Model for estimating the weight-loss ratio of damaged Korla fragrant pears

Yang Liu[1], Yurong Tang[1*], Hong Zhang[2], Hao Niu[1], Haipeng Lan[1]
(1. *College of Mechanical and Electrical Engineering, Tarim University, Alaer 843300, Xinjiang , China*;
2. *College of Water Resources and Architectural Engineering, Tarim University, Alaer 843300, Xinjiang , China*)

Abstract: To predict the weight-loss ratio of Korla fragrant pears effectively, improve commodity value and study the variation laws of the weight-loss ratio of damaged fragrant pears during storage, this study predicted the weight-loss ratio of fragrant pears by utilizing the generalized regression neural network (GRNN), support vector regression (SVR), partial least squares regression (PLSR) and error back propagation neural network (BPNN). The prediction performances of GRNN, SVR, PLSR and BPNN models were compared comprehensively, and the optimal model was determined. In addition, the optimal prediction model was verified. The results show that weight-loss ratio of fragrant pears increases gradually with the extension of storage time. During storage, the weight-loss ratio of fragrant pears is positively related to the degree of damage. The trained GRNN, SVR, PLSR and BPNN models can be used to predict the weight-loss ratio of fragrant pears. The BPNN model is the most accurate in predicting the weight-loss ratio of damaged fragrant pears (R^2=0.9929; RMSE=0.2138). It has also been proved to have good predictive effect in production practice (R^2=0.9377, RMSE=0.7138). The research findings can provide references to predict the delivery quality and time of delivery of Korla fragrant pears.

Keywords: Korla fragrant pears, weight-loss ratio, damages, storage time
DOI: 10.25165/j.ijabe.20141701.8300

Citation: Liu Y, Tang Y R, Zhang H, Niu H, Lan H P. Model for estimating the weight-loss ratio of damaged Korla fragrant pears. Int J Agric & Biol Eng, 2024; 17(1): 261–266.

1 Introduction

Korla fragrant pear is mainly produced in Korla and Aksu in southern Xinjiang, China. It is a product with a protected national geographic indication and is known as the ‘Treasure in Pear’[1-3]. In 2022, the total annual yield exceeded 1 million t. Korla fragrant pears have become the cornerstone of the forest and fruit industries in Xinjiang. Due to their thin pericarp, crisp pulp and poor tolerance to mechanical damage, the mechanical damage rate is higher in harvesting, transportation, classification, packaging and other process. There is a saying that states, ‘Korla fragrant pears turn to juice once they fall to the ground’. Practitioners abandon damaged fragrant pears during the warehouse inspection, resulting in a waste rate of over 38%[4]. According to industrial standards and previous research, the damaged Korla fragrant pears still have commodity values and they could be classified for special storage and marketing at the appropriate time[5,6]. Fruits are very susceptible to mechanical damage during production and processing, thus influencing the weight-loss ratio during storage. As a result, the delivery quality of fruits cannot meet the industrial requirements. The weight-loss ratio is an index used to evaluate the freshness basis of fruits, and it is the most intuitive index for determining changes in fruit quality[7]. It directly influences the shelf life and economic value of fruits. The weight-loss ratio is an important reference for practitioners to judge the delivery quality and time of delivery of fragrant pears[8]. The weight-loss ratio needs to be monitored in real-time during the storage to ensure the good quality and economic benefits of damaged fragrant pears at the time of marketing. Hence, studying variation laws of the weight-loss ratio of fragrant pears during storage and establishing an effective prediction model can provide references to control delivery quality and make decisions about when to deliver fragrant pears. They are critical for ensuring fruit quality and promoting the industrial growth of fragrant pears.

For researchers, it is a major challenge to accurately control the variation laws of the weight-loss ratio of damaged fruits during storage. Montero et al.[9] discovered that under room-temperature storage, the weight-loss ratio of Rainha’ tangerines was positively related to mechanical damages. Pathare et al.[10] studied the variation of weight-loss rate of tomatoes with different impact damage degrees stored at 10°C and 22°C. They discovered that as the impact height increased, the weight-loss ratio increased significantly. Wei et al.[11] found that the weight-loss rate of kiwifruit with vibration damage during storage was significantly higher than that of non-destructive kiwifruit. Previous research has demonstrated that mechanical damages have significant influence on the weight-loss ratio of fruits during storage. However, the influences of mechanical damages on the weight-loss ratio of fragrant pears during storage have not yet been investigated. Therefore, special emphasis will be paid to studying the influencing laws of mechanical damages on the weight-loss ratio of fragrant pears. Moreover, it has to adopt scientifically effective methods to predict the weight-loss ratio of fragrant pears during storage.

