Journal of
Food Process Engineering

Journal of Food Process Engineering ISSN 1745-4530

AN ARTIFICIAL NEURAL NETWORK-BASED METHOD TO IDENTIFY FIVE CLASSES OF ALMOND ACCORDING TO VISUAL FEATURES

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Received for Publication February 20, 2015
Accepted for Publication June 9, 2015

doi:10.1111/jfpe.12255

ABSTRACT

The quality evaluation is one of the key factors that have a major impact on the final price of agricultural products. Nowadays, image processing-based techniques are becoming as an acceptable and widespread in quality evaluation procedures. In this study, we develop a robust method based on image processing and computational intelligence for quality grading and classification of almonds. The images of five classes of almond including normal almond (NA), broken almond (BA), double almond (DA), wrinkled almond (WA) and shell of almond (SA) were acquired by a scanner. For segmentation of images, both H component in HSI color space and Otsu's thresholding method were applied. In the next step, the feature vector, which includes 8 shape features, 45 color features and 162 texture features, was composed. For choosing correlated and superior features among all the 215 extracted features, sensitivity analysis was applied. Principal component analysis method was also used to reduce the dimension of the feature vector. The classification of almonds into different classes was carried out by artificial neural networks (ANNs). Among different ANN structures, the 18-7-7-5 topology was the most optimum classifier. The accuracy of ANN classifier for each class was 98.92% for NA, 99.46% for BA, 98.38% for DA, 98.92% for WA and 100% for SA. The technique can readily be extended for online sorting machines.

PRACTICAL APPLICATIONS

One of the applications of this method is in the design and fabrication of real-time grading and sorting machines. The biggest advantage of the presented algorithm is its high precision. The developed classifier is able to detect and eject defected almonds (broken, double, wrinkled and shell of almonds) out of a stream of almonds in the sorting process line. Therefore, if the processing time of the method is improved further, it can readily be used in an online sorting machine.

INTRODUCTION

Almonds are one of the most nutritious of all nuts. They have the highest protein content of any nut and are packed with vitamin E, calcium, iron, magnesium, phosphorus and zinc. As products with high nutrition are advantageous, Iranian nuts (pistachios, almonds, etc.) are considered as one of the valuable nonoil exportable products. Iran had about 87,700 ha of land under almond cultivation in 2011. According to FAO (Food and Agriculture Organization) statistics, Iran with production of over 110,000 tons/year of almond was ranking as the world third biggest almond producer after the United States and Spain (Food and Agriculture Organization 2011).

There are numerous factors such as product variety, different steps of planting, growing and harvesting that play a role in promoting the quality of agricultural products. One of the most important postharvest processing operations, directly related to improving quality of the products, is grading or sorting operation. Increasing the quality of almond product by means of a new and reliable technique is a key factor in exporting and economic profitability of the final product. For implementing such operations, both human vision (HV) and computer vision (CV) are being used. However, the human-based vision methods are becoming less attractive due to their high costs, low speeds, requiring experienced staffs for grading of the product and low accuracies. In recent years, the application of advanced techniques based on CV for grading different agricultural products due to its high accuracy, low cost and high speed has become more widespread (Du and Sun 2004; Cakmak and Boyaci 2011; Kumar-Patel *et al.* 2012; Poonnoy *et al.* 2014).

Nowadays, the CV technology has often been used for quality classification and sorting of nuts for different applications and the results show high precision of CV methods compared to the methods which are based on HV (Okamura *et al.* 1993; Pearson and Toyofuku 2000; Jackman and Sun 2011). The CV algorithms often utilize combined shape, color and texture features for quality grading of agricultural products. Donis-González *et al.* (2013) used the components of three color spaces (RGB, HSV, $L^*a^*b^*$) and the combination of shape, color and texture features to classify chestnuts in five different classes. Also for raisin product, it was suggested that shape and color features can be used in RGB and Nrgb color spaces (Mollazade *et al.* 2012). Extracting relevant features of raisin images, color features in RGB and HSI color spaces, and gray level co-occurrence matrix (GLCM) has also been used and the results indicated the appropriateness of these features (Yu *et al.* 2012). Results also indicated the effectiveness of artificial neural networks (ANNs) and support vector machines for classification of raisins into four different classes (Mollazade *et al.* 2012; Yu *et al.* 2012). For classification of many agricultural products (based on available standards), using one set of features (e.g., shape, color or texture only) cannot guarantee proper performance. It is therefore better to combine various features in order to obtain a better classifier with high accuracy among different classes of a product (Paliwal *et al.* 2003; Wang *et al.* 2012). Kiratiratanapruk and Sinthupinyo (2011) found that combining of color features, extracted from images of corn seeds in RGB and HSV color spaces together with texture features, which were obtained from GLCM and local binary pattern, led 5–6 percentage more accuracy in the results as compared to the method at which these features were used separately for classification of corn seeds. Furthermore, in another research for wheat product classification in five different classes, the developed algorithm was evaluated in two ways. In the first approach, only shape, color and texture features were used, and in the second one their combinations were evaluated. The results showed that the overall accuracy was 96% by the second approach (Choudhary *et al.* 2008).

