Standard Issue – Article

Journal of Agricultural Engineering

https://www.agroengineering.org/

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Please cite this article as doi: 10.4081/jae.2024.1560

Submitted: 14/06/2023
Accepted: 13/11/2023

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Key words: convolutional neural network; green tea; hyperspectral image; principal component analysis; tea stalks.

Acknowledgments: this work was financially supported by the Key Research and Development Projects of the Xinjiang Uygur Autonomous Region (Research on Key Technologies of Automatic Recognition of Foreign Fibers in Machine-picked Long-Staple Cotton).

Conflict of interest: the authors declare no potential conflict of interest.

Abstract

Wuyuan green tea is a famous agricultural product in China and a product protected by national geographical indications. The processed green tea also needs to remove impurities, such as stones, tea stalks, etc. However, tea stalks cannot be classified from Wuyuan green tea using photoelectric sorting and 2D image recognition technology since they have similar colors. This paper adopts hyperspectral imaging technology to solve the problem of inaccurate sorting caused by their similar colors. Green tea containing tea stalks was imaged using a visible and near-infrared camera with a wavelength of 400nm-1000nm. What's more, Principal Component Analysis (PCA) was adopted to reduce the dimension of the collected hyperspectral image. And the Convolutional Neural Network (CNN) was used constructively to identify tea stalks in hyperspectral image, the CNN can automatically learn the corresponding features, avoid the complex feature extraction process. The experimental results showed that the recognition accuracy for tea stalks reaches 98.53%. The method has a high recognition rate and can meet the actual production requirements. After field testing, the selection rate is as high as 97.05%.

Introduction

Wuyuan green tea has green buds and leaves, clear soup color, rich aroma and mellow taste. Since 1997, Wuyuan green tea has been the most sold green tea in China to the EU, accounting for 70% of the domestic market sold to the EU. In fact, Wuyuan green tea has always played the role of an "unsung hero", because all Wuyuan green tea sold to the world is named "Chinese green tea" (Hu, 2015). The production of Wuyuan green tea in Wuyuan is traditional. The purchase of fresh leaves from the primary tea factory comes from thousands of households (Hu et al., 2016). And most of the fresh leaves are obtained by cutting them with large scissors. However, there may be tea stalks from excess shear mixed with fresh leaves. The fresh leaves form the finished Wuyuan green tea through a series of operations, but there are still a small amount of tea stalks. Therefore, it is necessary to manually pick out the tea stalks in the tea, but manual selection takes a lot of time. Moreover, the quality of tea depends to a large extent on the efficiency and quality of labor. Long-term work will inevitably lead to the incomplete removal of tea stalks in the tea, and the quality of the tea cannot be guaranteed. And it is urgent to find an innovative method to save time and cost.

In order to remove tea stalks, many experts have done a lot of experiments and research. Chen et al. (2014) used Hough linear transform to detect impurities with linear features in the tea. They used multi-gradient analysis and binarization to remove the shadow of the image, and then used Hough line transform to detect the impurities with straight line features on the processed image. In this way, the influence of shadow on the line detection can be avoided better, and the Hough transform is optimized to reduce the running time. The step-type tea stalk picker is a kind of equipment developed earlier. The step-type tea stalk picker uses a variety of unique mechanical structure, operation form, and the difference between the physical characters of tea leaves and tea stalks, so as to realize the picking of tea stalks (Quan, 2018). The gap tea stalk picking machine is also a kind of mechanical tea stalk picking machine. It is a stalk picking equipment that uses the principle of coarse and fine difference to pick tea leaves. The main operating parts are a pair of inclined and counter-rotating rollers. The precise gap formed between the rollers is used to separate the thicker leaf strips from the thinner tea stalks (Ren, 1989). According to the principle of water difference, the electrostatic stalk sorting machine takes advantage of the difference in electrical conductivity and dielectric properties between tea leaves and tea stalks to pick out impurities such as tea stalks. High-voltage electrostatic pedunculating machine is widely used in China and is the leading product of tea pedunculating machine (Xie et al., 2004). With the rapid development of high technology with computer as the core, combining high resolution image recognition and high speed micro jet, photoelectric tea stalk picker has been developed. It is based on the principle of color difference, the use of the original tea components between the color difference, by a specific wavelength of light after irradiation of the reflected light intensity difference this characteristic, the stalks and other debris separated. Chen Sun et al. proposed a fast and effective sorting method for photoelectric tea stalk picker based on the minimum error Bayes decision. The images of tea leaves and tea stalks collected by the digital camera are preprocessed, they raised the shape feature that the ratio of radius minimum circumcircle's with maximum inscribed circle's radius and built Gauss model using the single shape feature.Then applied the minimum error rate Bayes classifier to separate the image of tea leaves from tea stalks, in order to achieve rapid classification of tea leaves and tea stalks' target image (Chen et al., 2013). Sun et al. (1997) proposed a tea stalk picking machine controlled by single chip microcomputer. A/D conversion technology is used to determine the input and output curves of each photoelectric conversion circuit. According to the input and output curves of each photoelectric conversion circuit, the voltage sampling value corresponding to the threshold value of this circuit is calculated. This voltage sampling value is used as a reference for comparison. When the input voltage of this route is less than the reference value, it is considered as tea. On the contrary, it is considered to be the tea stalk, and the executive action will remove the tea stalks.

