Distinguishing tea stalks of Wuyuan green tea using hyperspectral imaging analysis and convolutional neural network

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Abstract

A well-known agricultural product in China, Wuyuan green tea is safeguarded by national geographical indications. In addition, the processed green tea must be free of contaminants like stones and tea stalks. Nevertheless, due to their similar colors, photoelectric sorting and 2D image recognition technologies are unable to distinguish tea stalks from Wuyuan green tea. In order to address the issue of incorrect sorting brought on by similar color matching, this paper uses hyperspectral imaging technology. Using a 400–1000 nm visible and near-infrared camera, green tea with tea stalks was photographed. Furthermore, the hyperspectral image that was gathered was reduced in dimension using principal component analysis. Additionally, tea stalks were successfully identified in hyperspectral images using the convolutional neural network, which can automatically learn the corresponding features and do away with the laborious feature extraction procedure. According to the experiment's findings, tea stalks can be recognized with an accuracy of 98.53%. The technique can meet the real production requirements and has a high recognition rate. The selection rate is as high as 97.05% following field testing.

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

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Introduction

Wuyuan green tea has green buds and leaves, a clear soup color, a rich aroma, and a mellow taste. Since 1997, Wuyuan green tea has been the most-sold green tea in China to the European Union (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 & He, 2016). 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. 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 and Wu (2014) used the 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 the 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 structures, operation forms, and the difference between the physical characteristics 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 machines (Xie *et al.*, 2004). With the rapid development of high technology with a computer as the core, combining high-resolution image recognition and high-speed micro jet, a 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 and Zhang (2013) 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 with maximum inscribed circle's radius and built a Gauss model using the single shape feature. Then, the minimum error rate Bayes classifier was applied 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 & Zhang, 2013). Sun *et al*. (1997) proposed a tea stalk-picking machine controlled by a single-chip microcomputer. Analog-to-digital 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 stalk.

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 a 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 a 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 distinguishing tea stalks of Wuyuan green tea using hyperspectral imaging analysis. Hyperspectral imaging can not only record 2D image information but also record multiple band information in space (ElMasry & Sun, 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, nondestructive, 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 (l) 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 a large amount of hyperspectral image data, principal component analysis (PCA) is used to reduce dimensionality and remove noise and unimportant features, thereby improving data processing speed (Uğuz H, 2011). At the same time, a convolutional neural network (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 imaging. The 2D-CNN is composed of an 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 *et al.*, 2016). The recognition accuracy is high.

Materials and Methods

Materials

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

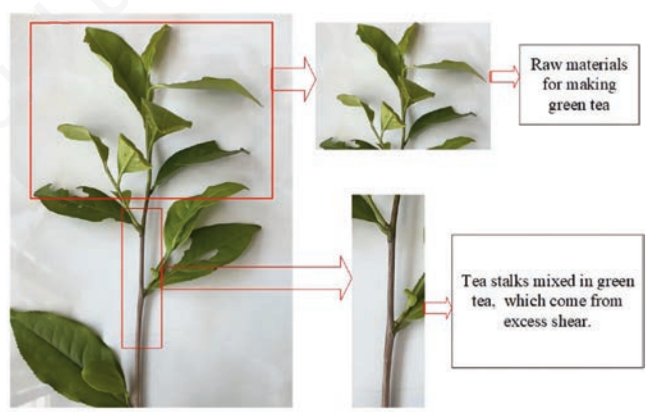

Figure 1. Tea tree structure.

Figure 2. Tea leaves with tea stalks.

Instrumentation

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 *et al.*, 2014).

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

where I_c denotes the 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 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 labeled 2D images are further used to train the CNN model. Therefore, it is necessary to visualize the original hyperspectral image and generate a 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 *et al.*, 2003). The three selected bands form a three-channel image with a good display effect. After the image was cropped, it was saved as a 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 and 3D images were saved in a format recognizable by the algorithm.