Existing models for predicting the quality of fruits can generally be divided into two types. One of them predicts the fruits

Received date: 2023-04-13 **Accepted date:** 2023-09-25
Biographies: Yang Liu, PhD, Associate Professor, research interest: agricultural products processing technology, Email: 120150012@taru.edu.cn; **Hong Zhang**, MS, Lecturer, research interest: agriculture geographic information system, Email: 18845161657@163.com; **Hao Niu**, Master, Lecturer, research interest: agricultural products processing technology, Email: 18167528125@163.com; **Haipeng Lan**, PhD, Professor, research interest: agricultural products processing technology, Email: lanhaipeng@126.com.
***Corresponding author: Yurong Tang**, Master, Senior Experimentalist, research interest: agricultural products processing technology, College of Mechanical and Electrical Engineering, Tarim University, Alaer 843300, Xinjiang, China; Tel: +86-15599725713, Email: 120110010@taru.edu.cn.

quality by using the traditional kinetic model, such as the Arrhenius Equation, Weibull model and Q10 value model[12-14], the other using the machine learning models, such as BPNN, GRNN, PLSR and SVR[15-18]. They can improve the accuracy of prediction by integrating multiple indicators together. GRNN, SVR, PLSR and BPNN models have strong self-learning and adaptive ability, and can process a large number of complex data and reveal the rules and trends in data, and can achieve high-precision and high-speed prediction and classification， have been widely used to predict fruits quality. In the prediction of quality of fruits, it was discovered that GRNN, SVR, PLSR and BPNN models had a better prediction effect compared to the traditional dynamic prediction models, and the four artificial intelligence (AI) algorithm have shown better performances[19-22]. The above scholars have achieved good effects in the prediction of fruit quality during storage by AI algorithm. Nevertheless, the prediction of the weight-loss ratio of damaged Korla fragrant pears during the storage period based on the AI algorithm has hardly been reported.

This study explored the influencing laws of damage degree on the weight-loss ratio of Korla fragrant pears during storage. Four neural network modelling methods, including GRNN, SVR, PLSR and BPNN, were applied to establish the prediction model of the weight-loss ratio of Korla fragrant pears, and their prediction performances were compared comprehensively. On this basis, the optimal prediction model was determined and verified.

2 Materials and methods

2.1 Sampling of Korla fragrant pears

On 15 September 2021, Korla fragrant pear samples were collected from 14-year-old pear trees in Pear Garden, 12th Regiment, 1st Division, Xinjiang Production and Construction Corps, China. As test samples, fragrant pears with similar shapes, uniform color, lack of damage, no distortion and no plant and insect diseases were chosen. The weight of the collected samples was (110±5) g. The test was carried out immediately after the harvest of fragrant pears.

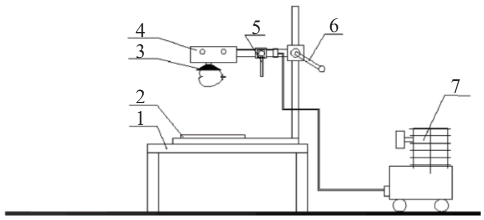
2.2 Storage test of damaged Korla fragrant pears

An impact damage system (Figure 1) was established for an impact damage test to obtain fragrant pears samples with different damage degrees. The process of an impact test system for fragrant pears was introduced as follows: the vacuum generator produced negative pressures, and fragrant pear samples were sucked up by the vacuum suction produced by the sucker. The height-regulating handle was controlled to adjust the falling height. Turn off the rotary switch to eliminate the sucking force, allowing the fragrant pears to fall freely from varying heights onto the contact object. The impact loads are controlled by adjusting the falling height, thus enabling to obtain fragrant pears with different damage degrees. In this study, corrugated boards were used as the contact object and falling heights were set at 30 cm, 50 cm, 70 cm, 90 cm, 110 cm and 130 cm, respectively. Korla fragrant pears were damaged and were then placed at room temperature until they were completely brown. The pericarp at the damages was eliminated by a knife. The major semi-axis (a) and the minor semi-axis (b) of the damaged area were measured, as shown in Figure 2. The damaged area was calculated using the measuring method of Wu[23], as shown in Equation (1). According to the falling height, the corresponding damage areas were 77.71 mm^2, 296.91 mm^2, 604.05 mm^2, 900.77 mm^2, 952.30 mm^2 and 993.42 mm^2, respectively.

