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Prediction of Physiological Characteristic Changes in Pears Subject to Dynamic Loading Using Artificial Neural Network (ANN)

Mohsen Azadbakht[1]*, Mohammad Vahedi Torshizi[2], Mohammad Javad Mahmoodi[2], Ahmad Abbaszadeh-Mayvan[1]

1 Department of Bio-System Mechanical Engineering, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran
2 Department of Mechanics, Faculty of Emam Ali, Kordkuy Branch, Technical and Vocational University (TVU), Golestan, Iran

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ABSTRACT

The current study was aimed to evaluate the physiological properties of pear influenced by two dynamics of loading force and the storage time. In this experiment, the pears were subjected to dynamic loading (300, 350 and 400 g) and different storage periods (5, 10 and 15 d). The amounts of fruit 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 for dynamic loading in a network with 5 neurons in the hidden layer and a sigmoid activation function were obtained for total phenol content (R^2 = 0.980), antioxidant (R^2 = 0.983) and Vitamin C (R^2 = 0.930). Additionally, considering the value of Epoch and Run for the network, the ability of the neural network to predict total phenol, antioxidant and Vitamin C contents can be used. 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.

Introduction

Researchers have documented that 35% of bruises occur during harvest and transportation stages. Considerable efforts and costs are made and carried to increase products' performance, but the profits gained from the production increase are jeopardized due to the use of improper handling methods after harvest. This resulting in exacerbation of the products' wastage. Inappropriate transportation of fruits can cause mechanical damage to them. The physical and biological composition of the products as well as various sorts of enforced loads including static, dynamic, and undulating loads define the outline figure caused by the damage. In cases where such a transformation exceeds the biological yield limits, the texture undergoes color changes within a short period of time and the fruit rots so that its ingredients will be rendered completely useless. The products spoiled during storage can also endanger the healthy materials in contact with them (Sitkei, 1987). Being subject to contact stresses under static, quasi-static and stroke loads, the mechanical damage in various kinds of fruits and vegetables causes a reduction in the product quality and its economic value. Bruises in fruits are defined as textural break in the vicinity of their surfaces under compressive or impact loads. The preliminary effect of the compressive forces imposed on fruits is exerted on the

*Corresponding author's email: azadbakht@gau.ac.ir
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membrane system of the cells constituting the flesh. One important role of the membrane is to isolate the intracellular liquid parts. The membrane is damaged by the injury in a part of the plant following which the plant cannot perform its duty. Subsequently, damage can cause the mixing of the enzymes extant in cytoplasm with (phenolic) molecules existing inside the vacuoles; this per se can lead to creation of brownish stains on the fruit surface, which are called bruise (Babic et al., 2012; Opara and Pathare, 2014; Stropek and Gołacki, 2015). In addition, some researchers had reported that as a result of the effects of lower force, the fruit may not change, but significant bruising occurs when the fruit is physically damaged by impact during storage. Furthermore, the physical evidence suggests cell breakage and color change in the fruit of interest occurring when the individual cells become subjected to pressure in their cell walls, and they finally break and this causes a change of color in the intended part (Opara and Pathare, 2014). The major reason for such mechanical damage (bruise) waste is impacted that can created from shaking or abrupt falling from various heights. In recent years, numerous studies have been conducted to evaluate the mechanical properties and bruise-sensitivity of the fruits and vegetables in which the bruise has been attributed to friction and pressure of a product with and on another adjacent product, packaging containers, and processing equipment parts and tree (Idah et al., 2007)

Artificial neural network (ANN) seems extremely appropriate to investigate and simulate the data. ANN is, in fact, a collection of mathematical methods, including artificial intelligence, and it attempts somehow to imitate the human brain. During the past two decades, the neural network has exhibited considerable potential in various science and engineering areas for its exceptional performance, internal organization and self-learning, overcoming the challenges and high solidity rate. Recently, there has been an increase in utilizing neural networks as a modeling tool in agriculture and food industry technologies. Neural networks have been successfully employed in several foodstuff processing technologies such as drying, post-harvest technologies, rheology of the foodstuff, microbial predictions, fermentation, and thermal processing (Lu et al., 2010). Artificial neural networks are also considered the most effective tools to process a large volume of information that was once a major challenge in various respects. The development trend of neural networks is suggestive of the importance of using them for information processing, since they have been proved to be highly successful in data analysis and they have been capable of undergoing development in various grounds. Moreover, the use of neural networks is promising in food production and foodstuff quality processing and evaluation methods wherein old methods of data processing might not provide us with accurate information or be substantially costly. Two important capabilities of neural networks, on wit prediction and classification scales, have drawn considerable attention. According to the internal competencies of artificial neural networks, they can be successfully applied in the agriculture sector (Hosu et al., 2014).

Many researchers have conducted studies in this regard. For instance, Lu et al. (2010) used ANN to estimate ascorbic acid, total phenol, flavonoids and antioxidants in asparagus. In these experiments, they employed a neural network with a hidden layer and varying numbers of neurons in the hidden layer, and it was found that the determination coefficient ranges between 0.8166 and 0.9868 for the neural network between the input and simulated data. Moreover, the quantity of the asparagus constitutes is assessed by the significant abilities of the neural network (Lu et al., 2010). Cheok et al. (2012) in one study on extracting the total phenol contents of *Garcinia mangostana* L. using ANN reported that the analysis through taking advantage of ANN predicted data with a determination coefficient equal to 0.945 and a mean absolute deviation (MAD) equal to 4.01% in the response surface methodology (RSM). The findings of the survey introduced ANN as a superior technique in modeling nonlinear data to estimate the total content of phenol (Cheok et al., 2012). Guiné et al. 2015 utilized ANN-based modeling to investigate phenol and antioxidant contents of bananas, and the results indicated that the ANN-based method exhibited a high accuracy rate in predicting the fruits' contents of phenol and antioxidants (Guiné et al., 2015). Taghaddomi-Saberi et al. (2014) investigated the potentials of neuro-fuzzy and ANN techniques in order to evaluate the antioxidant activity of ripened sweet cherry products and reported that the determination coefficients were 0.93 and 0.87 for ANN and neuro-fuzzy techniques, respectively. Based on the obtained results, they also reported that both of these networks presented considerable potential in property prediction (Taghadomi-Saberi et al., 2014)

Subsequent to the loading, the total content of phenol, vitamin C, and antioxidants were evaluated. Each of them has separate treatments. Loading and storage are dependent factors and the rest are independent factors. The susceptibility of fruits, especially the pear, to the impact and the changes in its qualitative properties, required more attention than before. Therefore, the objective of the present study was to investigate the ability of ANN in predicting the biochemical characteristics of pears subject to dynamic loading and during various storage periods. The study also evaluated the sensitivity of the studied traits subjected to loads and storage periods.

