Non-destructive detection of the fruit firmness of Korla fragrant pear based on electrical properties

Hong Zhang[1,2], Yang Liu[1,3], Yurong Tang[1,3], Haipeng Lan[1,3], Hao Niu[1,3], Hong Zhang[1,3*]

(1. *Modern Agricultural Engineering Key Laboratory at Universities of Education Department of Xinjiang Uygur Autonomous Region, Tarim University, Alaer 843300, Xinjiang, China*;

2. *College of Water Resources and Architectural Engineering, Tarim University, Alaer 843300, Xinjiang, China*;

3. *College of Mechanical and Electrical Engineering, Tarim University, Alaer 843300, Xinjiang, China*)

Abstract: In order to achieve the non-destructive detection of the firmness of Korla fragrant pear during the ripening period, the characteristic variables integrating the parallel equivalent inductance (*Lp*), quality factor (*Q*), parallel equivalent capacitance (*Cp*), dissipation factor (*D*), parallel equivalent resistance (*Rp*) and impedance (*Z*) were formulated through principal component analysis (PCA). Further, based on the characteristic variables, the models were established for predicting the firmness of Korla fragrant pear by using the generalized regression neural network (GRNN) and back-propagation neural network (BPNN). The results showed that firmness has significant correlations with the six electrical parameters. The first two principal components (PCs) were selected as the characteristic variables of the electrical parameters. GRNN exhibited the best performance in predicting firmness (R^2=0.9628, RMSE=0.383). The results could provide important references for non-destructive detection of the quality of Korla fragrant pear.

Keywords: Korla fragrant pear, firmness, electrical properties, principal component analysis, non-destructive detection

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1 Introduction

Korla fragrant pear is a kind of fruit with distinct regional characteristics in Xinjiang, China, and is one of the most important export fruits from China as well[1-3]. Fruit firmness is the most significant quality attribute of Korla fragrant pear that is of primary concern to consumers. It is also an important parameter in assessing the maturity, postharvest quality, and shelf life of fragrant pears[4-6]. At present, fruit firmness is commonly measured by using the fruit firmness tester, which can achieve precise measurement but is destructive. Therefore, non-destructive detection techniques should be developed to determine the fruit firmness of fragrant pear. Some non-destructive fruit firmness detection methods, such as near-infrared spectroscopy, electrical property, and acoustic detection, have been proposed[7-9]. Compared with other methods, the non-destructive detection methods based on electrical properties are more efficient, sensitive, and simple, and thus have been widely applied in the food industry, such as the measurement of protein content in milk, fruit sweetness, and quality evaluation in eggplant[10-12]. Fragrant pear is of abundant ionic compounds and moisture, and therefore from a microstructure perspective, the interior tissue has a large number of charged particles, which form a biological electric field. In the growth and development period, the physiological and biochemistries changes in fruit interior tissues usually occur along with the conversion of substance and energy, leading to changes in the quantity and spatial distribution of various chemical substances[13]. The macroscopic electrical properties of fruits have been found to be affected by the biological electric field. Apparently, the abundant ionic compounds and moisture of fragrant pear make it possible and feasible to apply non-destructive detection techniques to determine fruit firmness based on electrical properties.

In recent years, many researchers have proposed some techniques for the detection of fruit firmness based on electrical properties, providing valuable references for this study. For example, Guo et al.[7] predicted the fruit firmness of the Dangshansu pear during ripening by using dielectric spectrum combined with artificial neural network. Khaled et al.[14] demonstrated that several impedance parameters are correlated with fruit firmness. Li et al.[15] studied the relationship between fruit firmness and electrical parameters of kiwifruit during storage and suggested that dissipation factor (*D*) and parallel equivalent capacitance (*Cp*) are positively correlated with fruit firmness, while impedance (*Z*), parallel equivalent resistance (*Rp*), and parallel equivalent inductance (*Lp*) have negative correlations with fruit firmness. The above studies demonstrate the feasibility of detecting the fruit firmness of pears based on electrical properties. Firmness is the main index to measure the fruit quality in the harvest and post-harvest processes of fragrant pears. However, little research effort has been made to predict the fruit firmness of Korla fragrant pear based on its electrical properties.