Generally speaking, the methods of removing tea stalks are divided into mechanical sorting, electrostatic sorting and photoelectric sorting. They can pick out tea stalks to some extent, but they all have their own shortcomings. The mechanical sorting has low picking rate and high noise. The adaptability of electrostatic sorting is poor. The shape, temperature, clarity, moisture content, residual charge, ambient temperature, humidity and wind speed of tea have great influence on the performance of this method. The identification datum of photoelectric sorting is not easy to adjust, so it can only be solved by changing the color filter, and the adaptability is poor.

For this purpose, this paper proposed that distinguishing tea stalks of Wuyuan green tea using hyperspectral imaging analysis. Hyperspectral image can not only record 2D image information, but also record multiple band information in space (ElMasry G and Sun D W, 2010). Therefore, it can be used to distinguish items with similar colors. Photoelectric sorting cannot distinguish objects with similar colors.

Hyperspectral technology is an emerging, non-destructive and advanced optical technology. It combines mechanical vision with spectroscopy. Hyperspectral technology can obtain continuous monochromatic spectral images of the target or scene to be observed, and form a three-dimensional observation data cube through the (x, y) data of spatial dimension and (λ) data of spectral dimension, so as to provide researchers with spatial and spectral feature details of every point in the target or scene. Hyperspectral technology is mainly used in the detection field, including agricultural hyperspectral technology, animal hyperspectral technology imaging, mineral hyperspectral technology detection, etc. Hyperspectral technology has the characteristics of many bands, narrow spectrum range, continuous band and large information, which is the upgrade of multi-spectral technology (LIU, 2021). Hyperspectral imaging is widely used in agriculture, including estimating biochemical and physical characteristics of crops, and then for understanding crop physiological conditions and predicting yield, assessing nutritional status, monitoring crop diseases, etc (Lu et al., 2020).

In view of the large amount of data of hyperspectral image, PCA is used to reduce dimensionality, remove noise and unimportant features, thereby improving data processing speed (Uğuz H, 2011). At the same time, a CNN model was constructed for the identification of tea stalks. To reduce the training cost while ensuring recognition accuracy, 2D-CNN is used in this paper to identify hyperspectral image. The 2D-CNN is composed of Input layer, Revolution layer 1, Pooling layer 1, Revolution layer 2, Pooling layer 2, Full connected layer, and Softmax. Compared with the existing recognition methods, the method proposed in this paper can automatically extract features (Shaheen F et al., 2016). And the recognition accuracy is high.

The remaining part of the paper is organized as follows. In Section 2, the materials and methods are introduced. Section 3 illustrate the experimental test and results. Finally, the conclusions are drawn in Section 4.

Materials and Methods

Materials and instrumentation

Materials: 100g of Wuyuan green tea; 16 pieces of tea stalks of different lengths selected by skilled sorting worker, which come from excess shear, as shown in Figure 1. Tea leaves with tea stalks are shown in Figure 2.

Main instruments: GaiaField-V10E series portable hyperspectral imager (visible and near-infrared camera, band: 400nm-1000nm), HSIA-OLE23 imaging lens (focal length: 23mm, C-mount, f/2.4), Gaia Sorter-Dual standard type hyperspectral obscura. The background is a rubber conveyor belt (green rubber). Figure 3 is a schematic diagram of the structure of the imaging system.

Hardware and software environment: The main hardware environment used in this experiment is as follows. The processor is Intel® Core(TM) i7-6700 and the graphics card is NVIDA GeForce RT X 2080Ti. The main software environment is Pycharm 3.7.

Image data processing

The proposed algorithm includes three parts, image data processing (the key step is PCA dimensionality reduction), CNN model training and experimental test.

Reflectivity correction

To remove the influence caused by dark current during image acquisition, reflectivity correction was performed. Equation (1) represents reflectivity correction (Fu L et al., 2014).

$$I_c = \frac{I_r - I_d}{I_w - I_d} \tag{1}$$

where I_c denotes corrected image, I_d is the raw image, I_w is the meaning of the whiteboard image, I_d represents the black background image.

Image pre-processing

The acquired hyperspectral image (raw image) is as shown in Figure 4. The raw image is not directly usable and needs to be further processed. Since labels are to be added to the 2D image manually, the labelled 2D images are further used to train the CNN model. Therefore, it is necessary to visualize the original hyperspectral image and generate 2D image. The original hyperspectral image is transformed into three bands, and then displayed as three channels in the appropriate color space, while keeping the characteristics of pixel space unchanged.

Three suitable bands were selected, which are 50th band, 100th band, and 150th band (Lu R et al., 2003). The three selected bands form a three channel image with good display effect. After the image was cropped, it was saved as 2D image. The original hyperspectral image is saved as a 3D image after the same cropping.

The 2D image was labeled, the tea stalk corresponds to the label-Stalk, the background corresponds to the label-Background, and the tea corresponds to the label-Green tea. Simultaneous 2D image and 3D image were saved in a format recognizable by the algorithm.

Reflectivity curve

By selecting the ROI (Region Of Interest), the average reflectance of tea stalk, green tea and background was obtained respectively (Windham W R et al., 2002). And the obtained reflectivity curve is shown in the Figure 5. The reflectivity curves of these three types of samples have distinct differences, which can be used as the basis for the identification of tea stalks.

