International Journal of Horticultural Science and Technology (2024) Vol. 11, No. 4, pp. 491-502

International Journal of Horticultural Science and Technology
Journal homepage: http://ijhst.ut.ac.ir

Utilizing Artificial Neural Networks for Predictive Modeling Physicochemical Attributes in Maltodextrin-Coated Grapes with Potassium Carbonate and Pyracantha Extract in Storage

Maryam Ebrahimi [1], Rouhollah Karimi [2]*, Amir Daraei Garmakhany [3], Narjes Aghajani [4], Alireza Shayganfar [2]

1 Grape Processing and Preservation Department, Faculty of Agriculture, Research Institute of Grape and Raisin, Malayer University, Malayer, Iran

2 Department of Horticulture and Landscape Engineering, Faculty of Agriculture, Malayer University, Malayer, Iran

3 Department of Food Science and Technology, Toyserkan Faculty of Engineering and natural resources, Bu-Ali Sina University, Hamadan, Iran

4 Department of Food Science and Technology, Bahar Faculty of Food Science and Technology, Bu-Ali Sina University, Hamadan, Iran

ARTICLE INFO

Article history:

Received: 10 September 2023,
Received in revised form: 17 November 2023,
Accepted: 29 November 2023

Article type:

Research paper

Keywords:

Artificial neural networks,
Edible coating,
Grape fruits,
Pyracantha extract,
Storage time

ABSTRACT

Artificial neural networks (ANN) are a nondestructive method for estimating fruit and vegetable shelf life and quality attributes. This research used artificial neural networks to model a storage process for fruit grapes (*Vitis vinifera* cv. Rishbaba) coated with maltodextrin, including different levels of potassium nanocarbonate (0-2%) and pyracantha extract (0-1.5%). After applying these coatings, the fruits were stored for 60 days in cold storage (-1 °C), with a relative humidity of 90%. Measurements considered weight loss percentage, titrable acidity (TA), pH, texture firmness, color index (a*), and general fruit acceptance. Artificial neural networks predicted changes in fruits during the storage process. By examining different networks, the feedforward backpropagation network had 3-10-6 topologies with a coefficient of determination (R2) greater than 0.988 and a mean square error (MSE) less than 0.005. With a hyperbolic sigmoid tangent activation function, a resilient learning pattern and 1000 learning process were determined as the best neural method. On the other hand, the results of the optimized models showed that this model had the highest and lowest accuracy for predicting the weight loss percentage ($R^2 = 0.9975$) and a* ($R^2 = 0.5671$) of the samples, respectively.

Introduction

Grapes (*Vitis vinifera* L.) are popular fruits widely produced and consumed worldwide due to their beneficial effects on human health and economic importance. Grapes are a rich source of carbohydrates (12-18%), protein (0.5-0.6%), and

*Corresponding author's email:
R.Karimi@malayeru.ac.ir (R. Karimi).

fat (0.3-0.4%), which also has significant amounts of vitamin C and A, potassium, calcium, phosphorus and boron (Abdel-Hakeem, 2022). Grapes are a perishable, non-climacteric fruit with low physiological activity, and the long-term maintenance of this fruit may be associated with rotting, water loss, browning, and a decrease in marketability. Grape quality is essential in its pricing, so maintaining the quality of the grape is considered by the suppliers and exporters. For this reason, grape producers are constantly looking for new technologies to maintain the fresh appearance of grape clusters after harvest. Vineyards are usually away from the consumption market, and commercial harvesters use innovative technologies to control changes in the physicochemical attributes of fruits during their storage period (Leng et al., 2022). To date, low-temperature storage has been the most common postharvest technology that helps preserve fruit quality and other horticultural products while increasing their shelf life (Lado et al., 2019; Yuan et al., 2014). However, grapes cannot remain in cold storage for long periods, and their commercial value decreases without applying suitable treatments (Chen et al., 2018; Rosales et al., 2013). Therefore, different postharvest treatments and storage at low temperatures are essential for grape storage. Using SO_2 is the most common commercial method to preserve the quality and extend grape shelf life. In addition, using controlled atmospheres with a high CO_2 content is an effective tool for controlling postharvest diseases and extending the shelf life. However, in many countries, the use of controlled atmospheres and SO_2 is limited due to the possibility of some compounds in fruit that negatively affect human health (Balic et al., 2012; Rosales et al., 2013). Edible coatings are substances that can become effective when used on the surface of foods and are safe to use. With these coatings, fruits can be protected against light, microbial contamination, and mechanical damage. Polysaccharides, proteins, and lipids, or their combinations, are primary biopolymers used to create edible coatings (Pham et al., 2023). Edible coatings are an effective and environmentally friendly alternative to extend the shelf life of fruits. These coatings can create a barrier against the penetration of gases and water vapor, reduce the rate of respiration and weight loss, maintain the firmness of the fresh product, and cause the coated products to shine. In addition, coatings can be used as carriers of a wide range of functional materials, such as antimicrobial compounds, antioxidants, anti-browning agents, nutrients or flavoring compounds, and coloring agents, increasing food sustainability, quality, and safety (Sapper, 2018). Carbohydrate-based coatings such as pectin and maltodextrin increase fruit shelf life by delaying changes in weight loss, soluble solids, pH, total acidity, firmness, and color (Menezes and Athmaselvi, 2016). However, maltodextrin is a cause of tissue formation and fat substitutes. Maltodextrin is cost-efficient, has low viscosity, low sugar content, and is colorless (Kosasih et al., 2023). Although the use of maltodextrin improves the shelf life of the food matrix, the resulting coating alone is weak, so it must mix with other compounds to produce a suitable coating (Wongphan and Harnkarnsujarit, 2020). One of the compounds that can improve the performance of edible coatings is antioxidant extracts from different plants. These natural extracts are rich in bioactive or antioxidant compounds as they originate in different plant parts, such as leaves, fruit peels, byproducts, and wastes, due to their antioxidant, antimicrobial, and sometimes anti-transpirant properties. Thus, they improve the protective effect of edible coatings on fruits (De Bruno et al., 2023). Various researchers have reported improvements in the properties of edible coatings containing antioxidant compounds in the long-term storage of fruits and vegetables (Tahir et al., 2019; Kowalczyk et al., 2020).

