Comparison of Prediction Models for Determining the Degree of Damage to Korla Fragrant Pears

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Abstract: For a fast and accurate evaluation of the values of damaged fragrant pears, a prediction method of the damage degree of Korla fragrant pears was proposed. To study variation laws of damages of fragrant pears under different volumes of squeezing deformation, the partial least squares regression (PLSR), the generalised regression neural network (GRNN) and the adaptive neural fuzzy inference system (ANFIS) were chosen to predict the damage degree of fragrant pears and establish the optimal prediction model. The results demonstrated that with the increase of ripeness or deformation value, the damage degree of fragrant pears increases gradually. For performance comparison of prediction models based on PLSR, GRNN and ANFIS, it was found that the trained PLSR, GRNN and ANFIS can all predict the damage degree of Korla fragrant pears. The ANFIS, which inputs the membership function of dsigmf ($R^2 = 0.9979$, RMSE = 46.6) and psigmf ($R^2 = 0.9979$, RMSE = 46.6), achieves the best performance. Research results can provide theoretical references to the evaluation of the commodity value of damaged fragrant pears, quality grading of fragrant pears and design of the picking machine.

Keywords: Korla fragrant pears; damage degree; neural network; prediction model

1. Introduction

Korla fragrant pears are a traditional high-quality characteristic fruit in Xinjiang. They have extremely robust growing regions and are highly valued in both Chinese and foreign markets because of their rich nutritional value, juiciness and thin pericarp [1]. During the harvest season of fragrant pears, a significant grasping force will be generated to separate fragrant pears from trees during both mechanical and artificial picking, resulting in varying degrees of squeezing damage to fragrant pears [2]. It is little known that the epidermis of fragrant pear not only has a protective effect but also has a certain self-healing ability, which prevents rot and lesions on the pear immediately after injury, and also enables the fruit merchants to sell the pears that are damaged by machinery or man-made damage in time or store them in batches according to different degrees of damage. The national standards explicitly regulate that fruits with some surface defects or damages still have commodity values [3]. This shows that the damaged pears can still be marketable and edible. Fragrant pears with different degrees of damage can be used in different processing channels, which makes the commodity value of pears different. Therefore, the study of the degree of damage can provide a reference for determining the commodity value of pears to maximise the economic gains and reduce the waste of damaged pears. Therefore, studying the influencing laws of squeezing loads on the damage degree of fragrant pears and predicting that degree can not only provide theoretical references to the design of picking machines, but also play a significant role in determining the quality of the fruit and reduce processing losses.

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Currently, studies on the factors that influence fruit squeezing damage have mainly focused on the properties of fruits and squeezing loads. Van Zeebroeck proved that ripeness had a significant influence on fruit damage [4]. Blahovec et al. found that the damage was more evident when the ripeness of fruits was higher [5]. Li et al. found that squeezing deformation volume was the most significant influencing factor of the compression characteristics of fragrant pear fruits [6]. Liu discovered that the damage degree increased as the deformation volume increased, and that the damage degree and deformation volume differed to some extent depending on the ripeness [7]. Mahsa S. et al. found that the damage degree of pears presented linear growth with an increase in squeezing deformation volume [8]. Therefore, squeezing deformation volume and ripeness are important factors that determine the damage degree of fragrant pears. The damage degree influences the quality of fragrant pears. Disclosing the variation laws of the damage degree of fragrant pears, with ripeness and deformation volume and constructing the prediction model of damage degree, are key research targets for rapid and accurate quality classification and value assessment of fragrant pears. Nowadays, fruit-related prediction methods can be divided into the traditional linear regression model prediction and artificial intelligence model prediction. Some scholars, such as Al-Moha et al. [9], Al-Saif et al. [10], Meerasri and Sothornvit [11], Castro et al. [12], and Amoriello et al. [13], compared the prediction effects of these two models. These scholars have compared the linear regression or multiple linear regression model with the artificial intelligence model while predicting the fruit’s hardness, chemical properties, moisture content and other properties. The results show that the artificial intelligence model was better. Meanwhile, some other scholars have used artificial intelligence modelling methods to predict the degree of fruit damage. Among them, PLSR, GRNN and ANFIS have been widely applied due to their fast training rates and high-prediction accuracy. For example, Li et al. predicted the damage of apples effectively by using PLSR [14]. Yin et al. used the GRNN method to predict the area of tomato leaf disease [15]. Zheng et al. used the ANFIS method to predict waxberry damage and found that the model with gauss2mf as the input-membership function had the best prediction effect [16]. However, no scholars have used artificial intelligence modelling methods to predict the degree of damage to Korla pears. Therefore, this paper selects and compares the three aforementioned artificial intelligence techniques for predicting the degree of damage to Korla pears and determine the optimal model. The research of the prediction model can reduce the waste of damaged Korla pears, thereby increasing the income of fruit merchants, while also providing a reference for evaluating the value of Korla pears to maximise economic benefits.

