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

Group:9
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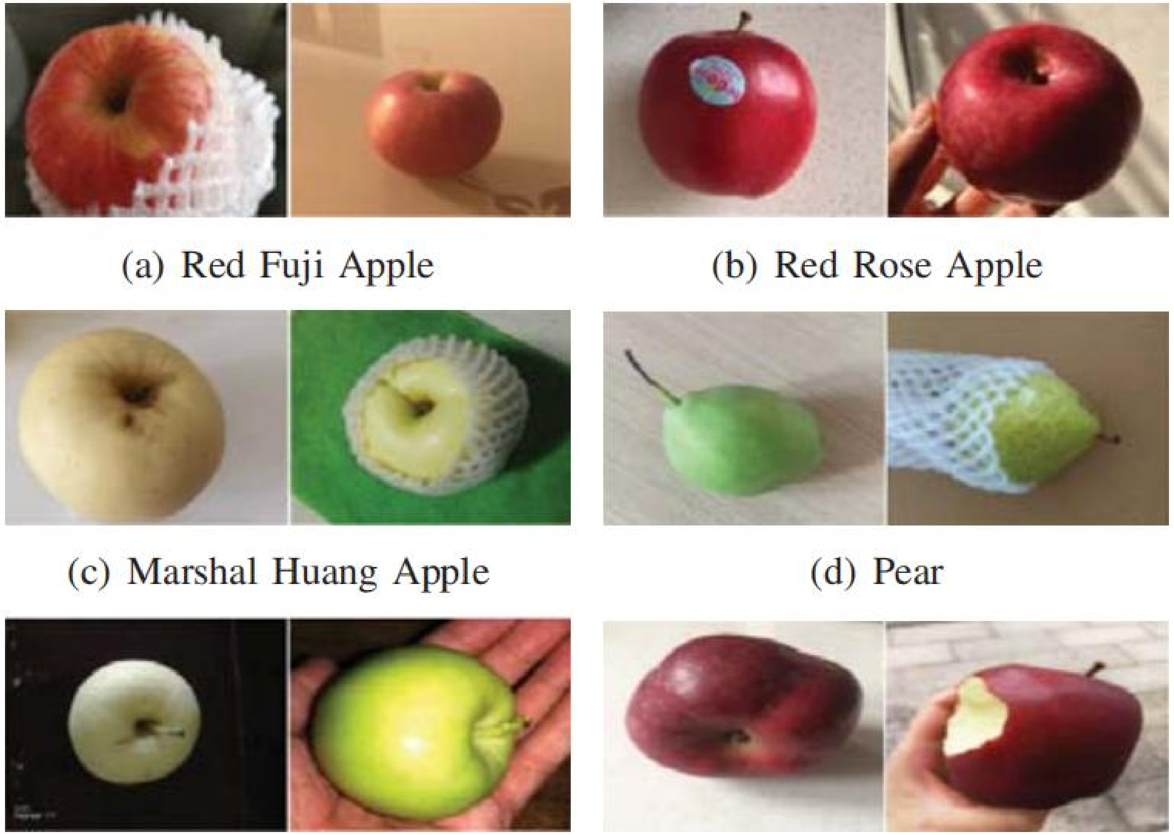
Motivation and Main Problem

Main problem

The problem addressed in the paper is the automatic and accurate classification of fruits using convolutional neural networks (CNNs). This task is challenging due to the high visual similarity between different fruit varieties, such as certain types of apples, pears, and peaches.



(a) Red Fuji Apple

(b) Red Rose Apple

(c) Marshal Huang Apple

(d) Pear

(e) Green Apple

(f) Snake Fruit

Motivation and Main Problem

Motivation

Fruit industry has become the third major industry after grain and vegetable.

Accurate fruit classification can greatly benefit fruit sellers by improving the efficiency of sorting and categorizing fruits, ultimately enhancing market operations and reducing manual labor.

Motivation and Main Problem

Challenge

- **Visual Similarity**: Some fruit varieties look very similar, making it difficult to distinguish them using traditional image processing methods.

- **Complex Backgrounds**: Real-world images often have complex backgrounds that can interfere with the accuracy of classification algorithms.

- **Data Diversity**: Limited and varied data sets can hinder the performance of machine learning models, requiring effective data augmentation techniques to enhance the dataset.

Motivation and Main Problem

Key Insights of the Proposed Work:

· **Convolutional Neural Networks (CNNs)**: The use of CNNs for automatic feature extraction and classification, which outperforms traditional methods in terms of accuracy.

