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Research article

A computer vision system and machine learning algorithms for prediction of physicochemical changes and classification of coated sweet cherry

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A B S T R A C T

The current research utilized visual characteristics obtained from RGB images and qualitative characteristics to investigate changes in surface defects, predict physical and chemical characteristics, and classify sweet cherries during storage. It was achieved with the help of ANN (Artificial Neural Network) and ANFIS (Adaptive Neuro-Fuzzy Inference System) models. The ANN used in this study was a Multilayer Perceptron (MLP) with SigmoidAxon and TanhAxon threshold functions, trained with the Momentum training function. Additionally, ANFIS with a Mamdani system and Triangle, Gauss, and Trapezoidal membership functions, was employed to predict sweet cherries' physical and chemical properties and their quality classification. Both models incorporate four algorithms. Additionally, the algorithms use color statistical features and color texture features combined with physical and chemical properties, including weight loss, firmness, titratable acidity, and total anthocyanin content. The image color and texture characteristics were used by ANN and ANFIS models to predict physical and chemical properties with high accuracy. ANN and ANFIS models accurately estimate sweet cherry quality grades in all four algorithms with over 90 % accuracy. According to the findings, the ANN and ANFIS models have demonstrated satisfactory performance in the qualitative classification and prediction of sweet cherries' physical and chemical properties.

1. Introduction

Consumers consider the quality of fruits and vegetables as a vital factor. Color, size, shape, and texture are important quality factors that can significantly impact the product's final quality when changes occur during storage. Many producers look for fast and non-invasive techniques to evaluate the quality of fruits and vegetables [1,2]. Visual methods can measure the critical qualitative characteristics of color and shape. Computer Vision System (CVS) is an artificial intelligence used to diagnose, separate, and classify fruits and vegetables. It is a fast, non-destructive, and reliable method that can extract many physical and chemical characteristics. In recent times, there have been significant improvements in imaging technologies and their analysis, which have increased the accuracy and efficiency of Computer Vision Systems (CVS) [3,4]. CVS is a rapidly developing technology with numerous applications in the food industry, particularly in quality control and classification of fruits and vegetables [3,5]. Various researchers have reported successful application of CVS in fruit and vegetable quality evaluations [5–14]. CVS can be utilized to detect surface damage on fruits and grade

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them with the help of different algorithms based on fuzzy logic and artificial neural networks (ANN). Several studies have reported detecting defects and surface damage in various agricultural products, including olive [15], banana [16], apple [17,18], citrus [19], and mango [20]. The color features have been already used to predict fruits physicochemical properties. Kaur et al. [21] estimated the maturity of plumps using the RGB coordinates. In this case, high correlations were found between the R/G ratio and TSS. Sharabiani et al. [22,23] successfully estimated titratable acidity (TA) and total soluble solids (TSS) of apple. Pourdarbani et al. [24,25] successfully identified Fuji apples' firmness, acidity, pH, TA, and starch content.

Obtaining information on the ripening stage of fruits and vegetables after harvest enables determining shelf life and quality of produce and identifying the exact spoilage time. This information is necessary to avoid a rise in the quality losses [1,26]. Therefore, many efforts have been made to establish a relationship between product quality changes and spoilage (physical, chemical, and microbial) during storage. Modeling is crucial in controlling and predicting changes in physical and chemical indicators during storage and processing [27]. Food is usually regarded as a complex nonlinear system regarding its qualitative and physicochemical characteristics. ANN and Adaptive Network-based Fuzzy Inference Systems (ANFIS) are new and efficient techniques that have been used in recent years to identify, classify, and model complex nonlinear systems [27,28]. ANN is a technique that emulates the functioning of the human nervous system. This method's precision, quickness, and ability to simulate complex and obscure processes that are hard to study through traditional means have led to its widespread adoption [27]. The ANFIS model combines ANN and fuzzy inference systems, where ANN determines fuzzy inference system parameters. The ANFIS model can be applied without requiring a clear relationship between input and output variables [29]. Various studies have reported the usage of ANFIS, fuzzy logic method, and ANN in the quality classification of pomegranate [30]. These methods have also been employed for predicting the drying process of onion [31], white mulberry [32], tomato [33], and apricot [34]. Additionally, the prediction of water quality [35], tomato ripening evaluation [36], and apple quality grading [37] have been carried out using these techniques.

Sweet cherry (Prunus avium L.) is popular for its attractive color, nutritional benefits, and delicious taste. The fruit's skin color is a vital indicator of its ripeness and quality, which is influenced by the concentration of anthocyanin and the ratio of total soluble solids to total acidity at harvest. Sweet cherries are susceptible to environmental factors, especially temperature changes, and quickly lose their quality after harvesting and during transportation and storage. Sweet cherries can experience post-harvest quality loss, including skin bruising, softening, loss of acidity, stem drying, browning, and fungal diseases [38,39]. Active packaging and coatings are crucial technologies that release active ingredients to protect garden products from microbial degradation and increase their shelf life. This research utilizes the visual features acquired from RGB images and the visual characteristics by applying the ANN and ANFIS. It is done to study the alterations in surface defects, estimate the physical and chemical properties, and categorize the quality of sweet cherries while they are in storage.

2. Materials and methods

2.1. Materials

Fresh and healthy sweet cherries, which were utterly ripe, undamaged, and uniform in shape, size, and color, were sourced from the orchards of Zanjan. Gelatin was procured from Fermand Co. (Iran). 2, 6-dichloroindophenol, Glycerol and Gallic acid were procured from Sigma (USA). Other laboratory-grade chemicals were obtained from Merck (Germany).

2.2. Preparation and storage of coating sweet cherries

Dill essential oil was extracted from dill seeds through water distillation [40,41]. A mixture was prepared using 1.5 % (v/w) solutions of Balango mucilage powder (BM) and gelatin in a 1:1 ratio. The mixture was prepared by adding glycerol (45 % based on biopolymer, w/w), DEO (35 % v/v), Tween 80, and DEO (0 %, 1 %, and 2 % v/v) along with zinc oxide nanoparticles (0.5 % and 1.5 % based on biopolymer, v/w) [42]. The mixture was homogenized for 20 min with the help of an ultrasonic homogenizer at 1000 RPM. The sweet cherries were dipped in the coating solution for 5 min and then stored in ventilated polyethylene terephthalate containers at a temperature of 4 °C [2].

2.3. Physicochemical characterization

The weight loss was calculated by dividing the weight difference of the samples at different times with zero time by the initial weight. Sweet cherry firmness was assessed using a penetration test and a texture tester (STM-5, Centam, Iran). A cylindrical probe with a diameter of 3 mm and a penetration speed of 10 mm s^{-1} was used, and the probe penetrated the sample to a depth of 10 mm. Titratable acidity was measured using the AOAC method. For total anthocyanin content (TAC) determination, 2 g of sweet cherry and 4 mL of methanol were homogenized, stored in freezer (1 h at −18 °C), and centrifuged at 10,000×g (15 min, 4 °C). The supernatant was loaded onto a C18 Sep-Pak cartridge, previously conditioned with 5 mL of methanol, 5 mL of pure water, and then with 5 mL of 0.01 N HCl. The cartridge was washed with 5 mL of pure water and then eluted with acidified MeOH (0.01 % HCl). Absorbance of the collected fraction was measured at 530 nm. Total anthocyanin contents were calculated using cyanidin-3-glucoside (molar absorption coefficient of 23900 l $cm^{-1}.mol^{-1}$ and molecular weight of 449.2 g mol^{-1}), and results were expressed as mg 100 g^{-1} [43].