$$S = \pi ab \tag{1}$$

where, S is the damaged area of fragrant pears, mm^2; a is the major semi-axis of the oval damaged area, mm; b is the minor semi-axis of the oval damaged area, mm.

After fragrant pears with different degrees of damage were acquired, they were stored immediately at room temperature at Tarim University, Alaer City, Xinjiang. The average temperature was 15°C and the average relative humidity was 56%.



1. Testbed 2. Contact object 3. Sucker 4. Vacuum generator 5. Switch 6. Height adjusting handle 7. Air compressor

Figure 1 Impact test system of fragrant pears

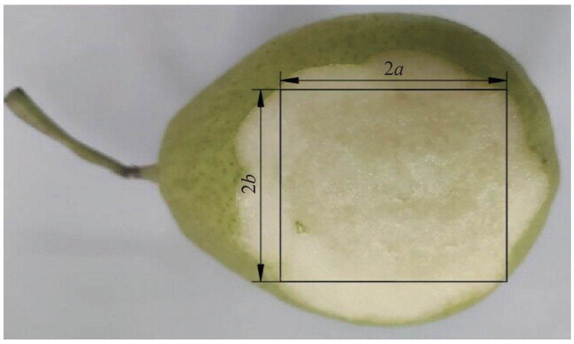


Figure 2 Measurement diagram of the damaged area

2.3 Measurement of the weight-loss ratio

The harvested fragrant pears were immediately returned to the laboratory and weighed. The weights of fragrant pears with different damage degrees were measured every five days during storage. Each time, ten fragrant pears were chosen randomly and data were recorded. As the final result, the mean weight was chosen and recorded as M_1. The calculation formula was as follows:

$$M = \frac{M_0 - M_1}{M_0} \tag{2}$$

where, M is the weight-loss ratio, %; M_0 represents the weight of Korla fragrant pears at harvest, g; M_1 is the weight of Korla fragrant pears at test, g.

2.4 Modelling methods

Four modelling methods were applied in this study, including GRNN, SVR, PLSR and BPNN. They were used to construct the prediction model of the weight-loss ratio of fragrant pears with different damaged area during storage. All four models used the damaged area and storage days of fragrant pears as the input of the network. The weight-loss ratio of fragrant pears was the output of the networks. A statistical analysis of the experimental data was carried out, which finally provided 63 groups of datasets. Among them, 70% of the experimental data were chosen randomly for training, while the remained 30% were used for verification.

2.4.1 GRNN model

GRNN carries out the nonparametric estimation by using nonparametric kernel regression as the basis and sample data as the posterior probability verification conditions[24]. Finally, the correlation density function between the dependent variable and the independent variable in the GRNN network is calculated from the training sample, and the regression value of the dependent variable relative to the independent variable is calculated. GRNN is advantageous for the convenient network parameter-setting function. The whole neural network only has to set the smooth factor in the kernel function to adjust the performances of the GRNN. Moreover, GRNN has good network adaptability. As a result, GRNN is widely applied for analyzing signal processes, control decision system structures and other fields.

2.4.2 SVR model

SVR is a regression algorithm based on support vector machine. The objective is to determine the relationship between dependent variables and independent variables in a non-linear regression problem and to construct an approximate function that minimizes the prediction error for training cases[25]. During error minimization, the flatness of the function was maximized to decrease the risk of overfitting. It is reliable for solving prediction problems.