Electrical properties indicated by electrical parameters such as quality factor (*Q*), *D*, *Cp*, *Lp*, *Rp*, and *Z* have been widely applied in the quality evaluation of food products. For instance, Zywica

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Biographies: Hong Zhang, MS, research interest: agriculture geographic information system, Email: hxtxylove@126.com; **Yang Liu**, PhD, Associate Professor, research interest: agricultural products processing technology, Email: 120150012@taru.edu.cn; **Yurong Tang**, Master, Senior Experimentalist, research interest: agricultural products processing technology, Email: 120110010@taru.edu.cn; **Haipeng Lan**, PhD, Associate Professor, research interest: agricultural products processing technology, Email: lanhaipeng@126.com; **Hao Niu**, Master, Lecturer, research interest: agricultural products processing technology, Email: 18167528125@163.com.

***Corresponding author: Hong Zhang**, Master, Professor, research interest: agricultural machinery and equipment design, College of Mechanical and Electrical Engineering, Tarim University, Alaer 843300, Xinjiang, China. Tel: +86-13899261091, Email: zhghog@163.com.

et al.[16] established the mathematical relationship described by the equation $y=a\pm bx$ between the TSS content in apple juice and Z, resistance, admittance, and conductance at any frequency of the test voltage over the range from 100 Hz to 100 kHz. Banach et al.[17] demonstrated that the mathematical relationships between the content of rapeseed oil in fat mixes and Z, Cp, and Q could be described with the equation of $y=ax\pm b$ at frequencies from 20 Hz to 2 MHz. Pierzynowska-Korniak et al.[18] suggested that single electrical parameters, including Z, resistance, and conductance, have high linear correlations with the puree content of apples at the frequency of 100 Hz. Zhu et al.[19] found that electrical parameters such as D, Q, Cp, Lp, Rp, and Z have high correlations with the chemical components during the fermentation process of black tea at the frequency of 100 kHz. These findings confirm that the quality of food products can be effectively determined by certain individual electrical parameters at a single frequency. Nonetheless, these electrical parameters that can be used to characterize the quality indices seem to be mutually independent, and their inner mutual relations remain unclear. Consequently, there is a lack of a comprehensive system of electrical parameters for the characterization of food quality.

Principal Component Analysis (PCA) is a conventional information processing method and has been applied in fruit firmness detection owing to its ability to establish comprehensive index systems and ignore overlapping information. Xie et al.[20] used hyperspectral imaging to determine banana firmness as well as classify ripe and unripe samples based on the spectral reflectance information extracted by PCA. For non-destructive measurement of pear quality by using the impulse response method, Zhang et al.[8] extracted the characteristic variables and used them as the neurons of Back-propagation Neural Network (BPNN) input layer to quantitatively analyze pear texture property. As a result, they found that PCA combined with the BPNN method has the highest accuracy in evaluating the flesh firmness of pears. Wei et al.[6] also used PCA to extract the characteristic data obtained by Voltammetric Electronic tongue (VE-tongue), which were then used as the input variables of Principal Component Regression (PCR), Partial Least Squares Regression (PLSR), and Leaset Square Support Vector Machines (LS-SVMs) to predict the fruit firmness of different pear cultivars. The above-mentioned studies suggest that it is highly feasible to extract characteristic variables from electrical parameters to establish comprehensive index systems for detecting the fruit firmness of Korla fragrant pear.

BPNN and Generalized Regression Neural Network (GRNN) are useful in expressing complex relationships between different variables with nonlinear models. However, the precision of BPNN and GRNN models is usually influenced by data overlap and noise. To overcome this problem, PCA is often used to extract indispensable information from large sets of original data. Several studies have shown that the quality of fruits could be predicted better accurately when combined BPNN and GRNN with PCA are applied[8,11]. However, little research effort has been made to predict the fruit firmness based on the electrical properties combined BPNN and GRNN with PCA.

