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Year Identification of Seeds in Peony (*Paeonia suffruticosa Andr.*) Using Hyperspectral Imaging

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Abstract: Seed storage year is one of the important indicators for evaluating the quality of peony seeds. It is of great significance for the development of the peony industry to carry out rapid and non-destructive year identification of peony seeds to provide a basis for the screening of aged seeds during seed breeding and processing. This study explores the feasibility of using hyperspectral imaging technology combined with machine learning methods to identify the two states of peony seeds (shelled and non-shelled) and then determines the most suitable state for the year identification of peony seeds. The two states of peony seeds (shelled and non-shelled) in 2017, 2018, and 2019 are employed as the research objects. Hyperspectral imaging data of two kinds of peony seeds in the spectral range of 935-1720 nm are collected. The machine learning methods based on the two states of peony seeds (shelled and non-shelled), including partial least squares (PLS-DA), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) classification models, are established and compared. It is found that the optimal year identification models of peony seeds (shelled and non-shelled) based on hyperspectral imaging technology have better recognition effects and the recognition accuracy is more than 99.5%. Moreover, the recognition accuracy of the year identification PLS-DA model established by non-shelled peony seeds is 99.96%, which is better than that of shelled peony seeds at 99.64%. This indicates that year identification of peony seeds based on hyperspectral imaging technology is feasible and efficient and that non-shelled peony seeds are more suitable for the year identification of peony seeds. The results can provide a theoretical and methodological justification for the screening of high-quality peony seeds.

Keywords: Peony Seed, Hyperspectral Imaging, Year Identification, Shelling

Introduction

Peony (*Paeonia suffruticosa Andr.*), as a world-famous ornamental plant, is also one of the important medicinal material resources and natural edible oil plant resources, with medicinal, edible, oil, and cultural values (Yan *et al*., 2020; Wu *et al*., 2020; Gong *et al*., 2020). The storage year of peony seeds is one of the important evaluation indexes of peony seed quality, which is closely related to the planting and promotion of peony and the development of the peony industry. In general, with the increase in storage years of peony seeds, the seeds will age year by year; the germination rate will decrease and the seed quality and nutritional value will continue to decline (Mei *et al*., 2022). As such, accurate and effective identification of peony seed years can improve the quality of peony seeds, the survival rate of peony planting, and the quality of peony-related by-products, which is of great significance to the healthy development of the peony industry.

The identification of peony seed years is usually determined by experienced agronomic experts by looking at the color and smell, combined with planting experiments or germination experiments (Zhu and Hong, 2007; Zhou *et al*., 2018). Influenced by the double dormancy characteristics of peony seeds (Marković *et al*., 2022), the traditional year identification method has the disadvantages of a long cycle, low efficiency, high cost, strong subjectivity, and destruction. Rapid and accurate identification of peony seed years is necessary.

In recent years, a spectral analysis technique with high analytical speed, simple operation, and high detection accuracy has emerged. Spectral analysis technology has been widely used in food and medicine due to its fast and non-destructive advantages. Hyperspectral imaging technology has gradually become a hot spot in crop detection. Combined machine learning with Near-Infrared (NIR) Hyperspectral Imaging technology (HSI), Duan *et al*. (2021) accurately identified the year of cotton seeds and six classification models: Logistic Regression (LR), Partial Least Squares Discriminant Analysis (PLS-DA), Support Vector Machine (SVM), Recurrent Neural Network (RNN), Long-Short memory network (LSTM) and Convolutional Neural Network (CNN) were established respectively. CNN and SVM models have better identification results in full-spectrum data modeling, with accuracy rates of 100 and 99.32%. Mei *et al*. (2022) studied different years of wheat seeds and constructed the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) spectral index. According to the coefficient of determination, the modeling of EVI was higher than that of NDVI and the accuracy of the prediction year reached 100%. Wang *et al*. (2021) used hyperspectral to identify rice varieties and established a variety identification model based on Support Vector Machine (SVM) by using full band, feature band, texture feature, and spectral-texture feature fusion data. The results showed that the classification accuracy of spectral-texture fusion features was the highest, with an accuracy rate of 94.12%. Zhang *et al*. (2019) used hyperspectral imaging technology to determine whether melon leaves were infected with Cercospora leaf spots. The results showed that hyperspectral images have a high discrimination rate (>97%) for healthy samples, which could be used to identify healthy samples and diseased samples. Maraphum *et al*. (2020) applied the PLSR model to predict the sugarcane straw for Bailey’s sugar content and moisture by using hyperspectral techniques. The results showed that the prediction determination coefficients of the two components were 0.7 and 0.68, respectively. Zhang *et al*. (2022) proposed a convolutional neural network regression model based on the attention mechanism. ACNNR was proposed to predict the oil content of individual maize kernels by combining hyperspectral imaging. Then, the performance of CNNR, ACNNR, and Partial Least Squares Regression (PLSR) were compared. The results showed that the embryonic side was more suitable for regression modeling. Onmankhong *et al*. (2022) used long-wave Near-Infrared Hyperspectral Imaging (NIRHSI) combined with machine learning and deep learning methods to detect Thai aromatic rice varieties. The results showed that the spectral imaging analysis based on selected wavelength NIR HSI data has the best recognition effect on rice and the SVM model based on the average NIR spectrum achieved the best classification accuracy of 95.4%. Yasmin *et al*. (2022) used a line Near-Infrared (NIR) hyperspectral imaging system to detect watermelon seed viability and the Partial Least Squares Discriminant Analysis (PLS-DA) model was used to predict the viability of seed samples in real-time. The results showed that the classification accuracy of the PLS-DA model for the three naturally aged watermelon varieties, Choiganggul, Sambaechea, and Leehyunglim, was 91.8, 80.7 and 77.8%, respectively.