Materials and Methods

Sample preparation

The pears (Spadana variety) were purchased from the markets of Gorgan, Golestan province, Iran. Subsequently, the obtained samples were transferred to the laboratory of Gorgan University of Agricultural Sciences and Natural Resources. They were kept in an oven at 103 °C for 16 h, and their moisture contents were measured. Environmental conditions for testing was conducted at a temperature of 18 °C and relative humidity of 72%.

Impact test

First, the pendulum and the required masses were made in a workshop in Gorgan Biosystem Mechanics Group (Fig. 1). The fruits in this experiment were appropriately positioned and the arm of the device was fixed at a 90° angle as well. Consequently, the pear was hit by the arm of the device in the provided circumstances. The pendulum had a 200-gram arm, and three different attachment masses of 100, 150, and 200 g for knocking. It should be noted that air resistance and friction were neglected through this procedure. Figure 2 shows the pears after each loading and storage.

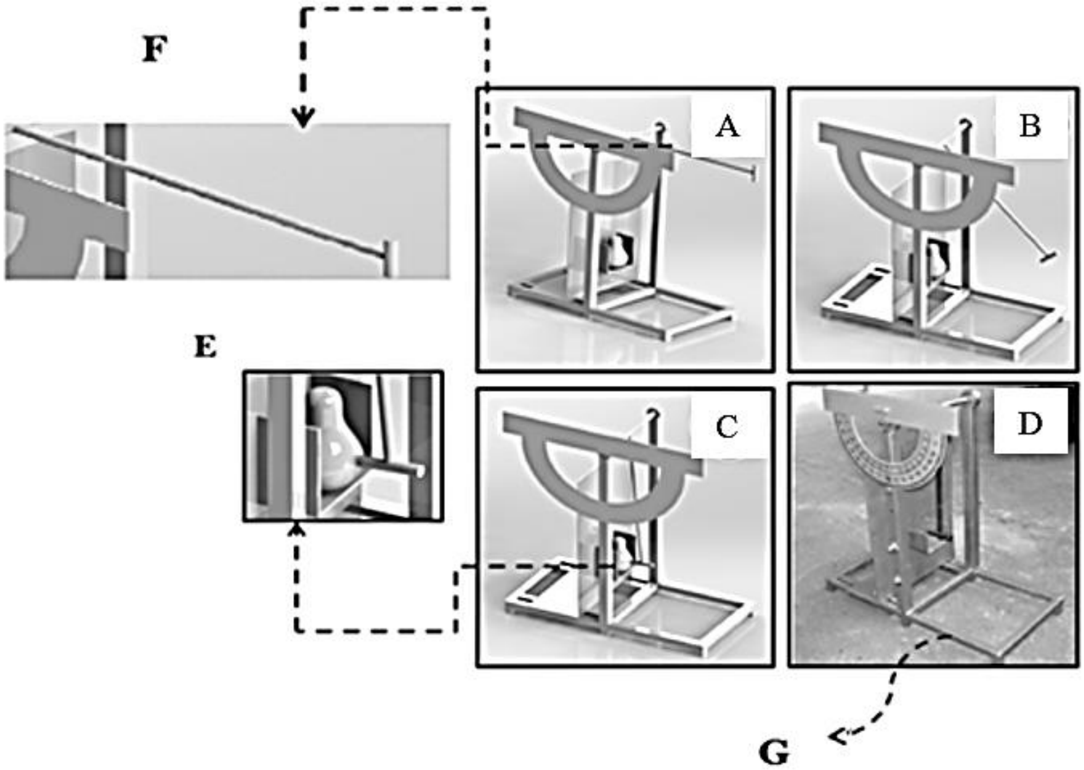


Fig. 1. Schematic of the impact machine
A: Pendulum at a 90 degree angle; B: Walking along the path; C: Collapse pendulum to pear; D: Main device profile; E: Place the pear; F: Pendulum blow; G: the base of the device.

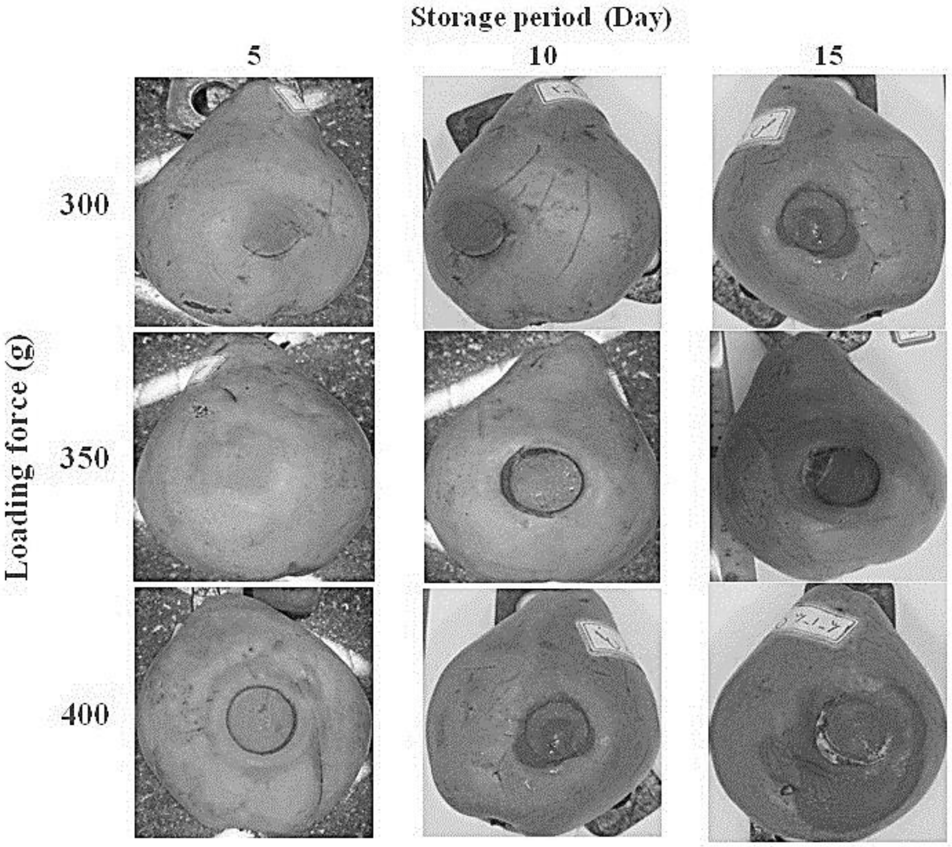


Fig. 2. pear picture after loading and storage period

Vitamin C

The 2 and 6-dichlorophenol indophenol titration method was used to estimate vitamin C. To do so, the contents were combined and subsequently extracted by citric acid in the first place. Then, the filtered extract was picked up and mixed with citric acid 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 15 s. Vitamin C amount was obtained by the following equation (Tavarini et al., 2008):

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

Biochemical properties measurement

To measure the total phenol content and the percentage of free radicals' neutralization, specimens equal to 0.5 g of each sample's wet callus was ground and homogenized using 5 milliliters of methanol 80% (at 1:10 ratio) in a cold mortar. The obtained mixture in homogenized form was centrifuged at 3000 rpm for 5 min after incubation in a dark room for 24 h on a shaker device. The upper part of the extract was used to measure the biochemical characteristics. For measuring total phenol content amount using folin-ciocalteu (f-c) reaction and in this experiment, the percentage of DPPH free radicals neutralization was measured based on the method proposed by Bandet et al. (Jaramillo-Flores et al., 2003; Li et al., 2012).

