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Estimation of nitrate content in tomato using image features

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ABSTRACT

The improper use of chemical fertilizers in crop production can result in unsafe food sources for consumers. This research focuses on estimating the accumulation of nitrate in tomatoes by analyzing images of tomato tissues. The experiments were conducted using a completely randomized design with four nitrogen levels: 400, 800, 1200, and 1600 kg.ha^{-1}. Fifty samples were randomly selected from each treatment to create images for feature processing and develop a prediction model. The samples were sliced to a consistent thickness, and their images were prepared. The nitrate contents of the same samples were then measured in the laboratory. Color features, including R, G, and B color components, as well as non-color features such as white pixel area (WPA), total slice surface area (TSA), and the ratio of white pixel area to total slice surface area (WPA/TSA), were extracted from the images. The results showed that the nitrate content of the samples increased significantly ($P<0.05$) in response to the applied nitrogen fertilizer, with measurements of 1.6%, 2.7%, 2.8%, and 3.3%, respectively. Moreover, a strong correlation was found between the color components, WPA, TSA, WPA/TSA, and nitrate accumulation in the samples. Multiple regression and multilayer perceptron neural network (MLP) models were employed to predict the nitrate content. The best subset method was used to build an appropriate regression model. Various topologies and transform functions were applied to identify the best MLP model. The results indicated that an MLP model with a 3-15-1 topology and the lowest mean relative percentage error (MRPE) was the most accurate neural network model. The final regression and neural network models were validated using 60 intact samples. The neural network model achieved a MRPE of approximately 3.5%, demonstrating its precise estimation of nitrate contents compared to the regression model with an MRPE of around 5.2%.

1- Introduction

Tomato (*Lycopersicon esculentum* M.) is one of the products that has the highest amount of consumption in the world. Tomatoes are rich in vitamin C and lycopene. Today, this fruit is consumed raw in various ways or as one of the necessary ingredients for preparing food, various sauces and drinks, and it forms an important part of the diet of people in many countries [1]. Due to its economic importance, this plant is the subject of many researches.

The planting and harvesting of tomatoes dates back thousands of years and it is one of the most consumed vegetables [2]. Tomato is one of the most important commercial vegetables in the world, with an area under cultivation of about three million hectares. According to the latest statistics provided in 2020, Iran was among the ten major tomato producing countries and has been in this list for many years. The global production of tomatoes has been reported as more than 186 million tons, and Iran's share of the total production was approximately 1.3%, which has grown by about 4% compared to the previous year [2].

The high per capita consumption of tomatoes in Iran has led to an increase in the cultivated area. In addition, to increase its productivity and performance, various fertilizers and chemicals are used. Feeding tomato plants with optimal amounts of nitrogen is very important for its growth, but excessive use of nitrogen will also cause vegetative growth and delayed flowering [3]. On the other hand, excessive use of nitrogen fertilizers increases nitrate concentration in edible organs of crops, especially vegetables, and causes nitrate pollution [4, 5]. Nitrate nitrogen is not toxic in small amounts, but the continuous consumption of vegetables containing high amounts of nitrates creates risks for human health [6-9]. It has been reported that accumulated nitrate in tomato fruit causes white texture (spot) in its flesh [10].

Various factors affect nitrate accumulation in plants. Different parts of plants have different ability to store nitrate, and depending on the species, variety and age of the plant, the amount of accumulation varies. Also, various environmental factors affect the plant's nitrate concentration and its absorption. The method of applying nitrogen fertilizer, its amount, source and rate of release have a positive and significant effect on nitrate accumulation in plants [11]. Other reports indicate more nitrogen accumulation in leafy greens. However, in the tests conducted, the amount of nitrate in the edible tissue of tuberous greens, including tomatoes, exceeded the limit reported by the World Health Organization [10, 12].

Recent studies have shown that the consumption of foods containing nitrates and nitrites produces some nitrogenous compounds such as nitrosamines in the digestive system, which are involved in causing cancer and various tumors of the tongue and esophagus and other body parts, and cause poisoning in large quantities. In the same sense, the amount of nitrates in food is observed in most countries, which varies depending on the type of product and the amount of local consumption of the products. Considering the excessive consumption of nitrogen in vegetable cultivation and on the other hand the high general consumption of vegetables in Iran, extensive studies have been carried out in the field of determining their nitrate content and the permissible standard ceiling of nitrate in vegetable and summer products using time-consuming laboratory methods [12-21]. Determining nitrate in vegetables and fruits using chemical methods [12, 20] or a chemical combination and a device such as ion chromatography [13, 15, 23, 24], gas chromatography [25], liquid chromatography with High performance [12], spectroscopy [26], and spectrophotometry [18, 23, 27] have been reported.