Therefore, this study aimed to 1) investigate the changes in the key electrical parameters of Korla fragrant pear through non-destructive detection based on electrical properties; 2) extract the characteristic variables by using PCA, and then apply them in GRNN and BPNN to establish models for the quantitative prediction of fruit firmness of Korla fragrant pear; 3) compare the accuracy of different models so as to provide a feasible non-destructive detection method for the fruit firmness of Korla fragrant pear.

2 Materials and methods

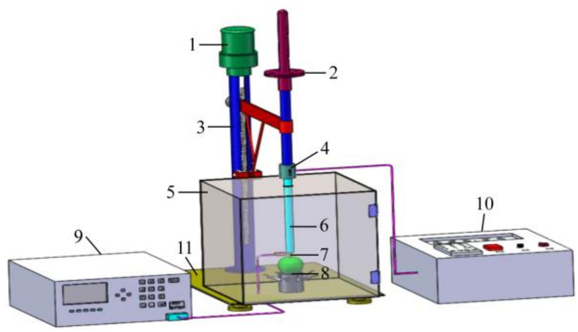
2.1 Test samples

Korla fragrant pear fruits were randomly picked from August 23 to October 2, 2019, from 15-year-old pear trees on the Tarim University campus, in Alaer, Xinjiang Region, China. At each sampling time, 10 pear fruits were randomly picked from the pear trees in the morning daily. All fragrant pear samples of regular shape and the same size without damage or defect were immediately measured after picking. A total of 41 sampling times were implemented, and 410 pears were used in the study.

2.2 Test methods

2.2.1 Procedures

The system used to acquire the electrical properties consisted of an LCR digital electric bridge tester (TH2828S type, Tonghui electronics equipment company, China), a parallel-plate electrode, an insulating bar, a loading electromotor, a fine adjustment hand wheel, a force sensor, a controller of measuring force, a holder, a pedestal and a shielded box. The schematic diagram of the measurement system of the electrical parameters is shown in Figure 1. It should be noted that in order to reduce errors before measuring, the system was warmed up for at least 1 h. The insulating bar and the upper electrode could move up and down together slowly under the loading electromotor driving to adjust the distance between the parallel-plate electrodes. By rotating the hand wheel to slightly adjust the upper electrode, individual pears could be supported and maintained in firm contact with the two electrodes with a diameter of 10 mm. The clamping force was maintained at 0.5 N to avoid damage to the pear. The pear fruits were washed with tap water to remove any wax or foreign materials on the surface, and allowed to equilibrate at 25 ℃ for the measurement. The initial measurement of electrical parameters was performed with the electrodes in firm contact with the fruit surface in the equatorial region at four points in 90° intervals. Due to the ellipsoid shape of fragrant pear fruits, a completely firm contact was not possible, which might further influence the detection accuracy[21]. Hence, conductive silicone was daubed as the electrical coupling on the contact surface between the electrodes and the fruits, so that any air gaps could be completely eliminated. The frequency had a magnitude of 1 kHz and the voltage had a magnitude of 100 mV for all measurements. Then, Lp, Q, Cp, D, Rp, and Z were taken as the principal measured parameters in this study, and were calculated by using this measurement system.



1. Loading electromotor 2. Fine adjustment hand wheel 3. Holder 4. Force sensor 5. Shielded box 6. Insulating bar 7, 8. Parallel-plate electrode 9. LCR digital electric bridge tester 10. Controller of measuring force 11. Pedestalrmness

Figure 1 Electrical parameter detection system

2.2.2 Determination of accumulated temperature

Determination of accumulated temperature is an essential index of crop growth and development and it is the sum of the daily average air temperature in the continuous period when daily average air temperature ≥10°C in a year[22-24]. It was calculated as the mean of the highest and lowest air temperature in one day[25].