Regarding this point that no comprehensive research for quality grading of almond products has been conducted so far, the objective of this research was to develop a robust method based on image processing and computational intelligence for quality grading and classification of this product. Almonds are graded into five different classes including normal almond (NA), broken almond (BA), double almond (DA), wrinkled almond (WA) and shell of almond (SA) according to UNECE (2009) standards. Considering the low-quality nuts inside the product bulk and the existence of BAs, almond shells and their broken particles, the algorithm can be used to detect and classify these classes simultaneously. This algorithm may also be adopted on sorting machines in order to increase the speed and accuracy.

MATERIALS AND METHODS

Figure 1 shows the framework for quality grading of almond product developed in this paper. In the first step, the images were taken from almond then by using appropriate algorithms for segmenting images; almonds were separated from the background. In the next step, after extracting useful features related to shapes, color and texture of almond images, features vector was formed. In order to classify almonds successfully, it was necessary to find correlated features. Accordingly, after choosing correlated features using sensitivity analysis, the extracted features were compressed by means of principal component analysis (PCA). In the final step, the almonds were classified into five different classes (NA, BA, DA, WA and SA) (UNECE 2009) by using ANNs.

All of the above-mentioned steps are presented in details in the following subsections. Matlab software was used for implementing the algorithms (MathWorks 2012).

Vision System

Initially, almonds of each class were manually separated, and then a CCD scanner (HP scanjet 3570C, California, US) was used for acquiring the images of almond. The images were taken in a way that in each image only almonds of one class were present (Fig. 1). The images were saved in BMP format with 300 dpi resolution. Finally, the acquired images were transferred to a personal computer (PC) for further analysis. A total of 150 samples were acquired for each class of almond including NA, BA, DA, WA and SA (Fig. 1).

Image Segmentation

Because of high quality of input images, there was no noise in the images so no preprocessing was necessary for promoting the quality of the images. The objective in the next

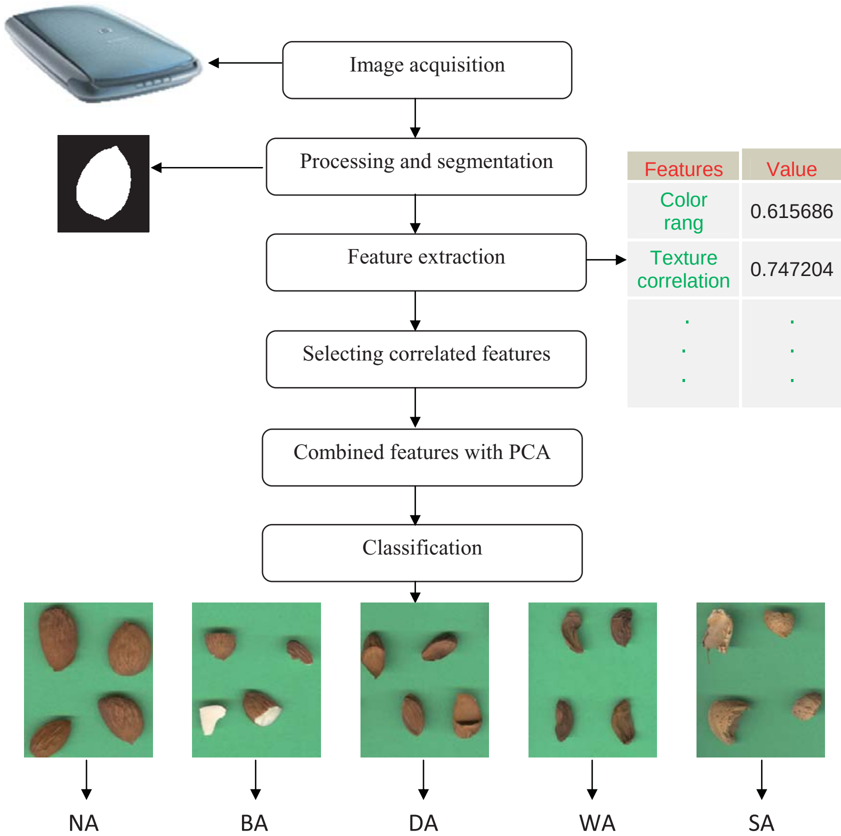

FIG. 1. THE FRAMEWORK FOR QUALITY GRADING OF ALMOND

step of the algorithm was to separate almonds from the background and the shadows that were around them (Fig. 2a). The segmentation step is one of the important steps in image processing and the performance of next steps such as feature extraction and classification is dependent on this step (Brosnan and Sun 2004). In previous studies, H component in HSI color space has been one of the appropriate channels for classification of agricultural products (Abbasgholipour *et al.* 2011). Furthermore, *K*-means clustering method was proposed for segmenting banana images (Hu *et al.* 2014). Accordingly, the images of almonds were all transformed from RGB color space to HSI color space. As shown in Fig. 2, the H component has made high contrast among almonds, background and shadows in the images. After that, the images were segmented by Otsu method (Otsu 1979), and almonds were separated from the background and the shadows successfully (Fig. 2).

