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Research Full Papers

Predicting the physiological characteristic changes in pears subjected to external loads using Artificial Neural Network (ANN)-Part 1: Static loading

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Abstract:

This research was aimed to study the effects of loading force and storage period on the physiological characteristic of pears. In this experiment, the pears were subjected to quasi-static loading (wide-edge and thin-edge) and different storage periods (5, 10 and 15 days). The amounts of the fruits' total phenol, antioxidant and vitamin C contents were evaluated after each storage period. In the present study, multilayer perceptron (MLP) artificial neural network featuring a hidden layer and two activating functions (hyperbolic tangent-sigmoid) and a total number of 5 and 10 neurons in each layer were selected for the loading force and storage period so that the amounts of the total phenol, antioxidants and vitamin C contents of the fruits could be forecasted. According to the obtained results, the highest R^2 rates for thin-edge and wide-edge loading in a network with 10 neurons in the hidden layer and a sigmoid activation function were obtained for total phenol content($R^2_{Thin\ edge}$=0.9539-$R^2_{Wide\ edge}$=0.9865), antioxidant ($R^2_{Thin\ sdge}$=0.9839-$R^2_{Wide\ edge}$=0.9649) and vitamin C ($R^2_{Wide\ edge}$=0.9758); as for wide-edge loading in a network with 5 neurons in the hidden layer and hyperbolic tangent activation function, the highest R^2 rate of vitamin C content was obtained equal to $R^2_{Wide\ edge}$=0.9865. According to the obtained results, the neural network with these two activation functions possesses an appropriate ability in overlapping and predicting the simulated data based on real data.

Keywords: Pears' internal contents, loading, storage, Neural Network, Activation function

Introduction

Pears have been recognized as sources of sugars, minerals, various ingredients (including vitamin C) and some phenolic compounds as well as natural antioxidants. The quality of pears is defined depending on their physical characteristics such as texture, size, color, and odor as well as chemical parameters such as sugar, organic acids, minerals and vitamins. These factors change subject to the type of the fruit, ripening level, cultivation and environmental conditions (Kazem et al., 2015) (Gurrieri et al., 2000). Although pears have abundant advantages, the reasons for lower uses of pears in respect to other fruits are relatively high prices and problems related to storage and quality of the pears. Pears respond to environmental conditions and these physical and chemical reactions of the harvested fruits cause drops in the quality of the products subject to various stresses and this causes wastages in the agricultural products. In addition, during storage, many factors might act as stressors as a result of which the fruits' useful life will be reduced (Galvis-Sánchez et al. 2004). On the other hand, external stresses such as falling down from the tree, compression during storage and so forth cause bruises in the pears and such a bruise in the fruit is created through the enzymatic oxidation of the phenolic

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ingredients, such as polyphenoloxidase, and the bruise level of the fruit depends on the nature and the amount of phenolic ingredients inside the fruits as well as the polyphenoloxidase activity. Plant phenols are easily oxidized by polyphenoloxidase which acts as a defending enzyme after a textural damage following which bruises appear on the fruits' surfaces (Malakouti et al., 2009).

The main reason for the reduction in marketability and quality of the agricultural products is the damage caused between harvesting and consumption. Fruits are prone to bruise during picking, packaging, transportation and retailing in the stores as well as during other stages and they are sensitive to damages caused through getting in contact with one another and/or being hit against a hard surface like ground and/or boxes. Although it has been made well clear that the bruise in the fruits is the result of extreme external forces on the fruit surface, it is yet to be clarified that what factors determine the difference in fruits' sensitivity to a given force (Yurtlu and Erdoğan, 2005). The artificial neural network is a topic discussed in artificial intelligence and it is an information processor trained using a percentage of input and output data and the system's performance method is stored in its memory (Mazloumzadeh et al., 2008). Artificial neural networks are trained based on the calculations on numerical data or examples. One feature of the neural networks is their ability in extracting the relationships between the inputs and outputs of a process with no need to complex environmental conditions. They are capable of connecting a multidimensional space to another space even if the information is imperfect and erroneous. These characteristics have made them appropriate for the problems related to the estimation and prediction in agriculture and industry and the neural network displays a good efficiency when the relations are nonlinear (Beale and Jackson, 1998; Menhaj, 2000). Various researchers have reported the use of ANN for evaluation and prediction of a combination of agricultural products:

Zarif Neshat et al (2013) have used bruise volume as a bruise damage index. They made use of radial basis ANN to evaluate the radial basis function model and regression model in predicting the bruise volume in apples. Their results indicated that the real and predicted values of bruise volume have been fit well with estimations of mean absolute percentage errors (MAPE) smaller than 2.82%. Their results also indicated that the radial basis function model enjoys a greater precision in comparison to regression model in predicting the apples' volume of a bruise (Zarifneshat et al., 2012).

An indicator of antioxidant capacity of sage in addition to moisture content, was added as an output of an optimized ANN using a multi-objective genetic algorithm and was presented by (Jebri et al., 2018).

The shrinkage of dried kiwifruit using digital images was modeled by Bai et al. (2018) while Nadian et al. (2015) modeled the color alterations of ginkgo biloba seeds along with drying kinetics of microwave drying and apple color changes during convection drying. It is evident than MLP ANNs can be applied for a range of agricultural products, describing accurately many properties of drying, as well as qualitative and quantitative indicators (Bai et al., 2018)(Nadian et al., 2015)(Chasiotis et al., 2019).

Torkashvand et al (2017) performed an experiment on the hardness and nutrient constituents of kiwi using multiple linear regressions (MLR) and artificial neural networks (ANNs) the results of which indicate that MLR model outperforms ANNs for Kiwi fruits in terms of precision (Torkashvand et al. 2017).

According to the fact that pears are very sensitive to impact and any stress on pears causes quality drops and that the pears have to be carefully handled during storage, the present study was aimed to investigate the data obtained from the experimenting and recognizing the ability of neural network in predicting the simulated data. Also, the overlapping and data sensitivity coefficients were studied.

Materials and methods

Sample preparation

Pears (Spadana variety) were purchased from the markets of Gorgan, Golestan province, Iran. Samples were taken to the laboratory of Gorgan University of Agricultural Sciences and Natural Resources. They were placed in an oven at 103℃ for 24 hours and their moisture contents were measured. The moisture content of the pears was calculated to be 77.92% (Azadbakht et al, 2019).

Quasi-Static test

To perform the wide and thin edge compression mechanical test, a pressure-deformation device (the Santam Indestrone - STM5-Made in Iran) with a load cell of 500 N was used. The compression test, where two circular plates were used, was performed at a speed of 5 mm/s with three forces of 70, 100, and 130 N and three repetitions. In this experiment, the pear samples were horizontally placed between the two plates and pressed, with the duration of the measurement recorded. Concerning thin edge compression test, we designed a double-jaw of plastic with a rectangular cross-section dimension of 0.3 × 1.5 cm. The test was performed at a speed of 5 mm/s with three forces of 15, 20, and 25 N and three repetitions (Fig. 1).

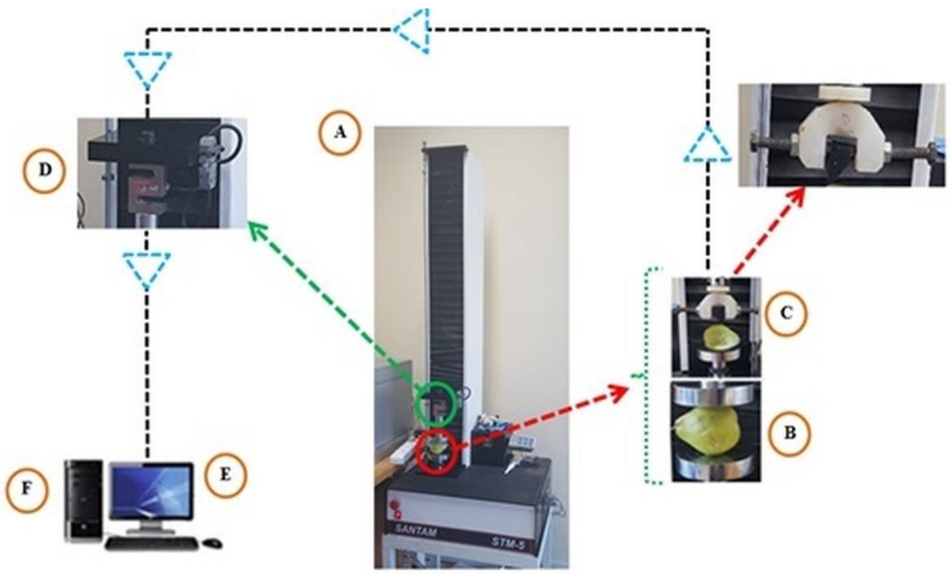


Fig. 1. Static quasi-load diagram of pear

A: The force-deformation device (Inestrone), B: Jaw wide edges C: Jaw thin edges D: Load Cell, E:Computer F: Information Extract

