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Full Research Paper

Classification of *Parus* strawberry fruit by combining image processing techniques and intelligent methods

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Abstract

Nowadays, in modern agriculture, the combination of image processing techniques and intelligent methods has been used to replace humans by smart machine. There is no international or domestic standard classification for *Parus* variety. In this study, an artificial image processing and artificial neural network (ANN) method was used to classify strawberry fruit of *Parus* variety. In the first step, the fruit was divided into 6 classes (ANN outputs) by the expert, and 100 samples were randomly collected from each class. In the next step, the images of the samples were captured and three geometric properties with twelve color properties (as ANN inputs) were extracted. Morphological and color characteristics of the area of the fruit were extracted using the functions defined in Matlab software. Optimum artificial neural network structures (15-18-6) considering root mean squared error (RMSE) and correlation coefficient (R^2) were investigated to classifiy the strawberry samples. Finally, the perceptron neural network with a structure of 6-18-15 was selected with the classification rate of 83.83%. The results obtained by ANN showed that the lowest and highest accuracy was related to small ripe (about 65%) and small raw (about 100%). Based on the accuracy of the results and economic aspects, ANN method is considered a proper method to classify strawberry fruit.

Keywords: Artificial neural network, Image processing, Intelligent methods, Strawberry classification.

Introduction

Strawberry is one of the finest and native fruits with delicious taste which cultivated in moderate region. Due to medicinal and nutritional properties the cultivation of strawberry is increasing (Nezmer *et al.*, 2018). This fruit is a rich source of vitamin C, minerals, and other ingredients which are essential in the body (Samimi and Khodaei, 2011). Typically, usually consumed raw and fresh, but also used in preparation of jellies, jams, ice creams and sweets (Taghavi, 2005). Iran with cultivation land of more than 3900 hectares of strawberries is the twentieth in the world among the countries which produce strawberries. The average yield of strawberries is 14 tons per hectare which has a good growth related to the European countries (FAO, 2017). According to the reports of agricultural organization of Iran, more than 25% of total strawberries production lost during the harvesting until marketing. The amount post-harvest waste of the strawberry fruit is very high due to the use of poor quality processing systems, lack of knowledge and skills in producing and harvesting, inappropriate postharvest mechanisms and activities associated with marketing channels (Salami *et al*., 2010).

Quality is a human concept that incorporates many parameters (Nemzer *et al.*, 2018). The quality of the fruit is defined by various parameters. According to various investigations, data such as color, shape, size and mass they are not sufficient for the consumer to buy a product; they would like to have more information about the fruit that is supposed to be consumed (Voca *et al.,* 2008; Doving and Mago, 2002). For example, in the case of strawberries, the quality is depending on the appearance of the fruit (the intensity and distribution of the color, the shape, size, non-destruction factor), its rigidity and its taste (as measured by the amounts of sugars, organic

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acids, phenolic acids and aromatic compounds). By increasing the content of the acid and increasing the amount of vitamin C, the soluble solids and the sugar of the fruit, the taste will be improved (Mitcham, 1996). Qualitative grading of various agricultural products can be effective in reducing post-harvest damage, maintaining quality and improving their commercial value. Strawberries are no exception to this rule. In recent years, attention has been focused on non-destructive methods for the qualitative grading of agricultural products. One of the common techniques is machine vision technology, which combines image processing techniques and intelligent methods. This technology has advantages over traditional and malicious methods such as no need for expert manpower, more precision, lower cost (Chen et al., 2002), quick response, identifying several indicators simultaneously and non-destructive (Liming and Yanchao, 2010). This technology can help to identify the apparent imperfections of the product during various process (Riquelme *et al.,* 2008), Qualitative Grading (Leemans and Destain, 2004) and the product classification based on shape and size (Abdullah *et al.*, 2006).

Several studies have been carried out on the use of machine vision in grading and classification of agricultural products. In order to cluster the strawberries, a technology of machine vision was used to recognize the number of features including the size (the largest diameter), shape (the edge of the fruit) and color (the a-channel) considering k-means algorithms. The accuracy of the clustering process using this algorithm was about 95%, 90%, 88% for the characteristics of the largest diameter, edge of the fruit and a-channel of color, respectively (Liming and Yanchao, 2010). It was also used to classify the raisin product on four grades: green without tail, black without tail, green with tail and black with tail. The algorithm was based on image processing and intelligent methods. The superior features of the raisin shape and color were selected after segmentation of the images by Otsu method (Otsu, 1979) using the Correlation-based Feature Selection which acts on the basis of the correlation of the selected properties. The classification was also carried out using backup vector machine, decision tree and artificial neural network, which was the most suitable method with accuracy of 96.33% (Mollazade *et al.,* 2012). In another research, almond image processing techniques were classified into three classes as: large, medium and small, based on the image area. After segmentation the images of the specimens, their area was measured. Then the weight of the samples was measured using a balance and it was selected as the basis for class selection with the accuracy of 99.70% (Castelo-Quispe *et al.,* 2013). In a study on the classification of strawberry fruit (not a specified variety) a new method without considering ANN method with accuracy of 0.94-0.97 was performed and the consumed time to define the class of the strawberry was about 0.4-0.55 s for each strawberry (Mar Oo and Zar Aung, 2018). Other methods were also used to grading the strawberry fruit (Feng *et al.,* 2008; Nagata *et al.,* 2000). Moreover other researchers used ANN method for classification of the fruits such as pineapple (Chia *et al.,* 2012), kiwi (Torkashvand *et al.,* 2017) and apple (Singh *et al.,* 2015) based on different parameters.