2.2.3 Determination of firmness

After measurement of the electrical parameters of the pear fruits, the peel in the equatorial region was removed, and the firmness was measured by a digital fruit penetrometer (GY-4) with an 8-mm-diameter penetrometer tip. An even force was applied to the penetrometer tip to penetrate the pear pulp. When the probe reached the tissue to the required scale, the force was removed, and the force gauge reading was recorded in kg/cm^2. The fruit firmness was measured on the four points where the electrical parameters were measured, and the measurement results were averaged.

2.3 Modeling methods

2.3.1 Principal component analysis

PCA is usually used to simplify data by reducing the number of variables into a smaller number of orthogonal variables and summarizes data by forming a few new variables, and the new variables are called Principal components (PCs)[26]. Based on these PCs, some more comprehensive and useful variables can be acquired. The PCs integrating the *Lp*, *Q*, *Cp*, *D*, *Rp*, and *Z* were formulated through PCA, and then apply PCs in BPNN and GRNN to establish models for the quantitative prediction of fruit firmness of Korla fragrant pear.

2.3.2 BPNN model

As a kind of multi-layer feed-forward network trained according to the inverse error propagation algorithm, BPNN has been widely used in the fields of pattern recognition and nonlinear fitting. It is based on the learning rule of the steepest descent method, and continuously adjusts the weight and threshold of the network through reverse propagation to minimize the error-square sum of the network that makes the predicted output approximate the expected output infinitely[27]. The topology of the BPNN model includes the input, hidden, and output layers. The principal component factor scores were used as network input, and firmness was set as the network output. The statistical experimental data yielded 41 sample groups. 28 groups of samples were randomly selected as the training samples, and the remaining 13 groups were used as prediction samples.

2.3.3 GRNN model

GRNN is an important variation of the radial basis function neural network, which consists of the input layer, pattern layer, summation layer, and output layer. It is a new type of neural network with the advantage of good local approximation performance and can use limited data to predict the target parameters, establish a parameter model through the program and solve complex nonlinear problems[28]. In addition, it is superior to classical neural networks in learning ability and speed and has an absolute advantage over the training set of small samples[29]. The network inputs were the principal component factor scores, while the network output was fruit firmness of Korla fragrant pear. According to the statistical experimental data, a total of 41 groups of datasets were gained, from which 70% of the experimental data were randomly chosen for a training set and the remaining 30% were chosen for a testing set.

3 Results and discussion

3.1 Changing patterns of electrical parameters and fruit firmness

Figure 2 shows the variations of fruit firmness with accumulated temperature during the ripening period. Clearly, the fruit firmness ranged from 8.19 to 4.24 kg/cm^2 in the mature stage, which could be further divided into three stages: the stable stage, the rapidly changing stage, and the stable stage. Interestingly, these changes are in conformity with the sigmoidal model. It is possible that before the fruits ripen, the pectin that composes the cytoderm is insoluble, and thus the cellular structure is complete, leading to higher firmness of the fruit. However, after the fruits ripen, soluble pectin is generated due to the degradation of protopectin, causing damage to the cellular structure and further reducing the firmness of the fruit flesh[30]. With the progress of maturation, there will be increases in membrane permeability and certain degrees of electrolyte leakage, causing the breaking up of cells[31]. Hence, the flesh firmness decreases gradually during the ripening period.