Shape and Color Features

As there are different shapes in each class of almonds, selecting the most relevant shape features from almonds can have a positive impact on the accuracy of final classifier (Fig. 3). The selected shape features are summarized in Table 1. These eight features were also suggested in various studies (Venora *et al.* 2009; Mebatsion *et al.* 2013).

Among the color spaces, three color spaces, namely RGB, Nrgb and CMY, were used. One of the advantages of these color spaces is clear distinction that is set in the relevant parameters of color and texture among different classes of almond. This clear distinction can play a vital role in separating almonds accurately. To examine these differences among classes of almond in different color spaces, various color descriptors were applied. For instance, the colors of some samples of BA class were different from the colors of other classes of almond; or the colors in samples of SA are slightly different from the colors of NA and BA classes (Fig. 3). Therefore, five descriptors, namely mean (μ), variance (Var), skewness, kurtosis and range parameters, were finally selected (Jackman *et al.* 2008; Donis-González *et al.* 2013; Mery *et al.* 2013). The expressions for these descriptors are listed below (Eqs. 1–5):

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (1)$$

$$\mathrm{Var} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu) \qquad (2)$$

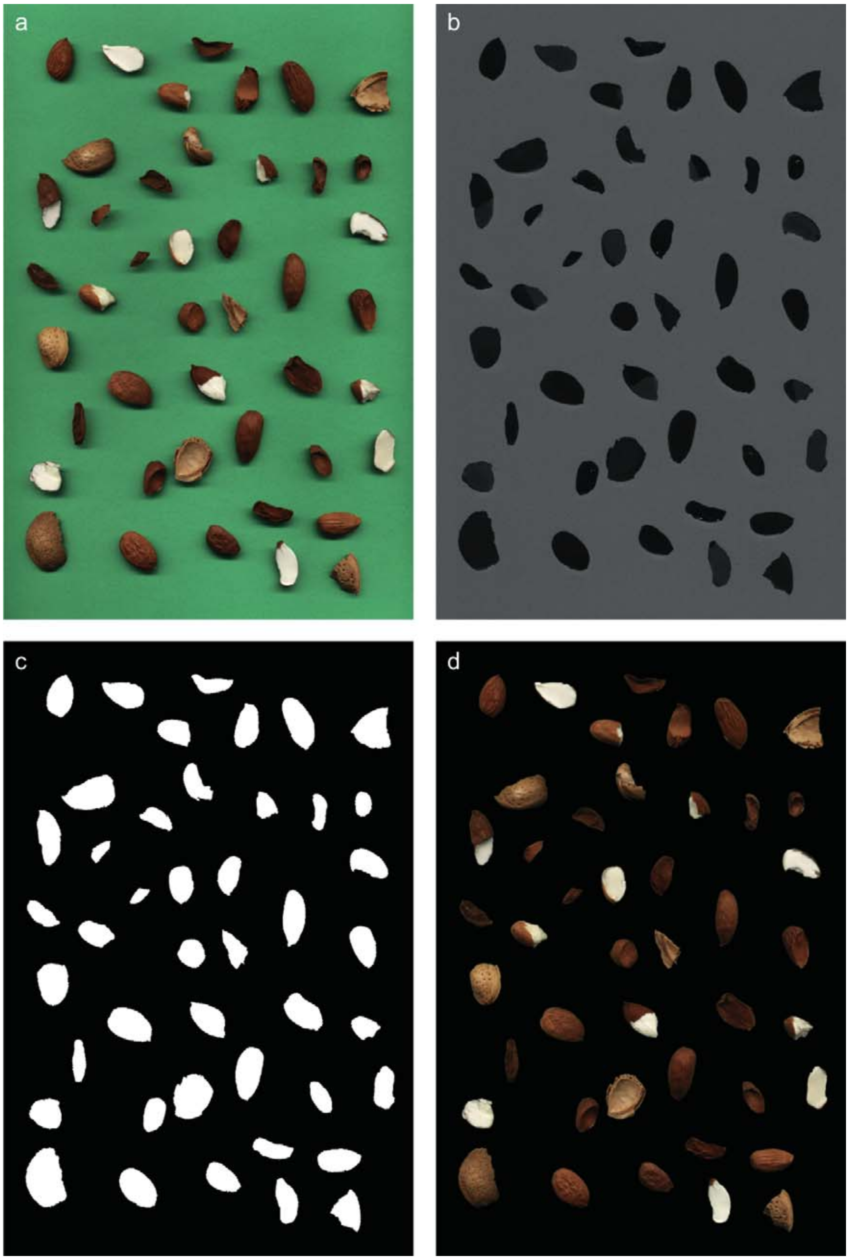

FIG. 2. SEGMENTING IMAGES OF ALMONDS USING OTSU METHOD IN H CHANNEL
(a) RGB image, (b) H component of almond image (note: different classes of almond have high contrasts with shadow and background), (c) the binary image obtained from Otsu method, and (d) the image obtained by multiplication of binary and RGB images