Artificial neural network modeling

In this research, the artificial multilayer perceptron (MLP) neural network was used to model and investigate pear components during storage and impact loading to predict total phenol content, antioxidant and Vitamin C by one hidden layer and 5 and 10 neurons using the Neuro Solution 5 software. For the input and output layer in hidden form, the activation function of hyperbolic tangent and sigmoid (Equation 3 and 4) was conducted as the most common activation functions. In this paper, 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 1). Before training the model, the input-output parameters in data sets were arranged, and the inputs in the data set were normalized between 0 and 1 range - using the equation. Because of the output layer activation function is linear (purlin) in all architectures; only the input parameters were normalized by Eq. (2). The impact loading value (27 data) and storage time (27 data) as network inputs Total phenol content, antioxidant and Vitamin C (27 data for each component) were the considered network outputs (Fig. 3) and for the network was set up separately for each parameter. A total of 5 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 the relationships were calculated using the formulas shown in Table 2. This experiment was performed with a number of different neuron values, but they were not suitable, and in fact these values were better than the values obtained from analyses, and the rest of the values obtained from these values were not more appropriate, hence the two values of the neuron were reported.

$$I_{norm} = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \qquad (2)$$

In Equation 2, I_{norm} is the normalized data, I is the measured data, I_{min} is the least measured and I_{max} is the most measured data.

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)	(; Azadbakht et al., 2018b)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)	(;Azadbakht et al., 2018a)Salehi and Razavi, 2012
$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(P_i - O_i)^2}{n}}$	(7)	(Khoshnevisan et al., 2013)
$\text{MAE} = \frac{\sum_{i=1}^{n}\lvert P_i - O_i\rvert}{n}$	(8)	(Azadbakht et al., 2017)

RSME: Root Mean Square Error, MAE: Mean absolute error Sig:Sigmoid Tanh: Tangent Hyperbolic

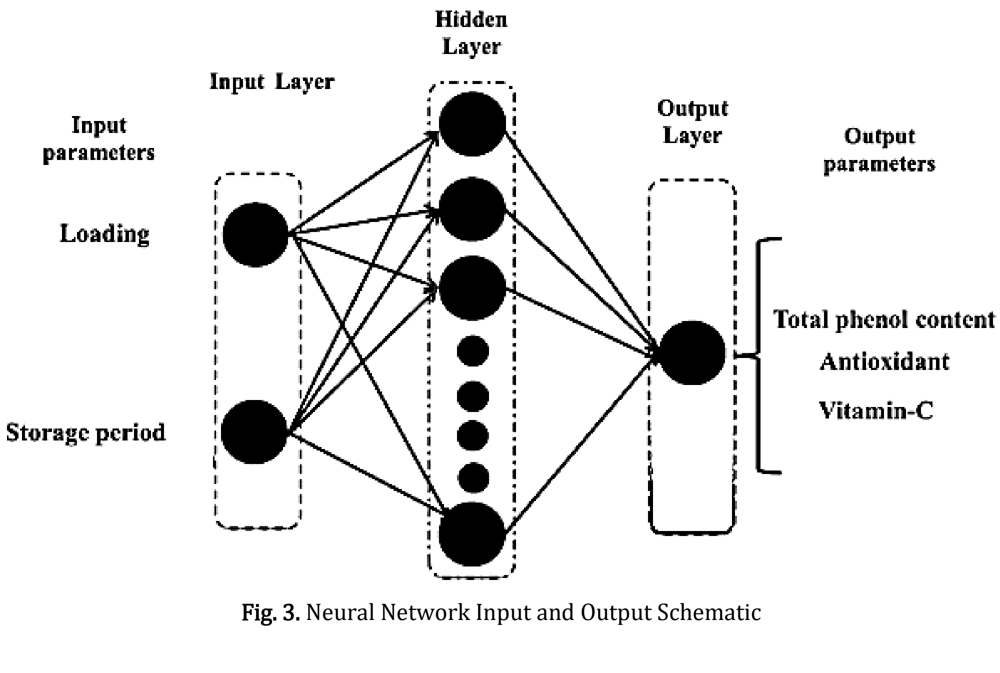


Fig. 3. Neural Network Input and Output Schematic

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	5	20%	10%	70%
1	Levenberg Marquardt	Hyperbolic tangent and	10	20%	10%	70%
1	Levenberg Marquardt	sigmoid	5	20%	10%	70%
1	Levenberg Marquardt	sigmoid	10	20%	10%	70%

Results

To predict the total phenol content, antioxidant and Vitamin C, a multi-layered perceptron (MLP) neural network model was used. In this regard, the network input included the storage period and the impact loading, and the network output was comprised of vitamin C as well as the antioxidant and total phenol content. 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. Table 3 presents the value of mean squared error, normalized mean squared error, mean absolute error, and correlation coefficient. Also the moisture content of the pears was calculated to be 77.92%.

The results show that neural network had 5 neurons in the hidden layer, and Sigmoid activation function for Total Phenol Content (R^2 = 0.960), Antioxidant (R^2 = 0.966) and Vitamin C (R^2 = 0.865) could predict Total Phenol Content Antioxidant and Vitamin C in different impact loading and storage time (Table 3). Furthermore, MAE and RMSE of training data were evaluated in a lower quantity in 5 neurons in the hidden layer and the activation function of Sigmoid concerning the total content of phenol (RMSE=0.989–MAE=0.853), Vitamin C (RMSE=0.241–MAE=0.185), and antioxidant (RMSE=1.379 –MAE=1.044).

