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Integration of computer vision and electronic nose as non-destructive systems for saffron adulteration detection

Sajad Kiani [a], Saeid Minaei [a,*], Mahdi Ghasemi-Varnamkhasti [b]

[a] Biosystems Engineering Department. Tarbiat Modares University, Tehran, Iran
[b] Department of Mechanical Engineering of Biosystems, Shahrekord University, Shahrekord, Iran

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ABSTRACT

This work deals with the development and evaluation of an integrated system based on computer vision system (CVS) and electronic nose (e-nose) for saffron adulteration detection. Ten saffron samples adulterated with two common illegal constituents, namely, Artificially Colored Safflower (ACS) and Artificially Colored Yellow Styles of Saffron (ACYSS) at levels ranging from 10 to 50% (w/w) were characterized in this work. First, the developed CVS and e-nose system were integrated to form a unit system. This set up was utilized to extract color and aroma characteristic variables of each sample. The extracted variables were processed using Principal Component Analysis (PCA), Hierarchical Cluster Analysis (HCA), and Support Vectors Machines (SVMs) to demonstrate the discrimination capability of the developed system. Two multilayer artificial neural network (ANN-MLP) models were also employed for saffron color and aroma strength prediction based on ISO standards. PCA and HCA results of the color and aroma datasets revealed that the adulterated samples have different color and aroma strength compared to authentic saffron and they can clearly be distinguished. SVMs classifier showed good agreement with the PCA results and reached 89% and 100% success rate in the recognition of the different saffron samples based on their color and aroma datasets, respectively. Results of the two ANN-MLP models proved that the developed system is capable of differentiating the authentic and adulterated saffron samples based on their color and aroma strength ($R^2_{Color\ analysis} \geqslant 0.95$ and $R^2_{Aroma\ analysis} \geqslant 0.97$).

1. Introduction

Saffron (*Crocus sativus* L.) is commercially important and widely consumed as spice. It possesses desirable flavor, therapeutic and medicinal properties. Due to the high demand for saffron, its price has been steadily increasing. Thus, saffron spice has been the subject of various adulterations, such as mixing with foreign materials to increase the volume and weight of its commercial lot. The most frequently encountered extraneous and adulterant materials are artificially colored yellow styles of saffron (ACYSS) and artificially colored safflower (*Carthamus tinctorius* L.) (ACS) (Heidarbeigi et al., 2014). On the other hand, saffron quality could be influenced by the geographical location of production, drying procedures, and storage conditions (Maghsoodi et al., 2012). This makes the important task of saffron quality monitoring more complicated. Saffron quality includes several main attributes such as color, aroma, and taste which are determined by its main chemical compounds, namely, Crocins ($C_{44}H_{64}O_{24}$), Picrocrocin ($C_{16}H_{26}O_7$), and Safranal ($C_{10}H_{14}O$), respectively (Maggi et al., 2009). Saffron samples receive different quality grades containing different amounts of these chemical compounds. Adulteration in saffron samples can reduce the amounts (per volume) of its main chemical compounds and thus its quality.

Different analytical methods for the detection of saffron quality and their adulteration exist, including Near Infrared spectroscopy (NIR) (Zalacain et al., 2004), thin layer chromatography (TLC) (Pathan et al., 2009), gas chromatography mass spectroscopy (GC–MS) (Jalali-Heravi et al., 2009), liquid chromatography mass spectroscopy (LC-MS) (Verma and Middha, 2009), UV–Vis spectroscopy (Sabatino et al., 2011), high performance liquid chromatography (HPLC) (Sheikh et al., 2013), Nuclear magnetic resonance (Petrakis et al., 2015), proton transfer reaction mass spectrometry (PTR-MS) (Nenadis et al., 2016), and Diffuse Reflectance Infrared Fourier Transform Spectroscopy (DRIFTS) (Petrakis and Polissiou, 2017). These methods are accurate and sensitive, but their industrial applicability is hindered by their time consuming and off-line nature, high costs, and the need for specialist operators (Ghasemi-Varnamkhasti et al., 2012a). Advances and developments in sensor technology, chemometrics and artificial

* Corresponding author.
E-mail address: minaee@modares.ac.ir (S. Minaei).

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intelligence make it possible to develop instruments based on artificial senses such as electronic eye or computer vision (CVS), electronic nose (e-nose) and electronic tongue (e-tongue) systems capable of measuring and characterizing color, aroma and taste of saffron. Details about these techniques have been expounded earlier (Kiani et al., 2016a; Ghasemi-Varnamkhasti et al., 2012b, 2016). Both CVS and e-nose techniques require little sample preparation and allow large data sets to be acquired in a short time. These two methods are nondestructive, inexpensive, and do not require skilled operator. Relatively speaking, e-tongue is much more complex, its sensors are contact type, and samples should be in liquid form. Sometimes, saffron adulteration may be so subtle that only using a single nondestructive evaluation method (such as CVS) is not capable of detecting it. More recently, applications of nondestructive tools in food quality assessment have been documented (Men et al., 2014; Forina et al., 2015; Borras et al., 2015: Peris and Escuder-Gilabert, 2016; Kiani et al., 2016b; Khulal et al., 2017). The authors of such reports have emphasized on the fact that integration of different techniques can provide more information about various aspects of the food materials and consequently the final judgment on quality indices is more accurate and reliable. To date, no report on integration of CVS and e-nose for saffron quality characterization has been published. Thus, the objectives of this study include: (1) development of an intelligent technique based on the integration of computer vision and e-nose systems coupled with multivariate methods, (2) evaluation of the developed system for detection of adulterated saffron samples based on their color and aroma profiling.