Vitamin C

Vitamin C amounts were calculated using 2,6-dichlorophenol indophenol titration method in such a manner that 5 grams of sample was mixed and extracted using 40 milliliters of citric acid 8% in the first stage. Afterwards, 10 ml of the filtered extract was picked up and mixed with 40 milliliters of citric acid 8% and subjected to titration using 2,6-dichlorophenol indophenol reagent. The termination point of titration was the appearance of a pale purple that lasted for about 15s. The vitamin C amount is expressed in milligram per 100 gram of the sample weight. vitamin C amount can be obtained by formula 1:(Tavarini et al., 2008)

$$\text{Vitamin C}=\frac{sample\ weight\times standard\ volume\ of\ \ reagent\ consumed}{volume\ of\ extract\ obtained\times volume\ of\ reagent\ used\times 10\times 2} \quad (1)$$

Biochemical properties measurement

To measure the total phenol content and the percentage of free radicals' neutralization, 0.5 gram of each sample pear was cut off and using 5 milliliters of methanol 80% (for a 1:10 ratio) in a cold mortar was homogenized. The homogenized mixture was placed on a shaker device in a dark room for 24 hours and then subjected to centrifugal force in 3000rpm for 5 minutes. The upper part of the extract was used for measuring the biochemical characteristics (Jaramillo-Flores et al., 2003) (Li et al., 2012).

Total phenol content

Folin-Ciocalteu (F-C) reaction was used to measure the total phenol content. To do so, 20 microliters of methanolic extract (0.5g in 5ml 80% methanol) was mixed with 100 microliters of F-C and 1.16ml of distilled water following which 300 microliters of 1molar sodium carbonate (10.6g in 100ml of distilled water) was added there after an 8-minute resting time. The aforesaid solution was placed in a vapor bath, 40°C, in a dark room for 30 minutes. In the end, the specimens were read in 765-nm wavelength. The absorption number of the specimen was replaced for y in the line equation to obtain the phenol amount (x) in milligram gallic acid per gram (Jaramillo-Flores et al., 2003).

Percentage of free radicals neutralization based on DPPH method

In this experiment, the percentage of DPPH free radicals' neutralization was measured based on the method proposed by Bandet et al (1997). At first, 2 milliliters of DPPH with a concentration of 0.1 millimoles (4 milligrams of DPPH in 100 milliliters of methanol) was mixed to the experiment tube and 2 milliliters of the prepared methanolic solution was next added following which the experiment tubes were placed in a dark environment and the absorption rates were immediately read using spectrophotometer in 517-nm wavelength. The evidence specimen contained 2 milliliters of DPPH and 2 milliliters of methanol. Methanol was applied to calibrate the spectrophotometer. The figures obtained from formula (2) substitutions were converted to neutralization percentages (Li et al., 2012).

$$DPPH = \frac{Ac-As}{Ac} \times 100 \qquad (2)$$

As= specimens absorption rates

Ac= evidence specimen absorption rate

Artificial neural network modeling

In this research, the artificial multilayer perceptron (MLP) neural network was used for modeling the investigated pear components during storage and loading different components to predict total phenol content antioxidant and vitamin-C using one hidden layer and 5 and 10 neurons using the Neuro Solution 5 software. Hyperbolic tangent and sigmoid activation functions (Equation 3,4), which are the most common type of activation functions, were used in the hidden input and output layer. In this study, the Levenberg-Marquardt algorithm was used to learn the network (Taheri-Garavand et al., 2018). Additionally, 70% of the data were used for training, 10% of them were used for network evaluation (Validating Data), and 20% of the data were used for testing the network (Testing data) (Table 2). The loading value (27 data) and storage time (27 data) as network inputs of total phenol content antioxidant and vitamin-C (27 data for each component) were the considered network outputs (Figure. 2). Five repetitions were considered to achieve the minimum error rate and maximum network stability as a mean of 2000 Epoch for the network. The error was estimated using an algorithm with back propagation error. Statistical parameters including, Root Mean Square Error (RMSE), R^2, and Mean Absolute Error (MAE) were calculated for inputs and relationships were calculated using the formulas shown in Table 1.

Table 1- Neural Network Relationships

Formula	Formula Number	Reference
$\text{Tanh} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	(3)	(Soleimanzadeh et al., 2015)
$\text{Sig}=\frac{1}{1+e^{-x}}$	(4)	(Salehi et al., 2017)
$R^2 = 1- \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{(P_i - O)^2}$	(5)	(Azadbakht et al., 2016)
$r = \sqrt{1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{(P_i - O)^2}}$	(6)	(Salehi and Razavi, 2012)
$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(P_i - O_i)^2}{n}}$	(7)	B. Khoshnevisan, Sh.) (Rafiee, M. Omid, 2013
$\text{MAE} = \frac{\sum_{i=1}^{n} \lvert P_i - O_i \rvert}{n}$	(8)	(Azadbakht et al., 2017)

Table 2- Optimization values for artificial neural network parameters

Number of hidden layers	Learning rule	Type of activation function	The number of hidden layer neurons	Testing data %	Validating data %	Training data %
1	Levenberg Marquardt	Hyperbolic tangent and sigmoid	5	20%	10%	70%
1	Levenberg Marquardt	Hyperbolic tangent and sigmoid	10	20%	10%	70%

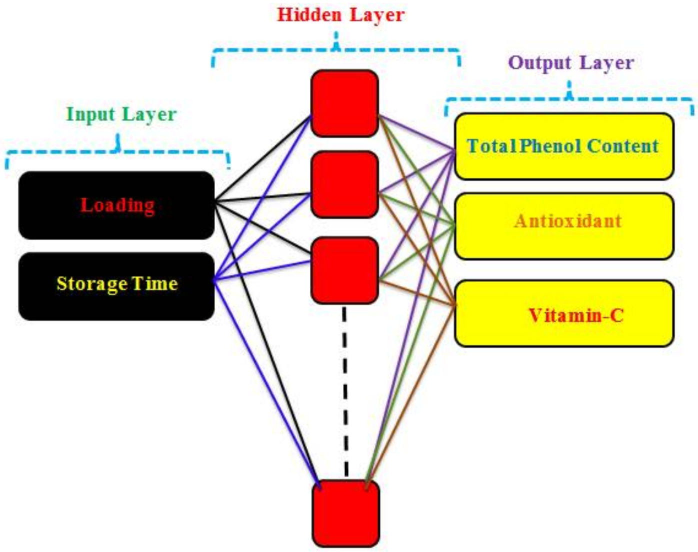


Fig. 2. Neural Network Input and Output Schematic

Results and discussion
Artificial neural network

As lower error value was obtained using the hyperbolic tangent and sigmoid activation function, this type of function was selected as the activation function in the hidden layer and the output. Based on the test method, 70% of the data were used for training and the network could learn the relationships between inputs and outputs well and 20 % of the data were used to test the network and 10 % of the data were used to cross validation network. The value of mean squared error, normalized mean squared error, mean absolute error and correlation coefficient are shown in tables 3 and 5.

Table 3- Error values for the quasi-static (thin edge) in predicting experimental data using optimal artificial neural network

	Activation function	Neuron number	MSE		RMSE		MAE		R^2	
			Training	Test	Training	Test	Training	Test	Training	Test
Total Phenol Content	hyperbolic tangent	5	1.7442	2.1133	1.320682	1.453719	1.2412	1.3638	0.9325	0.9259
		10	1.2475	0.5941	1.116915	0.770779	1.0058	0.6562	0.9335	0.9779
	Sigmoid	5	1.13868	1.224	1.209835	1.106345	0.93139	0.997	0.95307	0.796
		10	1.4637	1.3345	1.067089	1.155206	1.0343	1.085	0.9539	0.8811
Antioxidant	hyperbolic tangent	5	3.7115	9.3642	1.926525	3.060098	1.6048	2.7622	0.8988	0.9697
		10	1.2373	6.6489	1.11234	2.578546	0.9278	1.8905	0.9723	0.8610
	Sigmoid	5	3.71343	4.973	1.927026	2.230022	1.41926	1.577	0.93380	0.858
		10	0.7374	6.0616	0.85872	2.462032	0.7677	1.924	0.9839	0.8811
Vitamin-C	hyperbolic tangent	5	0.0440	0.0274	0.209762	0.165529	0.1687	0.1502	0.9389	0.9691
		10	0.0359	0.0356	0.189473	0.18868	0.1594	0.1459	0.9481	0.9362
	Sigmoid	5	0.03899	0.084	0.197459	0.289828	0.15294	0.245	0.95237	0.862
		10	0.0233	0.0305	0.152643	0.174642	0.1226	0.15	0.9758	0.9495

The quasi-static (thin edge)

The results showed that neural network has 10 neurons in the hidden layer and Sigmoid activation function for Total Phenol Content (R^2= 0.9539- RMSE=1.067089), Antioxidant (R^2= 0.9839- RMSE=1.11234) and vitamin-C (R^2= 0.9758- RMSE=0.152643) can predict Total Phenol Content Antioxidant and vitamin-C in different loading and storage time (table 3). In addition, the neural network with 5 neurons in the hidden layer and Sigmoid activation have the highest R^2 value, after the above-mentioned layers for Total Phenol Content and vitamin-C used. The highest value for antioxidant was showed in 10 neuron in hidden layer and function activation hyperbolic tangent. Lu et al.

used neural networks to estimate the losses of ascorbic acid, total phenols, flavonoid, and antioxidant activity in asparagus during thermal treatments, and concluded that the predicted values of the correlation coefficients between experimental and ANNs ranged from 0.8166 to 0.9868. Therefore, ANNs could be potential tools to predict nutrient losses in vegetables during thermal treatments (Lu et al., 2010).