In this study, the influencing laws of ripeness and deformation volume on the damage degree of fragrant pears were investigated. Damage degree prediction models of Korla fragrant pears were constructed using PLSR, GRNN and ANFIS. The prediction performances of these three models were compared, and the optimal model was determined, followed by performance verification. Effective prediction of the damage degree of Korla fragrant pears can provide theoretical references for assessing the commodity values of the damaged fragrant pears, quality classification of fragrant pears and design of the picking machine.

2. Materials and Methods

2.1. Test Materials

All fragrant pears used in the experiment were collected from the conventional management pear orchard Shilian, Shituan, Alaer City, 1st Division, Xinjiang Uygur Autonomous Region. All test pears were of similar shapes and sizes, with no distortion, scars, plant disease, insect pests or damages. Pear samples were collected every four days from 1 September 2021 to 29 September 2021. While picking pears, the pickers wore gloves and gently held them up to separate them from the branch. After picking, pears were covered with a net to prevent damage to them from human factors or short transportation. The harvest periods were designated as H1, H2, H3, H4, H5, H6, H7 and H8. The ripeness of
A widely used method (elliptical area method) was chosen to measure the damaged area. The fragrant pears after the static pressure damage test were put in static for a period and the pericarps at damage positions were removed with a knife. After extrusion, the pear damage is generally a hidden damage when the damage is small, and the damage is hidden under the peel. Therefore, the peel must be removed to observe the damaged state. As shown in Figure 2, the major semi-axis (a) and minor semi-axis (b) of the damage area were measured three times, respectively, and the means were collected. The damage area was measured and recorded. This process was repeated and the mean of measurement was set to 20 mm/min. The pear sample was placed horizontally and squeezed using a computer to control the universal compression testing machine. The pressure head stopped compression and lifted up automatically when the compression reached the pre-set deformation volume. The compressed test pears were placed in a static position for 2 h, the pericarp at the compressed positions was removed with a knife, and the damaged portion was measured and recorded. This process was repeated and the mean of measurement data of five pear samples was collected. The deformation volume increases successively from 3 mm to 13 mm. The above steps were completed on the day of each sampling.

2.3. Test Methods

2.3.1. Static Pressure Damage Test

Fragrant pears of similar size and weight were chosen by an electric balance and vernier caliper. A static pressure damage test of each fragrant pear was carried out using the universal compression testing machine. Five pears were chosen for each group of deformation volume. The compression rate of the universal compression testing machine was set to 20 mm/min. The pear sample was placed horizontally and squeezed using a computer to control the universal compression testing machine. The pressure head stopped compression and lifted up automatically when the compression reached the pre-set deformation volume. The compressed test pears were placed in a static position for 2 h, the pericarp at the compressed positions was removed with a knife, and the damaged portion was measured and recorded. This process was repeated and the mean of measurement data of five pear samples was collected. The deformation volume increases successively from 3 mm to 13 mm. The above steps were completed on the day of each sampling.

2.3.2. Measurement of the Damage Area

A widely used method (elliptical area method) was chosen to measure the damaged area. The fragrant pears after the static pressure damage test were put in static for a period and the pericarps at damage positions were removed with a knife. After extrusion, the pear damage is generally a hidden damage when the damage is small, and the damage is hidden under the peel. Therefore, the peel must be removed to observe the damaged state. As shown in Figure 2, the major semi-axis (a) and minor semi-axis (b) of the damage area were measured three times, respectively, and the means were collected. The damage area

Figure 1. The universal compression testing machine WD-D3-7.
was calculated according to the method proposed by Liu [9], Yu et al. [17] and Mohsenin et al. [18].

\[ S = \pi ab \]  

where \( S \) is the damage area of fragrant pears, \( a \) is the major semi-axis of the elliptic damage area, \( b \) is the minor semi-axis of the elliptic damage area.

