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Non-Destructive Testing of the Internal Quality of Korla Fragrant Pears Based on Dielectric Properties

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Abstract: This study provides a method for the rapid, non-destructive testing of the internal quality of Korla fragrant pears. The dielectric constant (ϵ') and dielectric loss factor (ϵ'') of pear samples were tested at 100 frequency points (range = 0.1–26.5 GHz) using a vector network analyzer and coaxial probe. The variations in the dielectric parameters of fragrant pears were analyzed. The linear relationships between the dielectric parameters and internal quality were explored. Internal quality prediction models for Korla fragrant pears were built using partial least squares regression (PLSR), support vector regression (SVR) and particle swarm optimization–least squares support vector regression (PSO-LSSVR). The optimal model was then determined. There was a weak correlation between the dielectric parameters and soluble solid content (SSC) under a single frequency. The model based on PLSR and using ϵ' as a variable predicted hardness the best, while the model based on PLSR using ϵ'' as a variable predicted SSC the best. Its R and MSE values were 0.77 and 0.073 in hardness prediction, respectively, and 0.91 and 0.087 in SSC prediction. This study provides a new method for the non-destructive online testing of the internal quality of Korla fragrant pears.

Keywords: Korla fragrant pears; non-destructive testing; dielectric properties; internal quality



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1. Introduction

Korla fragrant pears are in high demand for their thin pericarp, rich juice, sweet taste and crisp texture [1,2]. Korla fragrant pears were listed by China as a national product of geographical indication [3]. The hardness and soluble solid content (SSC) are the most important internal qualities of pears and are often used as indicators of the quality of Korla fragrant pears [4]. At present, the common apparatus used to measure the hardness and SSC of fragrant pears include fruit hardness testers and sugar detectors [5,6]. Although such methods can provide accurate results, they cause damage that cannot be repaired. Hence, it is difficult to use them for research and for developing online methods of detecting the internal quality and grade of fragrant pears, which significantly restricts their industrial development. Accordingly, developing a non-destructive and high-efficiency internal quality detection technique for fragrant pears is crucial in achieving the online detection of internal quality and for guiding sorting processes during and after harvest.

Dielectric property detection is an emerging technology that is rapid, sensitive, simple and non-destructive [7]. Based on internal physiological and chemical changes in response to an applied electric field, dielectric property technology has been applied to the quality detection of various agricultural products. For example, Guo tested the moisture content, hardness and SSC of apples, Nelson tested the moisture content and SSC of watermelons and Lan measured the SSC of fragrant pears [8–10]. However, there is a poor linear relationship between the dielectric properties and quality indicators when a single frequency is used for detection, resulting in difficulties in predicting fruit quality. Hence, Shang et al.

and Guo et al. constructed sugar content models of nectarines and apples based on a combination of dielectric constants under multiple frequencies and machine learning [11,12]. Both achieved good prediction results. Therefore, it is feasible to build models of fruit quality indicators based on a combination of dielectric properties under multiple frequencies and machine learning. In many machine learning methods, partial least squares regression (PLSR), support vector regression (SVR) and particle swarm optimization–least squares support vector regression (PSO-LSSVR) models have strong generalizability and predictive accuracy. They can handle large, complex datasets and identify patterns within them. They have been widely applied to the prediction of fruit quality, such as the hardness and SSC of Dangshansu pears, the SSC of apples, and the price of agricultural products [13–15]. Past research has provided a theoretical direction for the quality prediction of fragrant pears based on PLSR, SVR and PSO-LSSVR models. Nevertheless, there has been little research on predicting the hardness and SSC of fragrant pears based on a combination of dielectric properties under multiple frequencies and machine learning methods (PLSR, SVR and PSO-LSSVR).

This study tested the dielectric constant (ϵ') and dielectric loss factor (ϵ'') of Korla fragrant pear samples at 100 frequency points over a range of 0.1–26.5 GHz using a vector network analyzer and coaxial probe. The test records variations in these dielectric parameters with frequency. Moreover, the linear relationships between the dielectric parameters and internal quality were identified. Additionally, hardness and SSC models of fragrant pears were built using PLSR, SVR and PSO-LSSVR. The performance of these models was compared and the optimal model was verified. Finally, the internal quality of fragrant pears was predicted accurately.