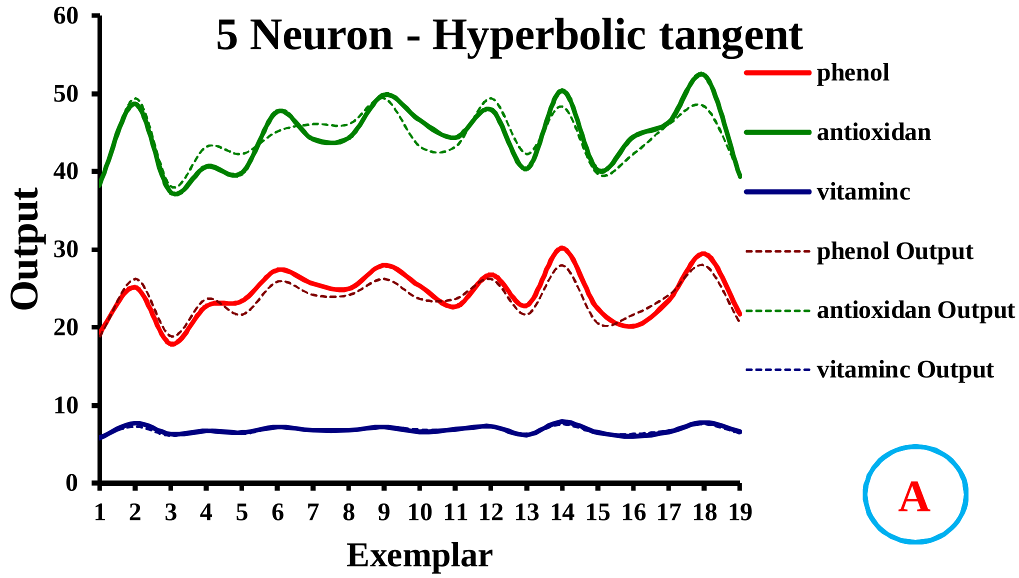
Also table 4 shows the best network between input data and data simulated by the network for each of the neurons in the hidden layer. The lower value of Epoch indicates that the number of neurons in the layer has been able to have learned from the neural network compared to an other number of neurons.

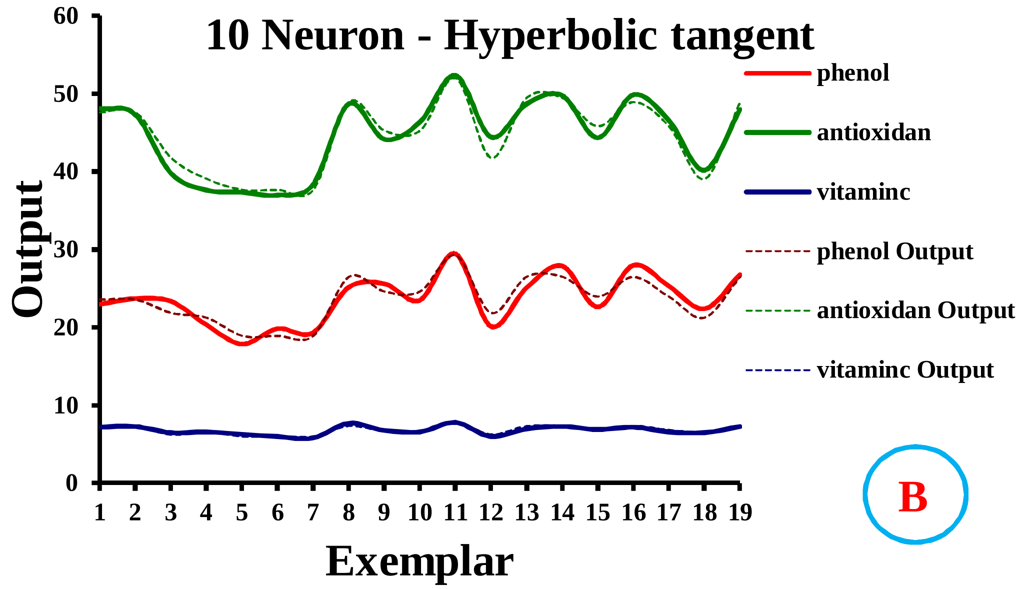
As shown in Table 4, the best network for Total Phenol Content at Training (Run= 1, Epoch = 19) in the 10-neuron state in the hidden layer and hyperbolic tangent activation reaches to constant value after about 19 Epoch of error, and the best network for Antioxidant Training (Run = 1, Epoch = 38) in 10-neuron state in the hidden layer and hyperbolic tangent activation. For vitamin-C of Training value (Run = 1, Epoch = 25), it was found in 5-neuron state in the hidden layer and hyperbolic tangent activation.

Table 4- Some of the best MLP neural network topologies to predict training values

	Activation function	Neuron number	Run		Epoch	
			Training	Cross Validation	Training	Cross Validation
Total Phenol Content	hyperbolic tangent	5	1	2	62	7
		10	1	4	19	11
	Sigmoid	5	1	5	28	22
		10	1	5	36	20
Antioxidant	hyperbolic tangent	5	1	1	69	15
		10	1	3	38	11
	Sigmoid	5	1	2	61	32
		10	1	4	38	6
Vitamin-C	hyperbolic tangent	5	1	4	25	8
		10	1	4	33	13
	Sigmoid	5	1	2	78	48
		10	1	5	45	16

Also, figure (3) illustrates the output amounts between the real and predicted data. Based on the figure (3), it can be observed that the neural network has been sufficiently capable of predicting and comparing the given numbers and it can be stated considering the closeness and similarity of the numbers outputted from the ANN to the real data that the neural network possesses an appropriate competency for data prediction. Moreover, considering the R^2 rates, the network with sigmoid activation function featuring 10 neurons in the hidden layer (figure 2-D) presents the best overlap with the real data.





