12th International Conference on Advanced Computational Intelligence (ICACI)
Dali, China, August 14-16, 2020

Fruit Classification using Convolutional Neural Network via Adjust Parameter and Data Enhancement

1st Liuchen Wu
School of Electrical and Information Engineering
Changsha University of Science and Technology
Changsha, China
E-mail:326823564@qq.com

2nd Hui Zhang
School of Electrical and Information Engineering
Changsha University of Science and Technology
Changsha, China
E-mail:zhanghuihby@126.com

3rd Ruibo Chen
School of Electrical and Information Engineering
Changsha University of Science and Technology
Changsha, China
E-mail:1317054806@qq.com

4th Junfei Yi
School of Electrical and Information Engineering
Changsha University of Science and Technology
Changsha, China
E-mail:460834447@qq.com

***Abstract*—Fruit is one of the most popular products in the market. Automatic and accurate classification of fruit can bring great convenience to fruit sellers. However, there are great similarities between some apple varieties and pears and peaches, and these kinds of fruit are generally popular, which has increased the difficulty of this task. Aiming at this problem, this paper proposes a method of fruit automatic recognition and classification based on convolutional neural network. First, we obtained two color fruit image data set (public data set and self-made data set). The public data sets is composed of fruit images with simple background, while the fruit images in the self-made data set are taken in a complex environment. Then, on the basis of convolutional neural network, we conducted several research experiments through parameter adjustment, and achieved the highest average classification accuracy of 99.8% on the public data set. In the self-made data set, the classification accuracy is 90.2%. Finally, we improved the classification accuracy of the self-made data set from the original 90.2% to 98.9% by adopting appropriate data enhancement techniques.**

***Keywords*—convolutional neural network, parameter adjustment, image data enhancement, fruit classification**

I. Introduction

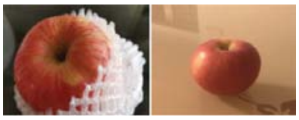
Fruit industry has become the third major industry after grain and vegetable. The rapid development of fruit industry has brought us visible economic benefits, but also brought us a series of problems, fruit classification is one of them. In order to pursue the high-precision fruit classification effect, simply relying on simple feature extraction methods such as [1] [2], can not meet the requirements. Today, the development of machine vision technology provides an effective method for automatic classification between fruit varieties, but traditional classification methods, such as kernel support vector machine (KSVM) [3]∼ [5], artificial neural network (ANN) [6]∼ [9], feedforward neural networks (FNN) [10]∼ [12] et al, still need to be further improved in classification performance. With the application of deep learning architecture in the field of image recognition, among them, convolutional neural network (CNN), as one of the typical deep learning models, has a good performance in classification [13]∼ [20], which has received extensive attention from researchers. In 2015, Zhang extracted wavelet entropy (WE) from fruit images and classified them based on the optimized method of biogeography, with a total accuracy of 89.47% [11]. In the same year, Kanade calculated quantitative information such as RGB color distribution, CIE1931 standard tristimulus value, chromaticity coordinate and mean value of guava fruit, and then estimate ripeness level of guava fruit through artificial neural network (ANN) [7]. In 2018, Sidehabi used K-Means clustering method to perform passion fruit segmentation, and then classification on Passion Fruits Ripeness through artificial neural network. The results showed that the accuracy of the system could reach 90% [8]. In 2018, Lu designed a six-layer CNN consisting of a convolutional layer, a pooled layer, and a fully connected layer. The method has good classification performance with an accuracy of 91.44% [14]. In the same year, Wang created an 8-layer deep convolutional neural network and replaced the normal rectifying linear unit with a parametric rectification linear unit. The dropout layer was placed in front of each connected layer, and a classification accuracy of 95.67% was obtained for the classification of 18 fruits [17]. In 2019, referring to the LeNet-5 convolutional neural network model, Zeng proposed a convolutional neural network structure suitable for fruit image classification and recognition, and obtained 98.44% classification accuracy on self-built data set [20]. In conclusion, the classification performance of convolutional neural network is superior to the traditional classification method. In this paper, using the deep learning module in halcon software, the fruit recognition and classification of the public image data set and the self-made image data set are carried out based on the convolutional neural network.

II. Method

A. Data Set

The public data set consists of the halcon software built-in data set, the background of all fruit images is black, which is simple. Fig. 1 shows a typical case diagram for each type of fruit. The total number of images in the data set is 758, distributed among five categories.