Hyperspectral imaging technology has been studied a lot in the detection of year identification, variety classification, and substance content and the commonly used data modeling methods mainly include CNN, SVM, PLS-DA, LSTM, and so on (Haque *et al*., 2022; Kandel *et al*., 2022; Fadlil *et al*., 2022). However, there are relatively few studies related to the identification of peony seed vintage based on hyperspectral imaging technology combined with modeling methods. In addition, due to the thick and hard characteristics of peony seed shells, it is not clear whether the seed shells carry year identification information during natural aging. Consequently, the effect of hyperspectral imaging technology on the year identification of shelled and non-shelled peony seeds is unclear. This study explores the feasibility of using hyperspectral imaging technology to identify the years of shelled and non-shelled peony seeds to determine the optimal model and method for year identification of peony seeds. The results will provide a data and methodological basis for the year identification and industrial development of peony seeds.

Materials and Methods

Experimental Materials

Peony seeds used in this experiment are healthy that are suitable for growth and free from impurities. A total of 600 peony seeds were selected, including 200 in 2017, 2018, and 2019, respectively. The seeds of each year are divided into 4 groups, with each group of 50 seeds. The seeds are numbered according to the year in Fig. 1.

Data Acquisition

In this study, the near-infrared hyperspectral imaging data of peony seeds were obtained by the SPECIM FX (Quantum Design China subsidiary company). Figure 2, the hyperspectral imaging data of shelled and non-shelled peony seeds were acquired separately.

Fig. 1: Peony seeds from 2017, 2018 and 2019

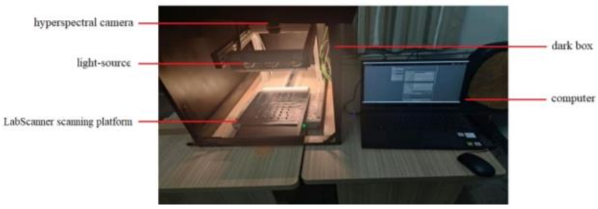

Fig. 2: SPECIM FX10 hyperspectral camera system

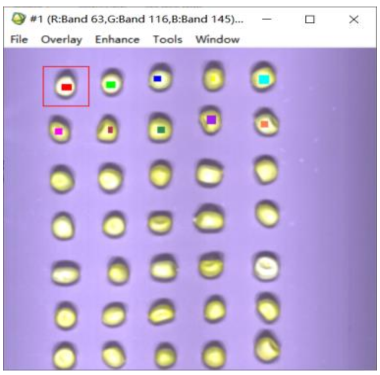

Fig. 3: Process of extracting spectral information from peony seeds

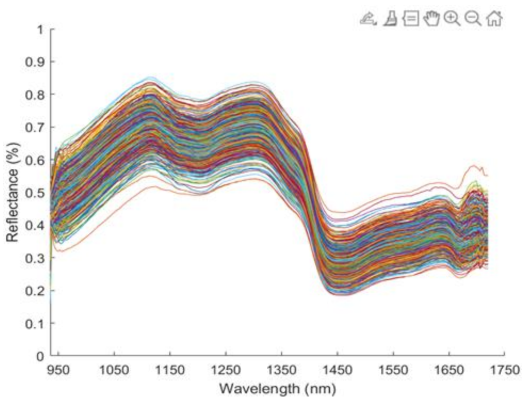

Fig. 4: Spectral reflectance curve of peony seeds

The peony seed samples were divided into 12 groups with each group of 50 seeds. The data acquisition was carried out in groups. The stage movement speed was set to 18.22 mm/s; the integration time was set to 4 ms and the number of integrations was set to 10 times.

The Lab Scanner scanning platform is an electric controllable displacement table driven by a stepper motor, in Fig. 3. The electric controllable displacement stage, also known as the sample stage, is made of high-strength surface oxidation treated aluminum material and the surface is black with high smoothness. The system can be calibrated using a white calibration board on the platform. The sample stage is controlled by the LUMO Scanner spectrometer software; the maximum horizontal scanning movement range is 400 mm and the maximum forward speed of the stepper motor is 65 mm/s.

