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Artificial neural networks to estimate, artichoke's antioxidant components evaluation based on the easily available soil properties

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Abstract

One of the most important requirements in planning production and processing of medicinal plants in order to obtain high yield and high-quality is the initial assessment of the soil physical and chemical properties, which can reduce the production cost by avoiding the use of unnecessary soil analysis. Artichoke (*Cynara scolymus* L.) is one of the useful and medical herbs which is considered as the plant qualitative index based on the secondary components like antioxidant components. Therefore, it is necessary to evaluate the yield performance of artichoke by means of fast and cheap methods with an acceptable accuracy. The present study aims at investigating the amount of antioxidants of artichoke by means of soil physical and chemical characteristics including: soil texture, percent of organic carbon, percent of neutralizing substances, pH, EC, CEC, phosphorus, potassium, nitrogen and apparent specific gravity by artificial neural network. So soil sampling conducted from 60 different agricultural and forest lands of Golestan Province, soil parameters measured in lab. Based on sensitive parameters different models have been designed. The results showed that all artificial neural network models were more efficient rather than multivariate regression model. The model 5 is selected with an overall view as an optimal model, as with a minimum input parameter with a function close to other models with the number of parameters. However, the number 4 model, because in the explanatory coefficient compared to the three models, will be chosen, especially in the case of the performance and cost of being selected, because with a test (soil texture), three parameters are measured. The results indicated that the neural network application was used to estimate antioxidant amount performance using soil parameters, but it is also suggested to continue to access the definitive results of similar research in this regard.

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Introduction

Artichoke plant (*Cynara scolymus* L.) is a variety of composite species. It is a perennial plant which grows to 1.5m height and has straight and grooved stems. Leaves in this plant are big and are divided into disordered and jagged pieces, the surface of the leaves is light green and underneath of them is matt and white colored due to lots of fluffs (Mahboubi, 2018). Artichoke contains big capitol with tubular red-purple flowers which are encircled around capitol. The bracts thickened in the junction point to the capitol and contains nutrition storage. The seeds are small with grooved surface and in light brown with dark brown lines (Guadalupe *et al.*, 2019).

Artificial neural network is simulated from human neural network and in fact is an imitation of human neural network and brain. Attempts have been made that this network prepares a structure to be able to learn, generalize and make decision like brain (Rao and Rao, 1996). In such structures the objective is to teach the model and to save the system performance in model memory by introducing a dynamic system performance to use it in facing with cases haven't been met before. Such systems have been recently used in Iran and especially in agricultural sciences but due to their ability to model so complicated processes with many influential factors in them, it would be possible to broadly use it in agricultural sciences. Among the applications of artificial neural networks in agricultural sciences are location prediction and precipitation time (Kaul *et al.*, 1999), predicting rainfed wheat performance (Mosaffa *et al.*, 2004) predicting evaporation and perspiration (Kumar *et al.*, 2002) and predicting CO_2 flow in ecosystems (Melesse and Hanley, 2005). No study has been conducted in the application of artificial neural network models in identification of minimum input parameters necessary to simulate the soil physical and chemical properties on artichoke leaf qualitative indices. The present study has been conducted on the determination of minimum effective input parameters on artichoke leaf qualitative indices by means of artificial neural network and the application of such networks to evaluate artichoke qualitative indices by means of soil readily available parameters in Golestan zone (Drummond *et al.*, 2003). The research objectives are: to determine the soil readily available parameters necessary to evaluate artichoke performance; to estimate the effectiveness of soil readily available parameters on artichoke performance by artificial neural network; and to determine the optimal model for soil readily available parameters, effective on antioxidant amount performance.

Materials and methods

The current study conducted in Gorgan University of Natural Resources and Agricultural Sciences Greenhouse in October 2014. The experiment conducted in random blocks design with three repetitions and in flowerpots. Agricultural soil of 60 different zones around Golestan province considered as control which transferred to the flowerpots for cultivation after collecting. Before beginning the experiment, 60 different zones selected from around Gorgan town for sampling, Table (1) and necessary agricultural harvested. Before cultivation, some of soil transferred to lab to determine some of soil physical and chemical properties, results of soil decomposition are in Table (2). Soil measured parameters were soil texture, apparent specific gravity, nitrogen, phosphor, potassium, and percent of organic carbon, percent of neutralizing substances (percent of lime), EC, pH and CEC.

In order to measure organic carbon, electrical conductivity and saturated soil paste acidity method have been used (Page *et al.*, 1987) and hydrometrical method used to determine soil texture (Movahedi and Rezaei, 1999). To measure soil nitrogen percent, amounts of ammonical nitrogen and nitrate nitrogen measured. Bremner and Mulvaney (1982) method used to measure ammonical nitrogen and Page and his colleagues (1987) method also used to measure soil potassium and sodium.

Preparing plant samples

The flowerpots filled with each of collected soils in three repetitions. Plastic flowerpots with 35cm height and 20cm diameter used in this experiment. Artichoke seeds supplied from Gorgan University of Natural Resources and Agricultural Sciences, Faculty of Gardening lab. Flowerpots soils mixed with one tenth of flowerpot volume with fine grained perlite and then watered, after some days 2 seeds planted during soil flattening and covered with a thin layer of peat moss in 2mm thickness, 7 days after planting the seeds started sprouting. During 4-leaf stage thinning conducted so as to keep a strong shrub in each flowerpot. To establish necessary and uniform conditions to grow and nourish the plants all the growing operation such as weeding and watering done manually, planting to harvesting period took 120 days.

Measuring morphological characteristics and performance components

120 days after planting, different control plants sampled in identical situations. Number of healthy leaves, number of unhealthy leaves (yellowed, dried and damaged), weight of a single shrub, and height of the shrub and length of root measured. To determine the wet weight digital 0.001 used and also 100cm ruler used to measure stem and root length.

Harvesting

When around 98% of the leaves margin turned from smooth and without thorn into toothed and serrated state, they were harvested (Baghalian and Naghdi-Badi, 2001). After harvesting the plants and the preliminary drying in the shadow, the leaves were separated and then placed in the oven for 48 hours in 45°C for the final drying and finally herb power prepared out of them.

Modeling through artificial neural network: expanding an artificial neural network necessitates designing its technical components. In order to achieve the objectives neural networks with different structures like Perceptron used to select and apply the best and the most efficient network as well as determining its error rate. Also sensitivity analysis used to achieve factors effective on antioxidants performance. At last the least Random Mean Squared Error (RMSE) and determination coefficient indices used to select the suitable and optimal model. In this study soil readily available parameters (soil texture, percent of organic carbon, percent of neutralizing substances (lime percent), nitrogen, phosphor, potassium, saltiness, acidity, cation exchange capacity, apparent specific gravity) considered as the input data and amount of antioxidants considered as the output data.

Data standardization

Basically, entering raw data reduces network speed and accuracy. To avoid from such situation and also in order to assimilate data values, input data has to be standardized before teaching the neural network. This prevents from weights to become so small (Saji Kumar and Tandavsara, 1999) meanwhile it would be possible to place neurons in a desired range and prevents from neurons early saturation by regulating input data in a specific range. Also this happens to data turns into numbers between 0 and 1, since most of threshold functions' output are numbers between 0 and 1 and the form of input data to it plays an important role in network learning. Neurons' weight variations will be the least for input near to 0 or 1, but neurons' response to input signals will be faster for input amounts near to 0.5. The following relationship is used to standardize the data:

Relationship (1)

$$X_n = 0.5 + 0.5\left(\frac{X - X_{mean}}{X_{max} - X_{min}}\right)$$

In this relationship, Xn is reagent of normalized data, X reagent of observational data and X_{mean}, X_{min}, X_{max} are reagents of mean, minimum and maximum data respectively.

Data classification

Artificial neural networks need a series of input and output data to design and teach to be able to extract the nonlinear relationships through rational analysis which is done between these data as sample and do the simulation for similar probable cases. Artificial neural networks need three clusters of educational, validation and test data for designing. Educational data used to find the relationship between observational input and output. Validation data used to control and observe the network correct learning and test data used to evaluate the suggested network evaluation. In the current study 60%, 20% and 20% of the total data assigned for teaching, validating and testing respectively.

Network designing

Percent of sand, silt and clay, organic carbon percent, soil acidity, saltiness, nitrogen, phosphor, potassium, cation exchange capacity and apparent specific gravity considered as input parameters antioxidant considered as the network output. Then 60% of data (60 soil samples) selected for model teaching, 20% of data (12 soil parameters) selected for model validation process and 20% (12 soil parameters) selected as model test data. Teaching process including weight variation among different layers during teaching period conducted to minimize the difference between real data (foe test data) and the predicted data. The educational principle of Levenberg-Marquardt and a hidden layer with Logsig threshold function and Tansig threshold function for the output layer have been used during teaching process. At last the best network structures have been selected for antioxidant amount based on the least amount of Mean Squared Error (MSE) and the most amount of Correlation Coefficient (R^2).

Evaluating model accuracy

Correlation coefficient (R^2) and RMSE used between measured and predicted data to evaluate model performance. RMSE statistics are mathematically explained as follows.

Relationship (2)

$$RMSE = \frac{\sqrt{\sum(t-a)^2}}{N}$$

In the above relationship, a and t are amounts of predicted and measured performance and antioxidant amount respectively and N is the number of data. RMSE amount shows to what extent the predictions have estimated the measure more or less. If the measured and the predicted amounts be equal RMSE will be 0. Correlation coefficient is also archived by line fitness between predicted data against measured data.

Sensitivity analysis

Sensitivity analysis process provides the model designer and architect with valuable information about model sensitivity to input variables. Identifying input variables effect on model prediction accuracy makes it possible to omit less effective variables from the network and to expand and develop a simpler model. In the other words, sensitivity analysis is used to detect which of the 12 parameters (inducing percent of sand, silt and clay, organic carbon percent, ...) has had the most effect on performance and antioxidant amount and its variation has had the most sensitivity. Coefficient without sensitivity dimension used in this study to do model sensitivity analysis (Hill, 1998) as follows: first 12-parameter model (without any variation in input) entered the network and the output extracted (control). Then one of the variables changed 10% and the other ones remained stable, the changed variable entered the network and finally the output network is calculated. Now the difference between these two outputs (control with changed) is calculated based on relationship (3-18):

Equation (3)

$$\delta\hat{y}_i = \hat{y}(i+0.1) - \hat{y}$$

Where, $\hat{y}(i+0.1)$ is the output one of corresponding inputs with that has changed 10% and network predicts it. $\hat{y}i$ is the output that network predicts it regardless of any variation in its inputs (control). Next, sensitivity coefficient is calculated for each of the patterns based on relationship (3-19), which is in fact demonstrative of model sensitivity to parameter in j^{th} observational data.