· **Parameter Adjustment**: Fine-tuning the parameters of the CNN to improve classification performance.

· **Data Enhancement**: Implementing data enhancement techniques to increase the diversity and size of the dataset, leading to improved model accuracy, particularly on self-made datasets with complex backgrounds.

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Problem Setting

To develop a method for automatic recognition and classification of fruits using convolutional neural networks (CNNs). Developing robust techniques for handling complex backgrounds and visually similar fruit varieties through advanced data enhancement and parameter tuning.

The goal is to achieve high classification accuracy for both public and self-made datasets.

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Related Work

- 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%

from： 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.

- Calculated quantitative information such as RGB color distribution, CIE1931 standard tristimulus values, chromaticity coordinates, and mean values for guava fruit, then estimated the ripeness level through an artificial neural network (ANN).

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.

- Used K-Means clustering to segment passion fruit and then classified the ripeness level of passion fruits through an artificial neural network(ANN), with a total accuracy of 90%.

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.

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Limitations of Prior Work

1. **Limited Feature Extraction Techniques**:
   1. Earlier studies, such as those by Zhang et al. (2015) and Kanade (2015), relied heavily on manually extracted features like wavelet entropy and color distribution metrics. These techniques, while useful, are not as powerful or flexible as the automatic feature extraction capabilities of deep learning models like CNNs.

2. **Restricted Dataset Complexity**:

   2. Many previous works used datasets with relatively simple backgrounds. For instance, Lu et al. (2018) and Wang (2018) used datasets where the fruit images had uniform or less complex backgrounds, which does not reflect the challenges of real-world scenarios where the background can be quite varied and complex.

Experimental Preparation

Database

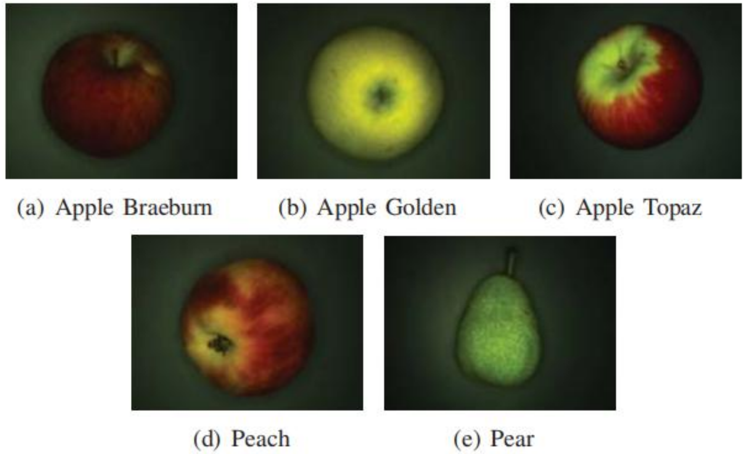

Fig. 1: Public Dataset

The public dataset is provided by halcon software have 758 copies in 5 categories with simple background.

