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Convolutional Neural Networks of Whole Jujube Fruits Prediction Model Based on Multi-Spectral Imaging Method

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Abstract — Soluble sugar is an important index to determine the quality of jujube, and also an important factor to influence the taste of jujube. The acquisition of the soluble sugar content of jujube mainly relies on manual chemical measurement which is time-consuming and labor-intensive. In this study, the feasibility of multispectral imaging combined with deep learning for rapid nondestructive testing of fruit internal quality was analyzed. Support vector machine regression model, partial least squares regression model, and convolutional neural networks (CNNs) model were established by multispectral imaging method to predict the soluble sugar content of the whole jujube fruit, and the optimal model was selected to predict the content of three kinds of soluble sugar. The study showed that the sucrose prediction model of the whole jujube had the best performance after CNNs training, and the correlation coefficient of verification set was 0.88, which proved the feasibility of using CNNs for prediction of the soluble sugar content of jujube fruits.

Key words — Jujube, Multi-spectral imaging, Convolutional neural networks.

I. Introduction

Jujube, native to China, is often cultivated in Asia, Europe and America. Jujube is rich in vitamins, polysaccharides, organic acids and trace elements needed by human body, etc. These internal contents affect the sweetness and flavor of jujube, which are important factors to determine the quality of jujube [1]–[5]. Chemical reagents are usually used to measure the content of jujube. First of all, the jujube fruits are dried, grounded and refined with chemical reagents, and the soluble sugar content is calculated. As it is time consuming, complicated, and causes damage to test samples, the traditional method is not efficient for identifying the internal content of jujube rapidly and nondestructively. In view of this situation, some scholars have devised relevant studies [6]–[9]. Li *et al.* studied the sugar content of "Lingwu" jujube by using hyperspectral method, and established two prediction models of sugar content by using different pretreatment methods, principal component analysis (PCA) and partial least squares regression (PLSR), and the results showed that PLSR model had better modeling effect (correlation coefficient larger than 0.82) [6]. Zhao *et al.* discussed the feasibility of nondestructive measurement of sugar content index of fresh jujube by using near-infrared spectroscopy. Principal component regression method was adopted for dimension reduction, and partial least squares prediction model was then established, with a predicted correlation coefficient of 0.9716 [8].

The combination of spectroscopy and traditional machine learning algorithm cannot meet the current situation that there are many varieties of jujube in the market and large numbers of data samples will cause economic losses. Therefore, it is necessary to study a low-batch, multi-variety, rapid, non-destructive and simple method for the internal quality detection of jujube. In the past decade, artificial intelligence related

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to deep learning (DL) has developed rapidly. One-dimensional convolutional neural networks (1D-CNNs) and autoencoders have gradually become popular in spectral modeling. A few scholars combine one-dimensional spectral data with DL methods to predict fruit internal quality [10]–[14]. For predicting different fruit traits, Puneet *et al.* established a multi-output 1D-CNNs model based on near infrared spectroscopy of fresh fruits [10]. Yu *et al.* used stacked auto-encoder (SAE) and fully-connected neural network (FNN) to predict hardness and soluble solid content (SSC) of Korla pear [12]. And computer vision which is based on DL is a new research direction in the field of artificial intelligence. For the input images, it has the characteristics of unsupervised or semi-supervised learning. It could be used in layering and feature extraction. Through computer vision, artificial selection features could be replaced by efficient algorithms. In agriculture, it is mainly used for disease detection, fruit maturity recognition, fruit and vegetable picking target recognition, etc. [15]–[23]. Among them, Zhang *et al.* proposed a novel artificial intelligence system that combines two-dimensional fractional Fourier entropy with rotation angle vector grid extraction feature. The system was used to extract features from fruit images. And a five-layer stacked sparse autoencoder was used as the classifier for multi-type fruit classification [22]. Nasiri *et al.* also applied DL to the identification of jujube, with an accuracy rate of 96.98% [23]. Therefore, the application of DL in agriculture has gradually become a trend. Combined multi-spectral imaging technology with CNNs, we established a regression model to detect the soluble sugar content of different whole jujube fruits. This research verified the feasibility of DL in the high-efficiency and non-destructive evaluation of the internal quality of fruits.

