Green Plums Surface Defect Detection Based on Deep Learning Methods

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ABSTRACT
Green plums are a characteristic fruit resource in China, with a long history of cultivation. Many surface defects will appear in the growth, transportation and preservation of green plums which seriously affect the processing quality of by-products. The existing manual sorting method of green plums is limited by the experience of workers. It is difficult to ensure the quality and speed of detection. Therefore, the formation of automatic detection of green plums surface defects is of great significance to the development of green plum industry. According to the surface defects of green plums, this paper divides green plums into five categories: rot, cracks, scars, rain spots and normal. A total of 1235 images of green plums were obtained by self-built image acquisition device. The WideResNet50-AdamW-Wce model based on WideResNet model was built to classify the surface defects of green plums. Accuracy, recall and F1-measure were selected as the indexes to evaluate the accuracy of classification. The accuracy of classification reached 98.95%, and the classification accuracy of rain spots, normal, scars, rot and crack reached 100%, 99.56%, 98.59%, 98.25% and 96.10% respectively. Comparing the performance of ResNet50-SGD, WideResNet50-SGD, WideResNet50-SGD-Wce, and WideResNet50-AdamW network models, the F1-Measure based on WideResNet50-AdamW-Wce is the highest in each defect, and more greengage defect features can be learned. The detection results can meet the production needs of plum deep processing enterprises – evaluating 1800 green plums per hour on the assembly line.

INDEX TERMS Green plum, surface defects, defect detection, deep learning.

I. INTRODUCTION
Green plum, also known as plum fruit and sour plum, is a characteristic fruit resource in China. It has been cultivated in China for more than 3,000 years. At present, the main planting areas of green plum include the southeast coast of China, Japan and Southeast Asia [1]. Green plum fruit is rich in vitamins, trace elements, amino acids that are beneficial to human protein composition and metabolic functions, and a variety of high-quality organic acids [2]. Since the early 1990s, with the increasing demand for green plums in Japan and South Korea, a large number of fresh green plums have been exported, and the output of green plums in China has also increased year by year [3]. Green plums are often sold to the market as processed products. Green plum processed products mainly include green plum wine, green plum juice, candied fruit, etc. At the same time, the newly developed green plum health care products such as green plum health lozenges and enzyme plums are also favored by consumers [4].

With the promotion of automatic picking technology, mechanical harvesting can ensure the harvesting efficiency of green plums, but the defective green plums mixed in after mechanical harvesting, as well as the defective green plums that are bumped and rotted during transportation and storage will affect the product quality. The existence of defects will seriously affect the product quality [5]. Before deep processing of green plums, these defective fruits need to be removed or graded in time. Defect classification refers to the process of identifying and processing the surface defect images of green plums. At present, the defect classification of green plums is still dominated by manual detection. This process mainly relies on the experience of operators, so it is highly subjective and inefficient. In addition, long-term operation is prone to
fatigue, which affects the quality of detection. The machine vision detection technology obtains the image of the surface defects of the green plum through the image acquisition device, and then achieves the purpose of defect classification through the selection of the algorithm and parameter adjustment. It has the advantages of high automation and high detection accuracy. Using machine vision technology to detect the surface defects of green plums can greatly improve detection accuracy and detection efficiency.