Equation (4)

$$ss_{ij} = \left(\frac{\delta\hat{y}_i}{\delta\beta_i}\right)\beta_j$$

Where, it is demonstrative of j[th] input variable to model.

Equation (5)

$$\delta\beta_j = 0.1\beta_j$$

$\beta\delta j$ is also the changed input which is calculated by (3-20) relationship (in this study the variables has changed 10%). These stages perform for all inputs, in the other words each time of the inputs are changed 10% and other variables are considered stable. In order to calculate model sensitivity, Composite Sensitivity Coefficient (CSS) used for all observations. (Hill, 1998) defined the amount of this coefficient for j[th] parameter as the following;

Equation (6)

$$CSS_i = \left(\frac{1}{N}\sum_{i=1}^{N} ss_{ij}\right)^{\frac{1}{2}}$$

Equation (3-22) is in fact the sensitivity coefficient average for each input. For simpler comparison, different variables CSS amounts has used CSS relative amount known as relative sensitivity coefficient (γ) as the following:

Equation (7)

$$\gamma = \frac{CSS_i}{max(CSS)}$$

Where, max (CSS) is the maximum amount of CSS for all input variables to the model. The most amount is equal with the unit and is related to a parameter with the maximum of CSS.

Data analysis

SPSS employed to compare different control group characteristics mean. Also in order to evaluate performance (weight of single shrub) of artichoke, Matlab artificial neural; network software was used.

Results and discussion

Variables description: experimental and field data have to be ordered as a mass of raw numbers for each type of statistical study or calculation.

Regulating numerical data and drawing their diagram is the first stage of statistical analysis.

Table 1. Statistical description of soils' chemical properties.

Parameter	Minimum	Maximum	Mean	Coefficient of variation	Chologi
Organic carbon	0.12	3.97	1.21	0.55	2.08
%TNV	0.5	36.3	15	0.69	0.26
CEC	7.02	26.2	10.85	0.26	2.80
EC	0.3	1.88	0.47	0.47	4.95
pH	6.12	8.08	7.67	0.038	3.59
N	0.02	0.9	0.12	0.89	5.64
P	4	86	16.7	1.04	2.94
K	106	754	303.47	0.40	1.07

This data contains important and useful information until be ordered. Tables 1 and 2 have summarized the statistical description of soils physical and chemical properties related to 60 soil samples, respectively. Soil variability is the key element in soil spatial specific management and provides valuable information about the nature of soil characteristics in farms (Ayoubi *et al.*, 2008). According to Table 1, pH has the least variations coefficient (0.038%) among physical and chemical variables. However, P variations coefficient has been higher and equal with 1.04 among chemical variables.

Skewness coefficient amounts in Tables 1 and 2 demonstrates that besides lime, potassium, sand, silt, clay and BD parameters which have normal distribution and have -1 to +1 skewness coefficient, other parameters have normal log distribution.

Artificial neural network modeling

This section shows results of the best artificial neural network structure by 12 input parameters for 60 soil samples. Also sensitivity analysis and its results are represented in the following. This study has used multilayer perceptron and transfer function in hidden layer and output layer, number of hidden layers, number of neurons in hidden layer for network were experiment and the best structure for antioxidant amount achieved by trial and error.

Selecting the best network for predicting antioxidant amount is also based on the least amount of RMSE and the most amount of R^2.

Table 2. Statistical description of soils' physical properties.

Parameter	Minimum	Maximum	Mean	Coefficient of Variation (CV)	Chologi
Sand	12	74	32.05	0.43	0.55
Silt	11	83	44.27	0.31	0.17
Clay	4	39	23.23	0.38	-0.35
Bd	0.85	2.16	1.66	0.16	-1.38

The best arrangement of hidden layer with Levenberg-Marquardt educational logarithm as a hidden layer, 34 neurons, Logsig threshold function for hidden layer and Tansig for output layer have been selected in modeling antioxidant amount with 12 parameters for 60 soil samples. Table 3 shows calculated statistical parameters for generated model during teaching, validation, testing and total stages for antioxidant amount respectively.

It is possible to obtain information about model performance through given fitness line gradient amount between predicted data against measured data.

Table 3. Calculated statistical parameters for stages of teaching, validation, testing and total in 12-parameter model for antioxidant components.

Level	R^2	RMSE
Education	0.99	0.001
Validation	0.99	0.003
Test	0.99	0.003
Total	0.99	0.002

Table 4. Results of soil readily available sensitivity analysis for antioxidant components.

Parameter	Relative sensitivity coefficient (γ)
pH	0.66
OC (%)	0.89
K	0.64
TNV (%)	0.96
CEC	0.58
EC	0.48
Bd	0.47
N	0.52
Clay	0.59
Silt	1
Sand	0.61
P	0.60

If given fitness line gradient be 1 between predicted data against measured data, it demonstrates that predicted amounts are equal with the measured amounts. Fig. 1 show given fitness line equation between predicted data with model against measured data of antioxidant amount during stages of model teaching and testing. According to Fig. 1 given fitness line gradient is 1 and 1 for antioxidant amount respectively which demonstrates the approximation of predicted data with measured ones and since R^2 is 0.99 and 0.99 in teaching and testing stages respectively, it is concluded that according to high amount of R^2 and less amount of RMSE this model's evaluation enjoys good accuracy.

Table 5. Design of different artificial neural network models due to the sensitivity analysis and minimum number of tests to obtain model inputs.

Model	Input parameter	Number of experiments
Model 1	Organic carbon	1
Model 2	TNV%	1
Model 3	PH	1
Model 4	Texture	1
Model 5	Organic carbon + lime %	2
Model 6	PH + Organic carbon	2
Model 7	PH + lime %	2
Model 8	Texture + Organic carbon	2
Model 9	PH + Organic carbon + lime %	3
Model 10	PH + Organic carbon + lime %	4

Table 6. Statistical parameters calculated for the stages of education, validation, test and total in the model (1) for antioxidant components.

Level	R^2	RMSE
Education	0.20	0.078
Validation	0.17	0.086
Test	0.15	0.073
Total	0.18	0.079

In this stage, a very accurate model has achieved to evaluate amount of antioxidant by means of 12 readily available parameters of soil. But since the objective of the current study is the fast and easy evaluation (less time and cost) of antioxidant amount by means of soil readily available parameters, so applying this model contradicts with the objectives of the present study, because it takes so much time and cost to measure 12 parameters. Therefore, it is possible to identify parameters sensitive to the evaluation of antioxidant amount by means of sensitivity analysis and then different models whose inputs are generated by means of the least number of experiments and less parameters by means of these sensitive parameters as the model inputs in order to evaluate antioxidant amount performance.

Table 7. Statistical parameters calculated for the stages of education, validation, test and total in Model (2) for antioxidant components.

Level	R^2	RMSE
Education	0.56	0.064
Validation	0.28	0.089
Test	0.22	0.092
Total	0.41	0.076

Sensitivity analysis

In the experiments related to plant, chlorophyll, carotenoid, antioxidant, phenol, flavonoid and antioxidant amount measured, but due to the importance of antioxidant amount (performance) only the tow parameters modeled. According, saltiness was the most sensitive parameter for chlorophyll, percent of neutralizing substances (lime percent) for carotenoid, organic carbon percent for phenol and acidity for flavonoid.

Table 8. Statistical parameters calculated for the stages of education, validation, test and total in Model (3) for antioxidant components.

Level	R^2	RMSE
Education	0.18	0.082
Validation	0.15	0.086
Test	0.10	0.075
Total	0.15	0.082

Table 9. Statistical parameters calculated for the stages of education, validation, test and total in Model (4) for antioxidant components.

Level	R^2	RMSE
Education	0.79	0.047
Validation	0.51	0.080
Test	0.37	0.090
Total	0.63	0.065

After modeling performance amount of antioxidant with 12 parameters by artificial neural network and achieving the best network regarding statistical parameters, sensitivity analysis without sensitivity dimension (Hill, 1998) conducted. Tables 4 show sensitivity results for single shrub weight performance. Hill (1988) maintained that if a parametric sensitivity coefficient be more than 0.1, that parameter belongs to model sensitive parameters. According to Hill (1998), performance antioxidant amount is sensitive to ail parameters. Total sensitivity coefficients of soil 12 different parameters has to be the basis of modeling for both output parameters of performance antioxidant amount. Nut since the objective of this study is to estimate antioxidant amount with the least number of experiments and the necessary parameters, Table 4 determined the most sensitive parameter regarding priority in evaluating antioxidant amount and accordingly evaluating antioxidant amount have been modeled. Based on Table 4 parameters coefficient amounts has decreased (parameters sensitivity has been decreased).

The results show that artichoke's performance antioxidant amount has the most sensitivity to pH and has the least sensitivity to soil phosphor and artichoke's to soil apparent specific gravity.

Table 10. Statistical parameters calculated for the stages of education, validation, test and total in Model (5) for antioxidant components.

Level	R^2	RMSE
Education	0.89	0.038
Validation	0.83	0.049
Test	0.80	0.053
Total	0.86	0.044

Designing different models of artificial neural network by sensitive parameters

As mentioned earlier in this study, the objective of this study was to evaluate less, more available and naturally lower cost input parameters, performance antioxidant amount. Thus, Table 5 shows how 4 soil readily available parameters which have more sensitivity in evaluating antioxidant amount have generated different models of artificial neural networks by increasing the number of input parameters and the number of conducted experiment respectively.

Table 11. Statistical parameters calculated for the stages of education, validation, test and total in model (6) for antioxidant components.

Level	R^2	RMSE
Education	0.66	0.058
Validation	0.52	0.073
Test	0.50	0.076
Total	0.59	0.065

Table 12. Statistical parameters calculated for the stages of education, validation, test and total in model (7) for antioxidant components.

