# Summary on fruit identification methods: A literature review

**Fangyuan Liu[1,a], Leonid Snetkov[2], Dimas Lima[3]**

[1]School of Computer Science and Technology, Nanjing Normal University, Jiangsu 210023, China

[2]ITMO University, Kronverksky Prospect 197101, Russian Federation

[3]Department of Electrical Engineering, Federal University of Santa Catarina, Florianópolis, Brazil

[a] 2191513453@qq.com

**Keywords:** fruit detection; pattern recognition; classification; computer vision; image processing

**Abstract:** (Purposes) This paper shows the importance and necessity of intelligent identification technology of fruit detection. (Methods) We enumerate several state-of-the-art methods and illustrate the specific application in the process of recognition, by selecting eleven highly related literature. (Results) On this basis, we make an analysis and comparison on the advantages and disadvantages of each approaches. (Conclusion) This summary can be beneficial to researchers who are interested in fruit identification.

## 1. Introduction

With the vigorous development of fruit industry, the use of effective technical methods to classify all kinds of fruits is a general trend [1, 2]. As we all know, manual check is not popular any more, we should apply pattern recognition methods to deal with this problem.

The emergence and development of pattern recognition technology is based on the people who use visual and auditory to identify various information [3, 4]. Pattern recognition is a state-of-the-art technique to process complex information automatically using computer and mathematical theory [5]. For these reasons, the researchers use pattern recognition as an intelligent technology to replace and even expand human daily mental activities. Pattern recognition is used in many domains, such as remote sensing [6, 7], multiple sclerosis detection [8, 9], Alzheimer's disease identification [10, 11], cerebral microbleeding detection [12,13], breast cancer classification [14,15], tea category identification [16, 17], brain image classification [18-20], etc.

The methods covered in this paper are applied on analyzing the category information of the fruit. We focus mainly on fruit detection and compare the accuracy of each approaches.

## 2. Methods

We searched the newly-published literatures related to fruit identification in several important academic databases: Web of Science, Elsevier, Springerlink, IEEE, Engineering Village, etc. Eleven literatures are selected and described below.

Ref. [21] presented a novel method that on the basis of multi-feature fusion to identify five kinds of fruits. The authors take advantage of global histogram, LBP, HOG and GaborLBP for selecting the optimal block. Before that it was proved that the four feature extraction methods when used together have the highest accuracy. Finally, the result achieves 81.35% using LibSVM.

Ref. [22] put forward a novel approach to classify fruits. Firstly, they use the split-and-Merge algorithm to complete the process of image segmentation. Then, to extract fruit futures on the combination of color histogram, texture and shape. The most important is that they construct three different SVMs: (i) WTA-SVM; (ii) MWV-SVM; (iii) DAG-SVM and choose three different kernels: (i) LIN; (ii) HPOL; (iii) GRB. In the test phase, not only the accuracy is discussed and the time computation of each classifier is also compared.

Ref. [23] designed an approach which focuses on extracting color and texture features. There are two descriptors, CLD and EHD, to extract features after the fruit image segmentation. And then the author takes advantage of SVM to accomplish the classification task. Their best result is 100% in the experiment of distinguishing fruit category.

Ref. [24]created a hybrid feature set and introduced FCSABC-FNN as a classifier. The feature set consist of fruit color, texture and shape and these conditions are achieved by color histogram, Unser's texture feature vector and mathematical morphology measures respectively.

Ref. [25] introduced a robust system based on "SESH + RF" to recognize fruits. SESH represents a combination of several feature descriptors, using SCD to extract color features, using EHD to evaluate texture information, using Hu7 and SH to select shape features. The performance of the category method is achieved 99.36%, so the prospect is encouraging.

Ref. [26] applied SIFT to extract features according to the fruits' appearance and using Random Forest (RF) as the classifier to determine the classes of fruits. The author compares RF with the following classifiers: (i) KNN; (ii) SVM. "SIFT + RF" achieves the best performance. However, the datasets of three kinds of fruits are unbalanced.