In recent years, with the development of deep learning technology, scholars at home and abroad have applied deep learning to the non-destructive testing of fruits and obtained better detection results, and hyperspectral technology [6] can simultaneously collect two-dimensional and three-dimensional information about fruits. Abdel salaam et al. [7] proposed a computer vision system for the detection of citrus external defects based on a hyperspectral camera. The overall accuracy of the detection of citrus surface defects reached 95%, which provided a direction for online fruit detection. Huang et al. [8] discriminated tomato maturity based on optical absorption coefficient spectrum and scattering coefficient spectrum, and used the partial least squares method to discriminate a total of 600 tomato samples at six maturity stages. The recognition rate of the established tomato maturity discrimination model reached 85.5%. Liu et al. [9] used hyperspectral imaging technology to identify the defects of hawthorn. The identification rates of single damage, single pest, damage and pest coexisting samples were 95.65%, 86.67%, and 100%, respectively. Huang et al. [10] used hyperspectral imaging technology to detect and discriminate nectarine defects. An extreme learning machine (ELM) model was built using principal component analysis and texture value fusion to detect external defects of nectarine. The discriminant accuracy rates for defective samples and intact samples were 91.67% and 100%, respectively. Jiang et al. [11] built a hyperspectral imaging (HSI) system covered visible and near-infrared (Vis-NIR, 400-1000 nm) range to identify Camellia oleifera fruit with three different natural mildew degrees (slight, moderate, and severe). Tian et al. [12] used a support vector machine to identify the insect-injured area, normal area, fruit stalk and calyx area of apple. The test results showed that the radial basis kernel function was the best for the identification of insect damaged fruit, and the overall identification rate was 97.8%. Pham et al. [13] developed an object rotating hyperspectral imaging system for jujube surface defect detection, which could scan 95% of the jujube surface in one scan. The classification accuracy rates using SVM and ANN models were 97.3% and 97.4%, respectively. The system can be adapted to other round fruits and integrated into the online hyperspectral detection system. Raj et al. [14] proposed a method based on multi-spectral technology to extract features from defects to achieve apple classification, and the average classification accuracy rate for healthy apples, mildly defective apples and severely defective apples was 94.66%. Sun et al. [15] used hyperspectral technology to measure the optical coefficient of peach after injury at different maturity levels. The optical properties showed that tissue damage was earlier than the appearance observed by naked eyes. Huang et al. [16] selected three effective bands for detecting apple damage based on hyperspectral imaging technology. The static and online detection results for minor damage were 91.5% and 74.6%, respectively, realizing the transformation from the hyperspectral research level to the multispectral application level. Unay et al. [17] built a multispectral imaging system for two-color apple grading, and proposed a two-class grading scheme with an overall detection accuracy of 93.5%. Yang et al. [18] made a comparison between the performance of using image classification networks (GoogLeNet and VGGNet) and object detection networks ((Faster R-CNN and YOLOv3) to detect broadleaves and grasses. The research found that the use of VGGNet as the decision-making system for the machine vision subsystem seems to be a viable option for the precise spraying of herbicides in alfalfa.

Domestic and foreign related technical personnel have more research on defect detection algorithm, according to the use of different algorithms will be roughly divided into four categories: defect detection based on statistics, based on frequency domain, based on model, and based on learning, their advantages and disadvantages are shown in Table 1.

Green plums are not big but the samples are numerous, it remains high similarity between different defects on the surface, increasing the difficulty to distinguish varies defects. Traditional machine vision technology requires manual extraction of defect features, which easily leads to incomplete features and affects detection results. The deep learning technology overcomes the shortcomings of manual feature extraction. Deep learning networks can automatically extract defect features from datasets through convolutional layers. In order to meet the needs of some domestic green plums products processing enterprise (Nanjing Longlijia Agricultural Development Co., Ltd. (China)) to dynamically detect 1800 plums per hour, in this paper, the improved WideResNet deep learning model was combined with machine vision technology to perform a multi-index classification of green plum surface defects.

The contribution of this paper are: a) multi-index classification of green plum surface defects; b) a self-designed green plum surface image acquisition device; c) the application of AdamW optimizer and Weighted cross entropy (Wce) loss function in the green plum defect detection network based on WideResNet network, to ensure the network can accurately learn the defect features of green plums and effectively improve the classification performance of the networks.

