed method, FDR is applied to select some important features from LBP or WLD. FDR takes both the mean and the variance of the features. For a two-class problem, the *i*th feature FDR is expressed as (1):

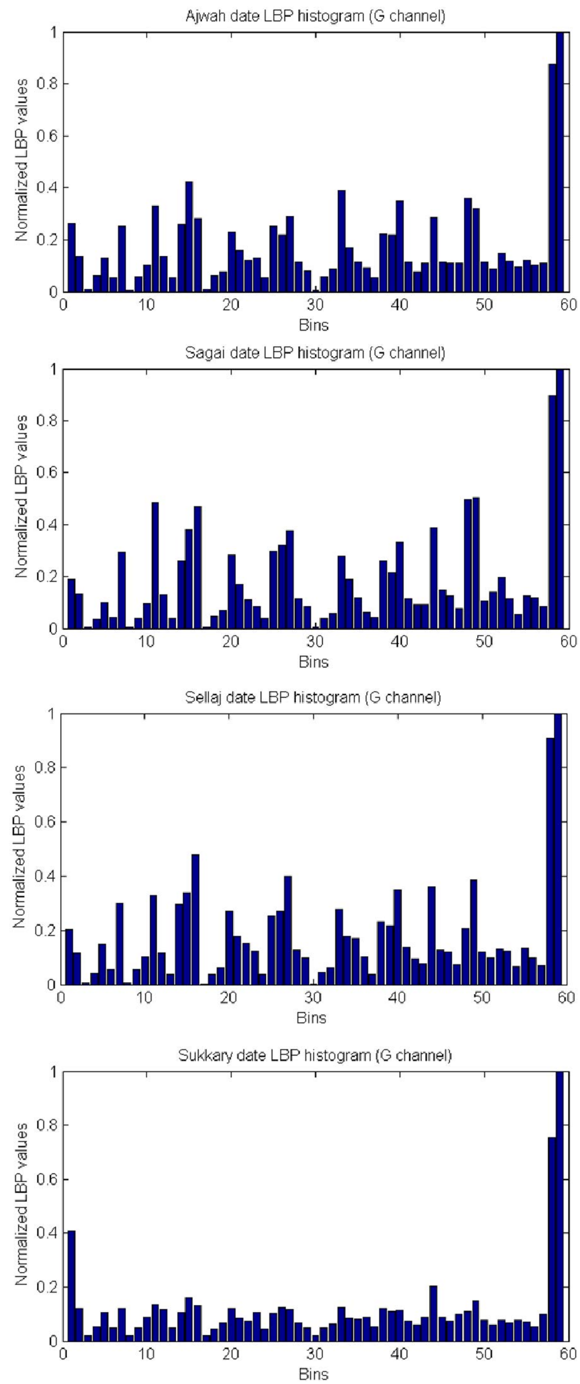

Figure 5. LBP histograms of green channel of four types of dates.

$$F_i = \frac{(\mu_{1i} - \mu_{2i})^2}{\sigma_{1i}^{\ 2} - \sigma_{2i}^{\ 2}} \quad (1)$$

where μ_{1i}, μ_{2i}, σ_{1i}^2, and σ_{2i}^2 are the mean values and the variances of the *i*th feature of class 1 and class 2, respectively. For *A* number of classes and *B* dimensional features, (1) will produce $[A\times(A\text{-}1)] \times B$ entries (column × row). The overall FDR for the *i*th feature can be calculated by (2):

$$FDR_i = \frac{\mu^2}{\sigma^2} \qquad (2)$$

where, μ and σ are column wise mean and variances of *Fi*. The higher the value of FDR, the better the feature for a given classification problem. After sorting the FDR values in the descending order, we select the highest 10 features from the LBP histogram or the WLD histograms. It can be mentioned that the total number of features in LBP histograms is 3 × 59 = 177 (3 channels, each channel has 59 bins), and in WLD histogram is 3 × 120 = 360. The 10 features are then combined with the shape and size features to feed into the classifier.