ENVI Data Processing

Specim Lumo Scanner software is used for hyperspectral processing of peony seeds; ENVI 5.3 software is used to extract spectral data of peony seeds and MATLAB software (version, R2021b) was used for data processing and analysis modeling.

The raw file for hyperspectral imaging of peony seeds is imported into the ENVI software. Then the Region of Interest (RoI) interface is opened and the spectral data of each peony seed is selected with a rectangular box. To facilitate the differentiation of peony seeds, each peony seed was selected with rectangular boxes of different colors, in Fig. 3.

Data Correction

This experiment was conducted in a dark environment. The spectral images of peony seeds were collected by using the hyperspectral imaging system. To ensure the stability of the output light source, the instrument needs to be preheated for 30 min before the experiment. The hyperspectral images of peony seeds in the range of 935.61 nm-1720.23 were obtained by pushing and scanning the sample on an electric displacement table at three different locations (Xuling *et al*., 2022).

To eliminate the effect of dark current, a spectral correction is required to calculate the sample reflectance, calculated as follows:

$$R = \frac{R_0 - R_D}{R_W - R_D} \quad (1)$$

where, R is the corrected reflectance; R_0 is the sample reflectance spectral intensity; R_D is the reflectance spectral intensity of the dark spectrum and R_W is the reflection spectral intensity of the reference spectrum (Gong *et al*., 2017).

The average reflectance curve of corrected peony seeds is shown in Fig. 4.

Evaluation Method of Discriminant Model

To evaluate performance of the model, the confusion matrix, recall, precision, F1-score, and accuracy are selected to evaluate the performance of the classifier (Theissler *et al*., 2022; Zhang *et al*., 2021a-b; Fu *et al*., 2022). The recall rate refers to the ratio of the predicted correct positive cases to the total predicted correct samples. The precision rate refers to the ratio of the predicted correct positive cases to all positive cases. The value of F1 is defined based on the harmonic average of the recall rate and precision rate, which can evaluate the recall rate and precision rate as a whole. The calculation formula for recall, precision, and F1 score is as follows (Yang, 2021):

$$Recall = \frac{TP}{TP + FN} \times 100\% \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{3}$$

$$F1\text{-}score = \frac{2 \times Recall + Precision}{Recall + Precision} \times 100 \tag{4}$$

TP, as true positives, represents the number of true positive samples correctly classified as positive samples. *TN*, as true negatives, represents the number of true negative samples correctly classified as negative samples. *FP*, as false positives, represents the number of true negative samples misclassified as positive samples. *FN*, as false negatives, represents the number of real positive samples misclassified as negative samples.

Results

This study adopts three models of Partial Least Squares (PLS-DA), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) to model the peony seeds before and after shelling. Then, the confusion matrix diagram of the training set and testing set is established to evaluate the results. Then the samples are randomly divided into a training set and a test set at a ratio of 2:1 before the experiment.

In the study, the samples of shelled and non-shelled peony seeds are randomly divided into training and testing sets at a ratio of 2:1. Then, based on the hyperspectral data of shelled and non-shelled peony seeds, three classification models, Partial Least Squares (PLS-DA), Support Vector Machine (SVM) and Convolutional Neural Network (CNN), are used as classifiers to identify the year of shelled and non- shelled peony seeds, respectively. The confusion matrix is used to analyze and compare the training set and testing set of the established models to determine the optimal model for the year identification of shelled and non-shelled peony seeds. The methodology is shown in Fig. 5.

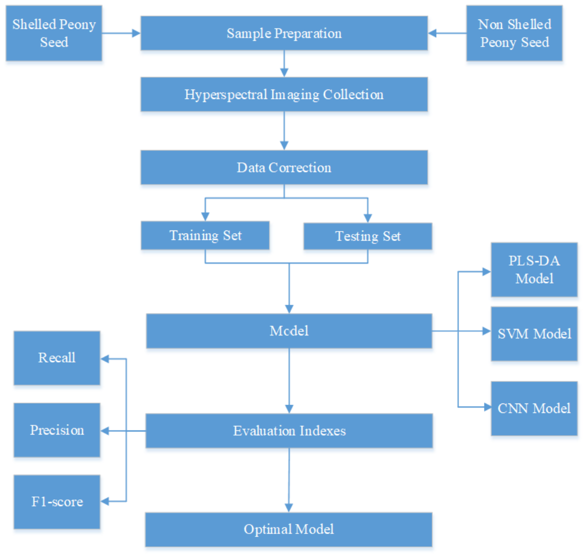

Fig. 5: Methodology of this study

Modeling of Shelled and Non-Shelled Peony Seeds

Partial Least Squares Discriminant Analysis (PLS-DA)