Reflectivity curve

By selecting the region of interest, the average reflectance of tea stalk, green tea and background was obtained respectively (Windham *et al.*, 2002). The obtained reflectivity curve is shown in 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.

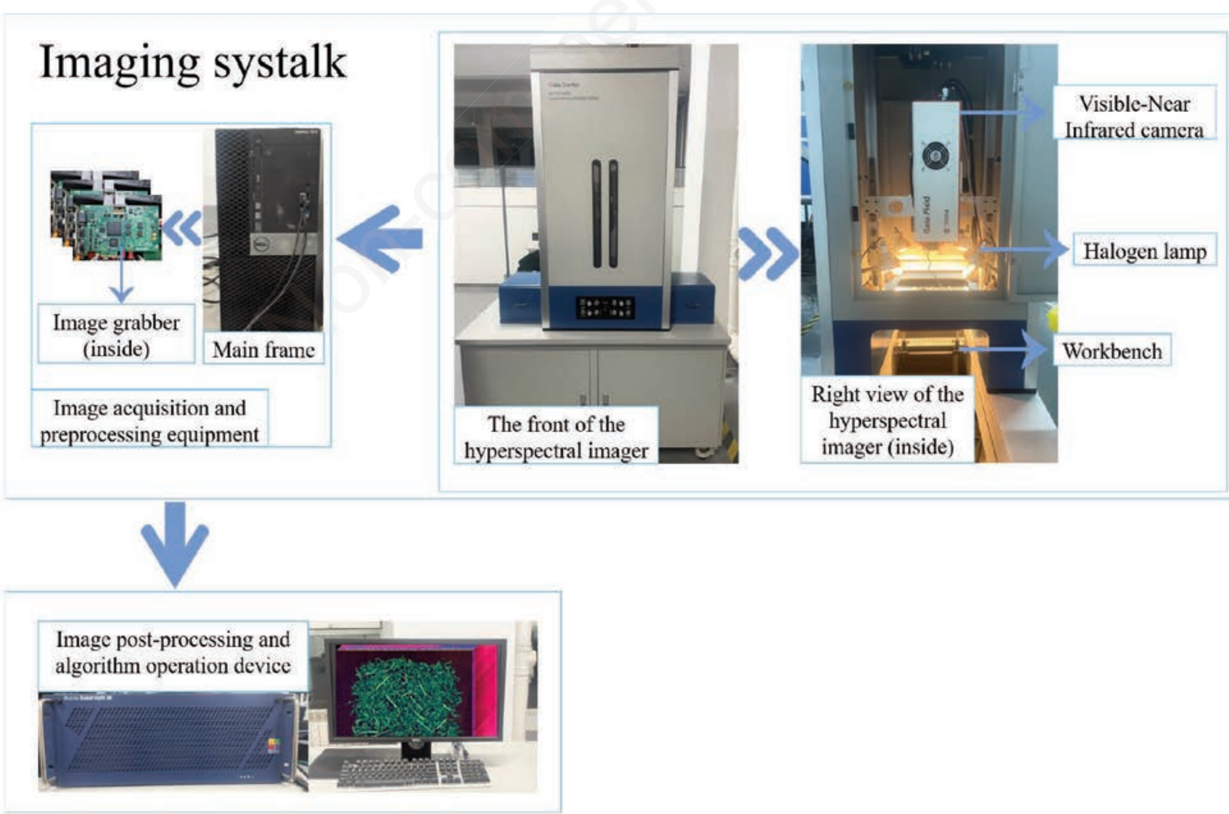

Figure 3. Schematic diagram of the structure of the imaging system.

Principal component analysis 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 a 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 *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.