Self-made data set are our own data set, obtained through two ways: (1) Taking a fresh fruit data set obtained by photographing with a camera; (2) Search the Internet for downloaded fruit data set that are challenging to classify. The self-made data set consists of fruit images with complex backgrounds, including fruit images with gaps, or covered fruit images, or fruit images under different light conditions. Fig. 2 shows a typical case graph of the data set. The total number of data in self-made data set is 1152, which is distributed among 7 classes. The types and quantities of fruit in both data set are shown in table I.



(a) Red Fuji Apple

(b) Red Rose Apple

(c) Marshal Huang Apple

(d) Pear

(e) Green Apple

(f) Snake Fruit

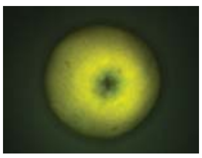
(g) Peach

Fig. 2: Self-made Datasets

B. Pre-processing

Before training, we will preprocess the data set. Since the fruits in each image of the homemade data set are in different backgrounds, uniform image processing methods cannot be used to extract the region of interest. For this data set, we do not go through the image preprocessing process and directly write the data set to the training network for training. The fruits in the public data set are placed on a dark black background, and the background is relatively simple. The corresponding image preprocessing will improve the classification accuracy of the public data set. First, we use the technique of converting multi-channel image to mono image to put the original image into the blue channel for retrieval. The colors of fruits in the public data set are all green or red, and in the blue channel, these colors will be very dark, resulting in a difference of chrominance from the bright blue background. In this way, we only need to use the global threshold method to segment the image well. Divide the image into several regions, and then we will select the region that is most likely to be fruit, usually fruit is one of the largest regions. we create a frame, and it is easy to know that the area in the background will intersect with the frame, so we find the largest area that does not intersect with the frame, which is the fruit area. Finally, the taken area is indented into a rectangular area of 224*224 size. Fig. 3 is a comparison of the public data set before and after processing.

(a) Apple Braeburn



(b) Apple Golden

(c) Apple Topaz

(d) Peach

(e) Pear

Fig. 1: Public Dataset

C. Classification Network

This study uses the pre-training network built in halcon software to classify and identify fruit images. Because halcon encapsulates the pre-training network and does not open the underlying source code, so the specific framework structure of the convolutional neural network is not given. However, in order to avoid the problem of too many parameters during operation and affecting the efficiency of operation, the network does not have a fully connected layer. Taking the public data set experiment as an example, the overall framework flow chart of the system is shown in Fig. 4.

TABLE I. Type of Dataset and Number of Samples

Class(Self-made)	Number	Public	Number
Red Fuji Apple	165	Apple Braeburn	150
Red Rose Apple	165	Apple Golden	150
Marshal Huang Apple	165	Apple Topaz	160
Pear	161	Peach	150
Green Apple	166	Pear	148
Snake Fruit	167		
Peach	143		

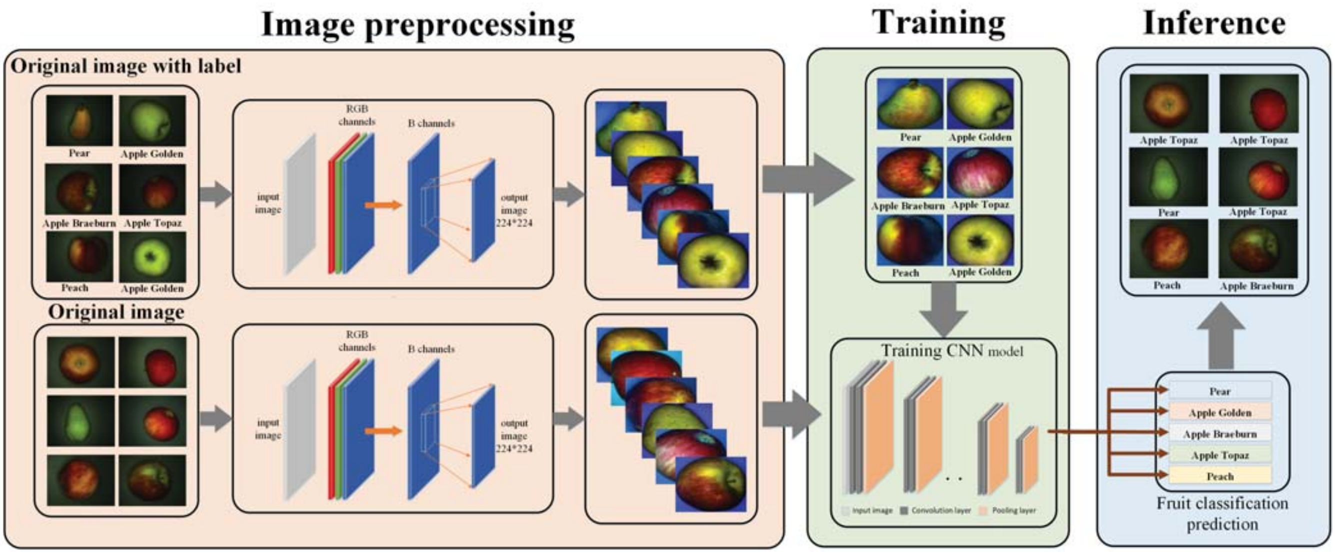
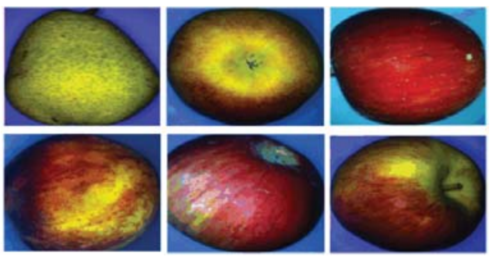