Partial Least Squares Discriminant Analysis (PLS-DA) is a widely used qualitative analysis method in spectral analysis because it is able to deal with problems related to data overlapping and co-linearity (Alizadeh *et al*., 2019; Vieira *et al*., 2021; Liu *et al*., 2022). As such, PLS-DA is used to establish a qualitative identification model between hyperspectral data of peony seeds and seed year. The principal component score set during PLS-DA modeling is 30. Figure 6 shows the accuracy line charts based on PLS-DA for the identification of shelled, non-shelled peony seeds. Figure 7 depicts the PLS-DA confusion matrix diagrams of non-shelled peony seeds for training and testing sets. Figure 8 presents the PLS-DA confusion matrix diagrams of shelled peony seeds for training and testing sets.

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a commonly used classification model, which can be used for quantitative and qualitative analysis (Jain *et al*., 2022; Akbarzadeh *et al*., 2018). It has a strong generalization capability and can obtain stable classification results by maximizing the decision boundary. Figure 9 displays the SVM confusion matrix of non-shelled peony seeds for training and testing sets. Figure 10 represents the SVM confusion matrix of shelled peony seeds for training and testing sets.

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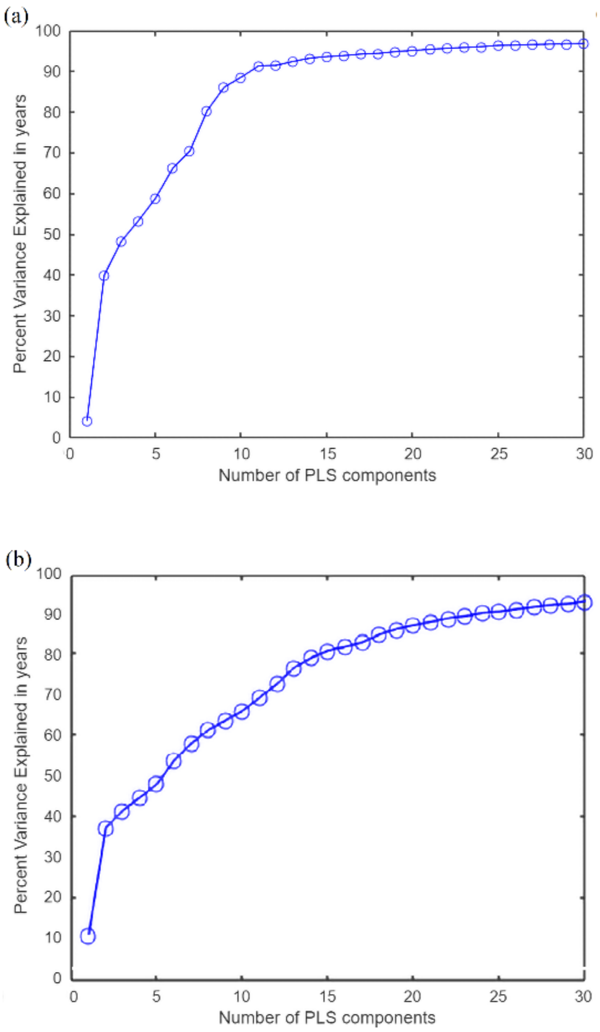
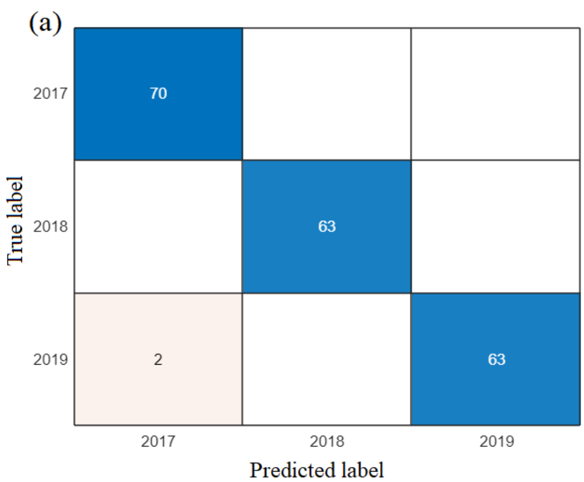


Fig. 6: Accuracy line charts of PLS-DA model for shelled and non-peony seeds; (a) Non-shelled peony seeds; (b) Shelled peony seeds