PCA dimensionality reduction

The purpose of dimensionality reduction is to reduce the amount of redundant data. The specific process of dimensionality reduction using PCA is as follows:

a) Matrixing of image data

Each band of the image data is converted into an one-dimensional vector. The image data has M bands and the image resolution is $L \times H$, so the image can be represented as a $L \times H \times M$ matrix (Ren J et al., 2014).

Equation (2) can be expressed as the i-th band.

$$x^i = \left[x_1^i, x_2^i, \ldots, x_{L\times H}^i \right], (i = 1,2 \ldots M) \tag{2}$$

b) Representation of feature space

Equation (3) can be expressed as the mean vector of all bands.

$$\overline{x} = \frac{1}{M} \sum_{i}^{M} x^i \tag{3}$$

Equation (4) can be expressed as the distance vector between x^i and $\overline{x}$.

$$d_i = x^i - \overline{x} \tag{4}$$

Equation (5) is the matrix A.

$$A = \left[d_1, d_2, \ldots, d_M \right] \tag{5}$$

Then equation (6) is the Co-variance matrix.

$$\frac{1}{M} AA^T = \frac{1}{M} \sum_{i}^{M} d_i d_i^T \tag{6}$$

Equation (7) is the transposed matrix of AA^T.

$$\left(AA^T \right)^T = A^T A \tag{7}$$

The eigenvectors of the first L (L is much smaller than M) larger eigenvalues of the Covariance matrix are too computationally expensive. Equation (7) is a low-dimensional vector of $M \times M$, and its eigenvalues can be obtained, as shown in equation (8).

$$v_k = Au_k\lambda_k^{-\frac{1}{2}}, \quad (k = 1, 2, ..., L) \tag{8}$$

where λ_k is eigenvalue of the formula, u_k represents eigenvector.

Equation (9) represents the eigenspace that can be composed of the eigenvalues v_k of the equation (8).

$$W = \{v_1, v_2, ..., v_L\} \tag{9}$$

c) Data post-processing

d_i is projected into the feature space (Jimenez L O and Landgrebe D A, 1999). and the i-th feature vector is denoted as equation (10).

$$P_i = W^T d_i, \quad (i = 1, 2, ..., M) \tag{10}$$

Equation (11) is the Euclidean distance.

$$\varepsilon_i = \|P_i - P_s\|^2, \quad (i, s = 1, 2, ...M) \tag{11}$$

The Euclidean distance is used as the Similarity detection between images. The smaller the Euclidean distance, the more similar the images, and the stronger the ability of the principal component information to represent the overall data (Celik T, 2009). After that, the x principal component bands with the smallest Euclidean distance tested are taken to form a new hyperspectral data-set (Panda A et al., 2021). Finally, to feed data into a deep CNN, a pixel in space is taken as the center, the block with the surrounding area of $y \times y$ is taken, that is, the volume of each small block is $y \times y \times x$.

CNN model training

Half of the samples were used in the first phase of training (The quantity is 276000). Half of them are training set and half are test set.

The specific process of feature extraction and recognition of hyperspectral image is shown in the Figure 6. First, in the processing phase, the hyperspectral image data is equally divided into training set and test set. After that, the training set is input into the improved model for parameter learning, and the loss function is minimized by stochastic gradient descent, and the weights (w) and biases (b) are continuously updated. Finally, the trained CNN model is applied to the test set, the recognition accuracy of each sample is obtained, and the parameter model with the highest accuracy is finally saved. The change of training and testing accuracy with the number of training is shown in the Figure 7. It can quickly converge within 50 times and achieve high recognition accuracy.

Common loss functions include mean square error function, cross entropy function, negative log-likelihood function, etc. In this paper, the multi-class cross entropy loss function with better effect is used, and equation (11) is its expression.

$$E=-\sum_{i=1}^{k} y_i \ln t_i \tag{12}$$

where k is the number of categories; y represents the true value. If the category is i, then $y_i=1$, otherwise $y_i=0$. t is the predicted value, that is, the probability of i. To speed up the training process, the method used to minimize the loss function is stochastic gradient descent (SGD). The training and testing loss curves are shown in the Figure 8. It can complete convergence within 50 iterations. The learnable parameter weights (w) and biases (b) of the CNN can be updated layer by layer with taking the first-order partial derivatives of the equation (12).

$$w'=w-\eta\frac{\partial E}{\partial w} \tag{13}$$

$$b'=b-\eta\frac{\partial E}{\partial b} \tag{14}$$

where w' and b' are the updated weights and biases; w and b are the existing weights and biases; η is the learning rate parameter, which is used to control the speed and step size of the weight update.

Results

Test of model effect

After the CNN model training, the actual test of the model needs to be carried out, which mainly includes the following four steps.

The corresponding confusion matrix is summarized by the "confusion matrix" function in the Sklearn package.

The original confusion matrix and the normalized confusion matrix are visualized by the Mat-plotib toolkit.

The original data-set is read and the entire data-set is classified. The prediction results are drawn by the spectral toolkit and represented in the form of image.