2.4. Computer vision system (CVS)

The methodology used in this research to monitor changes in sweet cherries during storage includes three main stages: image acquisition, preprocessing, and feature extraction. These stages involve extracting color and texture features from the captured images (Fig. 1). A white box, also known as an image processing chamber, was used for image acquisition purposes. The lighting system in this chamber consisted of a LED screen (15 w) installed on the ceiling, which emitted white light. Moreover, two SMD lamps (9 w) were positioned above and opposite each other, emitting white light. These lamps were adjustable and could be rotated to modify the lighting angle. The angle of the lamps was adjusted to minimize noise in the captured images. The imaging was carried out at a distance of 35 cm from the sample and in Raw mode, using a camera (Sony, model DSC-H5, Japan) with a shutter speed of 1.6 s, a focal length of 18 mm, and an aperture of f/1.5. The raw images were saved in TIFF format, with a resolution of 2304 × 3072 and a pixel resolution of 0.03 mm (Fig. 2a) [5,8].

The preprocessing for the images accomplished with using MATLAB R2019a software (Mathworks, USA). Firstly, the R, G, and B color channels were extracted separately from each image after image segmentation, Laplace transforms, and noise removal with the help of a Median filter (Fig. 2b). The images were then converted from RGB to Grayscale (Fig. 2c). After that, the grayscale image was converted to a binary image with pixel values of 0 and 1 (Fig. 2d) using the histogram of the image and the threshold level obtained by trial and error. This conversion made separating the healthy area from the defective area easy.

After removing the sweet cherry's tail (Fig. 3b), the defective part was isolated (Fig. 3c), and the ratio of the defective surface (S_d) to the total surface (S_t) was determined by measuring the uniformity of the pixels. The surface damage was calculated using Equation (1):

$$\textit{Surface damage}\ (\%) = \frac{S_d}{S_t} \times 100 \tag{2}$$

Fruits are classified into four quality grades based on the amount of surface damage. Grade 1 fruits have less than 5 % surface damage, grade 2 fruits have between 5 % and 15 % surface damage, grade 3 fruits have between 15 % and 25 % surface damage, and grade 4 fruits have more than 25 % surface damage. This grading system is based on research findings [5,8].

The RGB algorithm was utilized to categorize sweet cherries and determine their physical and chemical characteristics. The algorithm involved calculating the mean value of every color channel to classify each sweet cherry into three types of statistical features of color calculated for every channel [5]:

$$\textit{Average}\ (\mu) = \frac{1}{N}\sum_{i=1}^{N} P_i \tag{2}$$

$$\textit{Standard}\ \text{deviation}\ (\sigma) = \left(\frac{1}{N-1}\sum_{i=1}^{N}(P_i-\mu)^2\right)^{\frac{1}{2}} \tag{3}$$

Fig. 1. Scheme of CVS set-up.

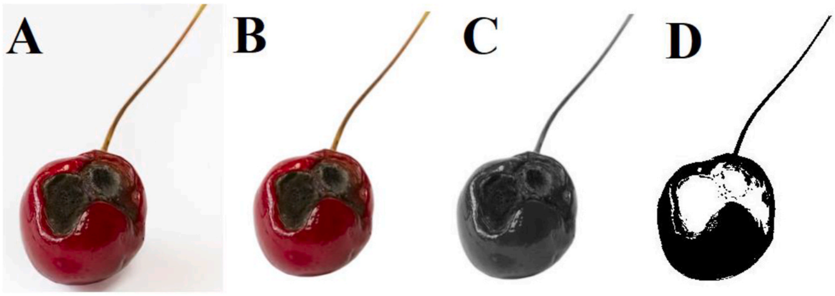

Fig. 2. (A) RGB image, (B) Image without background, (C) Gray image, and (D) Binary image.

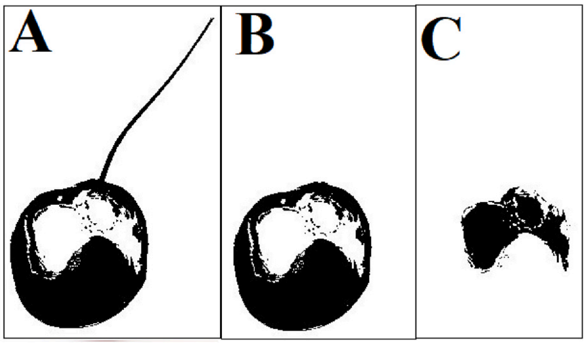

Fig. 3. (A) Threshold image, (B) Image after removing the sweet cherry tail, (C) Defected region image.

$$Skewness = \frac{\sum_{i=1}^{N}(P_i - \mu)^3}{N\sigma^3} \tag{4}$$

Where P_i is the intensity of each color channel in each pixel. Color texture features, including Contrast, Correlation, Energy, and Homogeneity, were used to detect the appearance defects caused by blackness or whiteness caused by mold or any similar color change. These features were obtained using the Gray level co-occurrence matrix (GLCM) of images [5]:

$$\text{Contrast} = \sum_{i,j=1}^{N} |i-j|^2 P_{ij} \tag{5}$$

$$\text{Correlation} = \sum_{i,j=1}^{N} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{6}$$

$$\text{Energy} = \sum_{i,j=1}^{N} {P_{ij}}^2 \tag{7}$$

$$\text{Homogeneity} = \sum_{i,j=1}^{N} \frac{P_{ij}}{1+|i-j|} \tag{8}$$

2.5. Artificial neural network (ANN)

The aim of employing ANN for modeling is to discover the optimal weights and biases in the inter-neuron connections via training. Multilayer perception (MLP) networks are widely used for classification, grading, and quality prediction among different artificial ANN architectures images [5]. Most studies on complex patterns use MLP to classify different groups based on training patterns. The study based on back propagation (BP) learning rule were utilized a MLP to predict sweet cherries' physical and chemical characteristics and quality class. During training by BP algorithm, layer weights were updated at the first epoch. The weight coefficients were updated by learning rules and weight values. This algorithm uses the supervised training procedure where the network weights and biases are initialized randomly at the beginning of the training phase. The process of error minimization is got by applying a gradient descent rule. Momentum training algorithms used for network training. Different transfer functions including SigmoidAxon and TanhAxon thresholds were used. After using learning algorithm and proper transfer function, the effect of neuron number and training epochs were investigated on ANN performance. The input data is repeatedly presented to the ANN and the error is computed for each presentation by comparing the output of the neural network with the desired output. The logarithmic sigmoid threshold function was used in all cases. 60 %, 15 %, and 25 % of the data were allocated to train, test, and validate the model. The training rate and momentum for the trial and error method were set to 0.05 and 0.15, respectively. The ANN was implemented using the MATLAB software's ANN toolbox (R2019a, Mathworks, USA).

ANN designed to predict physical and chemical properties (weight loss, firmness, titratable acidity, and total anthocyanin content) has an input layer with 21 neurons, including visual characteristics (color and texture) and one neuron in the output layer (weight loss, firmness, titratable acidity titer, and total anthocyanin content). This neural network architecture has one or two hidden layers, and its optimal number of neurons was determined through trial and error. The physical and chemical characteristics of sweet cherries and the color and texture obtained from the RGB image were utilized to predict the quality and determine the quality class of coated sweet cherries during storage at room temperature. Four ANN models predicted quality class using 210 images (seven treatments, six storage times). The surface damage percentage of all sweet cherries was determined through qualitative classification with CVS and visual inspection. In the first model, the input includes statistical features for each color channel, such as average, standard deviation, and skewness. In the second model, the input consists of color texture features such as Contrast, Correlation, Energy, and Homogeneity for each channel. The third model combines both Color statistical features and color texture features. In the fourth model, the input consists of weight loss, firmness, titratable acidity, and total anthocyanin content, which are physical and chemical properties.

2.6. Adaptive Network-based fuzzy inference system (ANFIS)

ANFIS is a hybrid system that combines ANN and fuzzy logic concepts. It employs a set of if-then fuzzy rules to predict and determine the quality characteristics of food products. Using fuzzy logic-based methods allows for the simulation of human behavior in non-deterministic decision-making processes. The technique mentioned in Fig. 4 is highly effective in predicting the quality of food products. It involves changing the values of the center and the range of membership functions in various iterations until an appropriate network is achieved based on the minimum available error (using the Back Propagation algorithm). ANFIS modeling was conducted using if-then fuzzy rules and the ANFIS toolbox of Matlab software (R2019a, Mathworks, USA) for the input and output variables. The Mamdani system was employed for this purpose. The optimal membership function among the Triangle, Trapezoidal, and Gauss functions, and their appropriate membership degrees for each input combination were obtained by trial and error. The optimal number of membership functions is usually determined through trial and error. Like the ANN model, visual properties and sweet cherry classification were used as inputs and outputs to predict physical and chemical properties. The study utilized a link learning algorithm that combined the error backpropagation algorithm and the least square method for training and matching with the fuzzy inference system. 70 % of the data was used for training, while the remaining 30 % was used for validation.