It was found that the combination of image processing techniques and computational intelligence is a reliable method to classify the agricultural products. Thus, in the present study, the processing techniques and also artificial neural network were used to classify the strawberry of *Parus* variety. Moreover, strawberry classification was carried out using artificial neural network as an input data to the system and several features were identified for this purpose. Also unlike the other studies in producing the images from the samples, the fruit flower bowl was not removed to maintain its quality.

Materials and methods

ANN structure:

An artificial neural network contains three layers including input, output and processing layers. Each layer has a group of nerve cells (neurons) that generally associated with all the neurons of the other layers, except the user limits communication between neurons; but this is the main point that the neurons in each layer do not correlate with other neurons in the same layer.

For the nervous cell c, we designate the input from the neural cell p to this b_{pc} cell. According to Schmidhuber, 2015 the weight of this input is ω_{pc}, and we designate the sum of the multiplications of inputs with their weights by a_c:

$$a_c = \sum_p \omega_{pc} \times b_{pc} \tag{1}$$

Now, the nonlinear function has to be applied to a_c and the output indicated by b_c.

$$b_c = \theta_c(a_c) \tag{2}$$

Similarly, the output from the nervous cell c enters the n cell named b_{cn} and its weight by ω_{cn}. Now we put all the weights of this neural network into a set called W to learn the weights to the network. Finally, by considering x as input and y as output data, the following equation obtained which must be minimized:

$$Q(W) = \sum_{i=1}^{n} l(h_w(x_i).y_i) \tag{3}$$

For the present study, first strawberry fruit samples were collected from Kurdistan province, Iran. Samples were kept in a lighting enclosure and after cutting fruit, images from the background the characteristics were extracted. Finally, the samples were classified using artificial neural network as shown in algorithm which depicted in Fig. 1.

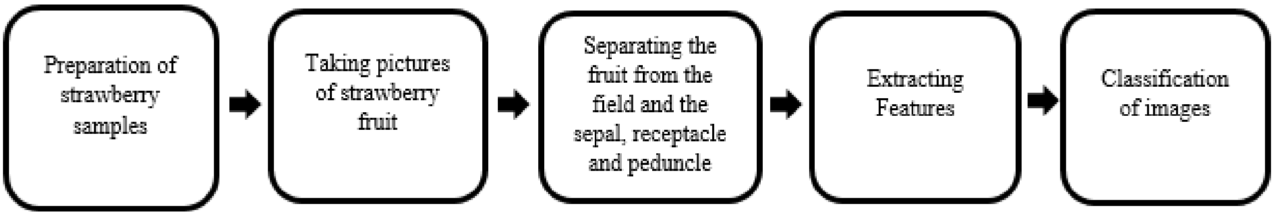

Fig. 1. The main steps of the proposed algorithm to classification

The number of neurons for the hidden layer was determined using the method of trial and error. The hidden layer is important for the ANN modeling process and it is directly affected on the performance of the collector. About 30 times run was performed to define the best structure based on output data and the relative error.

Collection and classification of samples

In Kurdistan province, strawberries are often cultivated in open area and the land under cultivation of *Parus* variety is surpassing other varieties due to the various reasons. Therefore, in the present study, *Parus* strawberry fruit samples were collected from a strawberry farm located in Noshur Sofla, a village of Kamyaran city, Kurdistan province, Iran in Spring 2014. Samples were transferred to the laboratory of agricultural machinery Department, University of Ilam. During the transportation process, no changes in color and texture were observed in the fruit.

Considering the other published papers related to the strawberry classifications, it was found that there was no international or domestic standard for *Parus* variety classification. Therefore, according to the expert's opinion and the characteristics of the size, shape and color, the samples were divided into six classes (Fig. 2). In order to verify the accuracy of the classification, some physical properties (geometric dimensions, mass, volume, apparent and actual density, porosity), mechanical properties (rigidity and bioavailability), and chemical properties (ascorbic acid, acidity, total soluble solids and flavor index) were considered as summarized in Table 1.