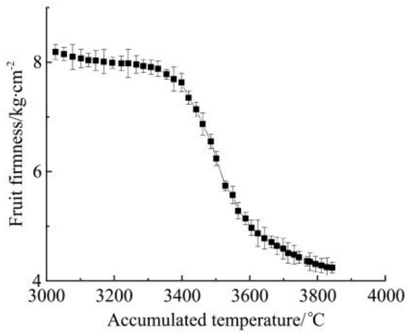


Figure 2 Relationship between accumulated temperature and fruit firmness

3.2 Formulation of characteristic variables for electrical parameters

Table 1 shows the results of the correlation analysis between the electrical parameters and pear fruit firmness. Fruit firmness has significant positive correlations with *Rp*, *Lp*, *Q*, and *Z*, whereas shows significant negative correlations with Cp and *D*. Six electrical parameters were suitable for evaluating the fruit firmness of pear. Most of the electrical parameters had significant correlations with each other, except for *Rp*, which is only correlated with *Z*. There were varying degrees of correlation among electrical parameters and a lot of miscellaneous or overlapping information, which may cause great difficulty in the analysis of the information. Thus, the electrical parameters were screened by applying PCA to eliminate the non-significant overlapping information, so as to retain a few comprehensive and significant parameters to simplify the analysis process. There were strong partial correlations between the above electrical parameters. Thus, Bartlett and Kaiser-Meyer-Olkin (KMO) tests were carried out to verify the feasibility. The test results are listed in Table 2. The PCA could be performed when the KMO numerical value was higher than 0.5[32]. The KMO numerical value was 0.794, higher than 0.5, suggesting that the data are suitable for formulating characteristic variables extracted from electrical parameters by PCA.

Distribution statistics of the principal component eigenvalues were conducted for the electrical parameters of fragrant pear. As listed in Table 3, the eigenvalue of Principal component 1 (PC1) is 4.144, accounting for 69.074% of the total variance of the original six variables, and the cumulative variance contribution rate is 69.074%. The eigenvalue of Principal component 2 (PC2) is 1.440, accounting for 24.000% of the total variance of the original six variables, and the cumulative contribution rate is 24.000%. According to the general principle of determining PCs, the PCs with eigenvalues higher than 1 or accumulative variance contribution rates above 80.000% should be selected[33]. Therefore, it is appropriate to extract the first two PCs, and it can be assumed that the change in fruit firmness can be mainly attributed to these two PCs.

Table 1 Correlation analysis between fruit firmness and electrical parameters

Index	*Lp*	*Q*	*Cp*	*D*	*Rp*	*Z*	Firmness
Lp	1.000						
Q	0.925**	1.000					
Cp	−0.981**	−0.932**	1.000				
D	−0.917**	−0.994**	0.922**	1.000			
Rp	−0.039	−0.252	0.048	0.281	1.000		
Z	0.606**	0.370*	−0.600**	−0.355*	0.422**	1.000	
Firmness	−0.887**	−0.914**	0.895**	0.936**	0.337*	−0.389*	1.000

Note: * refers to a significant correlation (p<0.05); ** represents an extremely significant correlation (p<0.01). *Lp* represents parallel equivalent inductance; *Q* represents quality factor; *Cp* represents parallel equivalent capacitance; *D* represents dissipation factor; *Rp* represents parallel equivalent resistance; *Z* represents impedance.

Table 2 Correlation test of KMO and Bartlett

Test method		Test results
Kaiser-Meyer-Olkin (KMO) test		0.794
Bartlett sphericity test	Approximate Chi-square	428.378
	Degree of freedom	15
	Test significance	0.00

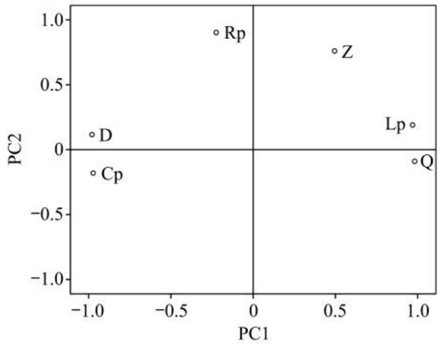
Table 3 Distribution statistics of characteristic variables

Component	Initial eigenvalue		
	Total	Variance/%	Cumulative/%
1	4.144	69.074	69.074
2	1.440	24.000	93.075
3	0.340	5.673	98.748
4	0.051	0.856	99.604
5	0.019	0.312	99.916
6	0.005	0.084	100