\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (K_E - K_P)^2}{N}} \]  

\( N \)—total data size, 
\( K_E \)—measured value, 
\( K_P \)—predicted value output by the model.

2.4. Modelling

In this study, the influencing laws of ripeness and deformation volume on the damage degree of fragrant pears were discussed. As inputs, ripeness and deformation volume were used, while the damage degree served as the output. The prediction models of the damage degree of fragrant pears were constructed by PLSR, GRNN and ANFIS. These three models were established using Matlab R2018a (MathWorks, Natick, MA, USA).

2.4.1. Partial Least Squares Regression (PLSR)

Canonical correlation analysis (CCA) can map the original feature space of two media to the two related feature subspaces to measure the similarity between two samples from different media. However, CCA has certain limitations. First, the feature processing is relatively rough. Second, CCA solely focuses on the relationship between \( X_1 \) and \( Y_1 \) after projection, and it cannot restore \( X \) and \( Y \) through this relationship. The emergence of PLSR makes up for the shortcomings. The PLSR algorithm is a regression modelling method of multiple dependent variables \( Y \) to multiple independent variables \( X \). During regression construction, the PLSR algorithm not only maximises the extraction of principal components in \( Y \) and \( X \), but also maximises the correlation among extracted principle components [19,20]. In brief, PLSR is a combination of the three basic algorithms of principal component analysis, canonical correlation analysis and multiple linear regressions.
2.4.2. General Regression Neural Network (GRNN)

GRNN is another deformation form of radial basis function network proposed by D. F. Specht in 1991, and it has a similar structure to the RBF network. It consists of four layers: the input layer, the mode layer, the summation layer and the output layer [21,22]. Based on non-parameter regression, GRNN used sample data as posterior conditions, executed Parzen non-parametric estimation, and calculated the network output according to the principle of maximum probability. Since GRNN is based on a radial basis network, it has excellent nonlinear approximation performances and is more convenient for training compared to a radial basis network. GRNN has been widely applied in various subjects and engineering fields, such as signal process, structural analysis and control decision system. The specific structure of GRNN is shown in Figure 3.

![GRNN Structure Diagram](image)

*Figure 3. GRNN structure diagram.*

Input layer: In the input layer, the number of neurons is equal to the dimension of the input vector in the learning sample, and the input variables are directly passed to the pattern layer.

Pattern layer: The number of neurons in the pattern layer is equal to the number of learning samples, and each neuron corresponds to different samples.

Summing layer: There are two types of summation of neurons in the summation layer. One is the arithmetic summation of the output of all mode layer neurons, and the other is the weighted summation of all mode layer neurons.

Output layer: The output layer has the same number of neurons as the dimension of the output vector in the learning sample. Each neuron divides the output of the summation layer. Finally, the neuron output corresponds one-by-one to the estimated result element.

2.4.3. Adaptive Network-Based Fuzzy Inference System (ANFIS)

ANFIS is a new fuzzy inference system structure that combines fuzzy logic and neuron networks organically. Using a combination of the back propagation algorithm and the least square method, it can automatically generate If-Then rules by adjusting the premise and conclusion parameters [23,24]. Based on the organic combination of neural network and fuzzy inference, ANFIS not only develops advantages of neural network and fuzzy inference but also offsets their disadvantages. The specific structure of ANFIS is shown in Figure 4.
When deformation volume was >13 mm, fragrant pears of all harvest periods developed with the increase of squeezing force, the plastic deformation of fruits is intensified and yield limit yet. The pericarp developed elastic deformation, as shown in Figure 6. When easily damaged.

and the disappearance of abundant cell wall structures [25]. The cell wall has a protective effect. Hence, the stress tolerance declines with increasing ripeness, and the fruits are more easily damaged.

When deformation volume was <3 mm, the deformation volume of 3 mm exceeds the yield limit of fragrant pears. When the deformation volume = 3 mm, fragrant pears of H1–H3 did not develop damage due to the high ripeness and high hardness in this period. The deformation volume of 3 mm cannot exceed the yield limit of fragrant pears. Differently, fragrant pears of H4–H8 all develop damage because the hardness of fragrant pears decreases with an increasing ripeness, and the deformation volume of 3 mm exceeds the yield limit of fragrant pears. When the deformation volume is ≥4 mm, the elastic deformation of the pericarp of fragrant pears is changed to plastic deformation and fragrant pears of all harvest periods develop damage. When deformation volume was >13 mm, fragrant pears of all harvest periods developed cracks, thus losing their commodity value, as shown in Figure 7. Given the same degree of ripeness, the damage areas of all fragrant pears with a small deformation volume are smaller than those of fragrant pears with large deformation volumes. This is because with the increase of squeezing force, the plastic deformation of fruits is intensified and the damage area increases accordingly. Given the same deformation volume, the damage areas of fragrant pears with low ripeness are smaller than those of fragrant pears with high ripeness. This is because as the squeezing force increases, the cell wall structure and composition of fruits change with the increase of ripeness, manifesting as thinning the cell wall and the disappearance of abundant cell wall structures [25]. The cell wall has a protective effect. Hence, the stress tolerance declines with increasing ripeness, and the fruits are more easily damaged.