2.4.3 PLSR model

The PLSR model enhances the prediction performance of the principal component regression model. The PLSR model has the advantages of these three methods and enables the comprehensive application of multiple data analysis methods. It can effectively solve the multiple correlation problems of independent variable sets. The basic principle of the PLSR linear model lies in the principal component analysis of independent variables and the typical correlation analysis of dependent variables to extract the principal components of independent and dependent variables[26]. Later, a regression analysis of the extracted principal components was carried out. The PLSR model has some advantages in the construction of a linear regression model with small sample data processing capacity, multiple independent variables and multiple linearities among variables.

2.4.4 BPNN model

The feedforward neural network that uses the back propagation learning algorithm is usually called a BPNN. The learning process is mainly composed of four parts, including forward propagation of input mode, back propagation of output error, cyclic memory training and judgement of learning outcome. During forward propagation, the input information was processed layer by layer from the input layer through elements of the hidden layer, and then transferred to the output layer. State of neurons of each layer only influences state of neurons of the next layer. If the output layer cannot get the expected output, the learning process turns to the back propagation to return the error signals along the original connection route. The error signals were reduced by adjusting the weights of neurons in each layer before entering the forward propagation process. Iterations continued until the error was smaller than the given value. BPNN has a very strong non-linear mapping ability, and it is the most basic and extensively applied neural network[27].

2.5 Judgement criteria of the optimum prediction model

In order to screen out the optimal prediction model of weight-loss rate of damaged Korla fragrant pear, the prediction performances of models were estimated according to the decision coefficient (R^2) and root mean square error (RMSE). The higher the R^2, the lower the RMSE and the greater the precision of the prediction model. The formulas for calculating R^2 and RMSE were as follows:

$$R^2 = 1 - \frac{\sum (M_j - T_j)^2}{\sum M_j^2 - \frac{\left(\sum M_j\right)^2}{n}} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\sum_{i}^{N} \frac{\left(M_j - T_j\right)^2}{N}} \tag{4}$$

where, M_j and T_j are the measured and prediction values of data j, respectively; n refers to the number of measured values, and N refers to the total amount of data.

3 Results and discussion

3.1 Variation laws of the weight-loss ratio of fragrant pears during storage

It can be seen from Figure 3 that as the storage time prolongs, the weight-loss ratio of fragrant pears increases continuously. The mean weight-loss ratio of Korla fragrant pears with different damage degrees increased from 0.38% at 5 d to 7.25% at 40 d. Moreover, differences in weight-loss ratio among Korla fragrant pears with different damage degrees became more prominent with the prolonging of storage time. In the first 10 d of storage, differences in weight-loss ratio among Korla fragrant pears with different damage degrees were relatively weak. After 10 d, the influences of the damage degree on the weight-loss ratio of fruits began to show up. Moreover, the weight-loss ratio of fruits increased gradually as the increase of damage degree. Hence, the damage could affect the weight-loss ratio of the fruits. It is recommended to avoid damaging the fruits to decrease the weight-loss ratio of fruits. The following reasons were analysed: during storage in a room-temperature environment, Korla fragrant pears lose nutrient and water supply after separating from the tree. The extension pressure of cells decreased due to continuous transpiration and water loss by tissues, without any supplementation[28]. Moreover, substances stored in cells are consumed continuously by respiration[29]. Therefore, the weights of fragrant pears decreased gradually during storage. The fruits with higher damage degrees have stronger respiration intensity and a quicker consumption of nutrients[30]. Hence, fruits with a higher damage degree suffered a greater weight-loss ratio under the same storage time.

