Intelligent Discrimination of Fruit Variety Quality Based on Bp Neural Network

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Abstract. In recent years, thanks to the development of computer vision technology and digital image technology, traditional agriculture and information technology have been deeply integrated. This study uses image recognition and bp neural network technology to identify the types of fruits and selects apples as objects for quality evaluation. First, 150 images of apples, bananas, peaches, avocados, and cherries were selected from the fruit database Fruit360 after grayscale processing as a data set. After the images were grayscaled, image denoising, edge detection, and other feature processing in MATLAB, The classification of five kinds of fruits has been successfully realized, and the correct rate of evaluation reached 94.8%. Then divide the data sets for apples of different varieties and qualities, and input them into the bp neural network for training. After testing, the 6-layer bp network has the highest accuracy rate, and can effectively classify and score apple images.

Keywords: BP neural network; Image recognition; Fruit quality evaluation.

1. Introduction

As people pay more attention to health, the consumption of fruit is increasing year by year. At present, the mainstream method of fruit identification in the market is manual selection. In recent years, computer vision technology and digital image processing technology have achieved rapid development. Traditional agriculture and The deep integration of information technology and the use of fruit automatic identification technology play a very important role in improving the efficiency of fruit picking, trading and other processing links [1]. At the same time, traditional fruit quality evaluation methods mainly rely on manual judgment, which has problems such as inaccurate evaluation and low efficiency. In order to solve these problems, apple quality evaluation methods based on technologies such as image recognition and machine learning have emerged in recent years. Among them, the fruit quality evaluation method based on BP neural network has high accuracy and stability and has broad application prospects in the fields of agricultural production and fruit quality monitoring [2].

Aiming at the above problems, this paper studies the method of pattern recognition in image processing. Taking 5 kinds of fruit images as the research object, the 5 kinds of fruit are preprocessed and the effective features of various fruit images are extracted to provide an accurate and stable solution for fruit image recognition. At the same time, the quality judgment was carried out for apples, and the influence of factors such as apple size, shape, and surface defects on apple quality was discussed in detail, and corresponding mathematical models were established for these factors. Then the data set was divided for different types and different qualities of apples, and the data set was trained by BP neural network. Finally, the apple image to be predicted is tested and compared with the SVM algorithm, which shows the effectiveness of our working mathematical model and the accuracy of the algorithm. At the same time, this paper also discusses the optimization strategy and application prospect of this method, which provides important reference and references for the research and practice in the field of fruit identification and quality evaluation.

2. Mathematical Model of Fruits

During the collection process of the fruit mathematical model image, it will be affected by the collection environment and collection equipment, and the image data will often be affected by some interference information. Therefore, before extracting the feature parameters of the image, the image should be preprocessed, the purpose is to divide the effective and interference information in the image and eliminate the interference information in the image. The main technical process is shown in Figure 1. Five kinds of fruit images on the fruits360 data set on Kaggle were selected as the research objects, and the images were pre-processed for noise reduction, and smoothing filtering was used to reduce the noise of the images. The image noise is suppressed and removed on the basis of [3].

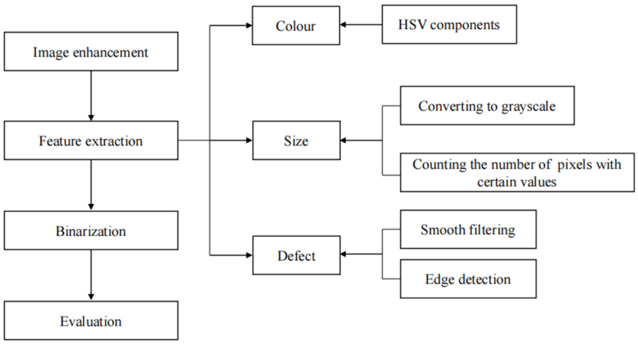

Fig.1 Recognition technology roadmap

3. Mathematical Model of Fruit Image Features

3.1 Color Characteristics

Most fruits have subtle or obvious differences in color characteristics. Color is one of the important parameters to evaluate the quality of fruits. It can be measured through the hue (Hue), saturation (Saturation), and brightness in the image color space model (Value), and other parameters are evaluated. First, convert the fruit image into the HSV color space model. The HSV color space model can describe colors through three parameters: hue (Hue), saturation (Saturation), and brightness (Value). The mathematical formula for color calculation is as follows:

$$C = \left(1 - \frac{\sum H}{360}\right) \times \frac{\sum S}{n} \times \frac{\sum V}{n} \tag{1}$$

where n is the number of color pixels in the image, and $\sum H$, $\sum S$ and $\sum V$ represent the sum of the hue, saturation, and lightness values of a pixel. $1-\frac{\sum H}{360}$ the formula is used to calculate the distribution of fruit color on the color wheel, $\frac{\sum S}{n}$ is used to calculate the average saturation of fruit color, and $\frac{\sum V}{n}$ is used to calculate the average brightness of fruit color.