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

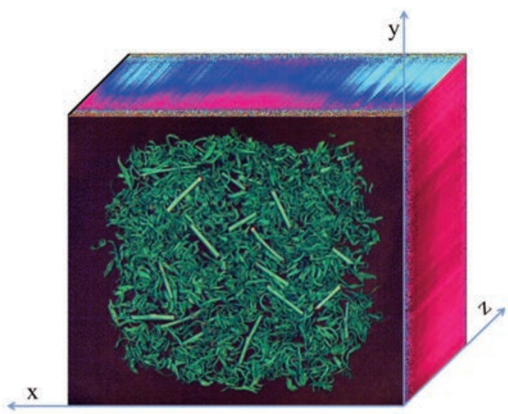

Figure 4. The acquired hyperspectral image (raw image).

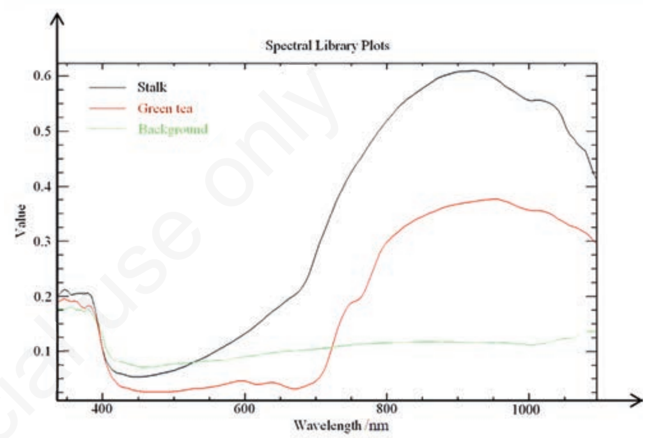

Figure 5. Schematic diagram of the structure of the imaging system.

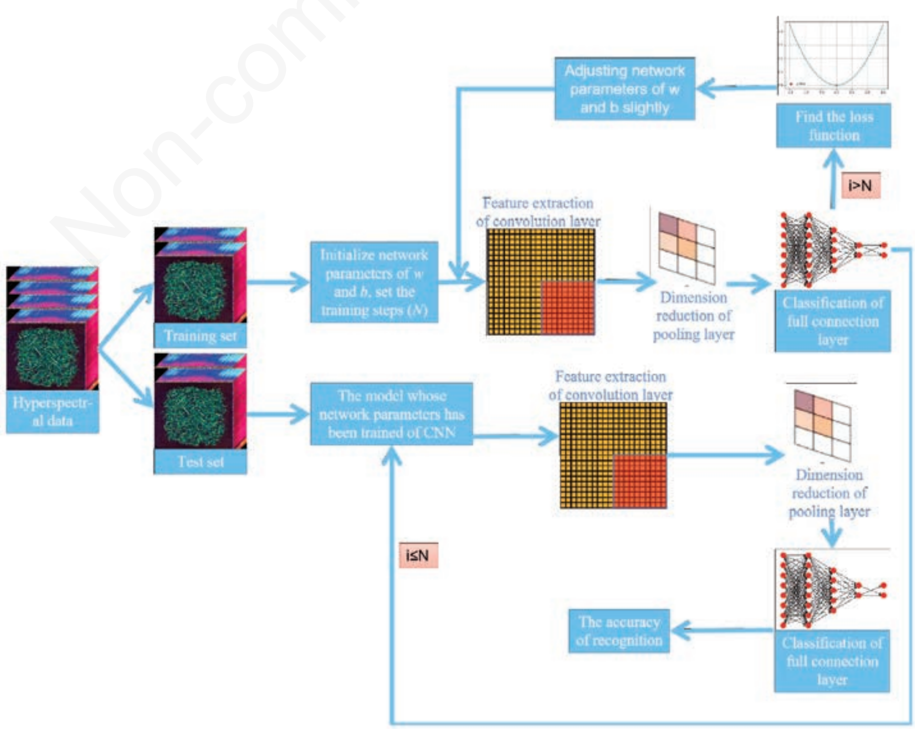

Figure 6. Specific process of feature extraction and recognition.