II. MATERIALS AND METHODS

A. IMAGING

The green plum samples in this paper were purchased from Yunnan, China. The defect features of green plum were divided into rot, cracks, scars, and rain spots. Rain spots and
TABLE 1. Defect detection algorithm classification.

| Types               | Concept                                                                 | Relative merits                                                                 |
|---------------------|-------------------------------------------------------------------------|---------------------------------------------------------------------------------|
| Based on statistics | This method is based on the gray distribution of the image and performs defect detection by extracting the histogram. | Suitable for images with periodic background consistency. a) simple and convenient detection  
b) small amount of calculation  
c) strict constraints on research objects and image capture environments  
d) poor flexibility |
| Based on frequency domain | Based on the time-frequency conversion of image, this method extracts effective information in frequency domain to complete the detection. | Suitable for detecting large area defects  
a) simple principle;  
b) high dependence on filter parameter design;  
c) poor detection of small defects  
Suitable for a variety of occasions.  
a) strong flexibility  
b) detection efficiency affected by model complexity and solving process  
Wide range of use.  
a) good detection effect  
b) high demand for samples  
c) high requirements for equipment large calculation |
| Based on model      | Based on the classification model, the detection is completed by separating the distribution of image points in the model. Such as Gaussian mixture model. |                                                                              |
| Based on learning   | This method is mostly based on machine learning models or neural networks to train effective parameters or dictionaries to complete the detection. |                                                                              |

Cracks were the original defect characteristics of green plums, while rot and scar features were artificially manufactured to ensure the reliability of the samples. Normal green plums are light green, with uniform surface color and smooth skin. Rot is irregular dark brown defects in a small area or a large area, and the rain spots are dark green round defects. Scars and cracks are similar in appearance, both are long-shaped defects, but obvious concave can be seen in the middle of the cracks. The normal green plum is shown in Figure 1a.

The image acquisition device shown in Figure 1b was used to collect pictures. The optical lens used in the image acquisition device was the M1620-MP2 industrial camera lens produced by Computer company (length: 16 mm, minimum object distance: 20 cm, pixel: 5 million). A MER-531-20GC-P industrial camera from Daheng Image Technology company was used, and the camera had an OnsemiPYTHON5000 frame exposure CMOS sensor chip. The light source selected was an LED ring light source. During the image acquisition phase, it was performed in a closed lighting environment. During the shooting process, the rotating table rotated to obtain multi-angle surface images of green plums.

The collected green plum samples were divided into five categories based on surface defects: rot, rain spots, scars, cracks and normal. Among them, there were 395 rot defect samples, 392 rain spot defect samples, 142 scar defect samples, 80 crack defect samples and 226 normal samples, totaling 1235 images.

B. PREPROCESSING IMAGES

The original collected green plum surface defect pictures were $2592 \times 2048$ pixels. In order to ensure the image processing efficiency and keep the green plum image as undistorted as possible, it was necessary to perform image pre-processing on the original green plum defect image. The main purpose of image preprocessing was to eliminate irrelevant information in images, restore useful real information, enhance the detectability of relevant information and simplify data to the greatest extent, standardized the images, thereby improving the reliability of feature extraction, image segmentation, matching and recognition. Common image enhancement methods include: histogram equalization, Gaussian filtering, etc. Finlayson et al. [19] proposed a new color invariant image representation based on an existing grey-scale image enhancement technique: histogram equalization. It showed that the method out performs all previous invariant
representations, giving close to perfect illumination invariance and very good performance across a change in device. In this paper, the original images were Gaussian filtered with an $11 \times 11$ convolution kernel, converted into a grayscale image, binarized with an adaptive threshold, filtered with Laplacian, and extracted with a canny operator to obtain the minimum outer rectangle of the edge. The image size was cut and finally adjusted to $224 \times 224$ pixels for testing. The image preprocessing flow was shown in figure 2.

### C. DATASET

Before the experiment, a total of 1235 images of rot, rain spots, scars, cracks and normal green plums were collected. After dividing the training set, test set, and verification set according to the ratio of 8:1:1, the images were enhanced to ten times of the original data by mirroring and rotating every 45°. After image expansion, a total of 12350 green plums defect samples were obtained. The distribution of the data set types after image enhancement is shown in Table 2.