3.2 Size and Shape

Assuming that the fruit size and shape score is composed of size score S and shape score T, which can be calculated according to the following formula:

$$S = \frac{V}{\left(L \times W \times H\right)} \tag{2}$$

Where L, W, and H represent the length and width of the fruit respectively, and height; V represents the volume of the fruit. The size score S in the formula indicates the compactness of the fruit, and the tighter the apple, the higher the score.

3.3 Fruit Surface Defects

It is assumed that the fruit surface defects score is composed of size score S and shape scoreT, which can be calculated according to the following formula:

$$\begin{aligned} T &= \frac{W}{L}\times\frac{H}{L} \\ D &= T\times\left(1-\frac{N}{A}\right)\times 100\% \end{aligned} \tag{3}$$

Among them, A represents the total surface area of the fruit, N represents the sum of the defect area of the fruit surface; L, W, and H represent the length, width, and height of the fruit, respectively. The size score D in the formula indicates the severity of fruit surface defects, and the fewer fruit surface defects, the higher the score; the shape score T indicates the regularity of fruit surface defects, and the more regular the fruit surface defect shape, the higher the score.

4. Experiment on Fruit Discrimination

4.1 Result of Fruit Recognition Experiment

Read the collected raw RGB color images into the computer and then grayscale them. Use the function (imadjust) provided by the Matlab system to adjust the grayscale range of Grayscale to adjust its grayscale. For different images, select appropriate parameters according to the actual situation, highlight the useful parts of the image, and facilitate the analysis of subsequent image features. After experimental testing, the adjusted grayscale image was binarized to achieve better results, retaining more details of the original image.

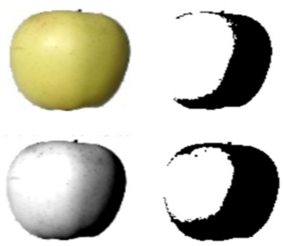

Fig.2 Comparison of binarization results of adjusting grayscale images

This article will collect 5 sets of fruit images and conduct experiments according to the process in Figure 2. A test set of 5 sets of fruit images was used for model testing, with 1,2,3,4,5 representing the types of peaches, bananas, avocados, apples, and cherries, respectively.

Fig.3 Fruit recognition results

The test results of the experiment are shown in Table 1. Multiple tests were conducted to distinguish fruits from multiple angles. A total of 50 tests were conducted for each group of fruit varieties. The specific data is shown in the table below. It was found that the BP neural network classification model has high accuracy in classifying fruits. The discrimination of special shapes such as bananas can reach 100%, while for fruits with slightly similar shapes such as apples and peaches, there may be differences in shooting lighting, leading to the similarity in binary images and reducing accuracy.

Table.1 Fruit Discrimination Test Results

Fruit Variety	Number of tests	Number of correct results	Recognition rate
Avocado fruit	50	49	98%
Apple	50	48	96%
Peach	50	45	90%
Cherry	50	45	90%
Banana	50	50	100%

5. Apple Quality Evaluation Experiment

5.1 Design of BP Neural Network Detection Scheme

In order to accurately identify targets, it is necessary to use a large number of data samples to repeatedly train the BP neural network, including training inputs and expected outputs. The training input refers to certain feature quantities of the collected image, while the expected output is the corresponding code of the image, which is the recognition result. The main process of target recognition based on the BP neural network is as follows [4].

Build neural network model: build a multi-layer Feedforward neural network model, in which the input layer contains apple size, shape, surface defects, and other parameters, and the hidden layer and output layer contain the evaluation results of apple quality.

Data preprocessing: For the selected apple sample data, preprocessing and feature extraction are carried out to convert it into the input format of the neural network, and the data is normalized to improve the training effect of the neural network.

Training neural network: use the Backpropagation to optimize the weights in the neural network, so that the output results of the neural network can approximate the real labels of the training data.

Testing and evaluation: Use the trained neural network model to predict new apple samples, and compare the predicted results with real labels to evaluate the predictive performance and accuracy of the neural network.