2. Materials and methods

2.1. Saffron samples and chemical analysis

The authentic saffron sample was directly procured from Tarvand Saffron Co. (Ghayen, South Khorasan, Iran). The crop, produced and harvested in 2015, had been dried at room temperature and in ventilated conditions. After purchase, the lot was refrigerated at 4 °C before the experiments. Yellow styles of saffron and safflower were used as foreign materials to prepare the adulterated samples. These were purchased from Tarvand Saffron Co. and the local market in Tehran. The authentic saffron sample was mixed with the colored foreign materials, adulteration ranging from 10 to 50% (w/w) for each additive. Therefore, 10 adulterated saffron samples were prepared. One gram of each sample was taken for analysis.

According to ISO 3632 standard, the maximum UV absorbance for the prepared aqueous samples in the 1 cm quartz cell tested at the wavelengths of about 440 nm and 330 nm, indicate the "color strength ($E^{1\%}_{1cm}$440nm) and aroma strength ($E^{1\%}_{1cm}$330nm)" of saffron corresponding to the amount of Crosins and Safranal compounds, respectively (ISO/TS 3632, 2011). It is worth mentioning that ISO 3632 standard specifies saffron color and aroma strength in the intervals $80 < E^{1\%}_{1cm}440nm < 190$ and $20 < E^{1\%}_{1cm}330nm < 50$, respectively, expressing the degree of quality from low to high (Gismondi et al., 2012).

2.2. Computer vision and electronic nose integrated set-up

The CVS set up is comprised of a CCD digital camera, standard lighting system and software for image processing and analysis (Figs. 1b and 2). More details about the structure of the developed CVS, image processing algorithm and effectiveness of each color feature have been reported elsewhere (Kiani et al., 2016c). The e-nose developed in our laboratory was coupled with the CVS to develop an integrated system (Figs. 1b and 2). The e-nose sensor array uses seven gas sensors. These include: TGS822, TGS813, TGS2611, TGS2610, MQ6, MQ136, and MQ137. More details about the sensor array of the e-nose and data pre-processing have been documented earlier (Kiani et al., 2016d). The integrated system was employed to receive and interpret both saffron color and aroma characteristic variables in sequence: first the image is captured in the camera enclosure, then, the sample is placed in the e-nose chamber for aroma data acquisition (Fig. 1b).

Both CVS and e-nose algorithms were written and combined in MATLAB software. Upon starting, the algorithm prompts the operator to place the sample into the camera enclosure and capture an image. After image acquisition, the system calls for placing the sample into the e-nose chamber. The trapped air in the e-nose chamber is allowed to become saturated with the saffron aroma. Steady state sensor responses occur at around 350 s and then ten consecutive times (351–360 s) are considered as the sample aroma features.

Finally, after the acquisition of the image and gas sensors signals, pre-processing is performed and the color and aroma features are extracted. Eleven color features including R, G, B, Y, I, Q, Cb, Cr, L*, a* and b* of four color spaces, namely, RGB, YIQ, YCbCr, and CIE L*a*b* are organized in a rectangular data matrix as a color dataset (i.e., 11 color features). In order to prepare a comprehensive color dataset for training CVS algorithm, 15 images of each saffron sample were captured (after each capturing, the sample was shaken). The e-nose measurement was organized as an aroma dataset by considering 7 aroma features (sensor signals) and a rectangular data matrix (i.e., 7 aroma features $*$ 10 consecutive data). Saffron samples were thus tested and their color and aroma characteristic variables were collected as datasets.

2.3. Data analysis

The extracted variables were analyzed using PCA, HCA and SVMs. The HCA provides a succinct graphical representation known as a dendrogram which shows how each object lies within its cluster. These dendrograms can be built in a bottom-up (Agglomerative) or top-down (Divisive) fashion. SVMs are supervised learning and kernel-based classification and regression models which were originally developed for the linear classification of two separable data, but they can be easily adapted to multiclass problems and nonlinear data utilizing kernel functions and an iterative training algorithm which maximizes a quantity called margin (Haddi et al., 2011). More details about PCA and HCA models have been reported by Scott et al. (2007) and details of the SVMs classifier and its application in the sensor areas can be found in literature (Haddi et al., 2011; Sanaeifar et al., 2016).

As discussed in Section 1, saffron samples may have different color and aroma quality due to their different cultivation and post harvesting conditions. Hence, a saffron sample of high color and aroma quality mixed with the adulteration material may exhibit the same quality as a sample with low color and aroma quality. Therefore, in addition to clustering of the saffron samples using PCA, HCA, and SVMs, it was decided to assess saffron quality by predicting it's $E^{1\%}_{1cm}$440nm and $E^{1\%}_{1cm}$330nm using ANN-MLP models. Since the obtained results present indices of saffron quality, saffron adulteration may be detected based on these results. Thus, the two previously developed ANN-MLP models were utilized to predict $E^{1\%}_{1cm}$440nm and $E^{1\%}_{1cm}$330nm of adulterated saffron samples based on their color and aroma features, respectively. These models were developed based on color and aroma datasets of 33 authentic saffron samples. These samples were collected from different geographical regions of Iran and their analysis has been reported by the authors previously (Kiani et al., 2017). In this study, the developed ANN-MLP models were evaluated using 10 adulterated