J. Agr. Sci. Tech. (2012) Vol. 14: 857-867

Modelling Some Physical Characteristics of Pomegranate (*Punica granatum* L.) Fruit during Ripening Using Artificial Neural Network

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ABSTRACT

Pomegranate is an important Iranian-native fruit, with many varieties cultivated. Although the volume of data on the importance of pomegranates in human nutrition has increased tremendously in the last years, the physical properties of the pomegranate fruit during fruit maturity have not yet been studied in detail. Thus, the present study aimed to evaluate changes in physical characteristics of six pomegranate fruits in three different stages from fruit set to ripening. Physical characteristics of pomegranate fruit including length to diameter ratio of fruit and calyx, peel and aril percentage, juice weight and percentage in a whole fruit in 'Aghaye' (A), 'Faroogh' (F), 'Rabbab-e-Fars' (RF), 'Shahvare' (S), 'Shirin-e-Bihaste' (SB) and 'Shirin-e-Mohali' (SM) were investigated. Different topologies of the artificial neural network were examined. Among different structures, a multilayer feed forward neural network based on 15 neurons in the single hidden layer with transfer function of tangent hyperbolic both in hidden layer and output layer and Levenberg-Marquardt learning rule was found to be the best model for predicting the physical characteristics of pomegranate fruit from the different cultivars. Results indicated that artificial neural network provides a prediction method with high accuracy. The correlation coefficients in the prediction of these physical characteristics were higher than 0.89.

Keywords: Artificial neural network, Fruit ripening, Physical characteristics, Pomegranate.

[DOR: 20.1001.1.16807073.2012.14.4.3.9]

INTRODUCTION

Pomegranate (*Punica granatum* L.) belongs to the *Punicacea* family (Harde *et al.,* 1970), and is one of the oldest edible fruits. It has been cultivated extensively in many tropical and subtropical regions and its cultivation has increased considerably in recent years. Iran is one of the main producers and exporters of pomegranate in the world. The total pomegranate production of Iran was 670,000 tons in 2005 (Anonymous, 2005), and its production is increasing sharply year by year. Pomegranate fruit is consumed fresh or as processed into juice, jams, syrup and sauce. The edible part of the fruit is called arils and constitutes 52% of total fruit weight (w/w), composing of 78% juice and 22% seeds (Kulkarni and Aradhya, 2005).

Artificial neural networks (ANNs) are effective modelling techniques that demonstrate analogies to the way arrays of neurons function in biological learning and memory. ANNs present several advantages over conventional modelling techniques. One of the reasons is their capability to model based on no assumptions concerning the nature of the phenomenological mechanisms and understanding the

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mathematical background of problem underlying the process. Another reason is their ability to learn linear and nonlinear relationships between variables directly from a set of examples. The basic building blocks of ANN are units called nodes (neurons) comparable to biological neurons and weighted connections that can be compared to synapses in biological systems. Nodes are simple information processing elements (Amiryousefi and Mohebbi, 2010).

Determination of a neural network structure is a crucial step in neural network modelling. Considering their possible structures, ANN can be categorized as, either feed forward or recurrent. Multilayer feed forward networks are an important class of neural networks, consisting of a set of units that constitute the input layer, one or more hidden layer(s) and an output layer, each composed of one or more computation nodes. Multilayer perceptrons (MLP) have been applied successfully to solve many difficult problems in a supervised manner with a highly popular algorithm known as back propagation (BP) based on the error-correction learning rule. BP is a supervised learning algorithm which computes output error and modification of the weights of nodes in a backward direction (Thompson and Kramer, 1994).

Morimoto *et al.* (1997) developed an ANN-genetic algorithm intelligence approach for optimal control of fruit-storage process. Additionally, ANN has been used to predict thermal inactivation of bacteria (Lou and Nakai, 2001).