Table 3. Error values for the impact (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	2.160	2.999	1.470	1.732	1.158	1.547	0.927	0.848
		10	2.395	6.385	1.548	2.527	1.258	2.184	0.912	0.986
	Sigmoid	5	0.978	1.640	0.989	1.280	0.853	1.028	0.960	0.929
		10	1.970	1.030	1.404	1.015	1.163	0.804	0.937	0.943
Antioxidant	hyperbolic tangent	5	5.101	7.120	2.259	2.668	1.924	2.412	0.939	0.841
		10	13.170	16.178	3.629	4.022	2.928	3.449	0.704	0.929
	Sigmoid	5	1.901	9.383	1.379	3.063	1.044	2.621	0.966	0.518
		10	4.362	6.538	2.088	2.557	1.709	2.178	0.906	0.897
Vitamin C	hyperbolic tangent	5	0.131	0.242	0.362	0.491	0.283	0.437	0.790	0.123
		10	0.357	0.415	0.597	0.644	0.517	0.591	0.348	0.645
	Sigmoid	5	0.058	0.104	0.241	0.323	0.185	0.291	0.865	0.723
		10	0.092	0.099	0.304	0.314	0.236	0.255	0.839	0.799

MAE: Mean absolute error MSE: Mean Square Error RMSE: Root Mean Square Error

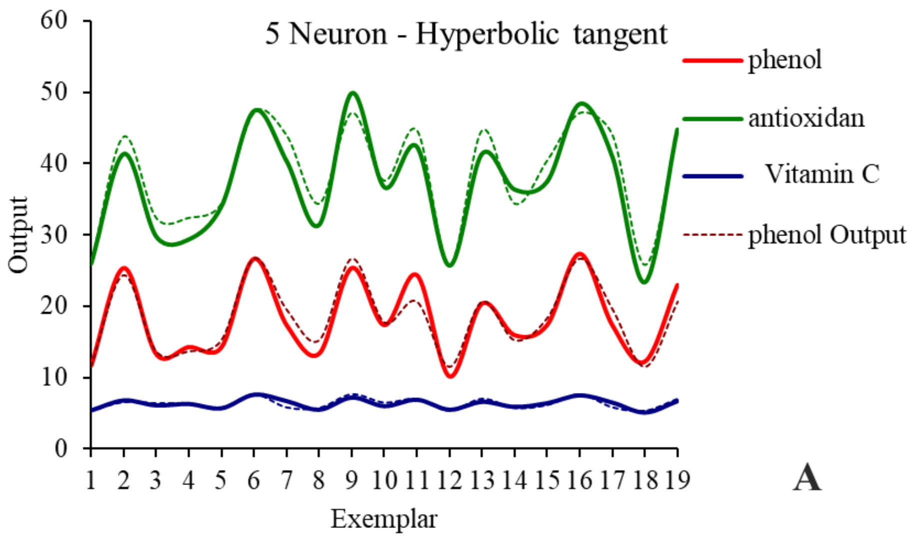
The most proper network identified between the network simulated data of each individual hidden layer neurons and the input data is demonstrated in Table 4. The lower value of Epoch indicates that the number of neurons in the layer has been able to learn from the neural network compared to another number of neurons. As Table 4 shows, the best network for Total Phenol Content at Training (Run = 1, Epoch = 17) in the 10-neuron state in the hidden layer and hyperbolic tangent activation function reaches a constant value after approximately 17 Epoch of error, and the best network for Antioxidant Training (Run = 1, Epoch = 16) in

10-neuron state in the hidden layer and hyperbolic tangent activation function. For Vitamin C of Training value (Run = 1, Epoch = 29), it was found in 10-neuron state in the hidden layer and hyperbolic tangent activation function. The networks indicated that the number run for networks learning and training was lower.

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	2	4	563	67
		10	1	3	17	12
	Sigmoid	5	1	5	150	16
		10	1	2	66	13
Antioxidant	hyperbolic tangent	5	1	4	101	6
		10	1	5	16	5
	Sigmoid	5	1	1	96	22
		10	1	5	55	32
Vitamin-C	hyperbolic tangent	5	1	2	161	30
		10	1	2	29	6
	Sigmoid	5	1	4	151	27
		10	1	3	50	7

In addition, Figure 4 illustrates the output amounts between the real and predicted data. According to the figure introducing the neural network as a proper method in estimation and comparison of the provided data, therefore, it is also compatible to estimate the output data of ANN, since these numbers are similar to actual data. Moreover, considering the R^2 rates, the network with sigmoid activation function featuring 5 neurons in the hidden layer (Fig. 4-C) presents the best overlap with the real data.



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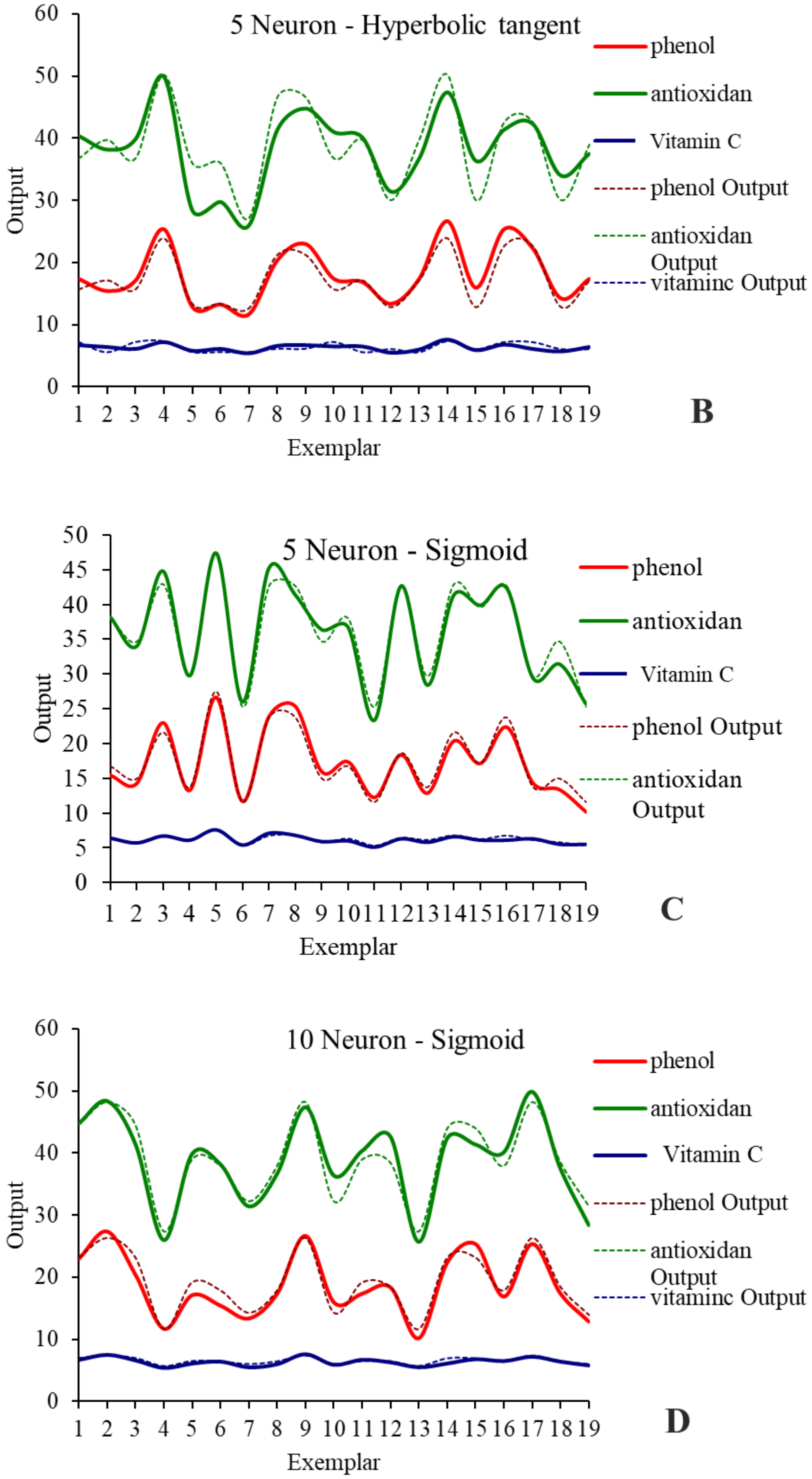