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

$$\frac{1}{M}AA^T = \frac{1}{M}\sum_{i}^{M} d_i d_i^T \quad (6)$$

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

$$\left(AA^T\right)^T = A^T A \quad (7)$$

The eigenvectors of the first L ($L$is much smaller than M) larger eigenvalues of the vo-variance 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).

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

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

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

$$W = \{v_1, v_2, \ldots, v_L\} \quad (9)$$

c) Data post-processing

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

$$P_i = W^T d_i, \quad (i = 1,2,\ldots,M) \quad (10)$$

Equation (11) is the Euclidean distance.

$$\varepsilon_i = \left\|P_i - P_s\right\|^2, \quad (i,s = 1,2,\ldots M) \quad (11)$$

The Euclidean distance is used as the similarity detection between images. The smaller the Euclidean distance, the more sim-

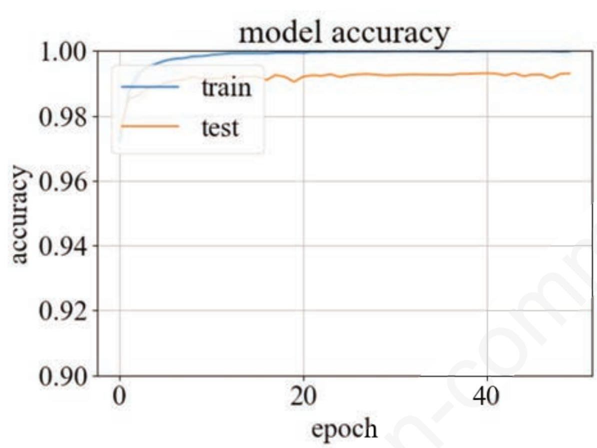

Figure 7. The change of training and testing accuracy with the number of training.

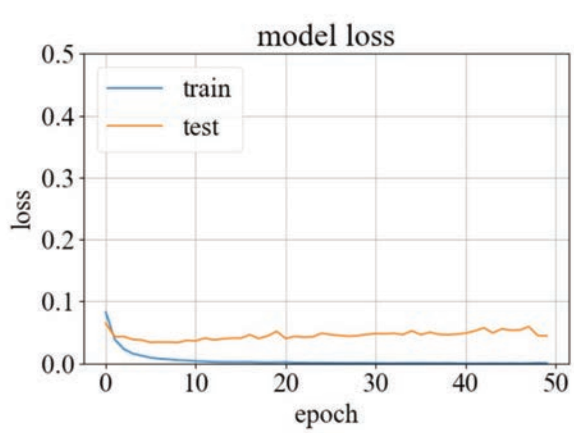

Figure 8. The training and testing loss curves.

Predicted

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

Figure 9. Original confusion matrix of the samples.

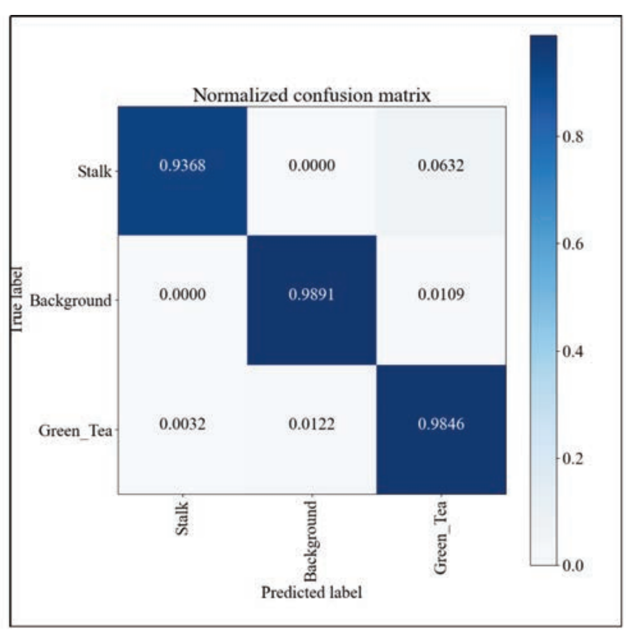

Figure 10. Normalized confusion matrix.