In spite of various pomegranate cultivars grown (more than 760 original, wild and decorative cultivars) in different regions of the Iran, few published results on the properties of the cultivars in the literature are available. Furthermore, although data on the importance of pomegranate in human nutrition has increased extensively in recent years, the physical characteristics of the pomegranate fruit during fruit maturity have not yet been evaluated in detail. Such data will assist with the cultivar selection for commercial production to meet market demand. This study aimed to investigate changes in physical characteristics of pomegranate fruit during ripening and study the efficiency of ANN for predicting these parameters.

MATERIALS AND METHODS

Pomegranate Cultivars

The studied pomegranate cultivars were: 'Aghaye' (A), 'Faroogh' (F), 'Rabbab-e-Fars' (RF), 'Shahvare' (S), 'Shirin-e-Bihaste' (SB) and 'Shirin-e-Mohali' (SM). Pomegranate cultivars were selected from the Agricultural Research Center of the Yazd province, Iran. Since pomegranate flowering occurs in about 3 distinct waves, about 500 flowers were marked at full bloom to provide fruit samples. The fruits were harvested at three different developmental stages, 20, 80 and 140 days from the onset of fruit set. The fruits were transferred to the laboratory soon after harvest in plastic bags, where pomegranates with defects (sunburns, cracks, cuts and bruises in peel) were discarded. Four replicates were maintained for each analysis each replication indicating a five pomegranate fruit.

Physical Properties

Twenty fruits of each cultivar were individually analyzed for physical characteristics. Fruits were weighed in air on a balance of 0.001 g accuracy. The length and diameter of the fruit and calyx were measured using a digital vernier caliper. The measurement of fruit length was made on the polar axis, i.e. between the stem-end and calyx-end of the fruits. The maximum width of the fruit, as measured in the direction perpendicular to the polar axis, is defined as the diameter. The length/diameter ratio of the fruit and calyx were obtained by the ratio of length to diameter of fruit and calyx, respectively. After measuring all fruit samples, the arils were manually separated from the fruits, and total weights of arils and peel per fruit were measured as above (Tehranifar *et al.,* 2010). Fruit juice content was measured by extracting total arils per fruit using an electric extractor (Toshiba 5020, Japan).

Artificial Neural Network

Establishment of the ANN

In this study, fully interconnected multilayer feed forward network, which is the most widely used ANN, and generalized feed forward network were applied to model some physical characteristics in pomegranate. One of the commonly used feed forward ANN architectures is the multilayer perceptron (MLP) network. The main advantages of MLP compared to other neural model structures are easy implementation and approximate mapping between input and outputs (Menhaj, 2008). The MLP consists of (a) an input layer with neurons representing input variables to the problem, (b) an output layer with neuron(s) representing the dependent variable(s), and (c) one or more hidden layer(s) containing neuron(s) to help capture the nonlinearity in the system (Figure 1).

Generalized feed forward networks are a generalization of the MLP such that connections can jump over one or more layers. Here we simply specify the number of layers, and the wizard will construct an MLP in which each layer feeds forward to all subsequent layers. In theory, an MLP can solve any problem that a generalized feed forward network can solve. In practice, however, generalized feed forward networks often solve the problem much more efficiently. Without describing the problem, it suffices to say that a standard MLP requires hundreds of times more training epochs than the generalized feed forward network containing the same number of processing elements (Ata *et al.,* 2009; Mohammadi *et al.,* 2005).

The complexity of the MLP network depends on the number of layers and the number of neurons in each layer. In the hidden and output layers, the net input (x_j) to node j is of the form:

$$x_j = \sum_{i=1}^{n} w_{ij} y_i + b_j \qquad (1)$$

Where, y_i are the inputs, w_{ij} are the weights associated with each input/node connection, n is the number of nodes and b_j is the bias associated with node j. The bias neurons do not take any input and they emit a constant output value across weighted connections to the neurons in the next layer (Razavi *et al.,* 2003).