The prediction results are binarized. The morphological processing method is used to open the binarized image to eliminate misidentified noise areas.

Results

Figure 9 shows the original confusion matrix, and the main diagonal represents the number of correctly classified samples. Figure 10 shows the normalized confusion matrix, and the main diagonal line represents the average recognition rate for each type of samples.

There is a small amount of misclassification between green tea and the background, because the junction of the edge contains both the reflection spectrum of green tea and the background, and the algorithm has misjudged. There is a misclassification of green tea and tea stalks, also because the edge junction contains both the reflection spectrum of green tea and tea stalks.

According to the original confusion matrix in Figure 9, the Overall Accuracy (OA) and the KAPPA coefficient can be calculated as shown in Table 1. The Overall Accuracy of the PCA-CNN algorithm is 98.53% and the KAPPA coefficient is 0.9712. The values of OA and KAPPA coefficients are close to 1, indicating the high classification accuracy and consistency.

To distinguish the classification effects more intuitively, the hyperspectral image is converted into pseudo-color image. In model test, the spectral toolkit is used to plot the prediction results, which are represented as two-dimensional images, as shown in the Figure 11. Figure 11(a) is a pseudo-color image of the hyperspectral image, Figure 11(b) is an image manually labeled according to the spectral reflectivity curve, and Figure 11(c) is a classification effect image recognized by the designed algorithm. The classification results in the Figure 11 below are consistent with the confusion matrix data in the Figure 10 above. Because there is a small amount of manual labeling errors at the boundary, the trained algorithm model has misidentification of pixels, resulting in noise areas. The algorithm used in this paper has achieved a recognition accuracy of more than 98.53% in the experimental test. Meanwhile, the classical image processing method of thresholding was adopted, and the results are shown in Figure 12. It can be seen that the sorting effect is not good, the accuracy is about 62.5%. The reason for this is that the tea and the tea stalks have similar colors.

Considering that the actual sorting device only needs to locate the spatial coordinate position of tea stalks, the classification results are merged from 3 categories to 2 categories of tea stalks and non-tea stalks, that is, green tea and background are classified as non-tea stalks. The merged binarized image is shown in Figure 13(b). Figure 13(a) is a standard binarized image obtained by manual labeled.

Application test

In order to test the performance of the proposed method, we carried out the actual tea stalks sorting experiment in the factory, as shown in Figure 14. The camera images the tea leaves and the algorithm processes the images to identify the tea stalks and their coordinates. The coordinate position is transmitted as input signal to the CPU, which sends a response signal to the actuator. Then the solenoid valve at the corresponding position in the actuator responds to remove the tea stalks. The working principle is shown in Figure 15.

Table 2 shows the sorting results of 10 experiments. The number of tea stalks sorted by experiment and the sorting rate are recorded in each experiment. After repeated tests, the overall sorting rate of the stalk can reach 97.05%, at an output of 250kg/h, which meets the requirements of actual application.

Conclusions

For the separation of tea stalks from tea, an innovative method based hyperspectral imaging was adopted in this paper. The main contributions are as follows.

1. The traditional photoelectric sorting method was changed, hyperspectral technology was used. Hyperspectral technology enables tea and tea stalks with similar colors to have spectral differences. At the same time, PCA was used to reduce data dimension and reduce computing power.

2. CNN network is applied to tea stalks separation, which can automatically extract features and have a fast recognition. And the tea stalks recognition rate is very high. The recognition rate of tea stalks is as high as 98.53%, which can meet the requirements of actual tea sorting. After field testing, the selection rate of stalk is as high as 97.05%.

In general, this paper proposes a new method for selecting tea stalks in the tea, which improves the quality of the tea to a certain extent and makes a considerable contribution to Wuyuan green tea. On the other hand, the proposed method can reduce manpower, save time and promote the process of agricultural mechanization.

The sorting method proposed by us is not only applicable to tea industry, but also applicable to other industries, such as cotton impurity removal and rice impurity removal. This method provides an innovative idea for the sorting of agricultural products. The future work will focus on super precision detection to meet the needs of industrial production. We hope to make greater contributions to saving time, saving money and promoting mechanization.

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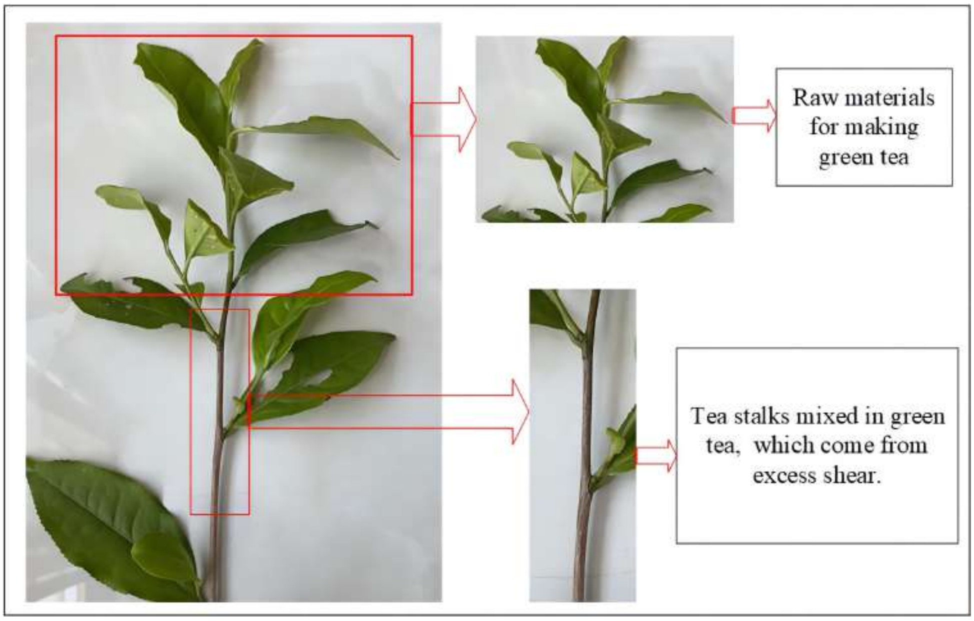


