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Discerning expiration status of edible vegetable oils based on color changes during oxidation process: Using digital image and linear discriminant analysis in both primary and secondary oxidations

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Abstract

Discerning the expiration status (non-rejected and rejected) of edible vegetable oils is very significant because of the hazardous primary and secondary oxidation products. Therefore, it is of outmost importance to monitor the quality and safety of these oils. Based on previous literature, reports and experimental observation, the oil color changes during oxidation. Thus, the present study investigates the use of image processing and linear discriminant analysis (LDA) for the classification of non-rejected and rejected edible vegetable oils during oxidation process at 85°C, with respect to the induced period in both primary and secondary oxidation of four oil type (Olive, Sunflower, Palm and Soybean). The purpose of this study was to find less costly and quicker methods with environmental protection, by using the color spaces (RGB, HSI, L*a*b* with Grayscale) instead of chemical analyses to determine the expiration status of edible vegetable oils. Results of this study indicated that the best classification for expiration status of known oils according to induced period of peroxide value in each color space, was achieved with LDA model were for palm with 100% (HSI and Grayscale), olive with 84.61% (L*a*b* and RGB), soybean with 95% (Grayscale) and sunflower with 100% (RGB and HSI), also in induced period of carbonyl value test, the best classification performance was achieved in palm with 100% (L*a*b*), olive with 100% (L*a*b*), soybean with 89.47% and sunflower with 95% (HSI).

Keywords: Edible Vegetable Oil; Oxidation; Peroxide Value; Carbonyl Value; Linear Discriminant Analysis; Imaging.

Introduction

Edible oils bring essential nutrient components for human beings such as vitamins, fatty acids, and micronutrients, which are necessary for daily life [1]. However, the use of expired edible oils leads to a decrease in the nutritive value and an increase in potential hazards to people's health [2]. Therefore, the authentication and identification of edible oils are of great importance in the field of food safety and quality monitoring.

A reliable, fast and non-destructive detection method to identify various types of edible oils is essential. Recently, different methods have been employed to identify the types of edible oils [3]. Several works have been reported in literature exploring the use of liquid chromatography [4], fluorescence spectroscopy [5], fourier transform infrared [6], differential scanning calorimeter [7], supercritical liquid chromatography (SFC) and gas chromatography [8], for the quality control of vegetable oils. However, most of these methods are highly sophisticated, expensive and involve laborious analysis.

Lipid oxidation in vegetable oils is associated with unsaturation of the oils. This reaction leads to the formation of a series of intermediate compounds named hydro peroxides. Hydro peroxides are the primary oxidation products of lipid oxidation. This is due to the unstable nature of these products which leads to their decomposition and turning into secondary oxidation products, such as carbonyl compounds. These products are generally unstable and decompose into a variety of secondary oxidation products, including carbonyl compounds [9].

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This condition causes flavor and odor change; Hydro peroxides do not play an important role in flavor deterioration, whereas carbonyl compounds are mainly responsible for the typical rancid off-flavors [10].

Two of the best analytical indicators of oxidative changes in fats and oils are peroxide (PV) and Carbonyl (CV) values [11]. Determination of these values provides valuable information in regard to primary and secondary oxidations [12]. However, due to the use of chemical materials (solvents such as chloroform, n- Hexane etc.), determination of these values is time- consuming, financially costly and costly in terms of damage to environment. Therefore, finding a quicker, less expensive and more environmentally friendly method is crucial.

Nowadays, digital imaging is becoming more important because of its ability to perform fast and non- invasive, low- cost analysis on foods. In fact, a wide variety of digital cameras and digitalization equipment has contributed to an increase in the number of papers published exploring the use of webcam [13], scanner [14], cell phones [15] and digital camera [16] to monitor the quality of several food samples. A positive feature of using digital image to monitor the quality of foods is that it replaces the human visual system, often employed in these types of analyses [17].

Therefore, the use of digital image eliminates the subjective character of analyses as well as the dependence of the human visual system, which is substantially influenced by ambient conditions and subject to inconsistencies [18].

Given this, techniques based on digital images are a promising alternative for the analysis of food and other products. Some studies have shown the availability of using the technique for quality control in various matrices, including shrimp [19], cereal grains [20], Kiwifruit [21], castor seeds [22], olive oils [23-25] and other edible vegetable oils [26]. Most of these studies use information from color models associated with pattern recognition techniques to cluster, or classifythe samples into categories, according to similarity standards.

The red, green and blue additive color added together to form RGB color space that was designed to match an intuitive human perception of the colors. In HSI color space, parameters are the intensity I, chromaticity hue H and saturation S. HSI approximates the way in which humans perceive and interpret colors.

At present, usually, the color of foods has been measured in L*a*b*. The L*a*b*, or CIE L*a*b*, color space is an international standard for color measurements, adopted by the Commission Internationale d'Eclairage (CIE) in 1976 [27].

However, at present available commercial colorimeters, measure L*a*b* only over a very few square centimeters, and thus their measurements are not very representative in heterogeneous materials such as most food items [27]. Some of the instruments most frequently used in the measurement of color are colorimeters (e.g Minolta chroma meter, Hunter Lab colorimeter and Dr. Lange colorimeters). There is, however, a disadvantage in using them [26, 28-29].

Using a computational technique with a combination of a digital camera, and image processing software has already been used to provide a less costly and more adaptable way to measure the color of many food products and foodstuffs instead of traditional color measuring instruments [27].

Although there have been many studies in the field of image processing and classification of foods, studies on the classification of edible vegetable oils based on image processing have been very limited especially in the field of determination of expiration status (rejected and non-rejected).

As was pointed before, understanding the first oxidation based on odor and flavor is not possible since the off flavor occurs in the second oxidation, therefore, it is critical to find a new technique for discerning oxidation. This is possible based on the color of oil, however, discerning the condition of rancid is impossible by the naked eye, therefore, it is necessary to use pattern recognition and image processing.

According to no significant color change just before and after rejection, the aim of this study was to determine rejected and non-rejected status of edible vegetable oils during oxidation process in specified intervals of two and six hours according to the induce period of peroxide and carbonyl value by using only the oil color changes instead of expensive and laborious current recognition and quality control methods of oils. To the best of our knowledge, this is the first study to investigate the expiration status of edible vegetable oils according to exact rejection point by using the color changes.