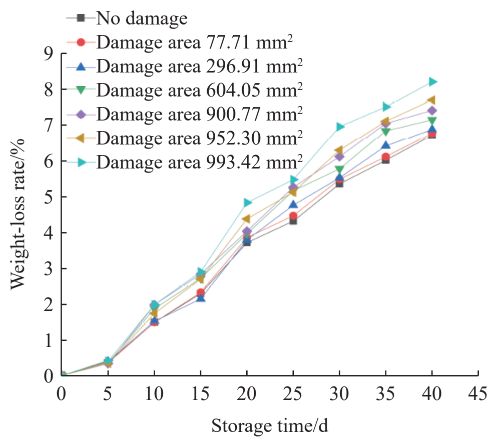


Figure 3 Variations in the weight-loss ratio of fragrant pears

3.2 Prediction of the weight-loss ratio of fragrant pears during storage

3.2.1 Prediction of the weight-loss ratio of fragrant pears based on the GRNN model

In this section, 44 groups of experimental data were randomly selected as the training set, and then the GRNN model was trained. By analyzing the training results, the optimal smooth factor in the prediction of the weight-loss ratio of fragrant pears σ was 0.11. At this time, the model's prediction performance is optimal, and its error is minimal. Then, the remaining 19 data is loaded into the trained model to get the predicted value. Linear fitting between the observed and predicted values was carried out, as shown in Figure 4. Furthermore, R^2 was 0.9836 and RMSE was 0.3180 when the GRNN model predicts the weight-loss ratio of fragrant pears. This indicates that the trained GRNN model could accurately predict the weight-loss ratio of fragrant pears with different damage degrees during storage.

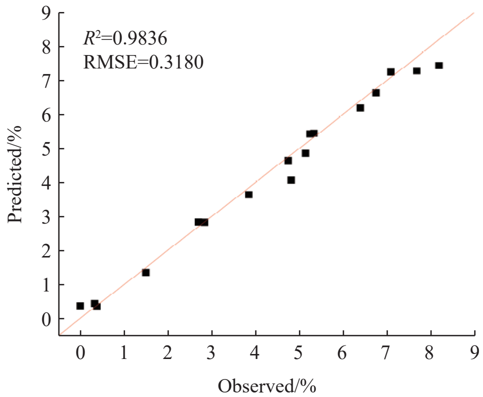


Figure 4 Correlation between the observed value and predicted value of the weight-loss ratio of fragrant pears based on the GRNN model

3.2.2 Prediction of the weight-loss ratio of fragrant pears based on the SVR model

44 groups of sample data were randomly selected for training, and the remaining 19 groups of sample data were loaded into the trained model for testing, and the predicted value was obtained. The measured value and the predicted value were analyzed by linear fitting process. Apparently, R^2 was 0.9882 and RMSE was 0.3116 when the SVR model predicts the weight-loss ratio of fragrant pears, as shown in Figure 5. This indicates that the trained SVR model could effectively predict the weight-loss ratio of fragrant pears with different damage degrees during storage.

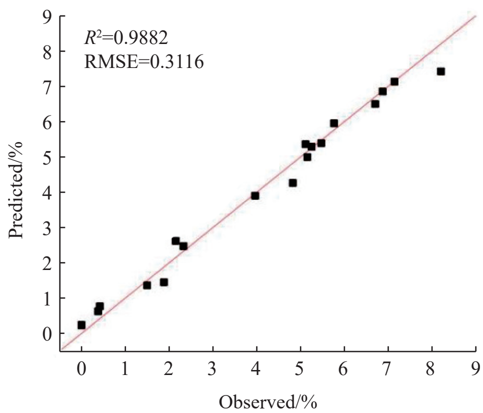


Figure 5 Correlation between the observed value and predicted value of the weight-loss ratio of fragrant pears based on the SVR model

3.2.3 Prediction of the weight-loss ratio of fragrant pears based on the PLSR model

44 groups of sample data were randomly selected for training, and the remaining 19 groups of sample data were loaded into the trained model for testing, and the predicted value was obtained. By analyzing the linear fitting results between the measured value and the predicted value, R^2 was 0.9790 and RMSE was 0.5064, as shown in Figure 6. This indicates that the weight-loss rate of fragrant pears with different damage degrees during storage can be effectively predicted by PLSR model after training.

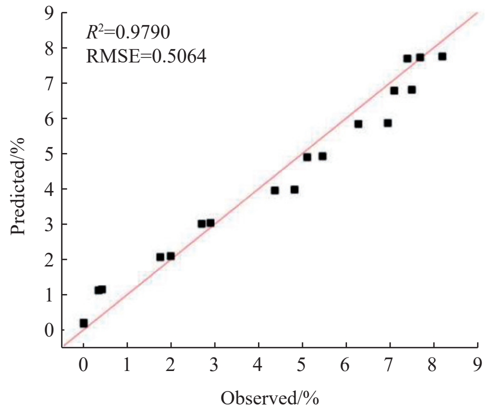


Figure 6 Correlation between the observed value and predicted value of the weight-loss ratio of fragrant pears based on the PLSR model