II. Materials and Methods

Fig.1 shows the overall work flow of the proposed method. Samples were prepared using different varieties of jujube from Xinjiang Uygur Autonomous Region (Xinjiang for short), China. The support vector machine (SVM) regression (SVR) model and partial least squares (PLS) regression (PLSR) model were established based on multi-spectral reflectance. After image segmentation and data augmentation, the CNNs was used to obtain the prediction model. Finally, the optimal model was selected according to the accuracy of the prediction.

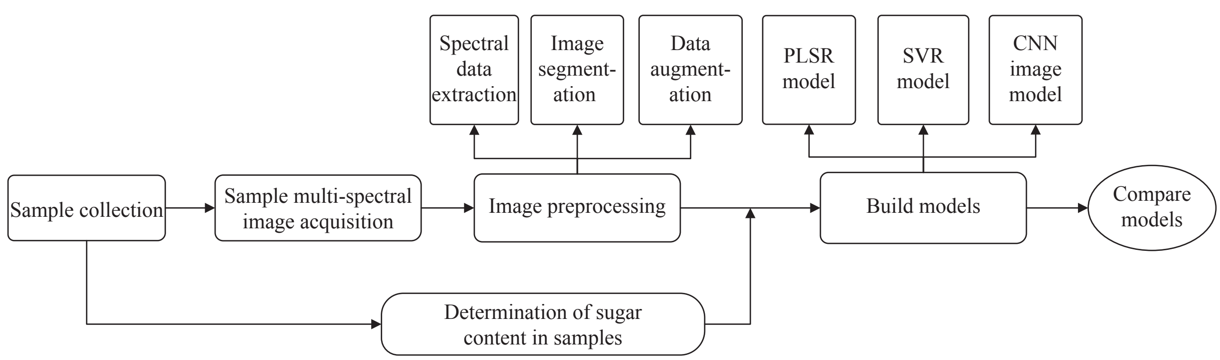

Fig. 1. Experimental flow chart of jujube sugar content prediction models based on multi-spectral image.

1. Sample

The fruits of 16 Chinese jujube varieties (“Junzao”, “Hupingzao”, “Hupingzao” (Shading treatment), “Zanxindazao”, “Huizao”, “Zaocuimizao”, “Laolingxiaozao”, “Xupujidanzao”, “Tailihongdazao”, “Fengtaixiaolingzao”, “Xiangzao”, “Lengbaiyu”, “Linyibenzao”, “Damaya”, “Malianxiaozao”, and “Ningxiadahongzao”), collected by Xinjiang Academy of Agricultural Sciences Experimental Station, were used as experimental materials. Each jujube variety contains six whole jujube fruit samples, a total of 96 samples. Xinjiang has a dry climate with little overcast and rainy days. The intensity sunlight lasts for a long time in the daytime, which allows plants to fully photosynthesize and produce nutrients. The large variation of the region temperature makes the plants respiration and nutrient consumption minimum at night, and the unique geography feature is conducive to fruit drying. Therefore, all samples grown on trees in Xinjiang were naturally dried and transported to Hebei Agricultural University in China (Baoding, Hebei Province) for study. In the spectral region of 365–970 nm, the spectral images of all samples were collected using a multispectral imaging instrument.

2. Sugar content determination method

In this study, the determination of sugar content of jujube was completed in cooperation with China Jujube Research Center. High performance liquid chromatography (HPLC) method was adopted, and the operational steps were as follows:

1) Sample treatment: the whole jujube fruit was

dried and crushed after the single fruit weight was measured by electronic balance.