Materials and Methods

Four vegetable oil samples including Soybean, Sunflower, Palm, and Olive oils were purchased from the Segol Co. (Nishaboor, Iran). They were stored at -18°C until the time of analysis. All chemicals and solvents were purchased from Sigma-Aldrich (St. Louis, MO) and Merck (Darmstadt, Germany). Images were taken in every two (Soybean, Sunflower oils) and six hours (Palm, and Olive oils), during the heating process (at 85°C in an oven). Also, the chemical (PV and CV) analysis was performed at the same time of imaging.

Peroxide value

The spectrophotometric method of Shantha and Decker [30] was used to determine the peroxide value (PV). The oil samples were mixed with chloroform: methanol in a glass tube. Ammonium thiocyanate and iron (II) chloride was then added. After that the sample was placed for 5-min at room temperature, the absorbance of the sample was read at 500 nm against a blank by using a spectrophotometer. Results were expressed in milliequivalents of oxygen per kilogram of oil.

Carbonyl value

The carbonyl value (CV) was measured by using 2-propanol and 2, 4-decadienal as solvent and standard, respectively. Any trace of carbonyl compounds which may present in the solvent was removed with mixed solution of sodium borohydride and 2-propanol. Standard aldehyde (2, 4-decadienal) dissolved in the solvent. The oil was mixed with 2, 4-Dinitrophenylhydrazine (DNPH) solution in a test tube. Then the test tube was stoppered and heated. After that, the sample was cooled in water, and 2% KOH solution was added. After centrifugation, the absorbance of the upper layer was measured at 420 nm by using a spectrophotometer against a blank. The results were expressed in micromols of 2, 4 decadienal per gram of oil [31].

Apparatus and digital image acquisition

Apparatus

The size of system that was built for imaging was 120 cm× 90 cm× 90 cm with dark walls to isolate the samples from external light. The compartment has camera canon model, EOS 1000D, which was connected to computer by a USB port. The illumination of the compartment was performed by using eight fluorescent lamps with 8 W (white color), the lamps were placed at a distance of 20 cm and 40 cm from the sample and with 45 degree angle for preventing the reflection of light.

The Illustration was performed by Zoombrower EX 0.5, the other characteristics of camera for imaging were as follow: flash (off), zoom (on), Iso speed (100), Aperture priority (F / 20) and Shutter speed (0.6 Sec). The illumination condition at compartment for each sample was the same.

Image color analysis

Image color analysis was performed using the MATLAB (R2013) software to convert images from R*G*B color space to L*a*b, HSI, Grayscale.

The recorded images contained 24-bit (16.7 million colors) and 3888 pixels× 2592 pixels spatial resolution, were stored in JPEG format (jpg). A circular region with a radius of 2.75 mm at the center of each image was selected for converting R*G*B to L*a*b, HSI and Grayscale. The extracted color values were then used for linear discriminant analysis (LDA) classification (Fig. 1).

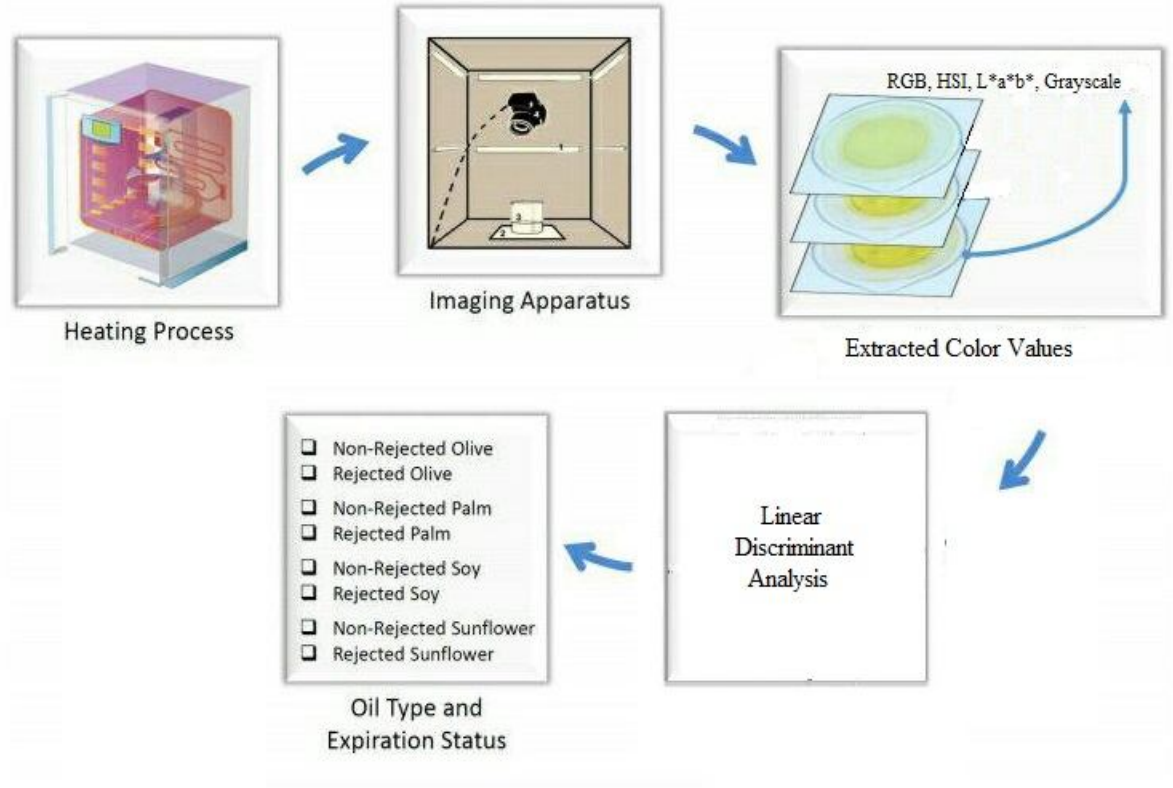

Fig. 1. System used in the acquisition of images and classification of oils samples.