2. Materials and Methods

2.1. Test Materials

Sampling of Korla Fragrant Pears

Korla fragrant pear samples were collected from a conventional pear orchard in Shilian, Shituan, Alear City, which is a high-quality fragrant pear production base in Southern Xinjiang, China. They were harvested on 1 and 8 October 2023. Only pears without implicit damage or pest/disease damage were used. The average weight was 115 g, with a deviation of ± 10 g. A total of 110 pears were collected on each date, making a total of 220. Among them, 110 were used for model construction and the rest were used for model verification. The pears were cleaned with water after harvest and then dried for the testing of the dielectric properties.

2.2. Measurement Methods

2.2.1. Measurement of Dielectric Parameters

The dielectric parameters (ϵ' and ϵ'') were measured using a vector network analyzer (3671D, Kesiye Science and Technology Co., Ltd. of China Electric Equipment Group, Qingdao, China; Figure 1). Specifically, ϵ' refers to the dielectric media's capacity to store an electric field energy, and ϵ'' reflects the energy lost from the dielectric media in an alternating electric field [16,17]. Before the test, the vector network analyzer and coaxial probe were preheated for 1 h and connected through a coaxial cable. Later, they were calibrated with an open circuit, short circuit, and loading standard components. Finally, the measurement frequency range was set from 0.1 to 26.5 GHz. A total of 100 frequency points were chosen for measurement by using the method of equally spaced measurements in a logarithmic coordinate system.

The dielectric parameter test of fragrant pears was carried out in the Textile Engineering Laboratory of Xinjiang Tarim University at room temperature (mean = 15 °C). During measurement, the coaxial probe was kept static and the pears were placed horizontally on a lifting platform with an adjustable height. The pericarp was placed in contact with the probe. Three points were selected on the equator of each pear at intervals of about 120° to measure ϵ' and ϵ'' . These three points were marked for the follow-up measurement of the

quality indicators. Each group of tests was repeated three times and the means of the test data were recorded.

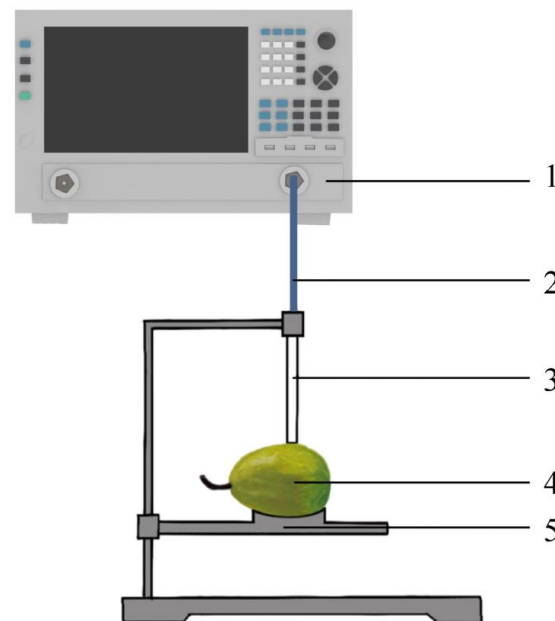


Figure 1. Dielectric property testbed for the fragrant pears. 1. Vector network analyzer; 2. connecting cable; 3. coaxial probe with an open end; 4. fragrant pears; 5. lifting platform.

2.2.2. Measurement of Hardness

The fruit hardness of fragrant pears was tested using a GY-1 fruit hardness meter. The pericarp at the dielectric measurement points was peeled off with a knife. The hardness meter was held perpendicular to the peeled surface, with its indenter pressed into the pear uniformly. The indenter stopped upon reaching a 10 mm depth and the hardness value was recorded. The reset button was rotated after each measurement to return the pointer to the initial scale line. The average hardness at three points was used (kg/cm^2).

2.2.3. Measurement of SSC

The SSC was tested using a B32T portable sugar refractometer. It was calibrated by making the bright–dark boundary of the viewfinder overlap with the zero scale line. Pulp with pericarp was collected near each of the three measurement points and squeezed manually to make juice drop onto the center of the mirrored surface of the refractometer for observation. The SSC value was read from the scale at the bright–dark boundary line. The refractometer was calibrated with distilled water after each measurement. The average SSC at the three points was used (%).

