Fruit Classification by HPA- SLFN

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***Abstract*—(Objective) Fruit classification remains a challenge because of the similarities involved by a large quantities of types of fruits. With the aim of recognizing fruits accurately and efficiently, this paper offered a novel fruit-classification tool. (Method) The proposed methodology consisted of following four processes: (i) A four-step preprocessing was performed. (ii) The color, shape, texture features were combined. (iii) Principal component analysis was employed for feature reduction. (iv) We presented a novel classification method with the combination of "Hybridization of PSO and ABC (HPA)" and "single-hidden layer feedforward neural-network (SLFN)", which was termed as HPA-SLFN. (Results) The experiment results demonstrated that the proposed HPA-SLFN achieved an 89.5% accuracy that was superior to existing methods. (Conclusion) The proposed HPA-SLFN was effective.**

Keywords—Fruit classification; machine learning; single-hidden layer feedforward neural-network; particle swarm optimization; artificial bee colony; principal component analysis.

I. Introduction

Fruit classification imposes a challenge in supermarkets and factories, because different fruits may have similar shape, color, and texture. Manual classification may fail due to its low efficiency. Barcodes has been widely used for packaged products; nevertheless, consumers usually prefer to select the products on their own. Another solution was to provide each cashier with an inventory with the pictures and codes of the products; however, it is also tedious and time consuming for cashiers to flip over the booklets. In the last decade, numerous fruit classification algorithms were proposed.

Baltazar, Aranda and González-Aguilar [1] utilized data fusion to handle fresh intact tomatoes, and a Bayesian classifier was used for classification. Pennington and Fisher [2] employed clustering approach to classify vegetables and fruits. Yang, Lee and Williamson [3] presented a blueberry classification software. Wu [4] introduced the max-wins-voting support vector machine (SVM) to classify fruits, with overall accuracy of 88.2%. Feng, Zhang and Zhu [5] utilized Raman spectroscopy to classify eight types of citrus. Breijo, Guarrasi, Peris, Fillol and Pinatti [6] developed an odor sampling system for classification of the aroma of Diospyros kaki. Cano Marchal, Martínez Gila, Gámez García and Gómez Ortega [7] offered an expert system (ES) for estimation of the impurity degree of olive oil. Fan, Ma, Ge, Peng, Riley and Tang [8] used back-propagation neural network with two hidden layers to predict extrusion food surface images. Ji [9] proposed a fitness-scaling chaotic artificial bee colony method to establish a fruit classification system, identifying eighteen types of fruits. Khanmohammadi, Karami, Mir-Marques, Garmarudi, Garrigues and de la Guardia [10] applied Fourier transform near infrared (FT-NIR) spectrometry for persimmon fruit classification. Wei [11] offered a novel classification system using wavelet entropy.

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Above existing techniques achieved good results, however, the performance can be improved [12]. The purpose of this study was to propose a new fruit-classification method with the help of computer vision [13] and artificial intelligence [14, 15]. The proposed classifier combined the single-hidden layer feedforward neural-network (SLFN) with a novel optimization method with the aim of reducing the misclassification rate.

The structure of the remainder was listed below: Section II lists the implementation procedures of the proposed system. Section III presents the experiment results. Section IV discusses the results, the contribution and limitation of the study. Final section V is devoted to conclusions.

II. Methodology

A four-step method described in [9] was employed for preprocessing. (i) We captured fruits using a digital camera, and labelled the classes of the images manually. (ii) We removed the background using image segmentation methods since our concentration is on the fruits only. Split-and-merge algorithm [16] was utilized. (iii) We used a square window to adjust the fruit to the center. (iv) All the square images were resized as 256×256. This step will accelerate the classification performance.

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A. Feature Extraction

A compound feature vector including color, texture, and shape features was used. 64 color features, 8 shape features, and 7 texture features were obtained totally. The feature extraction was essentially equal to a dimension reduction process. Original tri-color fruit image has 256×256×3 = 196,608 dimensions. The size of reduced feature is merely 64+8+7 = 79.

The color histogram was widely harnessed to analyze the distribution of colors in an image [17]. To produce color histogram of the fruit images, the colors in the image are first discretized into 64 bins, and pixel number of every bin is counted.

Eight morphology-based measures (MBM) were employed. They are: perimeter, area, convex area, Euler number, solidity, major length, minor length, and eccentricity.