Fig. 4. Compare actual data with network output data for phenol, antioxidant and Vitamin C content in four networks

Figure 5 shows the results of the sensitivity analysis for Total Phenol Content. Based on this figure, the highest sensitivity for training data was obtained for the impact loading in the hidden layers with 5 neurons and hyperbolic tangent activation and for storage was obtained in hidden layers with 10 neurons and hyperbolic tangent activation (Fig. 5-A). The highest sensitivity of the network was obtained from the hyperbolic activation function. In total, for Total Phenol Content, the storage sensitivity analysis was more than the impact loading sensitivity analysis. The reason for this can be justified by the fact that by creating stress (impact) 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, causing them to be decreased. Moreover, Fig. 5 shows the sensitivity analysis for Test and Cross Validation data. According to the figure, the highest sensitivity for Test and cross validation data was obtained for impact loading in the hidden layers with 5 neurons by sigmoid activation (Test) and 5 neurons in hyperbolic tangent activation (Cross validation) (Fig. 5-A). Additionally, the highest sensitivity for Test and cross validation data was obtained for the storage in the hidden layers with 5 neurons (Test) and 5 neurons (Cross validation) in hyperbolic tangent and sigmoid activation (Fig. 5-B).

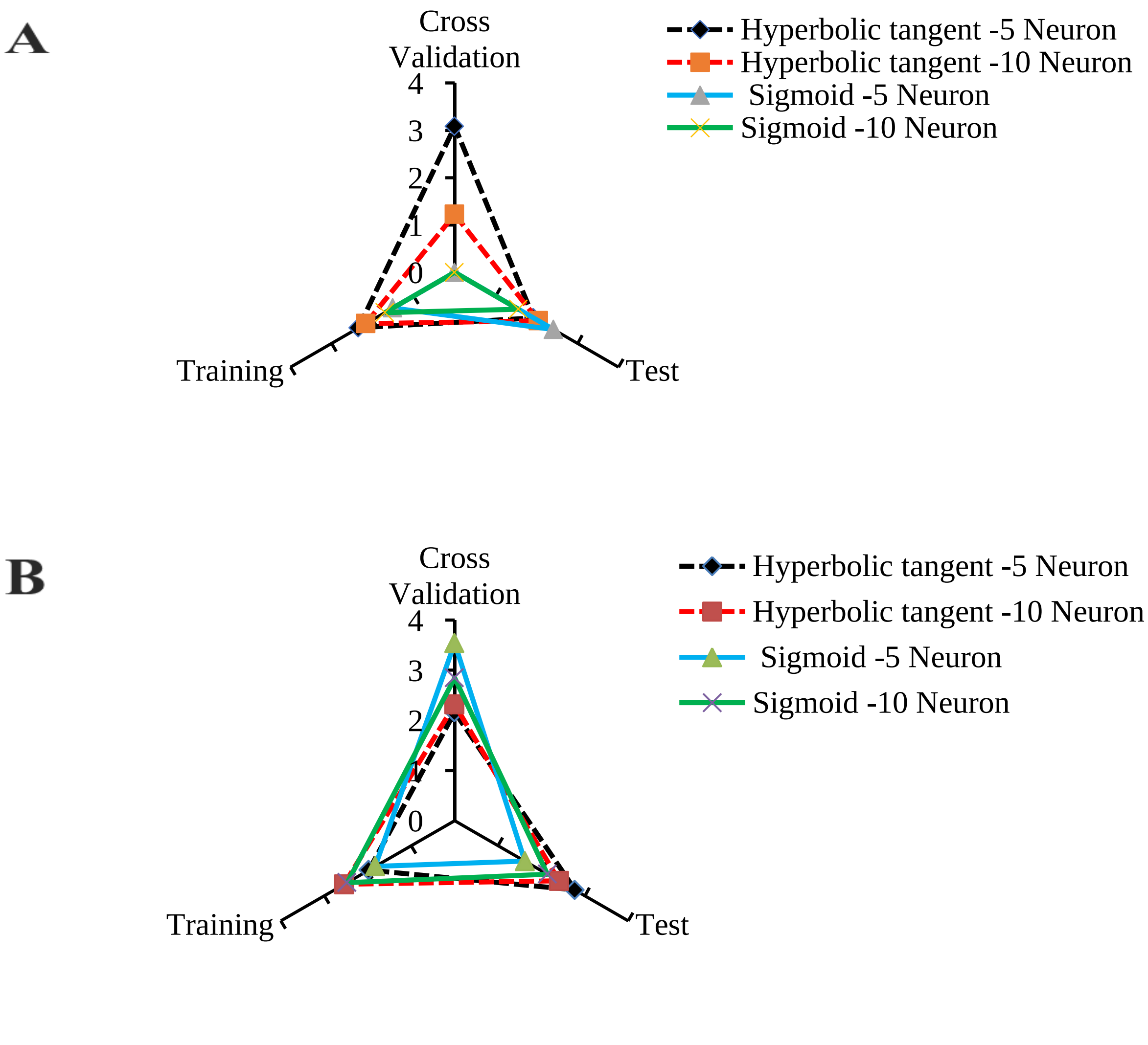

Fig. 5. Sensitivity coefficient for total phenol content in training, test and cross validation data for each networks: A: Loading B: Storage time

Figure 6 shows the results of the sensitivity analysis for Antioxidant. Based on Fig. 6, the highest sensitivity for the training data was obtained for the loading in the hidden layers with 5 neurons and hyperbolic tangent activation function and for storage period was obtained in hidden layers with 5 neurons and sigmoid activation function (Fig. 6-A). Furthermore, Fig. 5 presents the sensitivity analysis for Test and Cross Validation data. According to this figure, the highest sensitivity for Test and cross validation data was obtained for impact loading in the hidden layers with 5 neurons by hyperbolic tangent activation (Test and Cross validation) (Fig. 6-A). The figure (6-B) illustrates the highest sensitivity of data in regard to the Test and cross-validation of the storage of the hidden layers for activation function of hyperbolic tangent including 5 neurons (Test) as well as activation function related to sigmoid with 10 neurons (Cross-validation).