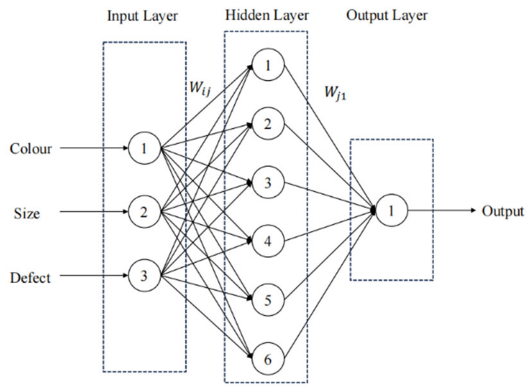

Fig.4 Structure diagram of BP neural network

5.2 Feature Data Extraction

In order to ensure the effectiveness of the results, image processing is crucial for extracting shape features and plumpness feature data. The collected images have undergone steps such as graying, image denoising, edge detection, and boundary fitting. Firstly, the program reads the Apple HSV format color image, counts the number of pixels in each component, and obtains the color feature values. Then use imageJ to extract the edge computing the size and volume, and get the size characteristic value. When making surface defect degree statistics for apples, the idea of detecting wrinkles on apples is to use the edge function and edge operator to mark the defect area and the outer contour of apples. After graying and binarizing the apple image, the defect degree feature values are obtained. The results of the three eigenvalues are shown in Table 2. Normalize and weight the three eigenvalues as the total score of an apple.

The number of input layer neurons is determined by the dimensionality of the feature parameters. They are color features, shape features, and surface defect degree, which are combined to form feature vectors. The output layer adopts a node that takes the total quality score of apples as the output layer of the BP network. Generally speaking, the more nodes in the hidden layer, the more accurately the network can approximate a given function. The approximate relationship between the number of neurons q in the hidden layer and the number of neurons M in the input layer is q=2M+1. Therefore, it is determined that there are a total of 7 nodes in the hidden layer, and the BP structure is 3-7-1.

Table 2 Apple image feature values

Group	Color	Size	Defect	Group	Color	Size	Defect
1-1	-0.91	7.45	0.67	10-2	-1.21	8.26	1.38
1-2	-1.00	8.33	0.58	11-1	-0.60	7.25	1.57
2-1	-1.06	7.69	0.56	11-2	-1.07	9.4	1.57
2-2	-0.88	8.4	0.49	12-1	-0.65	7.39	1.47
3-1	-1.11	6.26	0.83	12-2	-0.79	9.46	1.47
3-2	-0.93	7.94	0.82	13-1	-0.76	8.76	0.92
4-1	-1.09	6.32	1.02	13-2	-0.71	7.94	0.92
4-2	-0.81	7.46	1.01	14-1	-0.54	8.03	0.66
5-1	-0.92	6.92	0.68	14-2	-0.77	9.21	0.66
5-2	-0.95	6.26	0.67	15-1	-0.35	7.35	1.10
6-1	-0.91	8.47	0.71	15-2	-0.62	8.62	1.10
6-2	-0.94	9.02	0.70	16-1	-0.53	7.47	1.11
7-1	-0.84	8.81	0.85	16-2	-0.59	8.45	1.11
7-2	-0.82	9.13	0.85	17-1	-4.78	7.39	0.79
8-1	-0.84	8.25	0.84	17-2	-1.07	7.05	0.80
8-2	-0.84	8.92	0.88	18-1	-1.20	8.24	0.81
9-1	-0.98	7.54	1.39	18-2	-1.09	8.87	0.76
9-2	-1.07	8.93	1.39	19-1	-2.17	8.4	1.24
10-1	-0.78	8.32	1.38	19-2	-2.20	8.91	1.27

Firstly, the program reads the Apple HSV format color image, counts the number of pixels in each component, and obtains the color feature values. Then imageJ is used to extract the edge of the fruit color block to calculate the size and volume. When making statistics on the surface defect of apples, the idea of detecting the wrinkles on apples is to use the edge function and edge operator to mark the defect area and the outer contour of apples. The wrinkles formed on the surface of apples due to water loss are often narrow and elongated, and the marking of defect edges can be approximated as the marking of the entire defect area.

Among the commonly used edge detection operators, the Sobel operator usually performs well in processing images with grayscale gradients and high noise levels. The edges extracted by the Canny operator are relatively complete and have good continuity, mainly because it performs "non maximum suppression" and morphological connection operations. After comparing the processing effects with other operators, it was decided to use the Sobel operator to mark the surface wrinkles of the apple, and the canny operator to detect the outer contour of the apple.

Using image segmentation to detect speckled defects. Combining the apple Grayscale and gray distribution, observe the gray range of the main distribution of defects, and count the number of pixels within this range, which is approximately the defect area.

Fig.5 Sobel operator and Canny operator labeling result graph

5.3 BP Neural Network Training Results

To evaluate the comprehensive quality of apples, a comprehensive evaluation model for apple quality was established to obtain the comprehensive score of apples. In this study, a BP neural network algorithm was used to construct a learning model for apple samples. The input layer was the apple feature index, the output layer was the comprehensive score of apples, and the remaining three samples were validation samples to evaluate the predictive accuracy of the learning model.