2.2.4. Data Assignment

The dielectric parameters, hardness and SSC of 220 pear samples were measured using the above method. The data of 110 pears were randomly selected for model construction, and the data for the other 110 pears were used for model verification.

2.3. Modelling Methods

Three modelling methods, PLSR, SVR and PSO-LSSVR, were applied to build predictive models of the pear quality indicators. The model input variables were ϵ' and ϵ'' and the output variables were the hardness and SSC.

2.3.1. PLSR Model

PLSR is a multivariate statistical method that combines multiple linear regression, principal component analysis and typical correlation analysis [18]. PLSR aims to solve

the multicollinearity problem between independent and dependent variables. It extracts information on the independent and dependent variables by establishing components, thus realizing the goal of regression modelling. PLSR recognizes the direction of the maximum covariance between the predicted and response variables by projecting them into a new space. Then, the predicted variables most highly correlated with the response variables are extracted. These components not only combine the predictive variable information but also have very strong correlations with the response variables [19]. The PLSR algorithm calculates the scores, weights and loads of the components through iteration, thus obtaining the regression coefficients.

2.3.2. SVR Model

SVR is a machine learning method that is used to solve regression problems [20]. It seeks a hyperplane to fit data by mapping the original data onto a high-dimensional characteristic space, aiming to minimize the distance from the data points to the hyperplane [21]. Hence, the function can give a prediction of the input data as precisely as possible. SVR models are composed of an input layer, hidden layer and output layer. The input layer is responsible for generating a sample set. The sample input is generated by nodes. The hidden layer is responsible for the inner product operation. The output layer is responsible for weighting the operation values, thus obtaining the decision-making function. To process noise and uncertainty in regression problems, SVR introduces an insensitive loss function (ϵ). In other words, when the gap between the predicted and actual values is lower than the threshold ϵ , the prediction is accurate and no loss is generated.

2.3.3. PSO-LSSVR Model

Particle swarm optimization (PSO) is an optimization algorithm based on swarm intelligence. In the PSO algorithm, each solution is viewed as a “particle” in the search space. Each particle has a fitness value, which is calculated by the optimization function. Particles move in the search space and search for better solutions by updating their speeds and positions continuously. The PSO algorithm has the characteristics of easy operation and fast convergence [22,23]. It has been extensively applied in various fields, such as function optimization, neural network training, pattern recognition, image processing, and so on.

The least squares support vector regression (LSSVR) is a regression method based on the support vector machine [24]. LSSVR is a deformation algorithm of SVR. It transforms the loss function from an error sum into a square sum of errors by introducing it into a least squares linear system. It also changes the solving algorithm from a convex quadratic optimization equation into a linear equation set. In addition, the number of solving variables decreases from $2n + 1$ to $n + 1$ (where n is the number of training samples). In this way, it decreases the calculation load significantly.

Therefore, the PSO and LSSVR were combined to determine the optimal parameter values of the LSSVR model. This can improve the learning and generalization capacities of the model and its predictive accuracy.

2.4. Model Evaluations

The predictive performance of the models was evaluated in terms of the mean square error (MSE) and correlation coefficient (R). Generally speaking, a high-precision model should have a low MSE and high R-value. The formulas for calculating R and MSE are as follows:

$$R = \frac{\sqrt{\sum_{j=1}^N (M_j - T_j)^2}}{\sqrt{\sum_{j=1}^N (M_j - \bar{T}_j)^2}} \quad (1)$$

$$\text{MSE} = \sum_{j=1}^N \frac{(M_j - T_j)^2}{N} \quad (2)$$

where M_j and T_j are the prediction and measured values of the data j , respectively; $\bar{T}_j$ is the mean value of the measured values of the data j ; and N refers to the total amount of data.

3. Results and Analysis

3.1. Linear Correlation between Dielectric Parameters and the Internal Quality of Fragrant Pears

The means and standard deviations of the ϵ' and ϵ'' values of the 110 pears used for model construction and measured at 100 frequencies (0.1–26.5 GHz) are shown in Figure 2. The error bar was the mean $\pm$ standard deviation. It can be seen from Figure 2 that ϵ' declines gradually with increases in the frequency, with a greater decline in the low-frequency range. Within the frequency range of 0.1–2.33 GHz, ϵ'' declines rapidly with increases in the frequency up to 2.33 GHz, and then increases. There are some deviations in the electrical parameters of the 110 fragrant pears at each frequency. Pear fruits are living organisms that decompose respiratory substrates such as starches, sugars and organic acids into CO_2 and water through respiration. Changes in the composition of water and other substances affect the spatial charge distribution inside the fruit [7]. The distribution and intensity of the bioelectric field affect the dielectric properties of fruit on a macroscopic level. Therefore, there is an inevitable relationship between the internal quality of the fruit and the macroscopic dielectric properties. The variation in the internal quality of 110 fragrant pears leads to differences in the dielectric properties at every frequency.

