Received: 17 October 2019 | Revised: 24 February 2020 | Accepted: 11 March 2020
DOI: 10.1111/jfpe.13414

ORIGINAL ARTICLE

Journal of Food Process Engineering
WILEY

Indonesian fruits classification from image using MPEG-7 descriptors and ensemble of simple classifiers

Joko Siswantoro | Heru Arwoko | Monica Widiasri

Department of Informatics Engineering, University of Surabaya, Surabaya, Indonesia

Correspondence
Joko Siswantoro, Department of Informatics Engineering, University of Surabaya, Jl. Kalirungkut, Surabaya 60293, Indonesia.
Email: joko_siswantoro@staff.ubaya.ac.id

Funding information
Kementerian Riset Teknologi Dan Pendidikan Tinggi Republik Indonesia, Grant/Award Number: 025/SP-Lit/LPPM-01/DRPM/Multi/FT/III/2019

Abstract

Fruits classification from image is a very challenging task, particularly for Indonesian indigenous fruits, due to some similarities occurred in several types of the fruits. This study proposes a method to classify Indonesian fruits from image using MPEG-7 color and texture descriptors. The descriptors were directly extracted from the image without pre-processing and segmentation steps. Principle component analysis was then applied to reduce the dimension of the descriptors. Four simple classifiers, decision tree, naïve Bayesian, linear discriminant analysis, and k-nearest neighbor were used to classify the fruit image based on extracted descriptors. An ensemble of simple classifiers trained with some combination of MPEG-7 descriptors has been constructed to increase the classification accuracy of single simple classifier. To validate the proposed method, an Indonesian fruit images data set consisted of 15 classes was developed in this study. The experiment result showed that the ensemble of simple classifiers achieved the best accuracy of 97.80% by employing linear discriminant analysis, and k-nearest neighbor as base classifiers trained using CSD, SCD, and the combination of CLD and EHD. Therefore, the proposed method achieved a good classification accuracy and can be applied in vision-based classification system in industry.

Practical Applications

This study proposes a method to classify Indonesian fruits from image using MPEG-7 descriptors and the ensemble of simple classifiers. The proposed method can be applied in vision-based fruit sorting system in fruit industry as well as vision-based fruit pricing system in supermarket.

1 | INTRODUCTION

Indonesia is a tropical country located in Southeast Asia which has a very high diversity of fruit plants. There are more than 300 species of fruit grown in Indonesia. About 270 species of which have been known as edible fruits (Uji, 2007). Furthermore, several types of Indonesian indigenous fruits are difficult to distinguish from others due to the similarity in color, texture, or shape. Nowadays, there are many Indonesian indigenous fruits sold in both traditional market and supermarket (Siswantoro, Arwoko, & Widiasri, 2019). In supermarket, recognizing the type of fruit is a routine task performed by a salesperson during pricing process. To determine the price of a fruit, the salesperson usually uses code and picture provided in a booklet to recognize the fruit. The code is then entered to weighing scale to generate barcode containing the information about fruit name, weight, and price. This process is not only time consuming but also causing error in pricing process (Rocha, Hauagge, Wainer, & Goldenstein, 2010). Fruit recognition can also be applied to other fields such as the food industry as well as dietary management. In food industry fruit recognition is used in shorting (Kheiralipour & Pormah, 2017; Le, Lin, & Piedad Jr., 2019; Roomi, Priya, Bhumesh, & Monisha, 2012) and grading (Arakeri, 2016). Fruit recognition can be applied to determine nutrient content of fruit for dietary management in mobile application as reported by Waltner et al. (2015). In general, fruit recognition is a classification process that can be divided into two categories, inter-classification and intra-classification (Roomi et al., 2012). Inter-classification is used to classify multiple types of fruit, while intra-classification is used to classify a certain type of fruit into its variants.

Fruit classification from image is an automatic fruit recognition method that has good accuracy (Zhang et al., 2019) and can be used as alternative to manual classification method (Roomi et al., 2012). This method is inexpensive compared to manual recognition, since the user only needs to provide a digital camera and a computer once (Zhang et al., 2019). On the other hand, manual fruit recognition needs human experts who must be continually paid. Several fruit classification methods from image have been proposed by employing either machine learning model or deep learning model. In general, the steps in fruit classification method from image consist of image acquisition, pre-processing, segmentation, features extraction, and classification. Segmentation is a process used to separate object of interest in an image from its background (Gonzalez & Woods, 2018). Although images used in fruit classification are generally captured using same background color, segmentation is still carried out in almost all proposed fruit classification method from image. Furthermore, employing segmentation has an impact on increasing computational time (Siswantoro et al., 2019).

Roomi et al. (2012), Arakeri (2016), and Kheiralipour and Pormah (2017) have proposed intra-classification method for mango, tomato, and cucumber, respectively. The proposed methods used thresholding technique for segmentation. Roomi et al. (2012) extracted 11 features consisted of object contour modeling, region-based descriptor, and boundary-based descriptor from mango image. The features were used to classify three variants of mango using naïve Bayes and produced the accuracy of 90.91%. Arakeri (2016) used statistical color features and color texture features to identify the defective and ripeness of tomato. Sequential forward selection was also applied to reduce the number of features before inputted artificial neural network (ANN) classifiers. The classification accuracies for defective and ripeness were 100% and 96.47%, respectively. Kheiralipour and Pormah (2017) introduced new shape features for cucumber, namely centroid non homogeneity and width non-homogeneity. The features together with centroid and eccentricity were used to classify whether a cucumber has desirable shape or undesirable shape using ANN. The highest classification accuracy of 97.10% was obtained using three layers ANN with 4-20-2 structure. Deep learning model was also used in intra-classification method as proposed by Le et al. (2019) and Katarzyna and Paweł (2019). Le et al. (2019) employed mask region-based convolution neural networks (Mask R-CNN) to classify banana tiers into normal and abnormal tiers and produced the classification accuracy of 96.05% if data augmentation is used in training process. Katarzyna and Paweł (2019) used nine layers convolutional neural networks (CNN) trained with original image and individual image. You only look once V3 (YOLO V3) method was used to obtain the region of interest for single object. The two CNN models were then combined using the certainty factor to recognize six varieties of apple and obtained the recognition rate of 100%. Although the proposed intra-classification methods produce good classification accuracy, the methods are only used to classify object into a few numbers of classes. The accuracy might decrease as increasing the number of classes, as reported by Prabuwono, Siswantoro, and Abdullah (2015) and Siswantoro, Prabuwono, Abdullah, and Bahari (2017).

Koslowski, Santos, Borba, and Gamba (2013), Prabuwono et al. (2015), and Siswantoro et al. (2017) have proposed inter-classification method to classify fruits and vegetables from image with high classification accuracy. However, the proposed methods can only be applied to image containing single object. Furthermore, the object must be placed on a black background during image acquisition. Koslowski et al. (2013) used patch detection to find pixel in fruit image that has the brightest color intensity. The image was then cropped to a 192×192 window around the pixel. From the cropped image, 454 MPEG-7 descriptors were extracted. ANN and support vector machine (SVM) classifiers were used to classify eight types of fruit and obtained the classification accuracy of 93.75%. Prabuwono et al. (2015) and Siswantoro et al. (2017) used thresholding technique for segmentation process and extracted 16 statistical color and shape features from the segmented image. Three layers of ANN were used by Prabuwono et al. (2015) to classify three types of fruits with the classification accuracy 99.87%. Siswantoro et al. (2017) used hybrid ANN and linear model trained with Kalman filter to classify 10 classes of natural produces and obtained the classification accuracy of 98.40%.

Rocha, Hauagge, Wainer, and Goldenstein (2008), Rocha et al. (2010), and Faria, dos Santos, Rocha, and Torres (2012) have proposed inter-classification methods for fruit images from Supermarket Produce data set (Rocha et al., 2008). Each image in the data set contained different number of objects, acquired in different illumination intensity and different pose. However, most of the fruits in the data set cannot be categorized as Indonesian indigenous fruits. Rocha et al. (2010) employed background subtraction for segmentation, while Rocha et al. (2008) and Faria et al. (2012) did not implement segmentation process in their proposed method. The combination of various features with the length between 368 and 840, namely Unser's descriptors, color coherence vectors, border/interior pixel classification, appearance descriptors, global color histogram, color autocorrelogram, local activity spectrum, quantized compound change histogram, and edge orientation autocorrelogram, used to classify 15 classes of fruit together with the fusion of classifiers. Although the proposed methods produce accuracy between 96.60 and 98.80%, it requires a long computational time for features extraction and training process. As reported by Rocha et al. (2010), it required about 1 hr to train classifiers fusion using 720 images in training data on a 2.31 GHz computer with 2 GB of RAM.

Zhang and Wu (2012), Zhang, Wang, Ji, and Phillips (2014), Wang et al. (2015), and Zhang et al. (2016) have also proposed inter-classification method for fruit from image. The fruit images used in their experiment consisted of several objects from a type of fruit. Split and merge technique was used to separate object from its background in segmentation process. Zhang and Wu (2012) used 79 features from color histogram, Unser's descriptors, and shape features. Furthermore, principle component analysis (PCA) was used to reduce the dimension of features. The classification was done using multiclass SVM. Zhang et al. (2014) and (2016) extracted the same features as used by Zhang and Wu (2012) while Wang et al. (2015) used 30 features from wavelet entropy. They used also PCA for dimensionality reduction and employed feedforward neural network (FNN) trained with several swarm intelligent optimization methods. However, the proposed methods only achieved the classification accuracy less than 90%.

CNNs have also been applied for inter-classification of fruits from images as reported by Wang and Chen (2018), Zhang et al. (2019), and Steinbrener, Posch, and Leitner (2019). Segmentation process using split and merge technique was still carried out by Wang and Chen (2018) and Zhang et al. (2019) on fruit image before inputted to CNN. Wang and Chen (2018) used eight-layer CNN with parametric rectified linear unit (PReLU) and dropout technique to classify 18 types of fruit. They used data augmentation in training data and obtained the classification accuracy of 95.67%. Zhang et al. (2019) used 13-layer CNN with three types data augmentation methods, including image rotation, gamma correction, and noise injection, and achieved the classification accuracy of 94.94%. Steinbrener et al. (2019) used a popular CNN architecture, called GoogLeNet (Szegedy et al., 2015), to classify 13 class of fruit from hyperspectral image. The highest classification accuracy of 90.96% was achieved by combining GoogLeNet with two-layer CNN, called kernel model. The kernel model was used to transform 16 band hyperspectral image to three band images before inputted to GoogLeNet. Although CNN can produce accuracy greater than 90%, training CNN model requires both a high specification computer and a high computational time. As reported by Zhang et al. (2019), the computational time for training CNN with data augmentation was 414.55 hr on an Intel Core i5–3470 computer with frequency of 3.20GHz in CPU, while in GPU required 2.34 hr.

Siswantoro et al. (2019) have proposed Indonesian fruit recognition method from image using one of MPEG-7 visual descriptor, called color structure descriptor (CSD), and k-nearest neighbor (k-NN). The proposed method was used to classify seven classes Indonesian fruit image data set collected from Google Image. CSD was extracted directly from fruit image without segmentation process. A variance-based feature selection was used to reduce the dimension of CSD. The proposed method achieved the best classification accuracy of 90.86% with 10-fold cross validation.

MPEG-7 is a multimedia content descriptor developed by Moving Picture Experts Group (MPEG) and standardized by ISO/IEC. It is a complete audio-visual descriptor for describing multimedia data. MPEG-7 visual descriptor consists of color descriptor, texture descriptor, shape descriptor, motion descriptor, and localization descriptor (Bastan, Cam, Gudukbay, & Ulusoy, 2010). The advantage of using MPEG-7 descriptor is it can be directly extracted from entire pixel in the image without pre-processing and segmentation if the image is captured using homogeneous background, as reported by Siswantoro et al. (2019). Therefore, the using of other MPEG-7 visual descriptors to classify Indonesia fruit from image needs to be investigated.