Fig. 4: Fruit classification deep learning model in halcon software

(a) Before Pre-processing



(b) After Pre-processing

Fig. 3: Image pre-processing, comparison of pre-processed image (top) and processed image (bottom)

III. Experiment and Results

A. Selection of Convolutional Neural Networks

There are two kinds of pre-trained convolutional neural networks in halcon software, namely compact network and enhanced network. Both pre-training networks have their own advantages. The compact neural network has a relatively simple network structure, so it has a particularly high memory and runtime efficiency. The enhanced neural network has more hidden layers than the compact network, that is, there are more convolution and pooling layers in the middle layer, which enables the enhanced network to extract more feature vectors and generate more parameter weights. Therefore, it is usually suitable for more complex classification tasks. However, this comes at the cost of more time and RAM. We apply these two pre-training networks to the classification of common data sets respectively. The learning curve is shown in Fig. 5. The blue line represents the learning rate, the golden line represents the verification error rate, and the purple line represents the training error rate. From the figure we can get that the best verification error rate of compact neural network is 1.8%, and the best verification error of enhanced neural network is only 1.3%. As can be seen from the graph, the classification effect of the enhanced network is slightly better than that of the compact network.

Fig. 6 shows the confusion matrix obtained by classifying the public data set by two pre-training networks. Red is the number of classification errors, and blue is the correct number.

In the confusion matrix, the enhanced network incorrectly identified two braeburn apples as topaz apples and one braeburn apple as peach when classifying fruits, and the remaining fruits are all 100% correct. The overall classification accuracy is 98.7%. When the compact network is used for fruit recognition and classification, it mistakenly identified three braeburn apple as topaz apple and one peach recognized as braeburn apple, and the identification of the remaining fruits reached a 100% correct rate. The overall classification accuracy was 98.2%. Although the enhanced network has a slightly better performance curve than the compact network, it takes more than three times as much time as the compact network, and it takes up a lot of RAM space at runtime.

B. Parameter Study

In the image training phase, in order to ensure the number of verified images, we divided the data set into two subsets: training set and verification set. In order to study the influence of the proportion between training set and verification set

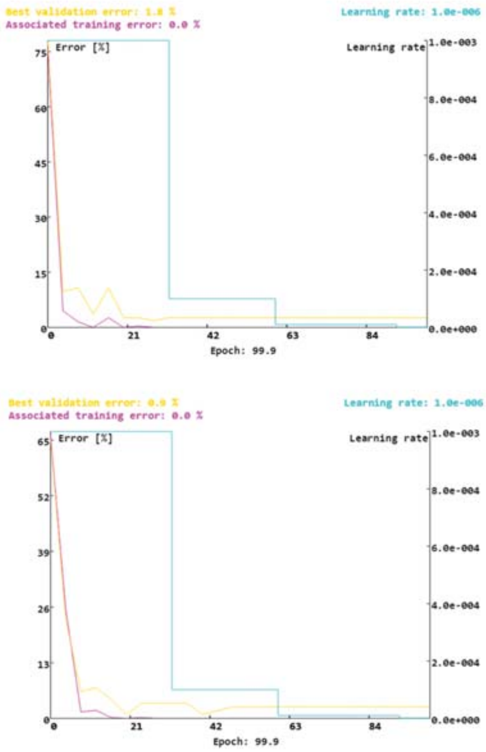


Fig. 5: Verification and training error rate for public datasets under compact network (top) and enhanced network (bottom)