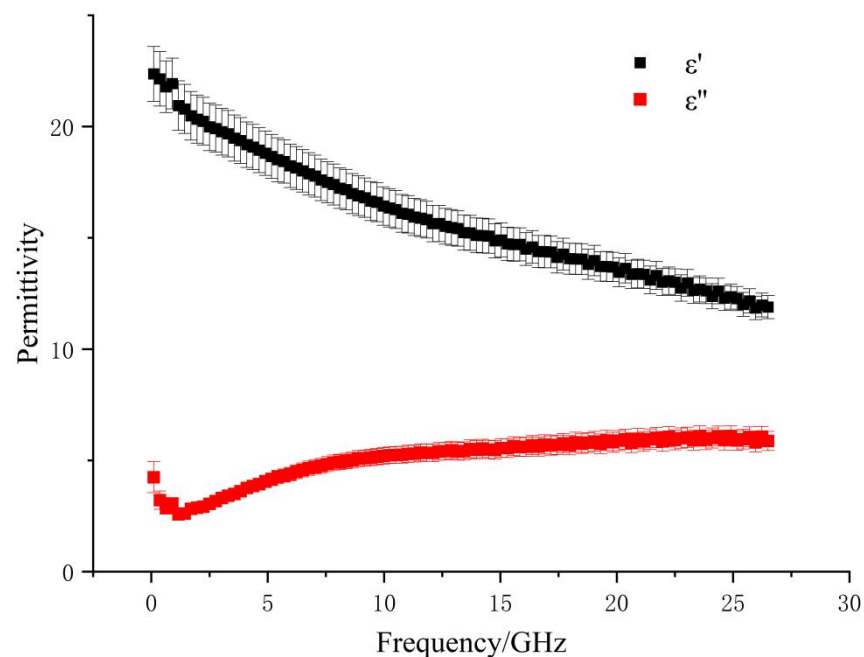


Figure 2. The standard deviation (mean $\pm$ standard deviation) of ϵ' and ϵ'' for the 110 pear samples was obtained at 100 frequencies from 0.1 MHz to 26.5 MHz.

The Pearson correlation analysis of ϵ' and ϵ'' with the hardness and SSC at different frequencies is shown in Figure 3. The Pearson correlation coefficient is a form of statistical data used to measure the degree of linear correlation between two variables, with values ranging from -1 to 1 . When the value of the Pearson correlation coefficient is close to 1 , it indicates a strong positive correlation between the two variables. When the value is close to -1 , it shows a strong negative correlation, and when the value is 0 , it indicates that no linear correlation exists between the two variables [25,26].