This study proposes a method for classifying Indonesian fruits from image using MPEG-7 color and texture descriptors. Three MPEG-7 color descriptors and two MPEG-7 texture descriptors were extracted from the fruit image and used as input features to classifier. PCA was applied to reduce the dimension of the features. Four simple classifiers, including decision tree (DT), naïve Bayesian (NB), linear discriminant analysis (LDA), and k-nearest neighbor (k-NN), were used to classify the fruit image. To increase the classification accuracy, an ensemble of simple classifiers was constructed based on LDA and k-NN trained using some combination of MPEG-7 descriptors.

2 | MATERIALS AND METHODS

2.1 | Materials

2.1.1 | Hardware and software

A Canon EOS Kiss X6i digital camera was used to capture the image of fruit samples. A LED lamp with two intensities, 1,050 and 160 lm, was used as illumination source during image acquisition. An Intel Core i7-8550U CPU @ 1.80GHz 2.00 GHz with Windows 10 Pro 64-bit Operating System, ×64-based processor and 20 GB RAM was used as hardware to conduct an experiment for validating the proposed method. The proposed method was implemented in Python 3.7.3 language programing supported by some libraries to perform feature extraction, and classification. An open source computer vision library OpenCV 2.3.1 (Bradski, 2000) together with an MPEG-7 Low Level Feature Extraction Static/Dynamic Library (Bastan et al., 2010) were used to extract MPEG-7 descriptors from the image in the data set. For classification, the proposed method employed a machine learning library in Python scikit-learn 0.20.3 (Pedregosa et al., 2011) and a Python library for scientific computing NumPy 1.16.2 (Oliphant, 2006).

2.1.2 | Ubaya-IFDS3000 image data set

One of contribution in this study is the developing of Indonesian fruit images data set called University of Surabaya—Indonesian Fruit Images Data Set 3000 (Ubaya-IFDS3000). The data set consisted of 15 classes of Indonesian fruits, including Ambarella, Avocado, Dragon fruit, Duku, Durian, Guava, Mangosteen, Pacitan orange, Persimmon, Pineapple, Salak, Sapodilla, Siam lime, Soursop, and Star fruit, as shown in Figure 1. The fruit samples were randomly collected from traditional market around Surabaya, East Java, Indonesia. The images of samples were then acquired in the laboratory. Every class in the data set consisted of 200 images or totally there were 3,000 images in the data set. The image in the data set was acquired in RGB (Red, Green, Blue) color space with 8 bits per channel. The dimension of the image was 2,592 × 1,456 pixels with the resolution of 72 dpi. The image was saved in a file in JPEG format. The resolution and the image format were chosen to demonstrate that the proposed method does not require high quality image. Therefore, it can be applied in vision-based fruit sorting system in fruit industry as well as vision-based fruit pricing system in supermarket using low cost camera.

Every image in the data set was acquired using five different background, white, pink, light yellow, light green, and light blue, as shown in Figure 2. The illumination source with two intensities, 1,050 and 160 lm, was used during image acquisition. In addition, the image was also acquired in two orientations, 0° and 45°. The examples of image acquired in different illumination intensities and orientations are shown in Figure 3. The number of objects in each image varied from one until almost covering the entire of image, as depicted in Figure 1. The presence of shadows in almost all images in the data set, as in Figures 1–3, will increase the complexity of the data set during classification. However, in real application the presence of shadows could decrease classification accuracy. To overcome this problem, the object needs to be placed right under the illumination source in certain distance.

2.2 | Method

2.2.1 | Image descriptors

The proposed method used features in MPEG-7 visual descriptors to classify Indonesian fruit images. MPEG-7 visual descriptors consist of basic visual features for multimedia content, including color descriptors, texture descriptors, shape descriptors, motion descriptors, and localization descriptors (Bastan et al., 2010). In this study, MPEG-7 visual descriptors used to classify Indonesia fruit image were color descriptors, including Color Structure Descriptor (CSD), Scalable Color Descriptor (SCD), and Color Layout Descriptor (CLD); and texture descriptors, including Edge Histogram Descriptor (EHD) and Homogeneous Texture Descriptor (HTD). Since the fruit image in Ubaya-IFDS3000 data set was captured using a homogenous background and noise-free, then the features used in this study were directly extracted from the entire image without preprocessing and

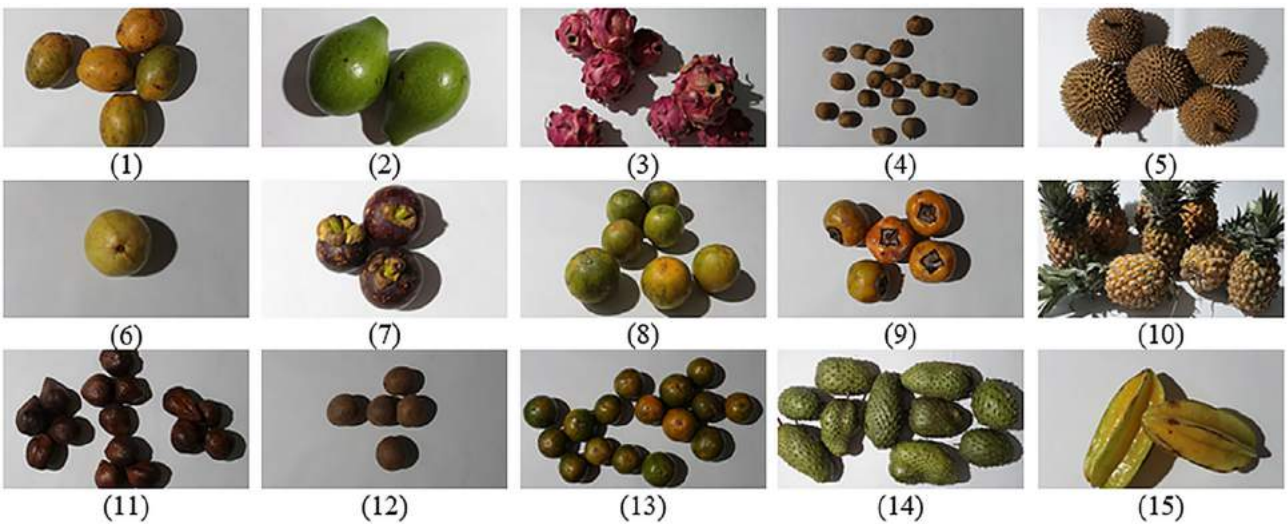


FIGURE 1 The examples of image in Ubaya-IFDS3000 data set: (1) Ambarella, (2) Avocado, (3) Dragon fruit, (4) Duku, (5) Durian, (6) Guava, (7) Mangosteen, (8) Pacitan orange, (9) Persimmon, (10) Pineapple, (11) Salak, (12) Sapodilla, (13) Siam lime, (14) Soursop, and (15) Star fruit

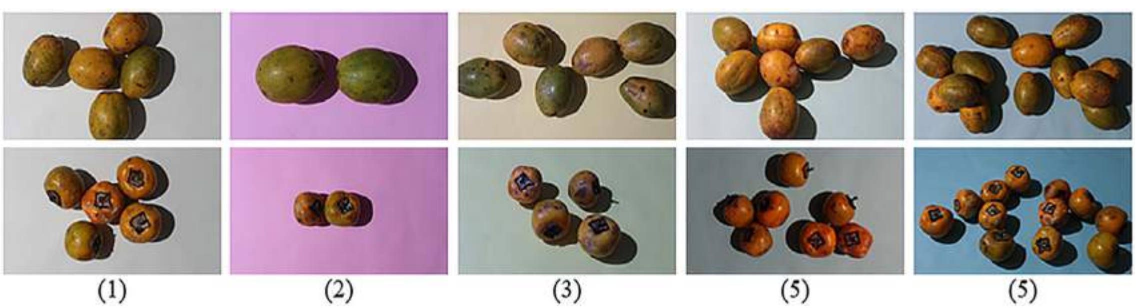


FIGURE 2 The examples of image in Ubaya-IFDS3000 data set with different background color: (1) white, (2) pink, (3) light yellow, (4) light green, and (5) light blue

FIGURE 3 The examples of image in Ubaya-IFDS3000 data set with different illumination intensity and orientation: (1) 1050 lm and 0°, (2) 160 lm and 0°, (3) 1050 lm and 45°, and (4) 160 lm and 45°

segmentation to reduce computational time. The following subsections describe the detail of each descriptor according to Manjunath, Salembier, and Sikora (2002).

Color structure descriptor

CSD is a color histogram which describes both the color distribution and the local color structure in an image. The descriptor is constructed by sliding a small structuring element, for example, an 8 × 8 structuring element, to entire the image. An N-bins color histogram is constructed by counting the number of colors c_i, i = 1, 2, …, N covered by the structuring element to obtain CSD features of length N. CSD is extracted in HMMD (Hue, Max, Min, Diff) color space quantized into N color, where N can be 256, 128, 64, or 32. The value of Hue component is equal to the value of Hue component in HSV (Hue, Saturation, Value) color space. The value of Max and Min channels is obtained by calculating the maximum and minimum values of R, G, and B components in RGB (Red, Green, Blue) color space, respectively. The value of Diff component is obtained from the difference between Max and Min components. The value of N used in this study was 256.

Scalable color descriptor

SCD describes the color distribution in an image. SCD is a color histogram in HSV color space with a uniform quantization of 256 bins, 16 levels in H component, four 4 levels in S component, and four levels in V component. The histogram is normalized and nonlinearly mapped into four-bit integer representation. The histogram is then coded using Haar transform which consists of a sum operation and a difference operation related to primitive low-pass and high-pass filters. The sum and difference operations are applied to every two adjacent bins of the histogram. These operations produce histogram with 128 bins from the sum operator and 128 bins from the difference operator or 256 bins in total. If the sum and difference operators are repeated these operations will produce histogram with 128, 64, or 32 bins. In this study, the length of SCD extracted from image was 256 bins.

Color layout descriptor

CLD represents the spatial color distribution of an image obtained by transforming 2D array of local representative colors in YCbCr (Luminance, Chrominance red, Chrominance blue) color space using Discrete Cosine Fourier Transform (DCT). To extract CLD, the image is firstly partitioned into 8 × 8 blocks. From every block, a representative color is chosen by calculating the average of pixel intensities in Y, Cb, and Cr components. DCT is then applied to each block. Some low frequency of DCT coefficients are selected by zigzag scanning and then nonlinearly quantized to form CLD. In this study, the length of CLD extracted from the image was 120 bins, which is 64 bins from Y component, 28 bins from Cb component, and 28 bins from Cr component.

Homogeneous texture descriptor

HTD describes the direction, hardness, and frequency of the pattern in the image. It is ideal for quantitative characterization of texture that has homogeneous characteristic. HTD represents the region texture using the mean and deviation of energy from 30 channels of 2D frequency space. The frequency space is divided into 30 channels with equal division in the angle direction (at 30° intervals) and octave division in the radial direction (5 octaves). HTD is constructed by filtering the image using Gabor-filtered Fourier transforms in every frequency channel and calculating the energy and the deviation of energy of the filter output. The HTD consists of 62 bins, one bin for the mean of pixel intensities, one bin for the standard deviation of pixel intensities, 30 bins for the energy, and 30 bins for the deviation of energy of the filter output.

Edge histogram descriptor

EHD describe the spatial edge distribution of image. To extract EHD, the image is firstly divided into 4 × 4 nonoverlapping large blocks. The edge information on each block is then calculated and classified into five categories, namely vertical, horizontal, 45° diagonal, 135° diagonal, and isotropic using four directional selective edge-detectors and one isotropic edge-detector. Therefore, EHD has 5 bins on each block or 80 bins on the whole image.