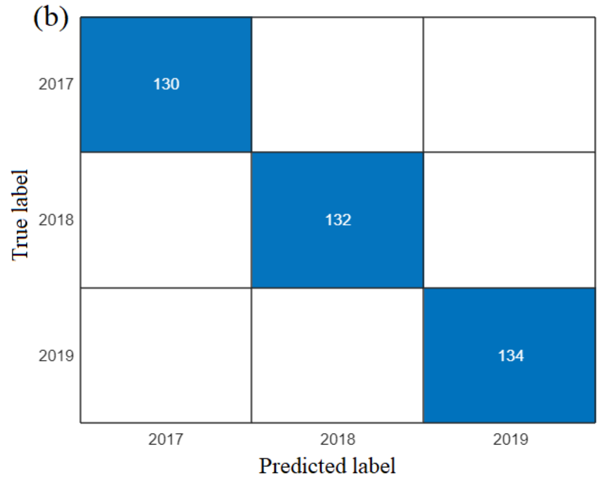


Fig. 7: PLS-DA confusion matrix of non-shelled peony seeds; (a) Training set (b) Testing set

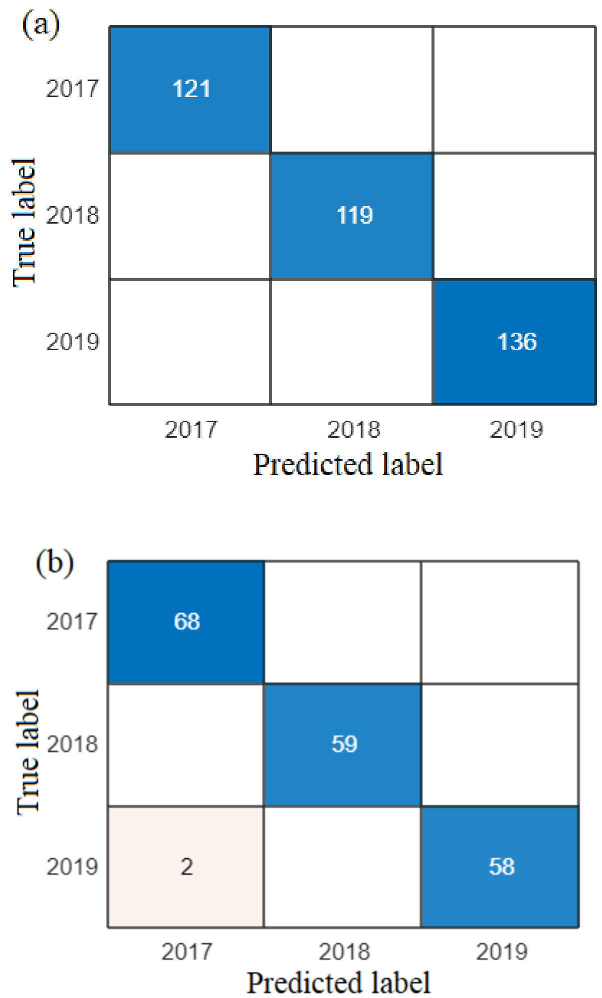


Fig. 8: PLS-DA confusion matrix of shelled peony seeds; (a) Training set (b) Testing set

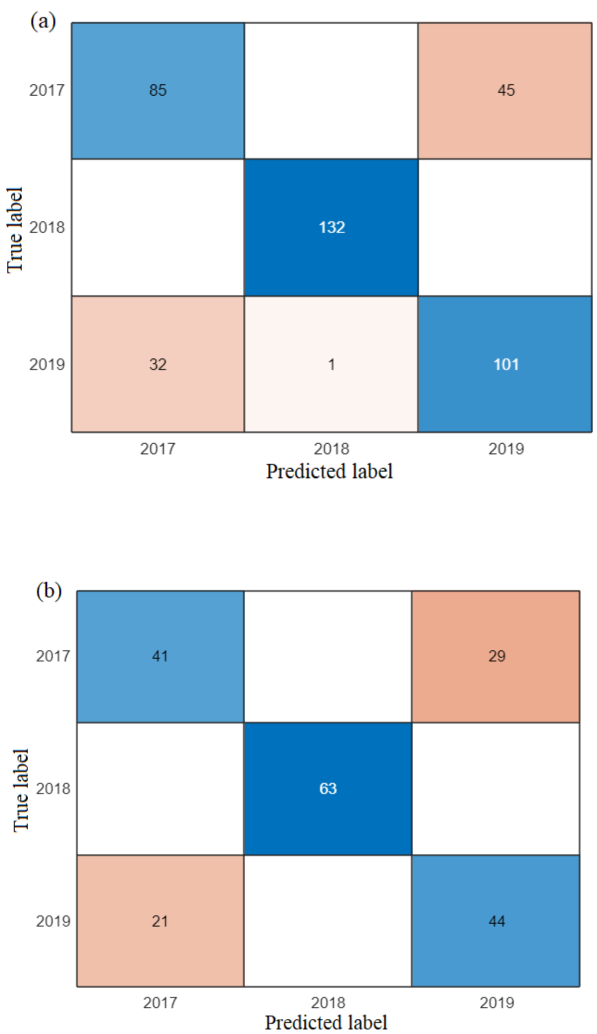
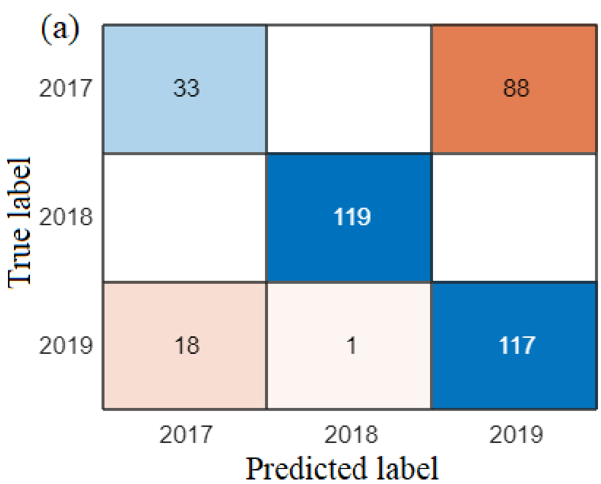