2) Took the sample of jujube powder 0.5–0.6 g accurately, added distilled water to a constant volume of 100 mL, shook it with ultrasonic for 30 min to dissolved it, filtered it with 0.22 μm filter membrane, and set aside the filtrate.

3) Shodex Asahipak NH2P-50 4E (5 μm, 250 mm × 4.6 mm) and ELSD detector were selected for the chromatographic column and detector. The ratio of acetonitrile to water in the mobile phase was 75:25, the flow rate was set at 1 mL/min, the elution time was 20 min, the column temperature was 32 ℃, and the injection volume was 5 μL.

4) Extraction and refinement: Collect the precipitate by water extraction and alcohol precipitation, then dry and weigh it.

5) Determination of polysaccharide content in the samples: The standard curve of glucose was established by phenol-sulfuric acid method [24]. After the collected polysaccharides were dissolved and diluted, the absorbance was determined, the glucose concentration in the sample solution was calculated by the regression equation, and finally the polysaccharide content in the jujube samples were calculated according to the formula X=FCD/W×100 [24].

3. Acquisition of multispectral images

Multispectral imaging equipment VideometerLab 4 (Fig.2(a)) was equipped with 19 different wavelengths of LED (covering the visible light imaging, UV ultraviolet imaging and NIR imaging of four basic modules, with a spectral range of 365 nm to 970 nm). Each LED in a closed sphere flashed in turn to illuminate the sample to generate a multispectral image (Fig.2(b)).

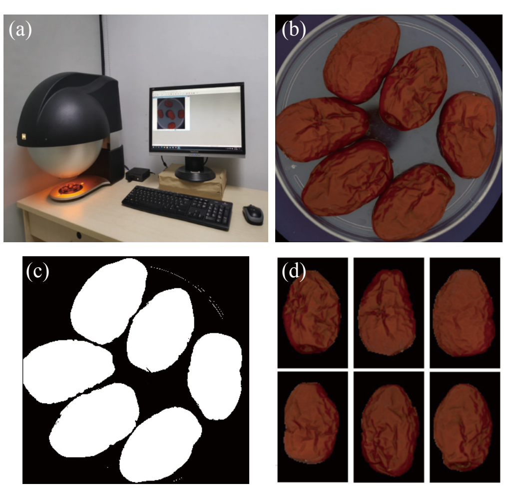

Fig. 2. Sample acquisition and processing. (a) VideometerLab4 device was used to sample images of jujubes; (b) Sample multi-spectral image; (c) After comparing 19 spectral bands, the clearest 880 nm grayscale images was selected for image preprocessing, then background and samples were separated by the threshold method; (d) The watershed algorithm was used to segment each sample into a separate multispectral image.

4. Data preprocessing

In the actual detection process, the work efficiency was reduced if the multi-spectral image extraction and prediction of a single fruit was carried out one by one. In addition, both the sample background and the adhesion of the whole jujube fruit affected the predictive ability of CNNs. Therefore, multiple fruits were used to obtain multispectral images together, and a data preprocessing algorithm was used to segment a single fruit. The specific steps were as follows. First, the original image was converted into grayscale image and 19 grayscale images of different wavelengths were compared. Spectral images at the wavelength of 880 nm are the easiest to distinguish between sample and background, as shown in Fig.2(c). The image processing algorithm of expansion and corrosion was then used to remove the grayscale image noise at the wavelength of 880 nm, and the threshold method was used to segment the target and background in the image. Finally, the watershed algorithm was used to separate each fruit to form a separate multi-spectral image, as shown in Fig.2(d).

In order to ensure the average distribution of whole jujube fruits of each variety in the process of model training and model verification. The processed sample data were divided into training data set and validation data set in a ratio of 5:1 for each breed. Finally, 80 training data sets and 16 validation data sets were obtained.