2.2.2 | Principle component analysis

The total length of MPEG-7 descriptors extracted from a fruit image was 774, consisted of 256 from CSD, 256 from SCD, 120 from CLD, 62 from HTD, and 80 from EHD. A large number of features using in classification can increase training complexity and computational time but it does not guaranty produce a high classification accuracy (Zhang & Wu, 2012). Therefore, reducing the number of features need to be considered to solve that problems. One of the methods that can be used to perform this task is PCA.

PCA is an unsupervised statistical method used to reduce the dimension of features vector contained correlated variables but still preserve the variability of variables in the original features vector as much as possible. The method performs dimensionality reduction by projecting the original features vector to a new vector space such that every variable in the new vector space, called principle component, is linearly uncorrelated to each other. The variables are ordered such that the most variation of variables in the original features vector is preserved in the first few of variables in new vector space (Jolliffe, 2002). In this study the number of principle components used in classification was heuristically determined during the experiment with the maximum of 200 components such that the higher classification accuracy is achieved.

2.2.3 | Classifiers

The proposed method employed four simple classifiers, including decision trees (DT), naïve Bayesian (NB), linear discriminant analysis (LDA), and k-nearest neighbors (k-NN), as base classifiers. All classifiers used default parameters implemented on scikit-learn 0.20.3 library except for k-NN. In the previous study on Indonesian fruits classification using CSD and k-NN, Siswantoro et al. (2019) have been reported that the highest classification accuracy of k-NN was achieved using $k = 1$. Therefore, the parameter k in k-NN was set to $k = 1$.

Suppose $\mathcal{F}$ is a set contained all possible combinations of CSD, SCD, CLD, HTD, and EHD. Therefore, there were $2^5 - 1$ elements in $\mathcal{F} = \{ f_i \mid i = 1,2,\ldots,31\}$, where f_i, i = 1, 2, …, 31 are defined in Table 1. To investigate which combination produces the best classification accuracy, each classifier was trained using every $f \in \mathcal{F}$ as input feature.

TABLE 1 All possible combinations of CSD, SCD, CLD, HTD, and EHD

i	f_i	i	f_i
1	CSD	17	CSD + SCD + HTD
2	SCD	18	CSD + SCD + EHD
3	CLD	19	CSD + CLD + HTD
4	HTD	20	CSD + CLD + EHD
5	EHD	21	CSD + HTD + EHD
6	CSD + SCD	22	SCD + CLD + HTD
7	CSD + CLD	23	SCD + CLD + EHD
8	CSD + HTD	24	SCD + HTD + EHD
9	CSD + EHD	25	CLD + HTD + EHD
10	SCD + CLD	26	CSD + SCD + CLD + HTD
11	SCD + HTD	27	CSD + SCD + CLD + EHD
12	SCD + EHD	28	CSD + SCD + HTD + EHD
13	CLD + HTD	29	CSD + CLD + HTD + EHD
14	CLD + EHD	30	SCD + CLD + HTD + EHD
15	HTD + EHD	31	CSD + SCD + CLD + HTD + EHD
16	CSD + SCD + CLD		

The best features set might come from one or more descriptor(s) partially. However, to determine which features in a descriptor can be included in the best features set is not a simple task due to the large number of features. To overcome this problem, before inputted to the classifier, every $f \in \mathcal{F}$ was transformed into a new feature space using PCA such that every feature in the new space is linearly uncorrelated to each other. The dimension of transformed features set was reduced to obtain reduced features set f_r by selecting some features in the new space with the largest variance. Some classifiers, such as LDA and k-NN, need to calculate distance between two points. If some features have a wide range of values, then the distance will be dominated by these specific features. Therefore, the result of PCA was then normalized to [0, 1] to avoid the domination of some features to the others using the following equation,

$$f_n = \frac{f_r - \min(f_r)}{\max(f_r) - \min(f_r)}$$

where f_r and f_n are reduced and normalized features, respectively; while $\min(f_r)$ and $\max(f_r)$ are the minimum and the maximum of reduced feature, respectively.

To increase accuracy and to reduce the variance of classification result, an ensemble of simple classifiers was proposed, as depicted in Figure 4. The proposed ensemble of simple classifiers is similar to independent ensemble methodology (Rokach, 2010), since it uses several independently trained classifiers. However, the proposed ensemble of simple classifiers employed selected features set and PCA to determine input features that produce high classification accuracy for each simple classifier. This step was performed to ensure the ensemble of simple classifiers also produce high classification accuracy. Let S be a training data set, F be a subset $\mathcal{F}$ containing n selected features set, and $\mathcal{M}$ be a set containing m simple classification models. Suppose S_f is the training data set with features set f used as input features, for an $f \in F$. For example, S_{f_1} is the training data set with f_1 (CSD) used as input features. PCA and normalization to [0, 1] were performed on the input features of S_f before used in training process. Each simple classification model in $\mathcal{M}$ was trained with S_f for all $f \in F$. Let $\mathcal{C}$ be the set of classifiers C_{Mf}, where C_{Mf} is built using classification model $M \in \mathcal{M}$ with training data set S_f. Therefore, there were $m \times n$ classifiers in $\mathcal{C}$ used in the proposed ensemble classifier. The detail steps for the proposed ensemble of simple classifiers are shown in Algorithm .

The steps for classifying an unknown image sample are explained as follow. Let x be the features extracted from the image and x_f be selected features set from x according to an $f \in F$. PCA and normalization to [0, 1] were then performed on x_f before inputted to appropriate classifiers in $\mathcal{C}$. The output of each classifier in $\mathcal{C}$ was combined to predict the label for the unknown image sample using majority voting scheme. In this scheme, the unknown image sample was assigned to the class using the following equation,

$$\text{class}(x) = \underset{k \in D_y}{\text{argmax}} \left(\sum_{M \in \mathcal{M}} \sum_{f \in F} I(y_{Mf}, k) \right)$$

Algorithm 1

Algorithm for the proposed ensemble of simple classifiers

```
Input: the training data set S, the set of
selected features sets F, the set of simple
classification models 𝓜.
Output: the set of trained classifiers 𝒞
Set 𝒞 = ∅
for M in 𝓜.
    for f in F
        Perform PCA on the input features of S_f
        Normalize the input features of S_f to
[0, 1]
        Build classifier C_Mf using
classification model M with training data set S_f
        𝒞 = 𝒞 ∪ C_Mf
    end for
end for
```

where D_y is the domain of class labels, y_{Mf} is the output of classifier C_{Mf} with input features x_f, and $I(y_{Mf}, k)$ is a function defined as follow.

$$I(y_{Mf}, k) = \begin{cases} 1, y_{Mf} = k \\ 0, \text{otherwise} \end{cases}$$

2.2.4 | Baseline

A classifier ensemble method called ensembles on random patches proposed by Louppe and Geurts (2012) was used as base line. The method was performed in the following steps.

1. Choose a base classifier
2. Select n_s samples from data set and n_f features from all extracted features at random
3. Train the classifier with selected samples and features from step 2.
4. Repeat step 2 and 3 for T times, where T is a predefined positive integer.
5. Aggregate the output of T trained classifiers using majority voting.

Ensembles on patches were applied on every $f \in \mathcal{F}$ and all simple classifiers: DT, NB, LDA, and k-NN. Furthermore, the ensemble used default parameters implemented on scikit-learn 0.20.3 library.

3 | EXPERIMENTAL SETUP

To validate the proposed method, an experiment has been carried out in the laboratory. In the experiment, Ubaya-IFDS3000 data set was randomly portioned into two mutually exclusive sub sets, training data set and testing data set using stratified random subsampling (Alpaydin, 2010). Five training data sets and five testing data sets were constructed from Ubaya-IFDS3000 image data set using stratified random sampling without replacement with proportion 50% for training data set and 50% for testing data set. Stratified random sampling was chosen to guaranty all classes have same proportion both in training data set and testing data set.