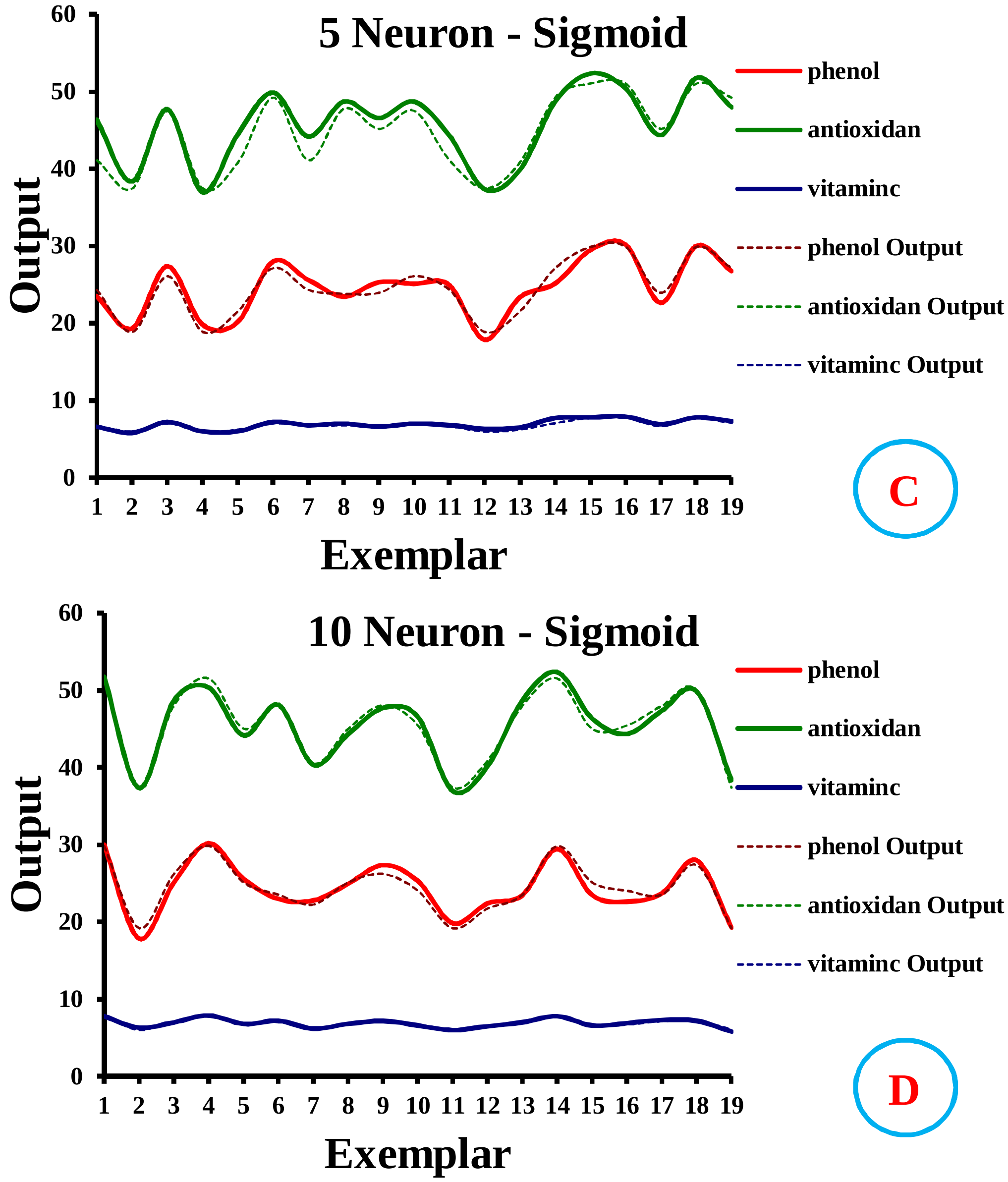


Fig. 3. Comparison of actual data with network output data

Sensitivity coefficient for quasi-static (thin edge)

The results of the sensitivity analysis for total phenol content are shown in Figure 4. Based on this figure, the highest sensitivity for training data was obtained for the loading in the hidden layers with 5 neurons and sigmoid activation and for storage was obtained in hidden layers with 5 neurons and hyperbolic tangent activation function (Figure 4). generally, in the case of total phenol content, it was loading sensitivity analysis more than storage sensitivity analysis, The reason for this can be justified by the fact that by creating stress (loading) in pears and causing internal damage to the fruit, some of the enzymes are released to repair the damaged tissue and reduce the activity of the fruit, which causes the decrease. As shown in figure 4, sensitivity analysis for test and cross validation data, According to figure highest sensitivity for test and cross validation data were obtained for loading in the hidden layers with 10 neurons by hyperbolic tangent activation (Test) and 5 neurons in sigmoid activation (Cross validation) for storage was obtained in hidden layers with 5 neurons and sigmoid activation (Figure 4). .Also, highest sensitivity for test and cross validation data were obtained for the storage in the hidden layers with 10 neurons (Test) and 5 neurons (Cross validation) in hyperbolic tangent activation for storage was obtained in hidden layers with 5 neurons and sigmoid activation (Figure4-B).

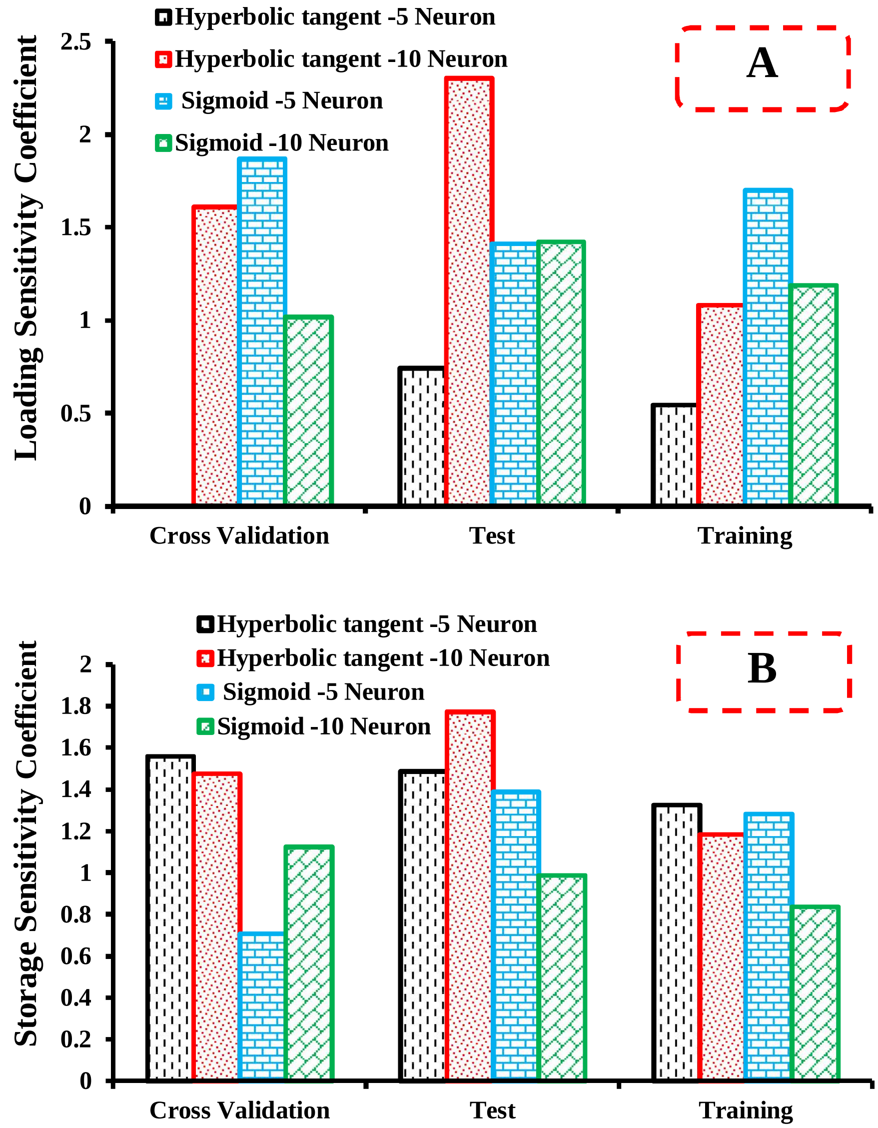


Fig. 4. Sensitivity coefficient for Total Phenol Content for A: Loading B: Storage time

The results of the sensitivity analysis for Antioxidant are shown in Figure 5. Based on this figure, the highest sensitivity for training data was obtained for the loading in the hidden layers with 5 neurons and sigmoid activation and for storage was obtained in hidden layers with 10 neurons and hyperbolic tangent activation (Figure 5).As shown in figure 5 the sensitivity analysis for test and cross calidation data, the highest sensitivity for test and cross validation data were obtained for loading in the hidden layers with 10 neurons by hyperbolic tangent activation (Test) and 5 neurons in sigmoid activation (Cross validation) (Figure 5). also, highest sensitivity for test and cross validation data were obtained for the storage in the hidden layers with 5 neurons in sigmoid activation (Test) and 5 neurons by hyperbolic tangent activation (Cross validation) (Figure5-B)