Figure 1. Tea tree structure.

Figure 2. Tea leaves with tea stalks.

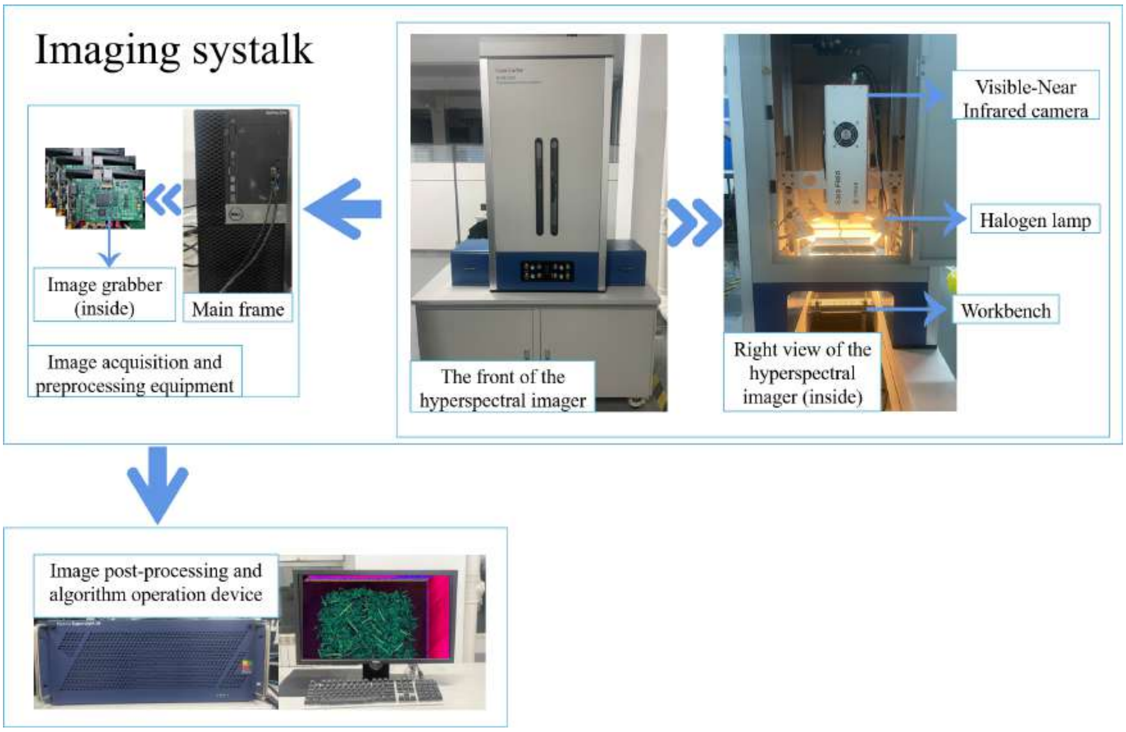


Figure 3. Schematic diagram of the structure of the imaging system.

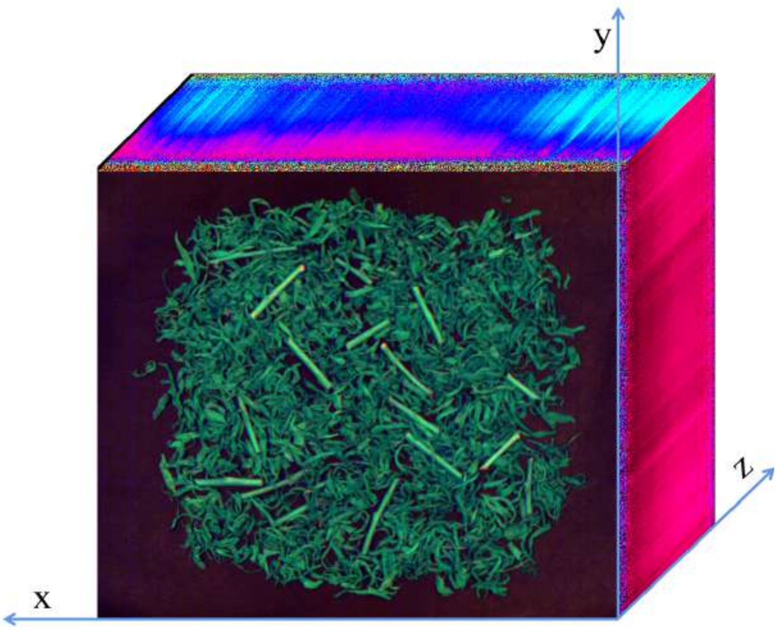


Figure 4. The acquired hyperspectral image (raw image).