Pyracantha (*Pyracantha coccinea*) is an evergreen shrub that has received attention since ancient times as an ornamental plant. Pyracantha produces small, bright red berry-like fruits that can help make jellies, jams, sauces, and marmalades. Also, in traditional medicine, these fruits have diuretic and tonic properties for the heart (Sarikurkcu and Tepe, 2015). The extracts of this fruit are known as an antioxidant compound with higher potency than BHT due to its high content of phenolic compounds such as catechins, anthocyanins, etc. (Wang et al., 2022). Recently, nanotechnology has been used in the development and improvement of edible coatings (in various nanosystems, including polymer nanoparticles, nanoemulsions, and nanocomposites) to control the release of polyphenols and fat-soluble vitamins, as well as to slow down reactions and enzyme activity (Zambrano-Zaragoza et al., 2018). Among antimicrobial compounds in edible coating formulations, different organic and inorganic salts may suitably replace synthetic fungicides. One of these compounds is potassium carbonate, the primary value of this salt. It has easy accessibility, relatively low cost, and high solubility in water, and its antifungal activity has proven effects on various fruits (Martínez-Blay et al., 2020). Today, with the development of computer processing technologies, artificial neural networks (ANN) are widely used to model food industry processes and predict desired parameters in the design and development of systems. Neural networks can model nonlinear and complex systems, with significant input and output data. They usually yield acceptable results and can be used as a non-destructive method to estimate the shelf life and quality properties of fruits and vegetables (Farzaneh et al., 2018; Salehi, 2020). Different researchers have applied ANN for modeling different unit operations in food technology, such as drying green malt (Aghajani et al., 2012), pumpkin (Mokhtarian et al., 2014a, b), courgette (Mokhtarian and Daraei Garmakhany, 2017) and tomato slices (Mokhtarian et al., 2021). Also, other researchers tried to provide neural network models to predict quality parameters in different products during storage, including previous studies on grapes (Farzaneh et al., 2018), pears (Azadbakht et al., 2022), and bananas (Adebayo et al., 2017). Therefore, this research aimed to predict changes in the physicochemical characteristics of grapes coated with maltodextrin, with potassium nanocarbonate and pyracantha extract, during the storage period using artificial neural networks.

Materials and Methods

Plant materials

'Rishbaba' grapes were purchased from a wholesale fruit market in Malayer, Iran, and immediately transferred to the Grape and Raisins Research Institute of Malayer University. The grapes were graded based on uniformity in maturity (ºBrix of around 18-19), size, color, and no fungal infection or physical injury symptoms. In this study, maltodextrin powder and sodium hydroxide were purchased from Merck Company in Germany. Potassium nanocarbonate from Nanotechnology Laboratory of Malayer University, Iran.

Extraction of pyracantha extract and preparation of studied coatings

For the preparation of pyracantha extract, pyracantha fruits were mixed with distilled water (25 g with 100 mL) (1:4 ratio) and then homogenized in ultrasonication apparatus (Topsonics, Lithuania) for 6 min with 400 W power. After filtering, the resulting extract was used in different concentrations to prepare coating solutions. To prepare maltodextrin solution (20% w/v), after adding its powder to distilled water, stirring was done in laboratory conditions to completely dissolve. Maltodextrin biopolymer was stirred for 30 min to dewater it after dissolving. The process led to three different concentrations of pyracantha (Pyracantha coccinea) aqueous extract (0, 0.75, and 1.5 % w/v) and potassium nanocarbonate (0, 1 and 2 % w/v). Coatings were prepared and subjected to 400 W ultrasonication for better homogenization for 5 min (Sahin et al., 2016; Todorović et al., 2022).

Fruit coating operations

Grape clusters were immersed in each prepared coating solution for 15 min. After placing the tissue paper at laboratory temperature and drying, the fruits were packed in polypropylene containers, transferred to the refrigerator (-1 °C and relative humidity of 90%), and stored for 60 days in these conditions. The samples were removed from the refrigerator every 30 days, and to simulate marketing conditions, they were kept at room temperature for 15 min. Changes in physiological properties were evaluated during the storage period.