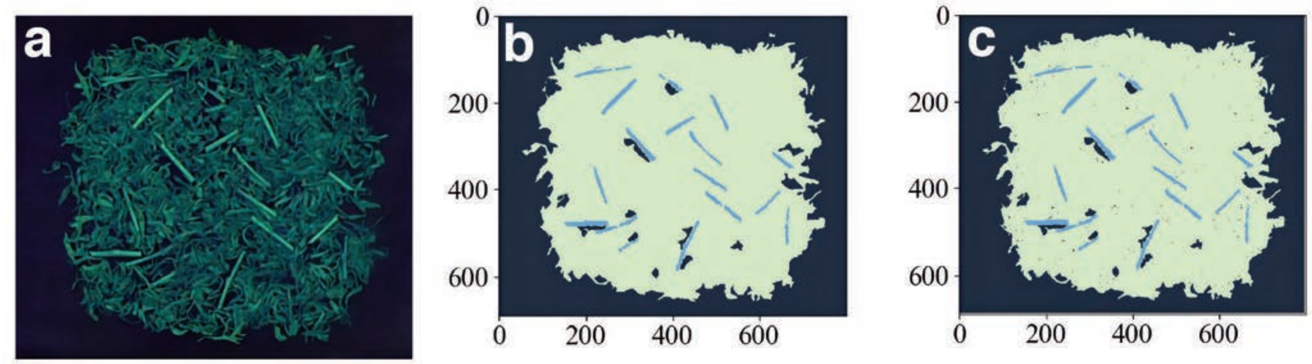

Figure 11. Classification results. **a**) Pseudo-color image; **b**) image manually labeled; **c**) result of algorithm recognition..

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

Convolutional neural network model training

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

The specific process of feature extraction and recognition of hyperspectral imaging is shown in Figure 6. First, in the processing phase, the hyperspectral image data is equally divided into the 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 SGD, 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 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 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).

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

Figure 12. The sorting effect of thresholding.

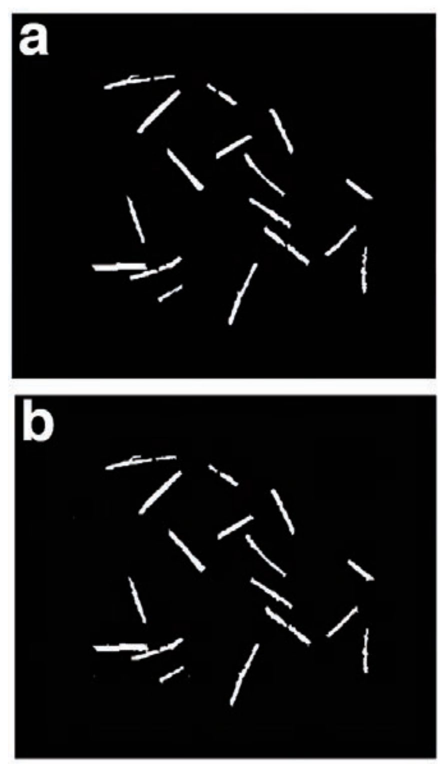

Figure 13. Binarized images. **a**) Standard binarized image; **b**) merged binarized image.

$$b' = b - \eta \frac{\partial E}{\partial b} \quad (14)$$

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 Matplotib 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

Figure 14. Sorting experiment.