### D. NETURAL NETWORK ARCHITECTURE

1) WIDERESNET

With the introduction of PyramidNet and ResNet, scholars tend to design deeper and thinner convolutional neural networks, because a deeper network can enhance the feature fitting ability of the network, and a thinner network can reduce the amount of parameters of the network, reducing the computational cost. However, Sergey et al. [20] did the opposite and proposed Wide ResNet in 2017. As the name suggests, this network structure widens the number of channels of ResNet, and breaks the mainstream neural network design concept.

Although ResNet can be used to alleviate gradient vanishing by adding skip connections, it is still possible that gradients only pass through skip layers during backpropagation without updating parameters. In order to solve this problem, the structure shown in Figure 3 is used to widen the number of channels of each convolutional layer, and reduce the depth of the network. In addition, due to the increase in the number of parameters, the network can achieve a better fitting ability.

**TABLE 2. Distribution of dataset.**

|                  | Rot | Spot | Scar | Crack | Normal |
|------------------|-----|------|------|-------|--------|
| Original Dataset | 395 | 392  | 142  | 80    | 226    |
| Augmented Dataset| 3950| 3920 | 1420 | 800   | 2260   |
| Training Dataset | 3160| 3136 | 1136 | 640   | 1808   |
| Test Dataset     | 395 | 392  | 142  | 80    | 226    |
| Validation Dataset| 395 | 392  | 142  | 80    | 226    |

**FIGURE 2.** Image preprocessing flow chart.

**FIGURE 3.** Schematic diagram of Wide ResNet network structure: (a) Basic widening; (b) Widening with dropout.
of channels, redundant feature maps will inevitably appear in each layer, so the occurrence of the Dropout layer method is additionally added to avoid overfitting. Through this network architecture, Wide ResNet can achieve the accuracy achieved by the 1000-layer ResNet with only 16 layers, and greatly shortens the training time.

2) AdamW LOSS FUNCTION WIDERESNET

AdamW optimization algorithm is optimized on the basis of Adam optimization algorithm. Since the emergence of the Adam optimization algorithm in 2014, it has been widely used in deep learning models such as image classification and scene recognition. Experiments found that Adam optimization algorithm has certain convergence problems, such as slow model convergence and non-convergence. And in some models, the experimental results are not as good as the effect of SGD plus Momentum algorithm. Subsequently, various improved versions of Adam appeared. Among them, the AdamW optimization algorithm added a regular term to the Adam loss function, calculated the gradient of the overall loss function to update the parameters, greatly improved the training speed and reduced overfitting. Therefore, this paper selected the AdamW optimization algorithm to train the green plum defect classification model. Different parameters in the AdamW optimization algorithm adaptively learn at different learning rates [21], as shown in formulas (1) and (2)

\[ m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \]  
\[ v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \]

where \( g_t \) is the gradient, \( m_t \) is the first moment of the gradient, \( v_t \) is the second moment of the gradient, \( \beta_1 \) is the decay factor of the first moment, and \( \beta_2 \) is the decay factor of the second moment. When the \( m_t \) and \( v_t \) values approach the 0 vector, the result will be biased. In order to solve this problem, the bias of the first-order moment and the second-order moment is corrected, as shown in formulas (3) and (4):

\[ \hat{m}_t = m_t / (1 - \beta_1^t) \]  
\[ \hat{v}_t = v_t / (1 - \beta_2^t) \]

AdamW optimization algorithm adds a regular term to the loss function of Adam optimization algorithm, and updates the parameters when updating the model parameters by calculating the gradient of the overall loss function with the regular term. Therefore, AdamW optimization algorithm has a faster training speed and can effectively prevent the overfitting problem during the training process. The loss function with the regular term of AdamW is shown in formula (5):

\[ L = \text{loss} + \frac{1}{2} \| \theta \|^2 \]  

The formula for AdamW parameter update is shown in formula (6):

\[ \theta_t = \theta_{t-1} - \eta \left( \alpha \hat{m}_t / \sqrt{\hat{v}_t} + \zeta \right) + \omega \theta_{t-1} \]

where \( \theta \) is the parameter, \( \eta \) is the learning rate, \( \alpha \) value is 0.001, \( \zeta \) value is \( 10^{-8} \), and \( \omega \) is a real number.

