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Identification and extraction method for fragrant pear based on image detection using the Internet of Things applications

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Abstract: In the traditional picking and sorting process of fragrant pears, the quality control process is not perfect, and the identification and extraction methods are not mature enough. By combining the Internet of Things (IoT) and image detection technologies, the image data of pear planting area in the orchard was obtained, and the image of pear was preprocessed, denoised, and feature extracted by the visual background extraction algorithm. In order to verify the actual effect of the optimized identification and extraction method for fragrant pears using IoT and image detection technologies, a comparative experiment was conducted. The results show that compared with the traditional pear recognition and extraction method, the optimized pear recognition and extraction method has a better predictive effectiveness in the process of pear image processing, and the recall and accuracy rates are improved by approximately 8% and 12.7%, respectively. This verifies the reliability and efficiency of the identification extraction method for fragrant pear based on IoT and image detection technologies. In this paper, the traditional pear identification and extraction methods are improved by IoT technology and UAV (unmanned aerial vehicle), which improves the picking efficiency and sorting quality of pear picking robots.

Key words: Internet of Things, unmanned aerial vehicle, fragrant pear, recognition extraction, big data

1. Introduction

With the development of the social economy, the fragrant pear industry is constantly changing, and the identification and extraction of fragrant pear in the natural environment has become a key link in the development of the fragrant pear industry (Yang et al., 2022). Because the growth of fragrant pear is in a complex environment with uneven care intensity, interleaved branches, leaves and flowers, and overlapping of fragrant pear fruits, it is difficult to carry out the work of fragrant pear picking smoothly. Traditional pear identification and extraction methods mostly rely on relevant experienced staff to carry out field investigations, and consume a lot of time, manpower and physical costs to develop pear picking plans. Such a workflow is relatively rigid, difficult to deal with emergencies caused by complex environments, and would waste many resources. With the progress of society, the quality standard of fragrant pear industry has put forward higher requirements, especially in the identification and extraction process of fragrant pear. In this paper, the wireless sensor network is used to arrange monitoring nodes in the orchard. In order to ensure the transmission and sharing of information between different areas, IoT and image detection technologies are tentatively introduced to collect information of fragrant pear. The installation of sensor nodes in various areas of the orchard through wireless sensor networks enables the monitoring of the surrounding environment of the pear in real time, the collection of environmental information from the orchard, and the transmission of the data to the data center through wireless signals. In order to enhance the efficacy of pear feature recognition, this paper preprocessed the collected pear influence data and employed the particle swarm optimization algorithm to automatically calculate and extract various pear features in the image. This approach aimed to achieve more accurate pear recognition and classification effect, thereby enabling the completion of the pear sorting and quantity statistics task in a more efficient manner.

IoT and image detection technologies have great potential in the field of agriculture, and their wide application in agricultural production has brought revolutionary changes (Liu, 2022). In this paper, a highly integrated sensor network is used to deploy sensor devices in fragrant pear orchards, which can be connected to

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the Internet to monitor environmental parameters in real time and analyze the environmental data from representative areas and fragrant pear images, combined with low-altitude drones, in order to achieve efficient agricultural production management. This paper uses the IoT and image detection technologies to obtain a large number of fragrant pear growth data. It also aims to obtain high-resolution image data at a lower cost and transmit the collected data and images to a cloud platform data center through wireless communication. The image preprocessing, feature extraction, and image enhancement are carried out to improve the accuracy of pear recognition and achieve automatic recognition and extraction of pear model. In this paper, the traditional pear identification and extraction method is analyzed, and IoT and image detection technologies are tentatively introduced to address the issue. This paper summarizes the shortcomings and limitations of traditional methods. This optimized pear identification and extraction method provides higher reliability for users' real-time monitoring and quality sorting tasks, reduces costs and improves the efficiency of agricultural production in practical applications. The introduction introduces the pear industry and the background of the issue, reviews relevant research through literature review, and then elaborates on the application and data processing process of Internet of Things technology. The article then elaborated on the optimized pear recognition and extraction method and experimental results, and finally summarized the importance and achievements of the research through conclusions. The innovation of this study lies in the integration of Internet of Things and image detection technologies, which improves the recognition effect of fragrant pears through environmental monitoring and image analysis. Compared to traditional methods, this article uses drones and sensor networks to achieve real-time monitoring, improves recognition accuracy through optimized algorithms, and provides a more reliable quality control method for the pear industry.

By integrating IoT and image detection technologies, we aim to improve the recognition and extraction methods of fragrant pears, in order to enhance the efficiency and quality of the fragrant pear industry. The traditional pear picking process has problems with insufficient quality control and immature identification and extraction methods. This study introduces drones and sensor networks to monitor the orchard environment in real time and combines image processing algorithms to identify and extract pears. The goal is to optimize the pear picking workflow, improve production efficiency, and ensure quality. Through the Internet of Things technology, researchers attempt to construct a more scientific and reasonable work architecture, introduce intelligence and advanced technology to the pear industry, and promote the progress and development of the pear industry. Through comprehensive calculation of environmental information, this study aims to provide a faster and more accurate solution for identifying fragrant pears under complex conditions, injecting new technological impetus into agricultural production.

2. Related studies

The fragrant pear industry has been widely concerned by the agricultural field, and the research on the identification and extraction methods for the fragrant pear planting and picking process is conducive to improving the understanding of the fragrant pear production process. In the process of harvesting fragrant pears, the quality of fragrant pears needs to be tested in real time, and the selection of fragrant pear identification methods is very important. Advanced technologies based on neural network and hyperspectral imaging have been widely used in the identification and detection of fragrant pear quality (Lan et al., 2020; Logensh, 2022). In order to achieve nondestructive testing of the hardness of fragrant pear at maturity stage, Zhang et al. (2022) established a pear hardness prediction model using generalized regression neural network and backpropagation neural network to predict the hardness of fragrant pears in orchards. This can facilitate a better understanding of the current condition of fragrant pear growth (Zhang et al., 2022). Lignin content is an important index affecting the quality of fragrant pears. Sheng et al. (2020) identified fragrant pear fruits based on near infrared spectroscopy and combined the collected data with intelligent algorithms to promote the progress and development of fragrant pear industry quality. This can simplify the calculation process and improve the identification efficiency of fragrant pear condition (Sheng et al., 2020). The physiological condition of fragrant pears after harvest is related to the level of industrial quality. Mao et al. (2022) carried out status identification and quality analysis of stored fragrant pears. They also combined with gas chromatography to detect the composition and content changes of pear skin wax to ensure the quality level of pear industry output (Mao et al., 2022). The above research has analyzed the status quo of fragrant pear identification methods. The predictive effectiveness of traditional fragrant pear identification methods is not sufficient, and the accuracy is inadequate, requiring further improvement and thorough research.