In on-line and continuous processes, there is a need to quickly measure chemical and physical properties, so using methods that can determine the required characteristics with acceptable accuracy is a matter of trust for agile and on-line systems. The color characteristics of agricultural products and food is one of the methods that has the capability of rapid measurement and has been studied in many researches. Image processing

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based on light waves in the visible range has shown its capabilities in detecting physical, chemical and mechanical properties and has been developed to determine the quality of agricultural products. This method has been used for destructive or non-destructive quality detection in various products, including tomatoes, to detect the antioxidants of tomatoes affected by environmental factors and nitrogen content [28]. The decrease in tomato lycopene content and the subsequent decrease in red color during the storage period were investigated by image processing method and a strong linear relationship with a correlation coefficient of 0.982 was reported [29]. In other researches, the contents of tomatoes that provide the possibility of quality grading have been studied. For example, it can be noted the feasibility of predicting the content of bioactive compounds and phenolic compounds and lycopene of tomato fruit by hyperspectral image processing [30], and the quality measurement of tomato fruit surface based on color indicators for classifying fruits [31]. According to the results, prediction and classification was performed with 96% and 98% accuracy, respectively. Image processing is widely used in determining the appearance quality for grading and categorizing fruits and vegetables. This method was used to distinguish the types of apples, watermelons, onions and citrus fruits based on the color and surface defects [32], quality assessment of fruits and vegetables [33], lemons, oranges and tomatoes [34], and classification of healthy and defected tomato and banana [35]. In the present research, the relationship between the color features that can be extracted by machine vision and the amount of nitrate in tomatoes was studied, and finally, modeling was done to estimate the amount of nitrate in tomatoes using the extracted color features.

2-Materials and methods

A number of Early Urbana tomato seedlings were purchased from a seedling production fund located in Farouq village, Marvdasht city, Shiraz, Iran and immediately planted in the prepared plots. The distance between the rows of cultivation was 2 meters and the distance on the row was 30 cm. Tomatoes were subjected to 4 nitrogen treatments of 400, 800, 1200 and 1600 kg/ha from the first stage (unripe) to the full ripening stage. The amount of these levels was determined according to the soil test results. Growmore fertilizer commercial brand was used to prepare nutrient solution. Iron (from Fe-EDTA source), magnesium (from $MgSO_2.7H_2O$ source) and potassium (from K_2SO_4 source) were added to the food solution as supplementary fertilizers. Irrigation was done by drip and once every 5 days for 12 hours. Nutrient solution was applied to the plants manually and equally according to the growth rate of the plant. Spraying and use of yellow card to control pests and whiteflies was done according to the recommendation of the Department of Plant Protection, Shiraz University. Weeding was also done weekly.

The harvesting of tomatoes started at the beginning of October. Tomatoes that were in the last physiological stage of ripening (when more than 90% of the fruit surfac e has turned red) were selected for testing, and to ensure that the tomatoes were harvested at the same ripening level, Color Grab software (v 3.6. 0) was used. Harvesting was done once every 3 days at 12:00 PM. About 150 samples of different treatments were randomly selected for the tests. Before each nitrate measurement and photography, the samples were first washed and dried and then weighed. AND scale (Japan) with an accuracy of ±0.01 g was used to weigh the samples. Next, the samples were sliced with uniform thickness of 8 mm. This thickness was obtained with several pre-tests to prevent the tomato from being crushed during cutting. In order to have the same thickness, a metal mold with 6 parallel blades (carpet cutter) with a distance of 8 mm was used. In the following, first, the samples were photographed and then tests were performed to detect nitrate and potassium elements.

Nitrogen determination trials was done by digestion, distillation and titration method in Keldal (AA670G, Shimatzo Company, Japan). In this method, the sample was dissolved in concentrated sulfuric acid to convert all its nitrogen into ammonium sulfate. Then, by adding sodium hydroxide and with the help of distillation, its ammonia was separated and