on classification results, we changed the proportion between training set and verification set on the basis of public data set, then trained the data set, and conducted correlation analysis on the obtained experimental results. The proportion of the training set is between 60% and 80%. We choose a set proportion for experiment every 2 percentage points, and the proportion of the corresponding verification set is between 20% and 40%, a total of 11 sets of data. In order to prevent the randomness of the experimental results, we will conduct multiple experiments on each set of proportions, and calculate the mean value and variance according to (1) and (2).

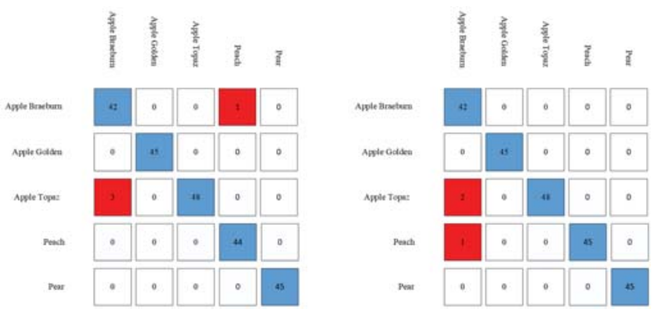


Fig. 6: Confusion matrix for public datasets under compact network (left) and enhanced network (right)

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{1}$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (X_i - \mu) \tag{2}$$

In the above two formulas, μ and σ^2 respectively represent the mean accuracy and variance, N represents the number of experiments under a set of parameters (here refers to the proportion), and X_i represents the experimental results of the ith experiment. Table II gives the experimental results of these 11 sets of data. MA stands for the mean accuracy and TP represents the proportion of training set.

From table II, we can conclude that when the proportion of training set is 64%, the average error rate reaches the highest, reaching 4.9 percentage points. At this time, the variance also reached the highest 5.688, indicating that the experiment was very unstable under this proportion, and the classification effect of fruit was not good. When the proportion of training set reached 76%, the performance of this experiment was the best, with an average accuracy rate of 99.8% and a variance of 0.06. Although there was a lower variance than this value, it showed that the experiment was very stable under this proportion. Since the individual experiments are all accidental to some extent, we need to find the best parameter set within the scope. We found that when the proportion of training set was within the range of 70%∼80%, the average classification accuracy was very high and the variance was relatively low. After 80%, we could find that the variance was gradually increasing. Therefore, we can think that the parameter data in this range has a better effect in fruit classification and recognition. Fig. 7 is a specific flow chart about the training steps.

C. The Choice of Batchsize

Batchsize: The batch size, which is the number of training samples taken in the training set per training. The size of this parameter has a very large impact on the experiment. Too small a value will result in inefficient training and the data will be difficult to converge, resulting in under-fitting. Too large a value will cause the program to take up too much memory when it runs, which will affect the classification results and operational efficiency. Therefore, choosing the appropriate batchsize value is also an important discussion point in this paper.

TABLE II. CLASSIFICATION ACCURACY UNDER DIFFERENT TRAINING AND TEST SET PROPORTION

TP	MA	Variance	TP	MA	Variance
60%	98.48%	0.1964	72%	99.1%	0
62%	95.3%	0.588	74%	99.1%	0.04
64%	95.1%	5.688	76%	99.8%	0.06
66%	98.52%	0.1816	78%	99.28%	0.0576
68%	98.32%	0.2176	80%	99.32%	0.1696
70%	99.12%	0.0816			