2.7. Statistical analysis

The model was evaluated and compared using two metrics called the coefficient of determination (R^2) and the Root Mean Square Error (RMSE) [44,45]:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (O-P)^2}{\sum_{i=1}^{n} (O-\overline{P})^2} \right) \tag{9}$$

$$\mathrm{RMSE} = \sqrt{\frac{(O-P)^2}{n-p}} \tag{10}$$

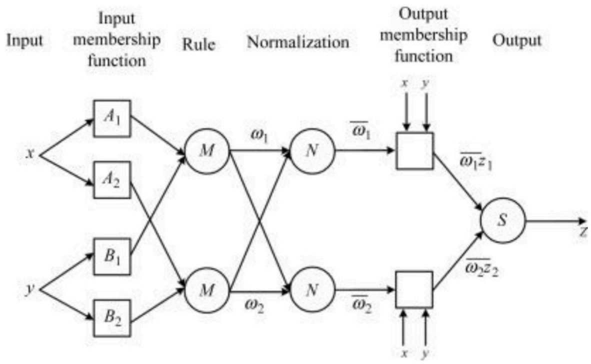

Fig. 4. ANFIS structure.

Where, O represents the experimental data, P represents the predicted data, p represents the number of observations, and n represents the model parameters. Excel software (V 2019, USA) was also used to plotting the graphs and calculating the error bar.

3. Results and discussion

3.1. Total anthocyanin content (TAC) and surface damage of sweet cherries

Anthocyanins are phenolic compounds and water-soluble pigments with high antioxidant potential, which makes it important to maintain higher amounts of these compounds during fruit storage [46,47]. A sharp decrease in TAC during cold storage time was observed in all the treatments (Fig. 5). Anthocyanins are easily degraded under the influence of pH, temperature, oxygen, light, and enzyme activities. Such a decrease in TAC is related to the decreased activity of enzymes influencing anthocyanin synthesis, i.e., phenylalanine ammonia lyase and anthocyanidin synthase [47]. TAC in coated cherries was significantly ($p<0.05$) higher compared to the Ctrl treatment. The barrier properties of the coating cause the change of the fruit internal atmosphere, leading to the decreased metabolic activities for anthocyanin degradation [46]. The addition of DEO and Zno-np to the BM-Ge coating also reduces pH fluctuations, which can lead to anthocyanin retention, in addition to limiting water loss and respiration [46]. The addition of essential oil to the coating improves its antioxidant properties. This significant increase in cherry antioxidant activity during the storage period can be attributed to the better preservation of phenolic content and TAC content. Similar results have been reported by other researchers [46–48].

The results indicate that surface damage and defects of sweet cherries increased significantly ($p<0.05$) during storage time (Table 1). During storage, physical and chemical changes and surface microbial activity result in these changes. Sweet cherry surface changes are connected to surface decay, correlated with the fruit's respiration rate. Sweet cherries have a high respiration rate, making them vulnerable to various types of fungal decay [49]. Table 1 shows a decrease in surface damage rate with increased DEO or ZnO concentration in the coating treatment. The coating treatment by formation a better physical barrier, creates of a modified atmosphere around the fruit surface and slows its respiration rate, and ultimately delays decay. Compared to the Ctrl treatment, the BM-Ge coating treatment reduces respiration rates due to its water vapor barrier properties. Increasing the concentration of DEO reduces water vapor permeability. It creates antimicrobial properties in the coating, which reduces physical and chemical changes and microbial activity and, as a result, reduces surface damage and defects. DEO creates a waterproof layer on sweet cherry surfaces, preventing pathogenic fungi and bacteria from adhering, invading, germinating, and reproducing [49,50].

The study found that the surface damage rate in coating treatments containing Zno-np was significantly lower ($p<0.05$) than in other treatments. It may be due to the antimicrobial properties of Zno-np, modifications to the internal atmosphere, and a reduction in sweet cherry respiration rate [51]. According to the results, EO 2%-Zno 0.5 % treatment showed the most minor surface damage. It is probably due to the creation of a relatively impermeable layer of oxygen. As a result, the oxygen levels decrease, microbial activities are reduced, and the respiration rate of sweet cherries is also reduced.

3.2. Prediction of physical and chemical properties

A trial and error approach was employed to examine the performance of MLP in predicting the physical and chemical properties of sweet cherries during storage time using visual properties. Different combinations of neurons in layers with varying architectures were explored. The study aimed to identify the most appropriate network configuration by analyzing the number of distinct neurons in the hidden layers. The accuracy of ANN was evaluated by analyzing the experimental and prediction data using MLP in three distinct stages: training, evaluation, and testing. After training different network structures, the best ANN architecture was obtained by evaluating the R^2 coefficient and RMSE. A summary of the results obtained for predicting weight loss, firmness, titratable acidity, and

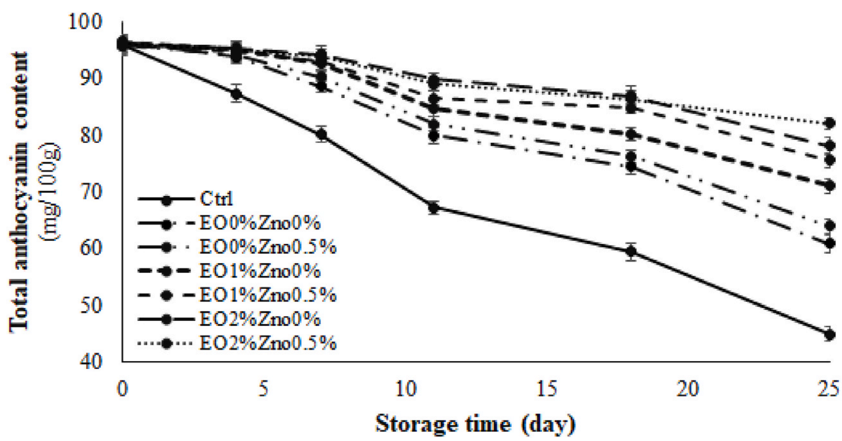

Fig. 5. TAC changes of sweet cherry during cold storage.

Table 1
Measured surface defects (%) of sweet cherry by CVS.

	Storage time					
	0	4	7	11	18	25
Ctrl	1.22 ± 0.65^{aA}	6.28 ± 0.35^{eB}	11.31 ± 0.78^{fC}	16.54 ± 0.92^{fD}	25.31 ± 0.81^{fE}	30.13 ± 0.83^{g8F}
EO 0%-Zno 0 %	1.03 ± 0.29^{aA}	4.24 ± 0.18^{dB}	6.63 ± 0.34^{eC}	10.11 ± 0.87^{eD}	18.56 ± 0.93^{eE}	23.46 ± 0.78^{fF}
EO 1%-Zno 0 %	1.14 ± 0.43^{aA}	3.77 ± 0.29^{cB}	5.11 ± 0.42^{dC}	7.45 ± 0.74^{dD}	11.53 ± 0.89^{dE}	16.89 ± 0.85^{eF}
EO 2%-Zno 0 %	1.16 ± 0.29^{aA}	2.97 ± 0.47^{bB}	4.26 ± 0.35^{cC}	6.18 ± 0.68^{cdD}	9.13 ± 0.93^{cE}	15.21 ± 0.96^{dF}
EO 0%-Zno 0.5 %	1.32 ± 0.31^{aA}	2.11 ± 0.25^{abB}	3.24 ± 0.31^{bC}	5.48 ± 0.78^{bcD}	7.67 ± 0.86^{bcE}	10.01 ± 0.89^{cF}
EO 1%-Zno 0.5 %	1.41 ± 0.25^{aA}	1.88 ± 0.42^{aA}	2.76 ± 0.29^{bB}	4.13 ± 0.79^{bC}	6.11 ± 0.84^{abD}	8.76 ± 0.92^{aE}
EO 2%-Zno 0.5 %	1.01 ± 0.19^{aA}	1.48 ± 0.39^{aA}	2.16 ± 0.28^{aB}	3.23 ± 0.93^{aC}	5.14 ± 0.98^{aCD}	6.93 ± 0.78^{aD}

total anthocyanin content simultaneously is presented in Table 2. Based on the color and texture characteristics of the image, Table 2 shows that the ANN was able to predict the values of weight loss, firmness, and total anthocyanin content with a high degree of accuracy. The R^2 coefficient was more significant than 0.928, and the RMSE was less than 0.095.