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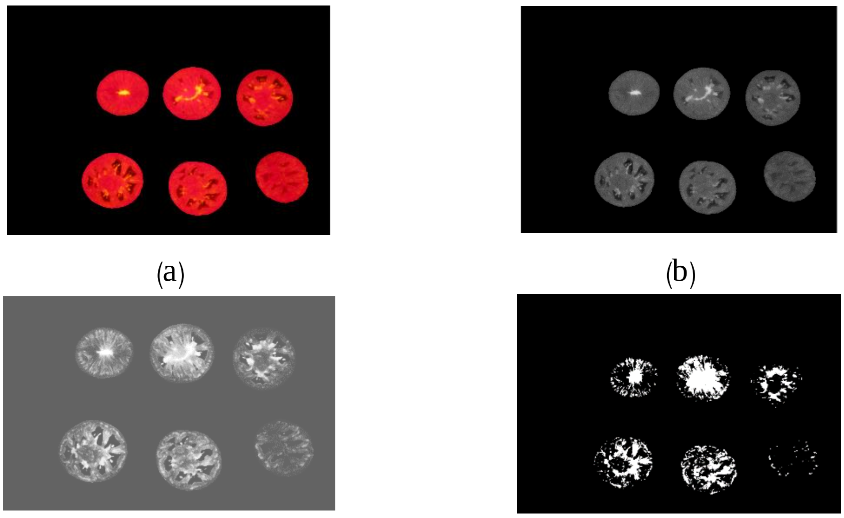
collected inside the standard boric acid solution. Then its nitrogen content was determined by titration [36]. In order to measure mineral substances, plant samples were burned in a furnace with a temperature of 500 ºC for 6 hours. Then it was dissolved in 5 ml of 2 molar nitric acid solution and finally the volume of the solution was brought to 25 ml with double distilled water and it was filtered with Whatman No. 1 filter paper. In this research, to determine the net effect of nitrogen on accumulated nitrate, the amount of potassium was not added to the soil for plant growth [7]. At the same time, the amount of potassium absorbed from the soil by tomato was measured with a flame photometer (Jenway PFP7 model, made in the UK).

Photography of whole fruit samples and cut slices was done in a special compartment using a Canon camera with a resolution of 12 megapixels (3000×4000 pixels), with the lighting of 4 halogen lamps. Images were coded and saved in jpg format. The prepared photos were transferred to a laptop (CPU core I5, RAM 4GB) and the required algorithms were designed using MATLAB R2014b software. The first step in image analysis is segmentation. Segmentation is a process that divides the image into its main component parts. This means that the various objects in the image are separated according to the intended use so that the analysis of the image can be done more easily in the next steps. In the next step, to convert the sample image into a binary image in order to count the white pixels associated with white strings, the threshold value was calculated using the Otsu method, and the sample image was converted into a binary image, so that the fruit assigned a value of one (white color) and the background a value of zero (black). Then, by counting white pixels, the area of white strings was calculated and the data was transferred to Excel software. Detection and counting of white streaks related to this part can be seen in Figure 1.

RGB color space was used to extract the color features of the images, and the R, G, B components of the whole tomato surface and slices were extracted from the corresponding images after removing the background (zero numerical value for the background). By dividing the sum of the values of each of these components by the area of the slices (which was equal to the number of pixels of the fruit slices in the image), the average value of each of the components was calculated. The obtained values, like shape features, were transferred to Excel software by writing a program for further analysis. In addition, total surface area (TSA), white pixel area (WPA) and the ratio of white pixel area to total surface area (WPA/TSA) were calculated for the slices.



(a) (b)

(c) (d)

Figure (1) A sample for exposing white spots of images a) color, b) binary, c)background elimination, d) white area detection and noise elimination

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To model the relationship between the amount of accumulated nitrate and the color features extracted from the images, two methods of multivariate regression and neural network were used. MINITAB 16 software was used to determine the multivariate regression relationships between the measured nitrate content and the features extracted from the images of the samples. For the regression model, the most suitable effective variables in the relationship (independent variables) were selected by the method of the best subset of variables. The most appropriate model was selected based on the statistics of adjusted coefficient of determination (R_a^2) and malose (C_p) according to relations 1 and 2, respectively [37-39].

$$R_a^2 = 1 - \frac{(1-R^2)(N-1)}{N-P-1} \quad (1)$$

$$C_p = \frac{SSE}{\hat{\sigma}^2} - N + 2P \quad (2)$$

In the above relations, R^2 is the coefficient of determination for regression equation, SSE is the sum of squared error (residual) of the model, N is the number of data, P is the number of independent variables, and $\hat{\sigma}^2$ is the standard error of the model. While the number of effective independent variables in the model was the same or close to the value of C_p statistic (in this case, the standard error of the model will be equal to the mean squared error, *ie.*, SSE/N-P, and as a result, C_p=P), this model from the number of variables point of view is appropriate. If the number of independent variables is the same but the variables are different in models, the value of the adjusted coefficient of determination is considered to select appropriate model. In this situation, the model with higher adjusted coefficient of determination is chosen as the final model. Considering that the regression coefficients are a function of the value and unit of the corresponding independent variable, to remove this effect, regression models with standardized data (z value) were also determined [40].

Data and variables similar to regression models, including the area of white pixels counted in the whole surface, the ratio of the white pixels to the whole surface and the color components of the slices as input, and the amount of accumulated nitrate as output, for training the multi-layer perceptron neural network were used (Figure 2).