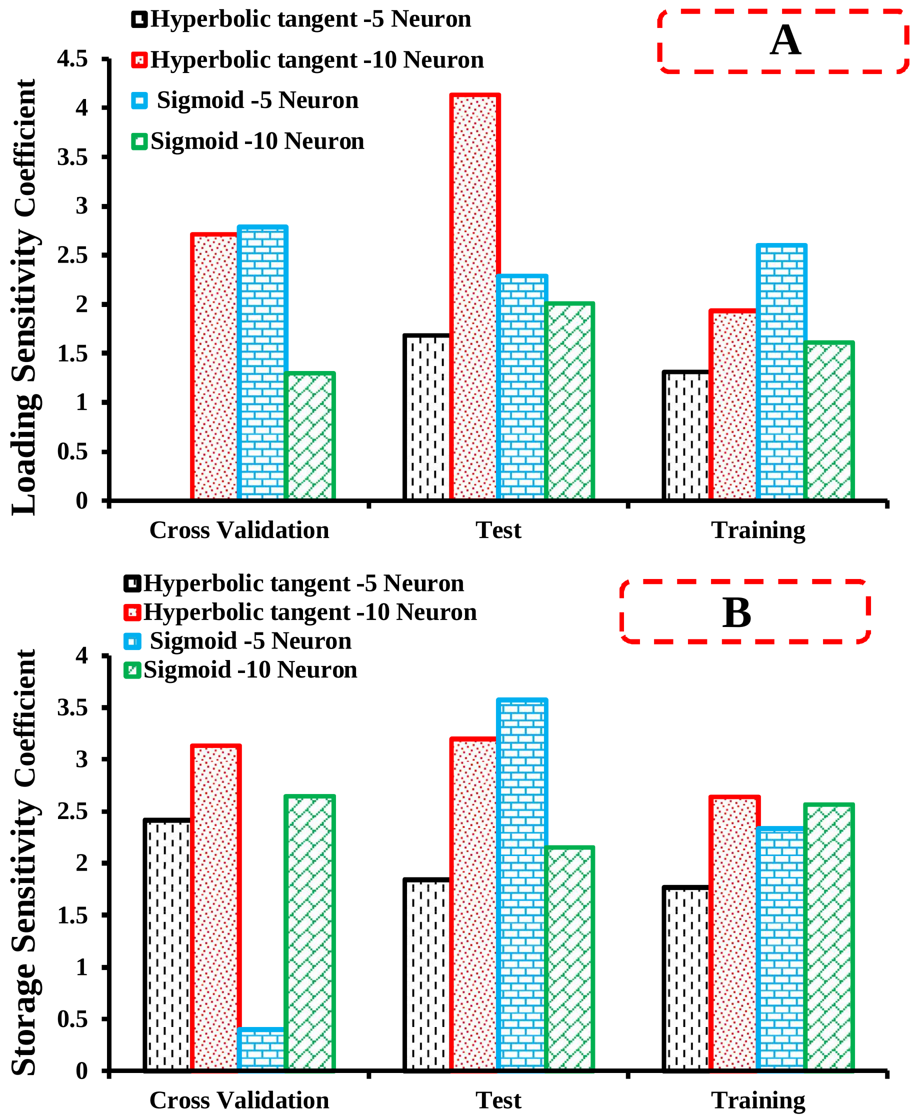


Fig. 5. Sensitivity coefficient for Antioxidant for A: Loading B: Storage time

The results of the sensitivity analysis for vitamin C are shown in Figure 6. Based on this figure, the highest sensitivity for training data was obtained for the loading in the hidden layers with 5 neurons and sigmoid activation and for storage was obtained in hidden layers with 10 neurons and hyperbolic tangent activation (Figure 6). As shown in figure 6, sensitivity analysis for test and cross Validation data, According to figure the highest sensitivity for test and cross validation data were obtained for loading in the hidden layers with 10 neurons by hyperbolic tangent activation (Test) and 5 neurons in sigmoid activation (Cross validation)(Figure 6). Also, highest sensitivity for test and cross validation data were obtained for the storage in the hidden layers with 10 neurons in hyperbolic tangent activation (Test) and 10 neurons by hyperbolic tangent activation (Cross validation) (Figure 6-B).

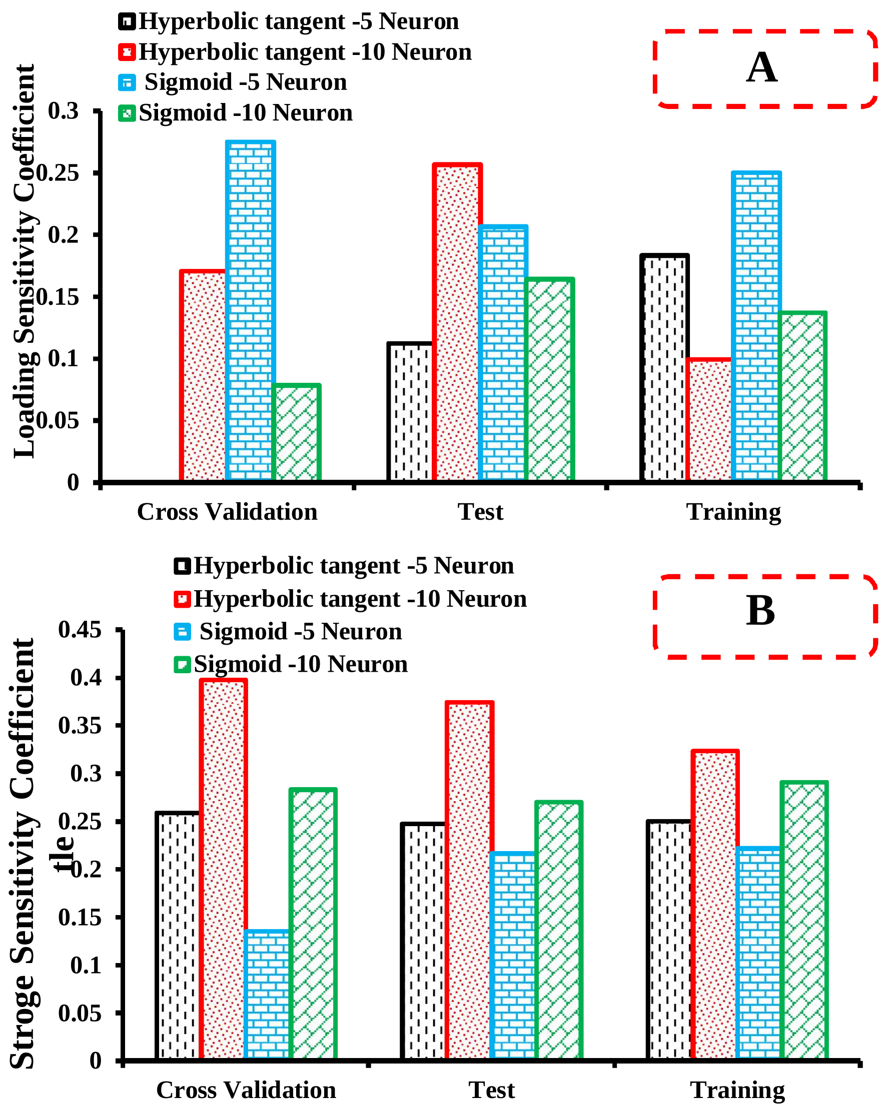


Fig. 6. Sensitivity coefficient for Vitamin-C for A: Loading B: Storage time

The quasi-static (Wide edge)

The results showed that neural network has 10 neurons in the hidden layer and Sigmoid activation function for Total Phenol Content (R^2= 0.9539), Antioxidant (R^2= 0.9839) and 5 neurons in the hidden layer and hyperbolic tangent activation function vitamin-C (R^2= 0.9758) can predict total phenol content, antioxidant and vitamin-C in different loading and storage time (table 5). In addition, the neural network with 10 neurons in the hidden layer and sigmoid activation have the lowest RMSE and MAE for total phenol content (RMSE= 0.713, MAE= 0.608) and antioxidant (RMSE= 1.475, MAE= 1.216) used. For vitamin-C (RMSE= 0.110, MAE= 0.086) the lowest RMSE and MAE value was obtained by the hidden layer was with 5 neurons and hyperbolic tangent activation. Guiné et al. (2014), using artificial neural network, modeled the antioxidant activity and phenolic compounds of bananas and neural network experiments, and showed that antioxidant activity and phenolic compounds could be predicted accurately from the input variables (Guiné et al., 2015)

Table 5- Error values for the quasi-static (Wide edge) in predicting experimental data using optimal artificial neural network

	Activation function	Neuron number	MSE Training	MSE Test	RMSE Training	RMSE Test	MAE Training	MAE Test	R^2 Training	R^2 Test
Total Phenol Content	hyperbolic tangent	5	0.6723	1.0166	0.820	1.008	0.7079	0.6759	0.9819	0.9125
		10	1.3521	3.7249	1.163	1.930	1.0071	1.7355	0.9677	0.8349
	Sigmoid	5	0.98172	1.32438	0.991	1.151	0.82638	1.08686	0.98331	0.96781
		10	0.50768	0.8524	0.713	0.923	0.60858	0.7414	0.98650	0.9845
Antioxidant	hyperbolic tangent	5	2.8978	5.6542	1.702	2.378	1.4681	2.1755	0.9641	0.9313
		10	2.7867	3.9211	1.669	1.980	1.3370	1.5821	0.9534	0.9331
	Sigmoid	5	5.63087	1.37952	2.373	1.175	1.90505	0.97900	0.92684	0.93299
		10	2.17461	4.4689	1.475	2.114	1.21664	1.8540	0.96493	0.9539
Vitamin-C	hyperbolic tangent	5	0.0121	0.0664	0.110	0.258	0.0861	0.2377	0.9814	0.6919
		10	0.0230	0.0358	0.152	0.189	0.1234	0.1456	0.9677	0.9165
	Sigmoid	5	0.02006	0.09722	0.142	0.312	0.12184	0.26934	0.97009	0.35506
		10	0.01434	0.0550	0.120	0.235	0.10509	0.2010	0.97565	0.9391