$$\text{Skewness} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^3}{\left(\sqrt{Var}\right)^3} \tag{3}$$

$$\text{Kurtosis} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^4}{\left(\sqrt{Var}\right)^4} \tag{4}$$

$$\text{Range} = max(x_i) - min(x_i) \tag{5}$$

where x_i is the gray level of each pixel in the image and n is the number of pixels. Altogether, 45 color features were extracted.

Textural Features

Various texture analyses in quality evaluation of agricultural products have been proposed, and it has been used for classification and defect detection of products (Mery *et al.* 2013). As illustrated in Fig. 3, which is an image of all

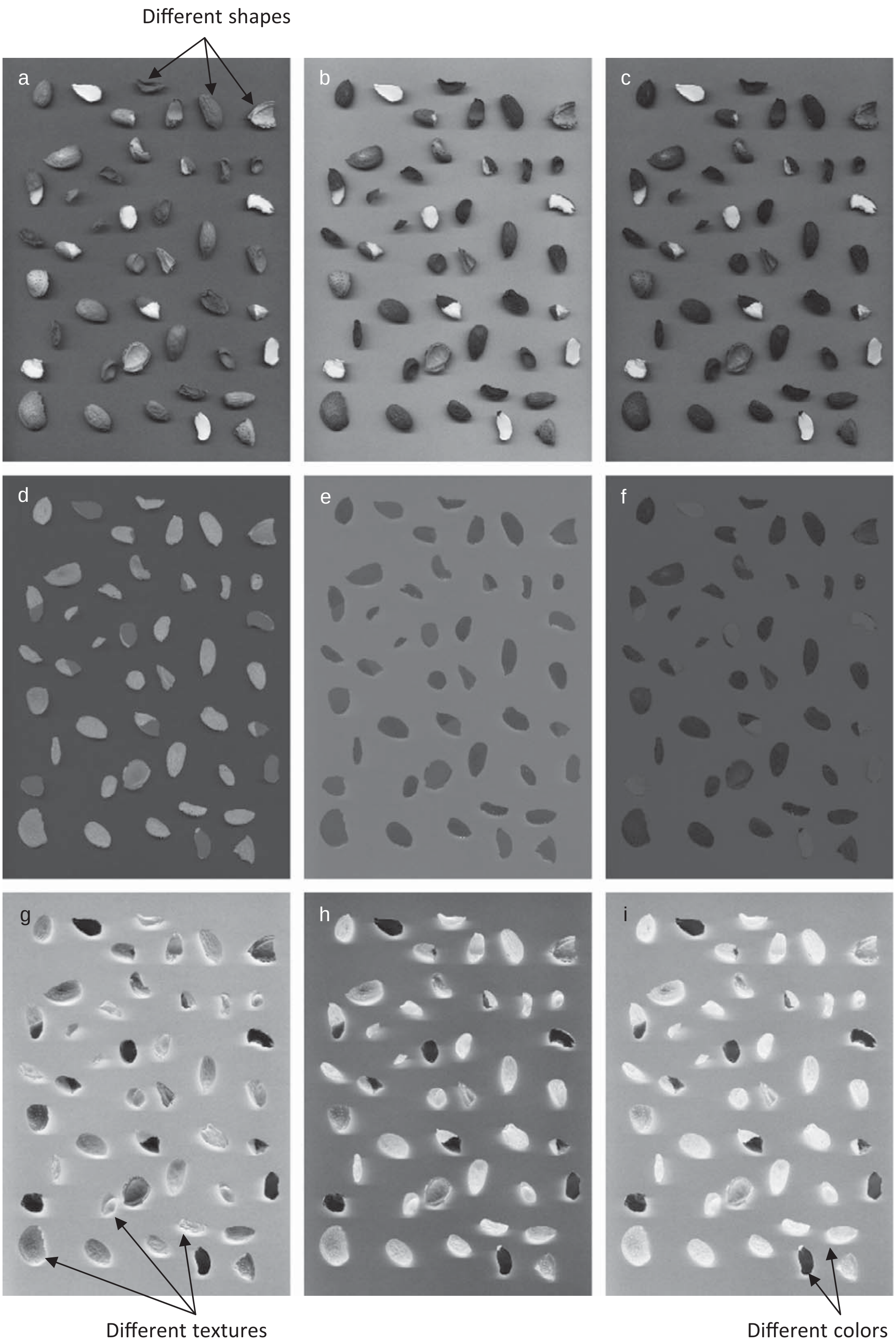

FIG. 3. DIFFERENT COLOR SPACES FOR ALL CLASSES OF ALMOND SHOWING DIFFERENT SHAPE, COLOR AND TEXTURE
(a) R component, (b) G component and (c) B component in RGB color space, (d) R component, (e) G component, (f) B component in Nrgb color space, and (g) cyan component, (h) magenta component and (i) yellow component in CMY color space