The development of IoT and image detection technologies has promoted the advancement of the process of agricultural intelligence; its application in the agricultural field has been analyzed; the importance of technological breakthroughs in agricultural development has been explored, while technical understanding has been strengthened. The extensive application of IoT has promoted the development of intelligent agriculture. Niu et al. used generalized neural network and adaptive neural fuzzy reasoning system model to establish a quality detection system for evaluating fragrant pear in the process of picking and storage. The reliability of the system has been demonstrated through numerous experiments (Niu et al., 2020). Soil texture, light measurement, fruit yield, and terrain distribution are all important parameter indicators in the process of agricultural planting. It uses low-altitude remote sensing technology to capture infrared images of the terrain and fruits in the planting area. Sams et al. (2022) collected these parameter data, which can effectively predict the quality law of fruit growth in the field. Low-altitude remote sensing equipment and deep learning data analysis techniques can be combined. By collecting the visible near-infrared images of fruits in orchards and analyzing the data, this structure combines the least square regression to establish the analysis framework for multiple datasets, thereby saving considerable costs and facilitating the beneficial evaluation of fruits (Li et al., 2019; Zhou et al., 2019). Quality control should be carried out during the picking and storage of fragrant pears with different maturity. Liu et al. (2021) predicted the quality changes of fragrant pears based on IoT technology and generalized regression neural network, which provided an important basis for the sorting of fragrant pears. Using convolutional neural networks, bidirectional long short-term memory, and attention mechanisms to pay attention to the unique spatiotemporal features of the original video stream, deep learning methods were implemented in the proposed framework to detect abnormal human activity (Kumar et al., 2023). The use of deep learning algorithms to monitor the growth of crops in greenhouses allows for the identification of the growth status, leaf color, and shape of crops. This enables the timely detection of the health status of crops, thereby improving growth efficiency (Akbar et al., 2024). In smart cities, the security and privacy protection of IoT smart devices are crucial. Blockchain and centralized authentication are two different security architectures that can be used to ensure secure communication and data exchange of IoT devices in smart cities (Usman et al., 2022). The intelligent sensing system based on the Internet of Things combines data interpretation and artificial intelligence technology, providing a wide range of application possibilities for various fields (Achyut, 2023). IoT and image detection technologies have the potential to improve the reliability of agricultural planting production. However, further research is necessary to fully achieve this potential.

The advantages and disadvantages of the methods mentioned in the literature are shown in Table 1.

3. Methods

IoT and image detection technologies can collect information efficiently (Hu, 2022), which is very suitable for application in the picking and sorting of fragrant pears. In this paper, the wireless sensor network is used to install sensor nodes in each area of the fragrant pear orchard to collect the environmental information of the orchard, in order to make overall calculation of the environmental characteristics of the fragrant pear growing (Shitharth et al., 2022). Various sensor nodes can monitor the surrounding environment of fragrant pear in real time. The collected pear growth environment data is transmitted to the data center through wireless signal, and the data center can carry out unified data interaction, query, and management control of the environmental data (Indira et al., 2023). Figure 1 shows the structure of data acquisition.

Figure 2 shows the data acquisition and processing structure involved in the system. The data center, which is at the core of the structure, serves as the central hub for the processing, analyzing, and collecting of data. The data acquisition process begins with various sensors deployed in the orchard environment. These sensors include temperature and humidity sensors, light sensors, and

Table 1. The advantages and disadvantages of the methods mentioned in the literature.

Method/technology	Advantages	Disadvantages
Hyperspectral imaging (Zhou et al., 2021)	Widely used for quality inspection	High cost, high equipment requirements
Neural network (Zhang et al., 2021)	Nondestructive testing, improve discrimination efficiency	Require a large amount of data and computational resources for training and adjusting the network
Gas chromatography (Chiu and Kuo, 2020)	Improve the quality of stored pear and ensure the level of quality	Complex equipment, cumbersome operation
UAV remote sensing technology (Wang et al., 2020)	Improve the accuracy of spatial growth quality prediction	Require professional operators and equipment
Internet of Things (Mouha, 2021)	Promote the development of smart agriculture	Network security and privacy issues

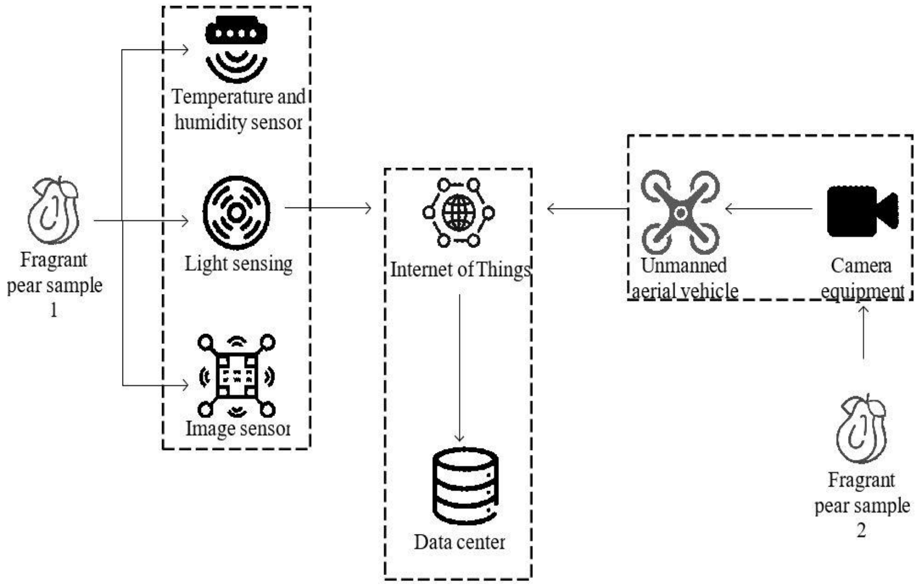


Figure 1. Structure of data acquisition.

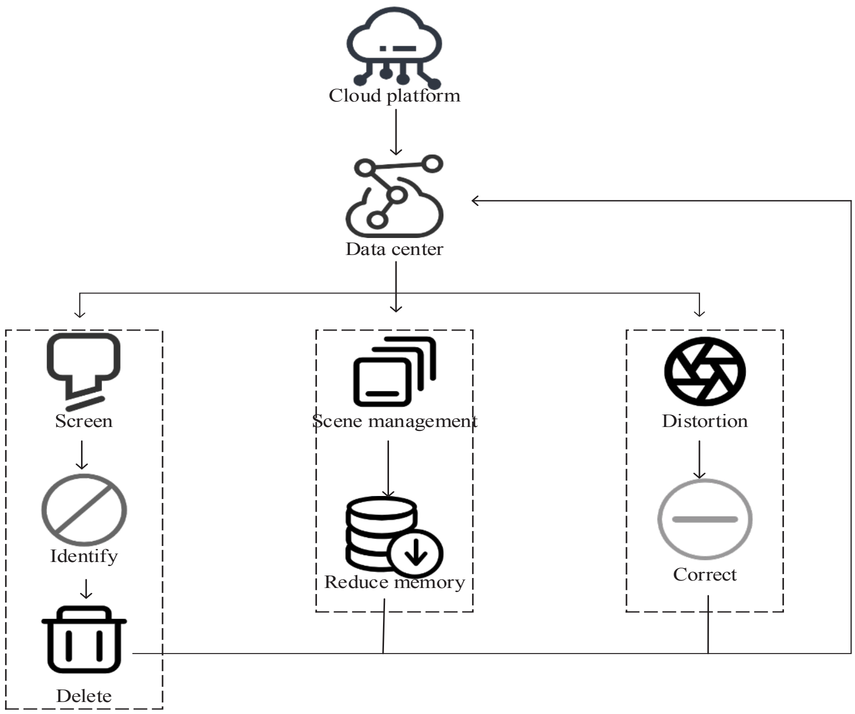


Figure 2. Structure of image data cleaning process.

image sensors. Temperature and humidity sensors monitor environmental conditions to ensure the best growth conditions of fragrant pear samples. Optical sensors help to monitor light intensity, which is very important for photosynthesis and overall plant health. Image sensor captures the visual data of fragrant pear samples, which provides valuable information for analysis. Internet of Things technology connects these sensors to achieve real-time data transmission to the data center. This connectivity makes it possible to seamlessly monitor and manage the orchard environment. In addition, unmanned aerial vehicles equipped with camera equipment contribute to data collection by capturing aerial images of orchards. This aerial photography perspective provides valuable insights into the overall health and development of fragrant pear samples.