3.2.4 Prediction of the weight-loss ratio of fragrant pears based on the BPNN model

The parameter setting of the BPNN was as follows: times of training=1000, error precision=0.001, number of neurons in the input layer=2, number of neurons in the hidden layer=10, and number of neurons in the output layer=1. Here, 44 groups of sample data were randomly selected for training. Next, the remaining 19 groups of sample data were loaded into the trained model for testing and the predicted value was obtained. Linear fitting between the measured and prediction values was carried out. Notably, R^2 was 0.9929 and RMSE was 0.2138 when the BPNN model predicts the weight-loss ratio of fragrant pears. The fitting effect is shown in Figure 7. It can be seen from Figure 7 that the correlation between the observed and predicted values is relatively high, with a small prediction error. This indicates that the weight-loss rate of fragrant pears with different damage degrees during storage can be accurately predicted by BPNN model after training.

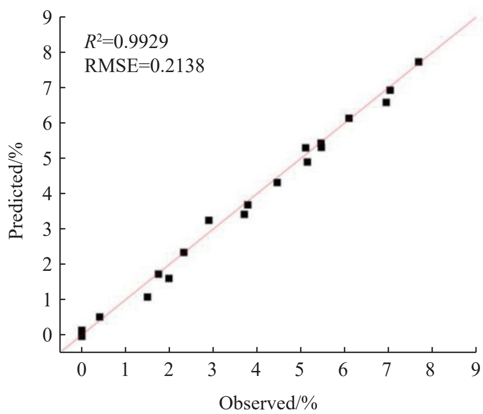


Figure 7 Correlation between the observed value and predicted value of the weight-loss ratio of fragrant pears based on the BPNN model

3.3 Determining the optimal prediction model of the weight-loss ratio of the damaged fragrant pears

During storage, four neural network models were used to predict the weight-loss ratio of fragrant pears with different damage degrees. Results demonstrated that during the prediction of the weight-loss ratio of fragrant pears, R^2 and RMSE of the GRNN model were 0.9836 and 0.3180, respectively. R^2 and RMSE were 0.9882 and 0.3116, respectively, for the SVR model. The PLSR model's R^2 and RMSE were 0.9790 and 0.5064, respectively. R^2 and RMSE were 0.9929 and 0.2138, respectively, for the BPNN model. R^2 of all four neural network models was higher than 0.9800, while the RMSE was smaller than 0.5064. The damaged area and storage time were used as input data, all four trained models could predict the weight-loss ratio of damaged fragrant pears. Although the R^2 of the four models in the prediction of the weight-loss ratio of fragrant pears showed small differences, the RMSE (0.2138) of the BPNN model was considerably lower than that of the other three models. Therefore, it is determined that BPNN model is the best in predicting weight-loss ratio of damaged fragrant pears (R^2=0.9929; RMSE=0.2138).

3.4 Model verification

On 15 September 2022, a storage experiment of damaged fragrant pears was conducted to verify the actual prediction performance of BPNN model. The experimental samples were manufactured, and the damaged areas of fragrant pears were 0 mm^2, 379.67 mm^2, 738.90 mm^2 and 1098.12 mm^2, respectively. The weight-loss ratio of fragrant pears was measured at 0 d, 10 d, 20 d, 30 d and 40 d. The correlation between the observed values and the predicted values of BPNN model was obtained, as shown in Figure 8.

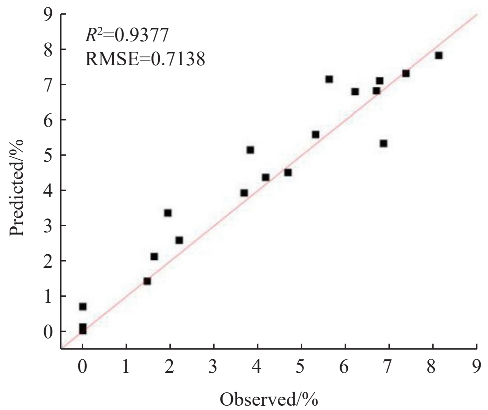


Figure 8 Correlation between the observed and predicted values of the weight-loss ratio of fragrant pears

According to the verification test, the BPNN model showed that the R^2=0.9377 and RMSE=0.7138 when it was used to predict the weight-loss ratio of fragrant pears during storage, showing high prediction precision. It is proved that the weight-loss rate of damaged pears during storage can be predicted by inputting the damaged areas and storage time into the trained BPNN model. The BPNN model achieved good practical performances in predicting the weight-loss ratio.