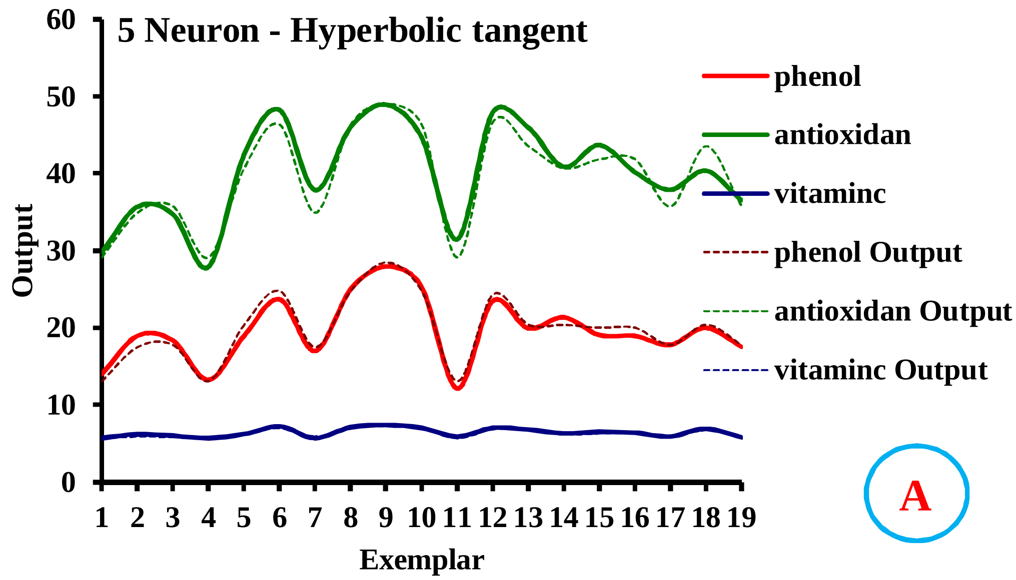
Table 6 also shows the best network between input data and data simulated by the network for each of the neurons in the hidden layer. The lower value of Epoch indicates that the number of neurons in the layer has been able to have learned from the neural network compared to an other number of neurons.

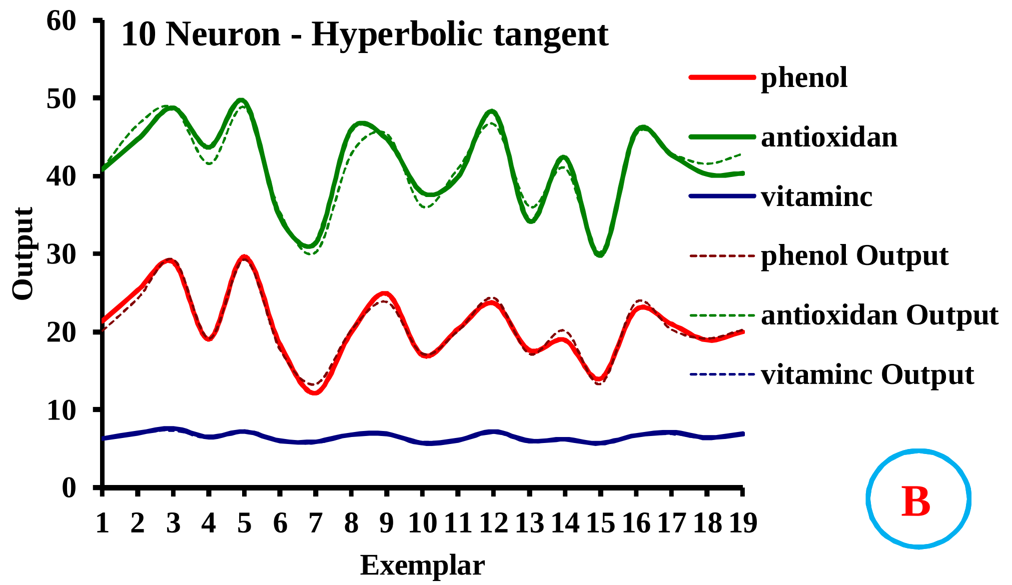
As shown in table 6, the best network for total phenol content at training (Run = 1, Epoch = 27) in the 10-neuron state in the hidden layer and hyperbolic tangent activation reaches to constant value after about 27 Epoch of error, and the best network for antioxidant training (Run = 1, Epoch = 27) in 5-neuron state in the hidden layer and sigmoid tangent activation. For vitamin-C of training value (Run = 1, Epoch = 42), it was found in 10-neuron state in the hidden layer and hyperbolic tangent and sigmoid activation.

Table 6- Some of the best MLP neural network topologies to predict training values

	Activation function	Neuron number	Run Training	Run Cross Validation	Epoch Training	Epoch Cross Validation
Total Phenol Content	hyperbolic tangent	5	2	2	603	21
		10	1	5	27	9
	Sigmoid	5	1	4	92	15
		10	1	1	49	14
Antioxidant	hyperbolic tangent	5	1	1	107	71
		10	1	1	33	13
	Sigmoid	5	1	1	27	11
		10	1	4	28	27
Vitamin-C	hyperbolic tangent	5	1	2	362	22
		10	1	1	42	7
	Sigmoid	5	1	2	50	40
		10	1	5	42	23

Also, figure (7) illustrates the output amounts of between the real and predicted data. It can be observed based on the figure that the neural network has been well capable of predicting and comparing the given numbers and it can be stated considering the closeness and similarity of the numbers outputted from the ANN to the real data that the neural network possesses an appropriate competency for data prediction. Moreover, considering the R^2 rates, the network with sigmoid activation function featuring 10 neurons in the hidden layer (figure 7-D) presents the best overlap with the real data.


5 Neuron - Hyperbolic tangent
Output
Exemplar
phenol
antioxidan
vitaminc
phenol Output
antioxidan Output
vitaminc Output
A


10 Neuron - Hyperbolic tangent
Output
Exemplar
phenol
antioxidan
vitaminc
phenol Output
antioxidan Output
vitaminc Output
B

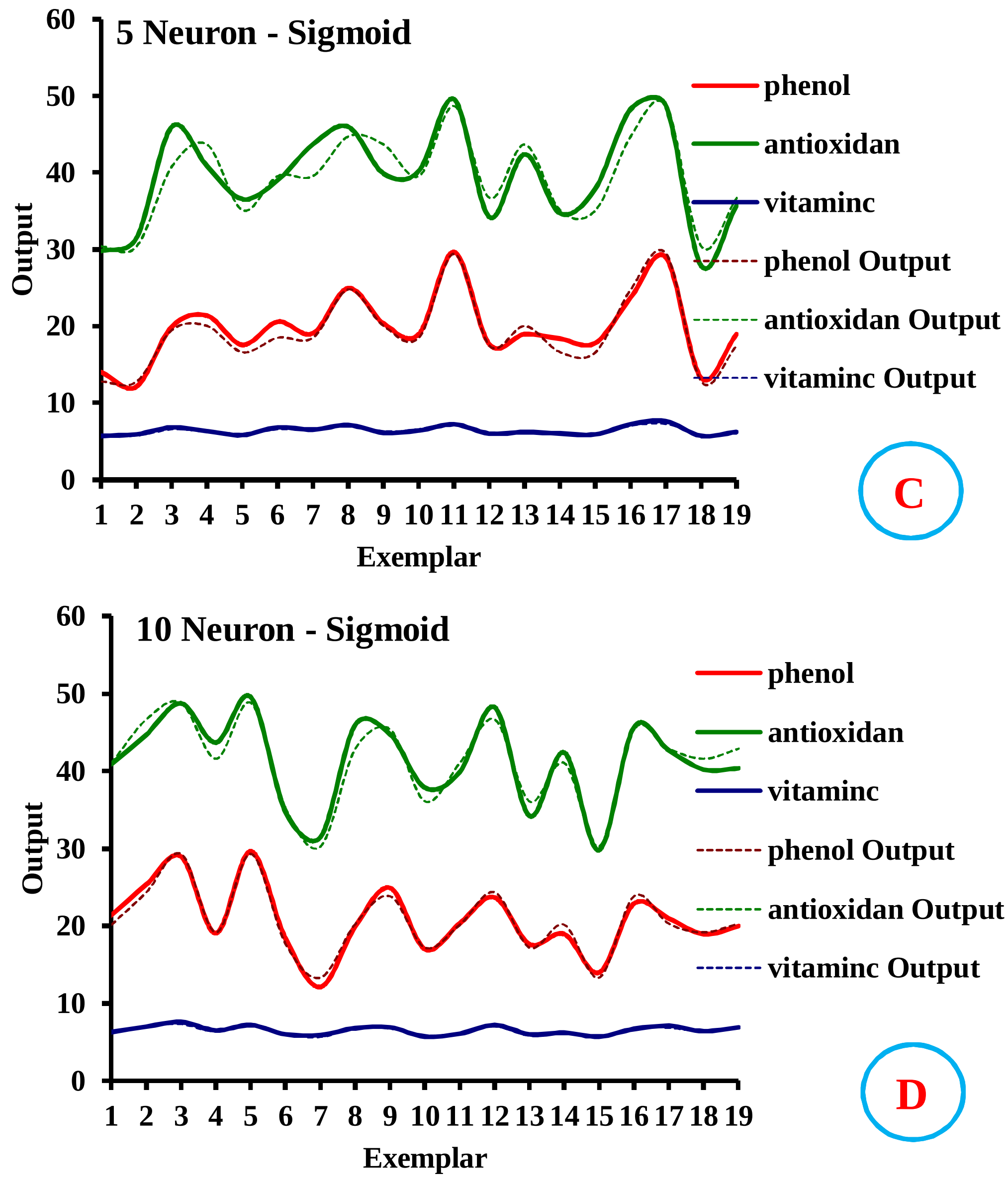


Fig. 7. Compare actual data with network output data

Sensitivity coefficient for quasi-static (wide edge)