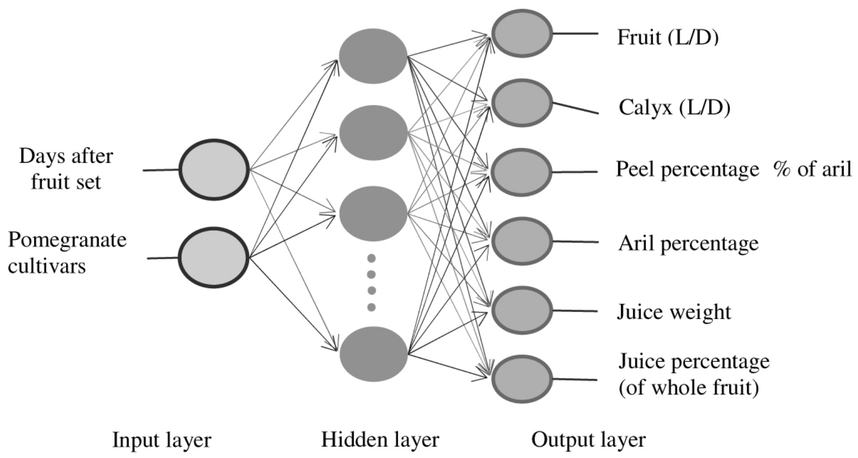

Figure 1. Multilayer feed forward neural network architecture with one hidden layer.

[DOR: 20.1001.1.16807073.2012.14.4.3.9]

Each neuron consists of an activation function expressing the internal activation level. Output from a neuron is determined by transforming its input using a suitable activation function. The activation function can be a linear or nonlinear function depending on the network topology. In this work, pomegranate cultivars and days after fruit set were used as inputs, and length/diameter of fruit and calyx, peel percentage, aril percentage, percentage juice and juice weight of the pomegranate from the different cultivars were considered as outputs. In this study, hyperbolic tangent (Tansig) and sigmoid (Logsig) activation functions (Equations (2) and (3)) were chosen to be used in the hidden layer, due to lower calculated mean-squared error values, while linear, hyperbolic tangent and sigmoid functions were used in the output layer.

$$\text{tansig}(x_j) = \frac{e^{x_j} - e^{-x_j}}{e^{x_j} + e^{-x_j}} \qquad (\mathbf{2})$$

$$\text{logsig}(x_j) = \frac{1}{1 + e^{-x_j}} \qquad (\mathbf{3})$$

Two important factors must be considered to ensure a successful modeling of MLP; first, the number of hidden layers and second, the number of neurons in each hidden layer. Since almost all the problems in neural network modeling could be solved with one hidden layer (Chen *et al.,* 2001; Kashaninejad *et al.,* 2009; Mitra *et al.,* 2011; Mohebbi *et al.,* 2007; Movagharnejad and Nikzad, 2007; Ochoa-MartÃ-nez *et al.,* 2007), an ANN with three layers was used in this research. In addition, using too many hidden layers may lead to the problem of data over-fitting, affecting the system's generalization capability (Abdullah *et al.,* 2006). Therefore, to find the best architecture, different networks were built with different hidden neurons varying from 2 to 15.

Data Training and Testing

In total, 72 data were collected for the 6 different pomegranate cultivars and 3 different days after fruit set. First, the data order was randomized and then the data were divided into three partitions. The first partition (training data) was used to perform the training of the network (60% of data). The second one (cross validation data) was used to evaluate the prediction quality of the network during the training (15% of data). For estimating the performance of the trained network on new data, a third partition, which was never seen by the artificial neural network during the training and cross-validation processes, was used (25% of data) for testing. During training, momentum value was fixed at 0.7, and learning rate was determined at level 1 on the hidden layer and 0.1 at the output layer.

The other applied learning algorithm was Levenberg-Marquardt (Shulman *et al.,* 1984.) algorithm which is an iterative technique that locates the minimum of a function expressed as the sum of squares of nonlinear functions. It is a standard technique for nonlinear least-squares problems and is a combination of steepest descent and the Gauss-Newton method.

