Modeling of physical properties of apple slices (*Golab variety*) using artificial neural networks

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Abstract: Apple is one of the most popular fruits and of high economic value. Sorting and grading of apple is needed for the fruit to be presented to local and foreign markets. A study of apple physical properties therefore is imperative. In this work, some physical properties of apples (*Golab variety*) such as main diameter, mass, volume and fruit density were determined and relation between mass and other parameters were modeled by using artificial neural networks. In this study, we used Feed-Forward Back Propagation (FFBP) network with training algorithms, Levenberg-Marquard and Momentum. The results show that Levenberg-Marquard algorithm give better result than Momentum algorithm do, and Feed-Forward Back Propagation (FFBP) network with topology 3-6-4-1, 3-6-1, 3-4-2-2-1 and 3-6-6-1; and Levenberg-Marquard algorithm could predict relation between mass and other parameters with error percentages 0.999999, 0.999999, 0.999999 and 0.999999; and mean square error 0.000078, 0.000118, 0.000158 and 0.000194.

Keywords: apple (Golab variety), artificial neural network, Feed-Forward Back Propagation, Levenberg-Marquard algorithm, Momentum algorithm, physical properties

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1 Introduction

Among fruits, apple is the most economical and industrial. It is consumed in different forms, such as fresh fruit, concentrated juice or thin dried slices. Apples contain a high percentage of their fresh weight as water. Apple was introduced into Iran many years ago. Iran currently ranks 6th among the apple producing countries of the world (ASB, 2004-2005). Grading and sizing of fruits is a prerequisite for proper packaging, but unfortunately not much importance has been attached in its study (ICRI, 2005).

There is no suitable set of standards for grading and sorting of fruits. Physical specifications of agricultural products constitute the most important parameters needed in the design of grading, transferring, processing, and packaging systems. Physical specifications, mechanical, electrical, thermal, visual, acoustic, and chemical properties are among attributes of useful engineering application. Mass, volume and center of gravity are the most important physical parameters of agricultural products used in sizing systems (Safwat and Moustafa, 1971). So we could model relation between mass and other physical parameters. For this work, artificial neural network (ANN) could be used for modeling.

Artificial neural network is the simplified model of human brain that is one of the tools for predicting a physical phenomenon. Neuron is the smallest unit of artificial neural network in which every network consists of one input layer, one output layer and one or more middle layers. Neurons of each layer link to other neurons by other neurons (Khanna, 1990). In the network training process, this weights and constant value (Bias) that add to them, change continuously until sum square error reaches to the minimum value (Kishan,

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Chilukuri and Ranka, 1996).

One of the most important applications of artificial neural network is training and prediction of outputs by new data (Dayhoff, 1990). In the Feed-Forward Back Propagation (FFBP) network with Error Back Propagation (BP) algorithm, at first output weights compare with desired value. If error was more than determined value, output weights was adjusted by adjusted principles and when training error was less than determined value, training process come to an end (Hagan and Menhaj, 1994).

Some researchers have used artificial neural network for predicting parameters for doing different works. Zbicincski, Strumillo and Kaminski (1996), used ANN for moisture transfer modeling in a dryer, Zbicincski and Ciesislski (2000) for heat transfer coefficient in different materials, Mittal and Zhang (2000) for determining heat and mass transfer.

Farkas, Remenyi and Biro (2000), studied the modeling of dried grains with ANN. In the research, relation between moisture distribution in the dried materials and physical parameters such as dryer temperature, moisture and velocity of drying air were estimated. Network inputs were air velocity (0.267, 0.178, 0.089 m/s), air temperature (81.6, 68, 54.4 ºC) and special moisture of drying air (26.2, 14.5, 2.8 gr/m³).

Islam, Sablani and Mujumdar (2003), studied about prediction of drying velocity by using ANN. The research was carried out on the tomato layers and air velocity was 0.5 to 2 m/s, drying air temperature was 40 to 55 ºC, relative humidity was 5% to 50% and thickness of layer was 3 to 10mm. In the research Page model was used for drying, and the model was analyzed using ANN.

In this study, some physical properties have been determined for apple cv. “Golab” has been analyzed using artificial neural network.

2 Materials and methods

2.1 Sample preparation

Apples used in this study were selected from cv. “Golab” which is an Iranian cultivar of apple. About 100 apples were randomly obtained from a local market (Tajrish market) in Tehran as a total. The apples were transferred to the Physical Laboratory of Biosystems Faculty in the University of Tehran for experiments.

Some parameters, such as volume, mass, the main diameter, and fruit density were obtained. Fruit mass was determined using a sensitive digital balance (GF3000, A&D, Japan) with a capacity of 0–3,000 g and accuracy of ±0.01 g. To determine fruit volume, container with water was placed on the balance, one needle was thrust in the fruit and one lever moved the needle, so that the fruit floated in water and the mass of displaced water was calculated. The main diameter was measured using a digital calliper, and fruit density was calculated (fruit mass per fruit volume).