4 Conclusions

As the storage time prolongs, the weight-loss ratio of damaged fragrant pears increases continuously. Under the same storage time, fragrant pears fruits the higher damage degree experience the greater weight-loss ratio. The prediction performances of GRNN, SVR, PLSR and BPNN models are compared. The study comes to the conclusion that all trained GRNN, SVR, PLSR and BPNN models can accurately predict the weight-loss ratio of fragrant pears. Moreover, the BPNN model has the optimal prediction performances (R^2=0.9929; RMSE=0.2138). Next, the optimal prediction model of BPNN is verified, yielding good practical prediction performances (R^2=0.9377, RMSE=0.7138). The research findings can be used to control the quality and time of delivery of Korla fragrant pears.

Acknowledgments

The authors express their acknowledgment to the Chinese Natural Science Foundation (Grant No. 32260618 and 32202139), the Bingtuan Guiding Science and Technology Plan Program (Grant No. 2022ZD094) for financial support.

[References]

[1] Wu J, Guo K Q. Dynamic viscoelastic behaviour and microstructural changes of Korla pear (*Pyrus bretschneideri* Rehd) under varying turgor levels. Biosystems Engineering, 2010; 106(4): 485–492.

[2] Wang B H, Sun X X, Dong F Y, Zhang F, Niu J X. Cloning and expression analysis of an MYB gene associated with calyx persistence in Korla fragrant pear. Plant Cell Reports, 2014; 33: 1333–1341.

[3] Yu X J, Lu H D, Wu D. Development of deep learning method for predicting firmness and soluble solid content of postharvest Korla fragrant pear using Vis/NIR hyperspectral reflectance imaging. Postharvest Biology And Technology, 2018; 141: 39–49.

[4] Liu Y. Study on Mechanical damage mechanism and effect evaluation on storage of Korla fragrant Pear. PhD dissertation. Harbin: Northeast Agricultural University, 2021. (in Chinese)

[5] NY/T 585-2002. Kurle fragrant pear. Agricultural industry standard of the People's Republic of China. The Ministry of Agriculture of the People's Republic of China. (in Chinese)

[6] Yu S H, Liu Y, Tang Y R, Li X L, Li W, Li C, et al. Non-destructive quality assessment method for Korla fragrant pears based on electrical properties and adaptive neural-fuzzy inference system. Computers and Electronics in Agriculture, 2022; 203: 107492.

[7] Li H B, Lv S, Feng L, Peng P, Hu L B, Liu Z B, et al. Smartphone-based image analysis for rapid evaluation of kiwifruit quality during cold Storage. Foods, 2022; 11(14): 2113.

[8] Pathare P B, Al-Dairi M, Al-Yahyai R, Al-Mahdouri A. Physiological response of stored pomegranate fruit affected by simulated impact. Foods, 2023; 12(6): 1122.

[9] Montero C R S, Schwarz L L, Dos Santos L C, Andreazz C S, Kechinski C, Bender R J. Postharvest mechanical damage affects fruit quality of 'Montenegrina' and 'Rainha' tangerines. Pesquisa Agropecuaria Brasileira, 2009; 44(12): 1636–1640.

[10] Pathare P B, Mai A-D. Bruise damage and quality changes in impact-bruised, stored tomatoes. Horticulturae, 2021; 7: 113.

[11] Wei X P, Xie D D, Mao L C, Xu C J, Luo Z S, Xia M, et al. Excess water loss induced by simulated transport vibration in postharvest kiwifruit. Scientia Horticulturae, 2019; 250: 113–120.

[12] Liu P H, Qiao Y C, Hou B R, Xi Z T, Hu Y H. Building kinetic models to determine moisture content in apples and predicting shelf life based on spectroscopy. Journal of Food Process Engineering, 2021; 44(12): e13907.

[13] Serrano O, Fortuny R S, Belloso O M. Influence of storage temperature on the kinetics of the changes in anthocyanins, vitamin C, and antioxidant capacity in fresh-cut strawberries stored under high-oxygen atmospheres. Journal of Food Science, 2009; 74(2): 184–191.