Level	R^2	RMSE
Education	0.84	0.043
Validation	0.72	0.058
Test	0.61	0.056
Total	0.78	0.049

In the model (1) due to the maximum sensitivity coefficient of organic carbon, only the organic carbon parameter is created as the artificial neural network model.

In the model (2), with the Lime percent parameter, the artificial neural network model is created.

In the model (3) with the pH parameter, the artificial neural network model is created.

In model (4) with the parameters of clay, silt and gravel, the artificial neural network model is created.

In model (5) the lime percentage parameter is added to the model (1).

In the model (6), the pH parameter was added to the model (1).

In the model (7), the pH parameter (2) was added to the model.

In model (8) the texture parameter was added to the model (1).

In the model (9), the pH parameter was added to the model (5).

In models (10), the texture parameter was added to the model (9).

Table 13. Statistical parameters calculated for the stages of education, validation, test and total in model (8) for antioxidant components.

Level	R^2	RMSE
Education	0.99	0.002
Validation	0.83	0.056
Test	0.69	0.078
Total	0.88	0.043

The overall expectation of models 1 to 10 is that by increasing the number of input parameters to models (model 1 to model 10), the R2 and RMSE values in a general view have the process of recovery in order to have a reduced R^2 level and the RMSE decreased.

The results of artificial neural network models with an experiment conducted in obtaining model inputs

Model results (1): In model number (1), the amount of single plant weight and antioxidant rate were estimated according to the organic carbon parameter. The best hidden layer makeup with Markwart - Levenberg educational algorithm was selected as a hidden layer, 34 neuron, and LOGSIG threshold function for hidden layer and Tansig for the output layer. Table 6 statistical parameters calculated for the stages of education, validation, test and total in the model (1) for antioxidant amount.

Table 14. Statistical parameters calculated for the stages of education, validation, test and total in model (9) for antioxidant components.

Level	R^2	RMSE
Education	0.86	0.041
Validation	0.83	0.052
Test	0.79	0.048
Total	0.84	0.045

Table 15. Statistical parameters calculated for the stages of education, validation, test and total in Model (10) for antioxidant components.

Level	R^2	RMSE
Education	0.99	0.002
Validation	0.88	0.044
Test	0.78	0.059
Total	0.92	0.033

Fig. 2 and 3 R2 index and the equation of the fitted line between the predicted data against the measured data showed antioxidant amount performance in the stages of training and test for the model (1). As shown in Fig. 2 and 3, the slope of the fitted line in the performance of antioxidant amount in the stages of training and test were 0.99 and 1.02, which expressed the approaching data predicted by the data of measurement, but due to the clarification coefficient in training and testing stages for antioxidant amount performance, it is concluded that the model is accurate estimation of antioxidant amount performance. Also, the level of explanatory in antioxidant amount performance compared to multivariate regression results was better at the test stage.

Table 16. Comparison of RMSE and R^2 in different models at the test stage in antioxidant components.

Model	RMSE	R^2
1	0.073	0.15
2	0.092	0.22
3	0.064	0.34
4	0.090	0.37
5	0.053	0.8
6	0.076	0.5
7	0.056	0.61
8	0.078	0.69
9	0.048	0.79
10	0.059	0.78
Multivariate regression	0.99	0.08

Results of Model (2): in model number (2) the antioxidant content was estimated based on the lime percentage parameter. The best hidden layer makeup with Markwart-Levenberg educational algorithm was selected as a hidden layer, 34 neuron, LOGSIG threshold function for hidden layer and Tansig for the output layer. Table 7 the statistical parameters calculated for the stages of education, validation, test and total in the model (2) in order for antioxidant amount performance and antioxidant rate. Fig 4 and 5, R2 index and the equation of the fitted line between the predicted data against the data measured in the antioxidant amount in the stages of training and test for models (2) and Fig 6 of the R2 index and the equation of the fitted line is between data Predicted in contrast to the measured data show antioxidant function in the stages of training and testing for Model 2.

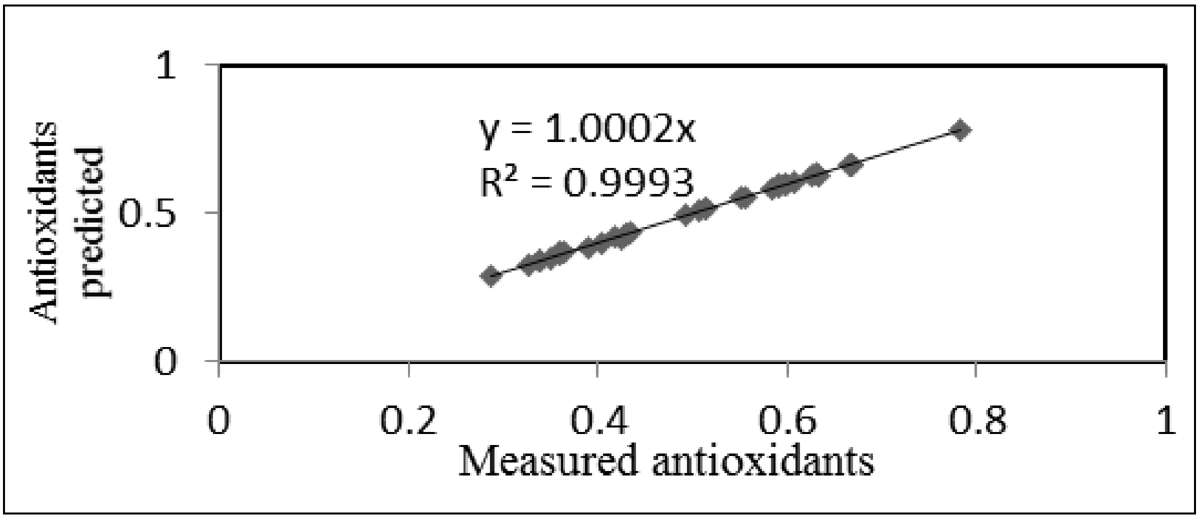

Fig. 1. Given fitness line between predicted data against measured data of antioxidant components in teaching stage in 12-parameters model.

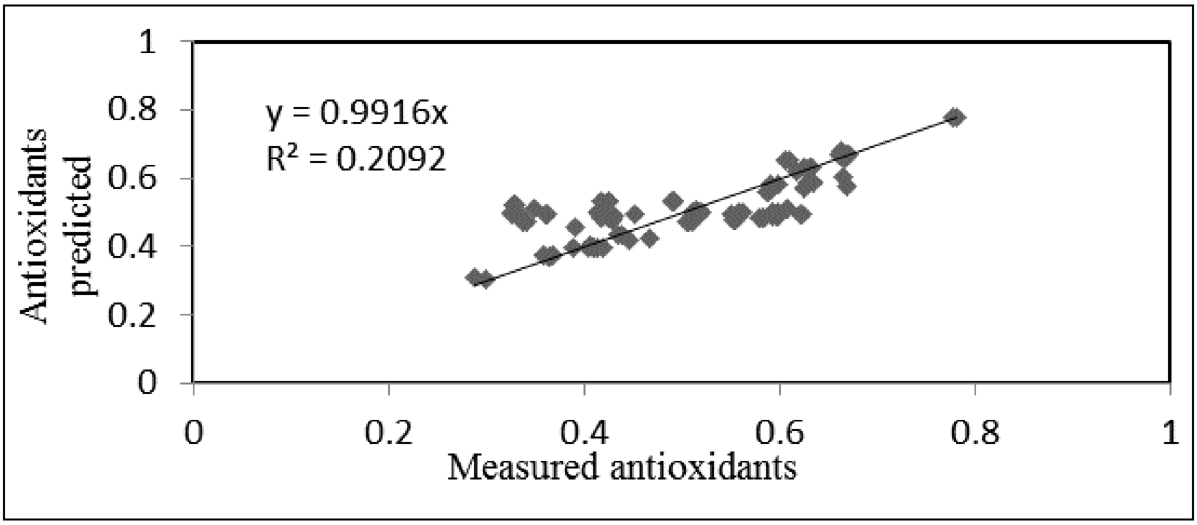

Fig. 2. The fitted line between the predicted data against the measured data of the antioxidant components in the training phase of the model (1).

As seen in the Fig 7, the slope of the fitted line in the performance of antioxidant amount in the training and test stages, respectively 0.98 and 1.04 and in the form of Fig 4 and 5, the slope of the fitted line in the process of training and tests, which indicates the approaching predicted values with data measured in the model (2). Also, the explanatory coefficient in the training and testing stages in the antioxidant amount were 0.56 and 0.22, respectively. Although the slope of the line in this model in the stages of education and testing, is close to 1 and the explanatory coefficient for antioxidant amount was higher in the stages of training and test compared to the previous model, however, the model does not have acceptable accuracy in estimating single-plant weight performance and antioxidant rate. Also, the level of explanation in plant weight was better than the multivariate regression results at the test stage.

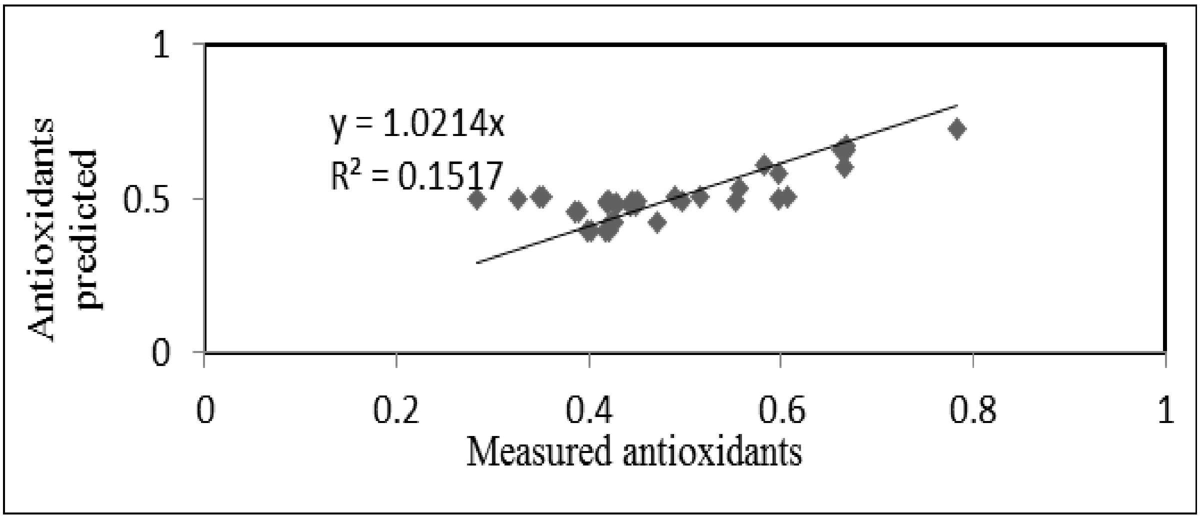

Fig. 3. The fitted line between the predicted data in front of the measured data of antioxidant components in the test stage model (1).