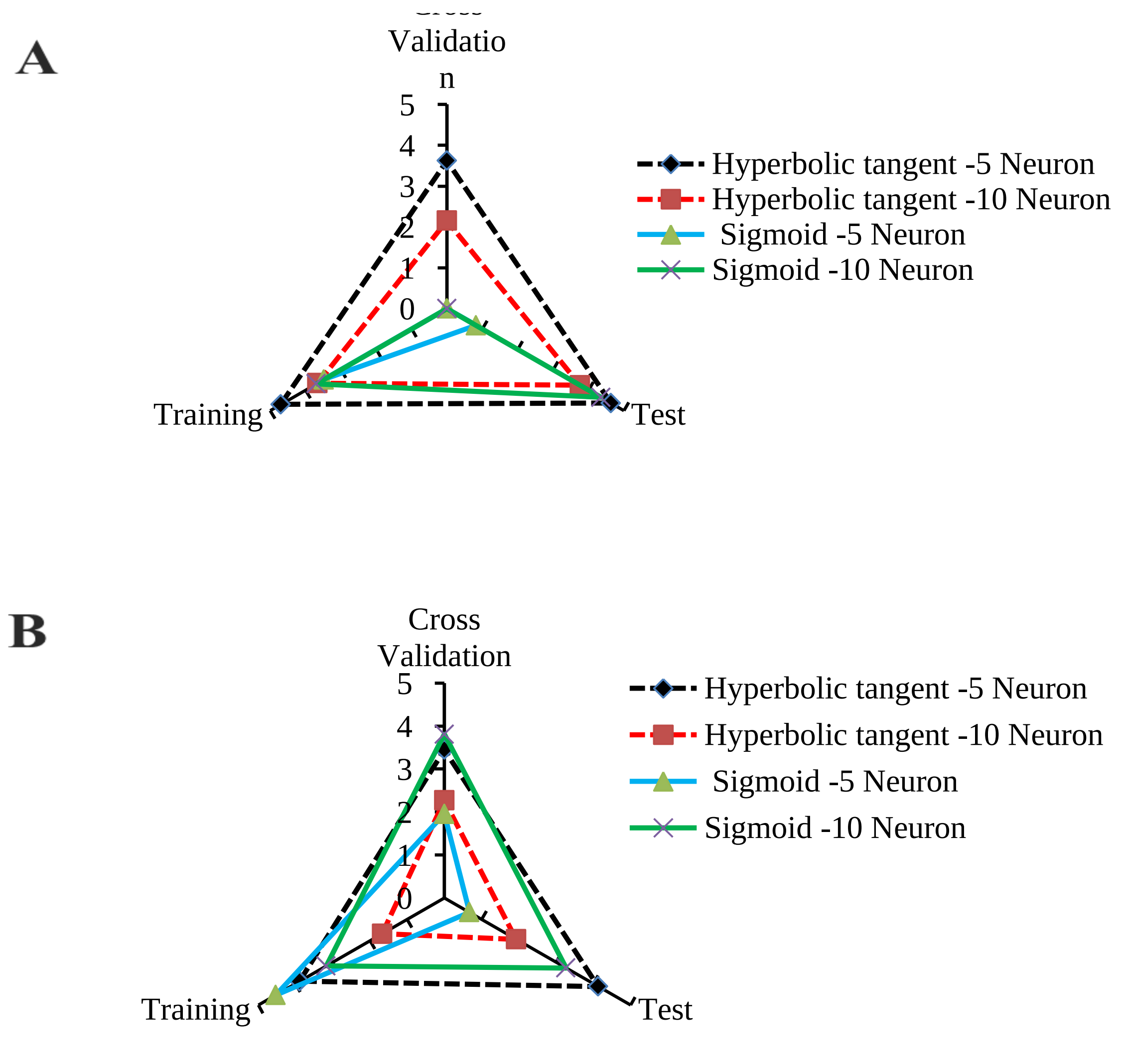

Fig. 6. Sensitivity coefficient for antioxidant in training, test and cross validation data for each networks: A: Loading B: Storage time

Figure 7 shows the results of the sensitivity analysis for Vitamin C. Based on this figure, the highest sensitivity for the training data was obtained for the loading in the hidden layers with 7 neurons and hyperbolic tangent activation function, and for storage, it was obtained in hidden layers with 10 neurons and hyperbolic tangent activation function (Fig. 7-A). Fig. 5 shows the sensitivity analysis for test and Cross Validation data. The highest sensitivity of the data extracted from the Test and cross validation was related to the impact loading of the hidden layers including 5 neurons using hyperbolic tangent activation (Test and Cross-validation) (Fig. 7-A). In addition, the highest sensitivity for Test and cross validation data was obtained for the storage in the hidden layers with 10 neurons in hyperbolic tangent activation function (Test and Cross validation) (Fig. 7-B).