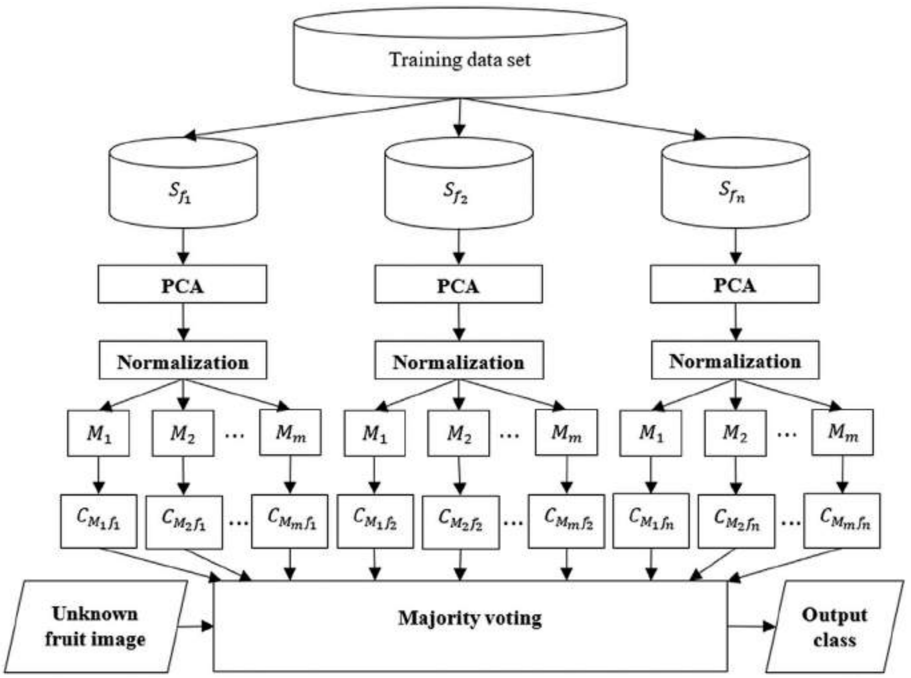


FIGURE 4 The proposed ensemble of simple classifiers

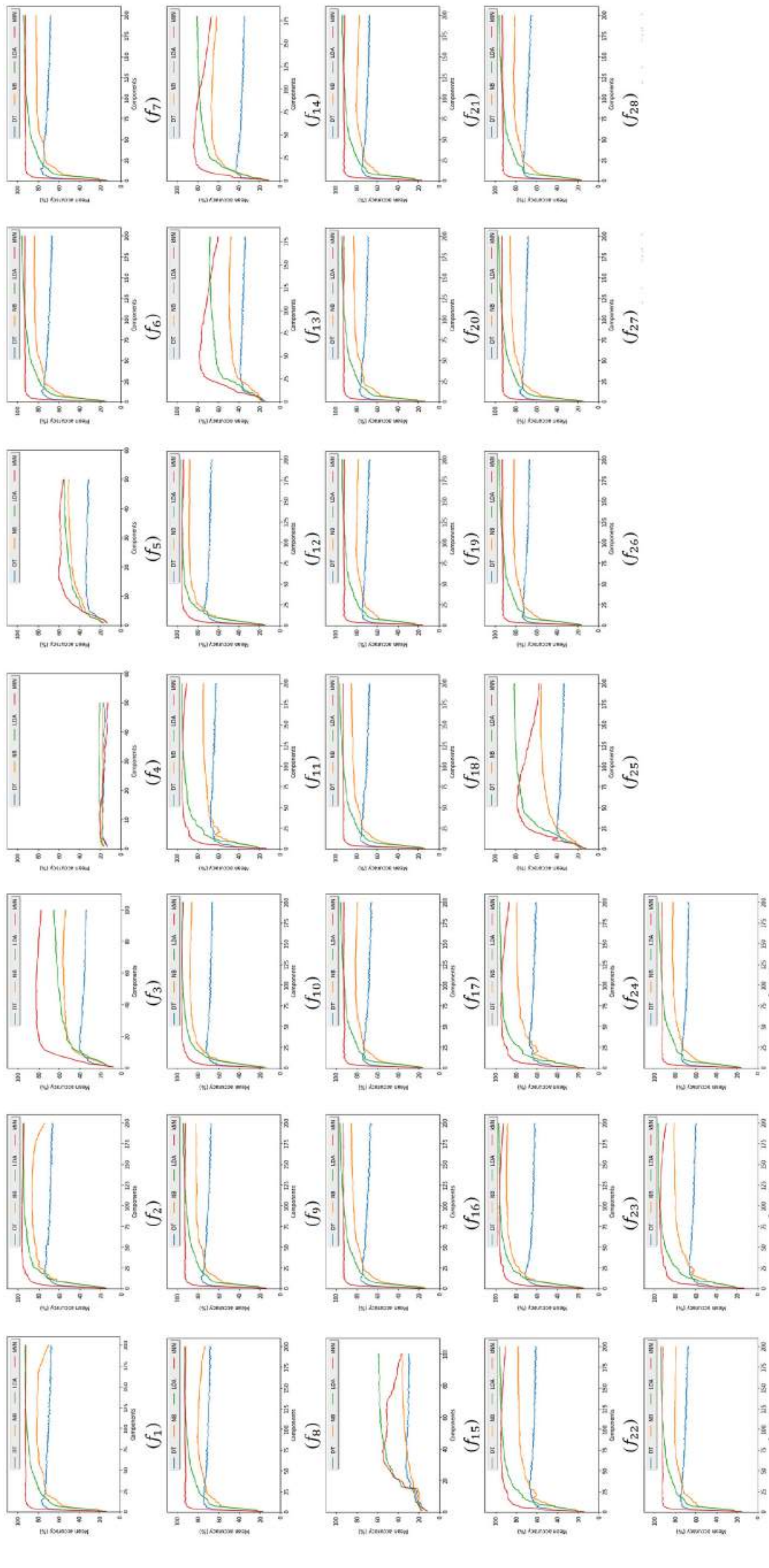


FIGURE 5 The averages of classification accuracy for each classifier trained using every $f \in \mathcal{F}$

Journal of Food Process Engineering

TABLE 2 The highest classification accuracy for each classifier trained using every $f \in \mathcal{F}$

	Accuracy (%)											
	Average				SD				The number of components			
$f \in \mathcal{F}$	DT	NB	LDA	k-NN	DT	NB	LDA	k-NN	DT	NB	LDA	k-NN
f_1	**77.21**	81.48	92.83	92.69	**0.67**	1.61	0.63	0.52	**14**	94	190	102
f_2	74.14	86.24	95.23	**96.09**	0.93	0.47	0.49	**0.33**	21	100	195	**73**
f_3	40.57	56.48	65.31	82.36	0.57	1.07	1.07	0.93	12	66	96	54
f_4	17.88	19.23	21.36	20.76	0.53	0.47	0.53	0.55	12	4	37	12
f_5	33.76	50.96	54.81	59.93	1.76	0.51	0.62	0.97	15	47	50	17
f_6	76.85	83.73	95.96	93.08	1.17	1.13	0.14	0.47	13	157	200	139
f_7	**77.89**	82.00	94.07	92.83	**1.42**	1.09	0.42	0.43	**15**	193	199	116
f_8	74.64	80.39	92.96	92.41	1.39	1.08	0.54	0.87	20	91	153	13
f_9	76.87	81.85	93.89	92.73	0.88	0.99	0.84	0.53	15	196	196	101
f_{10}	72.65	**87.69**	96.13	**96.28**	0.91	**0.33**	0.20	**0.37**	21	**111**	196	**83**
f_{11}	67.24	74.67	94.92	94.55	1.07	1.58	0.45	0.58	48	179	175	171
f_{12}	73.69	**88.19**	96.05	95.67	1.10	**0.80**	0.50	0.47	19	**113**	196	54
f_{13}	38.73	49.64	68.37	78.03	0.79	1.14	1.28	1.02	35	107	154	50
f_{14}	42.73	66.72	80.33	84.01	1.29	1.29	0.76	1.24	13	80	176	39
f_{15}	32.61	35.72	58.76	55.15	1.32	1.16	0.43	1.88	28	99	99	39
f_{16}	76.05	85.16	96.23	93.39	1.25	0.94	0.23	0.56	12	193	200	197
f_{17}	74.36	81.44	95.57	92.97	0.92	1.20	0.30	0.44	15	130	195	197
f_{18}	75.85	84.71	96.32	93.17	1.06	0.92	0.41	0.37	14	197	200	112
f_{19}	74.36	80.48	93.79	92.43	1.37	1.23	0.54	0.88	21	92	199	13
f_{20}	**77.36**	82.85	94.42	92.84	**0.85**	0.96	0.36	0.44	**15**	196	200	112
f_{21}	74.51	80.53	93.87	92.43	1.00	1.04	0.58	0.50	15	91	182	93
f_{22}	67.05	78.13	95.61	94.65	0.85	1.43	0.32	0.53	38	196	200	94
f_{23}	71.33	**89.53**	**96.57**	**96.09**	1.73	**0.42**	**0.29**	**0.67**	19	**140**	**196**	**69**
f_{24}	61.12	79.56	95.65	94.44	0.94	1.43	0.44	0.28	31	189	190	76
f_{25}	40.33	55.72	81.45	78.69	1.17	0.91	0.26	1.01	23	150	194	57
f_{26}	73.84	82.05	95.96	92.92	1.06	1.24	0.19	0.59	12	129	200	198
f_{27}	76.28	85.52	**96.45**	93.28	1.48	0.86	**0.46**	0.56	14	167	**200**	194
f_{28}	73.68	81.99	95.97	93.05	0.96	0.98	0.44	0.45	15	131	199	137
f_{29}	74.80	80.60	94.09	92.44	2.44	1.19	0.69	0.54	21	91	198	91
f_{30}	66.87	81.25	**96.49**	94.95	1.15	0.89	**0.32**	0.44	32	180	**198**	98
f_{31}	73.81	82.72	96.03	92.92	0.46	1.31	0.46	0.38	12	137	200	185

Note: Significance for the bold values in the tables is to show the reader that the classifier reaches the highest accuracy

Each training data set was used to train all classifiers used in this study. The performance of each classifier was evaluated using respective testing data set by calculating the classification accuracy on ith testing data set, acc_i, $i = 1, 2, 3, 4, 5$ using the following equation,

$$acc_i = \frac{Nc_i}{N_i} \times 100\%$$

where Nc_i is the number of correctly classified objects in ith training data set and N_i is the number of objects in ith training data set. The average and the standard deviation of acc_i were then calculated to obtain the final performance of each classifier.

4 | RESULTS AND DISCUSSION

The classification accuracy for each classifier trained using all $f \in \mathcal{F}$ and at different number of components to classify the fruit images in Ubaya-IFDS3000 data set are depicted in Figure 5. From Figure 5, it can be seen that the classification accuracy of k-NN and LDA were

TABLE 3 The classification accuracy for each classifier trained using other features

	Accuracy (%)							
	Average				SD			
Features	DT	NB	LDA	k-NN	DT	NB	LDA	k-NN
Statistical color features	50.51	33.72	61.60	65.25	1.02	1.19	0.59	1.48
Global color histogram	78.00	57.77	57.32	73.63	1.13	1.14	2.21	0.44
Unser's descriptors	63.12	51.08	66.64	52.88	1.27	0.53	0.63	0.63
Color coherence vectors	32.25	20.24	23.88	30.83	1.55	0.58	0.66	0.98
Border/interior pixels classification	79.56	61.63	68.73	73.96	0.50	0.66	1.71	0.76
Color autocorrelogram	30.68	45.60	59.35	18.24	1.26	1.10	1.33	1.24

TABLE 4 The results of the proposed ensemble of simple classifiers

		Accuracy (%)	
$f \in \mathcal{F}$	Classifiers	Average	SD
f_1, f_2	LDA, k-NN	96.49	0.23
f_1, f_3	LDA, k-NN	95.89	0.42
f_2, f_3	LDA, k-NN	97.28	0.32
f_1, f_2, f_3	LDA, k-NN	97.63	0.26
f_1, f_2, f_3, f_4	LDA, k-NN	97.13	0.15
f_1, f_2, f_3, f_5	LDA, k-NN	97.71	0.18
f_1, f_2, f_4, f_5	LDA, k-NN	**97.76**	**0.17**
f_1, f_2, f_3, f_4, f_5	LDA, k-NN	97.41	0.28
f_1, f_2, f_6	LDA, k-NN	**97.73**	**0.15**
f_1, f_2, f_{13}	LDA, k-NN	97.53	0.17
f_1, f_2, f_{14}	LDA, k-NN	**97.80**	**0.28**

Note: Significance for the bold values in the tables is to show the reader that the classifier reaches the highest accuracy

greater than DT and NB when the number of components is greater than 25 for almost all $f \in \mathcal{F}$ except for HTD. To achieve high classification accuracy k-NN required a smaller number of components compared to the other classifier. For some $f \in \mathcal{F}$, k-NN and LDA achieved the classification accuracy more than 90%, while DT and NB only achieved less than 78 and 90%, respectively.

For k-NN, increasing the number of components did not significantly increase the classification accuracy. In some $f \in \mathcal{F}$, increasing the number of components could decrease the classification accuracy of k-NN such as in f_3, f_5, f_{11}, f_{13}, f_{14}, f_{15}, f_{22}, f_{23}, f_{24}, f_{25}, and f_{30}. For DT, the highest classification accuracy was achieved when the number of components is less than 25 for almost all $f \in \mathcal{F}$. Increasing the number of components resulted in decreasing the classification accuracy of DT. In contrast with DT and k-NN, the classification accuracies of NB and LDA increased by increasing the number of components for almost all $f \in \mathcal{F}$.

The highest classification accuracy for each classifier trained using every $f \in \mathcal{F}$ is tabulated in Table 2. As can be seen in Table 2, DT achieved highest classification accuracy of $77.89 \pm 1.42\%$ when trained using f_7 with 15 components followed by f_{20} ($77.36 \pm 0.85\%$) with 15 components and f_{10} ($77.21 \pm 0.67\%$) with 14 components. For NB, the highest classification accuracy of $89.53 \pm 0.42\%$ was achieved when trained using f_{23} with 140 components followed by f_{12} ($88.19 \pm 0.80\%$) with 113 components and f_{10} ($87.69 \pm 0.33\%$) with 111 components. For k-NN, the highest classification accuracy of $96.28 \pm 0.37\%$ was achieved when trained using f_{10} with 83 components followed by f_2 ($96.09 \pm 0.33\%$) with 73 components and f_{23} ($96.09 \pm 0.67\%$) with 69 components. LDA achieved highest classification accuracy of $96.57 \pm 0.29\%$ when trained using f_{23} with 196 components, followed by f_{30} ($96.49 \pm 0.32\%$) with 198 components and f_{27} ($96.45 \pm 0.46\%$) with 200 components. From these results, it can be inferred that LDA produced the highest classification accuracy compared to other classifiers. However, LDA required the combination of more features and the greater number of components to obtain the best classification results. In addition, LDA also produced a low standard deviation of classification accuracy in the range of [0.14%, 1.28%] compared to DT [0.46%, 2.44%], NB [0.33%, 1.61%], and k-NN [0.28%, 1.88%]. This result shows that, the classification accuracy of LDA did not much vary when applied in different training and testing data sets. Furthermore, the highest accuracy of k-NN and LDA outperformed the highest accuracy of Indonesian fruit classification method using CSD and k-NN combined with variance based feature selection proposed by Siswantoro et al. (2019).