Weight loss percentage

The percentage of weight loss (WL) was calculated through the weight difference of samples before (W_1) and after storage (W_2) using equation 1 (De Souza et al., 2021).

$$\%WL = \frac{W_1 - W_2}{W1} \times 100 \qquad (1)$$

Titratable acidity (TA)

The TA was determined by the potentiometric titration method. For this purpose, 10 mL of grape extract was titrated with NaOH 0.1N until (pH = 8.1) and the results were expressed as grams of tartaric acid per 100 mL of extract (AOAC, 2005).

pH measurement

The pH value of samples was determined by measuring the pH of grape extract using a digital pH meter (DPH-2 ATAGO, UK) at 20 °C (Abdollahi et al., 2022).

Fruit tissue firmness

To determine the firmness of grape samples, a method described by Vargas et al. (2006) was used with slight changes. A fruit firmness tester (China) was used with a special probe (cylindrical rod), operating at a penetration depth of 10 mm. The results were expressed in Newton unit (Vargas et al., 2006).

Grape color measurement

Image Processing was applied to measure the color of the fruit by using the Canon Digital Camera Power Shot SX110 IS with 9 MP resolution. Grape samples under uniform and appropriate light and at a 45-degree radiation angle. Then the images were transferred to a computer. With Photoshop 6 software and Image Processing, we calculated the values of a* index (Hashemi Shahraki et al., 2014; Yam and Papadakis, 2004).

Evaluation of sensory properties

A 5-point hedonic scale was used for scoring sensory and qualitative characteristics of grape samples after the storage period. Ten panelists were trained and participated in this test. They evaluated the overall acceptability of the samples during the storage period. First, descriptions of color, brightness, texture, taste, appearance, or absence of mold and decay of the product were given, and the results were scored as very good (score 5) to very bad (score 1). The sensory evaluation was performed in three replications and water was used as a palate cleaner during the evaluation (Granato et al., 2011).

Predicting the trend of grape quality changes in cold storage using artificial neural networks

To determine the optimal neural network, the neural network tool of MATLAB software was used. To design this network, three inputs of grape storage time, concentrations of potassium nano carbonate, and pyracantha extract entered a three-line matrix. We defined targets as the percentage of weight loss, pH, texture, a* index, and overall acceptance in a 6-line matrix. Different neural networks, including different activation and learning functions, the number of neurons in the hidden layer, and their efficiency were specified using two criteria of determination coefficient (R^2) and mean square error (MSE) which were defined by equations 2 and 3, respectively. First, the feedforward back propagation neural network with the highest efficiency was selected by testing different neural networks, and the number of learning cycles was 1000.

Considering these cases, different neural networks with a hidden layer that could have different numbers of neurons from 1 to 10 cases were designed. To connect the input layer to the hidden layer, the activation functions of hyperbolic tangent sigmoid, logarithmic, and linear were used at different stages of network error and testing. Also, to connect the hidden layer to the output layer, the activation function of linear was used constantly. In addition to the mentioned cases, two different learning patterns, including Levenberg-Marquardt learning and resilient backpropagation (trainrp) algorithms, functioned in different networks. Their effects on network accuracy were evaluated. Equations 2 and 3 calculated the ratio of the predicted features by the network, characteristic ratios from the experiments, the mean ratio value through laboratory characteristics, and the total number of observations.

Y_{pi}, Y_{ei}, $\overline{Y}$ and N respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(Y_{pi} - Y_{ei}\right)^2}{\sum_{i=1}^{N}\left(Y_{pi} - \bar{Y}\right)^2}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{pi} - Y_{ei}\right)^2$$

Entering raw data reduces the speed and accuracy of the network, so we normalized the input data entering the network. If this step fails, the network cannot converge during the training phase, and the desired results cannot appear. In this study, equation 4 standardized the inputs and outputs between 0 and 1.

$$V_N = \frac{V_R - V_{min}}{V_{max} - V_{min}} \qquad (4)$$

In equation 4, V_R is the initial raw data, V_N is the normalized data, V_{max} and V_{min} are the maximum and minimum values of the primary data (Farzaneh et al., 2018; Dolatabdi et al., 2016).

Results

Tables 1 to 3 compared the effects of the number of hidden layer neurons and learning function type on the accuracy of prediction of the neural networks with hyperbolic, logarithmic, linear sigmoid tangent transfer functions and a 1000 learning cycle, respectively. Considering the mean squares of error and the determination coefficient in Tables 1 and 3, the feedforward back propagation neural network had hyperbolic sigmoid tangent transfer and resilient learning function, with 3-10-6 topology. It included an input layer with three neurons, one hidden layer with ten neurons, and an output layer with six neurons (Fig. 1) with a determination coefficient of more than 0.988 and a mean square error of 0.005, selected as an optimal neural network.

Also, a high determination coefficient for the predicted values obtained by this optimal network versus laboratory data for the six desired output variables can be another reason for the high accuracy of the developed ANN model. Thus, the selected model has the highest and lowest accuracy, respectively, in predicting the data obtained from the percentage of weight loss (R^2= 0.997) and a* index (0.567) of the samples (Fig. 2).