[14] Hu W X, Ding T, Liu D H. Application of kinetic modeling of food quality changes during storage. Journal of Chinese Institute of Food Science and Technology, 2017; 17(5): 161–167. (in Chinese)

[15] Liu Y, Zhang Q, Niu H, Zhang H, Lan H P, Zeng Y, et al. Prediction method for nutritional quality of Korla pear during storage. Int J Agric & Biol Eng, 2021; 14(3): 247–254.

[16] Guo W C, Fang L J, Liu D Y, Wang Z W. Determination of soluble solids content and firmness of pears during ripening by using dielectric spectroscopy. Computers and Electronics in Agriculture, 2015; 117: 226–233.

[17] Al-Saif A M, Abdel-Sattar M, Eshra D H, Sas-Paszt L, Mattar M A. Predicting the chemical attributes of fresh citrus fruits using artificial neural network and linear regression models. Horticulturae, 2022; 8(11): 1016.

[18] Guo W C, Shang L, Zhu X H, Nelson S O. Nondestructive Detection of Soluble Solids Content of Apples from Dielectric Spectra with ANN and Chemometric Methods. Food and Bioprocess Technology, 2015; 8(5):

1126–1138.

[19] Liu Y, Zhao J F, Tang Y R, Jiang X, Liao J A. Construction of a Chlorophyll Content Prediction Model for Predicting Chlorophyll Content in the Pericarp of Korla Fragrant Pears during the Storage Period. Agriculture, 2022; 12(9): 1348.

[20] Yu S H, Lan H P, Li X L, Zhang H, Zeng Y, Niu H, et al. Prediction method of shelf life of damaged Korla fragrant pears. Journal of Food Process Engineering, 2021; 44(13): e13902.

[21] Lu Y F, He Z H, Zeng X M, Xu X L, Han M Y. Investigation on egg shelf life and storage time prediction model based on BP neural network. 2022. Available:https://kns.cnki.net/kcms/detail/11.2206.TS.20221128.1104.005.html. Accessed on [2022-11-28]. (in Chinese)

[22] Cao M K. Research on characterization factors of postharvest quality change and low temperature shelf life prediction model of six apple varieties. Master dissertation. Yangling: Northwest A&F University, 2021; 82p. (in Chinese)

[23] Wu J. Study on dynamic viscoelastic property and impact bruise of Korla pear. PhD dissertation. Yangling: Northwest A&F University, 2011; 116p. (in Chinese)

[24] Niu H, Liu Y, Wang Z T, Zhang H, Zhang Y C, Lan, H P. Effects of Harvest Maturity and Storage Time on Storage Quality of Korla Fragrant Pear Based on GRNN and ANFIS Models: Part I Firmness Study. Food Science and Technology Research, 2020; 26(3): 363–372.

[25] Hu S J, Meng Y M, Zhang Y B. Prediction method for sugarcane syrup brix based on improved support vector regression. Electronics, 2023; 12: 1535.

[26] Wang Z T, Fu Z D, Weng W X, Yang D Z, Wang J F. An efficient method for the rapid detection of industrial paraffin contamination levels in rice based on hyperspectral imaging. LWT, 2022; 171: 114125.

[27] Lan H P, Wang Z T, Niu H, Zhang H, Zhang Y C, Tang Y R, et al. A nondestructive testing method for soluble solid content in Korla fragrant pears based on electrical properties and artificial neural network. Food Science Nutrition, 2020; 8(9): 5172–5181.

[28] Zhao J, Shen M S, Pu Y G, Chen A, Li H. Research on out-of-warehouse evaluation and prediction model of apple based on near-infrared spectroscopy combined with multiple quality indexes. Transactions of the CSAM, 2023; 54(2): 386–395. (in Chinese)

[29] Shao X. Study on compression damage and quality deterioration mechanism of *Citrus reticulata* Blanco. Master dissertation. Wuhan: Huazhong Agricultural University, 2020; 84p. (in Chinese)

[30] Yu Y Q. Effects of mechanical damage on postharvest physiology and biochemistry of Dangshan pear. Master dissertation. Hefei: Anhui Agricultural University, 2011; 46p. (in Chinese)