From Table 2, it can be observed that color descriptors (CSD, SCD, and CLD) were more discriminative compared to texture descriptors (HTD and EHD). Furthermore, SCD (f_2) was more discriminative among three color descriptors when used to train NB, LDA, and k-NN, while CSD (f_1) was more discriminative when used to train DT. For texture descriptors, EHD (f_5) was more discriminative than HTD (f_4) for all classifiers. For the combination of descriptors, SCD + CLD + EHD (f_{20}) was more discriminative compared to other combinations when used to train NB, LDA, and k-NN, while CSD + CLD (f_7) was more discriminative when used to train DT. Furthermore, it can be inferred from Table 2 that increasing the number of descriptors used in training a classifier did not always improve classification accuracy.

To compare the performance of MPEG-7 descriptors with other features, the fruit images in Ubaya-IFDS3000 data set were also classified using other features such as statistical color features in HSV (Hue, Saturation, Value) color space, global color histogram, Unser's

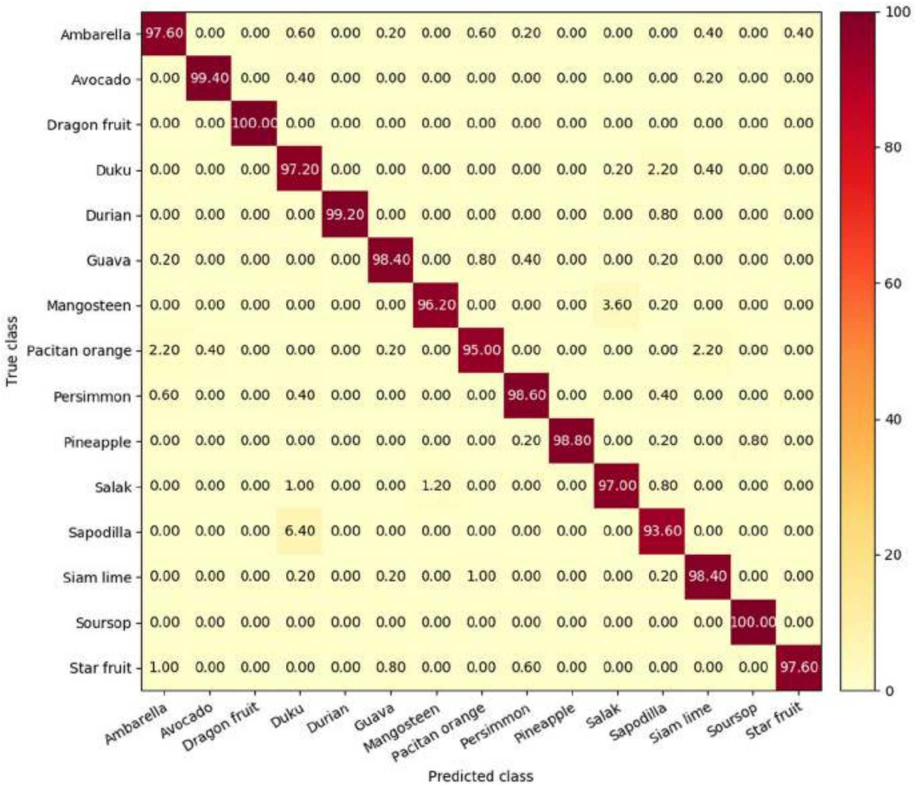


FIGURE 6 The confusion matrix (%) of the proposed ensemble using LDA and k-NN trained with f_1, f_2, f_{14}

TABLE 5 The minimum and maximum classification accuracy of ensembles on random patches for each base classifier

			Accuracy (%)	
	$f \in \mathcal{F}$	Base classifier	Average	SD
Minimum	f_4	DT	20.13	0.35
	f_4	NB	20.04	0.95
	f_4	LDA	19.33	0.45
	f_4	k-NN	19.80	0.23
Maximum	f_{18}	DT	92.57	0.90
	f_{27}	NB	71.68	1.31
	f_{20}	LDA	93.36	0.59
	f_{16}	k-NN	93.24	0.74

descriptors, Color coherence vectors, border/interior pixels classification, and color autocorrelogram. Image preprocessing and segmentation were performed to separate fruit pixels and background pixels before features extraction. Normalization to [0, 1] was also applied to the features before inputted to DT, NB, LDA, and k-NN. The classification accuracy for each classifier trained with other features is tabulated in Table 3. As can be seen in Table 3, MPEG-7 descriptors outperformed other features for all classifiers except DT. The classification accuracy of DT trained with global color histogram (78 ± 1.13%) and border/interior pixels classification (79.56 ± 0.50%) was slightly higher when compared to MPEG-7 descriptors (77.89 ± 1.42%). However, the performance of DT trained MPEG-7 descriptors was still better when compared to statistical color features (50.51 ± 1.02%), Unser's descriptors (63.12 ± 1. 27%), Color coherence vectors (32.25 ± 1.55%), and color autocorrelogram (30.86 ± 1.26%).

The proposed ensemble of simple classifiers, as depicted in Figure 4, was implemented using LDA and k-NN, since only these two classifiers produced classification accuracy greater than 90%. The classifiers were trained using some $f \in \mathcal{F}$ and the results are tabulated in Table 3. As can be seen in Table 4, the classification accuracy of the proposed ensemble of simple classifiers was better than the classification accuracy of single classifier when trained using the same features. The highest classification accuracy of 97.80 ± 0.28% was obtained if the ensemble used f_1, f_2, and f_{14} as input features to LDA and k-NN. The second place was f_1, f_2, f_4, and f_5 with the accuracy of 97.76 ± 0.17%, followed by f_1, f_2, and f_6 in the third place with the accuracy of 97.73 ± 0.15%. From Table 4, it can also be seen that the standard deviation of classification accuracy reduced to a value less than 0.50% by employing the proposed ensemble. Therefore, it can be concluded that the proposed ensemble of simple classifiers can increase the classification accuracy of single classifier as well as reduce the standard deviation of classification accuracy.

For further analysis, the confusion matrix is used to investigate the classification accuracy of the proposed ensemble of simple classifiers for each class in Ubaya-IFDS3000 data set. Figure 6 exhibits the confusion matrix of the proposed ensemble using LDA and k-NN trained with f_1, f_2, f_{14}. The diagonal elements of confusion matrix indicate the classification accuracy of images in each class which are correctly classified. The element of confusion matrix located at ith row and *j*th column, for $i \neq j$, indicates the classification accuracy of images from *i*th class classified as images from *j*th class. As can be seen in Figure 6, all images from Dragon fruit class and Soursop class in the testing data set were 100% correctly classified. It can happen since these two classes have color and texture that are very different from other classes, as shown in Figure 1. For other classes, a little part of the testing data set was misclassified. Almost all class had classification accuracy greater than or equal 97.00% except Mangosteen, Pacitan orange, and Sapodilla. There were 3.60 and 0.20% images from Mangosteen class misclassified as from Salak class and Sapodilla class, respectively. For Pacitan orange, 2.20% were classified as Ambarella, 0.40% as Avocado, 0.20% as Guava, and 2.20% as Siam lime. For Sapodilla, there were 6.40% classified as Duku. These facts indicate that the proposed ensemble of simple classifiers still has weakness in classifying the images from Mangosteen, Pacitan orange, and Sapodilla classes.

For comparison, the fruit images in Ubaya-IFDS3000 data set were also classified using ensembles on patches as described in the earlier section. In the experiment, ensembles on patches used DT, NB, LDA, and k-NN as base classifier and trained with every $f \in \mathcal{F}$. The minimum and maximum classification accuracies of ensembles on patches for each base classifier are tabulated in Table 5. As can be seen in Table 5, the minimum classification accuracy was obtained when ensembles on patches used HTD (f_4) as input features for all base classifiers. Ensembles on patches achieved the highest classification accuracy of $93.36 \pm 0.59\%$ when used LDA as base classifier and f_{20} as input features. In term of computational time, on average the proposed ensemble of simple classifiers only needed 6.12 s to perform training and testing processes, while ensembles on patches needed 24.81 s. These results demonstrate that the proposed ensemble of simple classifiers outperforms ensembles on patches both in accuracy and computational time. Furthermore, the proposed method required about 70.77 ms to classify a fruit image, 67.78 ms for features extraction and 2.99 ms for classification. Therefore, it is possible to apply the proposed method for fruit sorting in fruit industry or fruit pricing in supermarket.

5 | CONCLUSION

In this study, a classification method for Indonesia fruits from image is proposed. The proposed method used five color and texture descriptors from MPEG-7 as input features to simple classifiers. To identify the most discriminative descriptors, all possible combinations of the descriptors were used as input features to four simple classifiers. This study employed PCA to reduce the dimension of input features. From the experiments, it can be observed that color descriptors were more discriminative compared to texture descriptors. Furthermore, SCD was the most discriminative descriptor. It has been proven that combining some descriptors could improve classification accuracy. However, increasing the number of descriptors used as input features to the classifiers did not always increase classification accuracy. The best classification accuracy has been achieved using LDA with the combination of SCD + CLD + EHD used as input features. An ensemble of simple classifiers was proposed used LDA and k-NN as base classification models and trained with some combination of MPEG-7 descriptors. The experiment results show that the proposed ensemble classifier could increase the classification accuracy and reduce the standard deviation of classification accuracy of single simple classifier. In term of computational time the proposed method only required 70.77 ms to recognize a fruit image. Therefore, there is a chance to apply the proposed method in vision-based fruit sorting system in fruit industry as well as vision-based fruit pricing system in supermarket.

ACKNOWLEDGMENT

The authors would like to thank Ministry of Research, Technology, and Higher Education Republic of Indonesia and University of Surabaya for providing facilities and financial support under PDUPT Research Grant No. 025/SP-Lit/LPPM-01/DRPM/Multi/FT/III/2019.

CONFLICT OF INTEREST

The authors declare that there is no potential conflict of interest.

ETHICAL GUIDELINES

Ethics approval was not required for this research.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Joko Siswantoro https://orcid.org/0000-0002-5615-5496

REFERENCES

Alpaydin, E. (2010). *Introduction to machine learning* (2nd ed.). Cambridge: MIT Press.

Arakeri, M. P. (2016). Computer vision based fruit grading system for quality evaluation of tomato in agriculture industry. *Procedia Computer Science*, *79*, 426–433.

Bastan, M., Cam, H., Gudukbay, U., & Ulusoy, O. (2010). Bilvideo-7: An MPEG-7—Compatible video indexing and retrieval system. *MultiMedia, IEEE*, *17*(3), 62–73.

Bradski, G. (2000). The openCV library. *Dr Dobb's Journal of Software Tools*, *25*, 120–125.

Faria, F. A., dos Santos, J. A., Rocha, A., & Torres, R. S. (2012, 22–25 August). *Automatic Classifier Fusion for Produce Recognition*. Paper presented at the Graphics, Patterns and Images (SIBGRAPI), 2012 25th SIBGRAPI Conference.

Gonzalez, R. C., & Woods, R. E. (2018). *Digital Image Processing* (4th ed.). New York: Pearson.

Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). New York: Springer.

Katarzyna, R., & Paweł, M. (2019). A vision-based method utilizing deep convolutional neural networks for fruit variety classification in uncertainty conditions of retail sales. *Applied Sciences*, *9*(19), 3971.

Kheiralipour, K., & Pormah, A. (2017). Introducing new shape features for classification of cucumber fruit based on image processing technique and artificial neural networks. *Journal of Food Process Engineering*, *40*(6), e12558.

Koslowski, M. A., Santos, F. G., Borba, G. B., & Gamba, H. R. (2013). *Fruits classification using MPEG-7 descriptors from image patches*. Paper presented at the IX Workshop de Visão Computacional (WVC 2013).

Le, T.-T., Lin, C.-Y., & Piedad, E., Jr. (2019). Deep learning for noninvasive classification of clustered horticultural crops—A case for banana fruit tiers. *Postharvest Biology and Technology*, *156*, 110922.