Table 1. Comparison of the effect of neuron number in the hidden layer and the type of learning and activation function of hyperbolic sigmoid tangent on predicting the accuracy of various properties.

neurons number	Trainlm		trainrp	
	R^2	MSE	R^2	MSE
2	0.796	0.113	0.935	0.060
3	0.799	0.091	0.987	0.079
4	0.815	0.087	0.911	0.018
5	0.869	0.063	0.921	0.013
6	0.788	0.098	0.956	0.009
7	0.915	0.077	0.925	0.053
8	0.952	0.092	0.953	0.021
9	0.910	0.083	0.922	0.09
10	0.976	0.065	**0.988**	**0.005**

Table 2. Comparison of the effect of neuron number in the hidden layer and the type of learning and activation function of sigmoid logarithm on predicting the accuracy of various properties.

neurons number	Trainlm		trainrp	
	R^2	MSE	R^2	MSE
2	0.733	0.113	0.811	0.063
3	0.714	0.126	0.896	0.047
4	0.763	0.108	0.913	0.063
5	0.819	0.089	0.877	0.058
6	0.861	0.075	0.899	0.051
7	0.877	0.063	0.876	0.058
8	0.910	0.037	0.919	0.044
9	0.913	0.046	0.933	0.034
10	0.899	0.040	0.964	0.023

Table 3. Comparison of the effect of neuron number in the hidden layer and the type of learning and linear activation function on predicting the accuracy of various properties.

neurons number	Trainlm		trainrp	
	R^2	MSE	R^2	MSE
2	0.699	0.457	0.765	0.348
3	0.682	0.213	0.699	0.441
4	0.643	0.168	0.817	0.179
5	0.798	0.098	0.888	0.098
6	0.817	0.074	0.869	0.101
7	0.821	0.092	0.876	0.099
8	0.799	0.089	0.910	0.087
9	0.861	0.086	0.935	0.062
10	0.839	0.078	0.899	0.089

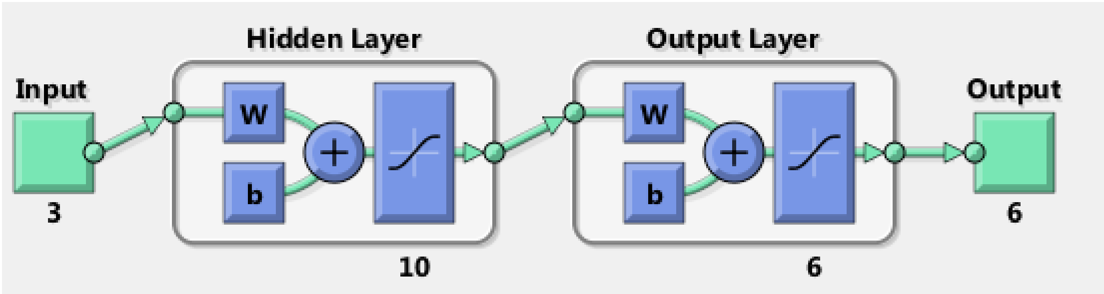
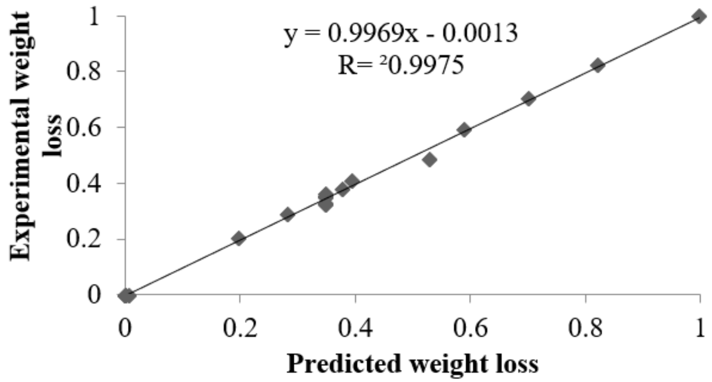
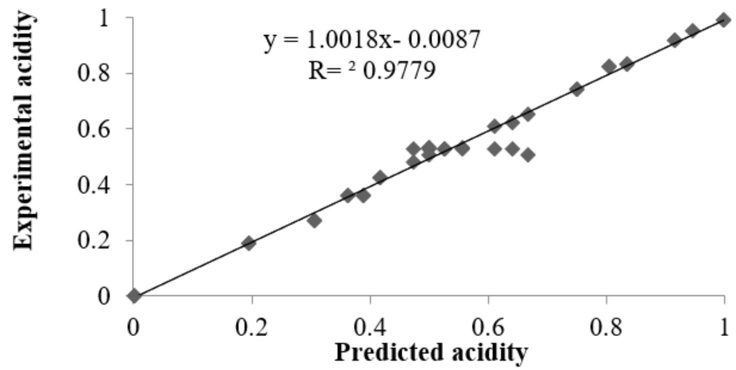


Fig. 1. Schema of a selected optimized network containing three neurons in an input layer, ten neurons in a hidden layer with an activation function of hyperbolic sigmoid tangent, and six neurons in an output layer with a hyperbolic sigmoid tangent activation function.