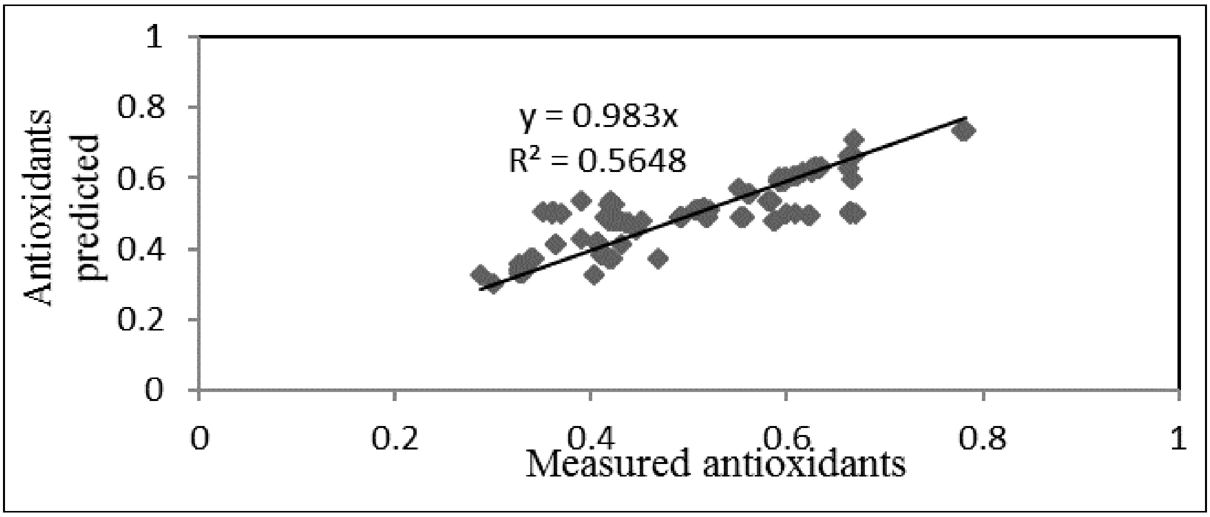

Fig. 4. The fitting line between the predicted data in front of the measured data of antioxidant components in the training Stage model (2).

Model results (3): In model number (3), the yield value of antioxidant content were estimated based on the Ph Parameter. The best hidden layer makeup with Markwart -Levenberg educational algorithm was selected as a concealed layer, 34, and the LOGSIG threshold function for the hidden layer and Tansig in the output layer. Table 8 the statistical parameters calculated for the stages of training, validation, test and Total (3) in order to antioxidant rate. Fig 6 and 7 R2 index and the equation of the fitted line between the predicted data against the measured data of antioxidant amount in the stages of training and test for model (3) of the R2 index and the equation of the fitted line between the data were Predicted in contrast to the measured data shows the antioxidant function in the training and testing stages for the Model (3).

As shown in Fig. 6 and 7, the slope of the fitted line for antioxidant function according to the Fig. 6 and 7, respectively, were 0.98 and 1.02, which indicates that the approaching predicted values with the measured data are in the Model (3). Also, the explanatory coefficient in training and testing stages in antioxidant amount performance were 0.18 and 0.10, respectively. The slope rate of the line in this model is not significantly different from the previous model, and the explanation in the stages of training and test compared to the previous model on the yield of plant weight, but still has the value of the explanation in the training and test stages of the model, and the Model (3) also does not have acceptable accuracy in estimating plant weight performance.

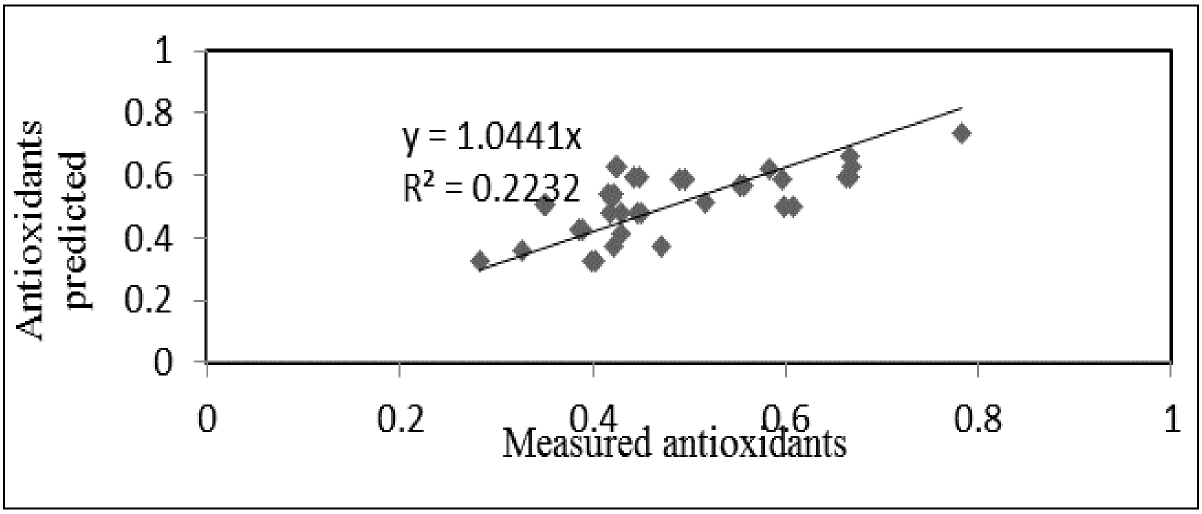

Fig. 5. The fitting line between the predicted data in front of the measured data of antioxidant components in the test stage model (2).

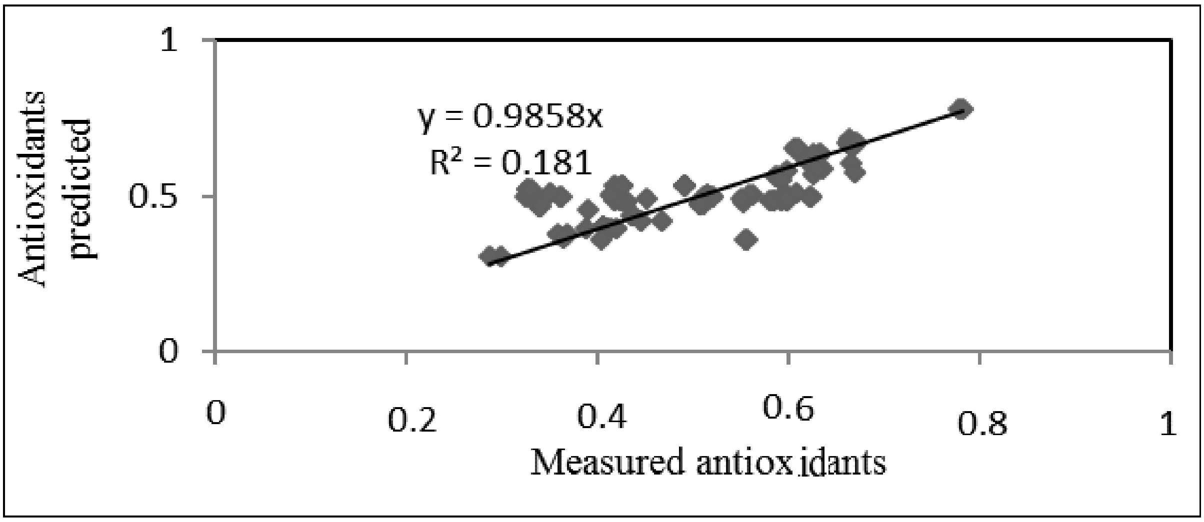

Fig. 6. The fitting line between the predicted data in front of the measured data of antioxidant components in the training stage model (3).

Also, the level of explanation in plant weight performance was better than the multivariate regression results at the test stage.Model results (4): In model number (4) the performance of antioxidant amount were estimated based on soil texture parameters. The best hidden layer makeup with Markwart -Levenberg educational algorithm was selected as a hidden layer, 34 neuron, LOGSIG threshold function for hidden layer and Tansig for the output layer. Table 9 the statistical parameters calculated for the stages of education, validation, test and total in the model (4), respectively, for antioxidant rate. The Fig. 8 and 9, R2 index and the equation of the fitted line between the predicted data against the measured data of antioxidant amount performance in the stages of training and test for model (4). As seen in Figure 8 and 9, the fitting line slope of antioxidant amount performance in the stages of training and test were 0.99 and 1.01, in training and test stages, indicating the approaching predicted values with measured data in the model (4). Also, the explanatory coefficient in the process of training and test in antioxidant amount performance were 0.79 and 0.37, respectively.