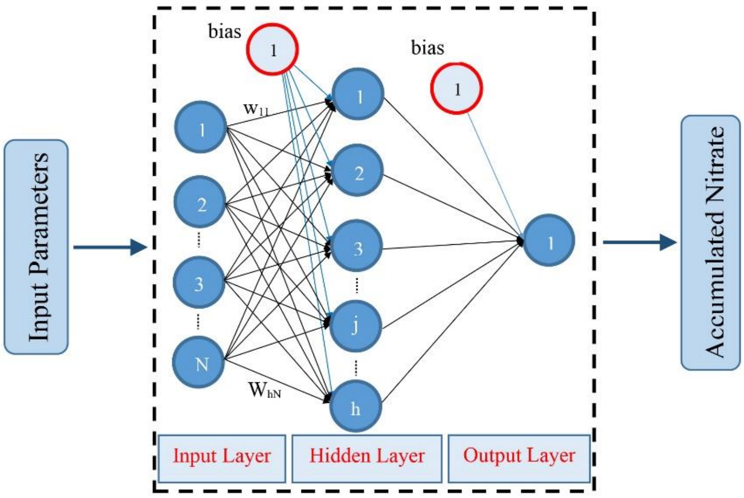

Figure (2) Schematic of multilayer perceptron neural network

To achieve the best back propagation neural network architecture with minimal error between measured and predicted data, after several calculations with different neural network structures, optimal neural network parameters such as number of hidden layers and neurons, type of transfer function and learning algorithm were selected. For this

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purpose, common transfer functions such as *logsig*, *tansig* and *pureline* and learning algorithms *trainlm*, *trainrp* and *traincgf* were evaluated. Finally, for this research, a back propagation neural network with a hidden layer, sigmoid transfer function and Lunberg-Marquardt optimization algorithm was applied. The inputs of two selected suitable regression models were used as inputs to design two neural networks. Based on this, the number of neurons for the first model (with three inputs WPA, WPA^2, the red color component of slices R) and the second model (six inputs including the three features expressed in the first model and their second power) were selected as 15 and 17, respectively. Network training was done in MATLAB software, version 2018, and the root mean square error (RMSE) and mean absolute percentage error (MAPE) indices were used as the comparison indices of two neural network models as described below. These indices were also used to compare between regression and neural network models.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(P_i - O_i)^2}{m}} \qquad (3)$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\frac{|O_i - P_i|}{O_i} \times 100 \qquad (4)$$

where m is the number of network input data, and P and O are the predicted network output value and the actual measured value corresponding to the model output, respectively. For regression and neural network modeling 70% and 30% of the data were used as training and test, respectively.

In order to verify the developed regression and neural network models, 60 separate samples (other than the experimentally treated samples) were prepared from the market and the previous measurements were repeated. The amount of nitrate estimated from the developed models were compared to the corresponding measured amounts. The values of mean bias error (MBE), agreement index (d) and MAPE were determined as indicators of model verification. The parameter of mean bias error indicates that the model underestimates or overestimates the desired variable. This measure was calculated according to equation 5 [41]. The agreement index measures the degree of agreement between two data series and it is not intended to measure correlation, but it evaluates the absence of error in the estimated values, whose value varies between zero and one. Whether this index is closer to one, the compatibility of two variables is more. The MAPE was also calculated to evaluate the error of the models. A lower value of this index indicates a higher accuracy of the model. The following relations were used to calculate the mean bias error and agreement index [42, 43].

$$MBE = \frac{1}{m}\sum_{i=1}^{N}(P_i - O_i) \qquad (5)$$

$$d = 1 - \left[\frac{\sum_{i=1}^{m}(P_i - O_i)^2}{\sum_{i=1}^{m}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2}\right] \qquad (6)$$

In these relations, N is the number of input data for evaluation, P_i is the predicted values, O_i is the actual values, and $\bar{O}$ is the average of the actual values. This experiment was conducted in the form of a completely randomized design. SPSS 21 software was used to analyze the variance of the data, and Duncan's test was used to determine the difference between treatments at the 5% level. In each of the treatments, 50 samples were used for the measured traits.

3. Results and Discussion

According to the results of the analysis of the variance inTable 1, it is observed that the effect of applied plant nitrogen treatments on the nitrate levels of the samples was significant at the level of 1 %, and increased nitrogen levels increased nitrate concentration in the samples. In agreement with the results of the present study, similar results show that the increase in the amount of nitrogen fertilizer applied, resulting in the amount of nitrate accumulated in the fruit and leaf of tomatoes [44-46]. It has also been reported that increasing nitrogen as ammonium solution has increased the amount of nitrate in tomato fruit [23].