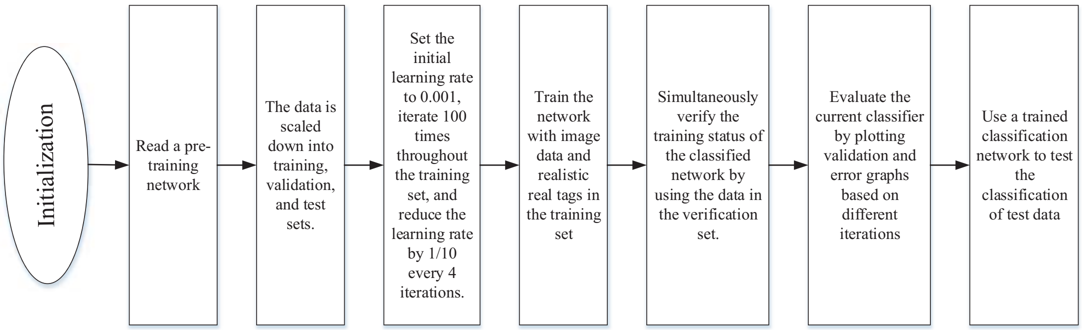


Fig. 7: Training step flow chart

We set the initial value of batchsize as 16 to start the experiment, and then added 4 values successively to repeat the experiment. When the batchsize reached 76, we had conducted 18 groups of experiments. Just like the experiment with the above proportional parameters, in order to prevent the randomness of the experimental results, we conducted several experiments on each batchsize and calculated its mean and variance. The experimental results are shown in table III. B.s stands for the value of batchsize.

By observing the experimental data in table III, we can find that when the batchsize value is an integer multiple of 8, compared with other values, it has higher average classification accuracy and more stable performance. At batchsize=56, the experiment achieved the highest average classification accuracy of 99.4%, and the variance was 0.204, which was within the stable category, and the classification effect of fruit was the best. When batchsize=64, the average classification accuracy of the experiment reached 99.12%, with the lowest variance of 0.0816, the smallest fluctuation of the experiment and the most stable classification result. To sum up, we can think that batchsize=56 and batchsize=64 are the best balance points between memory efficiency and memory capacity in this study, and the classification of fruit has the best stability and classification effect. At the same time, when the batchsize is 8, the experimental results are better. Obviously, this conclusion has nothing to do with experimental equipment, and it has better promotion and application value in experiments related to convolutional neural network.

TABLE III. OPTIMAL VERIFICATION ERROR RATE AND CLASSIFICATION ACCURACY UNDER DIFFERENT TRAINING AND TEST SET RATIOS

B.s	mA	Variance	B.s	mA	Variance
16	97.82%	0.2256	48	98.86%	0.0384
20	97.88%	0.3496	52	99.14%	0.4864
24	97.96%	0.1024	56	99.4%	0.204
28	98.68%	0.4056	60	99.22%	0.1176
32	98.96%	0.1264	64	99.12%	0.0816
36	98.32%	0.5056	68	98.76%	0.2544
40	99.04%	0.1104	72	91.92%	9.667
44	98.84%	0.1264	76	98.94%	0.2184

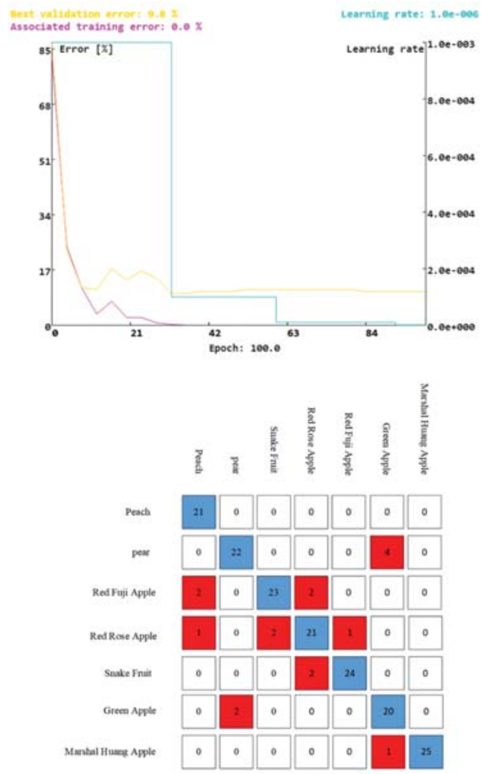


Fig. 8: Self-made dataset experiment results, the upper side is its verification and training error rate graph, and the lower side is its verified confusion matrix.

D. Data to Enhance

As the public data set have been processed accordingly, the fruit images are too simple and do not conform to the fruit images taken in the actual production and life. In order to better apply them to the reality, we conducted classification experiments on the fruit data sets made by ourselves – the self-made data sets. Without any processing of the data set, the experimental results are shown in Fig. 8 below.