In order to describe the practical significance of every PC, Kaiser-standardized orthogonal rotation method was applied to analyze the experimental data. Without changing the weight of electrical parameter variables, the load of each principal component was varied to obtain the principal component load matrix (Table 4), based on which the load diagram was plotted and shown in Figure 3. It can be observed that PC1 is mainly influenced by the changes of *Lp*, *Cp*, *Q*, and *D*. When the fruit was placed under an alternating-electric field, its interior tissue could produce alternating magnetic flux, and the Lp is the ratio of magnetic flux to the current that generates the magnetic flux[34]. *Cp* is related to the ability to store electrical energy, and *Q* is a non-dimensional value that represents the efficiency of a given capacitor in terms of energy loss. Both *Cp* and *Q* have been considered to be associated with multiple biochemical changes[19]. *D* is the reciprocal of *Q* and is also used as an index of the material's ability to generate heat[35]. PC2 was mainly influenced by the change of *Rp* and *Z*. As electrical conductance parameters, *Rp* and *Z* are directly related to the movement of free ions within an alternating electrical field in biological tissues[36]. To sum up, Korla fragrant pears during ripening demonstrate the characteristics of energy conversion and electromagnetism and are good ionic conductors.

Table 4 Load matrix of characteristic variables after rotation

Electrical parameter	Principal component (PC)	
	1	2
Lp	0.969	0.190
Q	0.982	−0.090
Cp	−0.972	−0.180
D	−0.979	0.116
Rp	−0.224	0.902
Z	0.495	0.760



Note: PC: Principal component.

Figure 3 Rotated factor loading diagram

To analyze the relationships between the two PCs and electrical parameters, the characteristic variables that could represent the six electrical parameters were formulated. The regression method was used to obtain the score coefficient matrix of the two PCs, and the results are listed in Table 5. Based on the score coefficients, the linear relationship between principal component factor scores and electrical parameters was analyzed as shown in Equation (1) and Equation (2), in which the electrical parameters must be standardized with Equation (3).

$$F_1 = 0.23 f_1 + 0.249 f_2 - 0.231 f_3 - 0.25 f_4 - 0.106 f_5 + 0.081 f_6 \quad (1)$$

$$F_2 = 0.077 f_1 - 0.116 f_2 - 0.07 f_3 + 0.134 f_4 + 0.633 f_5 + 0.495 f_6 \quad (2)$$

$$f_i = (X_i - \overline{X_i}) / \sigma_i \quad (3)$$

where, F_1 and F_2 are the principal component factor scores; f_i is the electrical parameter value after standardization; X_i is the electrical parameter value; $\overline{X_i}$ is the average value of the electrical parameter; σ_i is the standard deviation of the electrical parameter.

Table 5 Score coefficient matrix of characteristic variables

Electrical parameters	PC1	PC2
Lp (f_1)	0.230	0.077
Q (f_2)	0.249	−0.116
Cp (f_3)	−0.231	−0.070
D (f_4)	−0.250	0.134
Rp (f_5)	−0.106	0.633
Z (f_6)	0.081	0.495

Note: PC: Principal component.

3.3 Prediction of fruit firmness of Korla fragrant pear during ripening period

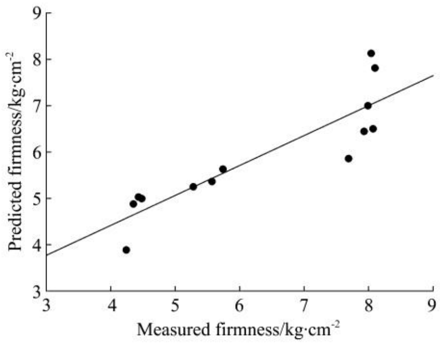
3.3.1 BPNN prediction

The two principal component factor scores were used as network input, and firmness was set as the network output. According to the determined network input and output, 28 groups of samples were randomly selected as the training samples, and the remaining 13 groups were used as prediction samples. The cross-validation method was used for the training with a frequency of four times. The mean variance of the target was set as 0.0004, and the number of iterations was set at 1000. The final parameter settings are listed in Table 6. Since the initial weight value of BPNN was selected randomly, each group of the network was trained 100 times repeatedly to save the network with the best prediction effect. The prediction results are shown in Figure 4.