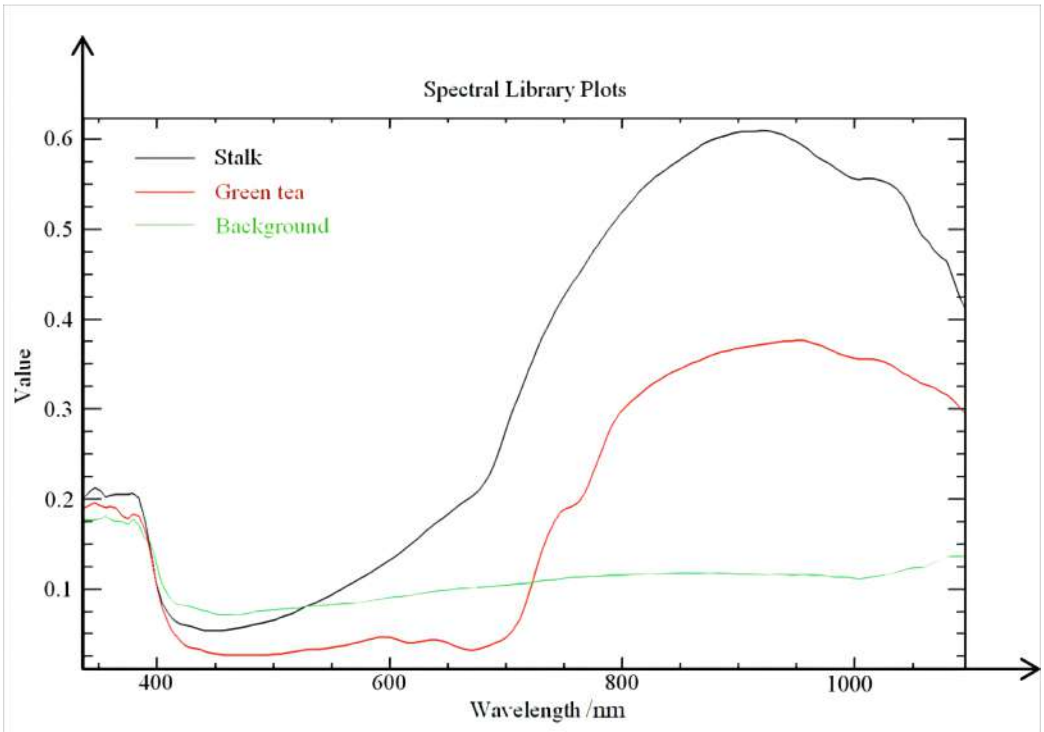


Figure 5. Reflectivity curve.

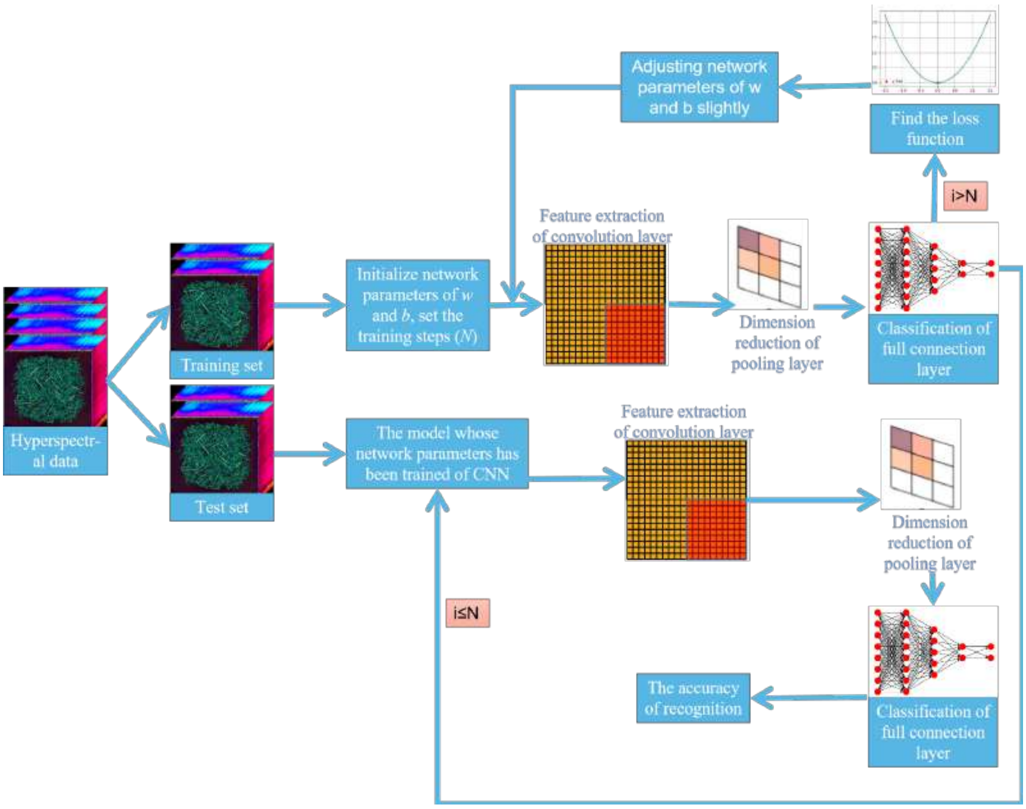


Figure 6. Specific process of feature extraction and recognition.