It can be seen from the experimental results that in the case of no processing on the self-made data set, The classification

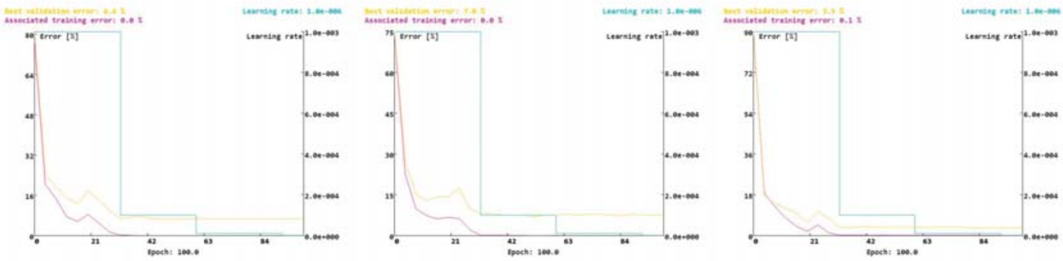


Fig. 9: The experimental results of the self-made data set after the artificial data enhancement. From left to right, it is brightened randomly cropped, and randomly flipped.

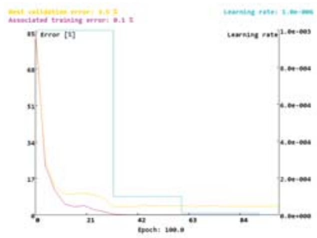
network in the halcon software has a classification accuracy of 90.2% for the self-made data set. Compared with many traditional classification methods, the classification accuracy has been able to achieve satisfactory results, but compared with the 95.67% and 98.44% classification accuracy in articles [17] and [20], there is still some deficiency. In order to improve the classification accuracy of self-made data set, and considering that the number of data set is relatively small, this paper proposes a method of data enhancement. Before the training, the data set was first enhanced, the number of data set is increased by enhancing the brightness of the image, and by randomly clipping and flipping the image, so as to improve the classification accuracy of the fruit image. Fig. 10 compares the original image with the image enhanced by data. First, we used the three data enhancement methods alone to obtain three sets of data sets, and then conducted classification experiments on these three sets of data sets. The experimental results are shown in Fig. 9 below.

By analyzing the experimental results, it can be seen that the optimal verification error rate of the experiment was reduced from the original 9.8% to 6.4% and 7% when enhancing the brightness of the image or randomly cropping the image alone. However, the data enhancement method for randomly flipping images, to some extent, it can make up for the disadvantage of translation invariance of convolutional neural networks, so

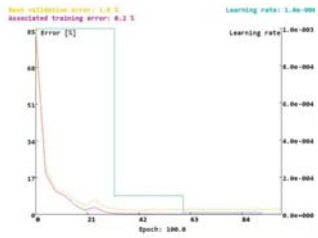
(a) The original image

(b) Enhanced image

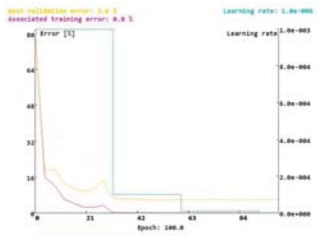
Fig. 10: Image comparison before and after artificial data enhancement. Above is the original image, and below is the image after data enhancement. From left to right, it is randomly cropped, flipped and brightened.



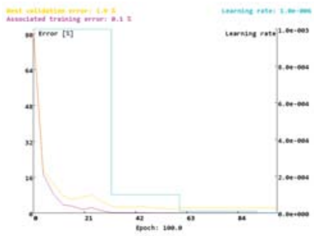
(a)



(b)



(c)



(d)

Fig. 11: Experimental results of three data enhancement methods combined with each other. (a)(b)(c) are the experimental results of the combination of random shear and random flip, the combination of enhanced brightness and random flip, and the combination of random shear and enhanced brightness, respectively. (d) is the experimental result after combining the three methods.

the best verification error rate of this method reached 3.5%. In contrast, this image enhancement method has a significant improvement in the classification and recognition of self-made data sets.

After that, we randomly combined these three image enhancement methods. The first is a combination of random cropping and random flip, the second is a combination of enhanced brightness and random flip, the third is a combination of random crop and enhanced brightness, and the fourth is a combination of random crop, random flip and enhanced brightness. We obtained 4 sets of fruit data sets through the above four methods and performed classification experiments on them respectively. The experimental results are shown in Fig. 11.