Louppe, G., & Geurts, P. (2012). *Ensembles on random patches*. Berlin: Heidelberg.

Manjunath, B. S., Salembier, P., & Sikora, T. (2002). *Introduction to MPEG-7: Multimedia content description interface*. Chichester: John Wiley & Sons.

Oliphant, T. E. (2006). *A guide to NumPy (Vol. 1)*. USA: Trelgol Publishing.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … Dubourg, V. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Prabuwono, A. S., Siswantoro, J., & Abdullah, A. (2015). Natural produce classification using computer vision based on statistical color features and derivative of radius function. *Applied Mechanics & Materials*, *771*, 242–247.

Rocha, A., Hauagge, D. C., Wainer, J., & Goldenstein, S. (2008, 12–15 October). *Automatic produce classification from images using color, texture and appearance cues*. Paper presented at the Computer Graphics and Image Processing, 2008. SIBGRAPI '08. XXI Brazilian Symposium.

Rocha, A., Hauagge, D. C., Wainer, J., & Goldenstein, S. (2010). Automatic fruit and vegetable classification from images. *Computers and Electronics in Agriculture*, *70*(1), 96–104.

Rokach, L. (2010). Ensemble-based classifiers. *Artificial Intelligence Review*, *33*(1), 1–39. https://doi.org/10.1007/978-3-319-41111-8_6

Roomi, S. M. M., Priya, R. J., Bhumesh, S., & Monisha, P. (2012, 14–15 December 2012). *Classification of mangoes by object features and contour modeling*. Paper presented at the 2012 International Conference on Machine Vision and Image Processing (MVIP).

Siswantoro, J., Arwoko, H., & Widiasri, M. (2019, August 22–23). *Image based Indonesian fruit recognition using MPEG-7 color structure descriptor and k-nearest neighbor*. Paper presented at the International Conference on Informatics, Technology, and Engineering 2019 (InCITE 2019), The Anvaya Resort in Denpasar, Bali, Indonesia.

Siswantoro, J., Prabuwono, A. S., Abdullah, A., & Bahari, I. (2017). Hybrid neural network and linear model for natural produce recognition using computer vision. *Journal ICT Research and Applications*, *11*(2), 184–198.

Steinbrener, J., Posch, K., & Leitner, R. (2019). Hyperspectral fruit and vegetable classification using convolutional neural networks. *Computers and Electronics in Agriculture*, *162*, 364–372.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., … Rabinovich, A. (2015). *Going deeper with convolutions*. Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.

Uji, T. (2007). Species diversity of indigenous fruits in Indonesia and its potential. *Biodiversitas*, *8*(2), 157–167.

Waltner, G., Schwarz, M., Ladstätter, S., Weber, A., Luley, P., Bischof, H., … Paletta, L. (2015). *MANGO-mobile augmented reality with functional eating guidance and food awareness*. Paper presented at the International Conference on Image Analysis and Processing.

Wang, S.-H., & Chen, Y. (2018). Fruit category classification via an eight-layer convolutional neural network with parametric rectified linear unit and dropout technique. *Multimedia Tools and Applications*, *2018*, 1–17.

Wang, S., Zhang, Y., Ji, G., Yang, J., Wu, J., & Wei, L. (2015). Fruit classification by wavelet-entropy and feedforward neural network trained by fitness-scaled chaotic ABC and biogeography-based optimization. *Entropy*, *17*(8), 5711–5728.

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. *Multimedia Tools and Applications*, *78*(3), 3613–3632.

Zhang, Y., Phillips, P., Wang, S., Ji, G., Yang, J., & Wu, J. (2016). Fruit classification by biogeography-based optimization and feedforward neural network. *Expert Systems*, *33*(3), 239–253.

Zhang, Y., Wang, S., Ji, G., & Phillips, P. (2014). Fruit classification using computer vision and feedforward neural network. *Journal of Food Engineering*, *143*, 167–177.

Zhang, Y., & Wu, L. (2012). Classification of fruits using computer vision and a multiclass support vector machine. *Sensors (Basel)*, *12*(9), 12489–12505.

How to cite this article: Siswantoro J, Arwoko H, Widiasri M. Indonesian fruits classification from image using MPEG-7 descriptors and ensemble of simple classifiers. *J Food Process Eng*. 2020;43:e13414. https://doi.org/10.1111/jfpe.13414

Volume 43 • Number 7 • July 2020

Journal of Food Process Engineering

Edited By: V.M. (Bala) Balasubramaniam

Journal of
Food Process Engineering

Overview

The *Journal of Food Process Engineering* publishes the best original research on applications of engineering principles and concepts to food and food processes. The processes include any physical properties and changes to the food product that result in preservation of the food, extending to transportation, product shelf-life, or improvements in the product quality attributes. Articles should address sustainability of process technology and means to reduce energy/water waste and consumption.

Aims and Scope

The *Journal of Food Process Engineering* publishes the best original research on applications of engineering principles and physics concepts to food and food processes with emphasis on process simulation, including mathematical models to describe processes and to allow for scale-up of processes for food manufacturing. Read by researchers, food, agricultural, biological, and chemical engineers, and industry experts, this is the only international journal specifically devoted to the engineering aspects of food processing. JFPE covers a range of topics, including:

- Transport of liquid and solid foods
- Heating and cooling processes
- Food freezing and frozen food storage
- Frying processes
- Membrane separation processes
- New and improved extrusion processes
- Packaging processes including Modified Atmosphere Packaging and intelligent packaging
- Non-thermal processes including irradiation processing, high pressure processing and other high pressure based technologies, pulsed electric fields, application of gases in food preservation, UV, Ultrasound, filtration, cold plasma, and other similar minimal processing technologies. Articles highlighting innovative combinations of nonthermal or thermal-nonthermal technologies for food manufacturing are also welcome.
- Cleaning and sanitation processes
- Process engineering technological solutions for produce safety
- Process development and design
- Process instrumentation and control including sensors for the detection and identification of contaminants in food safety and quality.
- Nanotechnology applications to food processes (nanosensors, new ingredients, new process technologies, sensors)
- Use of biotechnology to improve food processes
- Advanced processing technologies to improve food safety, quality, nutrition, and reduce food waste
- Green, clean, and sustainable process technology

Keywords

Food processing and packaging, engineering, post-production, food storage

Abstracting and Indexing Information

- AgBiotech News & Information (CABI)
- AgBiotechNet (CABI)
- AGRICOLA Database (National Agricultural Library)
- Agricultural Engineering Abstracts (CABI)
- Animal Breeding Abstracts (CABI)
- Biofuels Abstracts (CABI)
- CAB Abstracts® (CABI)
- Crop Physiology Abstracts (CABI)
- Current Contents: Agriculture, Biology & Environmental Sciences (Clarivate Analytics)
- Dairy Science Abstracts (CABI)
- Field Crop Abstracts (CABI)
- Food Science & Technology Abstracts™ (IFIS)
- Global Health (CABI)
- Horticultural Science Abstracts (CABI)
- InfoTrac (GALE Cengage)
- Journal Citation Reports/Science Edition (Clarivate Analytics)
- Maize Abstracts (CABI)
- Nutrition Abstracts & Reviews Series A: Human & Experimental (CABI)
- Nutrition Abstracts & Reviews Series B: Livestock Feeds & Feeding (CABI)
- Ornamental Horticulture (CABI)
- Pig News & Information (CABI)
- Plant Breeding Abstracts (CABI)
- Plant Genetic Resources Abstracts (CABI)
- Postharvest News & Information (CABI)
- Potato Abstracts (CABI)
- Poultry Abstracts (CABI)
- PubMed Dietary Supplement Subset (NLM)
- Review of Aromatic & Medicinal Plants (CABI)
- Review of Medical & Veterinary Entomology (CABI)
- Review of Medical & Veterinary Mycology (CABI)
- Review of Plant Pathology (CABI)
- Rice Abstracts (CABI)
- Science Citation Index Expanded (Clarivate Analytics)
- SCOPUS (Elsevier)
- Seed Abstracts (CABI)
- Soils & Fertilizers Abstracts (CABI)
- Soybean Abstracts Online (CABI)
- Sugar Industry Abstracts (CABI)
- Wheat, Barley & Triticale Abstracts (CABI)
- World Agricultural Economics & Rural Sociology Abstracts (CABI)

Tools

Submit an Article

Browse free sample issue

Get content alerts

Journal of
Food Process Engineering

EDITORIAL BOARD

Tools

- Submit an Article
- Browse free sample issue
- Get content alerts
- Subscribe to this journal
- Special Issue: Call for Papers

More from this journal

Journal of
Food Process Engineering

Volume 43, Issue 7

July 2020

< Previous Issue | Next Issue >

GO TO SECTION

Export Citation(s)

ISSUE INFORMATION

Free Access

Issue Information

First Published: 06 July 2020

PDF | Request permissions

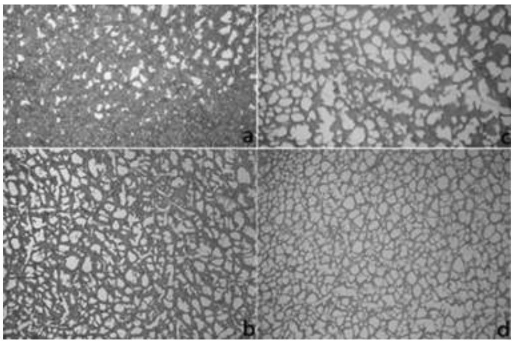
ORIGINAL ARTICLES

The quality evaluation method of tilapia fillets stored at 3 and −2°C based on fractal dimension changes

Zheng Chen, Aiguo Feng

First Published: 10 March 2020

Profile morphology of tilapia fillets stored at −2°C



under ×100 magnification: (a) fresh sample, (b) sample on 2 days, (c) sample on 6 days, and (d) sample on 12 days.

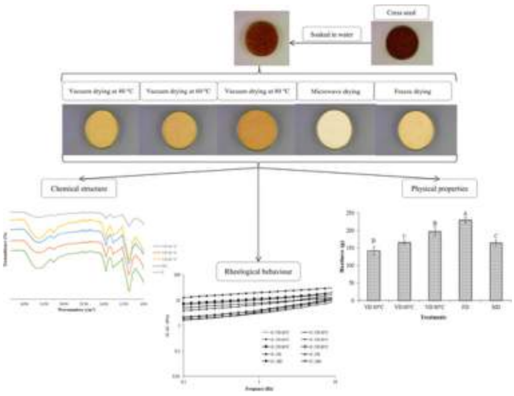
Abstract | Full text | PDF | References | Request permissions

---

Cress seed (*Lepidium sativum*) gum dried by vacuum, freeze, and microwave drying methods: Structural, rheological, emulsifying, and foaming properties

Hannaneh Moniri, Reza Farahmandfar, Ali Motamedzadegan

First Published: 18 March 2020

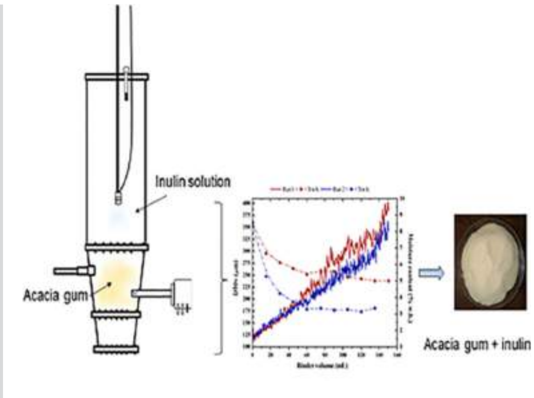


Abstract | Full text | PDF | References | Request permissions

Acacia gum fluidized bed agglomeration: Use of inulin as a binder and process parameters analysis