The training process was carried on for 1,000 epochs or, until the cross-validation data's mean-squared error (MSE) did not improve for 100 epochs to avoid over-fitting of the network. Backpropagation algorithm was used to implement supervised training of the network. Backpropagation is based on searching an error surface (error as a function of ANN weights) using gradient descent for point(s) with minimum error. Each iteration in backpropagation constitutes two sweeps: forward activation to produce a solution, and the backwards propagation of the computed error to modify the neurons' weights (Movagharnejad and Nikzad, 2007). Testing was carried out with the best weights stored during the training. Structures of ANN applied to model six physical characteristics of different pomegranate cultivars during ripening has been brought in Table 1

In this study, the ANN models were constructed by Neurosolutions for Excel software release 5.0, produced by

Table 1. Structures of ANN applied to model six physical characteristics of different pomegranate cultivars during ripening.

No.	Neural model	No. of neurons	Transfer function in hidden layer	Transfer function in output layer	Learning rule
1	MLP	2-15	Logsig	Linear	Momentum
2	MLP	2-15	Logsig	Logsig	Momentum
3	MLP	2-15	Logsig	Tansig	Momentum
4	MLP	2-15	Tansig	Linear	Momentum
5	MLP	2-15	Tansig	Logsig	Momentum
6	MLP	2-15	Tansig	Tansig	Momentum
7	MLP	2-15	Tansig	Tansig	LM
8	GFF	2-15	Logsig	Linear	Momentum
9	GFF	2-15	Logsig	Logsig	Momentum
10	GFF	2-15	Logsig	Tansig	Momentum
11	GFF	2-15	Tansig	Linear	Momentum
12	GFF	2-15	Tansig	Logsig	Momentum
13	GFF	2-15	Tansig	Tansig	Momentum

NeuroDimension, Inc. NeuroSolutions simulations are vector based for efficiency. This implies that each layer contains a vector of processing elements and that the parameters selected apply to the entire vector. The parameters are dependent on the neural model, but all require a nonlinearity function to specify the behaviour of the processing elements. In addition, each layer has an associated learning rule and learning parameters.

In applying neural networks, once the raw input data has been selected, it must be preprocessed; otherwise, the neural network will not produce accurate forecasts. The decisions made in this phase of development are critical to the performance of a network. In normalizing data, as the final pre-processing step, the goal is to ensure that the statistical distribution of values for each net input and output is roughly uniform. In addition, the values should be scaled to match the range of the input neurons.

One of the methods of data normalization is a simple linear scaling of data. Data must be scaled into the range used by the input neurons in the neural network. This is typically the range of -1 to 1 or zero to 1. Many commercially available generic neural network development programs like Neurosolutions used in this study, automatically scale each input.

Model Evaluation

Evaluation of the performance of the trained network was based on the accuracy of the network in the test partition. Therefore, MSE, normalized mean-squared error (NMSE), mean absolute error (MAE), and correlation coefficient (R) for each output were calculated using Equations presented by Amiryousefi and Mohebbi (2010) based on testing data and were used to compare the performance of different ANN architectures.

Statistical Analysis

The statistical analysis in this research has been done in a factorial design based on completely randomized design with four replications. Data were analysed by Statistical Analysis System (SAS) software version 9.1 using analysis of variance (ANOVA) and differences among means were determined for significance at $P< 0.05$ using LSD test.

RESULTS AND DISCUSSION

Physical Properties

Means of changes in physical properties of six pomegranate cultivars in each stage are presented in Table 2. Significant differences

[DOR: 20.1001.1.16807073.2012.14.4.3.9]

were detected among different stages in all measured parameters as concerned.