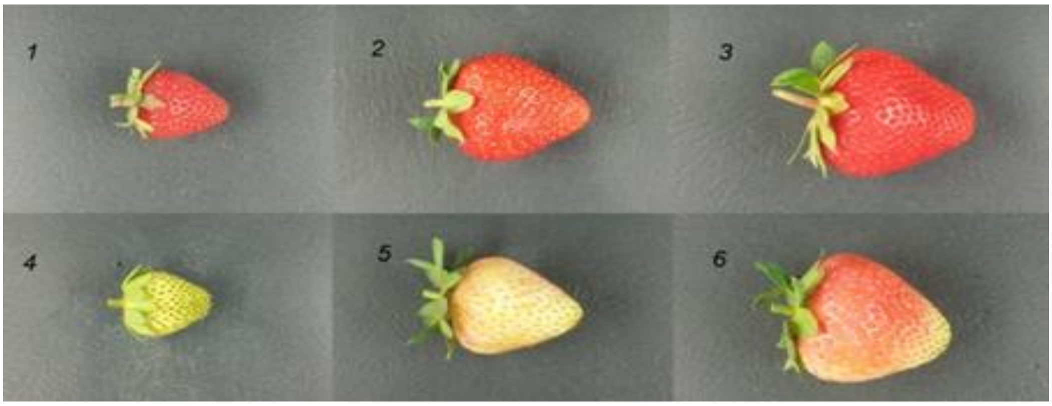

Fig. 2. Different classes of strawberry (Parus variety) used for this research: 1) small ripe, 2) medium ripe, 3) big ripe, 4) small raw, 5) medium raw, 6) big raw.

Table 1. The Strawberry properties

Properties	Class					
	1	2	3	4	5	6
Height (mm)	29.44	36.63	42.48	26.47	33.08	42.07
Mass (gr)	4.925	11.909	21.779	5.471	11.71	21.437
Apparent Density (kg/m^3)	942.367	962.449	970.166	860.592	861.623	881.513
Actual Density (kg/m^3)	561.743	430.873	401.441	498.408	385.318	376.956
Porosity	40.39	55.232	58.621	42.085	55.28	57.238
Rigidity (N/m^2)	10.1	7.8	5.2	28.2	13.7	11.5
Bioavailability (N)	13.7	16.9	29.7	74.5	50.1	35.1
Ascorbic Acid (10^{-5} gr/gr)	39.53	44.06	47.2	7.25	7.2	13.55
Acidity	0.55	0.64	0.67	1.08	1.1	0.99
Total Soluble Solids (%)	8.9	8.6	8.4	4	4.2	5.5
Flavor Index	16.3	13.5	12.6	3.6	3.8	5.5

Images preparation

About 100 images of each class were selected randomly for production of images. To remove environmental noise, an image processing box of 30*30*30 cm^3 was used. Tubular LED bulbs were also used inside the box to provide the best lightning quality and low disturbed noise on images. To eliminate the effect of the noises and the shadows, the black color was selected. To capture images, Samsung Galaxy S II with 8 megapixels (3248×2448 pixels) resolution camera was used which placed at a distance of 30 centimeters above the samples. For lightening D65 as standard value was considered for the process. The box made for the image processing and the lightning illustrated in Fig. 3.

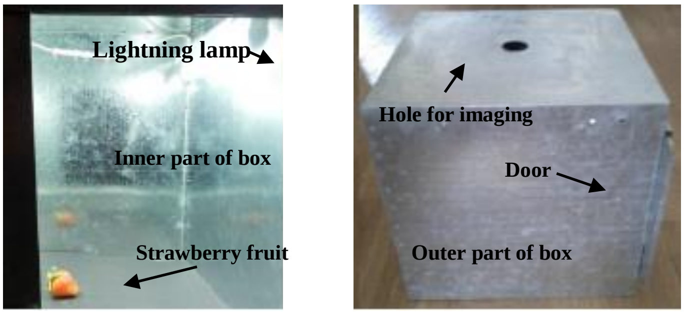

Fig. 3. The image processing box

Images segmentation

Image segmentation is one of the most important parts of image processing method. It is divided into pieces or constructive objects and there are several ways to segment the image. In this research, thresholding method was used using R, G, B color components in RGB color space to separate strawberry fruit from the background and flower bowl. After separating the strawberry fruit from the background and the flower bowl, a morphological operation of the dilatation and wear with a circular structure (using open and closed operators) was used to repair the edges of the strawberry fruit. Fig. 4 shows the various steps undertaken in the image processing (Gonzalez and Wood, 2018).