It indicates that the ANN is highly efficient in predicting these experimental physical and chemical indicators. Although ANN was used to predict the titratable acidity value, it did not perform well. The best configuration that could predict the results had a network structure of 1-6-14-21, with the TanhAxon threshold function. This network had 21 inputs, two hidden layers (one with 14 neurons and the other with 6 neurons), and one output. However, even with this configuration, the predicted results had an R^2 value of only 0.806 and an RMSE value of 0.432, which is not considered a good performance. This performance can be attributed to the small effect of titratable acidity changes on sweet cherry appearance.The study found that the following configurations were used to predict weight loss, firmness, and total anthocyanin content: 1-3-13-21 with SigmoidAxon threshold function for weight loss, 1-21-2-1 with SigmoidAxon threshold function for firmness, and 1-2-17-21 with SigmoidAxon threshold function for total anthocyanin content. They were chosen as the best configuration. These configurations can predict weight loss, firmness, and total anthocyanin content with R^2 coefficients of 0.976, 0.928, and 0.957 and MSE of 0.044, 0.095, and 0.059, respectively.

Different studies have shown that neural networks, as non-linear systems, can be used for predicting food quality parameters. They can also replace destructive tests and automate processes [5,52]. In addition to calculating the evaluation metrics, Fig. 6 shows the regression plot of the measured and predicted values by ANN. The dispersion curve has been plotted for the optimal configuration. According to the figure, the closeness of the data to the 45-degree lines with a high correlation coefficient indicates the high performance of the ANN in accurately predicting the studied parameters. As a result, the predicted data agrees excellently with the experimental data. Using the Mamdani inference system in the MATLAB software toolbox under if-then rules, a simultaneous prediction of weight loss, firmness, titratable acidity, and total anthocyanin content was made. Using 21 inputs, various membership functions, and degrees of membership, 128 If-Then rules were generally used to predict physical and chemical properties.

The prediction results with different membership functions and the best membership degree are shown in Table 3. In ANFIS, the

Table 2
Some of the best ANN topologies to predict physicochemical properties of sweet cherry.

Parameter	Activation function of hidden layer	Topology	Training		Test	
			R^2	RMSE	R^2	RMSE
Weight loss	SigmoidAxon	21-17-1	0.921	0.110	0.963	0.052
		21-13-3-1	0.929	0.103	0.976	0.044
		21-13-6-1	0.923	0.109	0.968	0.049
	TanhAxon	21-19-1	0.916	0.116	0.959	0.057
		21-15-5-1	0.920	0.109	0.967	0.050
		21-21-6-1	0.925	0.103	0.972	0.046
Firmness	SigmoidAxon	21-15-1	0.889	0.196	0.918	0.117
		21-21-1	0.892	0.183	0.928	0.095
		21-13-2-1	0.890	0.187	0.922	0.103
	TanhAxon	21-13-1	0.892	0.185	0.926	0.101
		21-16-2-1	0.870	0.199	0.919	0.115
		21-19-6-1	0.891	0.185	0.927	0.099
Titratable acidity	SigmoidAxon	21-8-1	0.753	0.579	0.798	0.441
		21-21-1	0.747	0.588	0.791	0.452
		21-8-3-1	0.743	0.593	0.789	0.459
	TanhAxon	21-13-1	0.752	0.580	0.793	0.448
		21-18-1	0.757	0.564	0.799	0.437
		21-10-2-1	0.762	0.569	0.806	0.432
Total anthocyanin content	SigmoidAxon	21-22-1	0.912	0.123	0.951	0.064
		21-19-1	0.915	0.120	0.953	0.061
		21-17-2-1	0.916	0.119	0.957	0.059
	TanhAxon	21-16-1	0.903	0.132	0.949	0.068
		21-22-1	0.904	0.129	0.950	0.067
		21-16-4-1	0.909	0.125	0.955	0.060

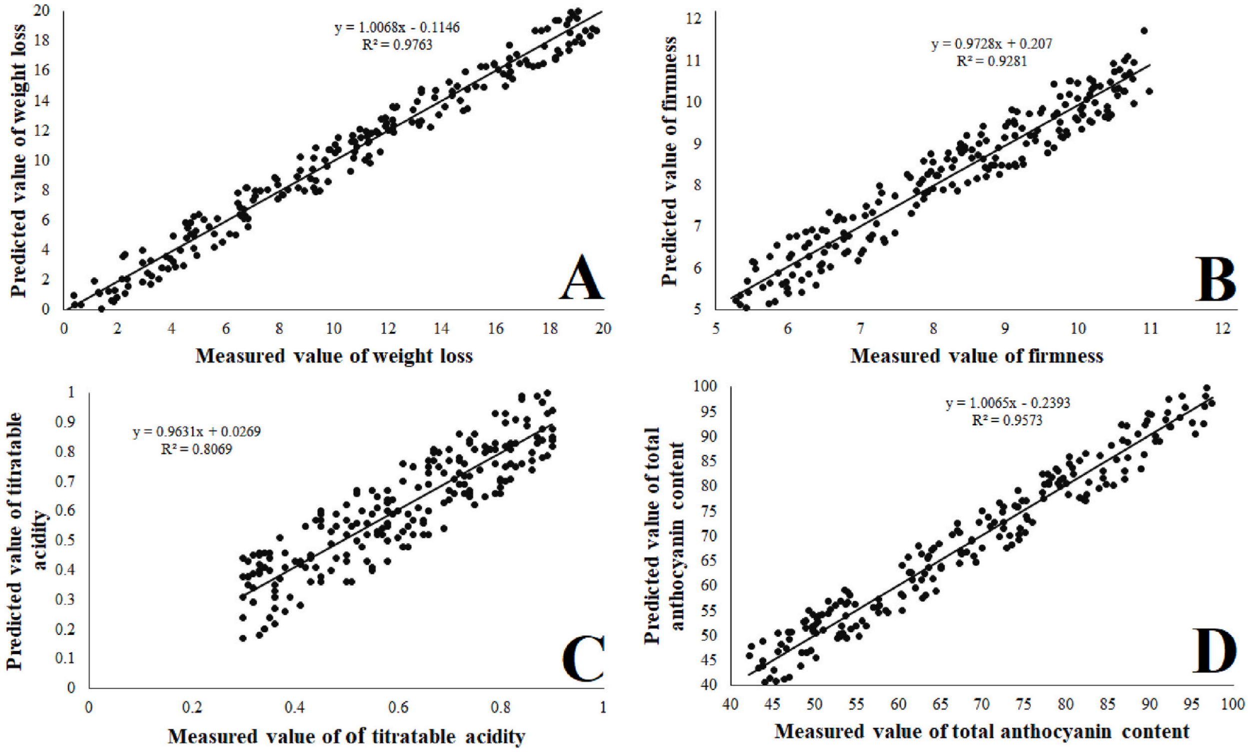

Fig. 6. Dispersion curve for the measured and the predicted values of (A) weight loss, (B) firmness, (C) titratable acidity and (D) total anthocyanin content by ANN for best model.