In this paper, based on the actual situation of the orchard, in order to ensure the completeness of the collected data types, high-resolution images of fragrant pear area in the orchard were collected using UAV equipment at low-altitude. Subsequently, the collected images were transmitted to the IoT data center through wireless signal transmission technology. Together with the environmental data collected by the wireless sensor network, it is managed by the data center. Due to limitations of the experimental conditions, the collected fragrant pear dataset was used for data preprocessing during the data cleaning process. The structural form of data acquisition combined with IoT and image detection technologies well meets the requirements of data acquisition quality. Figure 2 shows the structure diagram of image data cleaning process.

Data preprocessing is an indispensable step in image processing. This paper provides clean and accurate data for the subsequent image analysis and data processing process, which requires data cleaning operations on the relevant data collected by sensors and low-altitude UAV. It would filter a substantial number of images collected and delete useless, invalid or wrong data (Zhou et al., 2019; Huč et al., 2020). In the data center of data storage, multiple identical images are collected in the same scene for recognition, and the memory usage is reduced, and the detection efficiency is improved by removing one or more image data. For some irrelevant areas in the orchard, the image can be deleted to reduce the storage capacity of the image and the image processing time. Figure 3 shows the representative fragrant pear image data collected in this paper.

In order to improve the efficiency of phase identification and condition monitoring in the growing process of fragrant pear due to the complex growing environment, it is necessary to collect images of fragrant pear in different growing environments (Nie, 2022). As shown in Figure 3, Figures 3A–3H respectively represent the growth phase of fragrant pear in different time and growing environment, which can have more comprehensive detection and recognition effect in the process of model training and practical application. In the process of color image processing, it takes a lot of time and cost to process the image channel. In order to save the cost and improve the model processing speed, the color image collected by the sensor can be grayed, thus reducing the image data processing amount (Nie, 2022). In this paper, a representative fragrant pear image is selected from the collected fragrant pear images for gray-scale operation. Subsequently, the three methods—the average, maximum, and weighted average—are employed respectively in order to apply a gray-scale to the image of the fragrant pear. The identification of fragrant pear in the image is taken as an example. In this paper, the gray-scale method is selected as the primary technique for enhancing image clarity. Figure 4 shows the comparison diagram of the gray-scale effect of fragrant pear image.

As shown in Figure 4, the original pictures A, B, C, and D, along with their respective gray-scale versions produced using the average method, the maximum method, and the weighted average method, are displayed. This paper compares the gray-scale effect of three different gray-scale methods on images of fragrant pears. In this paper, the weighted average method is selected as the main image gray-scale processing method, and the sensitivity of human eyes to color is the standard. It distributes the weights of the three primary color components more reasonably, in order to obtain grayscale images that human eyes can recognize more clearly.

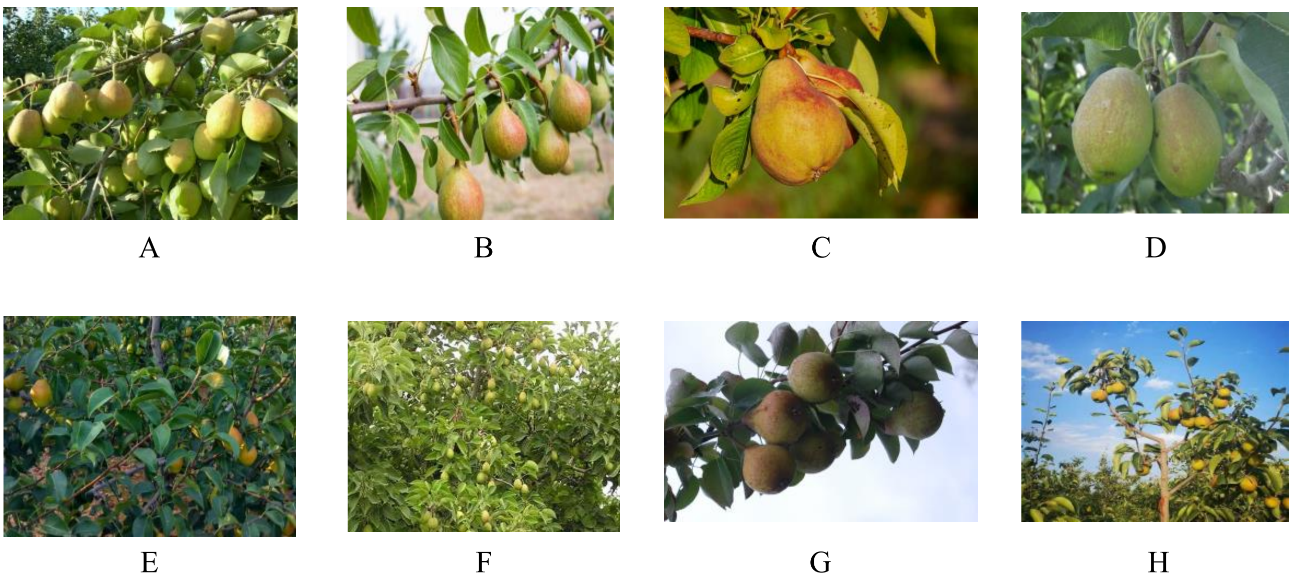


Figure 3. Pear image data display.

Figure 4. Comparison of gray-scale effect of fragrant pear image.

Image geometry transformation is an important step for image rotation, translation, and contraction in fragrant pear image preprocessing operation, so that image data can run more efficiently in the process of processing. In this paper, the accuracy and efficiency of subsequent processing can be effectively improved through image transformation operations, which ensure that the image conforms to the expected shape and position. This improvement is of great significance for image matching and fragrant pear recognition. In the process of the pear image acquisition by UAV, the image rotation, image translation, and image size are inconsistent due to the reasons of shooting angle, image acquisition position offset and shooting distance, etc. Consequently, the pear image can be transformed in a two-dimensional sense according to the actual needs. Figure 5 shows the effect of image transformation. In this paper, the weighted average method of gray fragrant pear image is taken as an example to carry out the operation of image transformation. This geometric transformation operation can better output reasonable images, which is convenient for the subsequent computer or algorithm model to carry out more accurate feature recognition and extraction of fragrant pear image.