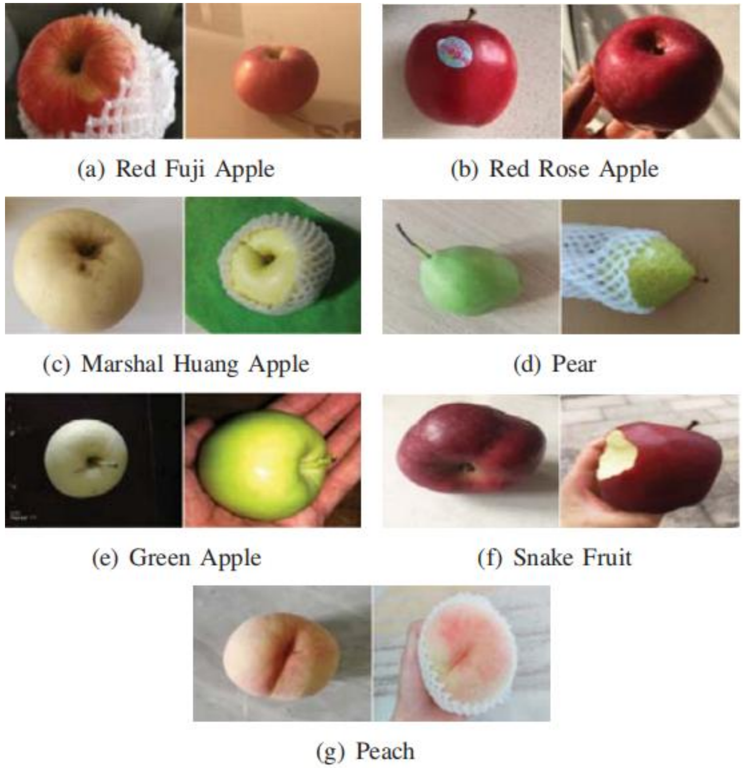

Fig. 2: Self-made Datasets

The self-made dataset was collected by oneself, mainly from the network and self-shooting with complex background and other adverse conditions, totaling 11527 categories

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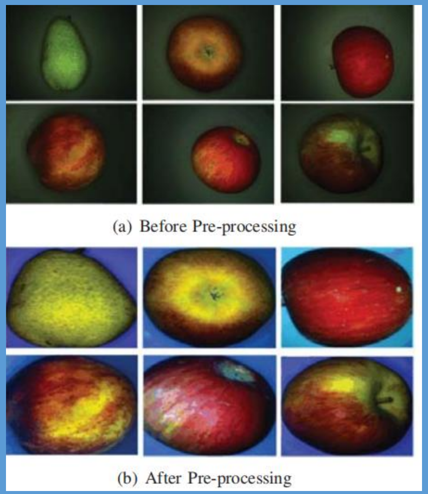
Experimental Preparation

Deep Learning



For the public dataset, it was placed in the blue color channel, and the accurate fruit image was obtained by global threshold retrieval and image cropping.

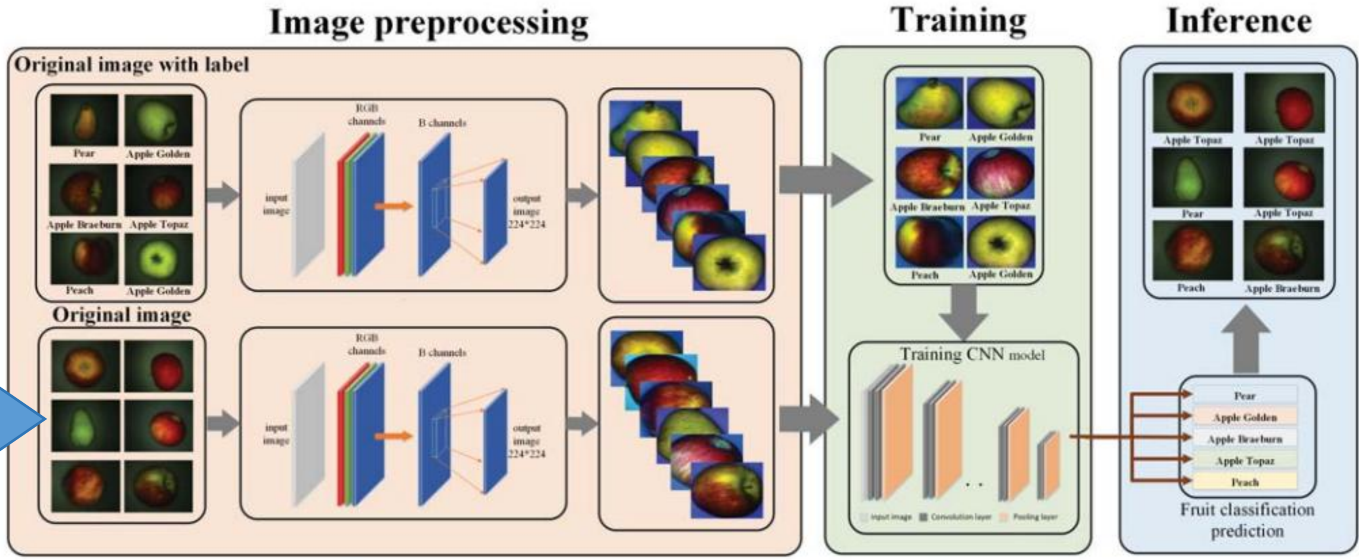


Fig. 4: Fruit classification deep learning model in halcon software

This experiment uses the training network built into halcon, because halcon encapsulates the pre-training network and does not open the underlying source code, so it does not give the specific framework structure of the convolutional neural network.