Unser's texture measure (UTM) was harnessed based on the non-normalized sum *s* and non-normalized difference *d* histograms with a relative displacement (δ_1, δ_2). The UTM in total is composed of seven measures as mean, contrast, homogeneity, energy, variance, correlation, and entropy.

Finally, principal component analysis (PCA) was employed for feature reduction. 95% variance was used as the threshold. In total, there are 79 features extracted from a preprocessed fruit image.

B. Classifier

When the feature extraction and reduction finished, we need to feed the feature vectors to the single-hidden layer feedforward neural network (SLFN) in batch mode [18, 19]. SLFN was widely used in approximation and classification [20], because it doesn't need to know about the priori probabilities of different classes [21]. It is clearly perceived that a SLFN consists of input layer, hidden layer, and output layer. Note that the neurons in adjacent layers are linked fully and directly. Every link is assigned with a weight.

Let N_I, N_H, and N_O represent the input neuron number, hidden neuron number, and output neuron number, respectively. Suppose ω_1 represents the weight matrix from input space to hidden layer, ω_2 denotes the weight matrix from hidden layer to output layer. The weights of single-hidden-layer SLFN were treated as the variables, and the average mean-squared error of output results and targets was set to be the fitness function. The optimization problem was to minimize average mean-squared error in order to find the best weights/biases.

C. Optimization

It is a difficult task to obtain the best weights/biases of SLFN [22, 23], because the traditional optimization algorithms are prone to be trapped in local extrema [24]. This indicates that the algorithms would likely terminate without attaining the optimal solution.

Particle swarm optimization (PSO) [25, 26] is carried out via a swarm of particles. Particles update their positions by iteration. The moving direction of each particle consists of the direction to its own previous best (abbreviated as *pbest*) position and the direction to global best (abbreviated as *gbest*) position among the population with the aim of obtaining the best solution [27].

$$pbest(i,t) = \underset{k=1,\dots,t}{\arg\min}\left[f\left(P_i(k)\right)\right], i \in \{1,2,\dots,N_P\} \tag{1}$$

$$gbest(t) = \underset{\substack{i=1,\dots,N_P \\ k=1,\dots,t}}{\arg\min}\left[f\left(P_i(k)\right)\right] \tag{2}$$

where i , N_P , t , f , and P represent the index of particle, total number of particles, iteration time, the fitness function, and the position, respectively. We update the velocity V as

$$\begin{aligned} V_i(t+1) = {} & \omega V_i(t) + \\ & c_1 d_1 \left(pbest(i,t) - P_i(t)\right) + \\ & c_2 d_2 \left(gbest(t) - P_i(t)\right) \end{aligned} \tag{3}$$

Then we update P as

$$P_i(t+1) = V_i(t+1) + P_i(t) \tag{4}$$

where ω means the inertia weight, c_i (i = 1,2) are positive constant parameters, d_1 and d_2 are random variables within [0, 1].

Artificial bee colony (ABC) is inspired by natural bees with the aim of obtaining optimal solution. In the colony of artificial bees, there are 3 groups: employed bees, scouts, and onlookers [28]. Only one employed bee is assigned for every food source. If the food source of the employed bee is abandoned, it becomes a scout [29].

Noticing ABC is good at searching but poor in exploitation, while PSO is good at exploitation but easily gets trapped into local best, hence, it is nature to combine PSO with ABC. Many hybridization approaches of PSO and ABC were proposed in latest literatures. In last year, Wang, Zhang, Dong, Du, Ji, Yan, Yang, Wang, Feng and Phillips [30] proposed a novel hybridization of PSO and ABC (HPA) and proved it was better than other hybridizations. Therefore, we introduced this HPA in this study and used it to train SLFN.

In HPA, the most important operation is recombination. At every iteration, the best solutions obtained by the PSO and ABC are recombined, and the solution (referred as "*TheBest*") is offered to the PSO as global best (*gbest*), and to onlooker bees of ABC to be neighbors. In following study, we applied the HPA to train SLFN, and proposed a novel classification method that was termed as HPA-SLFN.

D. Implementation

Cross validation approach was used to improve the generalization ability of the classifier [31]. *K*-fold cross validation [32] is chosen because it is simple and easy. The pseudocode can be seen in **Table 1**. As the K folds is totally random set, the distribution of different folds may be quite different. Hence, stratification technique was utilized with the aim that all folds have similar class distributions.