As can be seen from the graph above, the best verification error rates for the first method and the third method are 3.5% and 5.6%, respectively. In the previous experiment, the data enhancement method with random flip alone also achieved an optimal verification error rate of 3.5%, the same as the optimal verification error rate of the first method and lower than the 5.6% of the third method. It can be seen from the two subgraphs (b) and (d) in Fig. 11, the second method and the fourth method both achieved good classification results, with the optimal verification error rate reduced to 1.9%. However, in the fourth method, three data enhancements were used, one more than in the second method, and both methods achieved the same classification effect. From this we can draw the conclusion that data enhancement does not mean that the more data you enhance, the better the classification effect of fruit images will be. Only by finding appropriate enhancement times and data enhancement methods can the best classification effect be achieved. Compared with the whole data enhancement classification experiment, the three data enhancement methods in improving the classification effect of convolutional neural networks on self-made data sets, there are randomly flip $>$ enhance brightness $>$ randomly crop randomly. And after combining the two data enhancement methods of random flip and enhanced brightness, the classification accuracy of the self-made data set reached 98.1%.

Based on the above experimental results, in the face of relatively small amount of data, the classification accuracy of fruit images can be improved by proper data enhancement to the data set.

IV. Conclusion

Aiming at the classification problem of fruit images, this paper proposes a fruit classification method based on convolutional neural network, and deeply studies the influence of various training parameters on experimental results in the convolutional neural network. On this basis, it was applied to the classification of fruit varieties under complex background, and combined with data enhancement technology, the classification accuracy of the self-made data set was significantly improved. Through the experiment, the main conclusions are as follows:

1)The convolutional neural network mainly extracts the feature vectors in the image through self-learning, without adopting specific feature processing technology, and has a good classification effect on the fruit image;

2)Appropriate training parameters can improve the classification accuracy of fruit images by convolutional neural network to some extent;

3)Appropriate data enhancement methods can improve the classification accuracy of fruit images by convolutional neural network.

According to the experimental results, the method proposed in this paper provides a new and effective method for automatic recognition and classification of fruit images. And after the combined data enhancement, the fruit image in the complex background can also achieve satisfactory classification accuracy. The follow-up work of this paper will be carried out in the following two aspects:

1)Subsequent research will further focus on the promotion of methods and increase the types of fruits. And reclassify the same kind of fruit [21]$\sim$ [24] or fruit disease research [25], and make the classification towards a more detailed development of the direction.

2)The convolutional neural network used in this paper does not give a specific network structure. The convolutional neural network will be further studied and designed in the future, and the detailed structure of the network will be explained, so that it can achieve high classification accuracy without using other methods.

Acknowledgment

This research was supported in part by the National Natural Science Foundation of China under Grants 61971071, 61701047 and 81401490, in part by the National Key R&D Program of China under Grant 2018YFB1308200, Hunan Key Laboratory of Intelligent Robot Technology in Electronic Manufacturing under Grant IRT2018009,Hunan Key Project of Research and Development Plan under Grant 2018GK2022 and Changsha science and technology project under Grant kq1907087.

References

[1] F. Garcia, J. Cervantes, A. Lopez and M. Alvarado, "Fruit classification by extracting color chromaticity, shape and texture features: towards an application for supermarkets," IEEE Latin America Transactions, vol. 14, no. 7, pp. 3434-3443, 2016.

[2] G. Muhammad, "Date fruits classification using texture descriptors and shape-size features," Engineering Applications of Artificial Intelligence, vol. 37, pp. 361-367, 2015.

[3] Y. Zhang and L. Wu, "Classification of Fruits Using Computer Vision and a Multiclass Support Vector Machine," Sensors, vol. 12, no. 12, pp. 12489-12505, 2012.

[4] W. Astuti, S. Dewanto, K. E. N. Soebandrija, and S. Tan, "Automatic fruit classification using support vector machines: a comparison with artificial neural network," IOP Conference Series: Earth and Environmental Science. IOP Publishing, vol. 195, no. 1, pp. 012047, 2018.

[5] M. Khanmohammadi, F. Karami, A. Mir-Marqus, A. Bagheri Garmarudia, S. GarriguesbM, and de la Guardia, "Classification of persimmon fruit origin by near infrared spectrometry and least squares-support vector machines," Journal of food engineering, vol. 142, pp. 17-22, 2014.

[6] K. Kheiralipour and A. Pormah, "Introducing new shape features for classification of cucumber fruit based on image processing technique and artificial neural networks,". Journal of food process engineering, vol. 40, no. 6, pp. e12558, 2017.