Since AdamW optimization algorithm adds a regular term to the loss function of the Adam optimization algorithm, the overall convergence speed of the model is faster, and the overfitting is reduced. AdamW algorithm can also correct slow convergence speed, large loss function fluctuation and disappearance of learning rate in other optimization algorithms.

3) WEIGHTED CROSS ENTROPY LOSS FUNCTION WIDERESNET

Each sample will output an N-dimensional array through the softmax layer after the feature extraction of the complex network. Each dimension in the array corresponds to a different defect category, that is, the N classification problem, which can be expressed as formula (7):

\[ O = \begin{bmatrix} P(y = 1 | x; W_1, b_1) \\ P(y = 2 | x; W_2, b_2) \\ \vdots \\ P(y = N | x; W_N, b_N) \end{bmatrix} = \frac{1}{\sum_N} \begin{bmatrix} \exp(W_1 x + b_1) \\ \exp(W_2 x + b_2) \\ \vdots \\ \exp(W_N x + b_N) \end{bmatrix} \]

where \( O \) is the final output of the network; \( P(\cdot) \) is the matching probability between the output result and the corresponding category; \( n \) is the different defect categories; \( W_n \) and \( b_n \) are the weight matrix and bias of each category respectively; \( \exp(\cdot) \) is the exponential function.

The network uses the cross-entropy loss function to determine the gap between the actual output and the expectation, giving each sample an equivalent error loss. However, in the actual classification of green plum defects, different defects show an unbalanced distribution. In order to obtain excellent classification performance, the neural network model often ignores samples of few categories and focuses on most categories, resulting in high overall accuracy but the low accuracy of few categories samples. Therefore, in order to solve the difficulty of classification of unbalanced sample defect categories, the Weighted cross entropy Loss(WceLoss) function adds corresponding penalty coefficients to the error losses of different categories on the basis of the original loss function, and realizes the weighted average loss of different categories of errors. The penalty coefficient can be set according to the balance between different categories, which can be expressed as:

\[ c_n = \frac{\text{mean} \{ a_n \}^N_{i=1}}{a_n} \]

\[ a_n = \sum_{i=1}^{Q} 1 (y_i = n) \]

where \( c_n \) is the penalty coefficient; \( a_n \) is the number of different categories of samples; \( \text{mean} \{ \cdot \}^N_{i=1} \) represents the median of the number of N kinds of classification samples. \( Q \) is the total number of samples; \( 1 (\cdot) \) is the discriminant function, which is 1 when the parentheses are established, and
In order to better evaluate the accuracy of the network model, we set the parameters of the green plum defect classification network: batch size was set to 64, the initial learning rate was 0.001, the weight decay rate was 0.01, and the SWA learning rate was 0.05. After the parameters were set, the training set green plum data was imported into the network and trained until the loss reached the minimum value and remained stable for 20 epochs, which also meant that the green plum defect classification network model training was completed.

### A. RESULTS OF GREEN PLUM DEFECT DETECTION

In order to better evaluate the accuracy of the network model for the classification of green plum defects, the precision and recall rate were used to evaluate the classification accuracy.