Chemometric procedures

The extracted color features were analyzed based on two approaches. The first approach involved the classification of non-rejected and rejected status of each oil samples with respect to induced period of peroxide value, and the second classification involved the classification with respect to induced period of carbonyl value, to distinguish non-rejected and rejected status of edible oils according to primary and secondary oxidation. A total of 99 images of oils data were collected during the heating process. Data analysis was performed by classical multivariate procedures including LDA with MATLAB (R2013). The RGB, HSI, L*a*b* and Grayscale color space features were extracted from images of oils samples then they were used in LDA classification for both color changes during primary (90 images) and secondary (99 images) oxidation (Table 1).

Table 1. The total number of oil samples in both PV and CV tests.

		Palm	Olive	Soybean	Sunflower
PV	Non-rejected	20	16	7	7
	Rejected	5	10	12	13
	Total	25	26	19	20
CV	Non-rejected	24	20	11	11
	Rejected	10	6	8	9
	Total	34	26	19	20

To find the effect of oxidation process on the color of edible vegetable oils during time, the color changes in each oil type at each color spaces RGB, HSI, L*a*b* and Grayscale was considered.

Linear Discriminant Analysis (LDA) is a classification method that is commonly used as dimensionality reduction technique for pattern-classification and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects which was developed by Fisher [32]. Multi-class LDA is a generalization of standard two-class LDA that can handle arbitrary number of classes. We are seeking p projections (*i.e.*$\boldsymbol{y}_1, \boldsymbol{y}_2 \ldots \boldsymbol{y}_p$) of the input vector $\boldsymbol{x}$ by means of p projection vectors $\boldsymbol{w}_i$ as follows:

$$y_i = \boldsymbol{w}_i^T \boldsymbol{x}, \qquad i = 1,2, \ldots, \quad (1)$$

If we arrange all $\boldsymbol{w}_i$ in a projection matrix as $W=[\boldsymbol{w}_1,\boldsymbol{w}_2,\ldots,\boldsymbol{w}_p]$, it can be written:

$$\boldsymbol{y} = W^T \boldsymbol{x} \quad (2)$$

where

$$\boldsymbol{x} = [x_1 \quad \cdots \quad x_m]^T$$

and

$$\boldsymbol{y} = [y_1 \quad \cdots \quad y_n]^T.$$

By stacking all feature vectors in one matrix, we can write:

$$Y = W^T X \quad (3)$$

where

$$X = [\boldsymbol{x}^1, \boldsymbol{x}^2, \ldots, \boldsymbol{x}^n] = \begin{bmatrix} x_1^1 & x_1^2 & . & x_1^n \\ . & . & . & . \\ x_m^1 & x_m^2 & . & x_m^n \end{bmatrix} \quad (4)$$

$$Y = [\boldsymbol{y}^1, \boldsymbol{y}^2, \ldots, \boldsymbol{y}^n] = \begin{bmatrix} y_1^1 & y_1^2 & . & y_1^n \\ . & . & . & . \\ y_q^1 & y_q^2 & . & y_q^n \end{bmatrix} \quad (5)$$

For p-classes case, we will measure the within-class and between-class scatters with respect to the mean of all classes, respectively, as follows:

$$S_W = \sum_{i=1}^{p} \sum_{\boldsymbol{x} \in c_i} (\boldsymbol{x} - \boldsymbol{\mu}_i)(\boldsymbol{x} - \boldsymbol{\mu}_i)^T \quad (6)$$

$$S_B = \sum_{i=1}^{p} N_i (\boldsymbol{\mu}_i - \boldsymbol{\mu})(\boldsymbol{\mu}_i - \boldsymbol{\mu})^T \quad (7)$$

Where

$$\boldsymbol{\mu} = \frac{1}{N} \sum_{\forall_x} \boldsymbol{x} = \frac{1}{N} \sum_{i=1}^{p} N_i \boldsymbol{\mu}_i \quad (8)$$

$$\boldsymbol{\mu}_i = \frac{1}{N_i} \sum_{\boldsymbol{x} \in C_i} \boldsymbol{x} \quad (9)$$

Such that C_i represents the i-th class. Similarly, we can define the mean vectors for the projected samples as follows:

$$\tilde{\boldsymbol{\mu}}_i = \frac{1}{N_i} \sum_{\boldsymbol{y} \in C_i} \boldsymbol{y} \quad (10)$$

$$\tilde{\boldsymbol{\mu}} = \frac{1}{N_i} \sum_{\forall \boldsymbol{y}} \boldsymbol{y} \quad (11)$$

Similarly, the within-class and between-class scatter matrices of the projected samples can be given, respectively, by:

$$\tilde{S}_W = \sum_{i=1}^{p} \sum_{\boldsymbol{y} \in C_i} (\boldsymbol{y} - \tilde{\boldsymbol{\mu}}_i)(\boldsymbol{y} - \tilde{\boldsymbol{\mu}}_i)^T \quad (12)$$

$$\tilde{S}_B = \sum_{i=1}^{p} N_i (\tilde{\boldsymbol{\mu}}_i - \tilde{\boldsymbol{\mu}})(\tilde{\boldsymbol{\mu}}_i - \tilde{\boldsymbol{\mu}})^T \quad (13)$$

By using Eqns. (6) and (7) and some algebraic manipulations, we can obtain:

$$\tilde{S}_W = W^T S_W W \quad (14)$$

$$\tilde{S}_B = W^T S_B W \quad (15)$$

To obtaine an appropriate discrimination between all classes, the coefficients of W should be optimally adjusted such that the between-class scatter increases while simultaneously, the within-class scatter decreases. Thus, the optimal W^* can be obtained by maximizing the following objective function:

$$J(W) = \frac{|\tilde{S}_B|}{|\tilde{S}_W|} = \frac{|W^T S_B W|}{|W^T S_W W|} \quad (16)$$

$$W^* = index(\max_W J) \quad (17)$$

Where|.| computes the determinant of a matrix. For W^*, it is sufficient to set the differential of J (W) (with respect to W) equal to zero. It can be shown that the columns of W^* are the eigenvectors corresponding to the

largest eigenvalues of the following generalized eigenvalue problem:

$$S_W^{-1} S_B w_i^* = \lambda_i w_i^* \quad (18)$$

Where

$$W_i^* = [w_1^*, \ w_2^*, \dots, w_{p-1}^*].$$

Evaluation Measure

This feature was studied by using the accuracy (ACR) analysis as follow:

$$\mathrm{ACR} = \frac{TP+TN}{TP+FP+TN+FN} \quad (19)$$

Where TP, TN, FP, and FN are the true positive, true negative, false positive and false negative, respectively, TP (FP) or true positive (false positive) means all samples correctly (incorrectly) identified. Similarly FN or false negative means that those samples are incorrectly identified.