The length/diameter ratio of pomegranate fruit reduced significantly with the advance in fruit ripening. Similar results were also reported by Ben-Arie *et al.,* (1984). A significant decrease in length/diameter ratio of calyx was observed from 1.20 mm in the 20 day-old fruit to 0.73 mm in the 180 day-old fruit. The percentage of peel declined significantly while percentage of aril and juice increased significantly during fruit ripening. The lowest quantity of peel (32.03%) and the highest aril amount (67.96%) and juice amount (57.15%) were recorded in the 140 day-old fruit. About half of the total fruit weight during most stages of fruit ripening consisted of the aril. The results are comparable to those of Shulman *et al.* (1984) and also Gozlekci and Kayank (2000). Al-Maiman and Ahmad (2002) have reported that these differences could be attributed to metabolic changes during ripening.

The means of changes in physical characteristics of each three stages for length/diameter of fruit and calyx, peel percentage, aril percentage, juice percentage and juice weight of the pomegranate from the different cultivars are given in Table 3. Large significant differences were revealed among the pomegranate cultivars for length/diameter of fruit and calyx, peel percentage, aril percentage, juice percentage and juice weight.

The fruit length/diameter ratio was between 0.92 mm (Shahvar) and 0.98 mm (Rabbab-e-Fars) and calyx length/diameter ratio varied from 0.90 mm (Rabbab-e-Fars) to 1.03 mm (Faroogh). Valero and Ruiz-Altisent (2000) have reported that this information is particularly relevant in the design or selection of appropriate packaging for fruit handling and storage. As shown in Table 3, there are wide variations in percentage of peel (41.71–75.48%) and aril (42.26–58.28%) among the pomegranates of different cultivars. The highest aril percentage (58.28%) and the lowest peel percentage (41.71%) were recorded in ‘Faroogh’. According to the current study, the aril percentage was inversely correlated to peel percentage. One of the most important parameters from an industrial point of view is the juice content of the aril. The juice percentage (of whole fruit) of the studied pomegranate cultivars varied from 29.55% (Rabbab-e-Fars) to 42.57% (Faroogh), which is in agreements with the results reported by Fadavi *et al.* (2005).

The results of the physical properties of the pomegranate cultivars in this research demonstrated that the six cultivars are different in all measured parameters. The ‘Faroogh’ cultivar seems to be the most promising cultivar because of more percentage of aril and juice and least peel percentage, which is a highly desirable property in the food processing and beverage industry.

Artificial Neural Network Optimization

The optimum number of neurons in the hidden layer for different structures of

Table 2. Means of changes in physical characteristics of six pomegranates cultivars during fruit ripening.

Parameter	Days after fruit set		
	20	80	140
Fruit length/Diameter (L/D)	1.08±0.07[a]	0.97±0.02[b]	0.82±0.04[c]
Calyx length/Diameter (L/D)	1.20±0.10[a]	0.97±0.07[b]	0.73±0.03[c]
Peel percentage	71.77±4.71[a]	48.89±9.00[b]	32.03±5.80[c]
Aril percentage	28.22±4.71[c]	51.84±9.51[b]	67.96±5.80[a]
Juice weight (g)	7.44±2.84[c]	60.39±15.36[b]	152.91±33.01[a]
Juice percentage (of whole fruit)	10.31±3.48[c]	40.10±7.13[b]	57.15±5.69[a]

Means of six cultivar in each row followed by different letters are significantly different (* P< 0.05), ±= Standard deviation.

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network is determined by a trial/error procedure based on minimizing the difference between estimated ANN outputs and experimental values. The minimums of mean square error for estimation of our parameters during the training process of different architectures of ANN with two to 15 neurons in the hidden layer are shown in Table 4.

Artificial Neural Network Performance

Among 13 selected structures, a multilayer feed forward neural network based on 15 neurons in the single hidden layer with transfer function of tangent hyperbolic both in hidden layer and output layer and Levenberg-Marquardt learning rule was found to be the best model for predicting length/diameter of fruit and calyx, peel percentage, aril percentage, juice percentage and juice weight of the pomegranate from the different cultivars. Table 5 tabulates the reason of this selection in terms of mean square error (MSE), normalized mean square error (NMSE), mean absolute error (MAE), minimum absolute error (Min AE), maximum absolute error (Max AE) and the linear correlation coefficient (R) between experimental data and neural network outputs for testing data set in this structure.