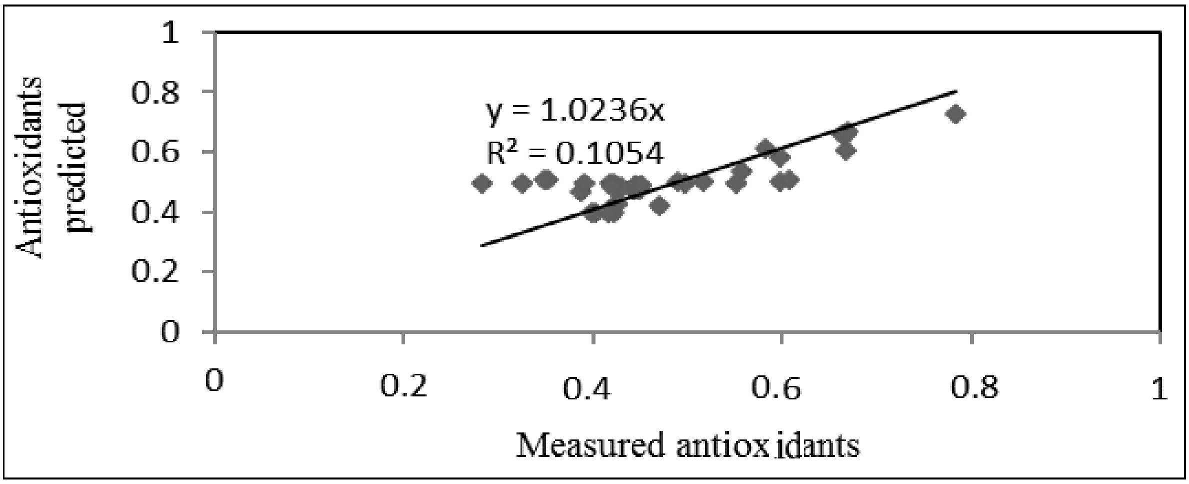

Fig. 7. The fitted line between the predicted data against the measured data of the antioxidant components in the test stage model (3).

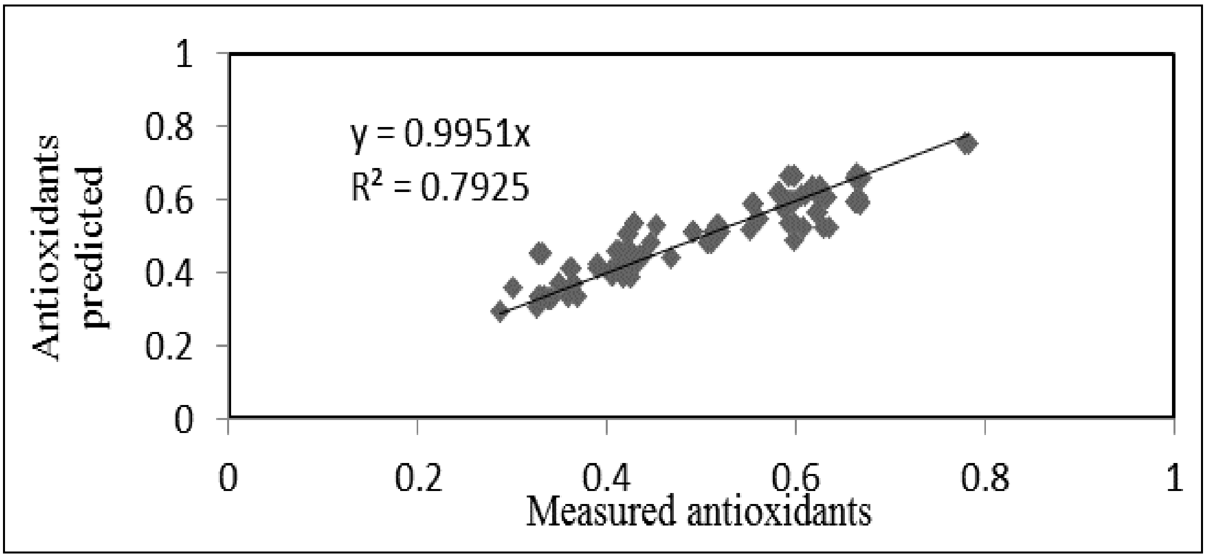

Fig. 8. The fitting line between the predicted data in front of the measured data of antioxidant components in the model of education (4).

The amount of line slope in the plant weight of this model in the test stage compared to previous models has little difference, and the explanation in the stages of training and testing was increased compared to previous models in antioxidant amount, and also acceptable accuracy in estimating antioxidant amount performance. Also, the level of explanation in antioxidant amount was better than the multivariate regression results at the test stage.

Artificial neural network models with two experiments conducted in obtaining the model inputs

Model results (5): In model number (5) the antioxidant amount was estimated based on the parameters of organic carbon and lime. The best hidden layer makeup with Markwart -Levenberg educational algorithm was selected as a hidden layer, 45 neuron, LOGSIG threshold function for hidden layer and Tansig for the output layer. Table 10 statistical parameters calculated for the stages of education, validation, test and total in the model (5) for the performance of antioxidant amount function.

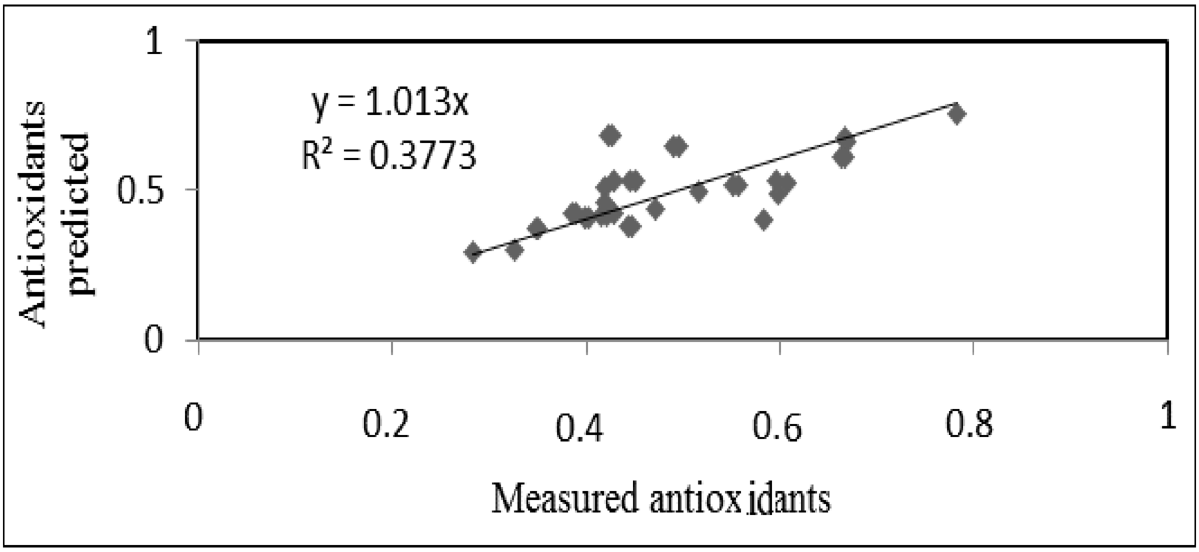

Fig. 9. The fitting line between the predicted data in front of the measured data of antioxidant components in the test stage in the Model (4).

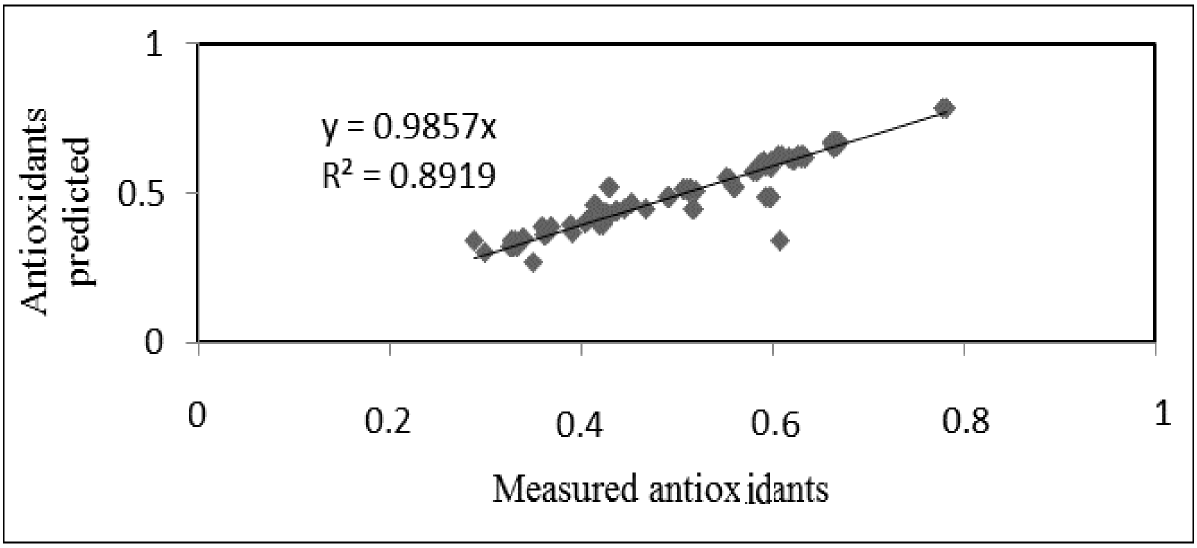

Fig. 10. The fitting line between the predicted data in the front of the measured data of antioxidant components during the training stage in model (5).

The Fig. 10 and 11 indicate R^2 index and fit line equation of the pre-predicted data were measured in front of the measurement data of plant weight in training and test stages for model (5). As shown in Fig. 10 and 11, the slope of the fitted line for antioxidant amount performance is 0.98 and 0.97, which indicates the approaching predicted values with the measured data in the model (5).

Also, the explanatory coefficient in training and testing stages in antioxidant amount performance were 0.89 and 0.80, respectively.