TABLE 1. THE LIST OF ALL SHAPE FEATURES THAT WERE USED

Shape features	Expression or formula in Matlab
Area	The number of pixels in binary image
Perimeter	The number of pixels in boundary of binary image
Eccentricity	The ratio of the distance between the foci of the ellipse and its major axis length
Solidity	(Area)/(Convex Area)
Extent	The ratio of pixels in the region to pixels in the total bounding box that are also in the region
Roundness	(4 π (Area)/(Perimeter)^2)
Aspect ratio	(Major axis/Minor axis)
Dimension 1	(Perimeter/Area)

classes of almond in the three color spaces of RGB, Nrgb and CMY, the difference is perceived in the textures of different almond classes. For instance, WA is different from NA and DA classes as wrinkles on relevant texture of WAs are noticeable. The difference between the texture of DA and NA is observed on the grounds of smooth surface (see Fig. 3), whereas the shape and the color of these classes are close to each other.

Two methods were applied for implementing texture analysis:

(1) Computing GLCM (Haralick *et al.* 1973);

(2) Texture analysis based on Fourier transform (Gonzalez *et al.* 2009).

GLCM. For computing the matrices in GLCM method, the possibility of occurrences in pairs of pixels which have certain structure in the images can be taken into account. The structure includes distance (d) and orientation among the pair of pixels (θ). GLCM was computed by

$$C_{\Delta x,\Delta y}(m,n) = \sum_{p=1}^{i}\sum_{q=1}^{j}\begin{cases}1, & \text{if } I(p,q)=n, \text{and } I(p+\Delta x, q+\Delta y)=m \\ 0, & \text{otherwise}\end{cases} \quad (6)$$

where C is the co-occurrence matrix, m and n are gray levels, i and j are sizes of image I, and Δx and Δy are offset parameters. In the present study, we used the structure with distance $d=1$ and orientation $\theta = 0°$. When GLCM was computed, six indices including energy, correlation, contrast, homogeneity, maximum probability and entropy were extracted as the texture features (Haralick *et al.* 1973). Altogether, 54 features (6 indices $\times$ 9 color components) were extracted as texture features (Table 2).

Texture Features with Spectral Measurements. One of the popular methods to measure spectral texture is computation of Fourier spectrum. Here, the images of almonds were transformed from the spatial domain to frequency domain by means of Fourier transform. In the next step, Fourier spectrum was transformed to polar coordinates and $S(r, \theta)$ function (r stands for frequency and θ for orientation) was calculated (Gonzalez *et al.* 2009). To extract correlated texture features, two-dimensional functions need to be transformed into two one-dimensional functions. Therefore, $S(r, \theta)$ function was transformed into $S_r(\theta)$ and $S_\theta(r)$. Then the total sum of frequency and orientation parameters was computed using the following expressions (Gonzalez *et al.* 2009):

$$S(r)=\sum_{\theta=0}^{\pi} S_\theta(r) \quad (7)$$

$$S(\theta)=\sum_{r=0}^{R_0} S_r(\theta) \quad (8)$$

By drawing the diagrams of these functions from 0 to π (for orientation) and from 0 to R_0 (for frequencies), some descriptors such as mean, variance, skewness, kurtosis, range, and difference between mean and maximum were computed and extracted as the texture features in the frequency domain. Altogether, 108 texture features were extracted from Fourier transform analysis.

Selecting Correlated Features

The performance of classifier is highly dependent on relevant features that are extracted from the images. Therefore, selecting correlated features among all features would lead to an improvement in the overall performance of the classifier (Mery and Soto 2008). To select correlated and superior features, different methods such as sequential forward

TABLE 2. TEXTURE FEATURES OBTAINED FROM GLCM FOR EACH ALMOND

Gray level co-occurrence matrix (GLCM)	Formula
Contrast	$\sum_{i,j} \lvert i-j\rvert^2 \cdot p(i,j)$
Correlation	$\sum_{i,j} \frac{(i-m_r)\cdot(j-m_c)\cdot p(i,j)}{\sigma_i\sigma_j}$
Energy	$\sum_{i,j} (p(i,j))^2$
Homogeneity	$\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j\rvert}$
Entropy	$-\sum_{i,j} p(i,j)\cdot\log_2(p(i,j))$
Max of probability	$Max(p(i,j))$

Note: *p(i, j)* is gray level co-occurrence matrix, *m* is the mean, σ represents the standard deviation.