In the article, a BP neural network is used to construct a classifier for sorting apple shape types. Compared with single-layer feedforward networks, multi-layer networks are easier to achieve learning objectives when achieving the same error target, and are more adaptable to the invariance of translation, rotation, or other transformations when dealing with problems in the field of pattern recognition. However, due to the presence of a large number of neural nodes and connection weights, more adjustments and calculations are required, resulting in high computational complexity and susceptibility to falling into local minima.

The number of input layer neurons is determined by the dimensionality of the feature parameters. Color features are represented by three eigenvalues, shape features are represented by one eigenvalue, and surface defect degree features are represented by two eigenvalues. The three features are combined to form a feature vector. The output layer adopts one node. Generally speaking, the more nodes in the hidden layer, the more accurately the network can approximate a given function. However, when the number of neurons in the hidden layer increases to a certain extent, the computational complexity increases, the Rate of convergence of network training will decrease, and the generalization ability of the network will become worse. Therefore, it is necessary to reasonably select the number of hidden layer units according to the scale of the problem. According to the empirical formula, the number of nodes in the hidden layer is 6, the system sets the training step size as 1000, and displays once every 10 steps. The target value of network training is 0.001, and the Learning rate is 0.01. The trainlm function is used as the training network.

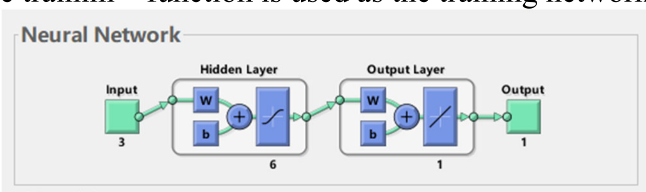

Fig.6 Identification network diagram

The feature values of apple images obtained through detection are encapsulated in a matrix format to generate a sample library as training recognition data. The training recognizer uses a BP neural network for training recognition. Due to the fact that feature values and labels have already been packaged together during training recognition, dataset segmentation needs to be performed before training. This time, 15% of the dataset was selected as the test set, and 85% of the dataset was used as the training set.

Before training, normalize the dataset and use the pattern recognition function pattern net to build the recognition network required for the classifier. The number of hidden layers greatly affects the recognition rate, and the number of neurons in the hidden layer also affects the recognition rate. In the test, the more neurons, the better. This time, a neural network with six hidden layers was used. When the hidden layer increases from 1 to 7, the recognition rates are 87.7%, 89.2%, 90.5%, 92.3%, 93.9%, 94.4%, and 90.8%, respectively. When the hidden layer is increased to the seventh layer, overfitting will occur, and the recognition rate will actually decrease. Therefore, this article selects 6 neurons in the hidden layer, and the recognition rate can reach 94.4%.

5.4 Analysis of Evaluation Results

This article selects 190 apple sample images as the dataset, selects image detection results as the evaluation criteria, and then evaluates the accuracy of apple ratings obtained through MATLAB training. The normalized eigenvalues are based on a percentage system, where a score of 90 or above is considered excellent, 80-89 is defined as good, and a score below 80 is defined as poor.

When using the BP neural network to classify images, the classification of apple images with excellent product rates is more accurate. After analysis, it is mainly believed that high-quality apples have a higher overall score in appearance and obvious feature values. Therefore, the boundary timing is also clearer, and SVM method is used for verification [6]. This experiment also verifies that support vector machine SVM does have excellent performance in classification and recognition. This also provides new references and ideas for the application of deep learning in the field of image recognition.

Table.3Comparison of SVM recognition results

level	Accuracy of Bp neural network	Accuracy of SVM neural network	Typical example images
Poor	88.6	89.2%	78.2 
Middle	85.4%	84.4%	86.3 
Excellent	91.3%	90.2%	95.9 

6. Conclusion

This article studies the use of BP neural networks to distinguish the types of five fruits and evaluate the quality of apples through appearance images. In terms of fruit type discrimination, the accuracy of the BP neural network classification model is relatively high, and the discrimination accuracy for special shapes such as bananas can reach 100%. In terms of apple quality detection, three feature models were established for color features, size and shape, and surface defect degree. From the perspective of these three features, an apple quality scoring scheme was designed. Using these three features as the input layer and the comprehensive score of apple quality as the output layer, a BP neural network classification model was constructed. It was found that the highest accuracy was achieved when the number of hidden layer nodes was 6, and the classification of apple images with excellent product rates was more accurate. At the same time, it was found that support vector machines perform excellently in classification and recognition. This article combines computer vision technology with digital image processing technology to explore a non-destructive method for fruit type identification and quality rating based on appearance images, providing new ideas for agricultural production and fruit quality inspection.

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