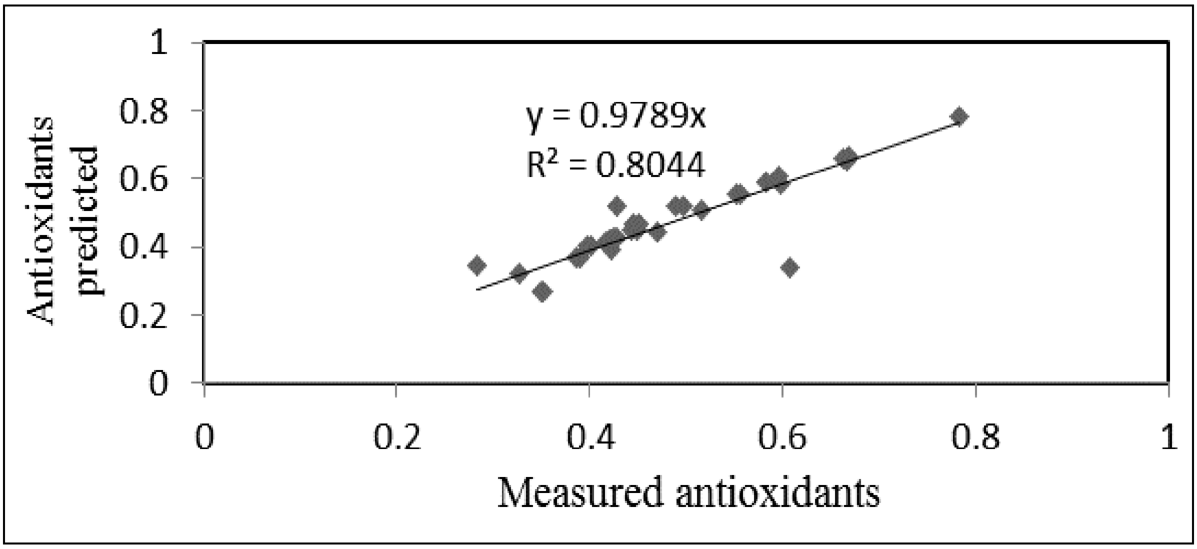

Fig. 11. The fitted line between the predicted data in front of the data measured by the two female operations in the test stage in the model (5).

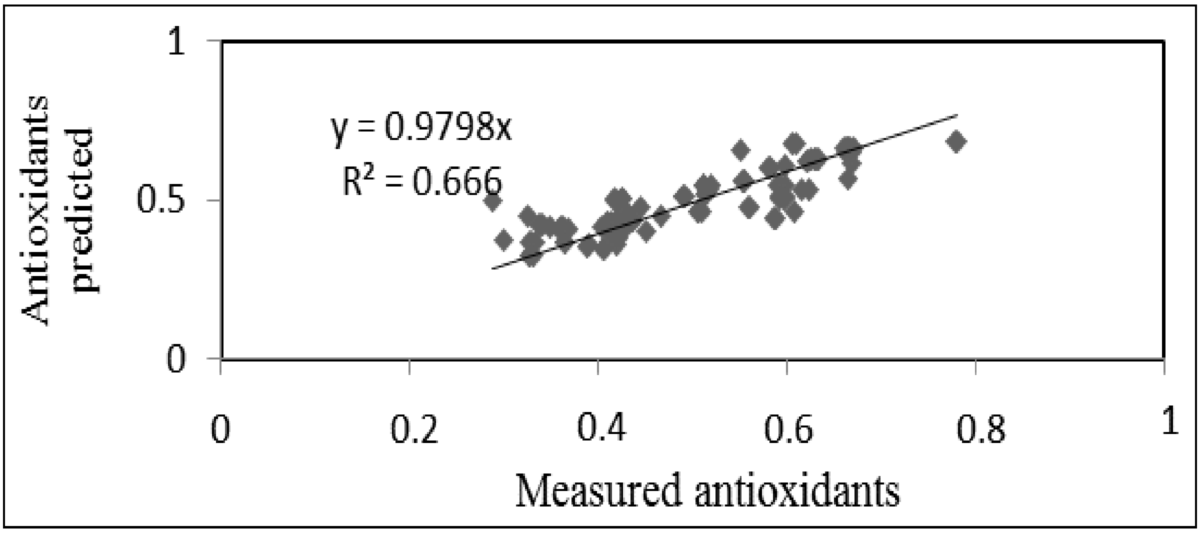

Fig. 12. The fitting line between the predicted data in the front of the measured data of antioxidant components during the training stage in model (6).

The slope rate of the line in this model has no difference in the stages of training and test in both antioxidant amount compared to other models. According to the mentioned points, the level of explanation in antioxidant amount performance was better than the multivariate regression results at the test stage.

Model results (6): In model number (6) the antioxidant amount was estimated according to the parameters of the organic pH and carbon. The best hidden layer makeup with Markwart -Levenberg educational algorithm was selected as a hidden layer, 34 neuron, LOGSIG threshold function for hidden layer and Tansig for the output layer. Table 11 indicates statistical parameters calculated for the stages of training, validation, testing and total in model (6) for antioxidant amount performance.

Figures 12 and 13 show R^2 index and the equation of the fitted line between the predicted data against the measured data of antioxidant amount in the stages of training and test for model (6). As seen in the Fig. 12 and 13, the slope of the fitted line for antioxidant amount performance is 0.97 and 1, respectively. Also, the explanatory coefficient in training and testing stages in antioxidant amount performance were 0.66 and 0.50, respectively. According to the mentioned points, this model does not have acceptable accuracy for estimating antioxidant amount performance. Also, the level of explanation in antioxidant amount performance was better than the multivariate regression results at the test stage.

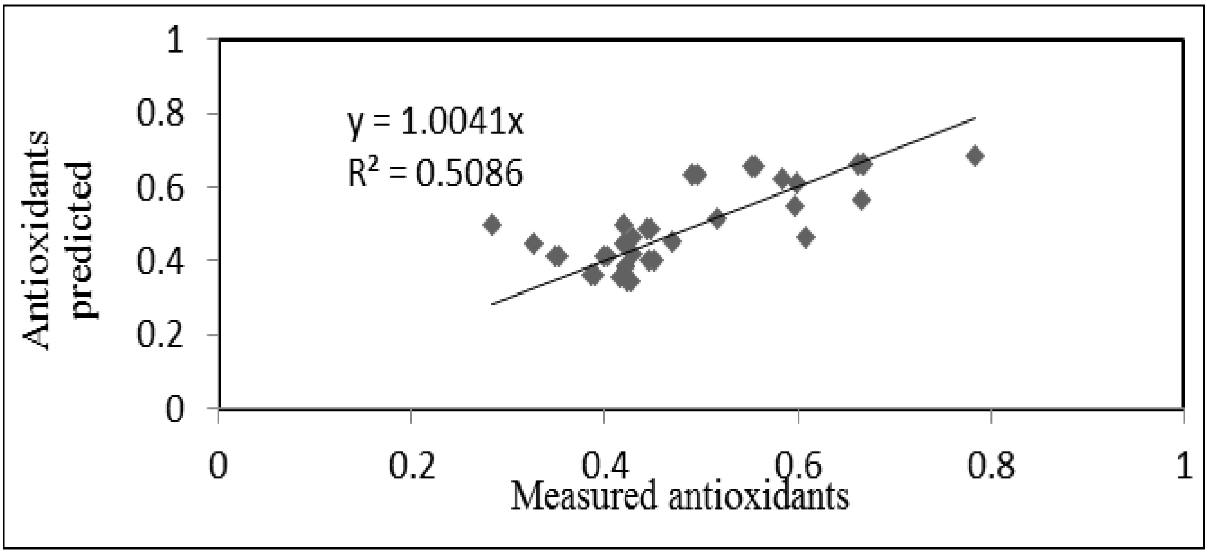

Fig. 13. The fitting line between the predicted data in front of the measured data of antioxidant components in the test stage in the Model (6).

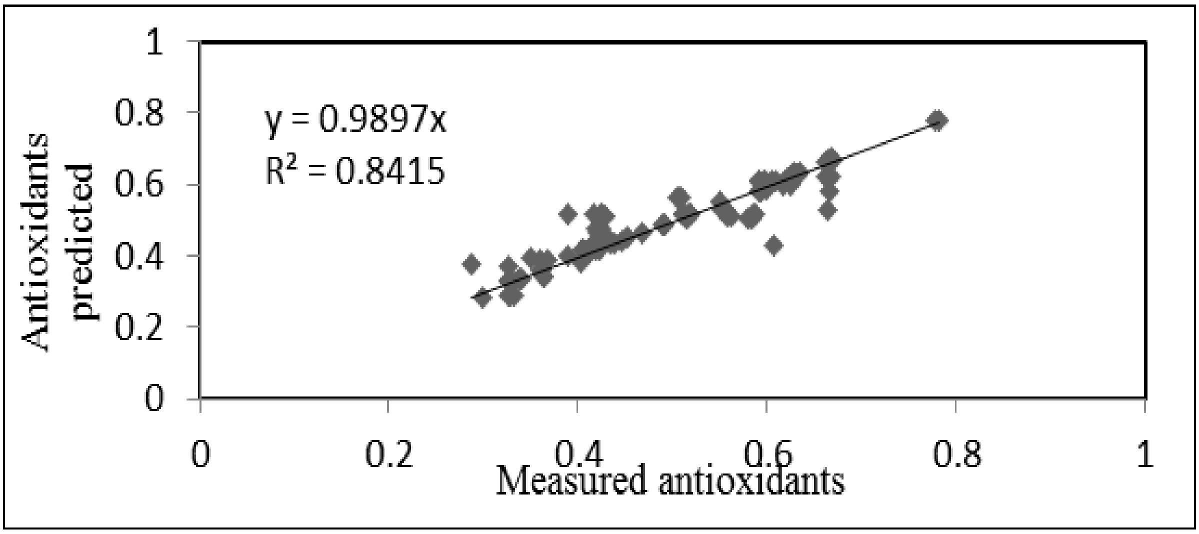

Fig. 14. The fitted line between the predicted data in front of the measured data of the two female operations in the training stage in the model (7).

Model results (7): In model number (7) the antioxidant amount was estimated based on the lime and pH parameters. The best hidden layer makeup with Markwart -Levenberg educational algorithm was selected as a hidden layer, 45 neuron, LOGSIG threshold function for hidden layer and Tansig for the output layer. Table 12 shows statistical parameters calculated for the stages of education, validation, testing and total in model (7) for antioxidant amount performance. Fig. 14 and 15 show R^2 index and the equation of the fitted line between the predicted data against the measured data of antioxidant amount in the stages of training and test for model (7). As shown in the Fig. 14 and 15, the slope of the fitted line for antioxidant amount performance is 0.98 and 1. Also, the explanatory coefficient in training and testing stages in antioxidant amount performance were 0.84 and 0.61, respectively. But this model is not acceptable for antioxidant amount. Also, the level of explanation in antioxidant amount was better than the multivariate regression results at the test stage. Model results (8): In model number (8) the amount of antioxidant amount was estimated based on soil and organic carbon texture parameters.