5. SVM regression model and partial least squares regression model

Support vector machines were developed from statistical learning theory. Compared with traditional machine learning methods, SVM is superior in problems of small samples, nonlinear, multi-dimensional numbers and local minima. PLS combine the advantages of principal component analysis, canonical correlation analysis and multiple linear regression analysis. PLS seeks a linear regression model by projecting predicted and observed variables into a new space, respectively. SVR model and PLSR model are the most common and effective regression analysis algorithms.

1) Spectral data extraction

First, the region of interest (ROI) of each sample after multi-spectral image preprocessing was obtained. VideometerLab software was used to extract the average multi-spectral reflectance of ROI, as shown in Fig.3(a). Second, the multi-spectral reflectance of the five points in the region of interest (upper left, upper right, lower left, lower right and center) was sampled. Fig.3(b) shows the locations of the five points.

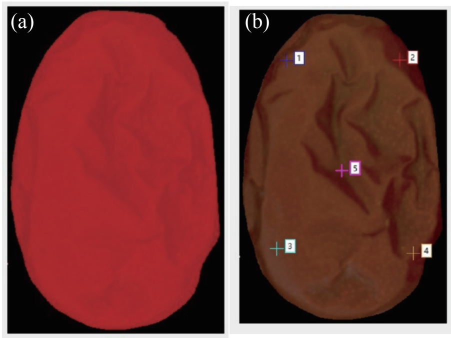

Fig. 3. Regions of interest for the multi-spectral reflectance of the sample. (a) Chart of the average multi-spectral reflectance range of jujube fruit; (b) Multi-spectral reflectance location map of the date fruit selection point.

2) Model development

In order to analyzed the spectral data more comprehensively, the spectral data obtained are divided into three models as the input data of the training model. Model 1 is the average reflectivity of 19 bands (365–970 nm) in the red region of interest in Fig.3(a). Model 2 selected the average reflectance of R (630 nm), G (490 nm) and B (470 nm) bands in the red region of interest in Fig.3(a). In Model 3, spectral reflectance of 5 points as shown in Fig.3(b) was selected, with 19 bands ranging from 365–970 nm. Support vector machine regression (SVR) model and partial least squares regression (PLSR) model of Model 1, Model 2, and Model 3 were established by The Unscrambler X 10.4 software.

6. Convolutional neural networks

Convolutional neural networks (CNNs), a class of feed forward neural networks that includes convolutional computing and has a deep structure, is one of the representative algorithms of DL [25], [26].

1) Data augmentation

Due to short of the samples, before we started with CNNs, data augmentation was applied [27]. As shown in Fig.4, each sample image was subjected to four data enhancement processes: 90-degree rotation, 270-degree rotation, left and right flip and up and down flip.

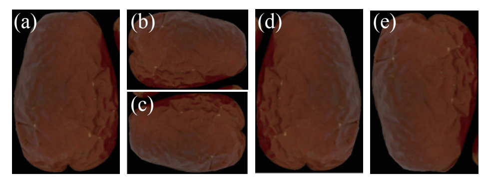

Fig. 4. Sample data augmentation. (a) Original image; (b) 90° rotation; (c) 270° rotation; (d) Left-right rotation; (e) Up-down rotation.

2) Model construction

In this study, 19 spectral images of different wavelengths of the whole jujube fruit were input into the convolutional neural network. Due to the relatively small number of jujube fruits, although the data set has been expanded through data enhancement, overfitting may still occur. Therefore, a shallow CNNs network architecture was manually constructed in this study, as shown in Fig.5.

