Fruit Recognition Based on Convolution Neural Network

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Abstract. Traditional fruit recognition is mainly manual, which is not conducive to automation. Deep convolution neural network (DCNN) has a strong ability of feature learning and expression. It is helpful to realize intelligence in fruit sales market if it is applied to the identification of fruits. Due to the lack of standard image databases and various types of fruits, image data sets used in this paper are obtained through taking pictures of fruits and network download. Considering the small number of samples, in addition to using common image processing technology for data expansion, transfer learning technology based on vgg16 model is also adopted for fine tuning, which can reduce the training time and alleviate over fitting. Finally, six kinds of common fruits are chosen for experiments, and the test results show that the average recognition accuracy reaches 94.16%.

1. Introduction
As a big agricultural country in the world, China's fruit output ranks first in the world, and with the improvement of people's living standards, the demand for fruits in people's daily life is greatly increased, and the scale of the fruit industry market continues to grow. At present, most supermarkets use manual input of various codes for manual weighing and pricing in fruit sales, which requires a lot of manpower and time-consuming. In some large supermarkets, there will be self-service fruit weighing equipment, but customers also need to select the corresponding name or picture from the given library, and the machine will automatically calculate the price after confirmation. Due to the variety of fruits, customers are still time-consuming and inefficient in searching a certain kind of fruit. Therefore, a system which can replace manual operation and has the function of automatic identification of fruit has a good application prospect in the fruit sales market, and is also conducive to the development of unmanned supermarket.

With the rapid development of machine vision technology, it has also been widely used in agricultural products detection. The image of fruit object is obtained by camera instead of human eye, and the object feature is extracted by image processing technology, and the recognition is realized by various classifiers. With the development and optimization of image processing technology, as well as the neural network, vector machine and other related algorithms, the accuracy of recognition is well guaranteed. Tao Huawei et al.[1] extracted and fused the texture and colour features of fruit images, then used nearest neighbour classifier to realize the classification and recognition of 46 kinds of fruits. Wang Shuiping et al.[2] extracted the area, colour and shape features of the fruits by transferring the colour space of the image, and used SVM classifier for recognition, achieving a recognition rate of 95.33%. However, the algorithm can not distinguish different varieties of the same category, and the recognition accuracy of similar features, such as lemon and orange, is not high. Zhang Zechen, Ju Zhong [3] extracted the colour moments and surf features of the image and used K-means clustering...
algorithm and SVM technology for classification and recognition, achieved 94% recognition rate. Cheng Ronghua et al. [4] used the principal component analysis method to realize the classification and recognition of 10 types of fruits, with a recognition rate of 93%. Yu Yueyang et al. [5] used feature extraction and BP neural network to realize common recognition, but there are still shortcomings in the algorithm, such as the recognition of green apple and red apple.

To sum up, due to the development of image processing technology, it has been widely used in fruit recognition. However, this method is mainly based on artificial experience for image feature extraction, and its implementation process is generally shown in Fig. 1 [6]. The common features of fruit are geometry, texture and colour. The extraction process of these features is artificial design, which is not universal. For example, due to the variety of fruits, their features are different, and there is no uniform feature extraction algorithm for all fruits. In the current artificial intelligence era, with the rise of deep learning technology, its superior performance in target recognition and classification has been widely concerned by researchers, and many researchers have tried to apply deep learning theory to the field of agricultural product detection. In this paper, deep learning technology is applied to the recognition of common fruits, which improves the recognition rate and can be widely used.

![Figure 1. Traditional way of recognition based on image processing](image1)

2. System design

Fig. 2 shows the model of fruit recognition system based on deep convolution neural network. The model is based on the classical DCNN VGG16, forming a fruit_vgg16 model by transferring the model structure and pre training parameters of 13 convolution layers, and modify the number of neurons in the last full connection layer according to the task of this paper, and use self-collected samples to fine tune the parameters of the last three connection layers, Finally, the trained model is saved to recognize different kinds of fruits.

![Figure 2. Model of fruit recognition system](image2)

Considering that deep learning depends on large samples, the database in this paper comes from taking pictures of fruits and network download, and the number is limited. In order to improve the training over fitting phenomenon caused by small samples, data augmentation and transfer learning technology are used. The process is shown in Fig.3.
2.1. Data set
At present, there is no unified fruit image set existed. The image set used in this paper is composed of three parts: (1) Taking photos of fruits taken from supermarkets, vegetable markets and other fruit sales occasions; (2) Fruit images from Taobao, pinduoduo and other network sales platforms; (3) Fruit image data set fruit-360 from kaggle database[7]. Six kinds of common fruits, including banana, blueberry, carambola, cherry, apple and apricot, are collected in the experiment. Fig.4 shows some samples used in this paper.