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Experimental Setup& Result

1.Neural Network

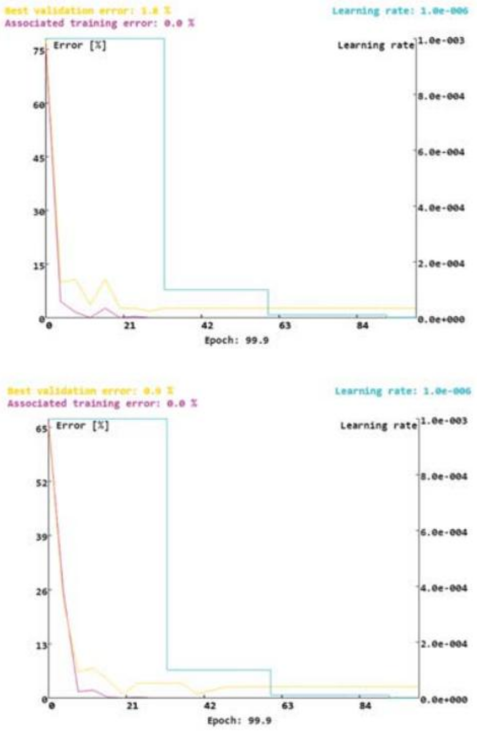

Fig. 5: Verification and training error rate for public datasets under compact network (top) and enhanced network (bottom)

Halcon software is configured with compact neural network and enhanced neural network former high memory, high operation efficiency, the latter has more convolution layers, so it can extract more features, data input to obtain the following data images.

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.

Blue lines indicate the learning rate

Gold lines indicate the validation error rate

Purple lines indicate the training error rate

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Experimental Setup& Result

2.Training Set Ratio

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			

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Experimental Setup& Result

3.Batchsize

Batchsize: The batch size, which is the number of training samples taken in the training set per training.

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

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Experimental Setup& Result

4.Picture Processing

(a) The original image

(b) Enhanced image

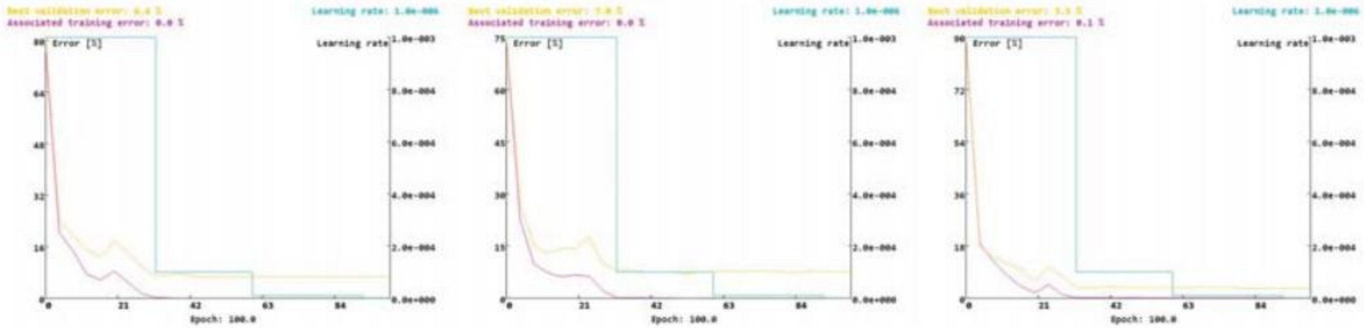

Fig. 9: The experimental results of the self-made data set after the artificial data enhancement. From left to right, it is brightened randomly cropped, and randomly flipped.