(A)



(B)

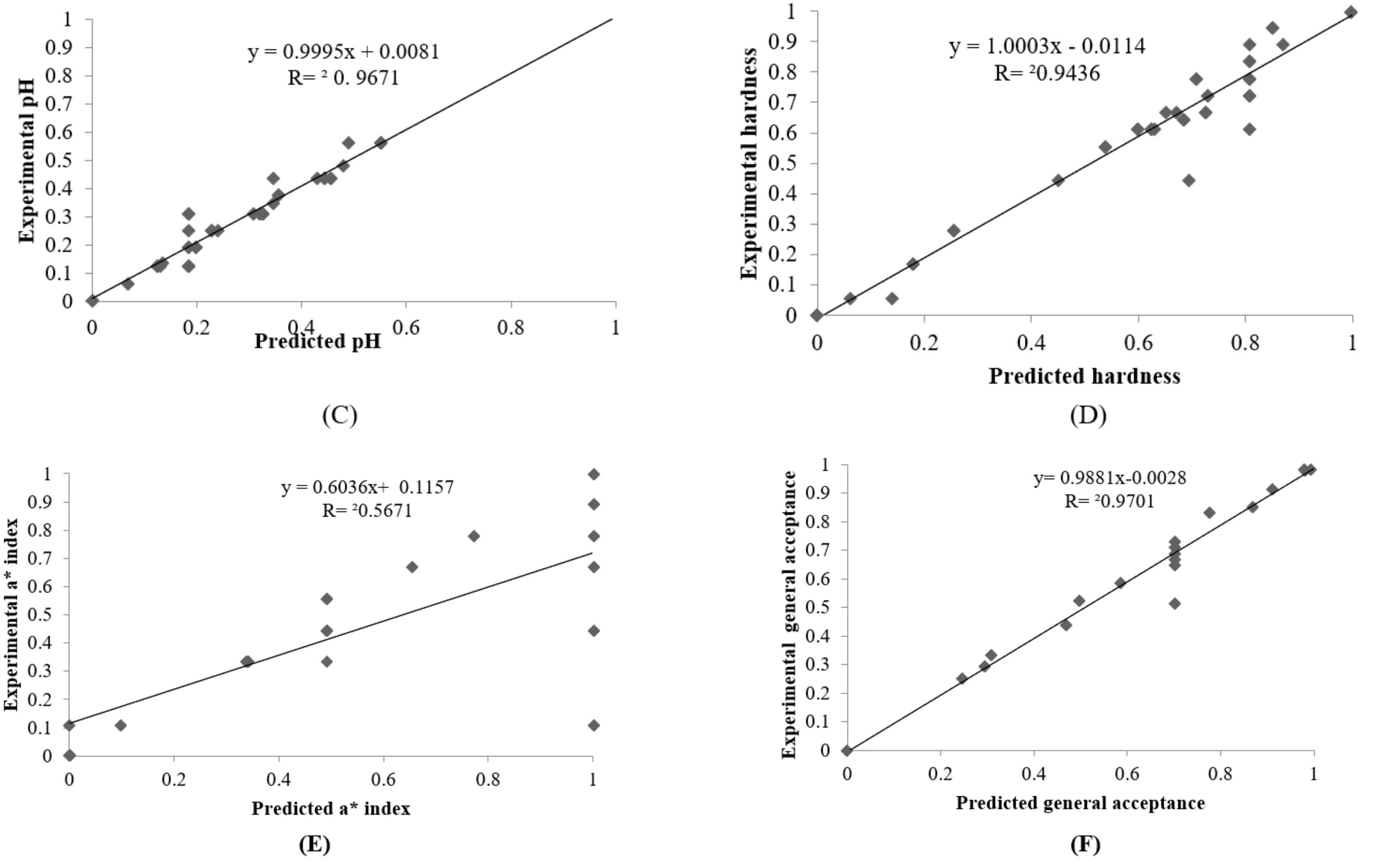


Fig. 2. Diagram of predicted values by the neural network for optimized topology (3-10-6) vs. experimental data for weight loss (A), acidity (B), pH (C), hardness (D), a* index (E) and general acceptance (F).

According to the selected neural network topology, i.e., 3-10-6, the weight matrix for the input layer to the hidden layer is a 3×10 Hessian matrix, connecting three input layer neurons to ten hidden layer neurons. For the hidden layer to the output layer, a 10×6 matrix, connecting ten hidden layer neurons to six neurons of the output layer, will be A and B matrices, respectively:

$$A=\begin{pmatrix} -1.7323 & 1.9938 & 1.0333 \\ -1.0961 & 1.0431 & 0.60282 \\ -2.0998 & 0.6031 & 0.28994 \\ 1.2087 & -2.2128 & 2.5002 \\ -4.035 & 1.8342 & 1.3355 \\ 0.18834 & -0.25044 & 2.8631 \\ 1.8363 & -2.1914 & 0.17958 \\ 1.1644 & 3.4728 & 1.8476 \\ -2.5163 & -1.729 & 1.2061 \\ -1.7869 & -2.4756 & -1.1918 \end{pmatrix}$$

$$B=\begin{pmatrix} -2.7917 & 0.07556 & 0.34793 & 0.17544 & 0.79981 & 0.94846 \\ 0.087276 & 0.66137 & -0.22958 & -0.16101 & 1.2428 & 0.9627 \\ 0.70219 & -0.69767 & 1.1992 & 0.93466 & 0.16968 & 0.10259 \\ -0.67263 & 1.2296 & 0.33013 & -0.83621 & 1.2285 & 0.11047 \\ -0.4949 & -0.2331 & -0.09391 & 0.57375 & -6.1084 & 0.39341 \\ 0.84442 & -1.2386 & -0.20722 & 0.8617 & 4.3918 & -0.05453 \\ 1.4302 & -0.46056 & -1.1059 & 0.20513 & 1.3913 & -0.69446 \\ 0.064208 & -0.24216 & 0.50646 & -0.10749 & -3.5233 & -0.11757 \\ -1.6355 & 0.41679 & 0.29821 & -0.77797 & 0.11487 & 0.96383 \\ -0.17092 & -0.73071 & 0.77872 & 0.61793 & 1.0944 & -0.5162 \end{pmatrix}$$