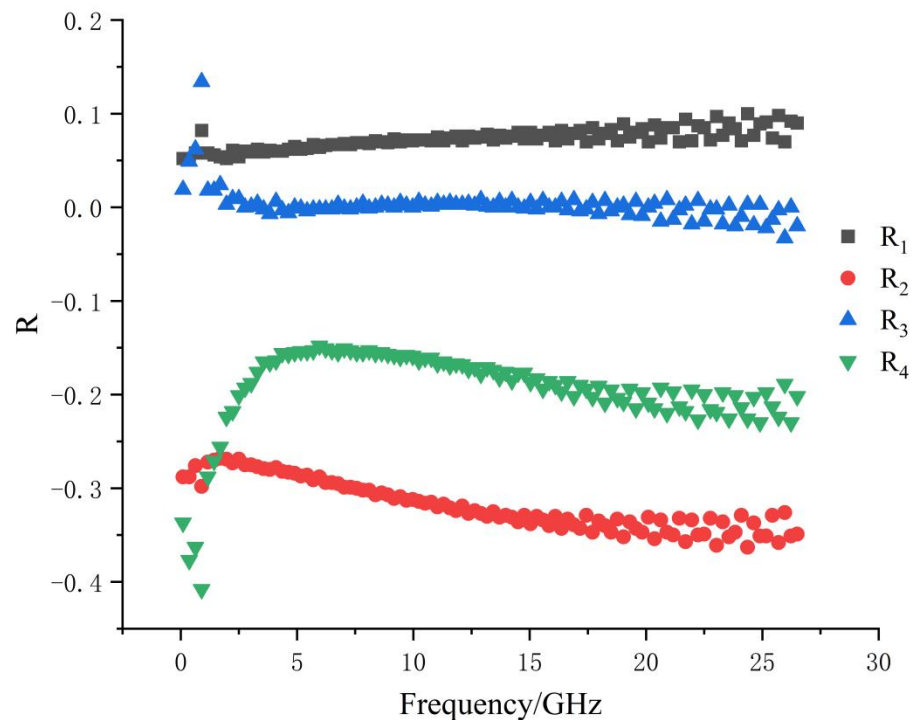


Figure 3. Linear relationships of ϵ' and ϵ'' with the hardness and SSC of fragrant pears at different frequencies. Note: R_1 represents the linear correlation coefficients of ϵ' with hardness. R_2 represents the linear correlation coefficients of ϵ' with SSC. R_3 represents the linear correlation coefficients of ϵ'' with hardness. R_4 represents the linear correlation coefficients of ϵ'' with SSC.

Specifically, R_1 and R_3 are the linear correlation coefficients of ϵ' and ϵ'' with hardness, respectively, and R_2 and R_4 are those with SSC. It can be seen from Figure 3 that ϵ' and ϵ'' are positively related to hardness but negatively related to SSC. The absolute values of all correlation coefficients are <0.4 , indicating that the dielectric parameters have weak correlations with the hardness and SSC under a single frequency. Therefore, it is very difficult to predict the hardness and SSC of fragrant pears based on dielectric parameters under a single frequency. This is consistent with the research of Guo et al. [13]. When dielectric characterization techniques are used to detect fruit quality indicators, the ability of different measurement frequencies to penetrate the fruit varies. A single frequency cannot obtain the fruit's spatial information. Multi-frequency dielectric parameters are used to detect the quality of fruit to ensure the penetration performance of the fruit and to obtain sufficient spatial information [27]. Hence, the hardness and SSC should be predicted by dielectric parameters under multiple frequencies.

3.2. Sample Division

The 110 samples were divided randomly into a training set (77 pears) and test set (33 pears) at a ratio of 7:3. The training set was used to determine the intrinsic laws of the data to build the training model, and the test set was used to verify the prediction accuracy of the training model. To improve the training model's prediction ability, the training set sample interval is usually divided into the maximum range. The minimum value of the training set sample should be smaller than that of the test set and the maximum value of the training set sample should be larger than that of the test set [13]. This process indicates that the sample division is reasonable.

The minimum, maximum, mean and standard deviation of the hardness and SSC for the whole pear sample are listed in Table 1. The maximum and minimum hardness values are 7.00 kg/cm^2 and 4.06 kg/cm^2 , respectively, a difference of 2.94 kg/cm^2 . The maximum and minimum SSC are 14.80% and 10.97%, a difference of 3.83%. These results show that

the sample had relatively wide ranges of hardness and SSC. The minimum hardness and SSC of the training set were both lower than those of the test set, while the maximum values were higher. This reveals that the sample division was reasonable.

Table 1. Statistics of fragrant pear sample division.

Quality Indicators	Sample Set	Minimum	Maximum	Mean $\pm$ Standard Deviation
Hardness	Total sample	4.06	7	5.46 $\pm$ 0.50
	training set	4.06	7	5.44 $\pm$ 0.49
	test set	4.58	6.44	5.50 $\pm$ 0.52
SSC	Total sample	10.97	14.80	12.65 $\pm$ 0.65
	training set	10.97	14.80	12.62 $\pm$ 0.65
	test set	11.70	14.33	12.72 $\pm$ 0.65