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Table 1- Effect of nitrogen levels on samples nitrate content (percent)

Source of Variations	df.	SS	MS	F
Nitrogen	3	85.1	28.4	85.2**
Error	196	65.3	0.3	
Total	199	150.3		

** shows significant difference at 1 % level of probability

Mean comparison results (Fig. 2) show that with increasing in nitrogen levels, the mean nitrate values in the samples have increased and the highest amount of nitrate content occurred at the highest level of nitrogen applied.

It has been reported that the increase in potassium and nitrogen fertilizer composition has an inverse effect on the amount of nitrogen absorption [44]. Therefore, as stated in the materials and methods, exess use of potassium fertilizer was avoided to prevent the negative effect of potassium on nitrogen absorption by the plant. However, the amount of potassium absorbed by the plant was measured from the soil. The amount of potassium samples showed a significant increase from 9.08 % to 9.53 % in applied nitrogen treatments from 400 to 800 kg/ha, and then applied nitrogen levels (from 1200 to 1600 kg/ha), with a significant decrease from 9.2 % to 9.09 % ($P < 0.05$). These changes in potassium can be attributed to the interaction of potassium (constant amount) and various levels of nitrogen. Other studies similar to such increasing and decreasing behavior [44, 47, 48] as well as the impact between nitrogen and potassium [49] have been reported. In addition, the difference in nitrogen and potassium interactions can be attributed to environmental conditions such as growth temperature, sunlight intensity, amount of irrigation water, soil alkaline, chemicals and plant type [27, 50].

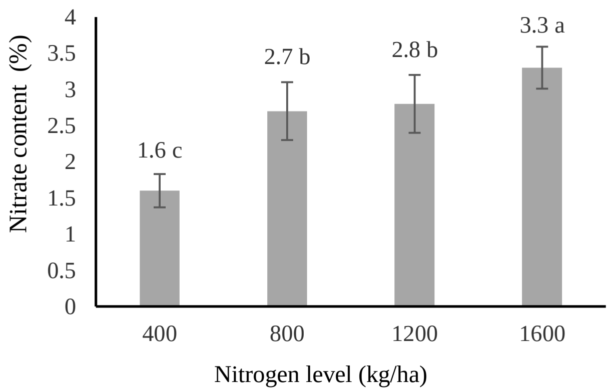

Figure (2) Mean comparison of nitrate content (%) of treatments (Different letters show significant difference at 5 % probability level)

Following these results, the effect of nitrogen on the color components of tomato on the surface of the fruit and slices were investigated. The results related to the comparison of the average values of R, G and B extracted from the surface of the samples as well as the slices are shown in Figure 3. According to these results, the nitrogen levels on the color components measured from the slices, unlike the corresponding values on the surface of the sample, are significant at the 5% probability level. The lack of differences between the color components of the fruit surface can be related to the harvesting of tomatoes at the same ripening time, so that the samples had the same ripening level (color) [51, 52]. For the color components of slices, with increasing nitrogen levels, R values decrease significantly, while G and B values increase. The highest value of R corresponds to the treatment of 400 kg/ha and the lowest value of R corresponds to the treatment of 1600

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kg/ha. In other researches, it has been reported that the lycopene content of tomato decreases and its redness decreases due to the increase of nitrogen levels, which can be effective in changing the amount of the red color component of the samples [28, 29].

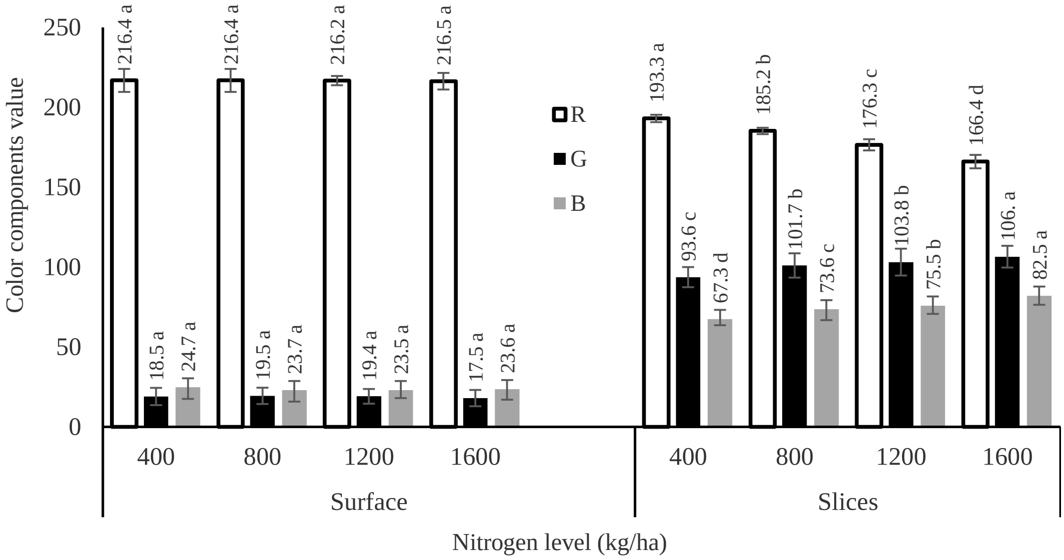

Figure (3) Mean of extracted color components from tomatoes' surface and slice
(In each color component and each part, the same letters show non-significant difference at 5 % probability)