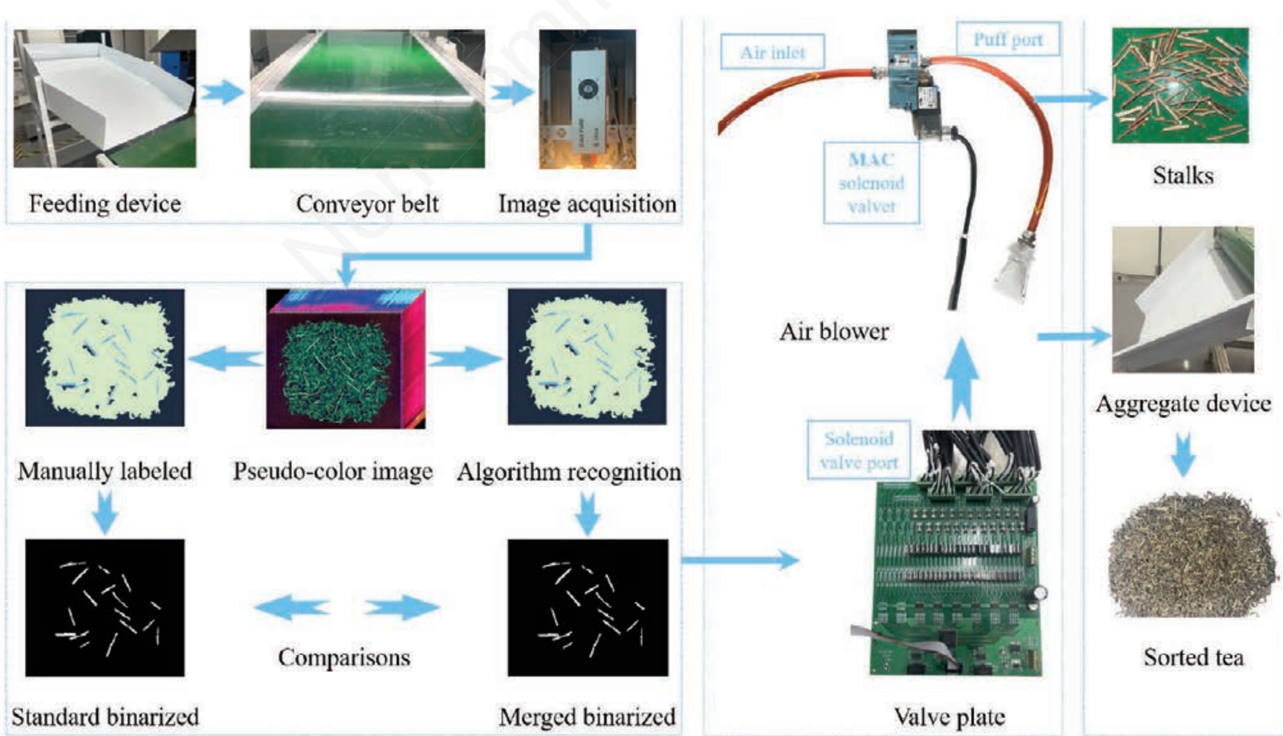

Figure 15. Working principle.

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 *Supplementary Table 1*. The OA 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 high classification accuracy and consistency. To distinguish the classification effects more intuitively, the hyperspectral image is converted into a pseudo-color image. In the model test, the spectral toolkit is used to plot the prediction results, which are represented as two-dimensional images (Figure 11). Figure 11a is a pseudo-color image of the hyperspectral image, Figure 11b is a manually labeled image according to the spectral reflectivity curve, and Figure 11c is a classification effect image recognized by the designed algorithm. The classification results in Figure 11 below are consistent with the confusion matrix data in 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 three categories to two 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 13b. Figure 13a is a standard binarized image obtained by manual label.

Application test

In order to test the performance of the proposed method, we carried out the actual tea stalk sorting experiment in the factory (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 an input signal to the central processing unit, 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.

Supplementary 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 the 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, and 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 is applied to tea stalk separation, which can automatically extract features and have fast recognition. The tea stalk 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 the 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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Online supplementary material:

Table S1. Overall accuracy and KAPPA coefficient.

Table S2. Statistics of experimental results.