Table 3
Some of the best ANFIS topologies to predict physicochemical properties of sweet cherry.

Parameter	Membership Function	Number of Membership Functions	Training		Test	
			R^2	MSE	R^2	RMSE
Weight loss	Gauss	3	0.947	0.078	0.986	0.029
	Triangle	2	0.954	0.061	0.993	0.010
	Trapezoidal	2	0.942	0.086	0.981	0.036
Firmness	Gauss	3	0.920	0.077	0.959	0.058
	Triangle	3	0.929	0.101	0.969	0.050
	Trapezoidal	2	0.923	0.072	0.962	0.055
Titratable acidity	Gauss	3	0.802	0.411	0.845	0.265
	Triangle	2	0.791	0.445	0.839	0.294
	Trapezoidal	2	0.783	0.487	0.832	0.310
Total anthocyanin content	Gauss	3	0.939	0.090	0.977	0.050
	Triangle	3	0.941	0.092	0.976	0.052
	Trapezoidal	2	0.947	0.082	0.981	0.033

selection of membership functions and their degree of membership is problematic, and the model's structure is typically determined through trial and error. During the training of the ANFIS structure, a hybrid method combined the least squares and backpropagation methods. An error limit of zero was set to establish a training stop criterion. For each input combination, the network was implemented to predict the physical and chemical properties of sweet cherries by using the training and test data and selecting the input and output membership function from among different functions and their degree of membership. The results showed that the best prediction for weight loss, firmness, titratable acidity, and total anthocyanin content, respectively, with the ANFIS model with Triangle membership functions (number of membership functions 2), Triangle membership (number of membership functions 3), Gauss membership (number of membership functions) 3) and Trapezoidal (number of membership functions 2) was performed. According to the table, using color and texture characteristics from images, ANFIS accurately predicted the weight loss, firmness, and total anthocyanin content of sweet cherries during storage under different conditions. An RMSE of less than 0.038 is considered acceptable.

The best ANFIS configuration for predicting titratable acidity had an R^2 coefficient of 0.845 and an RMSE of 0.265. The model's complexity increased with the number of membership functions, negatively affecting its efficiency. In addition to calculating the evaluation indices, the regression diagram between the measured and predicted values by ANFIS is shown in Fig. 7. As seen, the high

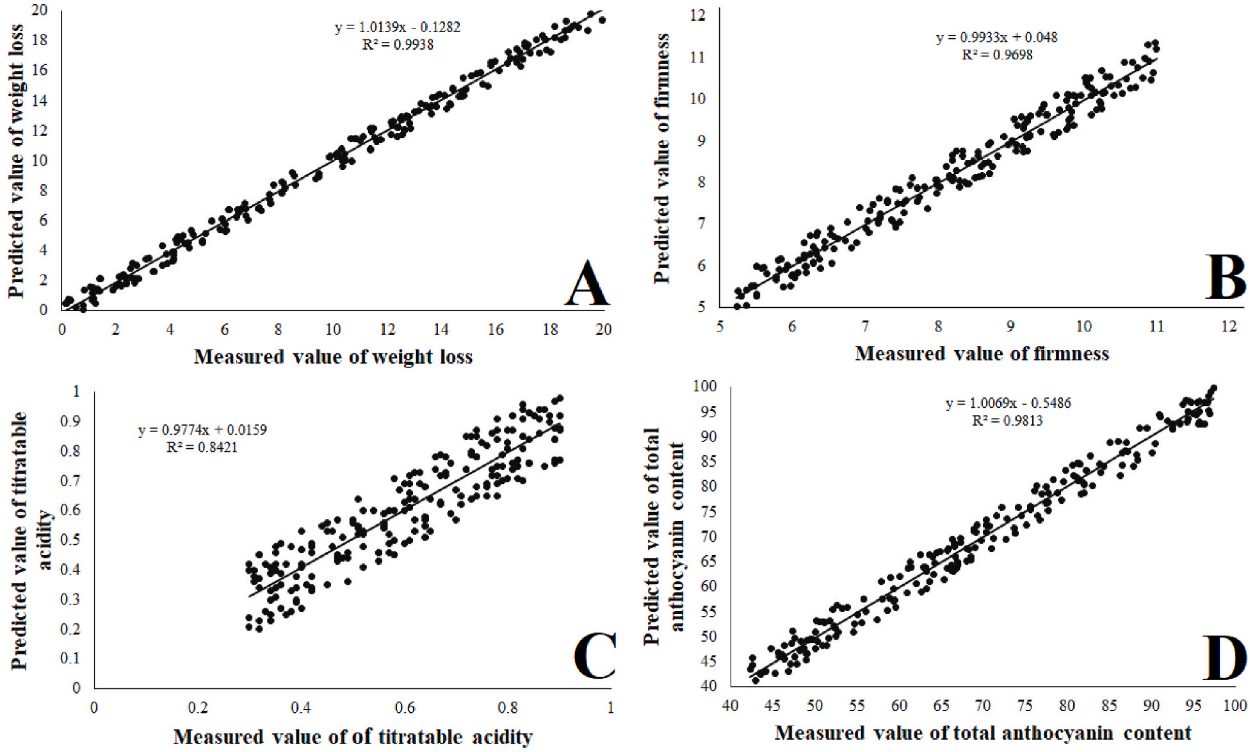

Fig. 7. Dispersion curve for the measured and the predicted values of (A) weight loss, (B) firmness, (C) titratable acidity and (D) total anthocyanin content by ANFIS for best model.

correlation of these data indicates the high accuracy of the selected ANFIS model. So far, limited research has been conducted to use ANFIS to predict quality characteristics during fruit and vegetable storage [2,53]. The results showed that both ANFIS and ANN models successfully predicted sweet cherries' physical and chemical changes during storage. However, both models were able to model with

Table 4
Some of the best ANN topologies to predict quality grade of sweet cherry by using color statistical, color texture, color statistical and texture, and physicochemical features.

ANN input	Activation function of hidden layer	Topology	Training		Test	
			R^2	RMSE	R^2	RMSE
Color statistical features	SigmoidAxon	9-15-1	0.870	0.191	0.901	0.130
		9-19-1	0.876	0.187	0.905	0.124
		9-15-4-1	0.872	0.189	0.903	0.127
	TanhAxon	9-12-1	0.867	0.198	0.900	0.133
		9-13-2-1	0.859	0.209	0.899	0.139
		9-19-6-1	0.874	0.198	0.901	0.132
Color texture features	SigmoidAxon	12-8-1	0.873	0.199	0.907	0.101
		12-12-7-1	0.881	0.172	0.909	0.095
		12-19-7-1	0.865	0.201	0.900	0.137
	TanhAxon	12-18-1	0.877	0.183	0.908	0.099
		12-15-5-1	0.873	0.192	0.903	0.129
		12-20-8-1	0.872	0.203	0.901	0.134
Color statistical and texture features	SigmoidAxon	21-8-1	0.898	0.149	0.926	0.095
		21-16-1	0.900	0.142	0.931	0.088
		21-12-3-1	0.903	0.136	0.938	0.082
	TanhAxon	21-19-1	0.896	0.156	0.930	0.087
		21-15-2-1	0.889	0.174	0.921	0.098
		21-18-5-1	0.892	0.168	0.925	0.087
Physicochemical features	SigmoidAxon	4-17-1	0.906	0.133	0.940	0.079
		4-16-4-1	0.914	0.125	0.943	0.075
		4-19-8-1	0.923	0.108	0.952	0.061
	TanhAxon	4-21-1	0.918	0.118	0.948	0.063
		4-12-6-1	0.901	0.140	0.939	0.082
		4-18-9-1	0.902	0.136	0.942	0.077

high accuracy. However, the ANFIS model had the best prediction performance, showing its higher accuracy. This relative superiority can be seen in the fact that the ANFIS model is a combination of two fuzzy models and ANN; that is, it uses ANN to train data, and the model is built by using a specific membership function and a series of fuzzy rules.

