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Classification of Fruits using Image Processing and Deep Neural Networks

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Abstract: Fruits have shown a crucial role in our daily life. Fruits provide us rich resources for our food, pharmacy and industrial materials. The automatic classification of fruits using artificial intelligence and image processing has attracted a large number of researches. However, there exists a large number of species of fruits, the accurate classification of fruits is a challenging task. The paper presents a method for the classification of fruits using the Alexnet, Resnet-50 and MobileNetV3. We collect and normalize various fruit images for the training and testing the deep learning models. The accuracy of 90% and 92% the methods using Alexnet and Resnet-50 on various dataset has shown the potential application of the method in reality. Moreover, the application of the MobileNetV3 improves the execution time of the classification of fruit images.

Keywords: Fruit classification, Machine learning, Feature extraction, Deep neural networks

1. INTRODUCTION

Fruits are important for our life. Fruits provide us rich sources for our food and industrial supply. There are a large number of species of fruits [1]. The classification of the fruits allows us develop various useful applications: e-commerce, production management. However, the classification of fruits is a challenging task. There exists several factors that have affected the accuracy of the recognition of fishes: (1) The similar shape and the high variation of species of fruits have caused the difficulties for the classification of fruit. (2) The complex background (e.g., leaves, grasses) of images caused the wrong classification of fruits. (3) The difficult conditions in captured images of fruits caused the errors of the classification. The manual classification of fruits is a time-consuming task. Automatic classification of the fruits helps us save time and human efforts by using the machine learning. Traditional methods extracted low-level visual features of fruits and applied machine learning classifiers for the classification. In recent years, deep learning helps us improve the classification performance [2]. We can improve the accuracy of the classification of fruits in real applications.

The paper applies the deep learning models including Alexnet [10] and Resnet-50 [11] to improve the classification performance of various species of fruits. Moreover, the MobileNetV3 [12] is applied in the paper to improve the execution time of the classification of fruit images. The datasets have been collected from multi sources to improve the diversity of fruits. We have applied the data augmentation techniques to improve the performance of the classification of fruits. Obtained results and the performance comparison with existing methods have shown the effectiveness of our proposed method.

Figure 1 Examples of various species of fruits

This paper is structured as follows. A survey on research sources is presented in section 2. Section 3 presents our proposed framework. Experimental settings and numerical results are displayed in section 4. The last section concludes our contributions and draws some future works.

2. RELATED WORK

This section reviews significant approaches for the classification of fruits. The classification of fruits can be performed using the feature extraction and machine learning classification [4]. The work in [6] applied various feature extractions based on the color, texture, shape. The neural network is applied to classify fruit images. The work in [5] extracted color features of papaya and the random forest algorithm is applied to predict the ripening of papaya. The work is evaluated on a small dataset of papaya fruits that consists of 114 images. The work in [8] applied the edge detection and Hough transform to detect and recognize apple images. In recent years, the development of convolutional neural network (CNN) and the hardware allow to improve the classification accuracy [9]. The work in [3] proposes a classification method of lemons using the CNN. The dataset is small and the lemons are classified into the healthy and damaged labels. The work in [7] applied the augmentation to enlarge the number of fruit images. Then, the work proposed a CNN to classify fruit images efficiently.

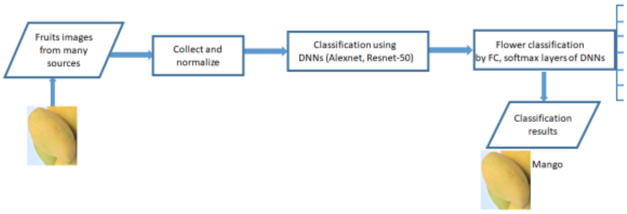

Figure 2 The flowchart of the classification of fruits

Figure 3 The augmentation of fruit data using the image processing

3. PROPOSED METHOD FOR THE CLASSIFICATION FRUITS

The proposed method for the classification of fruits in Fig. 2. The system consists of the following modules:

(1) Firstly, we apply the image processing techniques for input images. The input images are normalized at the size of 224x224x3 for the training and testing of deep neural networks (DNNs).

(2) One of the key factors that improves the performance of DNNs is the data. We apply the data augmentation techniques to enhance the number of images in the datasets of fruits. The rotation, color adjustment and Gaussian noises are addition are applied to generate new images. Fig.3 shows examples of the data augmentation using image processing techniques.

(3) Finally, different DNN models those are the Alexnet Mobilenet V3 and Resnet-50 are applied to classify fruits images efficiently.

The Alexnet consists of 7 layers. The Resnet-50 consists of 50 layers. Recently, the MobileNetV3 has been released to improves the execution time of the classification of images. The MobileNetV3 is designed to work on devices with limited computational resources. The network can search the optimizing network architectures for various device architecture.

Input sizes of image is 224x224x224. The learning rate is 0.0001. The optimization solver is SGMD algorithm. The momentum is set at 0.9. The "cross entropy' algorithm is applied for the loss function of the networks [11]. Fig. 4 shows the accuracy and the loss values during the training process of the classification.

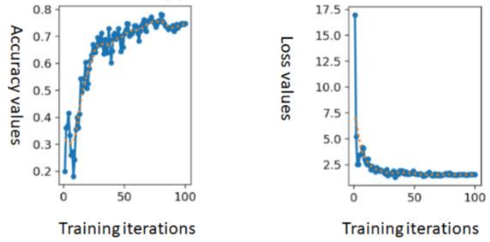

Figure 4 The accuracy and loss values of the training step of Alexnet for the classification of fruits.