Results and Discussion

Table 2 illustrates the Chemical indicators, Peroxide values (PV) and Carbonyl values (CV) of the oil samples. The PV and CV values of the soybean, sunflower, olive and palm oils after heating process are shown in Table 2. The PV and CV of the non-rejected oils were lower than 2 meq O_2/kg oil and 3.1 µmol/g for all samples and their levels after heating did differ significantly to reach their rejection points.

Table 2. Chemical indicates and Peroxide value (PV), and carbonyl value (CV) of the oils before and after heating process at 85°C.

	PV[b]	IP_{pv}Time (hour)	CV[c]	IP_{cv}Time (hour)
Palm R	0.69±0.021		3.06±0.012	
Olive R	1.99±0.46		3.047±0.072	
Sunflower R	0.28±0.034		0.26±0.005	
Soybean R	0.82±0.057		0.136±0.001	
Palm NR	62.74±0.11	119.09	8.74±0.21	140.68
Olive NR	32.053±0.90	93.64	10.96±0.15	114.66
Sunflower NR	2.23±0.13	13.70	4.61±0.03	21.42
Soybean N	1.89±0.19	12.94	4.52±0.04	21.39

a Mean value ± standard deviation, All values are means of three determinations.
b Peroxide value (meq O_2/kg oil).
c Carbonyl value (µmol/g).

During the heating process, a wide range of PV and CV was observed among the oil samples every 2 and 6 hour (from 0.82 to 1.89 meq O_2/kg oil for Soybean, 0.28 to 2.23 meq O_2/kg oil for sunflower, 1.99 to 32.053 meq O_2/kg oil for olive and from 0.69 to 62.74 meq O_2/kg oil for palm and also from 0.136 to 4.52 µmol/ g for Soybean, 0.26 to 4.61 µmol/ g for sunflower, 3.047 to 10.96 µmol/ g for olive and from 3.06 to 8.74 µmol/ g for palm, PV and CV values ,respectively), indicating that the oils had no similar rejection points. Table 2 also demonstrates the IPPV and IPCV for each oil type. The peroxide value (PV) for soybean was 12.94, sunflower 13.70, olive 93.64 and palm 119.09 hour And similarly carbonyl value (CV) for soybean was 21.39 sunflower 21.42, olive 114.66 and palm 140.68 hour.

These chemical analyses were carried out in order to find the exact rejection point of primary and secondary oxidation of these oils, so that their classification could be done accurately in all their different rancidities (Fig.2).

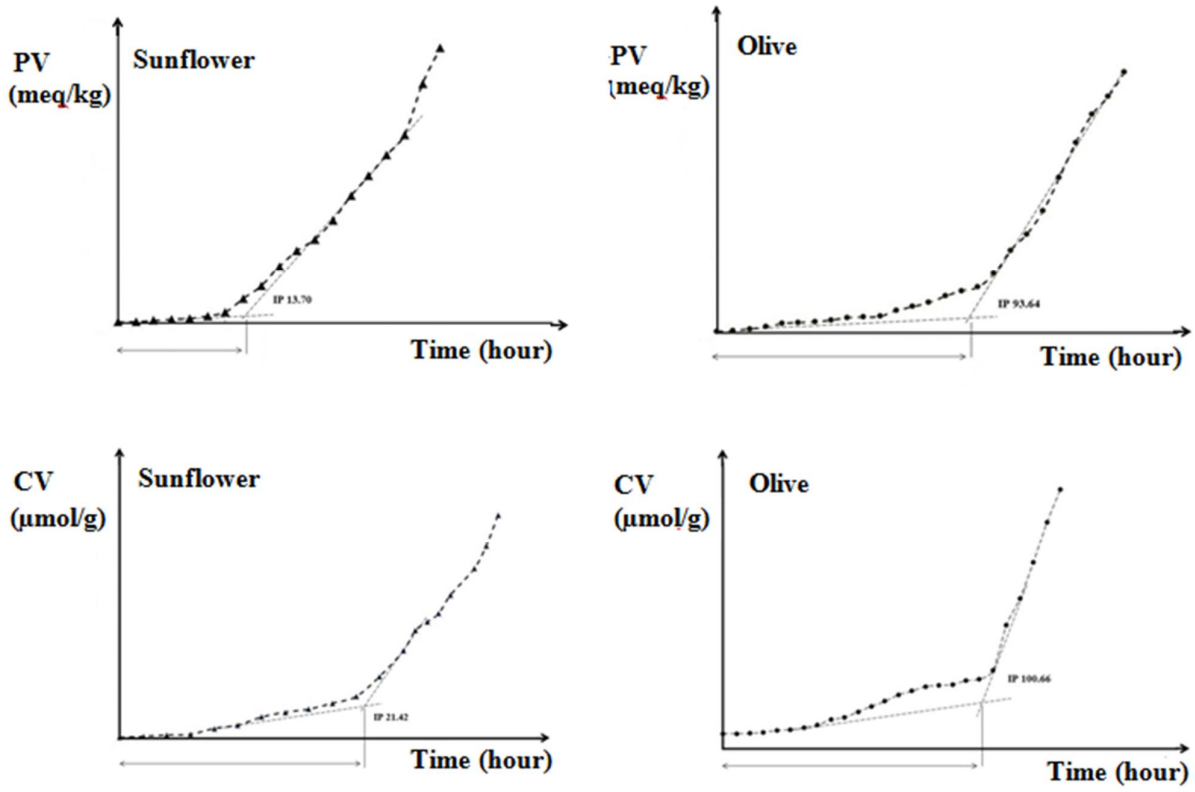

Fig. 2. A schematic kinetic curve of peroxide and carbonyl accumulation during oxidation of lipid systems in Sunflower and Olive oil.