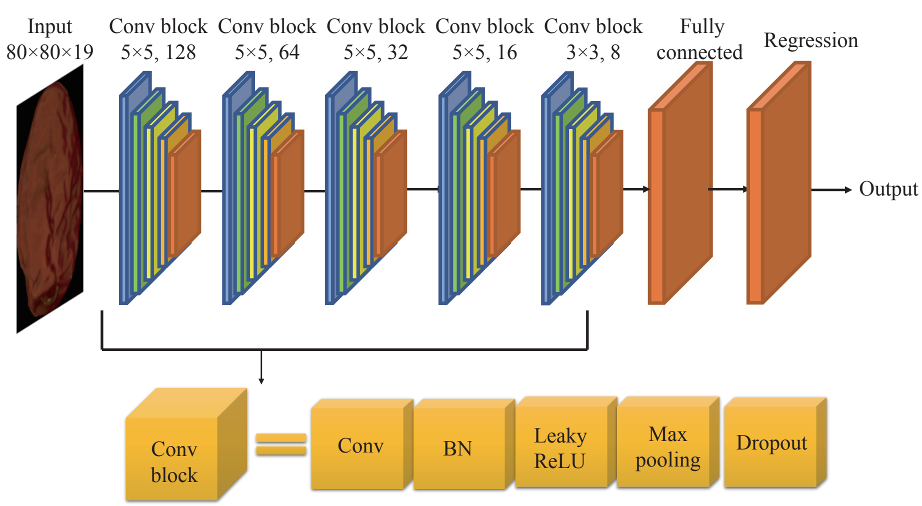

Fig. 5. Architecture diagram of CNNs: input sample images of 80 × 80 × 19, output after five convolutional modules, one full connection layer and one regression layer. The convolution modules included the convolution layer (Conv), the batch normalization layer (BN), the Leaky ReLU layer, the maximum pooling layer (Max pooling), and the dropout layer.

Fig.5 shows the CNNs prediction model, which mainly consists of five convolution modules, a full connection layer module, and a regression layer. Each convolution module consists of a convolutional layer, a normalization layer, a leaky ReLU (rectified linear unit) activation function layer, and a maximum pooling layer. The size of the convolutional kernel of the convolutional layer were 5 × 5 and 3 × 3; the number of feature images were 128, 64, 32, 16, and 8; the step size of all convolutional layers was 2; and the fill was 0. In the model, cross entropy loss function and Adam optimization algorithm were adopted, and the initial value of learning rate was set as 0.1.

7. Model evaluation

The evaluation of the CNNs model and the support vector machine regression model was determined by the correlation coefficient (R^2) and the root mean square prediction error (RMSPE). The R^2 is often used to reflect the regression model and is a statistical index to show the reliability of the dependent variable. And RMSPE is used to measure the data dispersion. R^2 was calculated with

$$R^2 = \frac{\sum_{i=1}^{N} (\widehat{y}_i - \bar{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{1}$$

The RMSPE formula is

$$\text{RMSPE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \widehat{y}_i}{y_i}\right)^2} \tag{2}$$

where, y_i represents the actual measurement, $\hat{y}_i$ is the predicted result of the model, and $\bar{y}$ represents the mean value of the experimental data.

III. Results

1. Support vector machine regression model and partial least squares regression model

In this study, we set up three regression models for support vector machines. The evaluation of its regression model was shown in Table 1. It can be seen from Table 1 that the R_c^2 and R_p^2 of SVR and PLSR obtained from three different input data were not exceeding 0.5.

Table 1. Evaluation indexes of SVR and PLSR

Model	Soluble sugar	R_c^2	R_p^2	RMSPE_C	RMSPE_P
Model1[1]+SVR	Fructose	0.46	0.37	0.22	0.05
	Glucose	0.35	0.33	0.24	0.24
	Sucrose	0.47	0.39	1.9	1.38
Model1+PLSR	Fructose	0.38	0.38	0.24	0.24
	Glucose	0.24	0.30	0.28	0.27
	Sucrose	0.33	0.35	2.05	1.43
Model2[2]+SVR	Fructose	0.20	0.03	0.31	0.37
	Glucose	0.15	0.02	0.33	0.37
	Sucrose	0.28	0.14	1.58	1.26
Model2+PLSR	Fructose	0.29	0.19	0.27	0.27
	Glucose	0.24	0.15	0.29	0.29
	Sucrose	0.40	0.33	1.62	1.27
Model3[3]+SVR	Fructose	0.26	0.30	0.28	0.26
	Glucose	0.18	0.22	0.30	0.30
	Sucrose	0.23	0.33	1.96	1.69
Model3+PLSR	Fructose	0.25	0.30	0.27	0.25
	Glucose	0.16	0.26	0.31	0.28
	Sucrose	0.23	0.35	2.12	1.68