As shown in Figure 5, the four groups of images represent the original images of images E, F, G, and H, the horizontal flip image, and the vertical flip image, respectively. When the UAV performs the actual pear image acquisition task, it would be interfered with the growing environment of the pear and the interleaving of branches and leaves. Therefore, it is necessary to

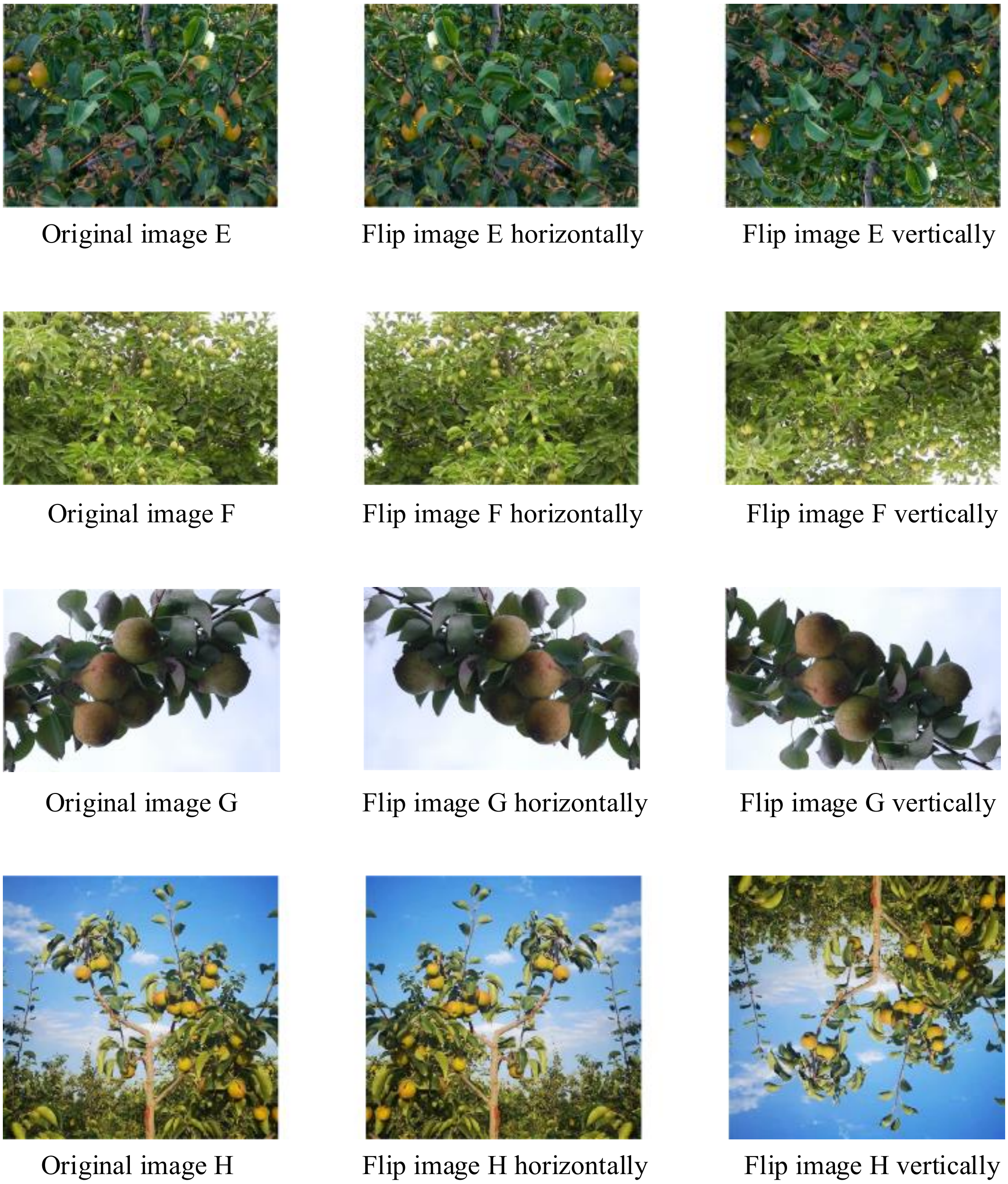


Figure 5. Image transformation effect schematic.

process the geometric position of the image, in order to obtain the image data which is more conducive to the identification and extraction of fragrant pear. In this paper, the collected image data is preprocessed to improve the accuracy of subsequent analysis. The clutter signal is passively introduced in the process of image acquisition, transmission, and storage, which leads to the degradation of image quality. As a source of image data for subsequent processing, the reliability of the processing results may be questioned. Therefore, before image processing, removing the noise in the image is an effective operation to ensure the reliability of the image data. This paper takes the collected fragrant pear images as the dataset and selects the representative fragrant pear images as an example to demonstrate. Three methods of median filter, mean filter, and Gaussian filter are used to denoise images, respectively. Figure 6 shows the comparison of processing effects of image denoising.

As shown in Figure 6, according to the comparison of image denoising effects, this paper selects Gaussian filtering as the main means of image data denoising operation. When a large amount of pear image data is acquired by sensor nodes and low-altitude UAV and transmitted to the cloud platform data center interactively, noise removal is

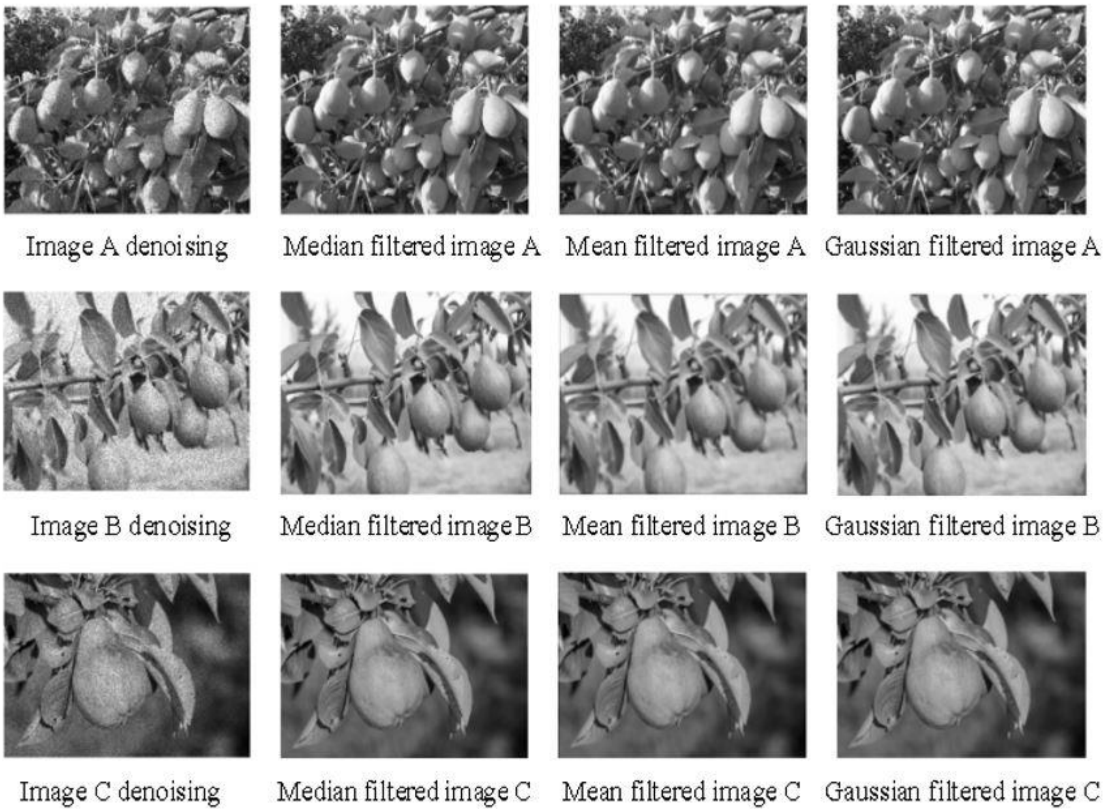


Figure 6. Comparison of processing effects of three types of image denoising operations.

carried out on all image data. Gaussian filtering method employs the Gaussian function to compute a weighted average of image pixels. It can effectively reduce the influence of Gaussian noise and white noise, improving the image display effect and greatly enhancing the details displayed in the fragrant pear image.