2.2 Artificial neural network modeling

In this work, artificial neural network was designed with three neurons (volume, fruit density and main diameter) for input layer and one neuron (fruit mass) for output layer (Figure 1). Neurosolutions software was used in this research. Feed-Forward Back Propagation (FFBP) network with training algorithms; Levenberg-Marquard and Momentum were used to obtain the best result. In the network training process, the weights and constant values (Bias) that added to them, changed continuously until sum square error reached the minimum value.

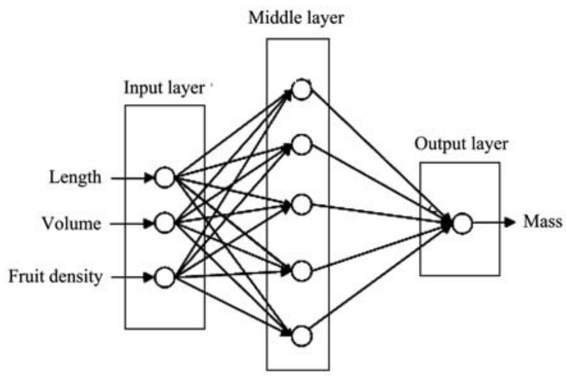

Figure 1 Schematic diagram of the designed artificial neural network

Actuator function for reaching the best result is (Khanna, 1990):

$$Y_j = \frac{2}{(1+\exp(-2X_j))} - 1 \qquad (1)$$

where, X_j was calculated by using the following equation:

$$X_j = \sum_{i=1}^{m} W_{ij} \times Y_i + b_j \tag{2}$$

where, m is the number of output layers; W_{ij} is weight of between i and j layer space; Y_i is i^{th} neuron output and b_j is amount of bias of j^{th} layer neuron.

In order to obtain the network with the best topology, mean square error was used that was computed using the method of Dayhoff (1990) and Khanna (1990):

$$E_{MS} = MSE = \frac{\sum_{p=1}^{M}\sum_{i=1}^{N}\left(S_{ip} - T_{ip}\right)^2}{NP} \tag{3}$$

were, E_{MS} mean square error; S_{ip} is network output at i^{th} neuron and p^{th} algorithm; T_{ip} is desired output at i^{th} neuron and p^{th} algorithm; N is the number of output neurons and M is the number of training algorithms.

Also for reaching to the best network, following statistical values were used (Dayhoff, 1990), (Khanna, 1990):

$$T_m = \frac{\sum_{k=1}^{T} S_k}{T} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{T}\left[S_k - T_k\right]}{\sum_{k=1}^{T}\left[S_k - T_m\right]}, r = \sqrt{\left(1 - \frac{\sum_{k=1}^{\tau}\left[S_k - T_k\right]}{\sum_{k=1}^{\tau}\left[S_k - T_m\right]}\right)} \tag{5}$$

$$E_{MA} = MAE = \frac{1}{T}\sum_{k=1}^{T}\left|S_k - T_k\right| \tag{6}$$

$$SD_{EMA} = \sqrt{\frac{\sum_{k=1}^{T}\left|S_k - T_k\right| - \left|\overline{S_k - T_k}\right|}{T-1}} \tag{7}$$

$$E_{NMS} = NMSE = \frac{\sum_{p=1}^{M}\sum_{i=1}^{N}\left(S_{ip} - T_{ip}\right)^2}{NP\sum_{p=1}^{M}\sum_{i=1}^{N}T_{ip}^2} \tag{8}$$

where, R^2 is fixing coefficient; r is error percentage; k is the number of samples; E_{MA} is mean absolute error; SD_{EMA} is mean absolute error standard deviation and *NMSE* is normalize mean square error.

3 Results and discussion

Table 1 and 2 show the effect of the number of hidden layers and neurons on fruit mass prediction accuracy at different volume, fruit density and main diameter, for Levenberg-Marquard and Momentum algorithms. Tables show that Levenberg-Marquard algorithm gave the best result with topology 3-6-4-1, 3-6-1, 3-4-2-2-1 and 3-6-6-1, Levenberg-Marquard algorithm can predict relation between mass and other parameters with error percentages 0.999999, 0.999999, 0.999999 and 0.999999, mean square error 0.000078, 0.000118, 0.000158 and 0.000194. According to many literatures, among these topologies, 3-6-1 is the best topology because of its simplicity of design with one hidden layer.