Juliana G. Rosa, Raul F. Nascimento, Kaciane Andreola, Osvaldir P. Taranto

First Published: 18 March 2020



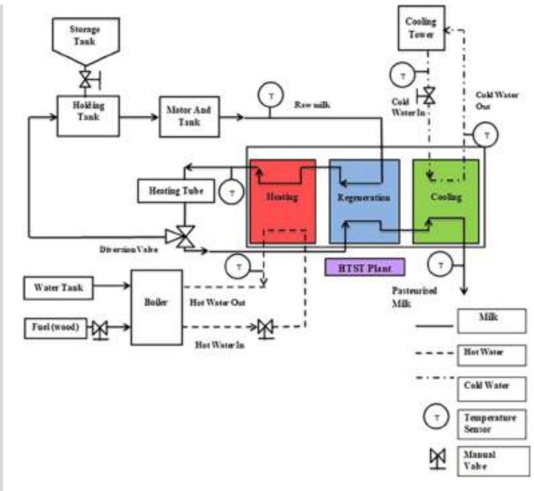
Abstract | Full text | PDF | References | Request permissions

---

Identification of high temperature short time milk pasteurization unit

Marimuthu Indumathy, Subramani Sobana, Rames C. Panda

First Published: 17 March 2020



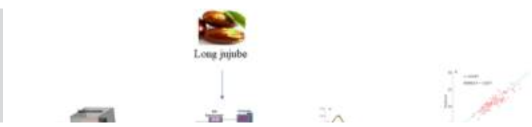
Abstract | Full text | PDF | References | Request permissions

---

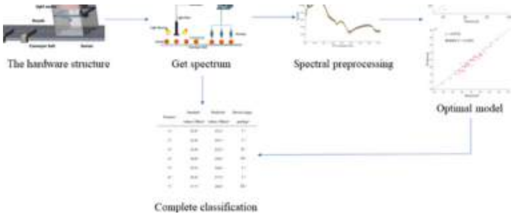
Development of near-infrared online grading device for long jujube

Ancheng Wang, Ren Sheng, Huanhuan Li, Akwasi Akomeah Agyekum, Md Mehedi Hassan, Quansheng Chen

First Published: 25 March 2020



A near-infrared grading device was constructed to grade the sugar quality of jujube. This has potential in



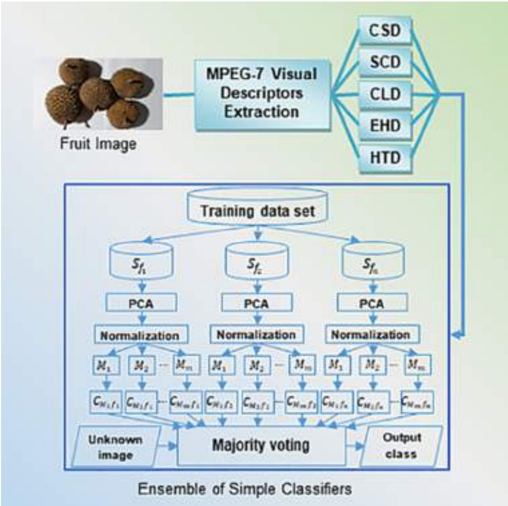
the application of fruit and vegetable quality classification.

Abstract | Full text | PDF | References | Request permissions

Indonesian fruits classification from image using MPEG-7 descriptors and ensemble of simple classifiers

Joko Siswantoro, Heru Arwoko, Monica Widiasri

First Published: 26 March 2020

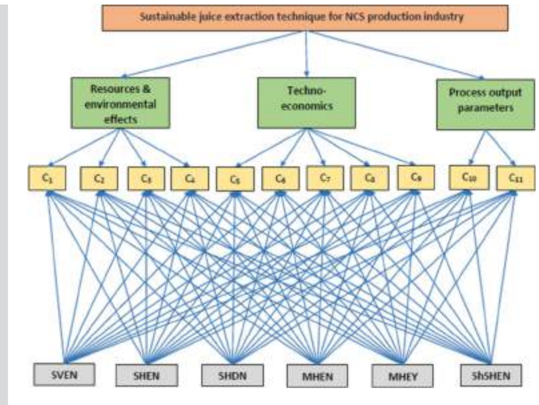


Abstract | Full text | PDF | References | Request permissions

Selection of sustainable juice extraction techniques for non-centrifugal sugar industry using multi-criteria decision-making methods

Sravya Beeram, Srinivas M, SP Raj, Reddy K.S

First Published: 01 April 2020



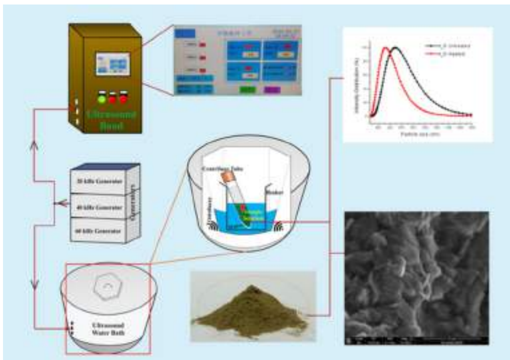
Abstract | Full text | PDF | References | Request permissions

---

Characterization of *Moringa oleifera* leaf polysaccharides extracted by coupling ionic liquid separation system with ultrasound irradiation

Phyllis Naa Yarley Otu, Richard Osae, Mustapha Taiye Abdullateef, Zhou Cunshan, Yu Xiaojie, Bright Kojo Azumah

First Published: 09 April 2020



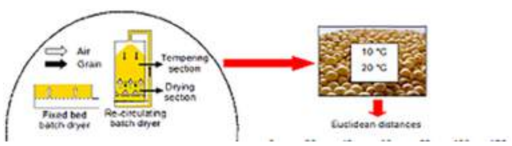
Abstract | Full text | PDF | References | Request permissions

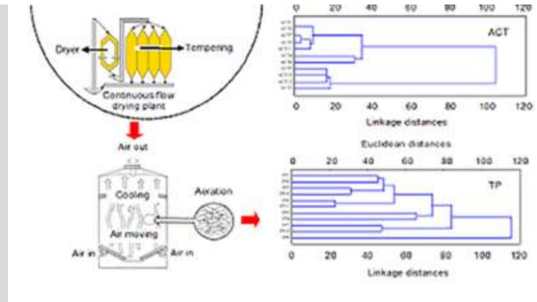
---

Quality of soybean cultivars in the drying and storage processes in real scale and experimental

Paulo C. Coradi, Amanda Müller, Guilherme A. C. Souza, Jontas I. Steinhaus, Roger Wagner

First Published: 13 April 2020



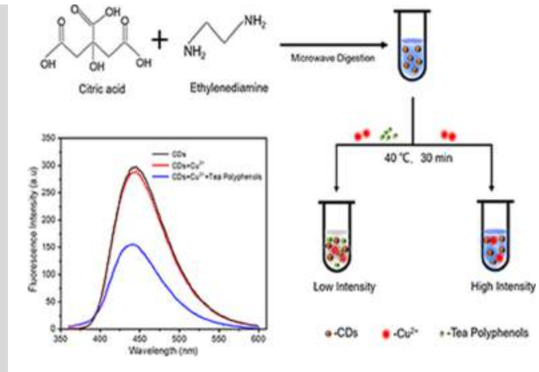


Abstract | Full text | PDF | References | Request permissions

Development of a fluorescent microwave-assisted synthesized carbon dots/Cu^{2+} probe for rapid detection of tea polyphenols

Qingyi Wei, Ting Liu, Hongbin Pu, Da-Wen Sun

First Published: 20 April 2020

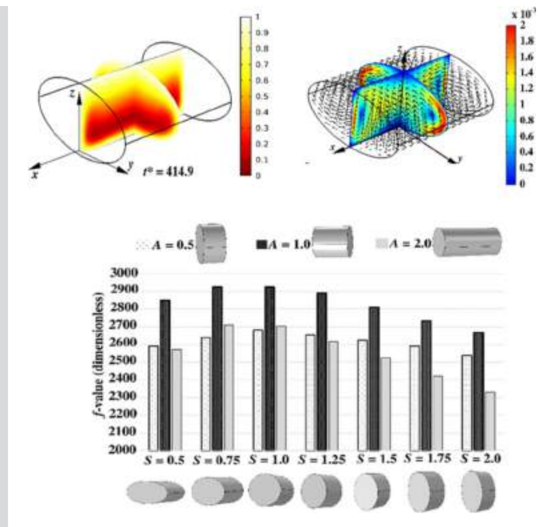


Abstract | Full text | PDF | References | Request permissions

Heating of liquid foods in cans: Effects of can geometry, orientation, and food rheology

Rituraj Borah, Sanjay Gupta, Lubhani Mishra, Raj P. Chhabra

First Published: 17 April 2020

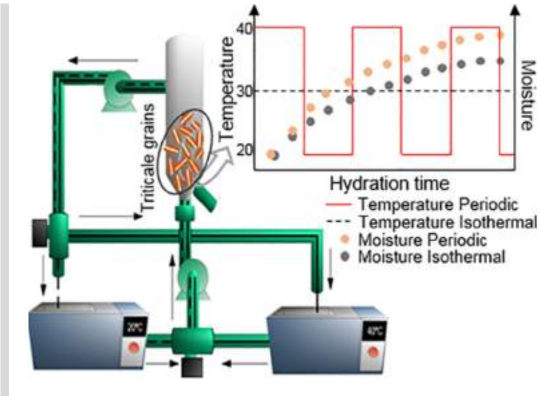


Abstract | Full text | PDF | References | Request permissions

Intensification of the triticale (× *triticosecale* Wittmac) hydration process using periodic operation

Lucas C. de Oliveira, Luiz M. de Matos Jorge, Regina M. M. Jorge

First Published: 15 April 2020

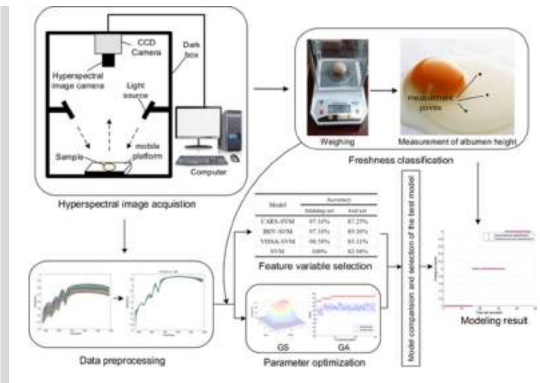


Abstract | Full text | PDF | References | Request permissions

Nondestructive detection for egg freshness grade based on hyperspectral imaging technology

Kunshan Yao, Jun Sun, Xin Zhou, Adria Nirere, Yan Tian, Xiaohong Wu

First Published: 25 April 2020

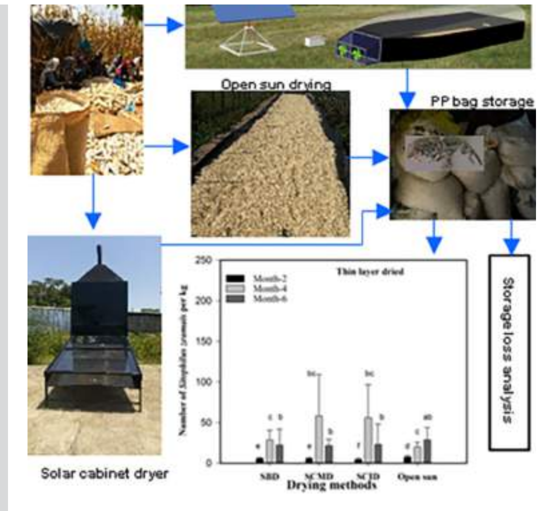


Abstract | Full text | PDF | References | Request permissions

Effects of grain drying methods on postharvest insect infestation and physicochemical characteristics of maize grain