Histogram equalization is also a common processing method for image enhancement. By adjusting the contrast of gray-scale image histogram, the processing effect of image gray balance can be achieved. Especially in the process of pear image acquisition, due to the complex growing environment, branches, leaves, and other environmental factors often obstruct the view of the pear fruit. As a result, the contrast between the pear and the environment in the pear image data collected by UAV is quite low. In this paper, the brightness of the fragrant pear image can be better distributed on the histogram, and the influence on the overall contrast of the fragrant pear image can be reduced as much as possible by enhancing the local contrast of the fragrant pear image. Finally, fragrant pear image data with more balanced gray distribution and more significant contrast effect is obtained. Figure 7 shows the comparison of square balance effect of gray image.

As shown in Figure 7, the horizontal axis of the square equalization diagram represents the interval distribution of the threshold value set to 0–255 gray values, while the vertical axis shows the frequency distribution of gray values within the same range. The gray value distribution of gray-scale image C is relatively dense in the range of 0–255, indicating low contrast between the fragrant pear fruit and the background. Local enhancement makes the gray value distribution of gray-scale image C more balanced after square equalization processing, and the contrast effect between fragrant pear fruit and background is more significant, which is conducive to the target recognition and feature extraction of fragrant pear image data. This gray distribution facilitates the ViBe algorithm to carry out the subsequent image processing process on the relevant fragrant pear image dataset collected by the UAV and sensor. Image data cleaning, image gray-scale, image geometric transformation, image denoising, and image gray-scale equalization are indispensable steps in image data preprocessing operations, which can significantly improve the accuracy and efficiency of subsequent image processing operations. Figure 8 shows the operation flow structure of image data preprocessing.

In the traditional image recognition of fragrant pear fruit, the image segmentation recognition is generally carried out manually. Due to the huge workload and low manual recognition accuracy, the completion effect of the

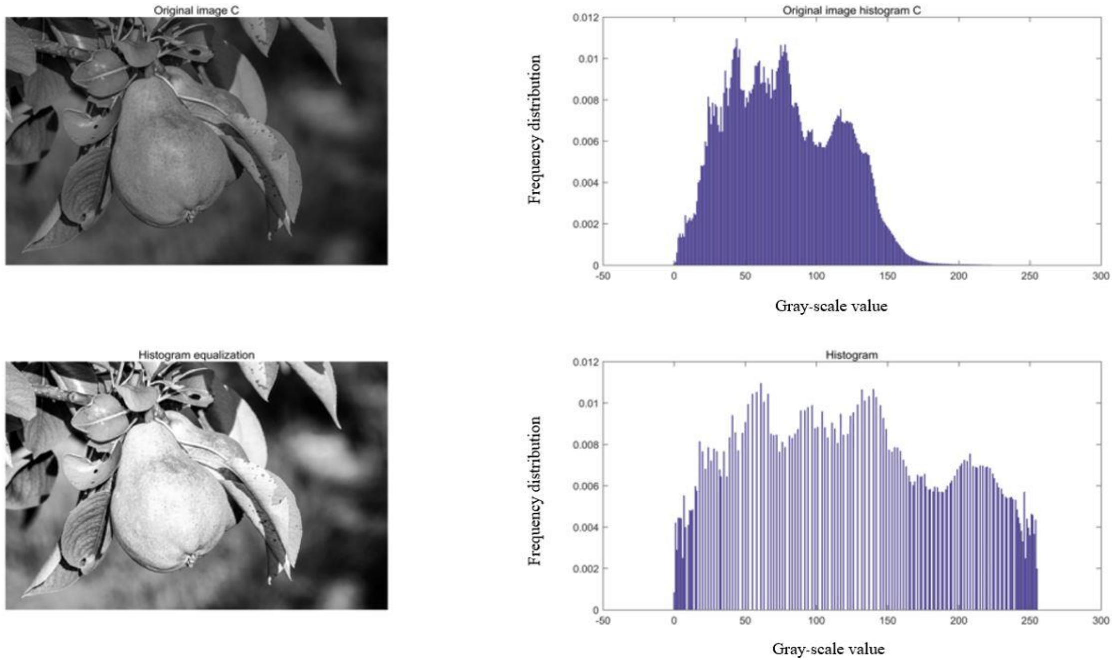


Figure 7. Comparison of square equalization effect of gray image.

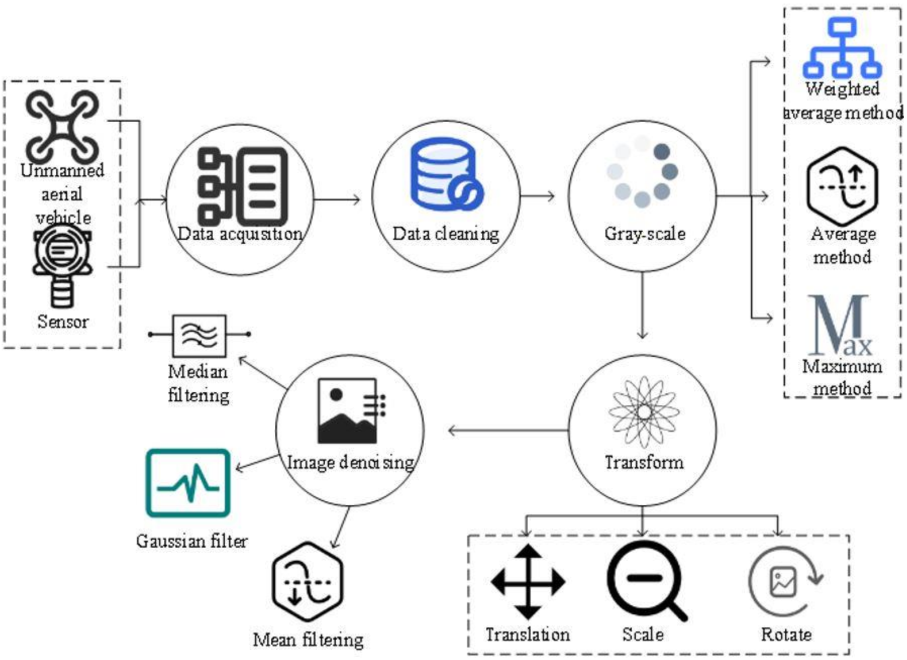


Figure 8. Operation flow structure of image data preprocessing.

fragrant pear identification task is not satisfactory, and it would cause a lot of cost consumption, limiting the progress and development of the fragrant pear industry (Yu et al., 2018; Ranjan et al., 2019). This paper analyzes the status of image recognition and feature extraction methods of fragrant pear images collected by low-altitude UAV. Using IoT and image detection technologies combined with ViBe algorithm, target recognition and feature extraction of fragrant pear images collected by sensors and low-altitude UAV are carried out. ViBe algorithm determines the change of pear target in the micromotion stage under the growth conditions according to the local pixel complexity of pear image, which can effectively break through the technical barriers caused by background similarity and light condition changes in the feature recognition process of pear target.

The construction process of the ViBe algorithm model involves statistical analysis of pear image pixels. The ViBe algorithm is a background modeling algorithm based on pixel neighborhoods, designed for foreground target detection in images. The algorithm computes the light compensation coefficient based on brightness features. A statistical analysis is performed on the preprocessed image pixels of the pear, selecting the top 5% of pixels based on brightness features for average calculation. The average values of the three primary color pixel features in the color representation are used as brightness information. The algorithm is implemented using Python, as shown in the following code snippet:

```
class ViBe Model:
    def __init__(self, image, num_samples=20, min_match=2, radius=20):
        self.num_samples = num_samples
        self.min_match = min_match
        self.radius = radius
        self.height, self.width = image.shape[:2]
        self.initialize_model(image)
```

The ViBe algorithm is renowned for its efficient real-time performance. In the processing of pear images, the algorithm rapidly conducts background modeling and foreground detection, adapting in real-time to varying lighting conditions and background changes, thereby ensuring timely monitoring of pear growth status.