Note: [1]Model 1 is the average reflectivity of 19 bands (365–970 nm) in the red ROI in Fig.3(a);
[2]Model 2 selected the average reflectance of R (630 nm), G (490 nm), and B (470 nm) bands in the red ROI in Fig.3(a);
[3]Model 3 was selected spectral reflectance of 5 points as shown in Fig.3(b), with 19 bands ranging from 365–970 nm.

2. CNNs

The CNNs is mainly composed of three parts: the input layer, the hidden layer, and the output layer. Only the input image is needed to find the feature region and get the output result through the network model. In this study, we used 16 varieties of whole jujube fruit to predict its fructose, glucose, sucrose, and total sugar content. Each variety had six whole jujube fruit samples, a total of 96. After data amplification, a total of 480 samples were used for CNNs network, of which 400 samples were used for training, and the remaining 80 samples were used for verification.

1) Establishment of the model

The training set of processed sample multispectral images (365–970 nm) was input into CNNs. The training cycle was 100 rounds, and the number of iterations per round was 16 times in total, and the test set was verified once every 25 times. Through the training set R_c^2 and RMSPE_c of the model evaluation index, the effect of the model was comprehensively evaluated and analyzed. The training results are shown in Table 2.

2) Model validation

The 80 samples that were not input into the CNNs network for training and testing were used for validation. In order to improve the accuracy of prediction, all the validation predicted values after data augmentation of a original sample were averaged. The final pre-

Table 2. Evaluation of CNNs model training set

Evaluation index	Fructose	Glucose	Sucrose
R_c^2	0.88	0.86	0.91
$RMSPE_c$ (mg/g)	0.11	0.12	0.48

diction model validation results of the CNNs were obtained, and the model evaluation was completed using R_P^2 and $RMSPE_P$ (Fig.6).

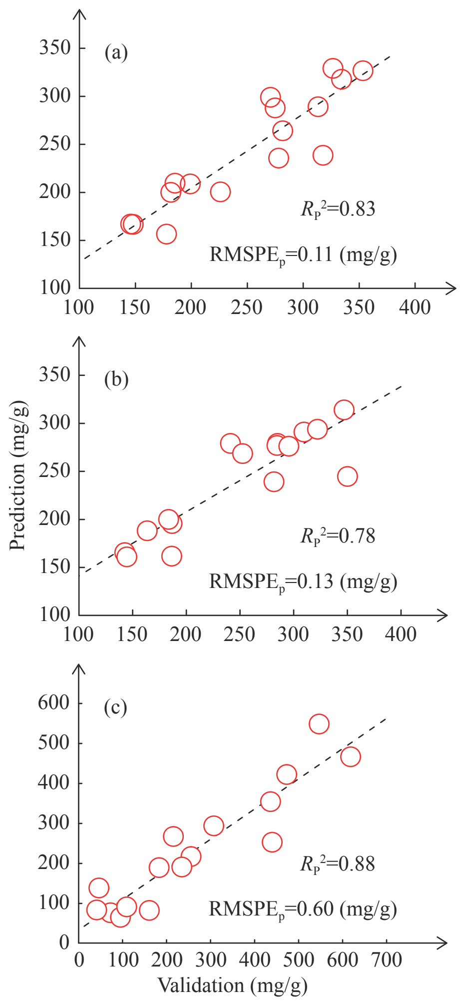

Fig. 6. Evaluation of three soluble sugar content prediction models of jujube by verification set. (a) Verification of fructose prediction model: $R_p^2 = 0.83$ and $RMSPE_p$=0.11 mg/g; (b) Verification of glucose prediction model: $R_p^2 = 0.78$ and $RMSPE_p$=0.13 mg/g; (c) Verification of sucrose prediction model: $R_p^2 = 0.88$ and $RMSPE_p$=0.60 mg/g.