The prediction efficiency of the chosen ANN model for testing data is presented in Figures 2(a-f) for length/diameter of fruit and calyx, peel percentage, aril percentage,

Table 3. Means of changes in physical characteristics of each three stages for six percentage cultivars.

Parameters	Cultivars					
	Aghaye	Faroogh	Rabbab-e-Fars	Shahvare	Shirin-e-Bihaste	Shirin-e-Mohali
Fruit (L/D)	0.94±0.12^{ab}	0.97±0.09^{ab}	0.987±0.13^{a}	0.92±11.90^{b}	0.98±0.16^{a}	0.96±0.12^{ab}
Calyx (L/D)	0.93±0.17^{bc}	1.03±0.23^{a}	0.90±0.14^{c}	1.01±11.85^{ab}	0.99±0.22^{ab}	0.94±0.23^{bc}
Peel percentage	41.71±20.15^{b}	75.48±19.46^{a}	57.73±14.46^{a}	50.00±1.16^{c}	54.20±17.01^{ab}	49.67±16.44^{c}
Aril percentage	47.92±20.15^{bc}	58.28±19.46^{a}	42.26±14.46^{d}	49.99±3.73^{bc}	45.79±17.01^{cd}	51.79±16.44^{b}
Juice weight(g)	53.08±62.49^{bc}	63.52±55.48^{a}	48.02±46.50^{c}	60.49±2.88^{a}	57.99±55.46^{ab}	59.78±86.88^{a}
Juice percentage (of whole fruit)	31.74±18.48^{c}	29.55±21.86^{c}	10.18±18.07^{abc}	38.48±0.12^{b}	35.52±20.90^{b}	37.25±21.82^{b}

Means of each of the three stages in rows followed by different letters are significantly different (* $P< 0.05$), ±= Standard deviation.

Table 4. Optimized structures of ANN applied to model six physical characteristics of different pomegranate cultivars during ripening.

No.	Neural model	Transfer function in hidden layer	Transfer function in output layer	Learning rule	No. of neurons	Minimum MSE
1	MLP	Logsig	Linear	Momentum	13	0.01125
2	MLP	Logsig	Logsig	Momentum	15	0.00420
3	MLP	Logsig	Tansig	Momentum	10	0.00985
4	MLP	Tansig	Linear	Momentum	11	0.00916
5	MLP	Tansig	Logsig	Momentum	14	0.00282
6	MLP	Tansig	Tansig	Momentum	13	0.00787
7	MLP	Tansig	Tansig	LM	15	0.00464
8	GFF	Logsig	Linear	Momentum	8	0.01466
9	GFF	Logsig	Logsig	Momentum	15	0.00399
10	GFF	Logsig	Tansig	Momentum	12	0.01409
11	GFF	Tansig	Linear	Momentum	5	0.00354
12	GFF	Tansig	Logsig	Momentum	7	0.00338
13	GFF	Tansig	Tansig	Momentum	12	0.01033