Considering the significant effect of nitrogen amount on the color characteristics of the slices, the correlation between the components and the amount of nitrate in the samples was calculated (Table 2). Correlation coefficients between nitrate values and non-color characteristics (area and ratio of white spots) were also calculated (Table 3). The strong correlation between the area of white pixels and nitrate content shows that the increase in nitrogen levels has caused the reduction of lycopene in tomatoes and as a result the area of white pixels has increased [28]. According to these data, the red color component and the area of the white pixels of the slices had the most linear relationship with the amount of cumulative nitrate in tomatoes.

Table 2- Correlation coefficients between nitrate content and color components

Slice			Surface		
R	G	B	R	G	B
-0.810	0.522	0.736	-0.058	-0.063	-0.065

Table 3- Correlation coefficients between nitrate content and non-color features of slice

WPA/TSA	WPA	TSA
0.835	0.920	0.603

Considering the strong correlation values between the colored and non-colored characteristics of the slices, and the measured nitrate content of the samples, neural network and multivariate linear regression models were developed. All color (R, G and B) and non-color (area of white pixels, total area of slices and ratio of area of white pixels to total area) characteristics of slices were used to determine the regression relationship of estimating the nitrate content of the samples. In addition, by adding the square of the area of white pixels as an extra independent variable along with the other aforementioned variables and applying the method of all suitable models in Minitab software, according to the values of the maximum adjusted coefficient of determination (0.935) and the suitable Malose index (2.8) of different regression models, the final relationship 7 was chosen for the original data. The selected independent input variables

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affecting the estimation of nitrate have been confirmed with the calculated values of the correlation coefficients in Tables 2 and 3. This model has a RSME value of 0.216 and a MAPE of 6.45.

$$N = -4.77 \times 10^{-12}\, WPA^2 + 1.00 \times 10^{-5}\, WPA + 6.53 \times 10^{-3}\, R - 2.75 \quad (7)$$

To reduce the value of the regression coefficients, the equation for the standardized data (dimensionless values) was obtained as in relation 8.

$$N = -1.49\, WPA^2 + 2.45\, WPA + 0.08\, R \quad (8)$$

In the above relationships, N is the accumulated nitrate content, R is the numerical value of the red color component, and WPA is the area of the white pixels of the slices. It should be noted that the regression model with the inputs of WPA, TSA, the ratio of WPA to TSA, and the color components R, G and B of the slices and the adjusted coefficient of determination of 0.910 was placed in the second choice position, whose corresponding relationship is expressed in relation 9. This model also had a RMSE of 0.254 and MAPE of 7.77. Corresponding to dimensionless data relation (relation 8), standardized data relation was also obtained for this model (relation 10).

$$N = -4.00 \times 10^{-6}\, WPA + 2.00 \times 10^{-6}\, TSA + 16.50\, \frac{WPA}{TSA} - 7.60 \times 10^{-4}\, R + 3.95 \times 10^{-3}\, G - 1.76 \times 10^{-3}\, B - 4.48 \quad (9)$$

$$N = -0.88\, WPA + 0.90\, TSA + 1.37\, \frac{WPA}{TSA} - 9.3 \times 10^{-3}\, R + 3.94 \times 10^{-2}\, G - 1.59 \times 10^{2}\, B \quad (10)$$

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The corresponding input and output variables of two regression models with the highest coefficient of determination were used to train the feed-forward neural network to be able to estimate the amount of nitrate. The results of a number of architectures used to train these two networks are listed in Table 4. Two architectures 1-17-6 and 1-15-3 were introduced for three (the first model) and six inputs (the second model), respectively, with the minimum values of RMSE and MAPE. Taking into account the results of Table 4 and the regression method, the first model with three inputs has the least dispertion within amount of predicted accumulated nitrate for both regression and neural network models.