3. Results and Analysis

Relations of Ripeness and Deformation Volume with Damage Degree

It can be seen from Figure 5 that the damage degree of fragrant pears increases with the increase of ripeness or deformation volume. When deformation volume was <3 mm, fragrant pears in all harvest periods had no damage, because they had not reached the yield limit yet. The pericarp developed elastic deformation, as shown in Figure 6. When deformation volume = 3 mm, fragrant pears of H1–H3 did not develop damage due to the low ripeness and high hardness in this period. The deformation volume of 3 mm cannot exceed the yield limit of fragrant pears. Differently, fragrant pears of H4–H8 all develop damage because the hardness of fragrant pears decreases with an increasing ripeness, and the deformation volume of 3 mm exceeds the yield limit of fragrant pears. When the deformation volume is ≥4 mm, the elastic deformation of the pericarp of fragrant pears is changed to plastic deformation and fragrant pears of all harvest periods develop damage. When deformation volume was >13 mm, fragrant pears of all harvest periods developed cracks, thus losing their commodity value, as shown in Figure 7. Given the same degree of ripeness, the damage areas of all fragrant pears with a small deformation volume are smaller than those of fragrant pears with large deformation volumes. This is because with the increase of squeezing force, the plastic deformation of fruits is intensified and the damage area increases accordingly. Given the same deformation volume, the damage areas of fragrant pears with low ripeness are smaller than those of fragrant pears with high ripeness. This is because as the squeezing force increases, the cell wall structure and composition of fruits change with the increase of ripeness, manifesting as thinning the cell wall and the disappearance of abundant cell wall structures [25]. The cell wall has a protective effect. Hence, the stress tolerance declines with increasing ripeness, and the fruits are more easily damaged.
Figure 5. Relationships between deformation volume and damage area of fragrant pears at different ripeness degrees.

Figure 6. Fragrant pears with deformation volume < 3 mm have no damages.

Figure 7. Fragrant pears with deformation volume > 13 mm develop cracks.
4. Construction of a Damage Degree Prediction Model of Fragrant Pears

Based on the test of the damage degree of Korla fragrant pears, the relationships between ripeness, deformation volume and damage area were investigated. The damage prediction models of fragrant pears were constructed using PLSR, GRNN and ANFIS, and the optimal model was chosen according to the predicted results.

4.1. PLSR Prediction Model

Ripeness and deformation volume were used as inputs, while damage area was used as the output. Among the 88 groups of datasets in statistics, 70% were chosen as the training set to train the model, while the remaining 30% were chosen as the test set, which was input into the trained prediction models to obtain the predicted results. A linear fitting between the predicted value and the measured value was carried out, as shown in Figure 8. The prediction model based on PLSR achieved relatively good prediction effects, with $R^2 = 0.9866$ and RMSE = 109.7. The error between the predicted value and the measured value was relatively small, and it could predict the damage degree of fragrant pears.

![Figure 8. Correlation between model results and predicted results of damage degree of fragrant pears.](image)

4.2. GRNN Prediction Model

Ripeness and deformation volume were used as inputs, while damage area was used as the output. Among the 88 groups of datasets in statistics, 70% were selected as the training set to train the model, while the remaining 30% were selected as the test set to input into the trained prediction models to obtain predicted results. A linear fitting between the predicted and measured values was performed, as shown in Figure 9. The prediction model, based on GRNN, achieved relatively good prediction effects with $R^2 = 0.9876$ and RMSE = 110.7. The predicted results are close to the measured values and the model can be used to predict the damage degree of Korla fragrant pears.
The ANFIS-based model achieved extremely good prediction results. Its $R^2$ values under different types of input membership functions are higher than 0.995. When dsigmf and psigmf are used as input membership functions, the results of the model’s prediction are consistent and highly accurate with an RMSE value of 46.6. Although the predicted results under other membership functions have extremely good effects, the prediction accuracy still has a small gap with those under the use of dsigmf and psigmf. Therefore, the ANFIS models using dsigmf and psigmf as the input membership function achieve optimal prediction accuracy of the damage degree of fragrant pears.