D. *Shape and size features*

The shape and the size of the dates are important features as they have high discriminative power between the types of the dates. To define the shape and the size of a particular date, the cropped image is fit with an ellipse using the best least-square fitting ellipse method [19]. Then the following four shape and size features are calculated in terms of pixels.

- Major axis length
- Minor axis length
- Ellipse eccentricity
- Area

The area feature is calculated by counting the number of black pixels in the black and white image (obtained before).

E. *SVM*

The SVM classifier is a binary classifier that is widely used for data classification in many applications. It follows a procedure to find the optimal boundary that separates two classes with the largest margin between separating boundary and support vectors. SVM nonlinearly transforms the original input space into a higher-dimensional feature space. This mapping maximizes the generalization capabilities of the classifier. Because SVM is a two-class classifier, the output given by this classifier for each image sample can be interpreted as the likelihood that the sample belongs to a specific class [20]. Support vectors are created during training phase, and these vectors are used to classify the samples during testing phase.

As the proposed method deals with four types of dates, we apply a multi-class SVM for classification. In the multiclass SVM, we adopted one versus others approach. For implementation, the well-known LIBSVM is used [21]. For the kernel, radial basis function (RBF) is used as it is more general and gives good results in other classification applications.

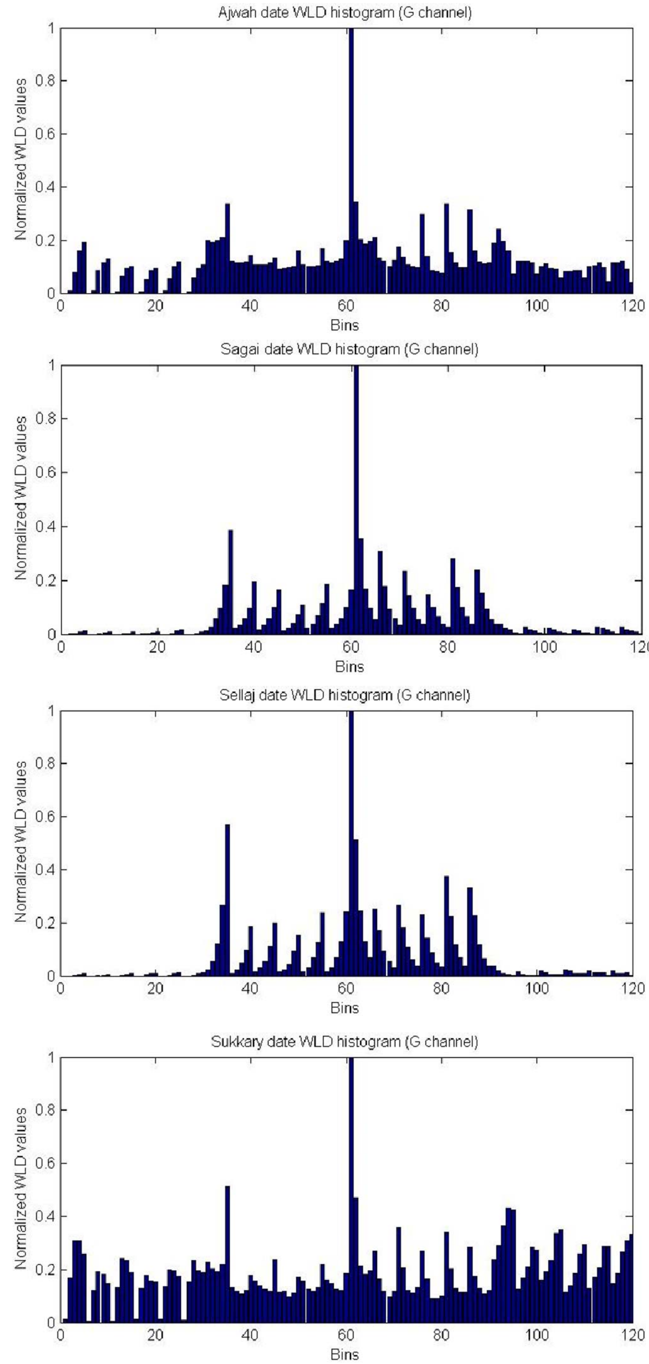

Figure 6. WLD histograms of green channel of four types of dates.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

To evaluate the proposed system, an image database was created. The database contains 80 different images of each of the four types of the dates (Ajwah, Sagai, Sellaj, and Sukkary). Therefore, the total number of images is 320 (all are distinct dates). The images are taken by iPhone 5 mobile. Each image contains only one date with uniform background.