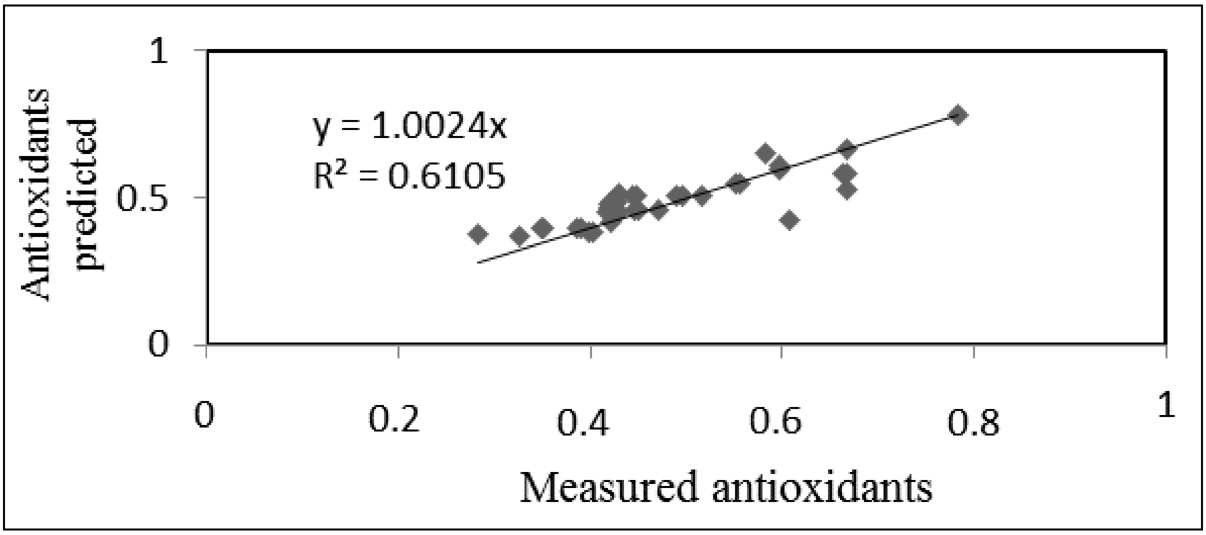

Fig. 15. The fitting line between the predicted data in front of the measured data of antioxidant components in the test stage in the model (7).

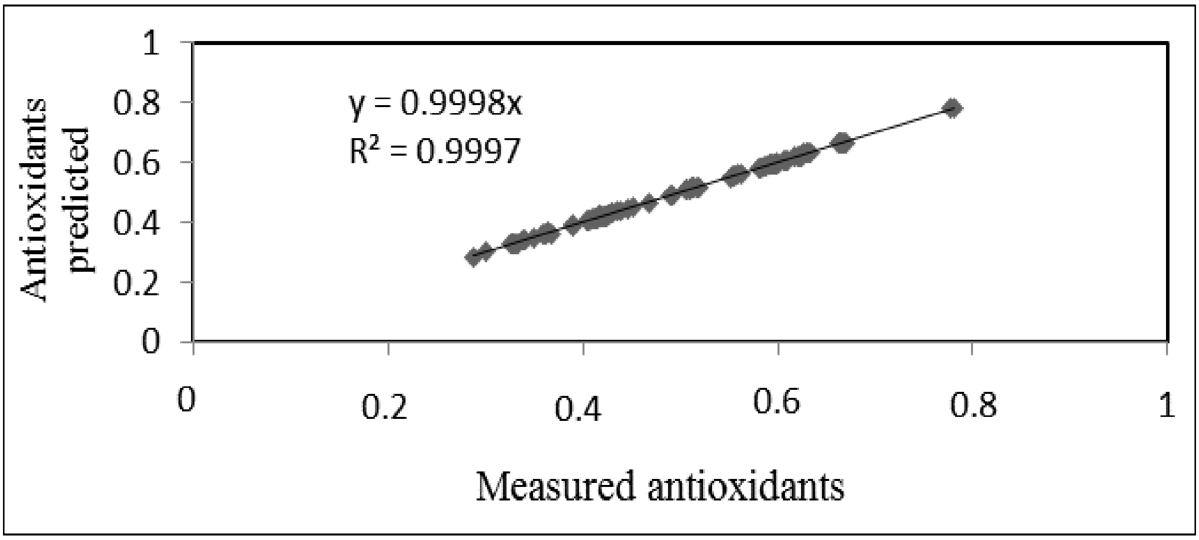

Fig. 16. The fitting line between the predicted data in front of the measured data of antioxidant components during the training stage in model (8).

The best hidden layer makeup with Markwart - Levenberg educational algorithm was selected as a hidden layer, 34 neuron, LOGSIG threshold function for hidden layer and Tansig for the output layer. Table 13 indicates statistical parameters calculated for the stages of training, validation, testing and total in model (8) for antioxidant amount performance. Fig. 16 and 17 indicate R^2 index and the equation of the fitted line between the predicted data against the measured data of antioxidant amount in the training and test stages for model (8). As shown in Fig. 16 and 17, the slope of the fitted line for antioxidant amount performance is 0.99 and 1.01. Also, the explanatory coefficient in training and testing stages in antioxidant amount performance were 0.99 and 0.69 level of explanation in antioxidant amount performance was better than the multivariate regression results at the test stage. The results of artificial neural network models with three experiments conducted in obtaining the model inputs: Model Results (9): in model number (9) the amount of antioxidant amount was estimated based on the parameters of organic carbon, the percentage of lime and pH.

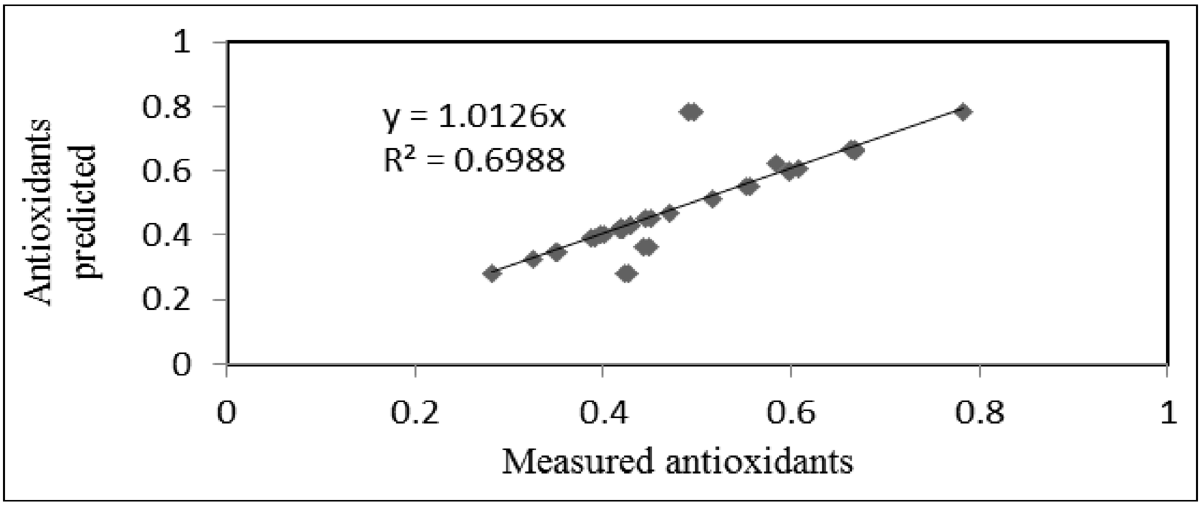

Fig. 17. The fitting line between the predicted data in front of the measured data of antioxidant components in the test stage in the model (8).

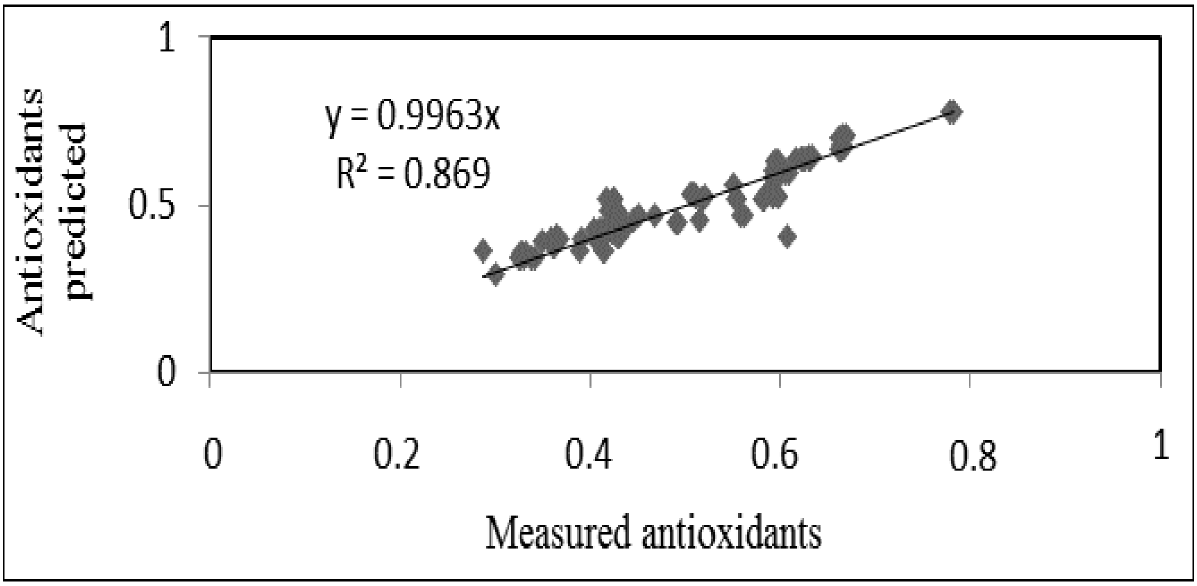

Fig. 18. The fitting line between the predicted data in front of the measured data antioxidant components during the training stage in model (9).