The results of the sensitivity analysis for total phenol content are shown in Figure 8. Based on this figure, the highest sensitivity for training data was obtained for the loading and storage in the hidden layers with 5 neurons and hyperbolic tangent activation (Figure 8-A). As shown in figure 8 sensitivity analysis for test and Cross Validation data, According to figure highest sensitivity for test and cross validation data were obtained for loading and storage in the hidden layers with 5 neurons by sigmoid activation for test and Cross validation (Figure 8- A, B).

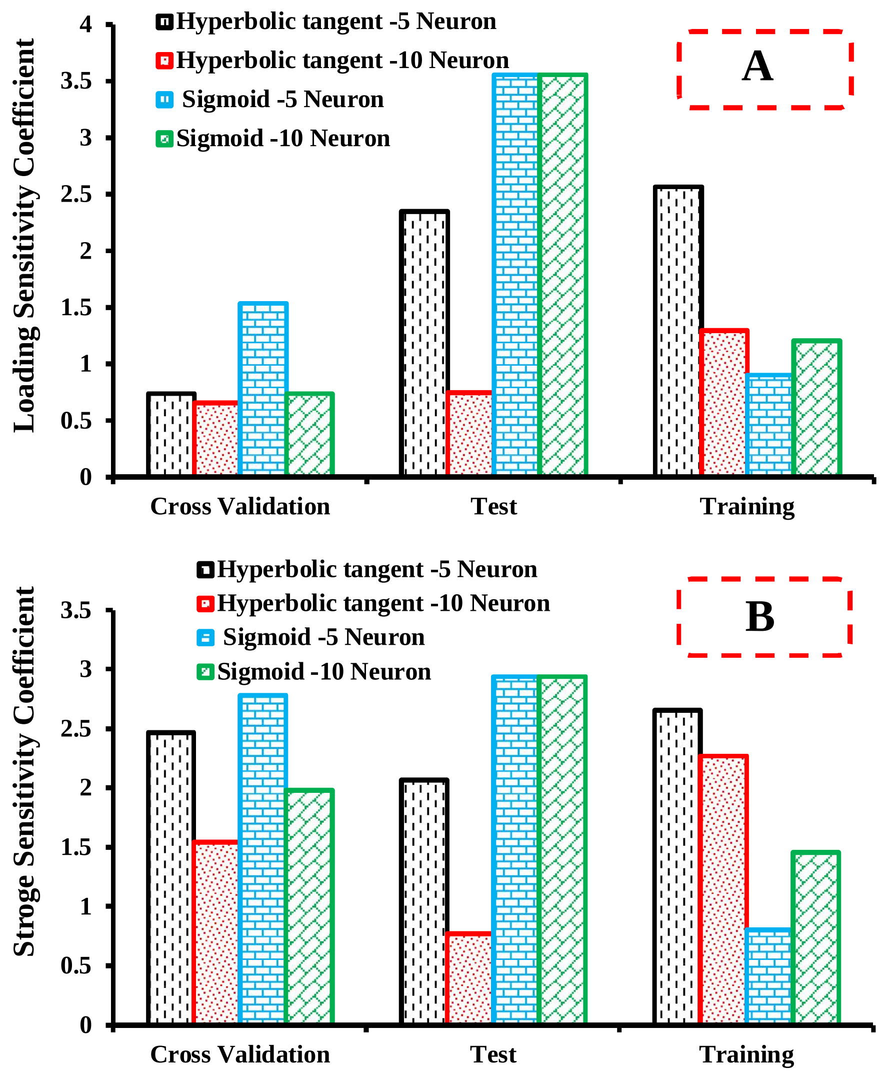


Fig. 8. Sensitivity coefficient for Total Phenol Content for A: Loading B: Storage time

The results of the sensitivity analysis for Antioxidant are shown in Figure 9. Based on this figure, the highest sensitivity for training data was obtained for the loading and storage in the hidden layers with 5 neurons and hyperbolic tangent activation (Figure 9- A). As shown in figure 9, sensitivity analysis for test and Cross validation data , According to figure the highest sensitivity for test and cross validation data were obtained for loading and storage in the hidden layers with 5 neurons by hyperbolic tangent activation (Test) and 10 neurons in sigmoid activation (Cross validation) (Figure 9- A, B).

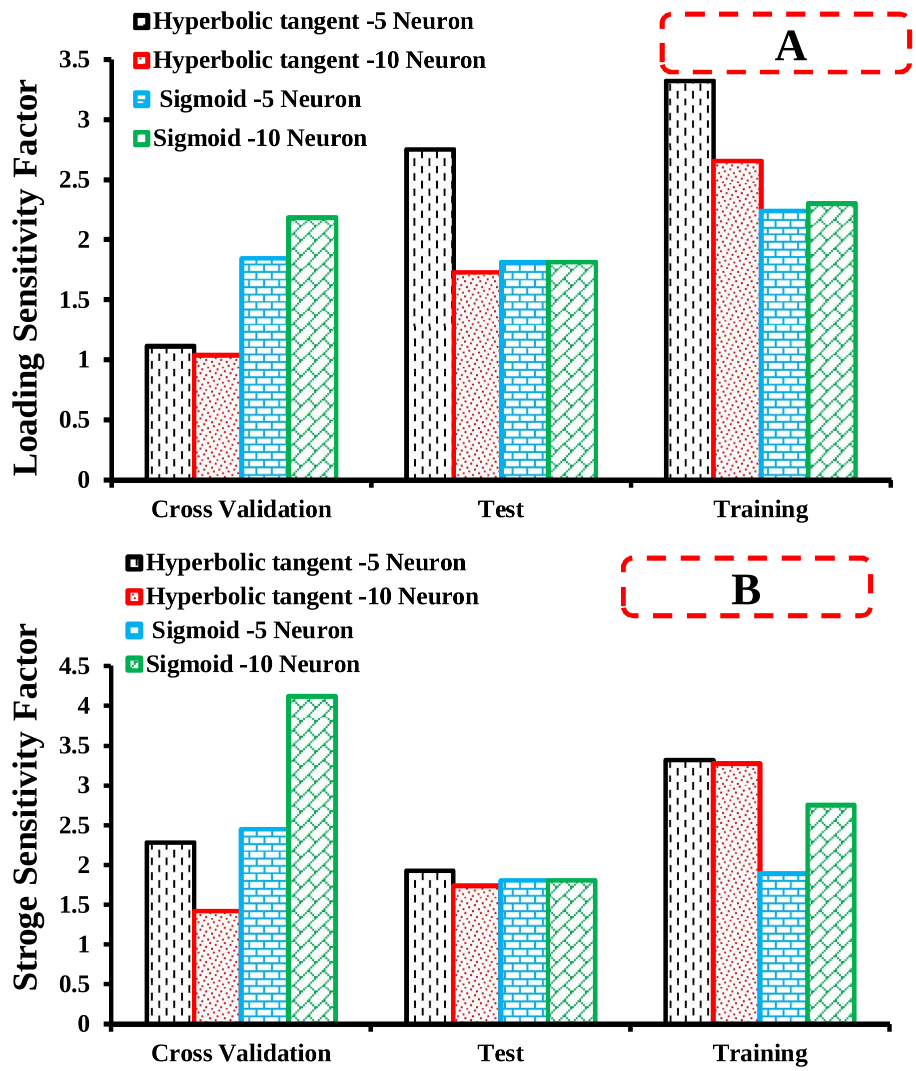


Fig. 9. Sensitivity coefficient for Antioxidant for A: Loading B: Storage time

The results of the sensitivity analysis for vitamin-C are shown in Figure 10. Based on this figure, the highest sensitivity for training data was obtained for the loading and storage in the hidden layers with 5 neurons and hyperbolic tangent activation (Figure 10-A). As shown in figure 10, sensitivity analysis for test and Cross validation data, According to figure the highest sensitivity for test and cross validation data was obtained for loading in the hidden layers with 5 neurons by hyperbolic tangent activation for Test and Cross validation (Figure 10-A, B) and For storage in the hidden layers with 5 neurons by hyperbolic tangent activation (Test) and 10 neurons in sigmoid activation (Cross validation)