3.3. Prediction of Hardness

The ϵ' and ϵ'' variables were used as model input parameters, with hardness used as the output variable. A total of 110 data points were randomly distributed into training and test sets at a ratio of 7:3 to evaluate the predictive performance of the trained models. The prediction results are listed in Table 2, which shows that in the prediction stage, ϵ' and ϵ'' were used as the model inputs. With the PSO-LSSVR and SVR models, the R-value of the training set is relatively high and the MSE value is relatively low, while the R-value of the test set is relatively low and the MSE value is relatively high, showing a poor goodness of fit. This indicates that the PSO-LSSVR and SVR models predict hardness poorly. With the PLSR model, the R and MSE values of the test set differ to some extent. When the input is ϵ' , R = 0.77 and MSE = 0.073, and when the input is ϵ'' , R = 0.64 and MSE = 0.148. The PLSR model using ϵ' and ϵ'' as model inputs can predict hardness well. The PLSR model using ϵ' as input achieves the maximum R value and minimum MSE value. This implies that the trained PLSR model using ϵ' as an input can predict hardness the best.

Table 2. Comparison of fragrant pear hardness prediction by different models.

Modeling Methods	Modeling Variables	Training Set		Test Set	
		R	MSE	R	MSE
PLSR	ϵ'	0.82	0.054	0.77	0.073
	ϵ''	0.81	0.055	0.64	0.148
SVR	ϵ'	0.74	0.112	0.39	0.233
	ϵ''	0.96	0.019	0.26	0.328
PSO-LSSVR	ϵ'	0.79	0.098	0.41	0.220
	ϵ''	0.89	0.046	0.46	0.300

3.4. Prediction of SSC

The variables ϵ' and ϵ'' were used as the model input parameters, while SSC was the output variable. A total of 110 data points were randomly distributed into a training set and a test set at a ratio of 7:3 and input into the trained prediction models. The predicted SSC values are shown in Table 3, which shows that in the prediction stage, ϵ' and ϵ'' are used as model inputs. With the PSO-LSSVR and SVR models, the R values of the training set are relatively high and the MSE values are relatively low, but the R-value of the test set is relatively low and the MSE value is relatively high, showing a poor goodness of fit. This shows that the PSO-LSSVR and SVR models poorly predict the SSC. In the PLSR model, the R and MSE values of the test set differ to some extent. When the input is ϵ' , R = 0.84 and MSE = 0.090, and when the input is ϵ'' , R = 0.91 and MSE = 0.087. The PLSR model that uses ϵ' and ϵ'' as model inputs can predict the SSC well. The PLSR model using ϵ'' as

the input achieves the maximum R value and minimum MSE. This implies that the PLSR model using ϵ'' as an input can predict the SSC the best.

Table 3. Comparison of fragrant pear SSC prediction by different models.

Modeling Methods	Modeling Variables	Training Set		Test Set	
		R	MSE	R	MSE
PLSR	ϵ'	0.91	0.055	0.84	0.090
	ϵ''	0.92	0.063	0.91	0.087
SVR	ϵ'	0.86	0.118	0.27	0.433
	ϵ''	0.97	0.04	0.15	0.378
PSO-LSSVR	ϵ'	0.95	0.055	0.45	0.347
	ϵ''	0.83	0.186	0.40	0.300

Based on the PLSR model, the prediction of hardness and the SSC of fragrant pears was better, while the prediction of the SVR and PSO-LSSVR models was worse. Additionally, the SVR and PSO-LSSVR models showed overfitting problems. To analyze this reason, compared with the PLSR model, the SVR and PSO-LSSVR models have more parameters and higher model complexity, which may not align with the experimental data samples, leading to the overfitting problem. Although the SVR and PSO-LSSVR models can predict the quality of other fruits and vegetables, they are not suitable for predicting the hardness and SSC of fragrant pear.

3.5. Model Verification

The PLSR model can predict hardness and SSC the best. However, the practical performance of PLSR models is still unclear. To verify the actual performance of the optimal predictive model, the dielectric properties and quality indicator data of the rest of the 110 fragrant pear samples were acquired. The dielectric parameters of the 110 fragrant pear samples were loaded as inputs into both trained models, and the predicted values of hardness and SSC were obtained, respectively. Through the linear fitting of the measured and predicted data (PLSR model), the performance of the optimal model was verified (Table 4).

Table 4. Performance verification of the optimal predictive model.