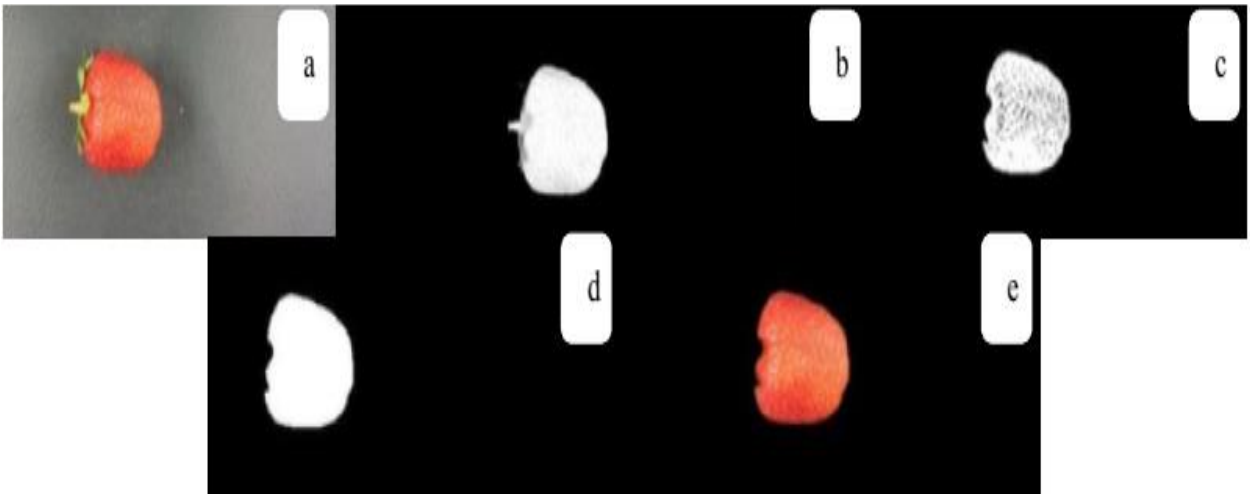

Fig. 4. Image segmentation: a) Sample image in RGB color space, b) Deletion of background, c) Deletion of sepal, receptacle and peduncle, d) Filling the holes and repairing the image border, e) Isolated fruit after segmentation.

To separate the fruit and bowl from the black background, three red, green and blue components were first extracted. A gray image was defined using the difference between the red and blue color components. In this image, the border between the fruit and the bowl with the background was visible. The threshold function with defined value in this boundary was applied to the image and the binary image was obtained with values of 1 for fruit and flower bowl and zero for background. By applying the opening and closing functions and their combination, bumps, troughs and pits were modified. After that by combination of three red, green and blue components of the original image, the color image of the fruit and bowl separated from the background (considering the binary image had zero value) was obtained. To separate the bowl from the fruit the similar steps were taken, except that the linear combination of all three color components was used to obtain the gray image. Morphological and color characteristics of the area were extracted using the functions defined in Matlab (R2012a).

Extraction of fruit features

Many features have been developed on image processing issues. The purpose of extracting image attributes is to describe the image based on some statistical descriptors. The features are categorized into three categories: morphological or geometric characteristics, colors and texture. Each of these features could be used for various applications, including morphological characteristics (diameter, environment, area, shape and volume) used in grading crops, color characteristics used to determine the level of handling, breakdowns and spoilage. The appearance of agricultural products and tissue features are used to determine the level of shrinkage of agricultural products and the recognition of plant diseases. In this study, fifteen characters, including three morphological characteristics and twelve color characteristics, were used to classify the strawberry fruit of *Parus* (Table 2).