By increasing the amount of PV and CV during time of heating, the color of the oils changed in each stage. According to the difference in values and color feature extraction of images, it may be possible to make a model for classification of expiration status of these oils without the necessity to perform high cost chemical experiments. Therefore, it is suggested that the oxidation can significantly affect the color.

In classification part, Table 3 illustrates the classification accuracy of non-rejected and rejected of each known oil type during the heating time at each color space separately to identify the expiration status according to carbonyl and peroxide values.

Table 3. Accuracy of each known oil type during the heating time at each color space in both PV and CV tests.

		Olive	Palm	Soybean	Sunflower
PV	L*a*b*	84.61%	100%	89.48%	90%
	RGB	84.61%	96%	78.95%	100%
	HSI	80.77%	100%	84.21%	100%
	Grayscale	80.77%	96%	95%	75%
CV	L*a*b*	100%	100%	84.21%	90%
	RGB	96.15%	91.18%	78.95%	90%
	HSI	84.62%	88.25%	89.47%	95%
	Grayscale	88.46%	100%	78.95%	70%

As it can be seen in Table 3, all rejected and non-rejected oils according to peroxide induced period in each color space and Grayscale were identified appropriately. It is apparent from the Table, that the highest accuracy among studied color spaces were 100% at L*a*b* and HSI for palm, 84.61% at L*a*b*, RGB color spaces for olive, 95% at Grayscale color space for soybean and finally 100% at RGB and HSI color spaces for sunflower.

Similarly, Table 3 shows the accuracy of edible oils according the carbonyl induced period. This indicated that, the best results for palm, olive, soybean and sunflower oils were achieved with 100% at L*a*b* and Grayscale, 100% at L*a*b*, 89.47% at HSI and lastly 95% at HSI color space respectively.

Table 4 illustrated the classification accuracy of four oils (Palm, Olive, Soybean and Sunflower) in non-rejected and rejected status in both oxidations. At first all non-rejected oils were classified in each color space (L*a*b*, RGB, HIS and Grayscale). As shown in Table 4 the best result belongs to HSI with 88% in primary oxidation and with regard to secondary oxidation L*a*b* with 91.04% have the best accuracy. For rejected oils classification the best color space are HSI and L*a*b* with 90% and 87.5% in primary and secondary oxidation, respectively.

Table 4. Accuracy of Non-rejected and Rejected four oils (Palm, Olive, Soybean and Sunflower) during the heating time at each color space in both PV and CV tests.

		L*a*b*	RGB	HSI	Grayscale
PV	**Non-rejected oils**	86%	80%	88%	68%
	Rejected oils	80%	77.5%	90%	75%
CV	**Non-rejected oils**	91.04%	68.66%	82.09%	58.21%
	Rejected oils	87.5%	81.25%	71.88%	56.25%

Figs. 3A and 3B show the score plots of the two discriminant functions (F2 * F1) obtained by the LDA classifier for the R and NR oils samples. It is possible to observe that Soybean-R, Sunflower-R, Olive-R and Palm-R oil samples are separated along the F1 direction. It is obvious that the F1 separated Soy-R and Palm-R groups from other groups.

As can be seen, the Olive-R and Sunflower-R sample has overlap with each other (Fig. 4A). Fig. 4B illustrated that Sunflower-NR, Soybean-NR, Olive-NR and Palm-NR oil samples presented a tendency of separation along the F1 direction. Although Sunflower-NR and Olive-NR samples well discriminated but Palm-NR and Soybean-NR have a slight overlap.

As it can be seen in Table 5, all rejected and non-rejected oils according to both oxidations in all color spaces and Grayscale were classified. It is apparent from Table 5 that the highest accuracy belongs to the classes with more sample numbers (according to Table 2). For example, Olive NR with 100% in both oxidations has best accuracy in comparison with the Olive R (30% and 50%). Because of different rate of expiration in each oil-type, the number of samples is quite limited in some classes. However, total accuracy of LDA classifier in primary and secondary oxidation relatively well performs with 74.44% and 75.76%, respectively.

The classification performance of LDA classifier is demonstrated by Fig. 4A and B, which presents the score plots of the first two discriminant functions (F2 * F1) for all Non-rejected and Rejected oils during the heating time at all color spaces in each oxidation. In case of carbonyl test (Fig. 4a), it is obvious Olive oil samples in both status (NR and R) are separated along the F2 direction with slightly overlap. F1 clearly distinguishes Olive oil samples from other oils classes.