**Figure 9.** Correlation between GRNN model results and predicted results of damage degree of fragrant pears.

**4.3. ANFIS Prediction Model**

Ripeness and deformation volume were used as inputs, while damage area was used as the output. Among the 88 groups of datasets in statistics, 70% was chosen as the training set to train the model and the remaining 30% was chosen as the test set, which was input into the trained prediction models to obtain the predicted results. In the training stage, eight types of input membership functions were chosen for data fuzziness. After the training stage, the ANFIS model was evaluated on an independent dataset to obtain the predicted value. A linear fitting was performed between the predicted results and the measured values, as shown in Figure 10. The RMSE and $R^2$ of fitting results are listed in Table 1. The ANFIS-based model achieved extremely good prediction results. Its $R^2$ values under different types of input membership functions are higher than 0.995. When dsigmf and psigmf are used as input membership functions, the results of the model’s prediction are consistent and highly accurate with an RMSE value of 46.6. Although the predicted results under other membership functions have extremely good effects, the prediction accuracy still has a small gap with those under the use of dsigmf and psigmf. Therefore, the ANFIS models using dsigmf and psigmf as the input membership function achieve optimal prediction accuracy of the damage degree of fragrant pears.

**Figure 10.** Cont.
Figure 10. Correlation between the predicted degree of damage to fragrant pears and the measured results of the ANFIS model based on different input membership functions. (a) trimf. (b) trapmf. (c) gbellmf. (d) gaussmf. (e) gauss2mf. (f) pimf. (g) dsigmf. (h) psigmf.

Table 1. RMSE and $R^2$ of predicted damage degree of fragrant pears based on the ANFIS model using different input membership functions.

<table>
<thead>
<tr>
<th>Membership Function</th>
<th>trimf</th>
<th>trapmf</th>
<th>gbellmf</th>
<th>gaussmf</th>
<th>gauss2mf</th>
<th>pimf</th>
<th>dsigmf</th>
<th>psigmf</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.9974</td>
<td>0.9974</td>
<td>0.9977</td>
<td>0.9973</td>
<td>0.9978</td>
<td>0.9979</td>
<td>0.9979</td>
<td>0.9979</td>
</tr>
<tr>
<td>RMSE</td>
<td>49.5</td>
<td>51.9</td>
<td>55.1</td>
<td>57.1</td>
<td>49.5</td>
<td>49.1</td>
<td>46.6</td>
<td>46.6</td>
</tr>
</tbody>
</table>

4.4. Selection of the Optimal Prediction Model

To determine the optimal prediction model of the damage degree of fragrant pears, the $R^2$ and RMSE of the three models were compared. It was discovered that prediction models based on PLSR, GRNN and ANFIS can all predict damage degrees of fragrant pears. However, the ANFIS models using dsigmf and psigmf as the input membership functions achieve the highest $R^2$ and the lowest RMSE, indicating high-prediction accuracy.
widely used in damage prediction and have better prediction performance than traditional
pears, thereby reducing pear waste and increasing the fruit merchants’ income.
changes with deformation and maturity can off damage degree can still be sold and eaten. This has been con
the fruit, resulting in an increase in the degree of fruit damage. The pears with a certain
functions achieve the highest R² and the lowest RMSE, indicating high-prediction accu-
damage degree of Korla fragrant pears. The damage area increases with the increase in maturity
functions are recommended. These prediction models achieve optimal prediction effects.
Model Verification
The squeezing damage test of fragrant pears was carried out in 2022 to verify the actual prediction effect of the optimal model. Pear samples were collected every four days from 1st September to 29th September. The harvest periods were designated as H1, H2, H3, H4, H5, H6, H7 and H8. The corresponding ripeness degrees were designated as 1, 2, 3, 4, 5, 6, 7 and 8, respectively. Under the squeezing deformation volumes of 3 mm, 5 mm, 7 mm, 9 mm, 11 mm and 13 mm, the damage area was measured. Using ripeness and deformation volume as inputs, the damage areas of fragrant pears were predicted. A linear fitting between the test values and the predicted values was carried out, as show in Figure 11.