In the experiments, a randomly selected 25% of the whole dataset samples are used for the feature selection step. For the SVM classification, a 10-fold cross validation approach is utilized. In the 10-fold cross validation approach, the whole dataset is divided into 10 folds (with equal number of each of the four types). In one iteration, 9 folds are used as training, while the remaining is used for testing. Therefore, after ten iterations, all the folds are tested. The optimal values for the RBF kernel parameter 'sigma' and the optimization parameter 'C" of SVM are automatically set by an intensive grid search process using the training set. The performance of the proposed system is given in terms of accuracy averaged over the 10 iterations.

The proposed system is evaluated with three different combinations, which are (i) selected LBP + shape, size features, (ii) selected WLD + shape, size features, and (iii) selected LBP and WLD + shape, size features. The feature dimension of each combination is 14 (FDR selected 10 features plus 4 shape, size features). In the third combination, FDR selects 10 features from 537 bins.

To compare the performance of the proposed system with other system, we chose the system described in [11], because it is the only one existing date classification system that was evaluated using many classifiers. There are 15 features in [11] and we chose the artificial neural network classifier to implement [11].

Fig. 7 shows the average accuracy obtained by the three combinations of the proposed system and the system in [11]. The standard deviations are also marked in the bar graphs. From the result, we find that the proposed system outperformed the system in [11]. In the proposed system, WLD performs better than LBP, while their combination achieves the best result. The best accuracy obtained is 99.67%. This result is significant because it uses only 14 features. The system in [11] gives 97.12% accuracy.

Table I shows the confusion matrix of the system. The results are given with the third combination. From the confusion matrix, we see that the dates Ajwah and Sukkary are always correctly classified; however, Sagai and Sellaj confuse between each other. This confusion is also evident visually from Fig. 3. Having said that, the proposed system's confusion is very little (less than 0.1%).

IV. CONCLUSION

An automatic date classification system based on local texture descriptors and shape, size features has been proposed. Four types of dates are used in the classification. The best result (99.67% accuracy) is obtained by the combination of selected LBP and WLD descriptors together with shape and size features.

In a future work, different color spaces such as HIS and YCbCr will be investigated in date classification system.

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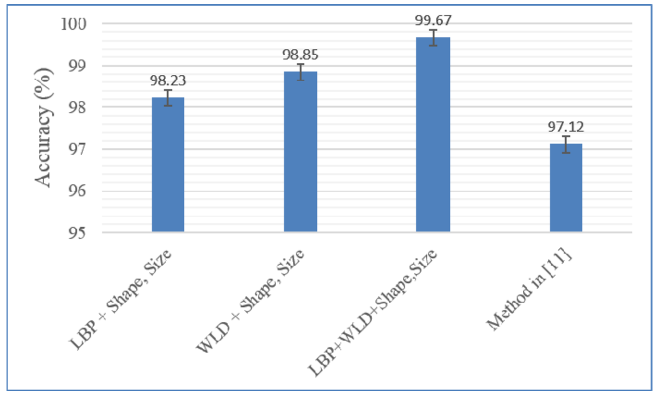

Figure 7. Average date classification accuracy of different combinations of the proposed system.

TABLE I. CONFUSION MATRIX OF THE PROPOSED SYSTEM WITH SELECTED LBP AND WLD + SHAPE, SIZE COMBINATION. THE NUMBERS INSIDE THE CELLS ARE IN % ACCURACY

		Output			
		Ajwah	Sagai	Sellaj	Sukkary
Input	Ajwah	100	0	0	0
	Sagai	0	99.2	0.8	0
	Sellaj	0	0.5	99.5	0
	Sukkary	0	0	0	100

REFERENCES

[1] Food and Agriculture commodities production, FAOSTAT 2012. Available at http://faostat.fao.org/site/567/default.aspx. Retrieved on 22 February 2014.