Table I Analysis information (number of images) of fruits in the dataset before and after using the data augmentation

Species of fruits	Before	After
Strawberry	250	750
Star fruits	250	750
Mango	250	750
Mangosteen	250	750
Banana	250	750
Pineapple	250	750

Table II Information of fruits for the training and testing the DNNs

Species of fruits	Training	Testing
Strawberry	500	250
Star fruits	500	250
Mango	500	250
Mangosteen	500	250
Banana	500	250
Pineapple	500	250

Table III Accuracy of the classification of fruits using various neural networks

DNN models	accuracy
Alexnet	90%
MobileNetV3	91.5%
Resnet-50 [11]	94%

4. EXPERIEMENTAL RESULTS

4.1. Dataset and evaluation metrics

The fruit dataset consists of 6 species. The accuracy metric is applied to evaluate the performance of the proposed method. The accuracy metric is defined as follows:

$$Accuracy = \frac{Correct\_predictions}{All\_predictions} \quad (1)$$

To evaluate the performance of the proposed method for the classification of fruits, we have collected a large number of fruits. There are 6 species of fruits. Table II shows the analysis information of the dataset. The data augmentation using image processing allows us to enlarge and balance the fruit dataset. Table I compares the number of fruit images before and after the data augmentation.

4.2. Performance evaluation

We have compared the accuracy of the classification of fruits using the Alexnet and the Resnet-50. Table III shows the performance comparison of the DNNs for the classification of fruits. Resnet-50 obtained higher accuracy due to the complex architecture. Resnet consists of more layers compared to Alexnet. The feature extraction and classification of Resnet are better than Alexnet. The Mobilenet V3 obtains higher accuracy compared to Alexnet. Figure 5 demonstrates the classification results of fruit images Fig. 6 illustrates the confusion matrix of the obtained results of detection and recognition of fruits. The classification of banana obtains the highest accuracy compared to other fruits. The shape and color of banana is clear to classify compared to other fruits. The system has been implemented in the computer with GPU NVIDIA Tesla T4, 16GB VRAM, Python 3.7 and Pytorch libraries.

Figure 5 Examples of the classification of fruits

Ground truth	Prediction					
	Strawberry	Star fruits	Mango	Mangosteen	Banana	Pineapple
Strawberry	225	0	0	0	0	0
Star fruits	0	230	10	0	0	10
Mango	15	10	220	10	0	0
Mangosteen	0	0	10	230	0	10
Banana	0	0	0	0	250	0
Pineapple	10	0.1	10	10	0	230

Figure 6 Confusion matrix of the classification of fruits

Table IV Comparison of execution time the classification of flowers using DNNs

DNN models	Execution time (milliseconds)
Mobilenet V3 [12]	9
Alexnet [10]	15
Resnet-50 [11]	35

In term of execution time, Mobilenet V3 allows to obtain the highest performance compared to Alexnet and Resnet-50. The Mobilenet V3 has been designed to improve the execution time of various hardware platforms.

5. CONCLUSION AND FUTURE WORKS

The paper has presented a classification method of fruits using deep neural networks. The Resnet-50 allows us obtain higher accuracy than Alexnet. The execution time of Alexnet is better. The data augmentation allow us to improve the performance of the classification. The application of the MobileNetV3 gains the highest performance in term of execution time. In the future, the results can be applied for the real applications such as industrial production and smart agriculture.

REFERENCES

1.Hassan, N.M.H., Nashat, A.A., 2019. New effective techniques for automatic detection and classification of external olive fruits defects based on image processing techniques. Multidimens. Syst. Signal Process. 30, 571–589.

2. Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., Liu, T., Wang, X., Wang, G., Cai, J., Chen, T., 2018. Recent advances in convolutional neural networks. Pattern Recognit. 77, 354–377.

3. Ahmad Jahanbakhshi et al. Classification of sour lemons based on apparent defects using stochastic pooling mechanism in deep convolutional neural networks. Scientia Horticulturae, 2020, Vol. 263, DOI: 10.1016/j.scienta.2019.109133.

4. Naik, S., Patel, B., 2017. Machine vision based fruit classification and grading-a review. Int. J. Comput. Appl. 170, 22–34.

5. Pereira, L.F.S., Barbon, S., Valous, N.A., Barbin, D.F., 2018. Predicting the ripening of papaya fruit with digital imaging and random forests. Comput. Electron. Agric. 145, 76–82.

6. Jana, Susovan, and Ranjan Parekh. Intra-class Recognition of Fruits using Color and Texture Features with Neural Classifiers. International Journal of Computer Applications 148.11, 2016.

7. Zhang, Y.D., Dong, Z., Chen, X., Jia, W., Du, S., Muhammad, K., Wang, S.H., 2019. Image based fruit category classification by 13-layer deep convolutional neural network and data augmentation. Multimed. Tools Appl. 78, 3613–3632.

8. Xu, L., Lv, J., 2018. Recognition method for apple fruit based on SUSAN and PCNN. Multimed. Tools Appl. 77, 7205–7219.

9. Wang, S.H., Chen, Y., 2018. Fruit category classification via an eight-layer convolutional neural network with parametric rectified linear unit and dropout technique. Multimed. Tools Appl. 1–17

10. Alex Krizhevsky, Ilya Sutskever and Geoffrey E. Hinton . ImageNet Classification with Deep Convolutional Neural Networks. Advances in Neural Information

Processing Systems 25 (NIPS 2012), 2012.
11. Kaiming He and X. Zhang and Shaoqing Ren and Jian Sun. Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

12. Andrew Howard et al. Searching for MobileNetV3 . https://arxiv.org/pdf/1905.02244, 2019.