The precision rate is the proportion of the number of samples (TP) that are correctly predicted as positive by the network model to the total number of samples that are predicted to be positive (TP and FP). For example, the precision of rain spot sample prediction refers to the proportion of green plums that are correctly classified as rain spot defects to all the rain spot defects. The recall rate is the proportion of the number of samples (TP) that are correctly predicted as positive by the network model to the total number of samples that are actually positive (TP and FN). For example, the recall rate of rain spot sample prediction refers to the proportion of rain spot defects that are correctly classified as rain spot defects to the actual rain spot defects. The accuracy rate is the ratio of the number of correctly predicted samples (TP+TN) to the total number of samples (TP+TN+FP+FN). That is, the proportion of the correct samples for all five types of defects to be predicted in the total samples.

The test set green plum data was imported into the trained green plum defect classification network model, and the test results were obtained after 30 trails, as shown in Table 4.

It can be seen that the accuracy rate of the WideResNet50-AdamW-Wce network for the classification of green plum surface defects reaches 98.95%, of which the classification precision of rain spots is the highest, reaching 100.00%. Followed by the classification precision of normal green plums is 99.56%, the classification precision of scars is 98.59%, the classification precision for rot is 98.25%, and the classification precision for cracks is 96.10%.

The confusion matrix obtained by the WideResNet50-AdamW-Wce network is shown in Figure 4. In the test set, 140 of the 142 scar green plum images were correctly classified, 1 image was misclassified as rot, and 1 image was misclassified as crack. 393 of the 395 rot green plum images were correctly classified and 2 images were misclassified as cracks. All 226 intact green plum images were correctly classified, 74 of the 80 crack green plums images were correctly classified, 1 image was misclassified as scar, and 5 images were misclassified as rot. 389 of the 392 rain spot green plum images were correctly classified, 1 image was misclassified...
FIGURE 5. Results of the test.

as scar, 1 image was misclassified as rot, and 1 image was misclassified as normal green plum.

From the confusion matrix in Figure 4, it can be seen that rot and cracks have more misclassification results. Figure 5 shows part of the predicted results of the test set, with the colored boxes selected as part of the test results that were misjudged as rot and cracks.

In Figure 5, scars in the red box were misclassified as rot, cracks in the yellow box were misclassified as rot, and rain spots in the orange box were misclassified as rot.

The reasons for the misclassification were analyzed. The main reason why scar defects were easily classified as rot might be the coexistence of rot and scar, and the scar and rot were irregular in shape and similar in color. The main reason why crack defects were easily classified as rot was that some scars and rots are similar to cracks in shape and color.

B. COMPARISONS OF DIFFERENT NETWORK MODELS

In order to further verify the performance of the green plum defect classification network, the WideResNet50-AdamW-Wce network was compared with ResNet50-SGD, WideResNet50-SGD, WideResNet50-SGD-Wce and WideResNet50-AdamW network respectively in terms of model performance. The accuracy, precision and average testing time of various defect classifications were used as performance comparison indicators.

The green plum defect classification network built in this paper was improved on the basis of the WideResNet50-SGD network. Therefore, in order to verify the classification performance of the model, the green plum data used for the WideResNet50-AdamW-Wce network test was imported into the WideResNet50-SGD network for testing. The momentum was set to 0.9, the learning rate was set to 1e^{-4}, and the batch size was set to 64. The model performance of the WideResNet50-AdamW-Wce network and the WideResNet50-SGD network were compared in the loss curve graph and classification performance respectively. The
The loss curve graph is shown in Figure 6. The test results are shown in Table 5.

In the loss curve graph, the red curve in figure 6a is the training loss of the WideResNet50-AdamW-Wce network, and the green curve is the training loss of the WideResNet50-AdamW network. The blue curve in figure 6b is the training loss of the WideResNet50-AdamW network, and the green curve is the training loss of the WideResNet50-SGD network.