3.3. Quality prediction

The study utilized color and texture features from RGB images and physical and chemical properties to predict sweet cherry quality using a post-release artificial neural network. The output of all four types of models was sweet cherry quality. In the first ANN model, the input includes color statistical features (average, standard deviation, and skewness for each color channel) with 9 inputs. In the second ANN model, the input includes Color texture features (including contrast, correlation, energy, and homogeneity for each channel) with 12 inputs. The third ANN model included color statistical features and texture features with 21 inputs. In the fourth ANN model, the input consisted of physical and chemical characteristics, including weight loss, firmness, titratable acidity, and total anthocyanin content. These inputs were connected to the output by a transfer function. In total, according to 7 treatments, 6 storage times and 5 repetitions, 210 images were obtained. From 210 sweet cherries images (grade 1: 95 images, grade 2: 80 images, grade 3: 25 images, and grade 4: 10 images), 126 images were used for training, 32 images for testing, and 52 images for network validation. The results were analyzed based on the type of input (Table 4). As can be seen in Table 4, the classification performed by algorithms based on physicochemical features and color statistical and texture features could be done with high accuracy. The reason for this is the important role of both color and visual characteristics as well as physical and chemical characteristics on the quality classification of sweet cherries.

Although the accuracy of algorithms based on physicochemical features and color statistical and texture features is higher than the algorithms based on color texture features and color statistical features, however the difference is insignificant. Following the evaluation of various topologies, the MLP network utilizing the SigmoidAxon transfer function and the topologies 1-8-19-4, 1-3-12-21, 1-7-19-12, and 1-19-9, correspondingly, were found to be suitable for algorithms based on physicochemical features. Color statistical and texture features, Color texture features, and Color statistical features were selected as the best topologies. These topologies predict the quality of sweet cherry with an accuracy of 90.2 %, which is a very high accuracy.

According to Table 5, it can be seen that the ANFIS model can predict the quality grade of sweet cherries with excellent performance in all four algorithms with R^2 greater than 0.943 and RMSE less than 0.077. As seen in Table 6, the prediction performed by algorithms based on physicochemical features, color statistics, and texture had higher accuracy. However, the difference between all four algorithms could have been better. The results of ANFIS analysis showed that the average accuracy of different algorithms in the best ANFIS topology for algorithms based on physicochemical features, Color statistical and texture features, Color texture features, and Color statistical features are 0.990, 0.986, 0.957, and 0.943 respectively. The results of grading apples [54], olives [55], and mangoes [56] showed that CVS can detect defects and surface damage with high precision and accuracy and grade accordingly.

3.4. Qualitative classification

ANN and ANFIS algorithms were also able to classify sweet cherries into different quality grades with high precision and accuracy. Previously, sweet cherries were classified into four qualitative grades based on experimental studies and the percentage of surface damage. With the help of the confusion matrix (Table 6), the classification accuracy percentage for each class can be determined for the ANN algorithm with the best configuration. In this matrix, the numbers on the diagonal are for the correctly classified samples, and the numbers outside the primary diameter represent the wrongly classified samples. In this table, the numbers in each column represent the predicted numbers, and each row represents the actual numbers. The results presented in the clutter matrix show the ability of the models based on the features extracted from the images to classify the results with high accuracy, like the algorithm based on the qualitative parameters. Based on the ANN classification results mentioned above, it can be concluded that the quality of sweet cherries during storage in different conditions can be classified using color indices (non-destructive) through CVS. It implies that it is feasible to predict the quality grade of sweet cherries by considering several color indicators. Using this method is simple, fast, non-destructive, and cost-effective. The ANN best topologies perform the classification with an accuracy of above 90.4 %, which is a very high accuracy.

Table 7 shows the confusion matrix results and the grading accuracy of each pattern base on the ANFIS algorithms. As can be seen, these algorithms could perform classification with high accuracy, among which Color statistical and texture features and physicochemical features algorithms had higher classification accuracy. The results of the present study show that the designed ANFIS has excellent performance in sweet cherry quality classification. Besides, due to linguistic variables in ANFIS, it can be easily used in the industry. Another critical point in the above results was that the model based on features extracted from the image (Color statistical and texture features, Color texture features, and Color statistical features) also performed very well. Finally, the results of ANN and ANFIS as sweet cherry classification models showed that both models could successfully separate sweet cherries based on quality grade and, with the help of visual or physical and chemical characteristics, with high accuracy. A similar algorithm was developed by Golzarian et al. (2017) to grade mangoes based on surface damage, which was able to grade with 90 % accuracy (based on the green channel) [65]. This research showed that it is possible to predict the quality grade of sweet cherries with several color indicators as a simple, fast, non-destructive, and low-cost method of Destructive tests. The method can replace human inspection by eye or other methods in cold stores, warehouses, factories, and gardens.

Table 5
Some of the best ANFIS topologies to predict quality grade of sweet cherry by using color statistical, color texture, color statistical and texture, and physicochemical features.

Parameter	Membership Function	Number of Membership Functions	Training		Test	
			R^2	MSE	R^2	RMSE
Color statistical features	Gauss	2	0.911	0.122	0.943	0.088
	Triangle	2	0.908	0.126	0.935	0.096
	Trapezoidal	2	0.909	0.129	0.939	0.091
Color texture features	Gauss	2	0.920	0.078	0.957	0.052
	Triangle	3	0.913	0.086	0.954	0.060
	Trapezoidal	3	0.911	0.085	0.952	0.059
Color statistical and texture features	Gauss	2	0.943	0.087	0.986	0.029
	Triangle	2	0.936	0.096	0.983	0.037
	Trapezoidal	3	0.931	0.101	0.978	0.045
Physicochemical features	Gauss	2	0.945	0.080	0.987	0.029
	Triangle	2	0.948	0.073	0.990	0.027
	Trapezoidal	2	0.942	0.085	0.982	0.035

Table 6
Confusion matrix for classification and validation of the result base on the best ANN topologies.

ANN input		Grade 1	Grade 2	Grade 3	Grade 4	R^2	RMSE
Color statistical features	Grade 1	90	3	0	0	0.9047	0.124
	Grade 2	3	73	1	1		
	Grade 3	2	3	21	1		
	Grade 4	0	1	2	8		
	Accuracy (%)	**94.73**	**92.00**	**88.00**	**80.00**		
Color texture features	Grade 1	91	1	0	0	0.9095	0.095
	Grade 2	2	69	0	0		
	Grade 3	2	4	22	1		
	Grade 4	0	1	3	9		
	Accuracy (%)	**95.78**	**92.00**	**88.00**	**90.00**		
Color statistical and texture features	Grade 1	93	1	0	0	0.9380	0.082
	Grade 2	1	71	0	0		
	Grade 3	1	3	24	1		
	Grade 4	0	0	1	9		
	Accuracy (%)	**97.87**	**94.66**	**96.00**	**90.00**		
Physicochemical features	Grade 1	94	1	0	0	0.9523	0.061
	Grade 2	1	73	0	0		
	Grade 3	0	1	23	0		
	Grade 4	0	0	2	10		
	Accuracy (%)	**98.95**	**97.33**	**92.00**	**100.00**		

Table 7
Confusion matrix for classification and validation of results.