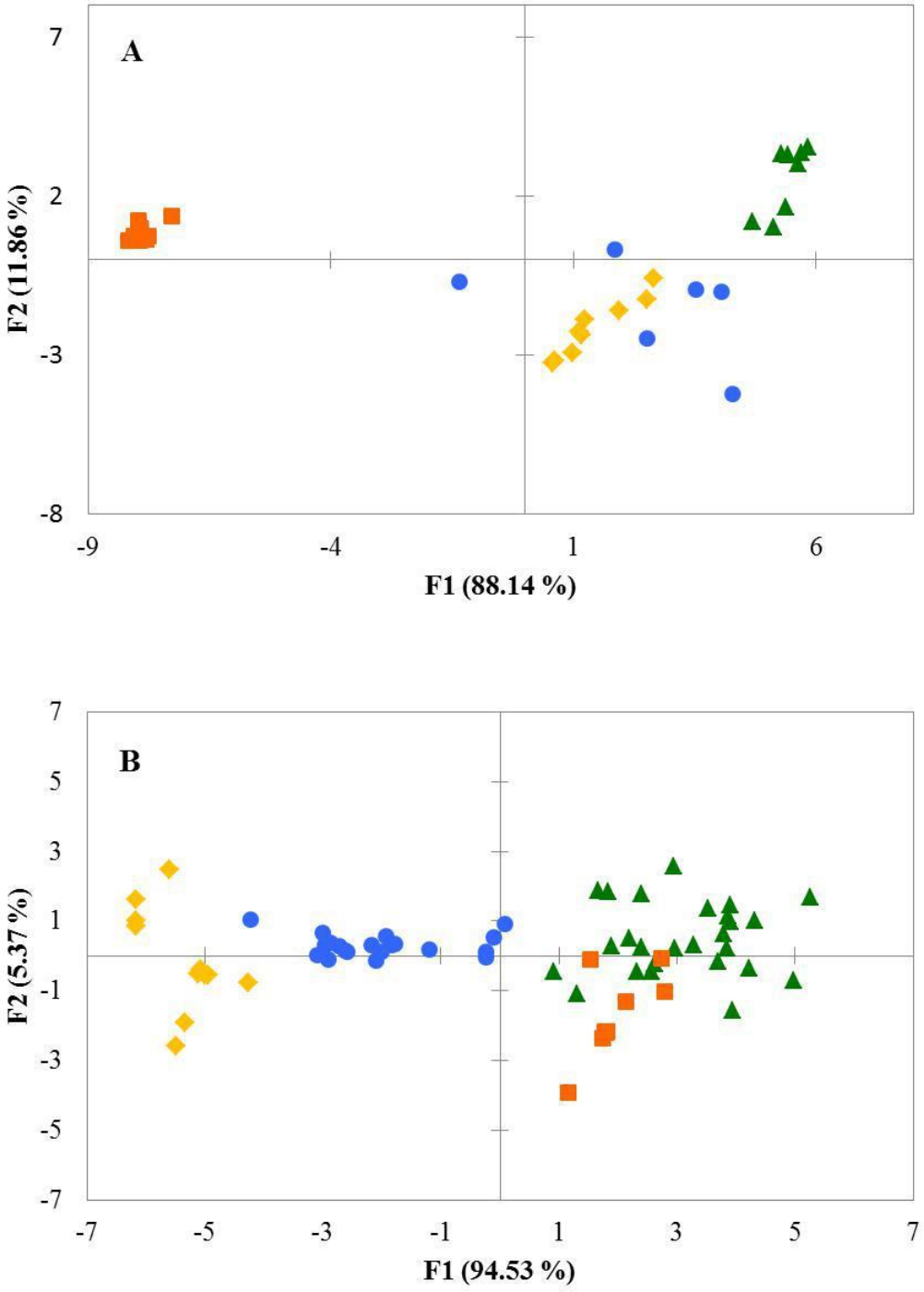

Fig. 3. F2× F1 score plots for Non-rejected and Rejected oils during the heating time atL*a*b*color space in carbonyl test (a) All R oilsand (b) All NR oils. Olive; ●: Palm; ▲: Soybean; ■and Sunflower; ◆.

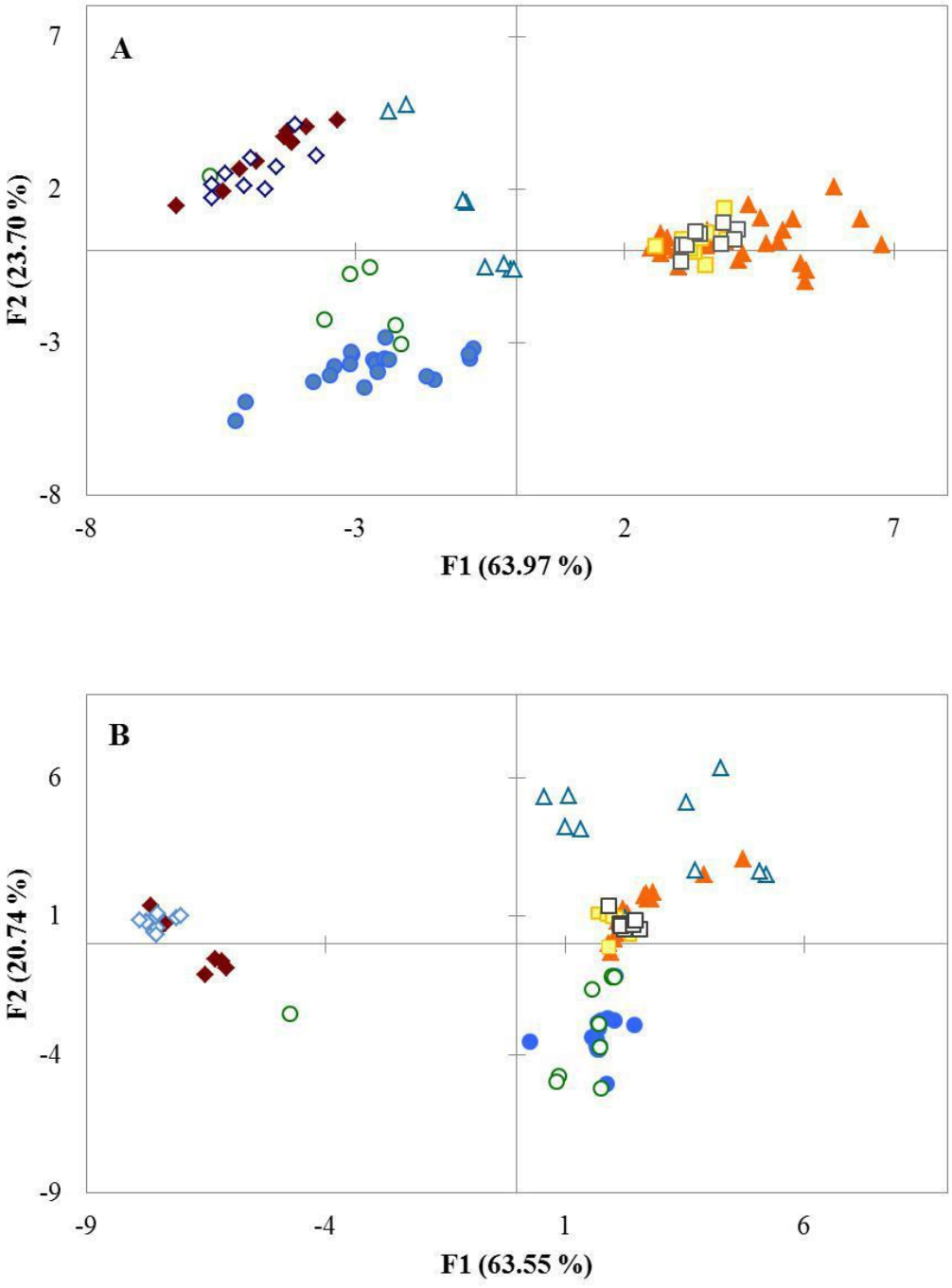

Fig.4. F2× F1 score plots for all Non-rejected and Rejected oils (Palm, Olive, Soybean and Sunflower) during the heating time at all color spaces (a) carbonyl test and (b) peroxide test. Olive NR; ●: Olive R; ○: Palm NR; ▲: Palm R; △: Soybean NR; ■: Soybean R; □: Sunflower NR; ◆and Sunflower R; ◊.