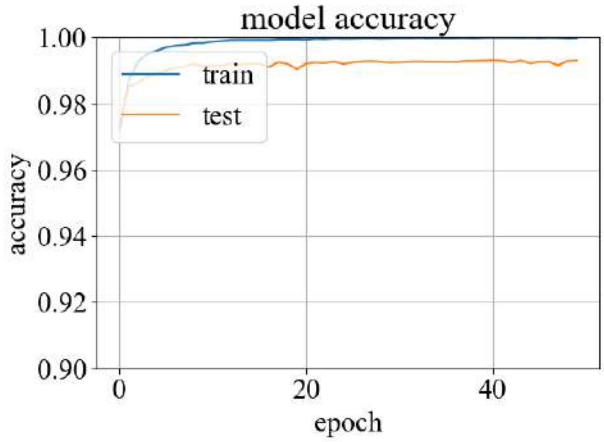


Figure 7. The change of training and testing accuracy with the number of training.

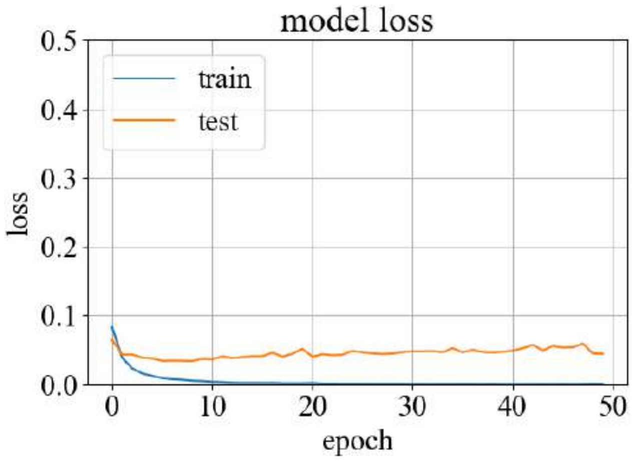


Figure 8. The training and testing loss curves.

		Predicted		
		Stalk	Background	Green tea
True	Stalk	5971	0	403
	Background	5	111408	1224
	Green tea	508	1909	154572

Figure 9. Original confusion matrix of the samples.

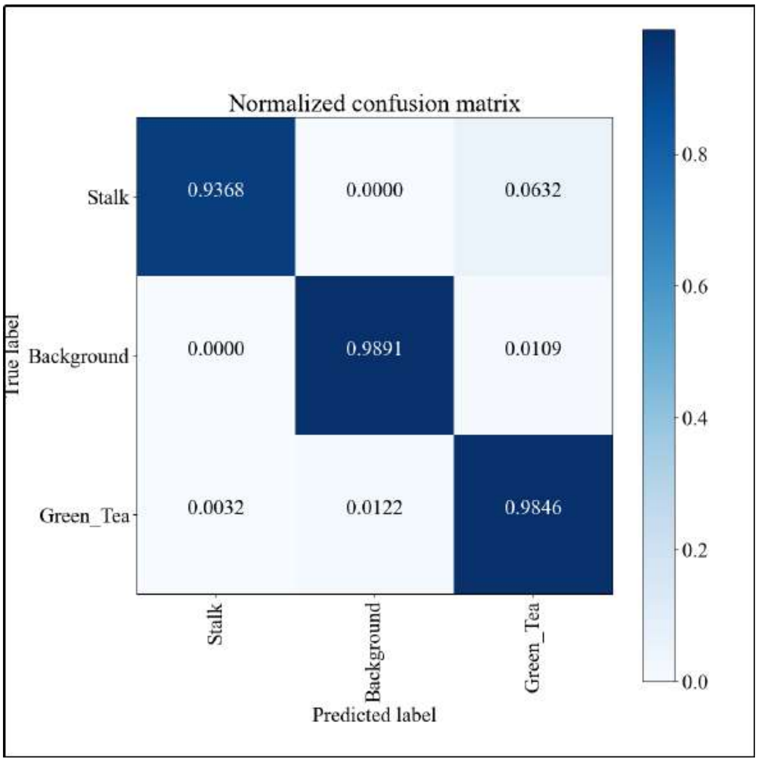
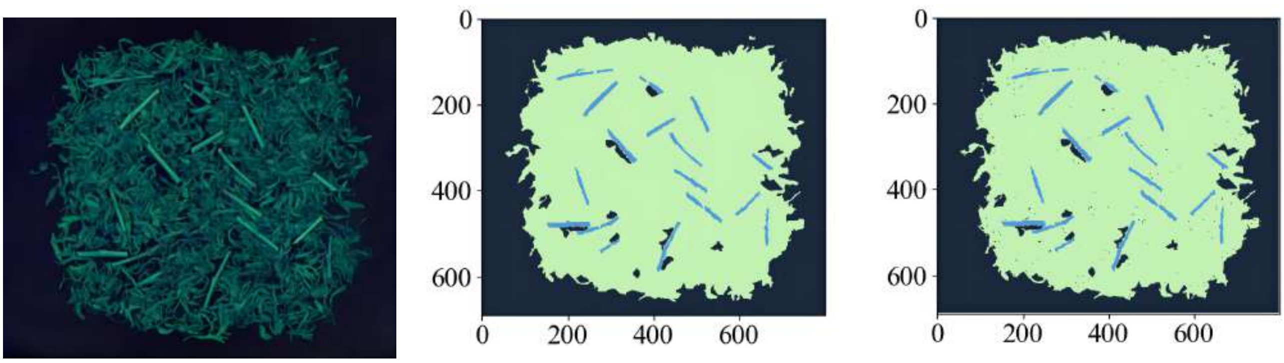