Fig. 9: SVM confusion matrix of non-shelled peony seeds; (a) Training set (b) Testing set



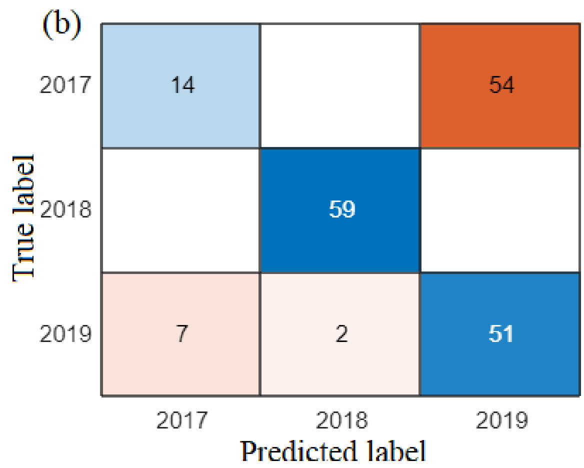


Fig. 10: SVM confusion matrix of shelled peony seeds; (a) Training set (b) Testing set

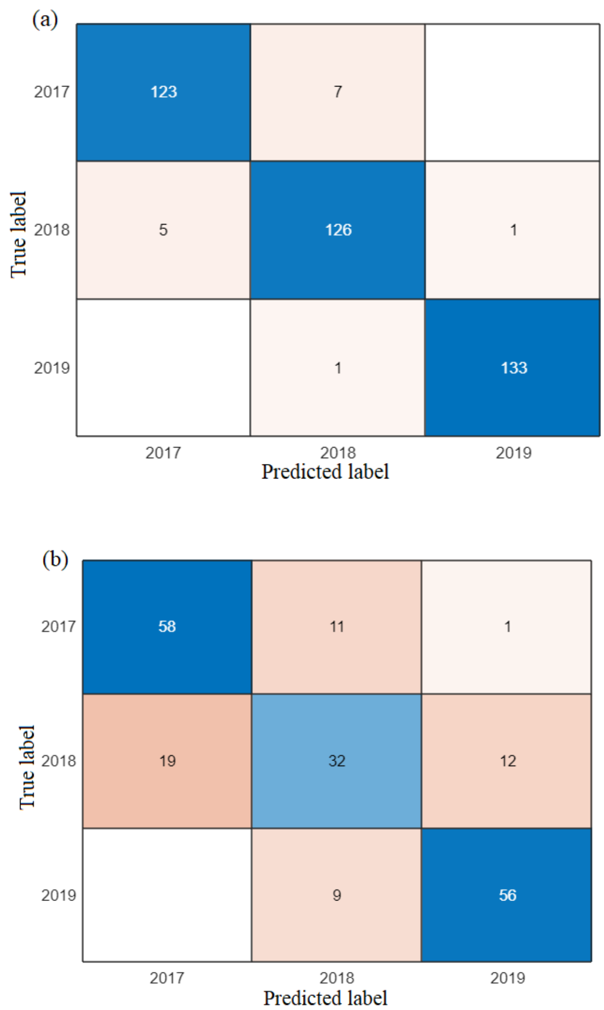


Fig. 11: CNN confusion matrix of non-shelled peony seeds; (a) Training set (b) Testing set

Table 1: Comparison of modeling results of non-shelled peony seeds

Non-shelled		2017		2018		2019	
Model		Train %	Test %	Train %	Test %	Train %	Test %
PLS-DA	Precision	100.00	100.00	100.00	100.00	100.00	96.92
	Recall	100.00	97.72	100.00	100.00	100.00	100.00
	F1-score	100.00	98.59	100.00	100.00	100.00	98.44
SVM	Precision	65.3858.57	100.00	100.00	75.37	67.69	
	Recall	72.6566.13	99.25	100.00	69.18	60.27	
	F1-score	68.8362.12	99.62	100.00	72.14	63.77	
CNN	Precision	94.6282.86	95.45	50.79	99.25	86.15	
	Recall	96.0975.32	94.03	61.54	99.25	81.16	
	F1-score	95.3578.91	94.74	55.65	99.25	83.58	