Due to the small scale of the database, it is easy to appear "over fitting" phenomenon in the training process, that is, it is easy to regard some characteristics of the sample itself as the characteristics of all potential samples, so that the generalization ability of the model is weak, which affects the accuracy of the test. Therefore, this paper uses some geometric transformation of the image, including rotation, scale and random clip of the image, so as to expand the data samples and alleviate the over fitting phenomenon. After the above image processing, the number of data samples is: 1800 apples, 1200 bananas, 1800 cherries, 600 apricot, carambola and blueberry, respectively. A total of 6600 fruit images are used in this experiment. The label value of each kind of fruit is set to 0 ~ 5 in storage. After reading the image, it is converted to the form of one hot coding for training and testing of the model. That is, the label value of each fruit is a vector \( y = \{a_0, a_1, a_2, a_4, a_5\} \). There is only \( a_i = 1 \) in the label value of class \( i \) fruit, other values are 0. The labelled samples are divided into training set, validation set and testing set according to the ratio of 8:1:1.

2.2. Transferring and model training
Transfer learning[8-10] is to use the existing knowledge to learn a new knowledge and find the similarities between the existing knowledge and the new knowledge. It is suitable for the training of small sample data sets and can further improve the over fitting problem. Transfer learning theory has
been successfully applied to text classification[11], image classification[12], biomedicine[13] and many other fields. Based on the vgg16 model which has achieved excellent results in image classification with Imagenet data set, this paper constructs the convolutional neural network model fruit_vgg16, the model includes 13 convolution layers, 5 pooling layers, 3 fully connected layers and 1 softmax layer. The structure of the model is shown in Figure 2, in which the model structure and parameters of the convolution layers and pooling layers are directly transferred from the vgg16 model. The weight parameters of the convolution layers are not updated during the new training process. The three full connection layers are set to be trainable and the number of neurons in the last full connection layer is modified to 6, and then fine-tuning the three full connection layers through training images. Because only the parameters of the last three layers are trained and learned, the pressure of insufficient size of fruit image data set is greatly reduced, and the powerful feature learning ability of convolutional neural network is full used, so that it can learn higher-level semantic features of fruit images. The training process of fruit_vgg16 model is shown in Fig. 5. The entropy loss function is defined as follows:

$$ \text{loss} = \sum_{i=1}^{n} y_i \log y'_i $$

where $y_i$ is the ideal probability of the fruit with kind of i, and $y'_i$ is its actual probability predicted by the DCNN model. The loss function value of each epoch is the average value of all samples. And the gradient descent method is used for optimization.

![Figure 5. Flow chart of training process](image)

3. Experiments
This experiment is performed based on Tensorflow deep learning framework, using python programming, visual studio 2019 as compiler. The learning rate is set to 0.001, and after training for 20 epochs, 132 batches in each epoch, and in each batch 50 images are input to the model, we applied the trained model for recognition. For each image to be recognized, the probability of belonging to 6
kinds of fruits is calculated by Softmax at the last layer of the model, and which probability value is the largest is considered as the category of fruit, as shown in Fig.6.

![Figure 6. Examples of recognition results](image)

Through the testing set image recognition experiment, the overall accuracy rate is high, up to 94.16%. It can be seen that the deep convolution neural network can learn the high-level features of fruits by using multi-level convolution and pooling operations, and can complete the classification and recognition of images without manual feature extraction. In order to further obtain the recognition accuracy of each kind of fruit, table 1 gives the recognition rate statistics of six kinds of fruits. It can be seen from Table 1 that the network model in this paper has achieved good results in fruit recognition after training, which verifies the effectiveness of the method.

| Fruit       | Apple | Apricot | Banana | Blueberry | Carambola | Cherry |
|-------------|-------|---------|--------|-----------|-----------|--------|
| Accuracy    | 95%   | 92%     | 98%    | 96%       | 95%       | 89%    |

### 4. Conclusion

In this paper, a fruit recognition system based on deep convolution neural network is designed. Based on vgg16 pre-training model, transfer learning technology is applied, which can reduce the training parameters and improve the training speed. The number of neurons in the last full connection layer is modified, and the new model is fine tuned by small sample set of fruit image. The test results show that the system has achieved a high accuracy in the recognition of fruits, which is helpful to the intelligent realization of fruit sales market. Due to the variety of fruits, this paper only tested six kinds of fruits, but this method can be extended to more kinds of fruits and vegetables recognition. In the next step, we will continue to enrich the database of fruit and vegetable images, so as to realize the automatic recognition of more varieties of fruits and vegetables.

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