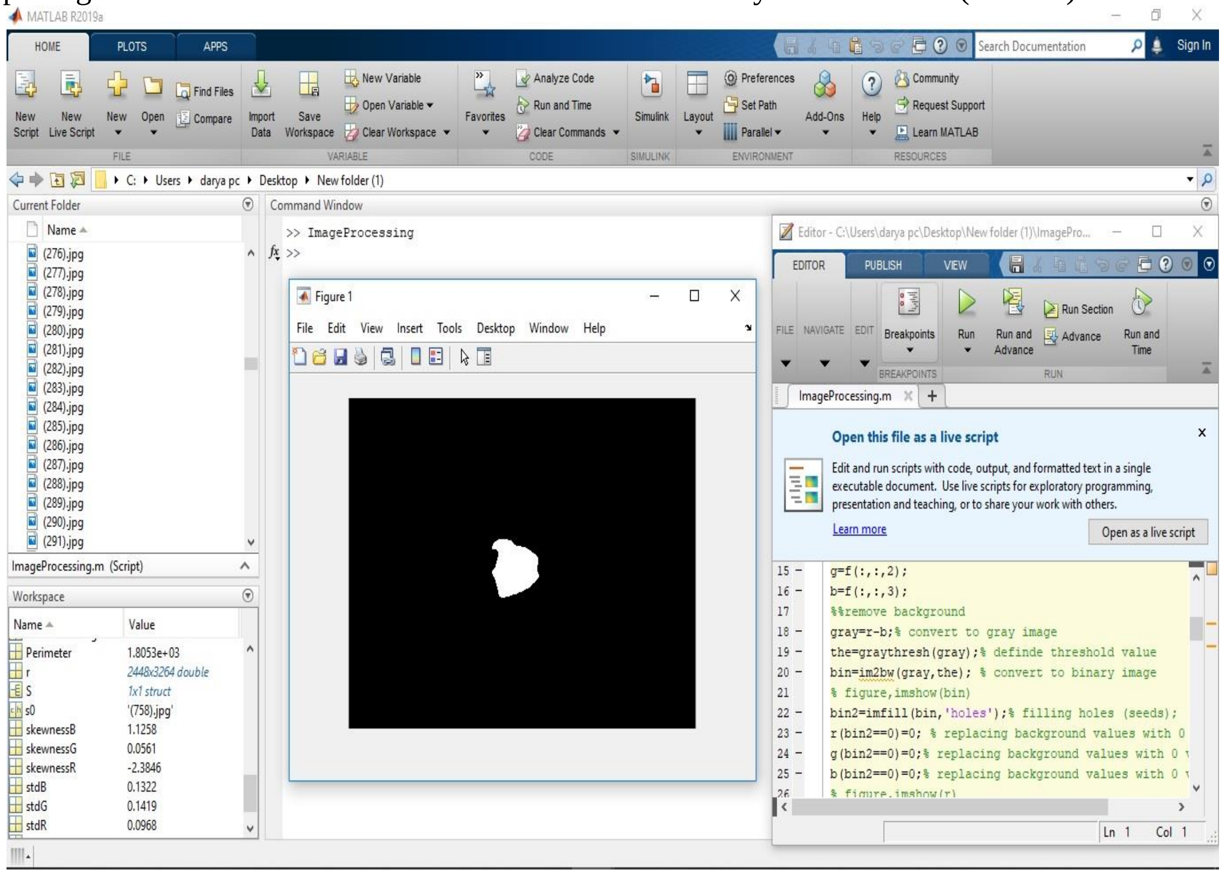

Fig. 5. A plot of Matlab environment applied for image processing of strawberry fruit

Table 2. The Features extracted from the images

Name	Color feature	Name	Apparent feature
F1	MeanR	F13	Area
F2	MeanG	F14	Perimeter
F3	MeanB	F15	AspectRatio
F4	StdR		
F5	StdG		
F6	StdB		
F7	SkewnessR		
F8	SkewnessG		
F9	SkewnessB		
F10	KurtosisR		
F11	KurtosisG		
F12	KurtosisB		

To calculate the morphological characteristics, the images were first converted to the binary images, and then three properties of the area, the environment and the ratio of the main diameter to the mean diameter of the samples were extracted. Due to the distinction between different classes in terms of shape and size, the morphological features were used for classification process. By examining different color spaces, the RGB color space was chosen because of the difference in color components at different classes. Four statistical descriptors related to the color including: mean, standard, skewness and kurtosis were extracted from strawberry samples. MATLAB software (R2012a) was used to plot the images and extract morphological features of color (Fig. 5).

R, G and B represented red, green, and blue components of the fruit image separated from the background and the bowl, respectively. Other parameters are presented by Eqs. 4-7 as follow

$$\text{Mean} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

$$\text{Std}= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)} \tag{5}$$

$$\text{Skewness} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^3}{\sigma^3} \tag{6}$$

$$\text{Kurtosis} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^4}{\sigma^4} \tag{7}$$

ANN setting

In order to classify strawberry fruit, the artificial neural networks (ANNs), one of the methods of data mining, was used (Omid *et al*., 2009). Each ANN structure consists of at least three layers of the neuron: 1. Input layer, 2. hidden layer, 3. Output layer. The number of neurons in the input, hidden, and output layers were identified as the number of inputs vector variables, the difficulty and complexity of the classification and the number of output classes, respectively. As shown in Fig. 6, the number of neurons in the input layer is equal to the number of properties extracted from the sample images (15 characteristics), and the number of output layer neurons is also considered equal to the number of grades. The model with the structure of 15-18-6 was concluded as the suitable.