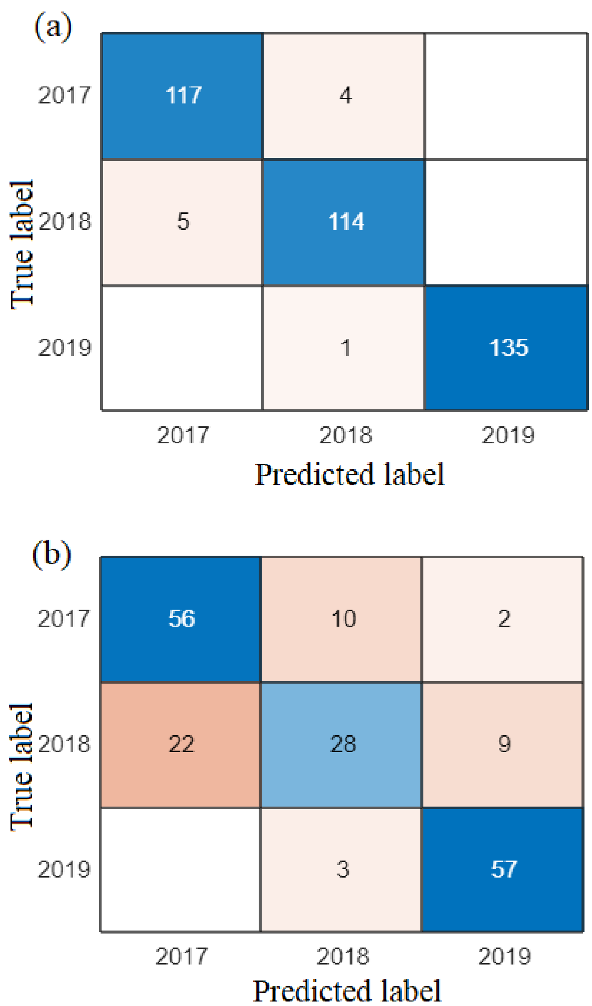


Fig. 12: CNN confusion matrix of shelled peony seeds; (a) Training set (b) Training set

Convolutional Neural Network (CNN)

Due to the two major advantages of local perception and weight sharing, convolutional neural networks perform better than shallow networks in feature selection and extraction, recognition, and classification (Agarwal *et al*., 2020; Sood and Singh, 2022). Figure 11 plots the CNN confusion matrix of non-shelled peony seeds for training and testing sets. Figure 12 shows the CNN confusion matrix of shelled peony seeds for training and testing sets.

Model Comparison

Model Comparison of Non-Shelled Peony Seeds

The differences between PLS-DA, SVM, and CNN models are compared using recall, precision, F1-score, and accuracy.

Table 1, the indicators of recall, precision, and F1-score in the PLS-DA model of non-shelled peony seeds are 100% for the training sets of different years and the testing sets are all more than 96%, indicating that the PLS-DA model is superior to SVM and CNN models.

Table 2, the accuracy of the PLS-DA model of non-shelled peony seeds is 99.96%, that of the SVM model is 78.45% and that of the CNN model is 88.89%. The PLS-DA model has the highest identification accuracy of 99.96%. It can be seen that it is feasible to identify the year of non-shelled peony seeds by hyperspectral imaging technology.

According to Table 2, the accuracy of the PLS-DA model for non-shelled peony seeds is 99.96%, that of the SVM model is 78.45% and that of the CNN model is 88.89%. The PLS-DA model has the highest identification accuracy, indicating that it is feasible to use hyperspectral imaging technology combined with the PLS-DA model to identify the year of non-shelled peony seeds.

Model Comparison of Shelled Peony Seeds

From Table 3, it can be seen that the recall, precision, and F1 score of the PLS-DA model of shelled peony seeds are 100% for different years of training sets and greater than 96% for testing sets. The PLS-DA model is superior to the SVM model and CNN model both in training and testing sets.