Ref. [27] proposed an effective methodology for fruit classification system. The highlight in this paper is that the author combines BBO and FNN to recognize eighteen fruit classes. In order to verity the superiority of BBO-FNN, which is compared with five existing methods. The performance of the proposed approach achieves 89.11%.

Ref. [28] provided two novel approaches: (i) WE + PCA + BBO-FNN; (ii)WE + PCA + FCSABC-FNN to classify fruits. BBO and FCSABC are both used to train FNN and show better performance when compare with GA, PSO and ABC. The accuracy of the two methods is the same after testing in this literature.

Ref. [29] used co-occurrence matrix and RBPNN with a statistical algorithm on detecting fruit surface defects. In this process, calculating three co-occurrence matrices to extract effective features and using RBPNN to categorize the defect areas. The accuracy of this experiment is 97.25% that shows the effectiveness of the method strongly.

Ref. [30] developed a new idea to transform each image into a one-dimension signal for solving problems caused by data-richness. The approach includes four primarily steps: (1) to acquire hyperspectral images that can evaluate the damage areas; (2) to complete hyperspectral images segmentation through a quick threshold way; (3) to construct the appropriate hyper spectrogram; (4) to use iPLS-DA to classify the extent of fruit bruises.

Ref. [31] developed a fuzzy incremental learning algorithm (FILA). Their proposed algorithm are smart computer vision systems. It can grade mangoes in four different types, determined based on value and distances of nearest markets.

## 3. Results and Discussions

Table 1 comparison of accuracy of several methods

| Method | Disadvantage | Accuracy |
|---|---|---|
| Color+HOG+LBP+GaborLBP +LibSVM [21] | The classifier needs to be strengthened. | 81.35% |
| MWV-SVM + GRB [22] | The number of significant features is insufficient. | 88.2% |
| Color and texture feature + SVM [23] | This work only extracts two vital features. | 100% |
| Hybrid feature set and FCSABC-FNN [24] | The prediction is unstable. | 89.1% |
| SESH + RF [25] | The computational complexity is high. | 99.36% |
| SIFT + RF [26] | The datasets are unbalanced in fruit category. | 96.97% |
| CH + Unser's texture measure + morophology + BBO-FNN [27] | The performance of feature extraction is lower than other methods. | 89.11% |
| WE + PCA +BBO-FNN<br>WE + PCA + FCSABC-FNN [28] | There are other classifiers superior to FNN and have better performance. | 89.5% |
| Co-occurrence and RBFNN [29] | Classification speed is slower than other algorithms. | 97.25% |
| Hyperspectrogram + iPLS-DA [30] | Classification is time-consuming. | 94.04% |
| FILA [31] | sensitive to the maturity and quality | 87% |

In general, we discuss the accuracy and weakness of each method that is mentioned above. The results are listed in Table 1. We gave the methodology, disadvantage, and accuracy of each method. Note that all the accuracies were recorded from the literatures themselves.

The support vector machine (SVM) is a powerful tool in traditional classifiers. The researchers are suggested to test advanced SVM classifiers, such as fuzzy SVM [32-35], generalized eigenvalue proximal SVM [36, 37], twin SVM [38, 39], etc.

In the future, we suggest researchers to apply deep learning method on fruit identification. Some typical deep learning techniques, such as convolutional neural network [40], sparse autoencoder, and deep belief network, have been successfully applied in computer vision. The researchers can learn from their applications, and test the feasibility of deep learning in fruit classification.

## 4. Conclusion

This study describes several pattern recognition methods from a series of articles for identify fruit information. The most effective approach can be found from this paper and the researchers are able to develop better ideas on this basis. Furthermore, pattern recognition methods are applied in other fields has a bright future.

## Acknowledgement

The paper is financially supported by Fundamental Research Funds for the Central Universities (LGYB201604), Open fund for Jiangsu Key Laboratory of Advanced Manufacturing Technology (HGAMTL1601), Open fund of Key Laboratory of Guangxi High Schools Complex System and Computational Intelligence (2016CSCI01).

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