Meanwhile, the bias matrices of the hidden layer (C matrix) and the output layer (matrix D) will be 10×1 and 6×1, respectively.

$$C=\begin{pmatrix} 3.829 \\ 3.989 \\ 2.767 \\ 1.692 \\ 1.095 \\ 1.075 \\ 2.362 \\ 1.785 \\ -2.531 \\ -2.732 \end{pmatrix} \qquad D=\begin{pmatrix} -1.207 \\ -0.365 \\ 0.345 \\ -0.929 \\ 1.191 \\ -0.733 \end{pmatrix}$$

Discussion

As mentioned in the results section, we selected the optimal neural network as a feedforward back propagation neural network with a hyperbolic sigmoid tangent transfer function, a learning function resilient, and a topology of 3-10-6, including an input layer with three neurons, one hidden layer with ten neurons, and an output layer with six neurons (Fig. 1). It had a determination coefficient of more than 0.988 and a mean square error equal to 0.005. Mohammed et al. (2022) studied the changes in quality characteristics of date palm fruit during the storage period using an artificial neural network. Their results showed that a neural net with 14 neurons in the input layer, one hidden layer with 15 neurons, and the output layer with four neurons were selected as the optimum network. This model had a determination coefficient higher than 0.85 and a mean error of less than 0.121, thus predicting the trend of changes in pH, soluble solids, moisture, and water activity of the samples. The feedforward neural network model facilitated the monitoring of physicochemical changes in banana fruit during storage. The results indicated a high accuracy of the selected models for forecasting changes in the quality attributes of banana fruit (Wang et al., 2015). Fathizadeh et al. (2021) used an artificial neural network to investigate changes in quality attributes of apple fruit during the storage period and classify the fruits based on quality parameters. The results showed that using a neural network increased the accuracy of fruit classification by up to 10%. Forecasting the temperature of fruits in refrigerated trucks was investigated by Badia-Melis et al. (2016). This study reduced costs and the number of temperature sensors needed in the car. The results showed that using these techniques reduced the number of sensors through temperature distribution and estimation on an industrial scale for strawberry transporters, thus reducing the commercial cost. However, using these methods, even when only one sensor appeared as a source for prediction, with an average error of less than 1.49 °C, had a better performance in more accurate shelf-life calculations and reducing product losses. Farzaneh et al. (2018) modeled and examined changes in the quality characteristics of grapes affected by harvesting and storage duration. They stated that through examining different networks, the feedforward backpropagation network with 5-8-2 topologies, a determination coefficient greater than 0.989, and an MSE less than 0.0019 appeared as the best neural model. In this model, the activation and learning function were respectively hyperbolic sigmoid tangent, using Levenberg–Marquardt and 1000 learning cycle. Evaluating the results of the selected optimal models also showed that these models with high determination coefficients (more than 0.957) predicted the change of quality attributes. Azadbakht et al. (2022) used an artificial neural network to predict the storage life of pear fruit, stating that the selected model with a determination coefficient of more than 0.930 with a low MSE was the best ANN model, using the hyperbolic sigmoid tangent activation function.

Conclusion

With the complexity and multitude of factors in food industry processes, especially on an industrial scale, neural networks appear as an acceptable model for modeling processes. In this study, we evaluated the physicochemical properties of grapes in refrigeration by artificial neural networks and predicted them after coating them with maltodextrin, potassium nano carbonate, and pyracantha extract. Different activation functions determined the best type of function in estimating grape characteristics. The results showed that the best modeling performance was observed in the function hyperbolic sigmoid tangent with resilient learning function and 3-10-6 topology, including an input layer with three neurons, one hidden layer with ten neurons, and an output layer with six neurons. This ANN model has the lowest relative error and the highest determination coefficient compared to other functions. While having weight and bias values, the neural model generated extractable relationships. By defining this simple mathematical relationship in computer software such as Microsoft Excel, an application can help predict the desired parameters in the storage process of grapes coated with maltodextrin containing potassium nano carbonate and pyracantha extract. Due to the high accuracy of the neural model, we can rely on the prediction of these models with high confidence and use these models to optimize and control the process, thus saving energy, cost, and time while creating a more desirable final product.

Acknowledgements

Funding was provided by the Vice-Presidency of Research and Technology of Malayer University, Iran (R. Karimi; Grant no. 84.9–148). The authors gratefully acknowledge Malayer University.

Conflict of Interest

The authors indicate no conflict of interest for this work.

References

Abdel-Hakeem A. 2022. Effect of some edible coating films on grapes quality properties during storage. Journal of Modern Research 4(2), 45-53.

Abdollahi M, Bazargani Gilani B, Aghajani N, Daraei Garmakhany A. 2022. Response surface optimization of the effect of *Aloe vera* gel coating enriched with golpar essential oil on the shelf life, postharvest quality, color change and sensory attributes of fresh-cut orange fruit. Journal of Food Processing and Preservation 46 (11), e17019. https://doi.org/https://doi.org/10.1111/jfpp.17019.