ANN input		Grade 1	Grade 2	Grade 3	Grade 4	R^2	RMSE
Color statistical features	Grade 1	91	0	0	0	0.9428	0.088
	Grade 2	4	76	2	0		
	Grade 3	0	3	22	1		
	Grade 4	0	1	1	9		
	Accuracy (%)	**95.79**	**95.00**	**88.00**	**90.00**		
Color texture features	Grade 1	92	0	0	0	0.9571	0.052
	Grade 2	2	77	0	0		
	Grade 3	1	2	23	1		
	Grade 4	0	1	2	9		
	Accuracy (%)	**96.84**	**90.58**	**92.00**	**90.00**		
Color statistical and texture features	Grade 1	94	1	0	0	0.9857	0.029
	Grade 2	1	79	0	0		
	Grade 3	0	0	24	0		
	Grade 4	0	0	1	10		
	Accuracy (%)	**98.95**	**98.75**	**96.00**	**100.00**		
Physicochemical features	Grade 1	94	0	0	0	0.9905	0.027
	Grade 2	1	80	0	0		
	Grade 3	0	0	24	0		
	Grade 4	0	0	1	10		
	Accuracy (%)	**98.95**	**100.00**	**96.00**	**100.00**		

4. Conclusion

With increasing storage time, the surface damage of sweet cherries also increased. However, coating treatment and increasing DEO and ZnO concentration reduced the rates of these damages. The outcomes indicated that the ANFIS and ANN models demonstrated successful predictions of the physical and chemical alterations occurring in sweet cherries during storage, leveraging image-based color and texture characteristics while exhibiting remarkable accuracy in their modeling. It has been discovered that the physical and chemical sweet changes of sweet cherries can be predicted using CVS, ANFIS, and ANN models. According to the study, both ANN and ANFIS models can accurately classify sweet cherries based on their quality grade, using either their visual characteristics or physical and chemical characteristics. The algorithms based on the sweet cherries' physical and chemical characteristics and those based on the color and texture of the sweet cherries can both classify them with high precision and accuracy. The algorithms achieved an accuracy rate of 90%–99 % in grading sweet cherry quality, as per the confusion matrix results. The study demonstrates that sweet cherries can be accurately classified and predicted using CVS, ANFIS, and ANN models. The algorithm's high diagnostic power enables its industrial use in greenhouses for diagnostics, control, and grading processes.

CRediT authorship contribution statement

Yashar Shahedi: Writing – original draft, Software, Methodology, Data curation. **Mohsen Zandi:** Writing – review & editing, Validation, Supervision, Formal analysis, Conceptualization. **Mandana Bimakr:** Writing – review & editing, Visualization, Supervision.

Ethics approval and consent to participate

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and material

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code availability

Not applicable.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] R. Jafari, M. Zandi, A. Ganjloo, Effect of gelatin–alginate coating containing anise (Pimpinella anisum L.) essential oil on physicochemical and visual properties of zucchini (Cucurbita pepo L.) fruit during storage, J. Food Process. Preserv. 46 (8) (2022) e16756, https://doi.org/10.1111/jfpp.16756.
[2] M. Zandi, A. Ganjloo, M. Bimakr, N. Moradi, N. Nikoomanesh, Effect of active coating containing radish leaf extract with or without vacuum packaging on the postharvest changes of sweet lemon during cold storage, J. Food Process. Preserv. 45 (3) (2021) e15252.
[3] S.K. Singh, S.K. Vidyarthi, R. Tiwari, Machine learnt image processing to predict weight and size of rice kernels, J. Food Eng. 274 (2020) 109828.
[4] M. Zandi, A. Ganjloo, M. Bimakr, Computer vision system applied to classification of medlar (mespilus germanica) during ripening stage at cold storage, Innovative Food Technologies (JIFT) 7 (3) (2020), https://doi.org/10.22104/JIFT.2019.3726.1886 (In persian).
[5] A. Ganjloo, M. Bimakr, M. Zandi, S. Monajem, Indirect estimation of mass and shape ratio changes of aloe vera gel coated cherry tomatoes using image processing technique, in: Persian), Innovative Food Technologies (JIFT) (In Press), 2021, https://doi.org/10.22104/JIFT.2020.4282.1990.
[6] M. Zandi, A. Ganjloo, M. Bimakr, Computer vision system applied to classification of medlar (mespilus germanica) during ripening stage at cold storage, Innovative Food Technologies 7 (3) (2020) 403–415.
[7] I. Nyalala, et al., Tomato volume and mass estimation using computer vision and machine learning algorithms: cherry tomato model, J. Food Eng. 263 (2019) 288–298.