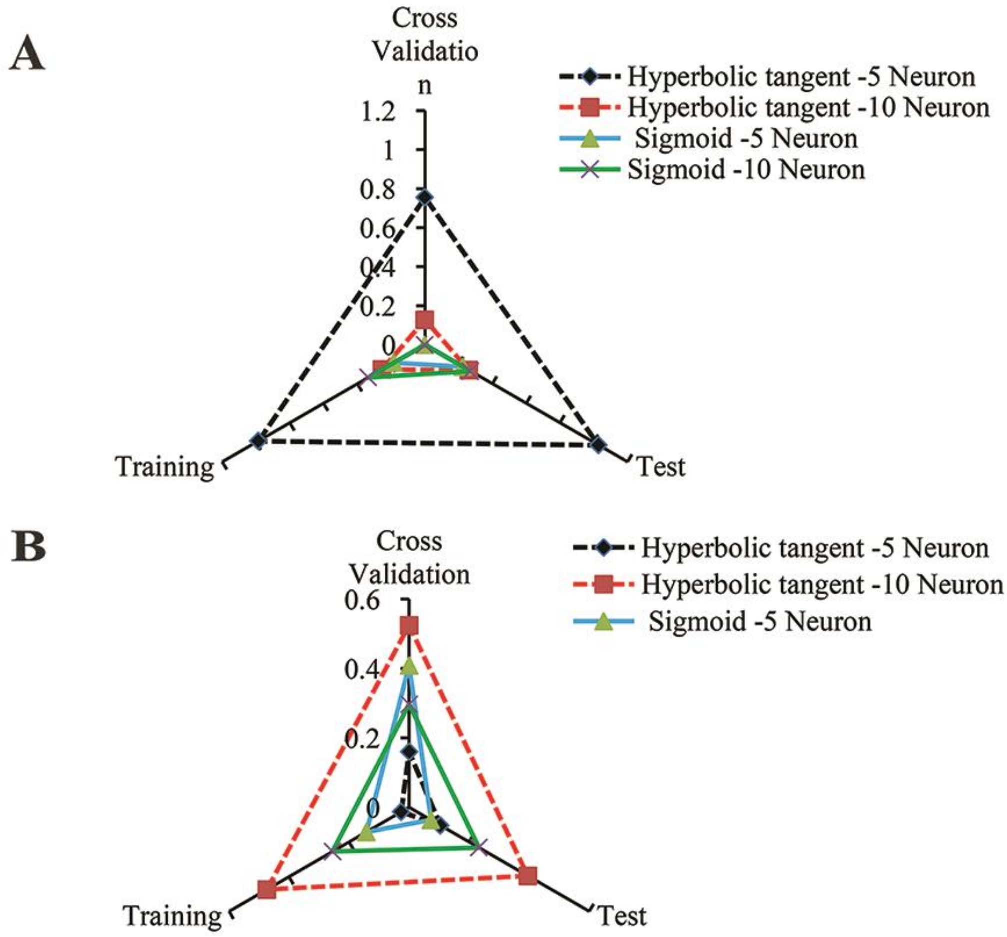

Fig. 7. Sensitivity coefficient for Vitamin C in training, test and cross validation data for each networks: A: Loading B: Storage time

The predicted values or outputs of the neural network versus the measured data (target) for total phenol content, anti-oxidant and Vitamin C are shown in Figure 8, 9 and 10. According Figure 8, between all networks for phenol content, the best value was in the netweork by 5 neuron in tagent hyperbolic activation function, the R^2 value for this network was 0.954 that had been showed in Fig. 8-B, Also the others R^2 were 0.944 (Fig. 8 –C) 0.942 (Fig. 8-A) and 0.921 (Fig. 8-D) respectivelity. The R^2 values for antioxidant content had showed in Fig. 9 and for antioxidant content, the best value for R^2 was in network by 5 neuron in sigmoid activation function by the amount 0.969 (Fig. 9-D). For others higher R^2 value than Fig. 9-D were 0.959 (Fig. 9-A), 0.926 (Fig. 9-B) and 0.904 (Fig. 9-C). At finally for Vitamin C, the best R^2 value was 0.851(Fig. 10-D) at network by 5 neuron in sigmoid activation function and after this network, the higher value was 0.848 (Fig. 10-C), 0.773 (Fig. 10-B) and 0.725 (Fig. 10-A).

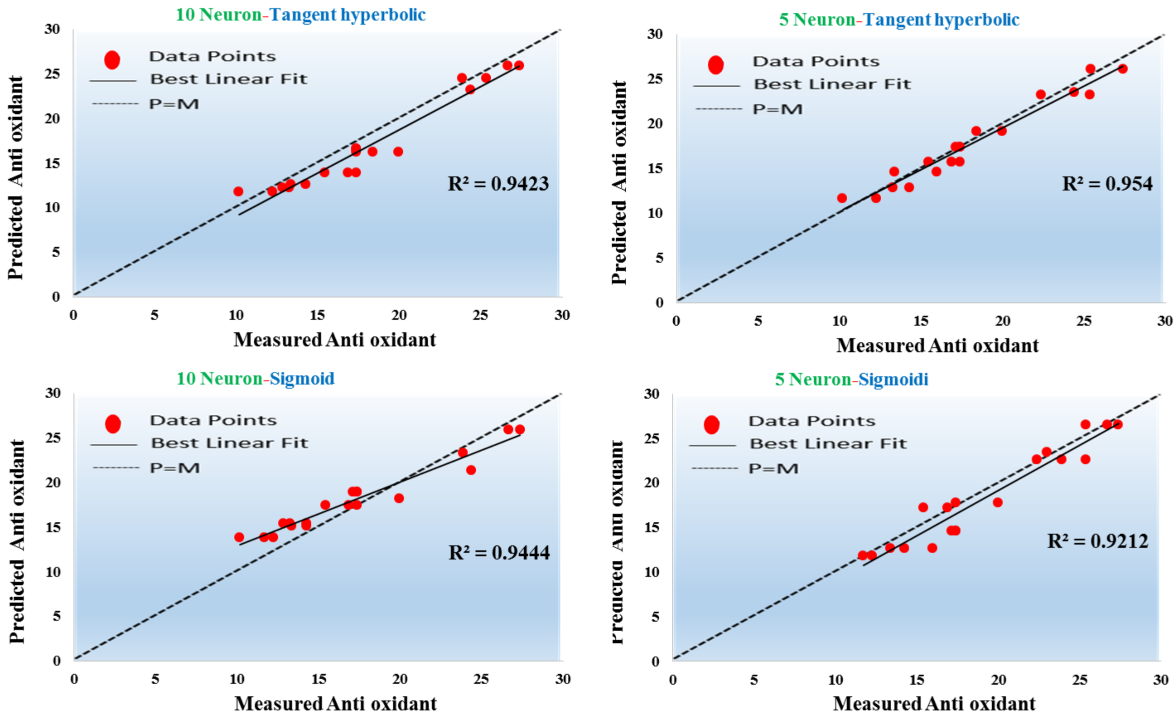

Fig. 8. Prediction of ANN and experimental values for phenol content in different networks