Aynadis Molla Asemu, Nigus Gabbiye Habtu, Bhadriraju Subramanyam, Mulugeta Admasu Delele, Karta Kaske Kalsa, Sajid Alavi

First Published: 27 April 2020

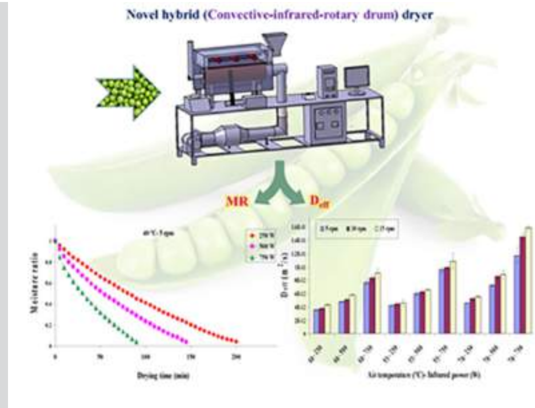


Abstract | Full text | PDF | References | Request permissions

Impacts of hybrid (convective-infrared-rotary drum) drying on the quality attributes of green pea

Mohammad Kaveh, Yousef Abbaspour-Gilandeh

First Published: 12 May 2020



Abstract | Full text | PDF | References | Request permissions

High-pressure treatment of hummus in selected packaging materials: Influence on texture, rheology, and microstructure

Jasim Ahmed, Linu Thomas, Mehrajfatema Mulla

First Published: 15 May 2020

Abstract | Full text | PDF | References | Request permissions

Centrifugal separation-assisted and extraction of crude palm oil from separated mesocarp fiber: Central composite design optimization

Mohd Hafizz Wondi, Rosnah Shamsudin, Robiah Yunus, G. Abdulkareem Alsultan, Aditya Hutama Iswardi

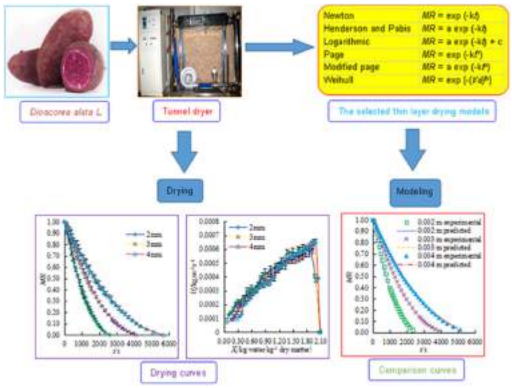
First Published: 25 April 2020

Abstract | Full text | PDF | References | Request permissions

Modeling and mass transfer performance of *Dioscorea alata L.* slices drying in convection air dryer

Aishi Zhu, Junzi Zhao, Yuanfeng Wu

First Published: 22 May 2020

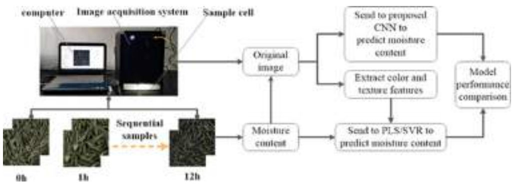


Abstract | Full text | PDF | References | Request permissions

Black tea withering moisture detection method based on convolution neural network confidence

Ting An, Huan Yu, Chongshan Yang, Gaozhen Liang, Jiayou Chen, Zonghua Hu, Bin Hu, Chunwang Dong

First Published: 27 April 2020

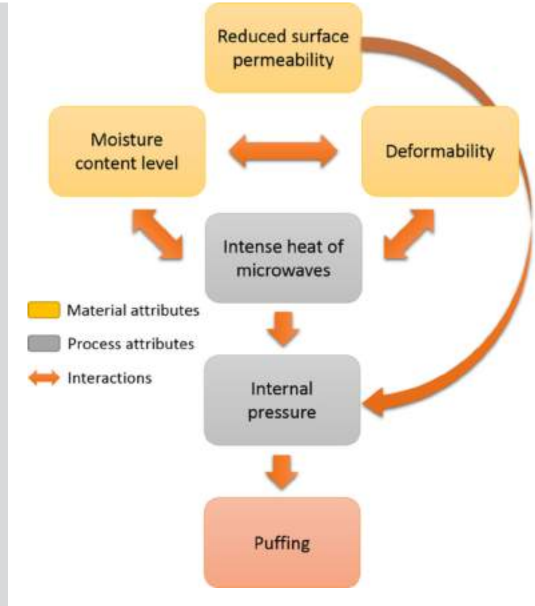


Abstract | Full text | PDF | References | Request permissions

Understanding puffing in a domestic microwave oven

Robert Pompe, Heiko Briesen, Ashim K. Datta

First Published: 05 May 2020



A mechanistic understanding was developed for microwave puffing of a starch-based snack. The development of the crust and its contribution to puffing were studied experimentally. The critical product and process factors in a microwave puffing process were identified. Thicker material and lower microwave power reduced expansion in the puffing process.

Abstract | Full text | PDF | References | Request permissions

Journal of Food Process Engineering

COUNTRY

United States

Universities and research institutions in United States

SUBJECT AREA AND CATEGORY

Agricultural and Biological Sciences
- Food Science

Chemical Engineering
- Chemical Engineering (miscellaneous)

PUBLISHER

Wiley-Blackwell

H-INDEX

45

PUBLICATION TYPE

Journals

ISSN

01458876, 17454530

COVERAGE

1977-2020

INFORMATION

Homepage

How to publish in this journal

balasubramaniam.1@osu.edu

SCOPE

The Journal of Food Process Engineering publishes the best original research on applications of engineering principles and physics concepts to food and food processes with emphasis on process simulation, including mathematical models to describe processes and to allow for scale-up of processes for food manufacturing. Read by researchers, food, agricultural, biological, and chemical engineers, and industry experts, this is the only international journal specifically devoted to the engineering aspects of food processing. JFPE covers a range of topics, including: -Transport of liquid and solid foods -Heating and cooling processes -Food freezing and frozen food storage -Frying processes -Membrane separation processes -New and improved extrusion processes -Packaging processes including Modified Atmosphere Packaging and intelligent packaging -Non-thermal processes including irradiation processing, high pressure processing and other high pressure based technologies, pulsed electric fields, application of gases in food preservation, UV, Ultrasound, filtration, cold plasma, and other similar minimal processing technologies. Articles highlighting innovative combinations of nonthermal or thermal-nonthermal technologies for food manufacturing are also welcome. -Cleaning and sanitation processes -Process engineering technological solutions for produce safety -Process development and design -Process instrumentation and control including sensors for the detection and identification of contaminants in food safety and quality. -Nanotechnology applications to food processes (nanosensors, new ingredients, new process technologies, sensors) -Use of biotechnology to improve food processes -Advanced processing technologies to improve food safety, quality, nutrition, and reduce food waste -Green, clean, and sustainable process technology

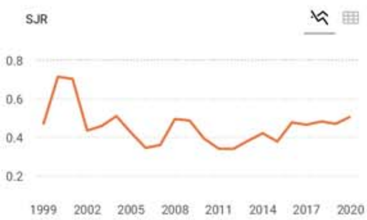
Join the conversation about this journal

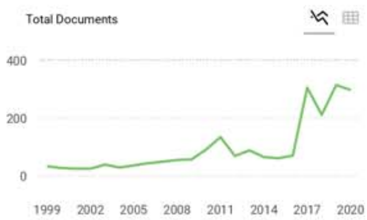
Quartiles

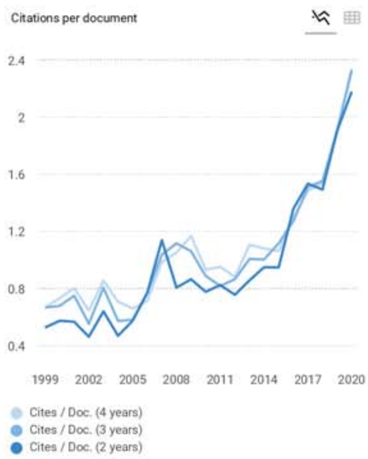
FIND SIMILAR JOURNALS

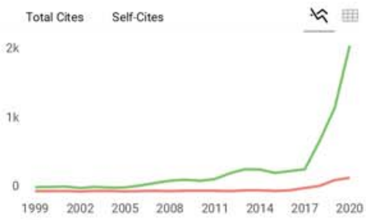
options

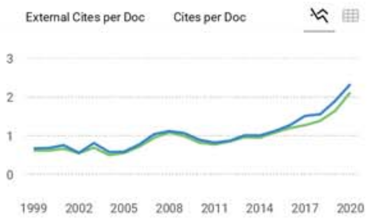
1	2	3	4	5
International Journal of Food Engineering	**Journal of Food Engineering**	**Food Engineering Reviews**	**Food and Bioprocess Technology**	**International Journal of Food Studies**
DEU	GBR	USA	USA	AUT
89% similarity	88% similarity	85% similarity	82% similarity	80% similarity

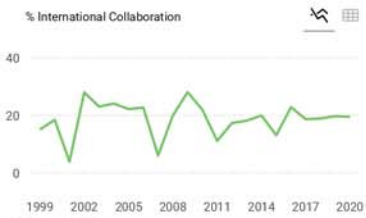


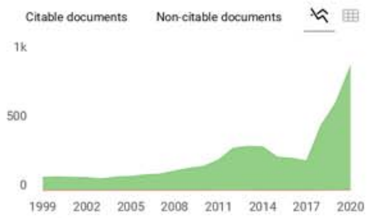


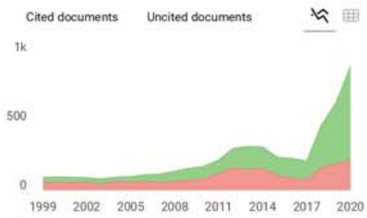












Metrics based on Scopus® data as of April 2021

K **Kester** 2 years ago

Dear SCIMAGO,
Please when will you provide the up-to-date ranking of journals as i can only see rankings up till 2017. when will you rank to 2020? Thank you.

reply

Melanie Ortiz 2 years ago SCImago Team

Dear Kester,
Thank you for contacting us.
The SJR's data are available until 2018 (not 2017). Our data come from Scopus, they annually send us an update of the data. This update is sent to us around April / May every year. Thus, the indicators for 2019 will be available in June 2020. Best Regards, SCImago Team

Leave a comment

Name

Email
(will not be published)

Submit

Source details

Journal of Food Process Engineering

Scopus coverage years: from 1977 to 2021
Publisher: Wiley-Blackwell
ISSN: 0145-8876 E-ISSN: 1745-4530
Subject area: Agricultural and Biological Sciences: Food Science | Chemical Engineering: General Chemical Engineering
Source type: Journal

View all documents > Set document alert Save to source list Source Homepage

CiteScore 2020
3.5

SJR 2020
0.507

SNIP 2020
0.890

CiteScore CiteScore rank & trend Scopus content coverage

i Improved CiteScore methodology

CiteScore 2020 counts the citations received in 2017-2020 to articles, reviews, conference papers, book chapters and data papers published in 2017-2020, and divides this by the number of publications published in 2017-2020. Learn more >

CiteScore 2020

$$3.5 = \frac{\text{3,896 Citations 2017 - 2020}}{\text{1,120 Documents 2017 - 2020}}$$

Calculated on 05 May, 2021

CiteScoreTracker 2021

$$3.7 = \frac{\text{4,075 Citations to date}}{\text{1,087 Documents to date}}$$

Last updated on 04 December, 2021 • Updated monthly

CiteScore rank 2020

Category	Rank	Percentile
Agricultural and Biological Sciences — Food Science	#104/310	66th
Chemical Engineering — General Chemical Engineering	#95/279	66th

View CiteScore methodology > CiteScore FAQ > Add CiteScore to your site