Table 6 Final parameter setting values of BPNN

BPNN parameters	Values of BP parameters
Number of neurons in input layer	2
Number of neurons in the hidden layer	12
Learning rate	1
Spread parameter	0.1

Note: BPNN: Back-propagation neural network.

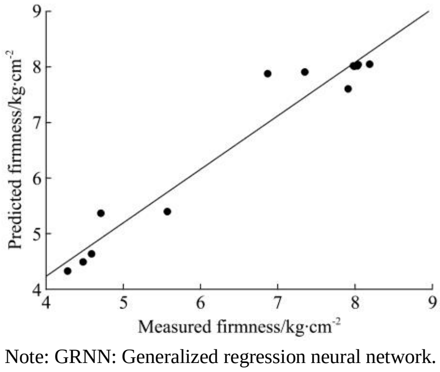


Note: BPNN: Back-propagation neural network.

Figure 4 Comparison between measured and predicted results of fruit firmness by BPNN

3.3.2 GRNN prediction

Two principal component factor scores were selected as network input and firmness was set as the network output. Similar to the analysis of BPNN, 28 groups of samples were randomly selected as the training samples, and the remaining 13 groups of samples were used as prediction samples. Due to the limited training data, a cross-validation method was employed for training, and the optimal smoothing factor was found by cycling. The training frequency was four times. A neural network toolbox was used to create GRNN for training and testing to establish GRNN model. Since the smoothing factor has a great influence on the prediction performance of the neural network, it is necessary to determine the optimal value of the smoothing factor. After checking the output results, the optimal value of the smoothing factor was found to be 0.1. The predicted results are shown in Figure 5.



Note: GRNN: Generalized regression neural network.

Figure 5 Comparison between measured and predicted fruit firmness by GRNN

3.3.3 Comparison of the prediction performance by BPNN and GRNN

The fruit firmness was respectively predicted by the models established by BPNN and GRNN, and the prediction results were compared as listed in Table 7. GRNN network (R^2=0.9628, RMSE=0.383) has much better prediction performance than BPNN (R^2=0.7828, RMSE=0.886), indicating that GRNN is the best model for predicting the fruit firmness of Korla fragrant pear.

Table 7 Comparison of the prediction results by BPNN and GRNN

Modeling method	RMSE	R^2
BP	0.886	0.7828
GRNN	0.383	0.9628

Note: GRNN: Generalized regression neural network.

4 Discussion

The measurement of electrical properties is simple, but its value is dependent upon being able to relate electrical measurements to the physiological or physical properties of mature, ripe, or overripe fruit[37]. The results demonstrated that it is possible to apply non-destructive detection technique based on electrical properties for predicting the firmness of Korla fragrant pear during the ripening period. However, the non-destructive detection method of firmness established in this paper is only applicable to Korla fragrant pear during the ripening period, but Niu et al.[4] showed that firmness also changed during the storage period of Korla fragrant pear. In addition, researchers have established non-destructive detection methods of firmness for the fruit ripening period, storage period, or selling period at present[5,38,39], but non-destructive detection methods of firmness for the whole life cycle of fruit from picking, storage, and selling are not available. Therefore, further research will be conducted on the non-destructive detection of firmness for the commodity life cycle of Korla fragrant pear.

5 Conclusions

The results of this study show that the fruit firmness of Korla fragrant pear decreases with the extension of ripening time and has significant correlations with the six electrical parameters (*Lp*, *Q*, *Cp*, *D*, *Rp*, and *Z*). Two principal components can be selected as the characteristic variables of electrical parameters, PC1 is mainly influenced by the change of *Lp*, *Cp*, *Q*, and *D*, and PC2 is mainly influenced by the change of *Rp* and *Z*. Some prediction models of the firmness of Korla fragrant pears during the ripening period are constructed by combining two nonlinear modelling techniques (GRNN and BPNN) and PCA. The GRNN established based on the characteristic variables has the best performance in predicting the fruit firmness of Korla fragrant pear (R^2=0.9628, RMSE=0.383). Hence, this study may provide a new method for the non-destructive determination of fruit firmness of Korla fragrant pear.

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