Table 4- Comparison of statistical indices of some multilayer perceptron neural network topology for nitrate prediction

Learning algorithm	Topology	Transfer function	RMSE	MAPE
trainrp	3-13-1	tansig	0.1504	6.0976
	3-15-1	logsig	0.1310	5.4769
trainlm	3-13-1	tansig	0.0540	4.8170
	3-15-1	**logsig**	**0.0249**	**3.7912**
traincgf	3-13-1	tansig	0.1495	5.4510
	3-15-1	logsig	0.0812	4.9399
trainrp	6-15-1	tansig	0.1914	6.5672
	6-17-1	logsig	0.1810	5.9941
trainlm	6-15-1	tansig	0.1827	5.2778
	6-17-1	**logsig**	**0.1798**	**4.9422**
traincgf	6-15-1	tansig	0.1885	5.6317
	6-17-1	logsig	0.1812	5.3830

After finalizing the appropriate predictive models, the new data obtained from the measurement of color and non-color characteristics and the amount of nitrate of the purchased samples were used to verify both regression and neural network models. The output of both models was plotted against the real values (one-to-one line) (Figure 4) and the pre-introduced statistics (RMSE, MBE, d and MAPE) were calculated (table 5). Based on the results listed in Table 5, the neural network with an average error of 3.5% was more accurate in determining the amount of accumulated nitrate in the samples, but if it is necessary to use simpler models, the regression relationship with a high correlation coefficient value and low estimation error, is also able to estimate nitrate amount with about 5% error. These two calculated values were lower than the values calculated during the test (calibration) of the regression and neural network models (3.79% and 6.45%, respectively) and confirm the model verification procedure. According to Figure 4, the highest error in the estimation of the regression model is in higher amounts of accumulated nitrate.

In the research of Rezaei et al. (2014), the linear relationship between absorbed waves and tomato nitrate ($y = 0.119\ x + 0.02$, x is the value of wave absorption at a wavelength of 538 nm and y is the value of nitrate) in the range of 2.5 to 15 mg/ kg was defined [11], while in the present study, the linear relationship in the neural network model is up to 4.5% and in the regression model up to 3%, the amount of nitrate is equivalent to 45 and 30 grams per kilogram, respectively, with an average error of less than 4%. Estimated nitrate. On the other hand, according to the index of the World Health Organization and FAO for the safe amount of nitrates in vegetables (2500 mg/1000 grams or equivalent to 0.25%), it was found that the distribution of 400 kg of nitrogen fertilizer per hectare is about 1.5%. It leads to nitrate, which is much more than the recommended amount [8, 13].

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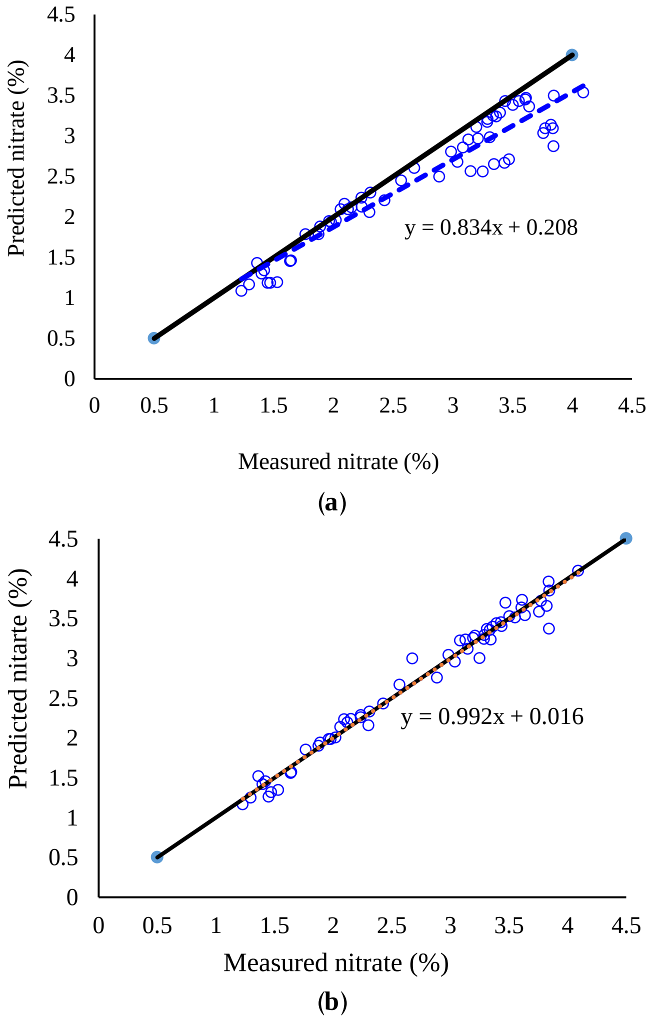

Figure (4) Verification of models a) regression and b) neural network

Line and dash-line show 1:1 line and predicted data fit line, respectively.