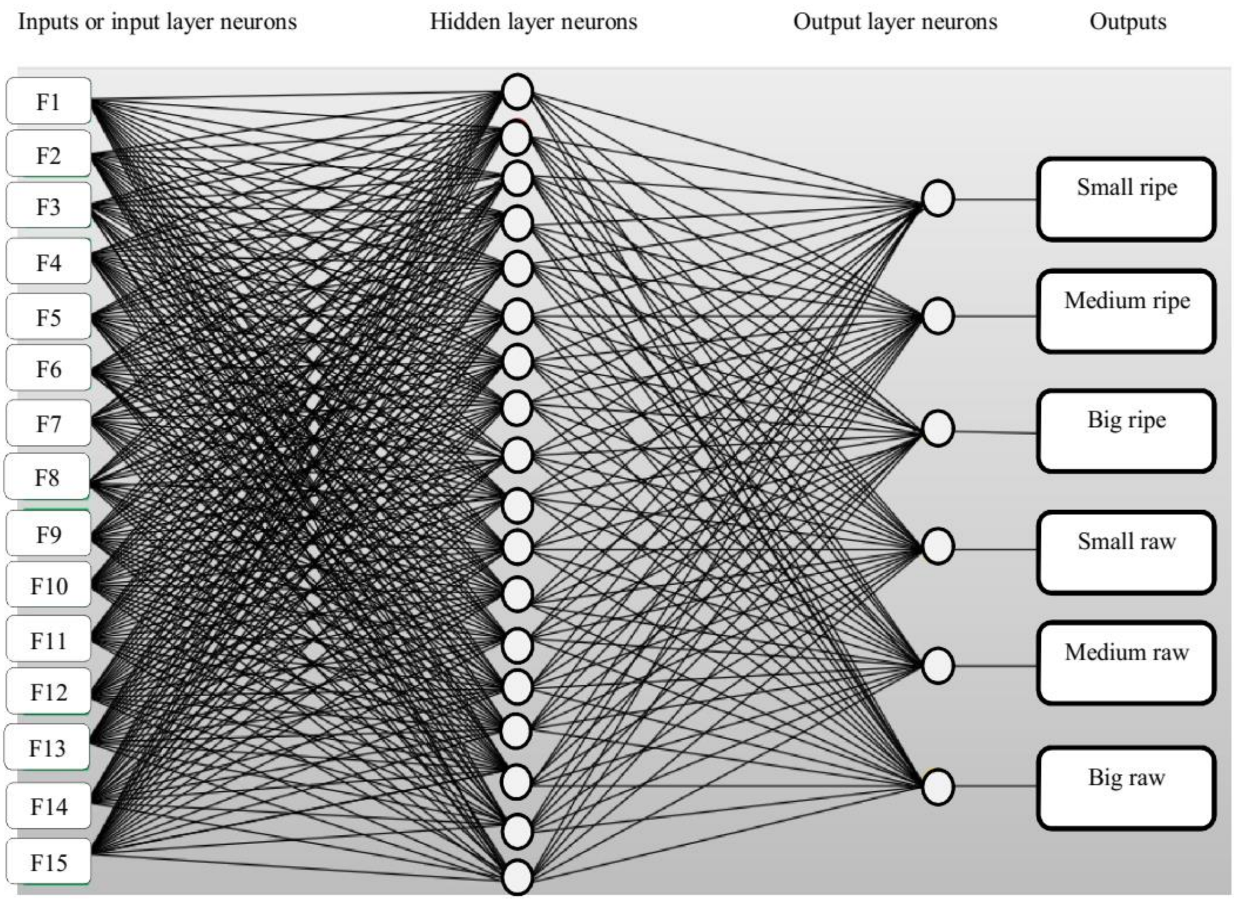

Fig. 6. ANN structure used for classification

It should be noted that there is always a tendency toward the lowest number of layers and neurons in the system. This reduces the size of the network and increases the speed of training which is very important in online studies. Other important factors in ANN design are activity function, training algorithm and number of training rounds. In this study, artificial neural network with multiplayer perceptron structure was used. This structure is appropriate for online structural applications, because there is no need for a timed order for input data and the input neuron activity function is linear. Also, in order to increase the learning speed and solve the complexity of the problem, the linear sigmoid activity function was used in the hidden layer neurons and the output layer. Training was also used bundled with momentum learning algorithm with momentum of 0.7 and learning factor of 0.6. This algorithm is one of the fastest learning algorithms which varies by varying the amount of momentum, changing the learning speed to match the inconsistency or incompatibility of input data, which results in the deletion of data from the learning process. Also in this algorithm, the stop index is the increase in the mean square error (MSE). Six hundred paired vectors were assigned to the network, of which 50% were used for training, 20% for assessment, and 30% for testing. ANN modeling was done in NEUROSOLUTION 5 software.

Evaluation of the results

In order to evaluate the ANN performance in classification of *Parus* strawberry fruit and to select the best structure of statistical indexes, classification rate (CCR (%)), correlation coefficient (r) and root mean square error (RMSE) were used in different training periods (Eqs. 8 and 9):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_A - x_p\right)^2} \quad (8)$$

$$r = 1 - \frac{\sum_{i=1}^{n}\left(x_A - x_p\right)^2}{\sum_{i=1}^{n} x_p^2} \quad (9)$$

Results and discussion

Selecting the best ANN structure

After implementing different ANN structures, the best structure was selected based on correlation coefficient (Fig. 7) and root mean square error (Fig. 8). The hidden layer which makes the model predict the class of the samples directly affected on the accuracy of the classification process. Fig. 7 shows that the pattern of the curve plots generated by ANN and the actual data are the same. The values of the correlation coefficient and root mean square error for the number of hidden neurons (2 to 20) and the number of different training periods (100, 300, 500, 750 and 1000 rounds) were investigated. It is clear from Figs. 7 and 8 that with increasing the number of hidden neurons and increasing the number of periods, the correlation coefficient increases as well. But the root mean squared error decreases, among which the single-layer perceptron structure with eighteen neurons in the hidden layer (with function linear sigmoid activity and momentum training algorithm with values of learning coefficient of 0.6 and momentum of 0.7) are less correlated to other structures with a higher correlation coefficient (0.83) and root mean square error (0.20).

ANN strawberry classification

After selecting the best structure of ANN, it was used for classification of strawberry fruit of *Parus* variety in six categories including: small ripe (first class), middle ripe (second class), big ripe (third class), small raw (fourth class), medium raw (fifth class) and big raw (sixth class). Also, in order to verify the network performance, the confusion matrix of the network (Table 3) was calculated and the classification rate (Table 4) was extracted.

The confusion matrix is a square matrix that the number of rows and columns is equal to the number of classes. The elements of the i-th column represent the i-class of the samples which classified by artificial neural network into different classes in the rows. Moreover, the classification rate shows the accuracy of the ANN in classifying the samples in each class.

For example, the i-class classification rate is obtained by dividing the a_{ii} element by the sum of i-class elements. In fact the optimal confusion matrix is the one which the elements in the main diagonal are 100% and the others are 0%. The elements in Table 3 show that the matrix is closer to diagonal matrix.