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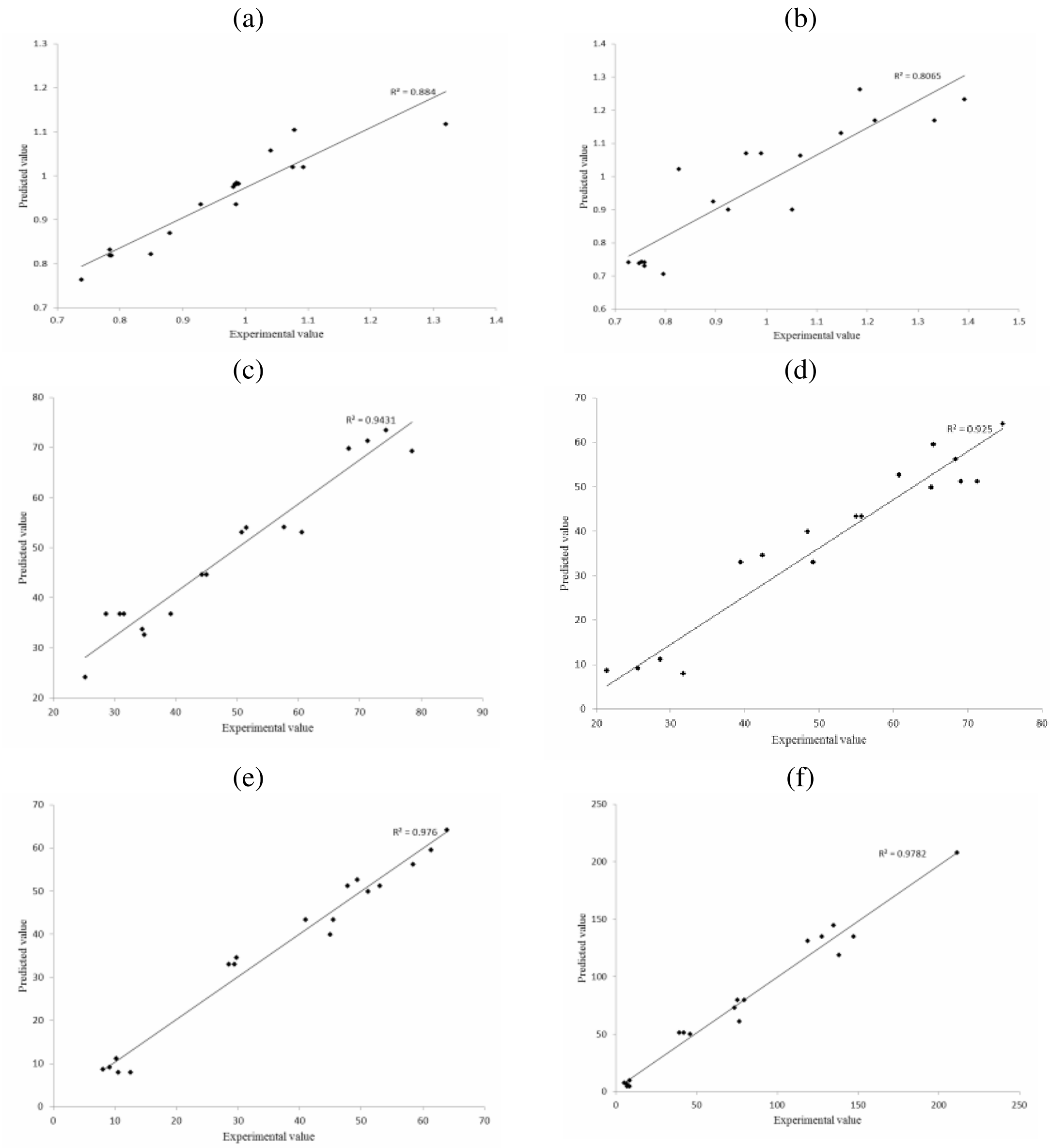

Figure 2. Experimental *vs.* predicted values for (a) length/diameter ratio of fruit (b) length/diameter ratio of calyx (c) peel percentage (d) aril percentage (e) juice percentage and (f) juice weight from different pomegranate cultivars by optimum ANN configuration.

Table 5. Performance of optimized ANN used for modelling six physical characteristics of different pomegranate cultivars during ripening.