TABLE 3. SELECTED CORRELATED FEATURES AMONG ALL FEATURES USING SENSITIVITY ANALYSIS

Shape features	Color features	Texture features (GLCM)	Texture features (Fourier descriptor)
Area	Mean(B)	Contrast(R)	Mean(G)^{F}
Perimeter	Mean(r)	Contrast(B)	Mean(b)^{F}
Solidity	Mean(g)	Contrast(r)	Mean(Y)^{O}
Roundness	Mean(b)	Contrast(g)	Var(R)^{O}
Aspect ratio	Mean(C)	Contrast(b)	Skewness(G)^{Om}
	Mean(M)	Contrast(C)	Kurtosis(r)^{O}
	Mean(Y)	Contrast(M)	Kurtosis(b)^{F}
	Var(G)	Contrast(Y)	Kurtosis(C)^{O}
	Var(b)	Correlation(R)	(Max-mean)(B)^{O}
	Var(C)	Correlation(G)	(Max-mean)(b)^{O}
	Var(M)	Correlation(r)	(Max-mean)(Y)^{O}
	Skewness(R)	Correlation(g)	(Max-Min)(R)^{F}
	Kurtosis(R)	Correlation(b)	(Max-Min)(b)^{O}
	Kurtosis(b)	Correlation(C)	(Max-Min)(Y)^{O}
	Kurtosis(M)	Correlation(M)	
	Grad(R)	Correlation(Y)	
	Grad(G)	Energy(R)	
	Grad(B)	Energy(G)	
	Grad(r)	Energy(g)	
	Grad(g)	Homogeneity(G)	
	Grad(b)	Homogeneity(g)	
		Homogeneity(b)	
		Homogeneity(C)	
		Homogeneity(M)	
		Max pro(R)	
		Max pro(b)	
		Max pro(C)	
		Max pro(M)	
		Entropy(B)	
		Entropy(C)	
		Entropy(M)	
		Entropy(Y)	

Note: F is the texture feature related to frequency and O is the texture feature related to orientation.

selection, factor analysis, correlation based on feature selection and sensitivity analysis (SA) have been suggested (Mollazade *et al.* 2012; Donis-González *et al.* 2013). In this work, SA method was used for separating correlated and efficient features from nonrelated and redundant features. Finally, 72 features were selected from SA. These are summarized in Table 3.

PCA

As the dimension of the feature vector is still high and, therefore, not suitable for real-time applications, it is appropriate to apply some feature reduction techniques. An effective procedure to reduce the dimension of the input vector is to use PCA. Here, PCA is applied for compressing correlated features (Wang and Hu 2011). PCA was implemented in Matlab software (2012 version). The technique was outlined by authors previously (Omid *et al.* 2010). In this analysis, principle components (PCs) are produced according to the number of features. At first, when the PCA method was applied on the correlated features, 72 PCs were extracted. But it was necessary to select the most optimum features that have the maximum of total variance. In general, the first PC (PC_1) contains more information than the remaining PCs (such as PC_2, PC_3). To obtain appropriate and optimum number of PCs, minimum average partial method was used (Velicer 1976). In this method for finding the most optimum PCs, the PC_1 is removed from the correlation matrix. Then the average squared components in off-diagonal are computed from the correlation matrix. In the next step, the first two PCs (PC_1, PC_2) are removed and the same process is repeated. After n times, first n PCs are removed from the correlation matrix and the above-mentioned process is repeated again. Obtained minimum of squared average value is the main criteria for selecting optimum PCs and successful implementation of this method. Finally, 18 PCs are selected as the most optimum PCs with squared average value of 0.0059. These 18 PCs contained 93.98% of total variance of the features and were used as inputs to ANN models.

Classification with ANNs

ANNs are one of the data mining methods that are developed in various contexts such as function approximation, modeling and classification of agricultural products (Marini *et al.* 2004). The structure of ANN consists of three or more layers including input layer, hidden layer(s) and output layer. In each layer, the number of neurons respectively depends on the number of PCs, complexity of classification task and the number of output classes. In this study, the inputs and outputs are fixed as selected among superior PCs (18) and almond classes (5), respectively. However, the number of neurons in the hidden layer(s) is obtained by trial and error. Multilayer feed-forward ANNs were used in this research. Activation functions in the hidden and output layers were hyperbolic tangent (*tansig*). Before representing the PCs to ANN, they were normalized between −1 and 1 using *mapminmax* function in Matlab. Furthermore, samples were divided randomly into three parts of training (65%), validation (15%) and testing (20%) sets to avoid overtraining. Matlab software was used for implementation of ANN classifiers. The structure of the ANN is one of the key factors that impact on the accuracy of final classifier. Accordingly, different ANN structures were designed and evaluated with different training algorithms. The following steps were implemented for selecting the most optimum ANN structure:

(1) Different ANNs having one and two hidden layers were examined. For networks with one hidden layer, 4, 6, 8, . . ., 18 neurons were used, and for networks with two hidden layers, [4 4], [5 5], . . ., [18 18] neurons were used;

(2) Four different training algorithms including Levenberg–Marquardt (LM), scaled conjugate gradient (SCG), one-step secant and variable learning rate gradient descent were selected for training the networks;

(3) The weights of the networks were initialized randomly for each run;

(4) To develop a statistically sound model, networks were trained 50 times and the best values were recorded for each parameter.