Table 1 Effect of the number of hidden layers and neurons on fruit mass prediction accuracy at different input layers for Levenberg algorithm

Numbers of hidden layer neurons			*MSE*	*NMSE*	*MAE*	*r*
first	second	third				
4	---	---	7.17483	0.081649	2.32595	0.988911
5	---	---	83.6075	0.471676	7.29930	0.966331
6	---	---	0.000118	0.000001	0.006642	0.999999
7	---	---	0.002206	0.000027	0.013127	0.999989
8	---	---	1.06826	0.008120	0.333019	0.997423
9	---	---	0.000227	0.000003	0.006039	0.999998
10	---	---	0.001231	0.000012	0.016560	0.999994
11	---	---	0.094839	0.000658	0.087893	0.999746
12	---	---	1.07229	0.006774	0.344529	0.997614
13	---	---	0.029231	0.000414	0.087466	0.999870
14	---	---	4.27475	0.042983	1.66552	0.997132
15	---	---	0.016561	0.000203	0.052485	0.999904
16	---	---	0.189625	0.002291	0.161297	0.999234
17	---	---	6.32133	0.057698	1.89081	0.984806
2	2	---	0.231342	0.0876547	1.87099	.986678
3	2	---	87.5555	0.715802	7.15804	0.895963
3	3	---	0.100338	0.001005	0.098061	0.999676
4	2	---	0.005950	0.000039	0.032050	0.999988
4	3	---	0.001889	0.000017	0.015116	0.999994
4	4	---	0.414164	0.002877	0.186986	0.998876
5	2	---	0.000292	0.000003	0.008261	0.999998
5	3	---	25.2505	0.228352	4.26332	0.943493
5	4	---	7.43236	0.069684	2.23174	0.965524
5	5	---	0.066843	0.000638	0.057923	0.999759
6	2	---	6.39019	0.039195	0.985006	0.989721
6	3	---	0.040890	0.000256	0.048263	0.999903
6	4	---	0.000078	0.000001	0.003416	0.999999
6	5	---	1.16634	0.007812	0.332557	0.997840
6	6	---	0.000194	0.000001	0.006150	0.999999
7	2	---	0.089656	0.000781	0.145332	0.999704
3	3	3	0.023492	0.000212	0.047269	0.999934
4	2	2	0.000158	0.000002	0.008265	0.999999
4	3	2	0.265963	0.001838	0.141576	0.999340
7	4	4	0.001454	0.000014	0.011058	0.999996

Note: *MSE* = mean square error, *NMSE* = normalize mean square error, *MAE* = mean absolute error, r= error percentage

Table 2 Effect of the number of hidden layers and neurons on fruit mass prediction accuracy at different input layers for Momentum algorithm

Numbers of hidden layer neurons			*MSE*	*NMSE*	*MAE*	*r*
first	second	third				
2	2	---	117.8430	1.326440	9.136480	0.823555
3	2	---	57.64290	0.682640	6.121470	0.875753
3	3	---	100.0670	0.952443	8.181810	0.823281
4	2	---	0.910051	0.777774	7.587020	0.904393
4	3	---	0.675431	0.876581	1.980650	0.912341
4	4	---	0.305644	0.005133	0.464031	0.998167
5	2	---	5.936440	0.048898	1.477410	0.986184
5	3	---	0.735488	0.856048	6.107180	0.849861
5	4	---	1.882790	0.022196	0.739579	0.990079
5	5	---	3.542270	0.030304	1.251110	0.990822
6	2	---	1.007410	0.009205	0.525835	0.995785
6	3	---	1.142550	0.887592	8.441180	0.957176
6	4	---	0.551315	0.009393	0.578977	0.996990
6	5	---	0.516916	0.006650	0.605712	0.997585
6	6	---	2.279430	0.023251	0.870413	0.989478
7	2	---	1.191500	0.246821	0.182588	0.902963
2	2	2	0.127563	0.183849	0.248829	0.921162
3	2	2	0.451877	0.040735	1.537790	0.982211
3	3	2	0.553368	1.046320	0.656162	0.865857
3	3	3	0.176575	0.132252	2.210520	0.964708
4	2	2	0.103288	0.097355	2.194580	0.960876
4	3	2	1.588730	0.142935	2.190480	0.938620
7	4	4	0.593644	0.048898	1.477410	0.986184

4 Conclusions

Artificial neural network predicted apple mass with three input parameters volume, fruit density and main diameter. The best network for data training, was Feed-Forward Back Propagation (FFBP) network with Levenberg-Marquard training algorithm and actuator function TANSIG for layers with topology -6-4-1, 3-6-1, 3-4-2-2-1 and 3-6-6-1, error percentages 0.999999, 0.999999, 0.999999 and 0.999999, and mean square error 0.000078, 0.000118, 0.000158 and 0.000194.

At last, the results of this research show that artificial neural network is a suitable tool for fruit mass prediction at “agricultural products physical properties” subject.

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