Modeling Methods	Modeling Variables	Quality Indicators	Model Accuracy	
			R	MSE
PLSR	ϵ'	Hardness	0.76	0.129
PLSR	ϵ''	SSC	0.85	0.095

The verification experiment shows that the R and MSE values of the PLSR model using ϵ' as inputs were 0.76 and 0.129 when it was used to predict hardness, showing a relatively high predictive accuracy. The R and MSE values of the PLSR model using ϵ'' as input were 0.85 and 0.095 when predicting the SSC, showing a relatively high predictive accuracy. In summary, the hardness and SSC can be obtained by inputting dielectric parameters into the trained optimal model. The PLSR model shows good actual performance.

4. Discussion

The results showed that the correlations between the dielectric parameters of the fragrant pear and the hardness and SSC at a single frequency were weak. The skin of the fragrant pear was thin and juicy, and there were many charged particles in it, forming biological electric fields. The distribution and intensity of the electric fields in different fragrant pears were different. During testing, dielectric parameters at a single frequency cannot fully reflect the internal electric field distribution of all fragrant pears [28], which has

significant limitations, resulting in weak correlation. The above problems can be avoided by using dielectric parameters at multiple frequencies. For example, Cao, Lin, Trabelsi et al. [29–31] conducted non-destructive testing of the fruit SSC and hardness. The dielectric parameters were tested at multiple frequencies and good results were obtained. Cavaco, Cruz et al. [32,33] outlined the application of near-infrared spectroscopy in fruit or plant detection. Near-infrared spectroscopy is a feasible method for detecting fruit quality, which has good accuracy and stability in the detection process. However, the hardness and SSC are non-uniformly distributed in the pear. Non-destructive testing techniques based on near-infrared spectroscopy do not have strong penetration capabilities and the required high sample uniformity. Furthermore, the acquisition is susceptible to the influence of the test area. Therefore, techniques with a high penetration depth are essential for acquiring sufficient information to comprehensively and accurately evaluate the internal quality of Korla fragrant pears. As a new high-penetration-depth technique, dielectric property detection has the advantages of simple operation, speed and sensitivity. When Cao et al. [27] used dielectric characteristics to detect the SSC of different varieties of pears, it was found that the effect of electrical detection was better than that of near-infrared spectrum detection. In this paper, the model established with ϵ' as the variable under the PLSR method has the best performance in predicting the pear SSC, and the model established with ϵ'' as the variable under the PLSR method has the best performance in predicting the pear SSC. In this case, the predicted hardness R and MSE were 0.77 and 0.073, respectively, and the predicted SSC R and MSE were 0.91 and 0.087, respectively. The results show that a combination of dielectric properties under multiple frequencies and machine learning can effectively predict the SSC and hardness of fragrant pear. In addition, they also reveal that the prediction effect of hardness is slightly worse than that of SSC, which is consistent with the prediction results of Fang et al. [34] when using dielectric parameters to predict the SSC and sugar content of pear fruit. The results of this study can provide a new method for the non-destructive online detection of the internal quality of Korla fragrant pear. Because all the samples used in the test were taken from the same pear garden, and the fragrant pear has a very strong growing region, different growing conditions or different fragrant pear varieties may cause large internal differences in fragrant pear. Whether this method is suitable for other varieties of fragrant pear or for different growing conditions still needs further verification. In the next step, fragrant pears in different growing environments can be collected to verify the model established, and the model can be further optimized to achieve the purpose of effectively predicting the quality of any fragrant pear.

5. Conclusions

With increases in frequency, ϵ' presents a declining trend while ϵ'' presents a V-shaped trend. The absolute values of the coefficients of the correlations between the dielectric parameters (under a single frequency) and hardness and SSC were <0.4 , indicating weak correlations. The PLSR model using ϵ' as a variable showed the optimal performance in predicting hardness ($R = 0.77$, $MSE = 0.073$). The PLSR model using ϵ'' as a variable showed the optimal performance in predicting the SSC ($R = 0.91$, $MSE = 0.087$). According to the verification results, the PLSR model using ϵ' as a variable achieves good performance in predicting hardness ($R = 0.76$, $MSE = 0.129$). The PLSR model using ϵ'' as a variable achieves good performances in predicting the SSC ($R = 0.85$, $MSE = 0.095$). This study provides a new method for the non-destructive online detection of the internal quality of Korla fragrant pears.

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Conflicts of Interest: The authors declare no conflicts of interest.

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