Performance Evaluation of ANNs

To examine the performance of ANN classifiers, three statistical indices including sensitivity (SE), specificity (SP) and accuracy (AC) are used:

$$Sensitivity = \frac{TP}{TP + FN} \tag{9}$$

$$Specificity = \frac{TN}{TN + FP} \tag{10}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

where the *TP*, *TN*, *FP* and *FN* are the numbers of true positives, true negatives, false positives and false negatives, respectively. For example, for NA class, *TP* is the number of almonds in NA class when they actually are NA class, and *TN* is the number of almonds in other classes (BA, DA, WA and SA) when they are actually related to these classes. Similarly, *FP* is the number of almonds in other classes when they are actually related to NA class, and *FN* is the number of almonds in other classes when they are actually related to NA class.

RESULTS AND DISCUSSION

Selecting the Best Structure for ANN

After implementing different structures of ANNs, the index of total accuracy in classification was used for selecting the best structure. Furthermore, the number of neurons in the hidden layer(s) is one of the effective parameters for real-time systems. Therefore, among several structures that have highest performances (highest average and lowest standard deviation), the structure that has fewer hidden layers and neurons was selected as the optimum topology.

By running of each network structure 50 times and recording the average value and standard deviation of accuracy index, the ANN with 18-7-7-5 topology using LM algorithm with the average of 94.31% and standard deviation of 1.61%, and the 18-10-10-5 topology using SCG algorithm with the average of 94.37% and standard deviation of 1.66%, have the best performances among all trained networks. But the structure 18-7-7-5 is simpler and it has fewer neurons. So this structure was chosen as the best topology (Figs. 4 and 5).

Classification with ANNs

After obtaining the most appropriate network architecture, the best results obtained after 50 runs were saved and its confusion matrix that relates to the classification of five almond classes was computed (Table 4).

Finally, the values of three statistical indices including SE, SP and AC (Eqs. 9–11) were obtained from confusion matrix. These results are presented in Table 5. As it is observed, the lowest performance belongs to DA class (with SE = 93.94%, SP = 99.34% and AC = 98.38%). This is due to the close similarity between this class and NA class. Furthermore, as illustrated in Fig. 3, this class is nearly similar to

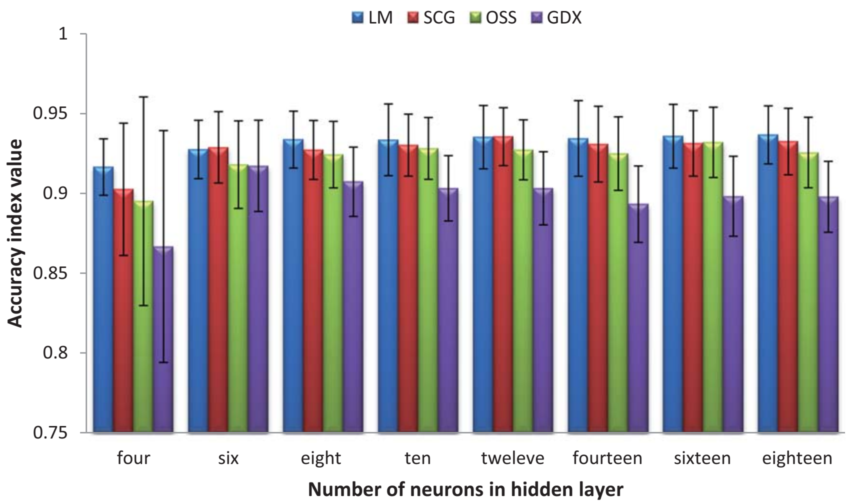

FIG. 4. PERFORMANCE OF DIFFERENT ANN STRUCTURES WITH ONE HIDDEN LAYER AND VARIOUS TRAINING ALGORITHMS (NOTE: THE ERROR BARS IN THIS FIGURE ARE STANDARD DEVIATION. LM STANDS FOR LEVENBERG-MARQUARDT, SCG IS SCALED CONJUGATE GRADIENT, OSS IS ONE STEP SECANT, AND GDX IS VARIABLE LEARNING RATE GRADIENT DESCENT).