Performance	Fruit (L/D)	Calyx (L/D)	Peel percentage	Aril percentage	Juice weight (g)	Juice percentage (of whole fruit)
MSE	0.97711	0.06268	17.32068	17.52862	75.88497	9.63428
NMSE	50.84098	1.47126	0.06104	0.06177	0.02189	0.02688
MAE	0.21403	0.07999	3.08848	3.21847	6.71974	2.67944
Min AE	0.00241	0.00432	0.03491	0.07709	0.15816	0.01394
Max AE	0.20271	0.19630	9.25358	9.00840	19.42219	5.07620
R	0.94021	0.89808	0.97115	0.97165	0.98904	0.98795

percentage juice and weight juice of the pomegranate from the different cultivars, respectively, in which the predicted values are plotted against their experimentally measured values for the best configuration ANN (15 neurons in the hidden layer). The calculated correlation coefficient values for the estimation of our parameters were acceptable and revealed good agreement between predicted and experimental values. Therefore, the configuration of ANN model including 15 neurons in the hidden layer is efficiently suggested for the prediction of length/diameter of fruit and calyx, peel percentage, aril percentage, percentage juice and weight juice of the pomegranate from different cultivars.

CONCLUSIONS

Changes in the physical characteristics of pomegranate, from fruit set to ripening, clearly explained their growth, development and ripening stages. In addition, these results showed that the physical properties differ between the cultivars studied. However, as there are many other cultivars in Iran, more studies of physical properties are required for them. A multilayer feed forward neural network based on 15 neurons in the single hidden layer with transfer function of tangent hyperbolic both in hidden layer and output layer and Levenberg-Marquardt learning rule was found to be the best model for predicting length/diameter of fruit and calyx, peel percentage, aril percentage, percentage juice and weight juice of the pomegranate from the different cultivars, showing minimum MSE (0.97711, 0.06268, 17.32068, 17.52862, 9.63428 and 75.88497, respectively) and high R (0.94021, 0.89808, 0.97115, 0.97165, 0.98795 and 0.98904, respectively) values. It seems that the application of artificial neural network can lead to an automated, objective, and rapid inspection as well as online control of sorting and grading of the pomegranate fruits.

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مدل‌سازی برخی ویژگی‌های فیزیکی میوه انار (*Punica granatum* L.) طی رسیدن با استفاده از شبکه‌های عصبی مصنوعی

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[DOR: 20.1001.1.16807073.2012.14.4.3.9]

چکیده

انار یکی از میوه‌های بومی ایران است و واریته‌های زیادی از آن کشت می‌شود. اگرچه اطلاعات در مورد اهمیت انار در تغذیه انسان طی سال‌های اخیر به طور شگرفی افزایش یافته است، در مورد جزئیات تغییر ویژگی‌های فیزیکی انار در مدت زمان رسیدگی مطالعه ای صورت نگرفته است. بنابراین هدف از مطالعه حاضر ارزیابی تغییرات فیزیکی ۶ گونه انار در ۳ مرحله متفاوت طی رسیدگی آن است. خصوصیات فیزیکی میوه انار شامل نسبت طول به قطر برای خود میوه و کالیکس آن، درصد پوست و درصد آریل در کل میوه، وزن آب‌میوه و درصد وزن آن به وزن کل میوه در ۶ گونه آقایی، فاروق، رباب فارس، شهوار، شیرین بی هسته و شیرین محالی اندازه گیری شد. به منظور مدل‌سازی برخی ویژگی‌های فیزیکی میوه انار، توپولوژی‌های مختلف شبکه های عصبی مصنوعی امتحان شد. از میان ساختارهای مختلف، یک شبکه عصبی پیش خور چندلایه با ۱۵ نرون در لایه مخفی، تابع فعالیت تانژانت هیپربولیک در لایه مخفی و لایه خروجی، و نیز قانون یادگیری لونبرگ- مارکوارت به عنوان بهترین مدل برای پیش بینی ویژگی‌های فیزیکی واریته‌های مختلف انار انتخاب شد. نتایج نشان از کارایی بالای شبکه های عصبی مصنوعی در پیش بینی این ویژگی‌ها داشت. ضرایب همبستگی در پیش بینی این ویژگی‌ها بیش از ۰/۸۹ بودند.

[DOR: 20.1001.1.16807073.2012.14.4.3.9]