In this paper, the image recording of fragrant pear during the growing process was carried out using sensor nodes distributed in the orchard and low-altitude UAV. Due to the interference of noise, care, and the performance of shooting equipment, the process of target feature extraction is hindered. Therefore, it is necessary to compensate the light in the image based on the brightness feature. Due to the limitation of the experimental environment, it is difficult to collect the image of fragrant pear fruit in the orchard during practical applications. Thus, this paper demonstrates the algorithm flow based on a collected dataset of fragrant pear images. First, the ViBe algorithm model was used to perform statistical analysis on each preprocessed pixel within the image of the fragrant pear. According to the brightness features, the top 5% of pixels were selected to calculate the average value, denoted as Ave. The average values of the three primary color pixel features in the color representation were used as the brightness information, and the light compensation coefficient was calculated by using Formula (1) (Huang et al., 2018).

$$Coe = 255/Ave \tag{1}$$

After obtaining the light compensation coefficient for the fragrant pear image, each pixel in the fragrant pear image is compensated by using Formula (2) in order to achieve the light compensation effect of the entire fragrant pear image. R^1, G^1, and B^1 represent the values of the three primary color pixels after light compensation. The color features of the target pear can then be more clearly extracted from the image of the pear with light compensation, allowing for the assessment of the pear's growth cycle and growth phase.

$$\begin{aligned} R^1 &= R * Coe \\ G^1 &= G * Coe \\ B^1 &= B * Co \end{aligned} \tag{2}$$

The texture feature of fragrant pear is a visual feature independent of color and brightness, capable of reflecting the homogenous characteristics of its surface. This feature can correlate the surface tissue characteristics of fragrant pear with its surrounding growth environment. In this paper, local ternary patterns (LTP) are used to measure the texture features of fragrant pear images. The calculation process of LTP texture features is shown in Formulae (3) and (4). Due to its unique gray-scale and rotation invariance, LTP has been widely used in texture feature extraction (Gogoi et al., 2018).

$$LTP_{N,R}^{\alpha}(a_v, b_v) = \bigoplus_{k=0}^{N-1} Q_\alpha(j_v, j_k) \tag{3}$$

$$Q_\alpha(j_v, j_k) = \begin{cases} 01, j_k > (1+\alpha)j_v \\ 10, j_k < (1-\alpha)j_v \\ 00, otherswise \end{cases} \tag{4}$$

The local ternary model introduces a floating interval of T size for the central value. In the process of texture feature extraction, when the absolute value of the difference between the neighborhood value and the center value is in the interval $(-T, T)$, it is marked as 0. When the neighborhood value is larger than the threshold value T, it is marked as 1. When the neighborhood value is smaller than the threshold value T, it is marked as –1. This approach enhances the robustness to noise and light changes in the extraction of fragrant pear texture features. In Formulae (3) and (4), α is the comparison range scale factor, a_v, b_v are the spatial domain coordinates, respectively, and j_v, j_k are the pixels in the fragrant pear image. The aforementioned ViBe algorithm process is used to facilitate the recognition and extraction of features from the preprocessed images of fragrant pears. This process enables the operational efficiency of the fragrant pear recognition model based on the IoT and image detection technologies.

The ViBe algorithm model is employed for pixel counting in fragrant pear images, and the light compensation coefficient is calculated through brightness characteristics to achieve the light compensation effect.

Subsequently, the local ternary pattern is used to extract texture features from the fragrant pear images, thereby enhancing sensitivity to surface texture features. This algorithm flow enables the recognition and extraction of features from fragrant pear images, thereby enhancing the operational efficiency of the fragrant pear recognition model based on Internet of Things and image detection technologies.

The algorithm has high complexity, which is mainly manifested in the multiple processing processes of the image, such as light compensation and texture feature extraction, and the detailed implementation of ViBe algorithm. These steps collectively constitute a relatively complex algorithm flow, which provides fine feature processing for the identification and extraction model of fragrant pears based on the Internet of Things and image detection technologies.

4. Results

With the continuous development of social economy, the level of intelligent agricultural production is also improving, and the output and demand of fragrant pears and other agricultural products are increasing year by year, which puts forward higher requirements for the development level of the fragrant pear industry. Most traditional pear identification methods overly rely on experienced staff or experts to manually identify and judge, such a work method in the face of the increasing trend of market demand is inevitably ineffective. While wasting a lot of manpower and material resources, the identification accuracy of fragrant pear is not high. The lack of advanced identification technology and scientific information processing capabilities in the fragrant pear industry is becoming increasingly apparent.

4.1 Preparation and collection of the fragrant pear image dataset

In this paper, the traditional pear identification and extraction method is improved; the highly integrated sensor network and image detection technology are used to collect the image of the pear in the fragrant pear orchard, and the data is transmitted by wireless communication to the cloud platform data center for unified deployment and processing. The ViBe algorithm is used to extract features and cluster attributes from the preprocessed fragrant pear image data, thereby obtaining a decision scheme with more accurate classification. It cannot only meet the task requirements of users to monitor the growth phase of fragrant pear in real time, but also bring industrial guarantee for predicting the trend of fragrant pear growth phase. However, the optimized pear identification and extraction method in this paper needs to be verified by more rigorous experiments.

The application experiment of the pear identification and extraction method was carried out in a fragrant pear orchard. The sensor equipment is situated within the fragrant pear orchard, and the layout process should ensure that each sensor monitoring node is able to communicate wirelessly with at least one group of sensor nodes. The highly integrated sensitive sensors comprise the sensor network, which covers the fragrant pear orchard. The low-altitude area is observed by the UAV, and the image data of the fragrant pear fruit at low-altitude is collected by the camera equipment carried by the UAV. The image data collected by the sensor and the low-altitude UAV are transmitted using wireless communication technology. It is then uniformly deployed by the data storage center of the cloud platform. In order to optimize the implementation of the identification and extraction method for fragrant pear, it is also necessary to preprocess the image data at the data center. Due to limitations of conditions, this paper did not include the steps of data acquisition of pear fruit images by sensors and drones. Instead, the subsequent image preprocessing and processing process were carried out based on the collected pear image dataset. The group using the traditional pear identification extraction method was designated as the control group, while the group using the optimized pear identification extraction method was designated as the experimental group.

4.2 Comparison and verification of the reliability of pear identification and extraction methods

First, the recall rate and accuracy rate of the traditional pear recognition and extraction methods were verified in the control group. In this paper, 100 pear images collected were selected for target recognition and feature extraction, and the recognition results were shown in Table 2.

As shown in Table 2, TP represents the number of correctly identified pear images and correct actual results in the predicted control group; FN represents the number of cases where the predicted control group incorrectly recognized fragrant pear images, but the actual result was correct; FP represents the number of correct identification of fragrant pear images in the predicted control group and

Table 2. Image recognition extraction results of fragrant pear in the control group.

Actual results		Forecast results			
		Correct identification	1	Incorrect identification	0
Correct identification	1	TP (44)		FN (6)	
Incorrect identification	0	FP (15)		TN (35)	

the number of errors in the actual results. TN represents the number of errors in predicting the control group's identification of pear images and the actual results. The recall rate and accuracy rate of the identification and extraction method of pear in the control group can be obtained by calculating Formulae (5) and (6), respectively.

$$R = \frac{TP}{TP+FN} \times 100\% \quad (5)$$

$$P = \frac{TP}{TP+FP} \times 100\% \quad (6)$$

According to Formulae (5) and (6), combined with the data in Table 1, the recall rate and accuracy rate of the traditional pear identification extraction method in the control group were 88% and 74.6%, respectively.