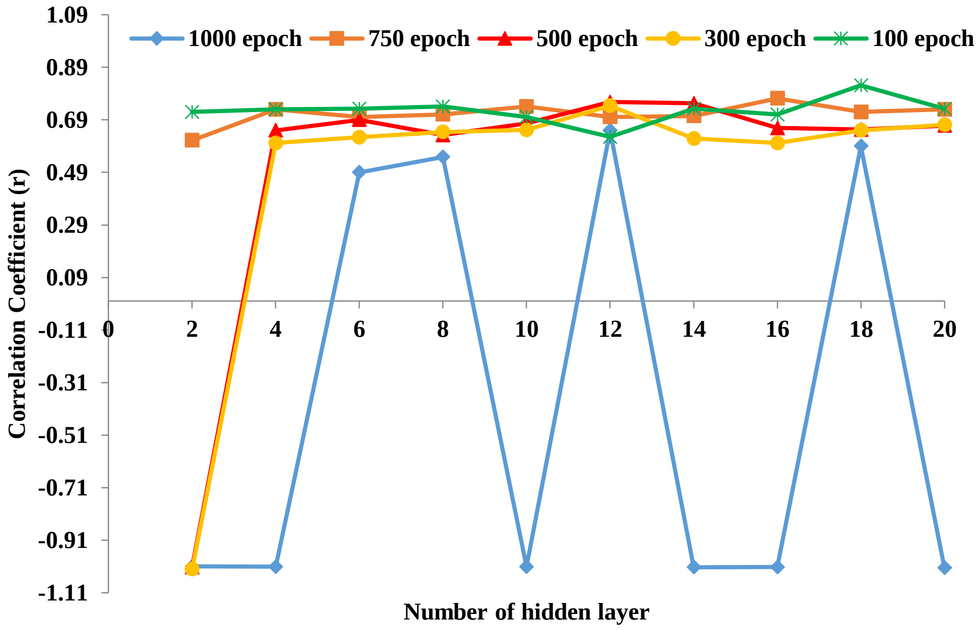

Fig. 7. Variations of Correlation coefficient with the number of hidden layer neurons and number of training courses

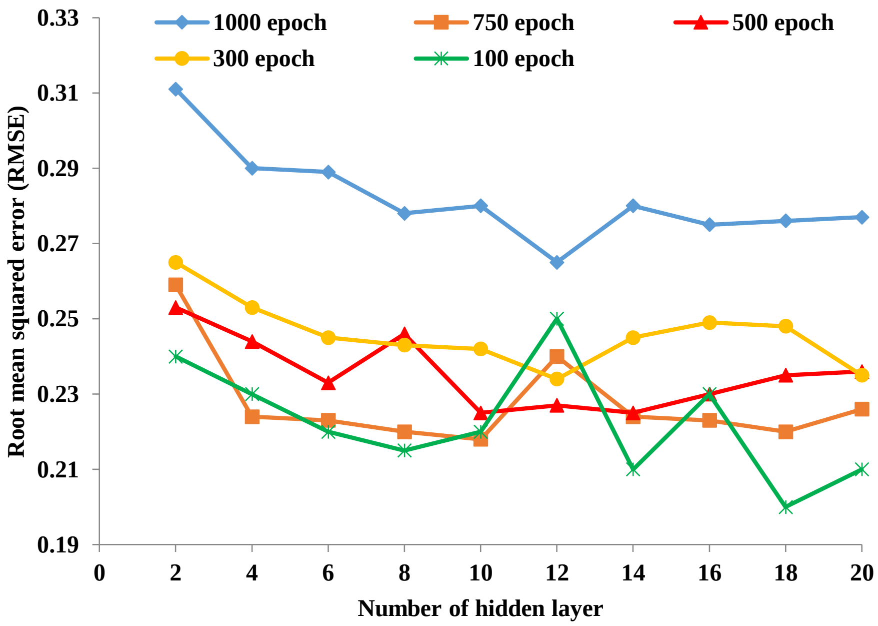

Fig. 8. Variations of RMSE withthe number of hidden layer neurons and number of training courses

Table 3. The confusion matrixof the network based on the number of output classes of ANN to validate the classification process ranged between 0-100%

ANN prediction	Real					
	Small ripe	**Medium ripe**	**Big ripe**	**Small raw**	**Medium raw**	**Big raw**
Small ripe	65	4	0	0	0	0
Medium ripe	35	90	12	0	0	2
Big ripe	0	4	81	0	0	13
Small raw	0	0	0	100	8	0
Medium raw	0	0	0	0	84	2
Big raw	0	2	7	0	8	83

Table 4. The classification rate for strawberry fruit

Statistical index	Real					
	Small ripe	**Medium ripe**	**Big ripe**	**Small raw**	**Medium raw**	**Big raw**
CCR (%)	65	90	81	100	84	83