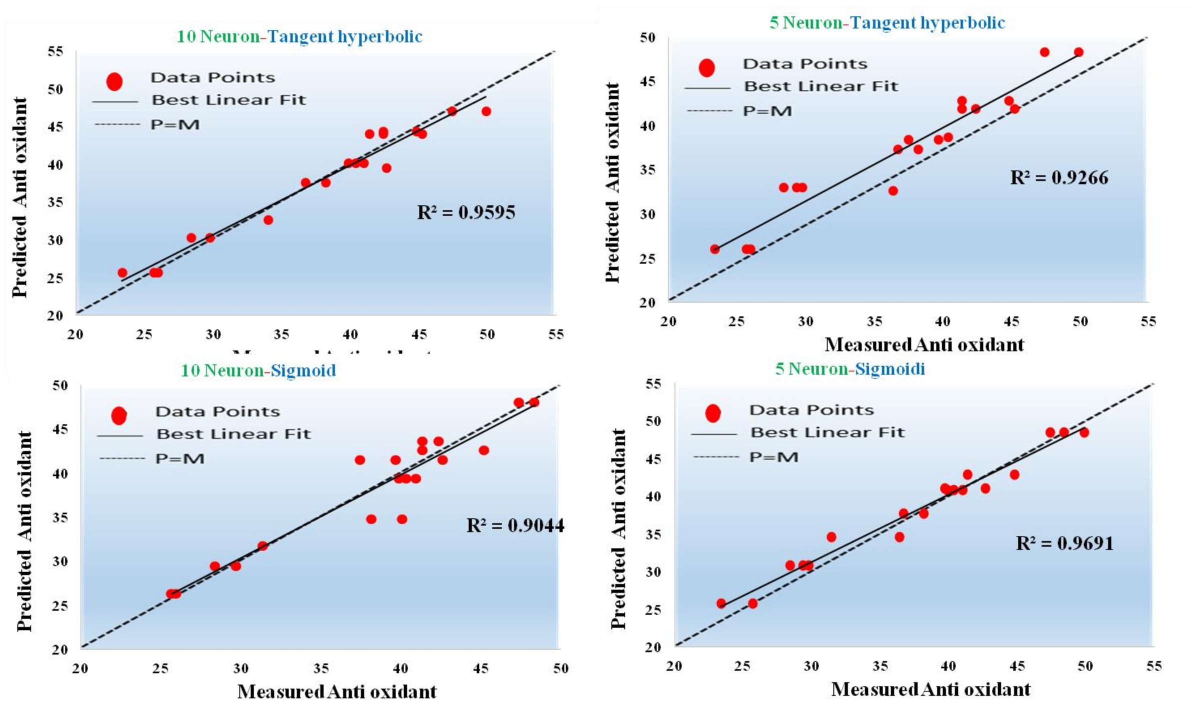

Fig. 9. Prediction of ANN and experimental values for antioxidant content in different networks

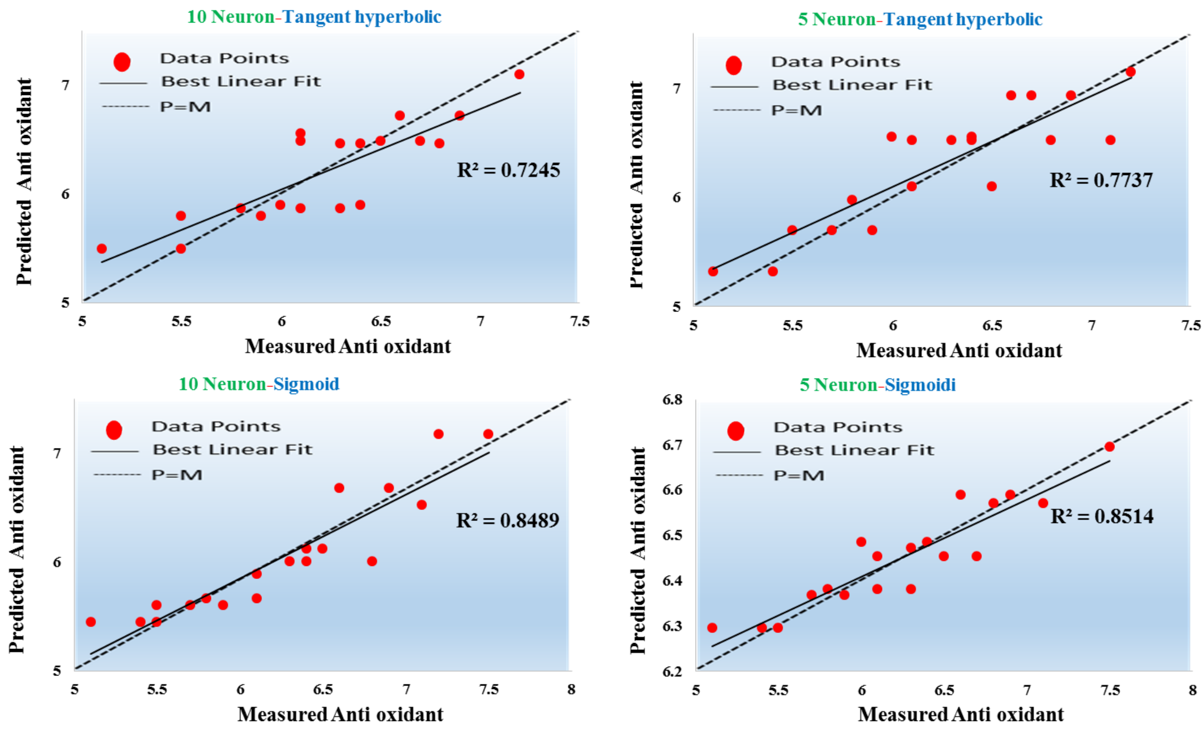

Fig. 10. Prediction of ANN and experimental values for Vitamin C in different networks

Discussion

The findings of the test data in this survey demonstrated the highest amount of MAE and RMSE as the neural network including 10 neurons in the hidden layer and activation function of sigmoid related to vitamin C, antioxidants, and the total content of phenol. Moreover, for R^2_{train} in neural network, the highest R^2 value was observed in networks with 5 neuron and sigmoid activation function for total phenol content and antioxidant and for Vitamin C. Lu et al. (2010) 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). Buciński et al. (2004) used artificial neural networks to predict antioxidant capacity of cruciferous sprouts and stated the ANN seemed to find application in the quality analysis of functional properties of food of plant origin for the predict the trolox equivalent antioxidant capacity (Buciński et al., 2004). Guiné et al. (2015), 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).

To confirm the output and target data with the aim of checking the network responses in detail, the regression analysis was conducted. The results showed that the model produced for the total phenol content and antioxidants had a sufficient accuracy in predicting, but for Vitamin C, there was not good value for the network with the hyperbolic tangent activation function, also the values obtained in the network formed by the sigmoid activation function are a bit more acceptable. The predicted values or outputs of the neural network versus the measured data (target) for total phenol content, antioxidant and Vitamin C are shown in Figures 8, 9 and 10. Regression coefficient (R^2), optimum model for total phenol content, antioxidant and Vitamin C were 0.954, 0.9691 and 0.8514, respectively. In total, the neural network has been able to produce good results. Eftekhari et al. (2018) reported good R^2 values using the artificial neural network on Grapevine (*Vitis vinifera*) Foliar Wastes. Also Cerit et al. (2017) performed on the amount of food composition using the experimental neural network, which reported that the obtained R^2 value was 0.9883, which is a good value for estimation using the neural network. (Cerit et al., 2017; Eftekhari et al., 2018).

Conclusion

According to the values obtained for the determination coefficient (R^2), ANN has been able to better estimate the wide-edge loading determination coefficient as compared 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 lower amount of RMSE and MAE related to the wide-edge loading in comparison to the thin-edge loading was estimated using ANN, therefore, ANN was determined as a better fit to estimate the higher loading force. According to the wide-edge loading force, the contents of phenol, vitamin C, and antioxidants had R^2 values of more than 0.90, as the acceptability indicator 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. The simulation figures of the network illustrate the appropriate overlap of the actual data and the simulated data. 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 what was calculated for thin-edge loading.

Conflict of interests

Authors have declared that no competing interests exist.

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