Table 1 K-fold cross validation

Pseudocode of K-fold Cross Validation	
Step A	Partition the dataset into K folds. All folds have similar class distribution
Step B	Repeat K times so that each fold serves as a test set
Step C	Initialize the SLFN
Step D	Use K-2 folds to train the SLFN, and 1 fold as the validation set to avoid over-fitting. Early stop technique was employed to stop the training when the classification results over validation set decreased
Step E	Submit the final left 1 fold as the test set to the trained SLFN.
Step F	Report the classification results over the test set
Step G	Jump to Step B
Step H	Combine all the classification results over the test sets, and report the averaged results

The implementation of the system was 2-fold (**Figure 1**): offline learning to train the classifier, and online prediction to recognize fruit type.

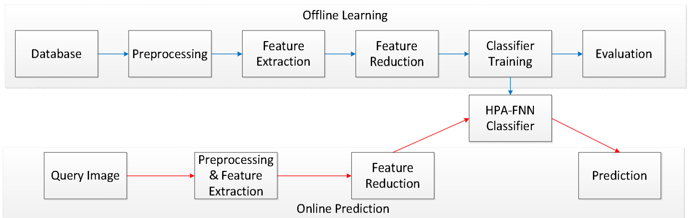

Figure 1: Flowchart of the proposed method

III. Experiments & Results

We obtained the fruit dataset by online collecting using Google (URL: http://images.google.com) and digital camera. The dataset consists of 1653 images 18 different types: Gold Pineapples, k, Green Plantains, Cantaloupes, Passion Fruits, Tangerines, Rome Apples, Anjou Pears, Green Grapes, Strawberries, Yellow Bananas, Granny Smith Apples, Bosc Pears, Red Grapes, Black Grapes, Blackberries, Watermelons, and Blueberries.

A. Feature Reduction

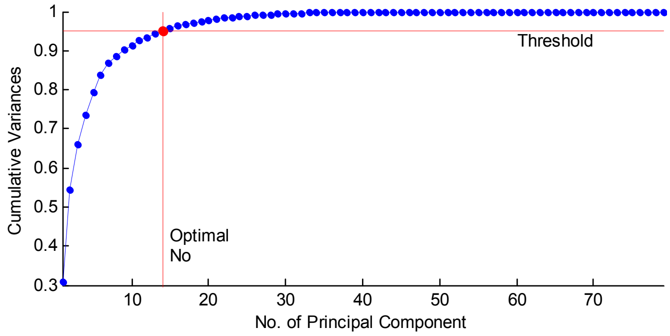

Figure 2: Feature reduction using PCA (Threshold was set to cover 95% of total variance by experience)

Table 2 The cumulative variances of PCA

Dimensions	11	12	13	**14**	15	16	17	18	19	20
Variance (%)	92.55	93.51	94.35	**95.08**	95.71	96.27	96.76	97.19	97.55	97.87

Figure 2 illustrates the cumulative sum curve of reduced feature number versus variance. **Table 2** shows the data in detail. It is obvious that **95.08%** of total energy can be preserved using merely 14 features. The reduced features require only 17.7% of the memory of the original features.

B. Comparison to Other Classification Methods

The proposed HPA-SLFN method was compared with five latest classification approaches: GA-FNN [33], PSO-FNN [34], ABC-FNN [35], kSVM [4], and FSCABC-FNN [9]. **Table 3** illustrated the detailed information.

Table 3 Classification accuracy comparison

Algorithm	Accuracy	Rank
GA-FNN [33]	84.8%	6
PSO-FNN [34]	87.9%	4
ABC-FNN [35]	85.4%	5
kSVM [4]	88.2%	3
FSCABC-FNN [9]	89.1%	2
HPA-SLFN (Proposed)	89.5%	1

C. Confusion matrix

Figure 3 showed the confusion matrix of HPA-SLFN. Every column denotes for the actual instances; meanwhile, every row denotes for predicted instances. Each correct classification case is painted in green, while the misclassification cases in yellow.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18
C1	52	4	0	0	0	5	3	0	0	0	0	0	0	0	0	0	0	0
C2	0	83	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C3	0	0	128	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	0	3	49	0	0	0	0	0	4	5	0	0	0	0	0	0	0
C5	0	0	0	0	112	0	0	0	0	0	0	0	0	0	0	0	0	0
C6	0	0	0	0	0	89	5	0	0	5	0	0	0	3	3	0	0	0
C7	2	0	0	0	0	4	62	0	0	0	0	0	0	0	0	0	0	4
C8	0	0	0	0	0	0	0	121	0	0	2	6	0	0	0	0	0	0
C9	0	0	0	0	0	0	0	0	89	0	0	0	0	0	0	0	0	0
C10	0	0	3	0	0	0	0	0	0	56	0	0	0	4	9	0	0	0
C11	0	0	7	0	0	0	0	0	0	0	72	9	0	0	0	0	0	0
C12	0	0	3	0	0	0	0	6	0	0	7	124	0	0	0	0	0	0
C13	5	0	0	6	0	8	0	0	0	0	0	2	53	0	0	0	0	0
C14	0	2	0	0	0	0	0	0	0	0	0	0	0	36	3	0	0	4
C15	0	0	0	0	0	0	0	0	0	8	0	0	0	2	112	0	0	0
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	88	5	0
C17	0	0	0	0	0	0	0	0	0	2	0	0	0	3	3	0	87	0
C18	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	4	0	66