Table 2: Comparison of accuracy of non-shelled peony seed models

Non-shelled	Train %	Test %	All %
PLS-DA	100.00	98.99	99.96
SVM	80.30	74.75	78.45
CNN	96.46	73.74	88.89

Table 3: Comparison of modeling results of shelled peony seeds

Shelled		2017		2018		2019	
Model		Train %	Test %	Train %	Test %	Train %	Test %
PLS-DA	Precision	100.00	100.00	100.00	100.00	100.00	96.67
	Recall	100.00	97.14	100.00	100.00	100.00	100.00
	F1-score	100.00	98.55	100.00	100.00	100.00	98.31
SVM	Precision	27.27	20.59	100.00	100.00	100.00	85.00
	Recall	64.71	66.67	99.17	96.72	99.17	48.57
	F1-score	38.37	31.46	99.58	98.33	99.58	61.82
CNN	Precision	96.69	82.35	95.80	47.46	99.26	95.00
	Recall	95.90	71.79	95.80	68.29	100.00	83.82
	F1-score	96.30	76.71	95.80	56.00	99.63	89.06

Table 4: Comparison of accuracy of shelled peony seed models

Shelled	Train %	Test %	All %
PLS-DA	100.0	98.93	99.64
SVM	71.54	66.31	69.80
CNN	97.34	75.40	90.05

As shown in Table 4, the accuracy of the PLS-DA model for shelled peony seeds is 99.64%, that of the SVM model is 69.80% and that of the CNN model is 90.05%. Among them, the PLS-DA model has the highest identification accuracy of more than 99.5%. It is feasible to identify the year of peony seeds of shelled peony seeds by using hyperspectral imaging technology.

Finally, the optimal year recognition models for non-shelled peony seeds and shell peony seeds are compared and analyzed. It is found that the optimal recognition models for non-shelled peony seeds and shelled peony seeds are both based on the PLS-DA algorithm, with accuracy rates of 99.96 and 99.64%, respectively. The accuracy of the PLS-DA model established combined with non-shelled peony seeds is higher than that of shelled peony seeds, indicating that non-shelled peony seeds can be preferentially used for the year identification.

Discussion

In this study, the feasibility of using hyperspectral imaging technology for year identification of shelled and non-shelled peony seeds is explored. The success rates of year identification for peony seeds (shelled and non-shelled peony seeds) based on hyperspectral imaging technology are greater than 99.5%, indicating that hyperspectral imaging technology is feasible and effective for the year identification of peony seeds. Similar results have also been reported in the year identification of wheat, corn, cotton, and other seeds (Wang *et al*., 2014; Duan *et al*., 2021; Mei *et al*., 2022). In this study, the accuracy rate of year identification of shelled peony seeds is 99.64% and that of non-shelled peony seeds is 99.96%.

The accuracy rate of year identification of non-shelled peony seeds is high, indicating that the seed shell of peony seeds may contain the year information of seed storage. Studying the change of components in seed shells with storage age is the basis of hyperspectral imaging research and the direction of further research.

The PLS-DA modeling method has higher accuracy in the year identification of peony seed (non-shelled peony seed with 99.96%, shelled peony seed with 99.64%) compared with CNN and SVM methods. The performance of the PLS-DA method is high in discriminant analysis of spectral data. These results are similar to the results of Zhang *et al*. in Cordyceps militaris discrimination, shellfish toxins identification, and milk powder brand classification (Chen *et al*., 2018; Zhang *et al*., 2021b; Jiang *et al*., 2023). However, some studies have shown that in qualitative analysis, such as adulteration in mutton, Korla pear disease identification, and honey adulteration, nonlinear methods like CNN, SVM, etc. may have better recognition and classification results (Fu-rung *et al*., 2019; Bai *et al*., 2021; Hu *et al*., 2022). This may be due to the different characteristics of the research object, the optimal modeling method is different. When performing qualitative analysis, it is necessary to try to compare more machine learning algorithms to determine a recognition algorithm with better accuracy and simple application.

Conclusion

In this study, the year identification models based on hyperspectral imaging technology for the two states of peony seeds (shelled and non-shelled peony seeds) have satisfactory recognition results. The year recognition accuracy of the two states of peony seeds is all more than 99.5%, indicating that it is feasible and efficient to use hyperspectral imaging technology to identify the year of peony seeds. In addition, compared with the year recognition model established by shelled peony seeds, the year recognition PLS-DA model established by non-shelled peony seeds has a high recognition rate of 99.96%. Non-shelled peony seeds are more suitable for seed year recognition (without shelling treatment and with higher identification results). Based on the conclusions, the optimization of peony seeds could improve the quality of peony seeds sold in the market, which is conducive to the healthy development of peony cultivation and the peony industry and then promote the development of China's economy. However, this study only involves the year identification of one peony variety; in future studies, peony seed samples of different years and varieties will be further expanded to our data set, establishing a peony seed identification model suitable for the identification of different years to effectively identify and characterize peony seeds.

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Author's Contributions

Yakun Zhang and Tingting Li: Designed and perform the experiment.

Libo Wang and Yalin Huang: Analyzed the data and prepared the paper.

Xingyang Yang and Hangxing Zhang: Participated to collect the materials related to the experiment.

Gang Wang and Jinguang Li: Designed the experiments and revised the manuscript.

Ethics

The authors declare their responsibility for any ethical issues that may arise after the publication of this manuscript.

Conflict of Interest

The authors declare that they have no competing interests. The corresponding author affirms that all of the authors have read and approved the manuscript.

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