[7] A. Kanade and A. Shaligram, "Development of machine vision based system for classification of Guava fruits on the basis of CIE1931 chromaticity coordinates," 2015 2nd International Symposium on Physics and Technology of Sensors (ISPTS). IEEE, pp. 177-180, 2015.

[8] S. W. Sidehabi, A. Suyuti, I. S. Areni, and I. Nurtanio, "Classification on passion fruit's ripeness using K-means clustering and artificial neural network," 2018 International Conference on Information and Communications Technology (ICOIACT). IEEE, pp. 304-309, 2018.

[9] A. K. Bhatt, D. Pant, and R. Singh, "An analysis of the performance of Artificial Neural Network technique for apple classification," AI & society, vol. 29, no. 1, pp. 103-111, 2014.

[10] Y. Zhang, P. Phillips, S. Wang, G. Ji, J. Yang, and J. Wu, "Fruit classification by biogeography-based optimization and feedforward neural network," Expert Systems, vol. 33, no. 3, pp. 239-253, 2016.

[11] S. Wang, Y. Zhang, G. Ji, J. Yang, J. Wu, and L. Wei, "Fruit classification by wavelet-entropy and feedforward neural network trained by fitness-scaled chaotic ABC and biogeography-based optimization," Entropy, vol. 17, no. 8, pp. 5711-5728, 2015.

[12] Y. Zhang, S. Wang, G. Ji, and P. Phillips, "Fruit classification using computer vision and feedforward neural network," Journal of Food Engineering, vol. 143, pp. 167-177, 2014.

[13] Z. M. Khaing, Y. Naung, and P. H. Htut, “Development of control system for fruit classification based on convolutional neural network,” 2018 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus). IEEE, pp. 1805-1807, 2018.

[14] S. Lu, Z. Lu, S. Aok, and L. Graham, “Fruit Classification Based on Six Layer Convolutional Neural Network,” 2018 IEEE 23rd International Conference on Digital Signal Processing (DSP). IEEE, pp. 1-5, 2018.

[15] Y. D. Zhang, Z. C. Dong, X. Q. Chen, W. j. Jia, S. D. Du, K. Muhammad, and S. H. Wang, “Image based fruit category classification by 13-layer deep convolutional neural network and data augmentation,” Multimedia Tools and Applications, vol. 78, no. 3, pp. 3613-3632, 2019.

[16] A. Patino-Saucedo, H. Rostro-Gonzalez, and J. Conradt, “Tropical Fruits Classification Using an AlexNet-Type Convolutional Neural Network and Image Augmentation,” International Conference on Neural Information Processing. Springer, Cham, pp. 371-379, 2018.

[17] S. H. Wang and Y. Chen, “Fruit category classification via an eight-layer convolutional neural network with parametric rectified linear unit and dropout technique,” Multimedia Tools and Applications, pp. 1-17, 2018.

[18] M. S. Hossain, M. Al-Hammadi, and G. Muhammad, “Automatic Fruit Classification Using Deep Learning for Industrial Applications,” IEEE Transactions on Industrial Informatics, vol. 15, no. 2, pp. 1027-1034, 2018.

[19] A. Nasiri and A. G. Taheri, “Zhang Y D. Image-based deep learning automated sorting of date fruit,” Postharvest Biology and Technology, vol. 153, pp. 133-141, 2019.

[20] P. P. Zeng and L. S. Li, “Research on Fruit Image Classification and Recognition Based on Convolutional Neural Network,” Mechanical design and research, vol. 35, no. 1, pp. 23-26, 2019.

[21] P. Constante, A. Gordon, O. Chang, E. Pruna, F. Acuna, and I. Escobar, “Artificial Vision Techniques to Optimize Strawberry’s Industrial Classification,” IEEE Latin America Transactions, vol. 14, no. 6, pp. 2576-2581, 2016.

[22] A. K. Bhatt and D. Pant, “Automatic apple grading model development based on back propagation neural network and machine vision, and its performance evaluation,” Ai & Society, vol. 30, no. 1, pp. 45-56, 2015.

[23] K. Dimililer and I. J. Bush, “Automated classification of fruits: pawpaw fruit as a case study,” International conference on manCmachine interactions. Springer, Cham, pp. 365-374, 2017.

[24] S. Marimuthu and S. M. M. Roomi, “Particle swarm optimized fuzzy model for the classification of banana ripeness,” IEEE Sensors Journal, vol. 17, no. 15, pp. 4903-4915, 2017.

[25] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, “Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks,” IEEE Access, vol. 7, pp. 59069-59080, 2019.