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Experimental Setup& Result

4.Picture Processing

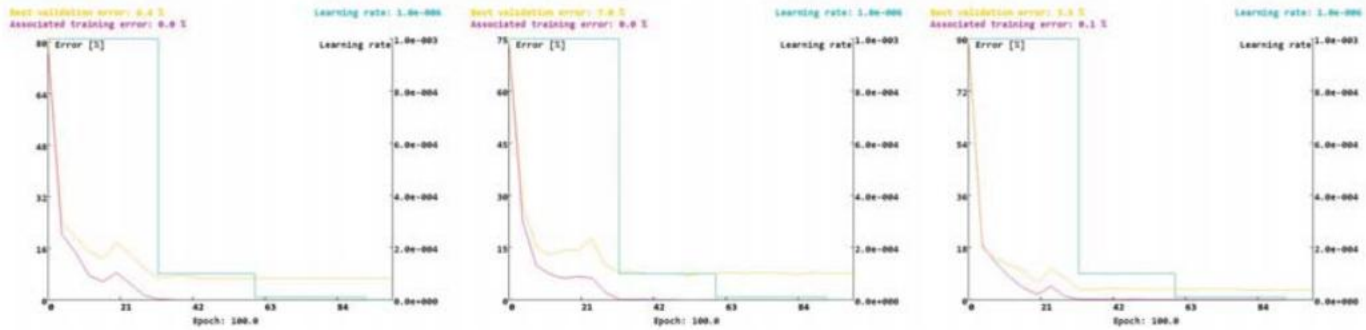
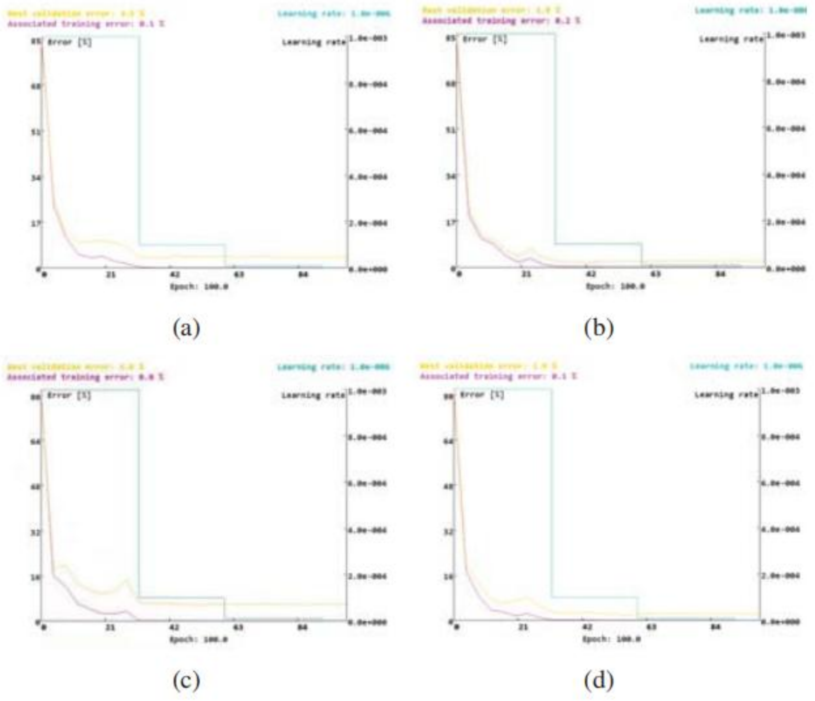


Fig. 9: The experimental results of the self-made data set after the artificial data enhancement. From left to right, it is brightened randomly cropped, and randomly flipped.

The classification network in the halcon software has a classification accuracy of 90.2% for the self-made data set. From the images, theverification erro rate was redued from original 9.8% to 6.4% and 7% when enhancing the brightness of the image or randomly cropping the image alone.But if we randomly flipping images verification error rate of this method reached 3.5% becaue this method has a significantimprovement in the classification and recognition of self-made data sets.

Experimental Setup& Result

4.Picture Processing


(a) (b) (c) (d)

There is random **random flipping> enhanced brightness> random cropping**

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Extended Readings

W. Astuti, S. Dewanto, K. E. N. Soebandrija, and S. Tan, "Automaticfruit classification using support vector machines: a comparison withartificial neural network," IOP Conference Series: Earth and Environmental Science. IOP Publishing, vol. 195, no. 1, 2018.

S. W. Sidehabi, A. Suyuti, I. S. Areni, and I. Nurtanio, "Classificationon passion fruit's ripeness using K-means clustering and artificialneural network," 2018 International Conference on Information andCommunications Technology (ICOIACT). IEEE, 2018.

S. Lu, Z. Lu, S. Aok, and L. Graham, "Fruit Classification Based onSix Layer Convolutional Neural Network," 2018 IEEE 23rd InternationalConference on Digital Signal Processing (DSP). IEEE, 2018

Summary

The following three conclusions are drawn in this paper:

1) Convolutional neural networks extract feature vectors from images mainly through self-learning, without using specific feature processing technology;
2) Appropriate training parameters can improve the classification accuracy of fruit images to a certain extent;
3) Appropriate data enhancement methods can improve the classification accuracy of fruit images by convolutional neural networks

Future Work