Figure 10. Normalized confusion matrix.



(**a**) Pseudo-color image

(**b**) Image manually labeled

(**c**) Result of algorithm recognition

Figure 11. Classification results.

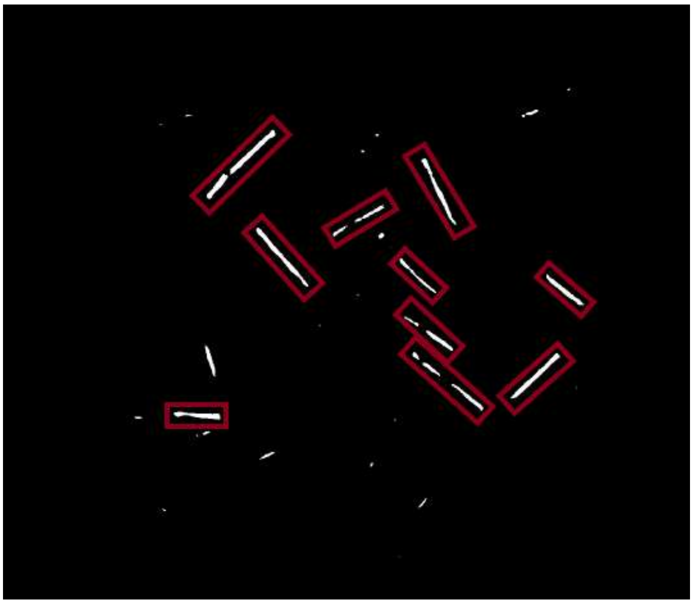


Figure 12. The sorting effect of thresholding.

(**a**) Standard binarized image

(**b**) Merged binarized image

Figure 13. Binarized images.

Figure 14. Sorting experiment.

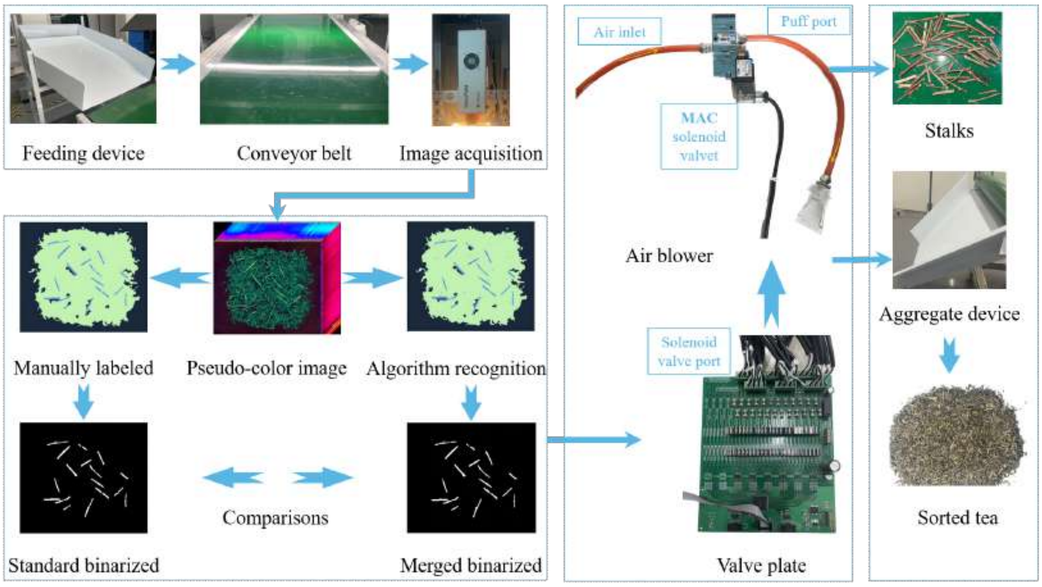


Figure 15. Working principle.

Table 1. Overall Accuracy and KAPPA coefficient.

Algorithm	Overall Accuracy	KAPPA
PCA-CNN	98.53%	0.9712

Table 2. Statistics of experimental results.

Experimental serial number	The actual number of tea stalks in tea	The number of tea stalks sorted by experiment	Sorting rate
1	134	130	97.01%
2	129	126	97.67%
3	124	121	97.58%
4	119	115	96.64%
5	114	112	98.25%
6	110	105	95.45%
7	105	102	97.14%
8	100	96	96.00%
9	95	92	96.84%
10	90	88	97.78%
Sum	1120	1087	97.05%