In Figure 6a, the WideResNet50-AdamW-Wce network and the WideResNet50-AdamW network were compared and analyzed. Since WideResNet50-AdamW-Wce had a weighted cross-entropy loss function, the loss value at the beginning of training was larger than the WideResNet50-AdamW network, and the loss value at the end of training was smaller than the WideResNet50-AdamW network. This was mainly because the addition of Wce balances the gap between the number of training samples. At the same time, it can be seen from Table 4 that the classification accuracy of the WideResNet50-AdamW-Wce network and the WideResNet50-AdamW network was close, but the latter had individual defect categories that were less accurate. This showed that the use of WceLoss function can balance the classification accuracy of the model better than CELoss (Cross Entropy Loss) function.

In Figure 6b, the WideResNet50-AdamW network and the WideResNet50-SGD network were compared and analyzed. The loss value of the former tended to be stable after 50 epochs of training iterations, and the loss value of the latter tended to be stable after 50 epochs of training iterations. It could be seen from the loss graph that the network using the AdamW optimizer converged faster. This showed that the use of the AdamW optimizer could achieve a good convergence effect while reducing the loss value faster during the training process.

From the test results in Table 5, it can be seen that the WideResNet50-AdamW-Wce network had good performance in each defect classification, and could identify and distinguish the main characteristics of each defect. The four contrasting convolutional neural networks did not all achieve high classification accuracy after training. When the main features were not correctly identified, misjudgment occurred, and the difference between different convolutional neural network structures and network parameters would affect the identification and differentiation of the main features. Therefore, the WideResNet50-AdamW-Wce network built in this paper was optimized on the basis of the WideResNet50 network. It can be seen from Table 5 that the accuracy of the WideResNet50-AdamW-Wce network for the classification of green plum surface defects reaches 98.95%. Compared with the WideResNet50 network, the classification accuracy of the former was increased by 2.77%. The WideResNet50-AdamW-Wce network had a certain improvement in the defect classification accuracy of rot, rain spot, scar, crack and normal green plums. Compared with the WideResNet50-SGD network, the precision rates were improved by 4.75%, 2.54%, 1.33%, 11.04% and 1.58% respectively. Among them, the classification precision of cracks has the highest
improvement rate, indicating that the use of AdamW optimizer and Wce loss function can increase the gap between different categories while narrowing the gap between the same category, thus helping CNNs learn more distinguishing features and improving the feature discrimination rate and classification accuracy.

Since the number of samples for various defects is different, F1-Measure is used to establish a balance between precision and recall. The formula for F1-Measure is:

$$F1\text{-Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The larger the value of F1-Measure, the better the classification performance of the model. The precision rate, recall rate and F1-Measure were used to judge the classification performance of ResNet50-SGD, WideResNet50-SGD, WideResNet50-SGD-Wce, WideResNet50-AdamW-Wce and WideResNet50-AdamW network model. The precision rate, recall rate, and F1-Measure of green plum surface defects are shown in Table 6, Table 7, Table 8 respectively.

It can be seen from, Table 6, Table 7, and Table 8 that the WideResNet50-AdamW-Wce network is the best in the evaluation performance. The F1-Measure value of the WideResNet50-AdamW-Wce network in the classification of scar, rot, normal, and rain spot is the highest among the five networks listed. Its crack F1-Measure value is second only to the crack F1-Measure value of WideResNet50-AdamW and its F1-Measure value for each defect is higher than the corresponding values of WideResNet50-SGD-Wce, WideResNet50-SGD, and ResNet50-SGD network. In terms of single defect classification effect, the F1-Measure value of WideResNet50-AdamW-Wce network for spot classification is 0.9961, indicating that WideResNet50-AdamW-Wce network model has the best defect classification performance. The proposed Resnet network provides a new direction for solving the problems of gradient disappearance, gradient explosion and degradation caused by the deepening of convolution layer and pooling layer. Comprehensive analysis, based on the WideResNet50 model, the WideResNet50-AdamW-Wce model proposed in this study has the advantage of using a 3×3 small convolution kernel, which can identify richer features and increase feature discrimination. The parameters were normalized by BN to reduce the occurrence of excessive changes in parameters due to the different amount of surface defect data of different plums. In order to reduce the false detection problem caused by the high similarity between rot and other defects, the WceLoss loss function can be used to improve the discrimination of features, thereby improving the classification accuracy. The data set composed of 12350 green plum surface defect images obtained after data enhancement has a large amount of data. Using AdamW optimizer, it can achieve good convergence effect quickly and smoothly. Compared with ResNet50-SGD, WideResNet50-SGD, WideResNet50-SGD-Wce and WideResNet50-AdamW-Wce network models, WideResNet50-AdamW-Wce model sacrifices some test time, but the recognition accuracy of the four defects of plum has been improved, which can fully meet the detection efficiency requirements of enterprises. WideResNet50-AdamW-Wce network learns more about greengage defect features.
IV. CONCLUSION