![Figure 11. Correlation between test values and predicted values of damage degree. (a) dsigmf. (b) psigmf.](image)

According to verification results, the ANFIS models using dsigmf (R² = 0.9977, RMSE = 47.5) and psigmf (R² = 0.9977, RMSE = 47.5) as the input membership functions show a relatively higher prediction accuracy of damage degree of fragrant pears. This demonstrates that these models have relatively strong actual effects in predicting the damage degree of Korla fragrant pears.

5. Discussion
In this paper, the relationship between maturity, deformation and damage area of Korla fragrant pears is explored. The damage area increases with the increase in maturity and deformation, which is consistent with the research results of Mazhar, M et al. [26], Liu et al. [27], and Yang et al. [17]. This is because the increase in maturity causes the decrease in fruit hardness [28], thus the fruit becomes softer, the resistance to extrusion load is weakened and the degree of damage rises. The increase in deformation is a result of the increasing extrusion load on the fruit, and the extrusion load destroys the cell structure of the fruit, resulting in an increase in the degree of fruit damage. The pears with a certain degree of damage can still be sold and eaten. This has been confirmed in the provisions of national standards and our previous studies. Therefore, research into how damage degree changes with deformation and maturity can offer theoretical guidance for the design of pear-picking equipment. It can provide a reference for batch storage and selective sales of pears, thereby reducing pear waste and increasing the fruit merchants’ income.

The choice of prediction models is based on the fact that these models have been widely used in damage prediction and have better prediction performance than traditional linear regression models. The traditional linear regression model method not only has low applicability but also more limitations. The artificial intelligence model has high precision, wide applicability and high-fault tolerance, and has been widely used to predict
the quality and chemical properties of other fruits. For example, Słupska et al. [29] used a linear regression model (R^2 = 0.93) to predict the damage area of apples under impact load, while the R^2 values of the three models presented in this paper were greater than 0.98. In particular, for the ANFIS model, Vesely et al. [30] found that in other aspects of forecasting, specifically, the fuzzy logic model compared to the traditional linear regression model, should be used by other scholars. Therefore, the artificial intelligence modelling method was applied to predict the damage degree of fragrant pears, and an optimal prediction model of the damage degree of fragrant pears was constructed. It provides theoretical references for the design of picking machines and has significant implications for quality classification and the reduction of process losses of fragrant pears. In this study, all fragrant pears in the test were collected from the same pear orchard. Despite the fact that the optimal model was successfully verified in its second year, and the verification outcomes were positive, further testing is still required to determine whether this model can be used in other pear orchards due to the diverse growth environments and planting conditions. Because the proposed artificial intelligence modelling method has been proven to be feasible by other scholars in predicting the damage degree of apples, tomatoes and bayberry, this study uses the artificial intelligence modelling method to predict the damage degree of pear. Significantly, the results show that the performance of the methods used in this study is excellent. Therefore, it is worth trying to use the ideas and methods proposed in this study to predict the damage degree of other fruits. The model is used to predict the degree of fruit damage. The prediction results can be used to guide the batch storage and selective sales of fruits during fruit storage, provide a reference for the value evaluation of fragrant pears and reduce the waste of fragrant pears. The findings of this study have the potential to guide efforts to reduce process losses, provide useful references for quality grading of fragrant pears, and play a pivotal role in advancing agricultural economic growth. Finally, even though the best prediction model chosen through comparison performed better after being verified, there may be other models that can deliver superior performance. Therefore, exploring better performance models or optimising the performance of existing models is the main goal of further research.

6. Conclusions

Some studies have found that the damage degree of Korla fragrant pears increases with the increase of squeezing deformation volume or ripeness. When deformation volume was <3 mm, none of the fragrant pears in all harvest periods developed damage. When deformation volume was ≥4 mm, fragrant pears were damaged during all harvest periods. When deformation volume was >13 mm, fragrant pears in all harvest periods developed cracks. Prediction model performances of the damage degree of fragrant pears based on PLSR, GRNN and ANFIS were compared. All three models can predict the damage degree of fragrant pears. The ANFIS models using dsigmf and psigmf as the membership functions achieve the optimal prediction performances and prediction results are consistent (R^2 = 0.9979, RMSE = 46.6). Research conclusions can provide theoretical references for the design of picking machines and have significant implications for quality grading and the reduction of process losses associated with fragrant pears.

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