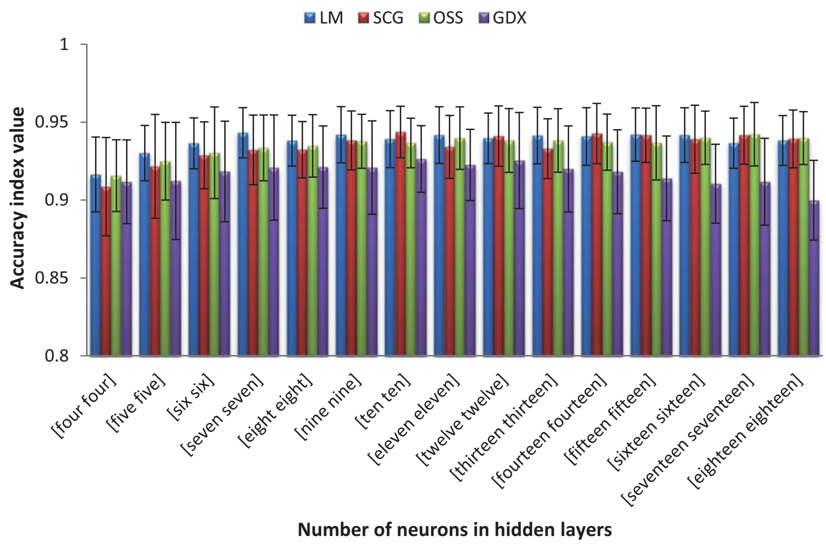

FIG. 5. PERFORMANCE OF DIFFERENT ANN STRUCTURES WITH TWO HIDDEN LAYERS AND VARIOUS TRAINING ALGORITHMS (NOTE: THE ERROR BARS IN THIS FIGURE ARE STANDARD DEVIATION. LM STANDS FOR LEVENBERG-MARQUARDT, SCG IS SCALED CONJUGATE GRADIENT, OSS IS ONE STEP SECANT, AND GDX IS VARIABLE LEARNING RATE GRADIENT DESCENT).

TABLE 4. CONFUSION MATRIX OBTAINED FROM VERIFICATION OF OPTIMUM ANN MODEL ON TESTING DATA SET

	Desired				
Predict	NA	BA	DA	WA	SA
NA	**38**	0	1	0	0
BA	1	**39**	0	0	0
DA	0	0	**31**	1	0
WA	0	0	1	**36**	0
SA	0	0	0	0	**37**

Note: In this table, NA is normal almond, BA is broken and split almond, DA is double or twin almond, WA is wrinkled almond, and SA is shell of almond. The bold entries represent the number of points for which the predicted label is equal to the true label, i.e., the number of correctly classified instances of each class.

NA class in terms of shape and color, but differs in the texture. Therefore, we expect this class to have a lower performance compared to other classes of almond. The highest performance belongs to SA class (with SE = 100%,

TABLE 5. VALUES OF SENSITIVITY, SPECIFICITY AND ACCURACY INDICES FOR ALL CLASSES OF ALMOND

	Class				
Parameters	NA	BA	DA	WA	SA
Sensitivity (%)	97.43	100	93.94	97.30	100
Specificity (%)	99.32	99.31	99.34	98.66	100
Accuracy (%)	98.92	99.46	98.38	98.92	100

Note: In this table, NA is normal almond, BA is broken and split almond, DA is double or twin almond, WA is wrinkled almond, and SA is shell of almond.

SP = 100% and AC = 100%), and after that is BA class (with SE = 100%, SP = 99.31% and AC = 99.46%). The main reason for the higher values of performance indices of these classes (SA and BA) is attributed to having the best correlations among extracted features. The majority of samples of these two classes differ from each other and other classes in terms of shape, color and texture features. Therefore, combining these features can play a positive role on the performance of overall classifier.

The results from confusion matrix (Table 4) and obtained statistical parameters (Table 5) show that by combining shape, color and texture features and applying ANNs would result in a high precision classifier as these features play important and effective role in quality grading of almonds based on available standards (UNECE 2009).

CONCLUSION

Quality classification of almond products has an important role in promoting the export of this valuable product. In this research, by using ANNs and image processing technique based on almond's shape, color and texture features, almonds were classified into five different classes based on defined standards (UNECE 2009).

Among different structures of ANNs which were evaluated, a structure having 18-7-7-5 topology was the most optimum structure. Results show that this structure has 97.84% accuracy. In choosing correlated and efficient features from all extracted features, sensitivity analysis method was used. Furthermore, because of the high dimension of the feature vector, the PCA was used for reduction in the dimension of the feature vector. Confusion matrix and statistical parameters show that using the combination of shape, color and texture features from RGB, Nrgb and CMY color spaces and applying ANNs to classify almond products are very efficient and successful. This method can be extended for real-time grading and sorting machines. Work in this direction is currently underway.

ACKNOWLEDGMENTS

The financial support provided by the Research Department of University of Tehran, Iran, under grant No. 1305051.01.08 is duly acknowledged. Financial support was also granted by the Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran.

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