[8] M. Zandi, A. Ganjloo, M. Bimakr, Development of quality grading system based on image processing for hawthorn classification during various storage condition (cold, refrigerator and room), J. Food Res. 30 (1) (2020) 195–209.
[9] S. Sabzi, Y. Abbaspour-Gilandeh, G. García-Mateos, A new approach for visual identification of orange varieties using neural networks and metaheuristic algorithms, Information processing in agriculture 5 (1) (2018) 162–172.
[10] H. Nouri-Ahmadabadi, M. Omid, S.S. Mohtasebi, M.S. Firouz, Design, development and evaluation of an online grading system for peeled pistachios equipped with machine vision technology and support vector machine, Information Processing in Agriculture 4 (4) (2017) 333–341.
[11] S.K. Vidyarthi, R. Tiwari, S.K. Singh, H.W. Xiao, Prediction of size and mass of pistachio kernels using random Forest machine learning, J. Food Process. Eng. 43 (9) (2020) e13473.
[12] S.K. Vidyarthi, R. Tiwari, S.K. Singh, Stack ensembled model to measure size and mass of almond kernels, J. Food Process. Eng. 43 (4) (2020) e13374.
[13] D. Halac, E. Sokic, E. Turajlic, Almonds classification using supervised learning methods, in: 2017 XXVI International Conference on Information, Communication and Automation Technologies (ICAT), IEEE, 2017.
[14] R.R. Calixto, L.G.P. Neto, T. da Silveira Cavalcante, M.F. Aragão, E. de Oliveira Silva, A computer vision model development for size and weight estimation of yellow melon in the Brazilian northeast, Sci. Hortic. 256 (2019) 108521.
[15] N.M. Hussain Hassan, A.A. Nashat, New effective techniques for automatic detection and classification of external olive fruits defects based on image processing techniques, Multidimens. Syst. Signal Process. 30 (2019) 571–589.
[16] N. Hashim, S.E. Adebayo, K. Abdan, M. Hanafi, Comparative study of transform-based image texture analysis for the evaluation of banana quality using an optical backscattering system, Postharvest Biol. Technol. 135 (2018) 38–50.
[17] M.A. Khan, et al., An optimized method for segmentation and classification of apple diseases based on strong correlation and genetic algorithm based feature selection, IEEE Access 7 (2019) 46261–46277.
[18] P. Moallem, A. Serajoddin, H. Pourghassem, Computer vision-based apple grading for golden delicious apples based on surface features, Information processing in agriculture 4 (1) (2017) 33–40.
[19] U.-O. Dorj, M. Lee, S.-s. Yun, An yield estimation in citrus orchards via fruit detection and counting using image processing, Comput. Electron. Agric. 140 (2017) 103–112.
[20] P. Chithra, M. Henila, Defect identification in the fruit apple using k-means color image segmentation algorithm, Int. J. Adv. Res. Comput. Sci. 8 (8) (2017).
[21] H. Kaur, B. Sawhney, S. Jawandha, Evaluation of plum fruit maturity by image processing techniques, Journal of food science and technology 55 (2018) 3008–3015.
[22] V.R. Sharabiani, S. Sabzi, R. Pourdarbani, E. Solis-Carmona, M. Hernández-Hernández, J.L. Hernández-Hernández, Non-destructive prediction of titratable acidity and taste index properties of gala apple using combination of different hybrids ANN and PLSR-model based spectral data, Plants 9 (12) (2020) 1718.
[23] V.R. Sharabiani, S. Sabzi, R. Pourdarbani, M. Szymanek, S. Michałek, Inner properties estimation of gala apple using spectral data and two statistical and artificial intelligence based methods, Foods 10 (12) (2021) 2967.
[24] R. Pourdarbani, S. Sabzi, J.I. Arribas, Nondestructive estimation of three apple fruit properties at various ripening levels with optimal Vis-NIR spectral wavelength regression data, Heliyon 7 (9) (2021) e07942.
[25] R. Pourdarbani, S. Sabzi, M.H. Rohban, G. Garcia-Mateos, J. Paliwal, J.M. Molina-Martinez, Using metaheuristic algorithms to improve the estimation of acidity in Fuji apples using NIR spectroscopy, Ain Shams Eng. J. 13 (6) (2022) 101776.
[26] P. Karami, M. Zandi, A. Ganjloo, Evaluation of physicochemical, mechanical, and antimicrobial properties of gelatin-sodium alginate-yarrow (Achillea millefolium L.) essential oil film, J. Food Process. Preserv. 46 (7) (2022) e16632, https://doi.org/10.1111/jfpp.16632.
[27] R. Jafari, M. Zandi, A. Ganjloo, Modeling of microwave-and ultrasound-ohmic-assisted hydro-distillation extraction of the Pimpinella anisum essential oil, J. Food Process. Eng. 46 (11) (2023) e14428.
[28] M. Ligus, P. Peternek, Determination of most suitable low-emission energy technologies development in Poland using integrated fuzzy AHP-TOPSIS method, Energy Proc. 153 (2018) 101–106.
[29] M. Bahram-Parvar, F. Salehi, S.M. Razavi, Adaptive neuro-fuzzy inference system (ANFIS) simulation for predicting overall acceptability of ice cream, Engineering in agriculture, environment and food 10 (2) (2017) 79–86.
[30] M. Fashi, L. Naderloo, H. Javadikia, The relationship between the appearance of pomegranate fruit and color and size of arils based on image processing, Postharvest Biol. Technol. 154 (2019) 52–57.
[31] S.M. Jafari, M. Ganje, D. Dehnad, V. Ghanbari, Mathematical, fuzzy logic and artificial neural network modeling techniques to predict drying kinetics of onion, J. Food Process. Preserv. 40 (2) (2016) 329–339.
[32] S.J. Rad, M. Kaveh, V.R. Sharabiani, E. Taghinezhad, Fuzzy logic, artificial neural network and mathematical model for prediction of white mulberry drying kinetics, Heat Mass Tran. 54 (11) (2018) 3361–3374.
[33] M.S. Iraji, A. Tosinia, Classification tomatoes on machine vision with fuzzy the mamdani inference, adaptive neuro fuzzy inference system based (anfis-sugeno), Australian Journal of Basic and Applied Sciences 5 (11) (2011) 846–853.
[34] Y. Abbaspour-Gilandeh, A. Jahanbakhshi, M. Kaveh, Prediction kinetic, energy and exergy of quince under hot air dryer using ANNs and ANFIS, Food Sci. Nutr. 8 (1) (2020) 594–611.
[35] H. Gharibi, A.H. Mahvi, R. Nabizadeh, H. Arabalibeik, M. Yunesian, M.H. Sowlat, A novel approach in water quality assessment based on fuzzy logic, J. Environ. Manag. 112 (2012) 87–95.
[36] N. Goel, P. Sehgal, Fuzzy classification of pre-harvest tomatoes for ripeness estimation–An approach based on automatic rule learning using decision tree, Appl. Soft Comput. 36 (2015) 45–56.
[37] E.I. Papageorgiou, K. Aggelopoulou, T.A. Gemtos, G. Nanos, Development and evaluation of a fuzzy inference system and a neuro-fuzzy inference system for grading apple quality, Appl. Artif. Intell. 32 (3) (2018) 253–280.
[38] A. Etxabide, J. Uranga, P. Guerrero, K. de la Caba, Development of active gelatin films by means of valorisation of food processing waste: a review, Food Hydrocolloids 68 (2017) 192–198, https://doi.org/10.1016/j.foodhyd.2016.08.021.
[39] J. Ju, Y. Xie, Y. Guo, Y. Cheng, H. Qian, W. Yao, Application of edible coating with essential oil in food preservation, Crit. Rev. Food Sci. Nutr. 59 (2018) 1–62, https://doi.org/10.1080/10408398.2018.1456402.
[40] S. Hashemi, M. Niakousari, M. Zandi, M. Saharkhiz, Application of ultrasonic Ohmic hydrodistillator system in production of essential oil from Zenyan, Int. Food Res. J. 23 (1) (2016) 135–140.
[41] R. Jafari, M. Zandi, A. Ganjloo, Effect of ultrasound and microwave pretreatments on extraction of anise (Pimpinella anisum L.) seed essential oil by ohmic-assisted hydrodistillation, Journal of Applied Research on Medicinal and Aromatic Plants 31 (2022) 100418.
[42] R. Jafari, M. Zandi, A. Ganjloo, Characterization of alginate-gelatin edible film containing anise (pimpinella anisum L.) essential oil, J. Polym. Environ. (2022) 1–16.
[43] W. Zam, Effect of alginate and chitosan edible coating enriched with olive leaves extract on the shelf life of sweet cherries (Prunus avium L.), J. Food Qual. 2019 (1) (2019) 8192964.
[44] M. Zandi, M. Mohebbei, Investigation of encapsulated diacetyl colloidosome release profile as a function of sintering process and release media properties, Flavour Fragrance J. 29 (6) (2014) 364–370.
[45] M. Zandi, Evaluation of the ainetics of ascorbic acid release from alginate-whey protein concentrates microspheres at the simulated gastro–intestinal condition, J. Food Process. Eng. 40 (1) (2017) e12334.
[46] M. Hosseinifarahi, M. Radi, L. Taghipour, H. Zafarzadeh, F. Bagheri, P. Assar, Preservation of postharvest quality and bioactive compounds in sweet cherry using carboxymethyl cellulose films enriched with Thymus vulgaris L. essential oil, J. Food Meas. Char. (2023) 1–11.
[47] M. Abdipour, P.S. Malekhossini, M. Hosseinifarahi, M. Radi, Integration of UV irradiation and chitosan coating: a powerful treatment for maintaining the postharvest quality of sweet cherry fruit, Sci. Hortic. 264 (2020) 109197.

[48] N. Mahfoudhi, S. Hamdi, Use of almond gum and gum Arabic as novel edible coating to delay postharvest ripening and to maintain sweet cherry (P runus avium) quality during storage, J. Food Process. Preserv. 39 (6) (2015) 1499–1508.

[49] Y.-L. Zhang, et al., Effect of edible carboxymethyl chitosan-gelatin based coating on the quality and nutritional properties of different sweet cherry cultivars during postharvest storage, Coatings 11 (4) (2021) 396.

[50] C. Gutiérrez-Jara, C. Bilbao-Sainz, T. McHugh, B.-S. Chiou, T. Williams, R. Villalobos-Carvajal, Effect of cross-linked alginate/oil nanoemulsion coating on cracking and quality parameters of sweet cherries, Foods 10 (2) (2021) 449.

[51] A.A. Wardana, P. Kingwascharapong, L.P. Wigati, F. Tanaka, F. Tanaka, The antifungal effect against Penicillium italicum and characterization of fruit coating from chitosan/ZnO nanoparticle/Indonesian sandalwood essential oil composites, Food Packag. Shelf Life 32 (2022) 100849.

[52] M. Asghari, Z. Azarsharif, A. Farrokhzad, H. Tajic, Use of an edible coating containing galbanum gum and cumin essential oil for quality preservation in sweet cherries, International Journal of Food Science & Technology 57 (8) (2022) 5123–5131.

[53] M. Zandi, A. Ganjloo, M. Bimakr, Applying adaptive neuro-fuzzy inference system and artificial neural network to the prediction of quality changes of hawthorn fruit (crataegus pinnatifida) during various storage conditions, Journal of Agricultural Machinery 11 (2) (2021) 343–357.

[54] M. Golzarian, M. Shamili, O. Doosti Irani, P. Azarkish, Detection of surface defects caused by mechanical damages on Mangos of Kelk-e Sorkh variety with the use of color image processing, Iranian Food Science and Technology Research Journal (IFSTRJ) 12 (5) (2017) 652–662.

[55] N.M.H. Hassan, A.A. Nashat, New effective techniques for automatic detection and classification of external olive fruits defects based on image processing techniques, Multidimens. Syst. Signal Process. 30 (2) (2019) 571–589.

[56] D. Sahu, R.M. Potdar, Defect identification and maturity detection of mango fruits using image analysis, American Journal of Artificial Intelligence 1 (1) (2017) 5–14.