Adebayo SE, Hashim N, Abdan K, Hanafi M, Zude-Sasse M. 2017. Prediction of banana quality attributes and ripeness classification using artificial neural network. Acta Horticulturae 1152, 335-344.

Aghajani N, Kashaninejad M, Dehghani AA, Daraei Garmakhany A. 2012. Comparison between artificial neural networks and mathematical models for moisture ratio estimation in two varieties of green malt. Quality Assurance and Safety of Crops and Foods 4(2), 93-101.

AOAC. 2005. Official methods of analysis of the association of official analytical chemists. Association of Official Analytical Chemists, Arlington.

Azadbakht M, Vahedi Torshizi M, Mahmoodi MJ, Abbaszadeh-Mayvan A. 2022. Prediction of physiological characteristic changes in pears subject to dynamic loading using artificial neural network (ANN). International Journal of Horticultural Science and Technology 9(3), 275-289.

Badia-Melis R, Carthy MC, Uysal I. 2016. Data estimation methods for predicting temperatures of fruit in refrigerated containers. Biosystems Engineering 151, 261-271.

Balic I, Moreno A, Sanhueza D, Huerta C, Orellana A, Defilippi BG, Campos-Vargas R. 2012. Molecular and physiological study of postharvest rachis browning of table grape cv Red Globe. Postharvest Biology and Technology 72, 47–56.

Chen SJ, Wang HO, Wang RR, Fu QQ, Zhang W. 2018. Effect of gaseous chlorine dioxide (ClO_2) with different concentrations and numbers of treatments on controlling berry decay and rachis browning of table grape. Journal of Food Processing and Preservation 42 (7), e13662.

De Bruno A, Gattuso A, Ritorto D, Piscopo A, Poiana M. 2023. Effect of edible coating enriched with natural antioxidant extract and bergamot essential oil on the shelf life of strawberries. Foods 12, 488. https://doi.org/10.3390/foods12030488.

De Souza WFC, De Lucena FA, Da Silva KG, Martins LP, De Castro RGS, Sato HH. 2021. Influence of edible coatings composed of alginate, galactomannans, cashew gum, and gelatin on the shelf- life of grape cultivar 'Italia': physicochemical and bioactive properties. LWT- Food Science and Technology 152. 112315, ISSN 0023-6438.

Dolatabadi Z, Elhami Rad AH, Farzaneh V, Akhlaghi Fiezabadi SH, Estiri SH, Bakhshabadi H. 2016. Modeling of the lycopene extraction from tomato pulps. Food Chemistry 190, 968–973.

Farzaneh V, Ghodsvali A, Bakhshabadi H, Dolatabadi Z, Farzaneh F, Carvalho IS, Sarabandi K. 2018. Screening of the alterations in qualitative characteristics of grape under the impacts of storage and harvest times using artificial neural network. Evolving Systems 9, 81–89.

Fathizadeh Z, Aboonajmi M, Hassan-Beygi SR. 2021. Classification of apples based on the shelf life using ANN and data fusion. Food Analytical Methods 14, 706–718.

Granato D, Katayama U, de Castro A. 2011. Phenolic composition of South American red wines classified according to their antioxidant activity, retail price and sensory quality. Food Chemistry 129, 366–373.

Hashemi Shahraki M, Mashkour M, Daraei Garmakhany A. 2014. Development and application of a computer vision system for the measurement of the colour of Iranian sweet bread. Quality Assurance and Safety of Crops and Foods 6(1), 33–40.

Kosasih EA, Dzaky MI, Zikri A, Rachmanudiputra A, Abizar F, Fauzi MB, Suharyadi YS. 2023. Microencapsulation of maltodextrin and gelatin using spray drying with double-condenser compression refrigeration systems. Case Studies in Thermal Engineering 45. 102931. ISSN 2214-157X.

Kowalczyk D, Skrzypek T, Łupina K. 2020. Effect of carboxymethyl cellulose/candelilla wax edible coating incorporated with ascorbic acid on the physicochemical and sensory qualities of prepackaged minimally processed carrots (*Daucus carota* L.) during cold storage. Journal of Food Processing and Preservation 44(9), e14713.

Lado J, Gurrea A, Zacarias L, Rodrigo MJ. 2019. Influence of the storage temperature on volatile emission, carotenoid content and chilling injury development in Star Ruby red grapefruit. Food Chemistry 295, 72–81.

Leng F, Wang C, Sun L, Li P, Cao J, Wang Y, Zhang C, Sun C. 2022. Effects of different treatments on physicochemical characteristics of 'Kyoho' grapes during storage at low temperature. Horticulturae 8, 94. https://doi.org/10.3390/horticulturae8020094.

Martínez-Blay V, Pérez-Gago MB, de la Fuente B, Carbó R, Palou L. 2020. Edible coatings formulated with antifungal GRAS salts to control citrus anthracnose caused by *Colletotrichum gloeosporioides* and preserve postharvest fruit quality. Coatings 10, 730. https://doi.org/10.3390/coatings10080730.

Mehrazin AR, Zendehdel A, Taghipour M. 2013. Training radial neural networks on the basis of statistical models variables and comparing them in predicting the bankruptcy. Investment Knowledge Scientific Research Quarterly 2(7), 149-166.