The values of classification rate of strawberry fruit (*Parus* variety) are listed in Table 4. Based on the turbulence confusion matrix, the lowest accuracy of the strawberry classification was related to the small class (first class) which was about 65% due to the similarity of this class with the middle class. It can be implied that about 35% of the samples (in the first class) were mistakenly classified in the second class. As shown in Fig. 1, only the morphological features of these two classes can be distinguished, while color-based features do not make any distinction between the mentioned classes. In this study, during preparing the samples, the top section of the strawberries was not separated from the fruit because it has significant impact on maintaining the fruit quality. In the other hand by removing the top section of the fruit the spoilage rate increases. Therefore in image processing operations, to remove the top section even by applying image restoration techniques some parts were lost or eliminated from the texture of the fruit. This leads an error in the calculation of morphological properties which affected on the classification process. Also, a significant number of the first class specimens were located at the boundary between the first and second class, morphologically. The highest precision was related to the small raw class (fourth grade) with the accuracy of 100%. This was due to the entire class distinction with the other classes based on morphological and color characteristics. The accuracy of the classification in the other columns revealed that the classification accuracy was between 80% and 90%. Other researcher's studies on the classification process of fruit reported the same results (Hameed *et al.,* 2018). The factor that may reduce classification accuracy in this study is the lack of standard classification and presence the large number of samples on the boundary between the two classes defined by the expert. Also the large number of classes can be another factor for reducing the accuracy of the network. In this research, the classification rate was about 83.83 %, which shows that the qualitative grading of strawberry of *Parus variety* based on morphological and color characteristics using ANN methods can be very applicable especially in the design of grading and sorting machines. The results obtained by the present study are in agreements with the results obtained for the classification of the strawberry (Nagata *et al.*, 2000; Feng *et al.*, 2008; Liming & Yanchao, 2010; Mar Oo and Zar Aung, 2018).

Comparison between the data obtained experimentally and by the software showed that the time taken to classify the one hundred of strawberries by an expert is about 117 s while for the software it was about 2.5 s. In addition, if the erosion and fatigue factors of the expert are considered, then the classification time is increased. For a farmer maximizing the harvest or post harvest process with low price is considered as the main goal especially for the strawberry which the different conditions such as weather, atmospheric conditions and workers skill directly affecting the yield. Thus based on obtained results of ANN method applied to classification of *Parus* variety, and economic considerations it can be implied that ANN method is a suitable method used for grading strawberry fruit.

Conclusion

One of the main stages of harvesting and post harvesting processes is classification of food materials produced in agricultural sector. *Parus* variety is the popular strawberry planted in the west of Iran, especially Kurdistan province. Artificial neural network as a fast and accurate method mostly used for prediction the phenomenon such as classification. In this study, strawberry of *Parus* variety classified in six classes using image processing techniques and artificial neural network based on expert's opinion. The extracted features were included twelve color properties and three morphological characteristics. The best artificial neural network, was neural network with two-layer perceptron with eighteen neurons in the hidden layer, sigmoid activity function, momentum education algorithm (with momentum values of 0.7 and learning factor of 0.6). The accuracy was about 83.83 %. The results also showed that, using various neural networks and morphological and color characteristics could be more efficient in maintaining the quality of strawberries.

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طبقه بندی توت‌فرنگی رقم پاروس با ترکیب تکنیک پردازش تصویر و روش‌های هوشمند

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چکیده

امروزه در کشاورزی مدرن ترکیبی از تکنیک‌های پردازش تصویر و روش‌های هوشمند برای جایگزینی ماشین‌های هوشمند به‌جای انسان استفاده می‌شود. هیچ استندارد بومی و بین‌المللی برای طبقه‌بندی توت‌فرنگی رقم پاروس وجود ندارد. در این مطالعه از روش پردازش تصویر مصنوعی و شبکه عصبی مصنوعی (ANN) برای طبقه‌بندی میوه توت‌فرنگی رقم پاروس استفاده شده است. در گام اول این میوه توسط یک متخصص به شش کلاس طبقه‌بندی شد (به‌عنوان خروجی ANN) و از هر کلاس ۱۰۰ نمونه به‌طور تصادفی جمع‌آوری گردید. در گام بعد تصاویر نمونه‌ها ضبط شده و سه خصوصیت هندسی با ۱۲ ویژگی رنگ (به‌عنوان ورودی‌های ANN) استخراج گردید. خصوصیات مورفولوژیکی و رنگ سطح میوه با استفاده از توابع تعریف شده در نرم‌افزار Matlab استخراج شد. ساختار شبکه عصبی بهینه (۱۵-۱۸-۶) با توجه به خطای میانگین مربعات (RMSE) و ضریب هبستگی (R^2) برای فرآیند طبقه‌بندی نمونه‌های توت‌فرنگی در نظر گرفته شد. در نهایت شبکه عصبی پرسپترون با ساختار ۱۵-۱۸-۶ با دقت طبقه‌بندی ۸۳/۸۳٪ انتخاب گردید. نتایج به‌دست آمده از ANN نشان داد که کمترین و بیشترین دقت به‌ترتیب به کلاس‌های کمتر رسیده (تقریبا ۶۵٪) و کمتر نارس (تقریبا ۱۰۰٪) مربوط است. با توجه به نتایج و ملاحظات اقتصادی، ANN روش مناسبی برای طبقه‌بندی میوه توت‌فرنگی می‌باشد.

واژه‌های کلیدی: شبکه عصبی مصنوعی، پردازش تصویر، روش‌های هوشمند، طبقه‌بندی توت‌فرنگی.

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