Then, the recall rate and accuracy rate of the optimized pear recognition extraction method in the experimental group were verified. Additionally, 100 pear images selected by the control group were used for target recognition and feature extraction, and the recognition results were shown in Table 3.

According to Formulae (5) and (6), combined with the data in Table 3, the recall rate and accuracy rate of the optimized pear identification extraction method in the experimental group were 96% and 87.3%, respectively.

The recall rate and accuracy rate are the evaluation indexes of the recall and precision levels of the evaluation method model, respectively. This paper optimized the identification and extraction method of fragrant pear based on IoT and image detection technologies. Compared with the traditional pear identification extraction method, the recall rate and accuracy rate of the optimized pear identification extraction method increased by 8% and 12.7%, respectively. Obviously, the optimized pear identification extraction method has more complete identification coverage and higher identification accuracy rate. The optimized identification extraction method, which applies advanced IoT technology and big data analysis, is more reliable in practical applications.

A confusion matrix is an important tool for evaluating the performance of a classification model. By comparing the model's prediction results with the actual observation results, a detailed analysis of the model's performance is provided. The confusion matrix can be used to calculate several performance indexes, such as accuracy, recall, accuracy, and F1 score, in order to evaluate the effectiveness of the classification model more comprehensively. By analyzing the confusion matrix, we can deeply understand the performance of the model across different categories and further optimize the model to improve its overall performance.

4.3 Time comparison experiment of pear recognition

In order to address the significant task of pear recognition and meet the actual needs of users to monitor the growth quality and status trend of pear in real time, it is necessary to compare the duration of pear recognition and extraction methods. In this paper, 20 random pear images were processed using both traditional and optimized pear recognition and extraction methods, and the processing time for each method recorded. During the experiment, the group applying the traditional pear identification and extraction method was designated as the control group, while the group applying the optimized pear identification and extraction method was designated as the experimental group. Figure 9 illustrates the time comparison between the traditional and optimized methods.

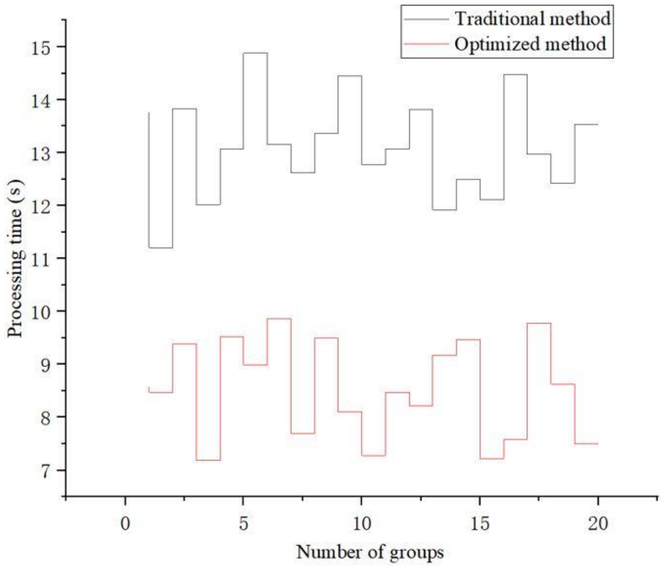
As illustrated in Figure 9A, the X-axis is the number of sample groups in the comparison test, while the Y-axis is the sample processing time of each fragrant pear image data. In Figure 9B, the X-axis is the type of method applied in the experiment, and the Y-axis is the range of time used to apply the method. In the control group, the average processing time of pear image data was 13.10 s. In the experimental group with the optimized pear image recognition extraction method, the average processing time for pear image data was 8.53 s. Compared with the traditional pear image recognition extraction method, the optimized pear image recognition extraction method based on the IoT and image detection technologies takes a shorter time to process the pear image, with an average reduction of 4.57 s. With the rapid development of IoT and image detection technologies, processing image data for big data has become more convenient and faster, and the intelligent development of the fragrant pear industry has been greatly promoted.

4.4 Comparison of predictive effectiveness of pear identification and extraction methods

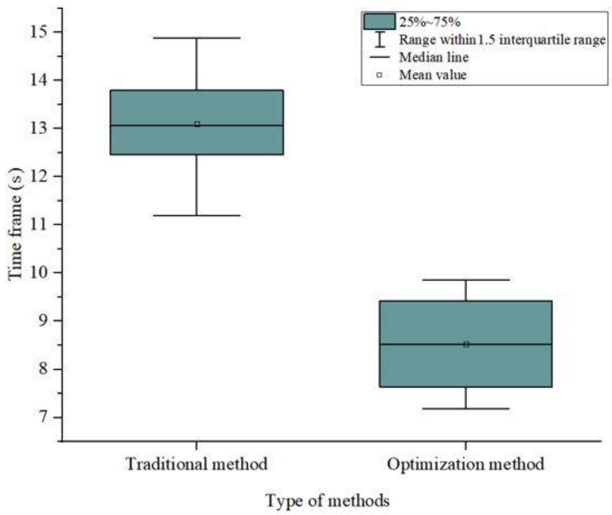
The working structure of the traditional pear identification and extraction method is difficult to complete the real-time monitoring of pear status, which leads to the failure of the traditional pear industry to deal with the sudden risk disaster in a timely and effective manner. How to monitor the status of fragrant pear in real time through advanced

Table 3. Image recognition extraction results of pear in the experimental group.

Actual results		Forecast results			
		Correct identification	1	Incorrect identification	0
Correct identification	1	TP (48)		FN (2)	
Incorrect identification	0	FP (7)		TN (43)	



A. Duration comparison line chart



B. Duration comparison box diagram

Figure 9. Comparison of time between traditional and optimization methods.
A. Duration comparison line chart.
B. Duration comparison box diagram.

information technology has become a research direction in the agricultural field. In this paper, the traditional pear recognition and extraction method was optimized and improved using IoT and image detection technologies. The combination of high-sensitivity sensor network and image detection technology enables comprehensive coverage of fragrant pear orchards, real-time acquisition of fragrant pear images, and computer-based target recognition and feature extraction. The training using a large dataset of pear images enables the optimized pear recognition and extraction method to address the gap in the prediction of pear quality. Therefore, further comparative experiments are needed to verify the predictive effectiveness of the optimized pear recognition and extraction method.

Confusion matrix is an effective method for evaluating the predictive effectiveness of a statistical model. In this paper, 200 fragrant pear image data samples were randomly selected for comparative testing. The predictive effectiveness of traditional and optimized pear identification and extraction methods was compared and analyzed by combining the confusion matrix with experimental data. In the experiment, the pear quality was classified based on the predicted results of the pear image dataset, using six grades from 1 to 6 to indicate quality from low to high. In this paper, the group using the traditional pear identification extraction method was designated as the control group, and the group using the optimized pear identification extraction method was designated as the experimental group. In order to prevent interference from additional factors, 200 randomly sampled pear image datasets were used in both experiments. Figure 10 shows the comparison of predictive effectiveness between traditional and optimized methods.