IV. Discussion

In this study, the SVR model, PLSR model and CNNs model for the soluble sugar content of different jujube varieties were compared. The experimental results show that it is feasible to predict the soluble sugar content of jujube by using multi-spectral imaging method combined with DL. Compared with SVR model and PLSR model based on one-dimensional data, CNNs model based on multispectral images has a better performance in prediction of soluble sugar content. The R_c^2 values of SVR and PLSR model ranged from 0.15 to 0.47, and the R_p^2 values ranged from 0.02 to 0.39. The R_c^2 of CNNs model were between 0.86 and 0.91, and the R_p^2 were between 0.78 and 0.88. The accuracy of CNNs model have improved by more than 0.39, which was related to the input object of traditional machine learning models and CNNs model. One-dimensional spectral data within the range of 365–970 nm was used as the input of SVR model and PLSR model. Model 1 took the one-dimensional data of the mean spectral reflectance of all pixels in 19 bands as the input. Model 2 took the average spectral reflectance of the RGB channel in Model 1 as the input. And Model 3 took spectral data of five points of the interest as the input. According to the results of traditional machine learning models, the results of Model 1 were better than the other two models. Which indicated that more spectral data is beneficial to establish more accurate models. Multispectral images of 19 bands were used as the input of CNNs model, which not only included spectral data of all pixels of the jujube, but also included fruit traits such as texture and shape. For small batches of jujube with multiple varieties, this study proved that CNNs was more suitable for the detection of soluble sugar content than SVR and PLSR.

A method for predicting soluble sugar content of jujube was proposed based on two-dimensional convolutional neural networks. Compared with the traditional measurement method, this method is relatively simple to operate, time efficient, and non-destructive, which provides a reliable theoretical basis for a large number of subsequent sample experiments. This study collected data of 16 varieties of jujube, but there are other varieties in the market. In order to meet greater market demand, we will increase the number of varieties of jujube in subsequent studies. Second, based on deep migration learning, models of different scales or regions are combined, which is equivalent to expanding the sample size to improve model accuracy. In future, with the accumulation of data, the advantages of DL algorithm will be gradually highlighted.

V. Conclusions

In this study, we proposed a multi-spectral imaging method combined with CNNs to predict the soluble sugar contents of whole jujube fruits. A CNNs prediction model were established using spectra of 19 different wavelengths obtained for 16 different jujube varieties. The results showed that the CNNs model were more suitable than SVR model and PLSR model for prediction of soluble sugar content in jujube. Both $R_c{}^2$ and $R_p{}^2$ of CNNs model were above 0.78, and sucrose model had the best effect ($R_c{}^2 = 0.91$, $R_p{}^2 = 0.88$). The feasibility of multispectral image combined with DL in nondestructive detection of soluble sugar content in jujube was verified.

We provide the data and codes of this work available at: https://pan.baidu.com/s/1i2w9hvoLvfDzILKFO_75Uw?pwd=7777 (extraction code: 7777) including two folders: figures and cnn. The former includes original data of the fruits of 16 Chinese jujube varieties. The latter consists of three files: cnndata.xlsx for actual determination data of sugar content and model prediction data, inputdata.docx for input data code of Matlab, and cnn.docx for CNN code of Matlab.

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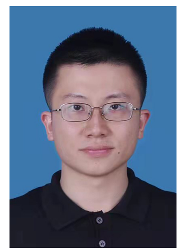

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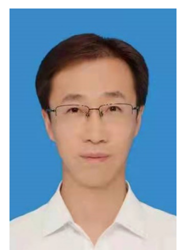

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