Table 5- Statistical indices for models verification

Model	**Verification indices**			
	MAPE	**d**	**MBE**	**R^2**
Regression	5.172	0.9647	-0.2440	0.903
Neural Network	3.529	0.9952	-0.0063	0.988

In a study that conducted by Rezaei et al. (2014), the linear relationship between absorption waves and tomato accumulated nitrate ($y = 0.119\ x + 0.02$, x is the value of wave absorption at a wavelength of 538 nm and y is the value of nitrate) in the range of 2.5 to 15 mg/ kg was defined [11], while in the current study, the amount of accumulated nitrate with neural network and regression models that was up to the maximum amount of 45 (equal to 4.5 percent) and 30 grams per kilogram (equal to 3 percent), respectively, was estimated on average with an error of 4.4 %. According to the index of the World Health Organization (WHO) and FAO for the safe amount of nitrate in vegetables (2500 mg/kg or equivalent to 0.25%), it was found that the consumption of 400 kg of nitrogen fertilizer per hectare will cause tomatoes to be contaminated with nitrates up to 1.5 %, that is much higher than the recommended amount [8, 13].

4- Conclusion

In this research, the possibility of estimating the amount of nitrate accumulated in tomato tissue was investigated with the help of image processing. The results showed that

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some features extracted from the images, including the red color component and the surface area of white pixels, have a strong relationship with nitrate content. Two multiple regression models and a perceptron neural network with a hidden layer were used to predict nitrate values, and the results showed that the neural network with an mean absolute percentage error of 3.5 % and the regression model with a corresponding value of about 5.2 % are able to estimate nitrate content. Due to the fact that the color changes were investigated both destructively (slices) and non-destructively (full sample), it was found that the change in the amount of accumulated nitrate did not cause any symptoms on the surface of the samples. Therefore, among the limitations of this method, it can be mentioned the impossibility of using it in a non-destructive way and the complete dependence on the color changes of the sample. However, the main advantage of this method is the rapid measurement and use in online tests and applications, and it is also suitable for further research.

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تخمین محتوای نیترات گوجه‌فرنگی با استفاده از ویژگی‌های تصویر

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چکیده

کاربرد ناصحیح کودهای شیمیایی در تولید محصولات کشاورزی بروز بیماری برای مصرف‌کنندگان را ممکن می‌سازد. در این مطالعه تخمین مقدار نیترات تجمع یافته در میوه گوجه‌فرنگی به کمک پردازش تصویر بررسی شد. این پژوهش در قالب طرح کاملا تصادفی با چهار تیمار نیتروژن در سطوح ۴۰۰، ۸۰۰، ۱۲۰۰ و ۱۶۰۰ کیلوگرم بر هکتار انجام شد. از هر تیمار ۵۰ نمونه به طور تصادفی برای تهیه تصاویر و ایجاد مدل تخمین انتخاب شد. نمونه‌ها با ضخامت یکسان برش زده شدند، عکس‌برداری صورت گرفت و سپس نیترات نمونه‌ها به روش آزمایشگاهی اندازه‌گیری شد. مولفه‌های رنگی R، G و B مرتبط با سطح و محتوای داخلی نمونه‌ها و همچنین ویژگی‌های غیررنگی از جمله مساحت پیکسل‌های سفید ورقه‌ها ، مساحت کل ورقه‌ها و نسبت مساحت پیکسل‌های سفید به مساحت کل استخراج شدند. نتایج نشان داد متناسب با سطوح نیتروژن اعمال شده، مقدار نیترات نمونه‌ها به ترتیب ۱/۶، ۲/۷، ۲/۸ و ۳/۳ در صد اندازه‌گیری شد که این افزایش معنادار بود ($P<0.05$). افزون بر آن، مشخص شد محتوای رنگی ورقه‌ها، مساحت پیکسل‌های سفید ورقه‌ها و نسبت مساحت پیکسل‌های سفید به مساحت کل همبستگی بالایی با محتوای نیترات نمونه‌ها داشت. برای پیش‌بینی میزان نیترات، مدل رگرسیون چندگانه و شبکه عصبی چند لایه پرسپترون بکاربرده شد. روش بهترین زیر مجموعه رگرسیون برای انتخاب مناسب‌ترین مدل رگرسیون بکاربرده شد. برای انتخاب بهترین مدل شبکه عصبی، معماری‌ها و توابع انتقال مختلف به کار برده شد و بر اساس نتایج شبکه با ساختار ۱-۱۵-۳ با کمترین مقدار ریشه میانگین مربعات خطا به عنوان بهترین مدل انتخاب شد. برای واسنجی بهترین مدل رگرسیون و شبکه عصبی از ۶۰ نمونه جدید استفاده شد. ساختار معرفی شده توانست با درصد میانگین خطای نسبی ۳/۵ درصد در مقایسه با مدل رگرسیون با مقدار ۵/۲ درصد مقدار محتوای نیترات را تخمین بزنند.

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