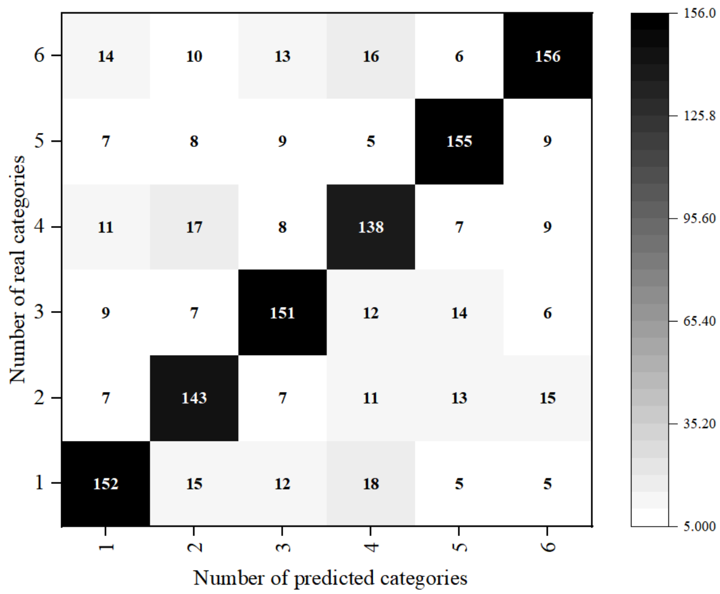
As shown in Figures 10A and 10B, the category quantity statistics of pear quality predicted by their respective recognition and extraction methods are taken as the horizontal coordinate, and the actual category quantity statistics of pear quality are taken as the vertical coordinate. The diagonal line represents the number of samples predicted correctly by the pear recognition extraction method. According to the properties of the confusion matrix, the higher the value of statistical information on the diagonal, the better the predictive effectiveness of this method. The area outside the diagonal represents the value of the prediction error: the smaller the value of statistical information in this area, the better the predictive effectiveness of this method. The value of the statistical information is represented by the color depth, with darker colors representing higher values. From grades 1 to 6, the average value of the diagonal data in the statistical heat map predicted by the optimization method was 171.17. Compared with the traditional method of predicting the average 149.17 from the diagonal data of statistical heat map, it can be found that the predictive effectiveness of the optimized fragrant pear identification and extraction method based on IoT and image detection technologies in this paper is more reliable.

5. Discussion

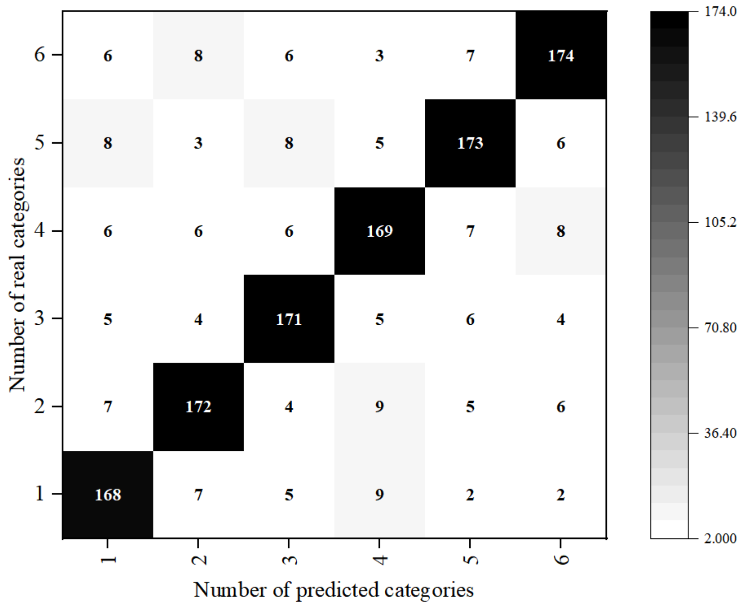
With the development of the economy and continuous advancements in scientific knowledge, the fragrant pear industry is rapidly moving towards mechanization and modernization. In order to enhance the efficiency of phase recognition and condition monitoring tasks during the picking process of fragrant pears and to promote the modernization process of intelligent agriculture, this paper optimized and addressed the shortcomings and limitations of traditional fragrant pear identification and extraction methods based on the IoT and image detection technologies. The feasibility of these optimized methods was verified through the practical application. Due to limitations in ability and experimental environment, the experimental results of this paper have certain limitations. During the actual experiment process, the lack of practical operational experience has led to several issues. Difficulty in gathering comprehensive pear image datasets has resulted in insufficient depth in the algorithm training iteration process. The insufficient coverage of experimental samples diminishes the objectivity and accuracy of the experimental results to a certain extent. Regarding the experimental results, the pear recognition accuracy of the optimized pear recognition extraction method in this paper is insufficient, and the application universality of the ViBe feature extraction algorithm needs to be further studied and improved. The issue of pesticide residue identification in fragrant pear fruit remains unresolved. In the future explorations, more complex auxiliary variables should be added to reflect the characteristics of fragrant pear fruit species recognition and growth state to optimize the identification results, in order to expect higher progress in the field of fragrant pear recognition and extraction. In this paper, the Internet of Things and image detection technologies are introduced into the fragrant pear industry, and the identification of fragrant pears is optimized by ViBe algorithm. It overcomes the shortcomings of traditional methods and improves the predictive effectiveness and production efficiency. However, the robustness of the algorithm and its application in complex environments are not fully discussed. Future research can strengthen the optimization of algorithm performance, explore the application of deep learning, and improve the adaptability to diverse environments.

6. Conclusion

The rapid advancement of science, technology, and agricultural economy has heightened the society's requirements for the quality of agricultural products, and the update and iteration of communication technology has promoted the advancement of the intelligent process within the fragrant pear industry, thereby stimulating its rapid growth. Due to the limited planting environment and growing conditions, the backward production technology of traditional fragrant pear, and the excessive reliance on artificial recognition and judgment, the quality of fragrant pear industry has declined. In order to enrich methods for pear identification and extraction, enhance the efficiency of pear production, improve the task flow of pear identification, and build a more scientific and reasonable working structure, the traditional methods of pear identification and extraction were analyzed. In this paper, the drawbacks of traditional pear identification and extraction methods are thoroughly explored. By studying advanced technologies commonly used in today's fragrant pear industry, the traditional pear identification



A. Heat map statistics of predictive effectiveness of traditional methods.



B. Heat map statistics of predictive effectiveness of optimization method.

Figure 10. Comparison of predictive effectiveness between traditional and optimization methods.
A. Heat map statistics of predictive effectiveness of traditional methods.
B. Heat map statistics of predictive effectiveness of optimization method.

and extraction methods can be tentatively optimized, thereby enhancing the industry awareness and improving technical proficiency. In this paper, the process structure of recognition and extraction method for fragrant pear was improved using IoT and image detection technologies, combined with ViBe algorithm. The reliability of the optimized pear identification extraction method was verified through comparative experiments in actual applications. Compared with the traditional pear identification and extraction method, the optimized pear identification and extraction method in this paper achieves a higher recall rate and accuracy rate, and reduces costs, and improves the production efficiency in the pear industry. It promotes not only the integration and development of advanced technology in the fragrant pear industry but also the intelligent process in the agricultural field.

This paper does not fully discuss the robustness of ViBe algorithm in complex environments, and the resistance to noise still needs to be improved. In the future, we can study and optimize the performance of the algorithm to increase the adaptability to multiillumination and various orchard environments. Additionally, the deep learning method can be considered to improve the accuracy of image recognition, thereby enabling more comprehensive application in agricultural Internet of Things system.

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