The traditional machine vision technology generally extracts features manually, which leads to incomplete features and has a great impact on the detection results. The accuracy of defect recognition cannot be guaranteed, and the deep learning network automatically extracts defect features from the data set through the convolutional layer to avoid this problem. Due to the small size of green plums, the four defects of rot, crack, scar and rain spot are not large and have certain similarities. For example, some scars are formed by air drying at the decay position, and the two coexist. The shape of the defect is irregular and the color is similar. Due to oxidation of cracks caused by external force cutting, the color of defect surface is similar to rot; rain spots are similar in shape and color to rotting pits. These similarities would cause false detection.

In addition, the images and data of green plums surface defects collected in the experiment are numerous after data enhancement. It is difficult for traditional methods to complete the detection requirements with high efficiency and high quality, so it is necessary to use the deep learning network model. With the emergence of deep learning network models, ResNet, DenseNet, ResNeXt, WideResNet and other network models have their own advantages and disadvantages in processing images. In order to meet the requirements of dynamic detection of 1800 green plums per hour in green plum processing enterprises, this paper uses the self-designed image acquisition device to collect the surface images of green plums according to the requirements of grading and classifying green plums according to surface defects. Aiming at the problem that there were many defects on the green plum surface and they were difficult to correctly identify and classify, based on WideResNet50, the AdamW optimizer and WceLoss function were applied to the green plum defect classification network to establish the WideResNet50-AdamW-Wce model. The network achieved effective classification of green plum surface defects, and the classification accuracy reached 98.95%. The classification accuracy rate of rain spots was the highest, reaching 100.00%, followed by the classification accuracy rate of intact green plums was 99.56%, the classification accuracy rate of scars was 98.59%, and the classification accuracy rate of rot was 98.25%. The lowest classification accuracy rate was crack, which was 96.10%. The recognition rate of crack was low, which may be due to the small sample size of scar and crack data.

The established network is compared with ResNet50-SGD, WideResNet50-SGD, WideResNet50-SGD-Wce and WideResNet50-AdamW networks for precision, recall and F1-Measure values. The WideResNet50-AdamW-Wce network has the highest F1-Measure of each defect and can learn more greenengage defect features. The superiority of WideResNet50-AdamW-Wce network in defect classification performance over other network methods is verified, and the blank of automatic defect detection method of greenengage is made up. Although not the fastest at detecting a single plum surface defect, only 103ms, it is enough to meet the 1800 per hour requirement.

Based on the static classification of green plums surface defects, this paper completed the construction of the WideResNet-based green plum surface defect classification model WideResNet50-AdamW-Wce, and obtained a better surface defect classification result. Under dynamic conditions, it can meet the requirements of enterprises to detect 1800 pieces per hour. In the subsequent research, multi-view vision technology should be considered to obtain the full surface image of green plum. The three-dimensional model of green plum can be obtained by three-dimensional modeling, which can reduce the influence of curvature change caused by three-dimensional entity dimensionality reduction into two-dimensional image on surface defect characteristics.

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