Menezes J, Athmaselvi KA. 2016. Study on effect of pectin based edible coating on the shelf life of Sapota fruits. Biosciences Biotechnology Research Asia 13(2), 1195-1199.

Mohammed M, Munir M, Aljabr A. 2022. Prediction of date fruit quality attributes during cold storage based on their electrical properties using artificial neural networks models. Foods 11(11), 1666. doi: 10.3390/foods11111666. PMID: 35681416; PMCID: PMC9180397.

Mokhtarian M, Heydari Majd M, Koushki F, Bakhshabadi H, Daraei Garmakhany A. Rashidzadeh Sh. 2014a. Optimization of pumpkin mass transfer kinetic and predict final moisture content by ANN and RSM modeling. Quality Assurance and Safety of Crops and Foods 6(2), 201-214.

Mokhtarian M, Daraei Garmakhany A. 2017. Prediction of ultrasonic osmotic dehydration properties of courgette by ANN. Quality Assurance and Safety of Crops and Foods 9(2), 161-169.

Mokhtarian M, Heydari Majd M, Daraei Garmakhany A, Zaerzadeh E. 2021. Predicting the moisture ratio of dried tomato slices using artificial neural network and genetic algorithm modeling. Research and Innovation in Food Science and Technology 9(4), 411-422.

Mokhtarian M, Koushki F, Bakhshabadi H, Askari B, Daraei Garmakhany A, Rashidzadeh SH. 2014b. Feasibility investigation of using artificial neural network in process monitoring of pumpkin air drying. Quality Assurance and Safety of Crops and Foods 6(2), 191-199.

Pham TT, Nguyen LLP, Dam MS, Baranyai L. 2023. Application of edible coating in extension of fruit shelf life: a review. Agricultural Engineering 5, 520-536.

Rosales R, Fernandez-Caballero C, Romero I, Escribano MI, Merodio C, Sanchez-Ballesta MT. 2013. Molecular analysis of the improvement in rachis quality by high CO_2 levels in table grapes stored at low temperature. Postharvest Biology and Technology 77, 50–58.

Şahin S, Aybastier O, Demir C. 2016. Optimization of ultrasonic-assisted extraction of quercetin and cyanidin from *Pyracantha coccinea* and their scavenging effect on free radicals. Food Biochemistry 40(4), 472-479.

Salehi F. 2020. Recent advances in the modeling and predicting quality parameters of fruits and vegetables during postharvest storage: a review. International Journal of Fruit Science 20, 506-520.

Sapper M, Chiralt A. 2018. Starch-based coatings for preservation of fruits and vegetables. Coatings 8, 152. https://doi.org/10.3390/coatings8050152.

Sarikurkcu C, Tepe B. 2015. Biological activity and phytochemistry of firethorn (*Pyracantha coccinea* M.J. Roemer). Journal of Functional Foods 19, 669-675.

Tahir HE, Xiaobo Z, Mahunu GK, Arslan M, Abdalhai M, Zhihua L. 2019. Recent developments in gum edible coating applications for fruits and vegetables preservation: a review. Carbohydrate Polymers 224, article 115141.

Todorović A, Šturm L, Salević-Jelić A, Lević S, Osojnik Črnivec IG, Prislan I, Skrt M, Bjeković A, Poklar Ulrih N, Nedović V. 2022. Encapsulation of bilberry extract with maltodextrin and gum arabic by freeze-drying: formulation, characterization, and storage stability. Processes 10(10), 1991. https://doi.org/10.3390/pr10101991.

Vargas M, Albors A, Chiralt A, Gonzalez-Martinez C. 2006. Quality of cold-stored strawberries as affected by chitosan–oleic acid edible coatings. Postharvest Biology and Technology 41, 164–171.

Wang L, Li R, Zhang Q, Liu J, Tao T, Zhang T, Wu C, Ren Q, Pu X, Peng W. 2022. *Pyracantha fortuneana* (Maxim.) Li: a comprehensive review of its phytochemistry, pharmacological properties, and product development. Frontiers in Sustainable Food Systems 6, 940900. doi: 10.3389/fsufs.2022.940900.

Wang NN, Yang YC, Sun DW, Pu H, Zhu Z. 2015. Shelf-life prediction of 'Gros Michel' bananas with different browning levels using hyperspectral reflectance imaging. Food Analytical Methods 8, 1173–1184.

Wongphan P, Harnkarnsujari N. 2020. Characterization of starch, agar and maltodextrin blends for controlled dissolution of edible films. International Journal of Biological Macromolecules 156, 80-93.

Yuan XZ, Wu ZM, Li HD, Wang Y, Liu F, Cai H, Newlove AA, Wang Y. 2014. Biochemical and proteomic analysis of 'Kyoho' grape (*Vitis labruscana*) berries during cold storage. Postharvest Biology and Technology 88, 79–87.

Zambrano-Zaragoza ML, González-Reza R, Mendoza-Muñoz N, Miranda-Linares V, Bernal-Couoh TF, Mendoza-Elvira S, Quintanar-Guerrero D. 2018. Nanosystems in edible coatings: a novel strategy for food preservation. International Journal of Molecular Sciences 19(3), 705. doi: 10.3390/ijms19030705. PMID: 29494548; PMCID: PMC5877566.