In the case of Sunflower oil samples, this class was well discriminated, but the NR and R status are intense overlap in both directions. The Palm oil samples overlap with other oil classes but the NR and R status were separated well in F1 direction. Finally, the worst classification performance was presented by Soybean oil samples in both directions which had severe overlap with Palm-NR.

Milanez and Pontes [25] tried to distinguish the type and conservation state of four different edible oils based on color image processing and linear discriminant analysis (LDA). They only attempted in classification of different type of oil, and also classification expired and non-expired oils without considering the oxidation process of oils during time with analytical experiments.

It could be inferred from our study that, it is appropriate to use color space to identify the expiration status of each oil type during heating process. As much as the oil color changes with different rates during oxidation, it could be possible to detect the exact rejection state (based on both the primary and secondary oxidation) of known oil sample.

It seems that while classification of edible oils from color features can be applicable, selection of the suitable color space and classifier are significant steps to develop new simple and inexpensive method for detection of the non-rejected and rejected status of unknown oil.

Table 5. Accuracy (%) of all Non-rejected and Rejected oils (Palm, Olive, Soybean and Sunflower) during the heating time at all color spaces in both PV and CV tests.

	Olive NR	Olive R	Palm NR	Palm R	Soybean NR	Soybean R	Sunflower NR	Sunflower R	Sample Number	Accuracy
PV	100	30	93.33	90	63.64	62.50	44.44	81.82	90	74.44
CV	100	50	92.31	37.50	40	44.44	81.82	88.89	99	75.76

Conclusions

The purpose of this paper was to find less costly and quicker method with environmental protection, by using the color spaces (RGB, HSI, L*a*b* with Grayscale) instead of chemical analysis to determine the expiration status of edible vegetable oils in both PV and CV induced period.

The results obtained from this study indicated that the best classification result of expiration status of known oils according to induced period of peroxide value at each color space, was achieved with LDA model were in palm with 100% (L*a*b* and HSI), olive with 84.61% (L*a*b* and RGB), soybean with 95% (Grayscale) and sunflower with 100% (RGB and HSI), also in induced period of Carbonyl value test, the best classification performance was achieved in palm with 100% (L*a*b* and Grayscale), olive with 100% (L*a*b*), soybean with 89.47% and sunflower with 95% (HSI).

As pointed out in the result and discussion part, it is recommended that by using each color feature it would be possible to identify expiration status (reject or non-reject) of known edible oils and classification unknown oils. Although there is no significant color change just before and after rejection, but also this study enables to classify reject and non-reject status of each oil type according to IP value. This methodology can be applied for automated control in identification expiration status of edible vegetable oils. It is worth mentioning that distinguish the expiration status (non-rejected and rejected) of edible vegetable oils is more applicable and will lead to high accuracy of the applied procedure.

References

B. Zhang, W. Huang,J. Li, C. Zhao, S. Fan, J. Wu, C. Liu, Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. Food Res Int. 62, 326-343 (2014)

S. Gomez-Alonso, V. Mancebo-Campos, M. Desamparados Salvador, G. Fregapane, Oxidation kinetics in olive oil triacylglycerols under accelerated shelf-life testing (25–75 °C). EUR J LIPID SCI TECH. 106, 369–375 (2004)

M. Yin, S. Tang, M. Tong, Identification of edible oils using terahertz spectroscopy combined with genetic algorithm and partial least squares discriminant analysis. Anal. Methods. 8, 2794-2798 (2016)

A.H.El-Hamdy, N.K. El-Fizga,Detection of olive oil adulteration by measuring its authenticity factor using reversed-phase high-performance liquid chromatography. J. Chromatogr. A. 708, 351–355 (1995)

E. Guzm´an, V. Baeten, J.A.F. Pierna, Garcia-Mesa J.A. Evaluation of the overall quality of olive oil using fluorescence spectroscopy. Food Chem. 173, 927–934 (2015)

N. Vlachos, Y. Skopelitis, M. Psaroudaki, V. Konstantinidou, A. Chatzilazarou, E. Tegou, Applications of Fourier transform-infrared spectroscopy to edible oils. Anal. Chim. Acta. 2573–574, 459–465 (2006)

E. Chiavaro, E. Vittadini, M.T. Rodriguez-Estrada, Cerretani L, Bendini A. Differential scanning calorimeter application to the detection of refined hazelnut oil in extra virgin olive oil. Food Chem. 110, 248–256 (2008)

8.D.S. Lee,B.S. Noh, S.Y. Bae, K. Kim, Characterization of fatty acids composition in vegetable oils by gas chromatography and chemometrics. Anal. Chim. Acta. 358, 163–175 (1998)

R. Farhoosh, S. Pazhouhanmehr, Relative contribution of compositional parameters to the primary and secondary oxidation of canola oil. Food Chem. 114 (3), 1002-1006 (2009)

B. Reindl, H.J. Stan, Determination of volatile aldehydes in meat as 2, 4-dinitrophenylhydrazones using reversed-phase high-performance liquid chromatography. J. Agric. Food Chem. 30, 849–854 (1982)

F. Farhoosh, J. Tavakoli, M.M.H. Khodaparast, Chemical Composition and Oxidative Stability of Kernel Oils from Two Current Subspecies of Pistacia atlantica in Iran. J Am Oil Chem Soc. 85(8), 723–729 (2008)

R. Farhoosh, M.M.H.Khodaparast, A. Sharif, S.A.Rafiee, Olive oil oxidation: Rejection points in terms of polar, conjugated diene, and carbonyl values. Food Chem. 131 (4), 1385 – 1390 (2012)

K.D.T.M. Milanez, M.J.C. Pontes, Classification of extra virgin olive oil and verification of adulteration using digital images and discriminant analysis. Anal. Methods.7, 8839-8846 (2015)