Figure 3: Confusion matrix of HPA-SLFN

Based on the confusion matrix, we can calculate the sensitivity, specificity, and accuracy of each class versus its corresponding out-of-class (i.e., Granny Smith Apples vs. non-Granny Smith Apples) as shown in **Table 4**.

Table 4 Evaluation of 18 classes

ID	Name	Sensitivity	Specificity	Accuracy
1	Granny Smith Apples	81.25%	99.56%	98.85%
2	Rome Apples	**100.00%**	99.62%	99.64%
3	Yellow Bananas	96.97%	98.95%	98.79%
4	Green Plantains	80.33%	99.37%	98.67%
5	Tangerines	**100.00%**	**100.00%**	**100.00%**
6	Hass Avocados	84.76%	98.90%	98.00%
7	Watermelons	86.11%	99.49%	98.91%
8	Cantaloupes	93.80%	99.61%	99.15%
9	Gold Pineapples	**100.00%**	**100.00%**	**100.00%**
10	Passion Fruits	77.78%	98.80%	97.88%
11	Bosc Pears	81.82%	99.11%	98.19%
12	Anjou Pears	88.57%	98.88%	98.00%
13	Green Grapes	71.62%	**100.00%**	98.73%
14	Red Grapes	80.00%	99.07%	98.55%
15	Black Grapes	91.80%	98.56%	98.06%
16	Blackberries	90.72%	99.74%	99.21%
17	Blueberries	91.58%	99.68%	99.21%
18	Strawberries	90.41%	99.49%	99.09%

IV. Discussions

Data in **Table 3** showed that HPA-SLFN obtained the highest classification accuracy of 89.5%. Next is FSCABC-FNN of 89.1%, kSVM ranked third of 88.2%. Sensitivity is the most important indicator that measures the rate of actual category of each class is correctly identified. Checking the sensitivities of **Table 4**, the 2nd class (Rome Apples), the 5th class (Tangerines), and the 9th class (Gold Pineapples) obtained the best result of 100%. The reason may lie in that those categories have distinct color, shape, and texture features.

Nevertheless, a few categories were not identified so successfully. The sensitivities of the 13th class (Green Grapes) and the 10th class (Passion Fruits) suffered from the worst results of 71.62% and 77.78% (below 80%). Let us revisit **Figure 3**, it was clear 5, 6, 8, and 2 instances of Green Grapes were mislabeled as 1st class (Granny Smith Apples), 4th class (Green Plantains), 6th class (Hass Avocados), and the 12th class (Anjou Pears), respectively. Meanwhile, 3, 4, and 9 instances of Passion Fruits were misclassified as 3rd class (Yellow Bananas), 14th class (Red Grapes), and 15th class (Black Grapes), respectively. The reason was those categories had similar features in either color, or shape, or texture, which gave a challenge to the proposed classification system.

V. Conclusion

In this study, we presented a new fruit classification approach as HPA-SLFN. The results showed the classification accuracy of HPA-SLFN of 89.5% was better than existing classification methods. The limitations of the proposed system were revealed as follows. First, the weights/biases of SLFN cannot be directly interpreted as understandable rules for experts in food engineering. Second, two types of fruits (Green Grapes and Passion Fruits) were not identified well.

In our future research, we will try to use HPA to evolve the number of hidden neurons. Besides, we will test fruits in complex conditions, for example dried, canned, and sliced fruits. We shall add more fruit-image features improve the performance of the classifier. The HPA-SLFN will also be tested in other images, such as CT images [36] and magnetic resonance images [37, 38]. Another research direction is we shall test other advanced training methods, such as Jaya algorithm [39] and hybrid genetic algorithm [40].

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