[2] A. A. Al-Janobi, "Application of co-occurrence matrix method in grading date fruits," in ASAE Paper, no. 98-3024, 1998.

[3] A. Al-Janobi, "Date inspection by color machine vision," Journal of King Saud University, vol. 12, no. 1, pp. 69-97, 2000.

[4] D. Wulfsohn, Y. Sarig, R.V. Algazi, "Defect sorting of dry dates by image analysis," Canadian Agricultural Engineering, 35 (2), pp. 133–139, 1993.

[5] Z. Schmilovitch1, A. Hoffman, H. Egozi, R. Ben-Zvi, Z. Bernstein and V. Alchanatis, "Maturity determination of fresh dates by near infrared spectrometry," Journal of the Science of Food and Agriculture, vol. 79, pp. 86-90, 1999.

[6] A. I. Hobani, A. M. Thottam and K. A. Ahmed, "Development of a neural network classifier for date fruit varieties using some physical attributes," King Saud University-Agricultural Research Center, 2003.

[7] M. Fadel, "Date fruits classification using probabilistic neural networks," Agricultural Engineering International: the CIGR Ejournal, vol. 9, 2007.

[8] Y. Al Ohali, "Computer vision based date fruit grading system: Design and implementation," Journal of King Saud University – Computer and Information Sciences, 23(1), pp. 29-36, Jan 2011.

[9] K. M. Alrajeh and T. A. Alzohairy, “Date Fruits Classification using MLP and RBF Neural Networks,” International Journal of Computer Applications, 41 (10), pp. 36-41, 2012.

[10] N. Alavi, “Qualilty determination of Mozafati dates using Mamdani fuzzy inference system,” Journal of the Saudi Society of Agriculral Sciences, 12 (2), pp. 137 – 142, June 2013.

[11] A. Haidar, D. Haiwei, and N. Mavridis, “Image-based date fruit classification,” 4th International Congress on Ultra-Modern Telecommunications and Control Systems and Workshops (ICUMT), pp. 357-363, 2012.

[12] Abdellahhalimi, A. Roukhe, B. Abdenabi, and N. El Barbri, “Sorting dates fruit bunches based on their maturity using camera sensor system,” Journal of Theoretical and Applied Information Technology, 56(2), pp. 325-337, Oct 2013.

[13] Date Palm Research Group, King Saud University, Riyadh. Website is available at http://colleges.ksu.edu.sa/FoodsAndAgriculture/PlantProduction/Pages/Date%20palm%20reserese%20unit.aspx

[14] Z. Xiaobo, Z. Jiewen, and L. Yanxiao, "Apple color grading based on organization feature parameters," Pattern Recognition Letters, 28, pp. 2046–2053, 2007.

[15] P. M. Mehl, Y. Chen, M. S. Kim, D. E. Chan, "Development of hyperspectral imaging technique for the detection of apple surface defects and contaminations," Journal of Food Engineering, 61, pp. 67–81, 2004.

[16] G. ElMasry, N. Wang, A. ElSayed, M. Ngadi, "Hyperspectral imaging for nondestructive determination of some quality attributes for strawberry," Journal of Food Engineering, 81, pp. 98–107, 2007.

[17] T. Ahonen, A. Hadid, and M. Pietikainen, " Face Description with Local Binary Patterns: Application to Face Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 28, No. 12, December 2006.

[18] J. Chen, S. Shan, C. He, G. Zhao, M. Pietikainen, X. Chen, and W. Gao, “WLD: A robust local image descriptor”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, no. 9, pp. 1705–1720, 2010.

[19] A. Fitzgibbon, M. Pilu, and R. B. Fisher, "Direct least-squares fitting of ellipses", IEEE Trans. Pattern Analysis and Machine Intell., 21(5), pp. 476-480, 1999.

[20] V. Vapnik, *Statistical Learning Theory,* Wiley, New York, 1998.

[21] C.C. Chang, C.J. Lin, “LIBSVM: a library for support vector machines”, ACM Trans. Intell. Syst. Tech., 2/27, pp. 1-27, 2011.