G. Dalen, Determination of the size distribution and percentage of broken kernels of rice using flatbed scanning and image analysis. Food Res. Int. 37, 51–58 (2004)

F. Kong, J. Tan, DietCam: Automatic dietary assessment with mobile camera phones. Pervasive Mob Comput. 8, 147–163 (2012)

V. Briones, J.M. Aguilera, Image analysis of changes in surface colour of chocolate. Food Res. Int. 38, 87–94 (2015)

C.J. Du, D.W. Sun, Pizza sauce spread classification using colour vision and support vector machines. J Food Eng. 66,137–145 (2004)

A. Antonelli, M. Cocchi, P. Fava, G. Foca, G.C. Franchini, D. Manzini, A. Ulrici,Automated evaluation of food colour by means of multivariate image analysis coupled to a wavelet-based classification algorithm. Anal. Chim. Acta. 515, 3–13 (2004)

M. Mohebbi, M.R Akbarzadeh-T, F. Shahidi, M. Moussavi, H.B. Ghoddusi,Computer vision systems (CVS) for moisture content estimation in dehydrated shrimp. Comput Electron Agric. 69 (2), 128-134 (2009)

H.K. Mebatsion, J. Paliwal, D.S. Jayas, Automatic classification of non-touching cereal grains in digital images using limited morphological and color features. Comput Electron Agric. 90, 99–105 (2013)

M. Fathi, M. Mohebbi, S.M.A. Razavi, Application of Image Analysis and Artificial Neural Network to Predict Mass Transfer Kinetics and Color Changes of Osmotically Dehydrated Kiwifruit. FOOD BIOPROCESS TECH. 4, 1357–1366 (2011)

W.T.S, Vilar, R.M. Aranha, E.P. Medeiros, M.J.C. Pontes, Classification of Individual Castor Seeds Using Digital Imaging and Multivariate Analysis. J. Braz. Chem. Soc. 26, 102–109 (2015)

J.K. Fernandes, T. Umebara, M.K. Lenzia, E.T.S. Alves, Image analysis for composition monitoring. Commercial blends of olive and soybean oil. ACTA SCI-TECHNOL.35, 317–324 (2013)

P.C. Marchal, D.M. Gila, J.G. García, J.G. Ortega, Expert system based on computer vision to estimate the content of impurities in olive oil samples. J Food Eng.119(2), 220-228 (2013)

K.D.T.M. Milanez, M.J.C. Pontes. Classification of edible vegetable oil using digital image and pattern recognition techniques. Microchem J. 113, 10–16 (2014)

F. Mendoza, J.M. Aguilera, Application of image analysis for classification of ripening bananas. J. Food Sci. 69, 471–477 (2004)

K. Leon, D. Mery, F. Pedreschi, J. Leon, Color measurement in L*a*b* units from RGB digital images. Food Res Int. 39(10), 1084-1091 (2006)

S.E. Papadakis, S. Abdul-Malek, R.E. Kamdem, K.L. Yam, A versatile and inexpensive technique for measuring color of foods. Food Technol. 54(12), 48–51 (2000)

S. Segnini, P. Dejmek, R. O¨ste, A low cost video technique for colour measurement of potato chips. LWT - Food Sci and Technol. 32(4), 216–222 (1999)

N.C. Shantha, E.A. Decker, Rapid, sensitive, iron-based spectrophotometric methods for determination of peroxide values of food lipids. J. AOAC Int.77, 421–424 (1994)

Y. Endo,C.M. Li, M. Tagiri-Endo,K. Fugimoto, A modified method for the estimation of total carbonyl compounds in heated and frying oils using 2- propanol as a solvent. J Am Oil Chem Soc. 10, 1021–1024 (2001)

R.A. Fisher, The use of multiple measurements in taxonomic problem. Ann. Eugen. 7, 179–188 (1936)

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تعیین تاریخ انقضاء روغن‌های خوراکی مبنی بر تغییر رنگ طی فرآیند اکسایش: کاربرد تحلیل تصویر رقمی و آنالیز افتراقی خطی طی اکسایش اولیه و ثانویه

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چکیده

تشخیص وضعیت انقضا (سالم و تند شده) روغن‌های گیاهی خوراکی به‌خاطر محصولات اولیه و ثانویه اکسیداسیون حائز اهمیت است. بنابراین بررسی کیفیت و سلامت روغن‌های خوراکی بسیار مهم است. بر اساس گزارشات و آزمایشات تجربی رنگ روغن طی اکسیداسیون تغییر می‌کند. پژوهش حاضر به شرح بررسی انجام شده توسط پردازش تصویر و تحلیل تفکیک خطی (LDA) برای طبقه‌بندی روغن‌های گیاهی خوراکی سالم و تند شده در طی اکسیداسیون در دمای 85 درجه سانتی‌گراد با توجه به اکسیداسیون اولیه و ثانویه در چهار نوع روغن (پالم اولئین، زیتون، سویا و آفتابگردان) پرداخته است. هدف از این پژوهش یافتن روش‌های ارزان و سریع‌ترو همچنین حافظ محیط زیست به جای آزمون‌های شیمیایی به کمک فضاهای رنگی (RGB، HSI، L*a*b* با Grayscale) برای تعیین وضعیت انقضا روغن‌های خوراکی است. این مطالعه نشان داد که بهترین نتیجه برای تشخیص وضعیت انقضا در روغن‌های معلوم با توجه به دوره القا عدد پراکسید در هر فضای رنگی توسط طبقه‌بند LDA برای پالم 100% (HSI و سیاه وسفید)، زیتون 84/61% (L*a*b* و RGB)، سویا 95% (سیاه و سفید) و آفتابگردان 100% (RGB و HSI) می‌باشد. همچنین با توجه به دوره القا آزمون عدد کربونیل بهترین عملکرد طبقه‌بند در پالم 100% (L*a*b*)، زیتون 100% (L*a*b*)، سویا 89/47% و آفتابگردان 95% (HSI) بدست آمد.

واژه‌های کلیدی: روغن گیاهی خوراکی، اکسیداسیون، عدد پراکسید، عدد کربونیل، تحلیل تفکیک خطی، تصویرگیری.

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