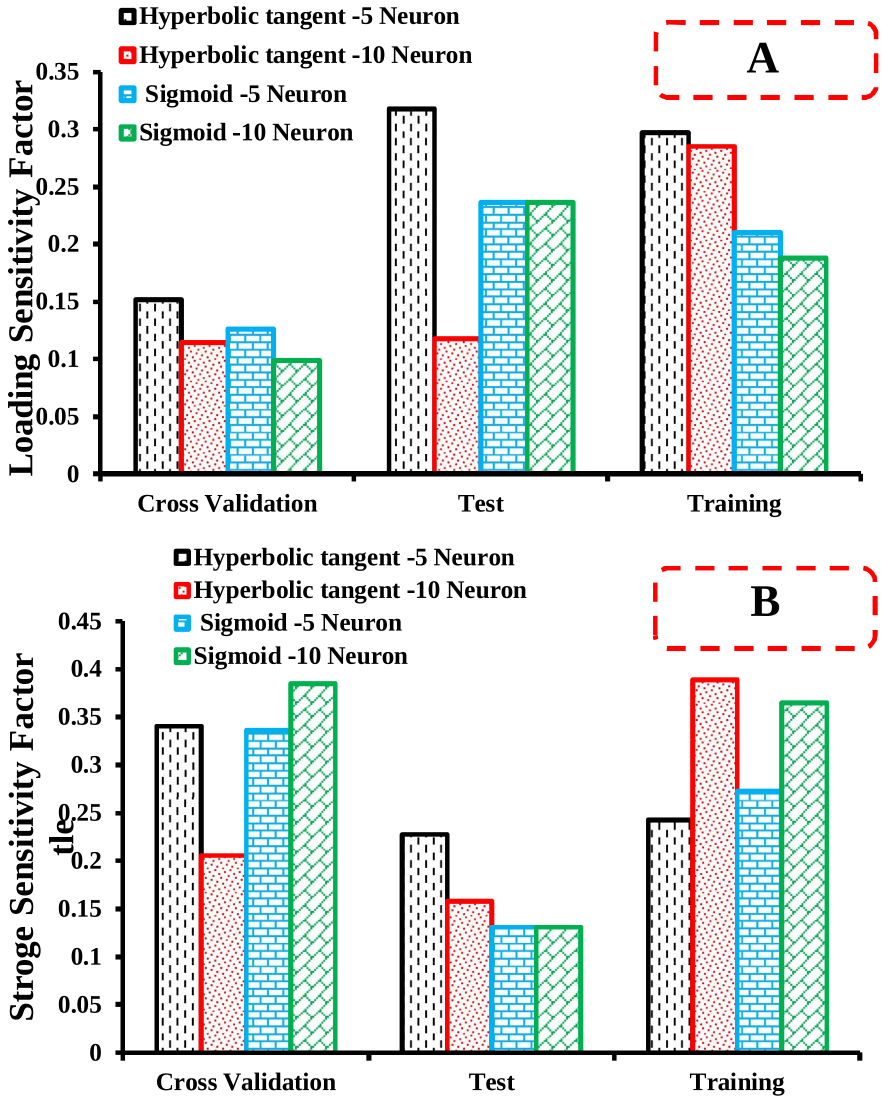


Fig. 10. Sensitivity coefficient for Vitamin-C for A: Loading B: Storage time

Conclusion

According to the values obtained for the determination coefficient (R^2), ANN was able to estimate the wide-edge loading determination coefficient comparing to the thin-edge loading determination coefficient and this is indicative of the idea that the ANN offers better abilities for the higher loading forces. The amount R_{test} for phenolic, antioxidant and vitamin C content in wide loading showed that the best values were in 10 neuron with sigmoid activation function and the amounts R_{test} were 0.9845, 0.9539 and 0.9391, respectively also in addition, in thin loading the highest R_{test} showed for phenol content in 5 neuron and hyperbolic tangent (0.9779) and for antioxidant and vitamin C showed in 10 neuron and hyperbolic tangent (0.9697 and 0.9691 respectively).

ANN has been able to estimate lower RMSE and MAE for wide-edge loading in contrast to thin-edge loading and this is suggestive of the idea that the ANN better fits higher loading forces' estimation.

As for the wide-edge loading force, R^2 values obtained for phenol, antioxidant and vitamin C contents were above 0.90 indicating the acceptability of the network.

According to the results obtained for wide-edge and thin-edge loading, the network with 10 neurons in the hidden layer and a sigmoid activation function can be accompanied with the best performance.

According to the simulation figures obtained by the network, the real and simulated data appropriately overlap.

The sensitivity coefficient obtained in training for wide-edge loading forces and storage periods in 5 and 10-neuron states of the hidden layer featuring a hyperbolic tangent activation function and 10-neuron state of the hidden layer with sigmoid activation function was higher than the one which was calculated for thin-edge loading.

As for the wide-edge loading, the highest sensitivity coefficient was obtained using a network with 5 neurons in the hidden layer and a hyperbolic tangent activation function in terms of total phenol, antioxidant and vitamin C contents. Moreover, the highest total phenol and antioxidant contents have also been found for the same number of neurons and activation function in terms of the storage period. As for the vitamin C content, the network with 10 neurons and hyperbolic tangent activation function has given the highest sensitivity coefficient.

In regard of the thin-edge loading, the highest sensitivity coefficient in terms of total phenol, antioxidant and vitamin C contents was obtained in the network with 5 neurons in the hidden layer and sigmoid activation function. Also, the highest vitamin C and antioxidant content in terms of the storage period were obtained in a network with 10 neurons in the hidden layer and hyperbolic tangent activation function. And, in terms of the total phenol content, the network with 5 neurons and the hyperbolic tangent activation function has had the highest sensitivity coefficient.

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پیش‌بینی تغییرات خواص فیزیولوژی در گلابی‌های تحت بارگذاری خارجی با استفاده از شبکه عصبی مصنوعی: بخش 1: بارگذاری استاتیکی

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چکیده

در این مقاله به بررسی اثر نیروی بارگذاری و دوره انبارداری بر میزان محتویات درونی گلابی پرداخته شده است. در این آزمایش گلابی‌ها تحت بارگذاری شبه استاتیکی (لبه نازک-لبه پهن) و دوره‌های انبارداری مختلف (5، 10 و 15 روز) قرار گرفته است. پس از هر دوره انبارداری میزان محتوای فنول کل میوه، آنتی‌اکسیدان و ویتامین C میوه مورد بررسی قرار گرفت. در این پژوهش شبکه عصبی مصنوعی پرسپترون چندلایه (MLP) با یک لایه پنهان و دو نوع تابع فعال‌سازی (Hyperbolic tangent - sigmoid) و تعداد 5، 10 نرون در هر لایه برای نیروی بارگذاری و دوره انبارداری جهت پیشگویی میزان میزان محتوای فنول کل میوه ، آنتی‌اکسیدان و ویتامین C انتخاب گردید. با توجه به نتایج به‌دست آمده بیشترین مقدار R^2 برای بارگذاری لبه نازک و پهن در شبکه‌ای که دارای 10 نرون در لایه پنهان و تابع فعال‌سازی sigmoid برای محتوای فنول کل ($R^2_{Wide\ edge}$ =0.9865 - $R^2_{Thin\ sdge}$=0.9539) ، انتی‌اکسیدان ($R^2_{Wide\ edge}$ =0.9649 - $R^2_{Thin\ sdge}$=0.9839) و ویتامین C ($R^2_{Thin\ edge}$=0. 9758) بوده است و برای ویتامین C ($R^2_{Wide\ edge}$=0.9865) بارگذاری لبه پهن بیشترین مقدار R^2 در شبکه با 5 نرون در لایه پنهان و تابع فعال‌سازی Hyperbolic tangent بوده است. با توجه به نتایج به‌دست آمده شبکه عصبی با این دو نوع تابع فعال‌سازی توانایی مناسبی در همپوشانی و پیش‌بینی داده‌های شبیه‌سازی شده با داده‌های واقعی را داشته است .

واژه‌های کلیدی: محتویات درونی گلابی، بارگذاری، انبارداری، شبکه عصبی، تابع فعال‌سازی

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