The best hidden layer makeup with Markwart - Levenberg educational algorithm was selected as a hidden layer, 34 neuron, LOGSIG threshold function for hidden layer and Tansig for the output layer. Table 14 indicates statistical parameters calculated for the stages of training, validation, testing and total in model (9) for antioxidant amount performance. Fig. 18 and 19 indicate R^2 index and the balanced line equation between the predicted data against the measured data of antioxidant amount in the stages of training and test for model (9). As seen in Fig. 18 and 19, the slope of the fitted line for the operation of the antioxidant amount is 0.99 and 1.01. Also, the explanatory coefficient in training and testing stages in antioxidant amount performance were 0.86 and 0.79, respectively. This model was acceptable for antioxidant amount. Also, the level of explanation in antioxidant amount performance was better than the multivariate regression results at the test stage.

Artificial neural network models with four experiments conducted in obtaining the model inputs

Model results (10): In model number (10) the amount of antioxidant amount was estimated based on the parameters of organic carbon, soil texture, limestone percentage and pH. The best hidden layer makeup with Markwart -Levenberg educational algorithm was selected as a hidden layer, 34 neuron, LOGSIG threshold function for hidden layer and Tansig for the output layer.

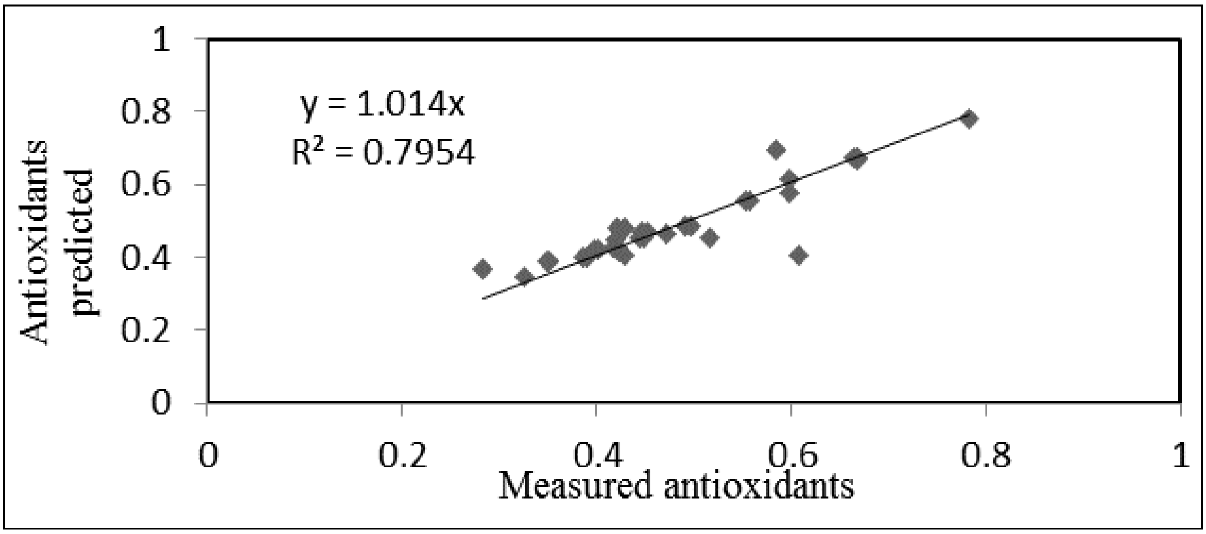

Fig. 19. The fitting line between the predicted data in front of the measured data of antioxidant components in the test stage in the model (9).

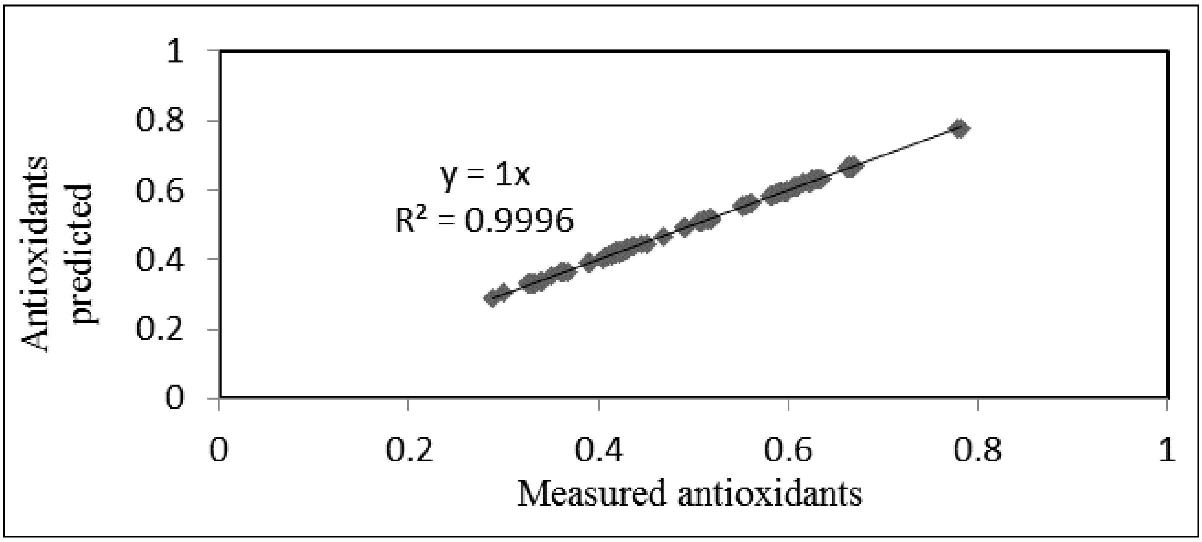

Fig. 20. The fitting line between the predicted data in the front of the measured data of antioxidant components during the training stage in model (10).

Table 15 indicates statistical parameters calculated for the stages of education, validation, testing and total in Model (10) for antioxidant amount performance. Fig. 20 and 21 show R^2 index and the fit-line equation of the pre-projected data were measured in front of the measure of plant weight performance in training and test stages for model (10). As shown in the Fig. 20 and 21, the slope of the fitted line for antioxidant amount performance, respectively 1 and 0.98 respectively, that expression is approaching the predicted values with the measured data in the model (10). Also, the explanatory coefficient in training and testing stages in antioxidant amount performance were 0.99 and 0.78, respectively. This model has an acceptable result for antioxidant amount. Also, the level of explanation in antioxidant amount performance was better than the multivariate regression results at the test stage.

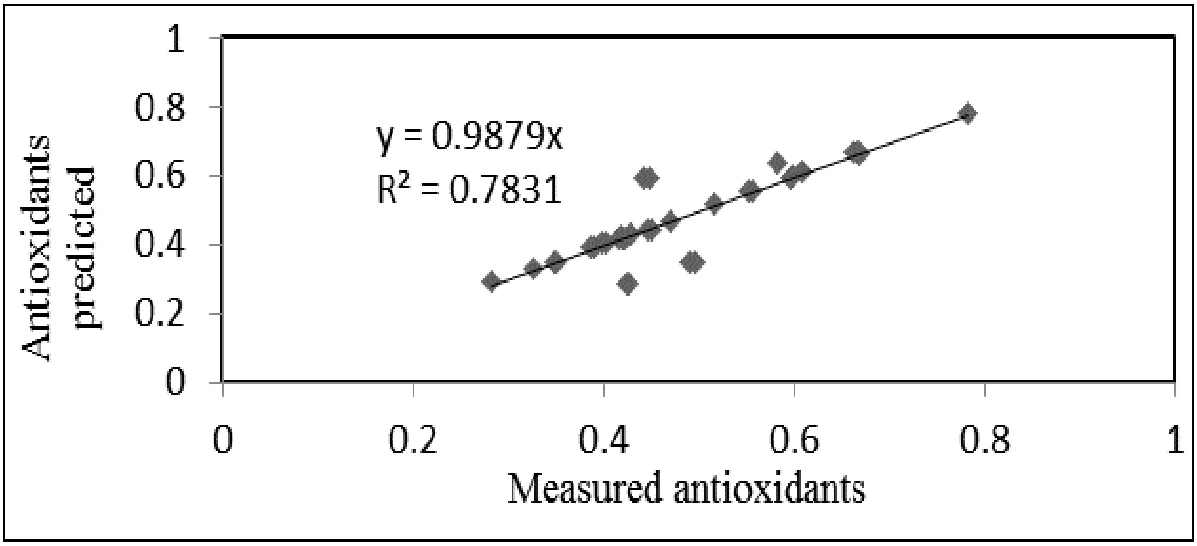

Fig. 21. The fitting line between the predicted data in front of the measured data of antioxidant components in the test stage in the model (10).

Comparison of the results of models designed with sensitive parameters

As mentioned in the previous sections, the purpose of this study was to create a network with the least number of tests (the minimum number of early parameters found) to introduce the best model of performance estimates antioxidant amount. For this purpose, by comparing the results of 10 models designed as well as multivariate regression model, the best model of antioxidant amount performance estimates are determined.

According to the Table 16, with a general view of the addition of input parameters, increase the amount of R^2 and reduce the amount of RMSE in the stages of training, validation and testing on antioxidant amount performance, indicating the improvement of the model accuracy, by increasing the number of input parameters in the antioxidant amount estimation, it is that is quite obvious.

This result is also seen in researches of Shop *et al.*, (1998), Shop and the Lich (1998), Moazen Zadeh *et al.*, (1388). All neural network models to estimate antioxidant amount performance were better compared with multivariate regression model 1-4 models have a nearly similar function. However, the model 5 is selected with an overall view as an optimal model, as with a minimum input parameter with a function close to other models with the number of parameters. However, the number 4 model, because in the explanatory coefficient compared to the three models, will be chosen, especially in the case of the performance and cost of being selected, because with a test (soil texture), three parameters are measured. The results indicated that the neural network application was used to estimate antioxidant amount performance using soil parameters, but it is also suggested to continue to access the definitive results of similar research in this regard.

Conclusion

The results showed that the method of artificial neural network has high accuracy in estimating antioxidant components Artichoke, so that in seven models of 10 models (explaining coefficient in the test stage), change the antioxidant components in the studied area using 12 characteristics. Antioxidant function depends largely on acidity, organic carbon, potassium and soil lime percentage.

This study showed that the acidity parameter of the order is the most important factor affecting antioxidant components performance in the region. Also, the percentage parameter of silt was identified as the most effective factor in antioxidant function. The results obtained in this study are only available for the studied area and other similar areas in terms of topography, climate, soil and managerial operations. However, it can be done like such a study using artificial neural networks in other areas.

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