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DETERMINATION OF ANIMAL OIL ADDED IN VEGETABLE OIL BY STANDARD CHEMICAL METHOD COUPLED WITH IMAGE TEXTURE ANALYSIS TECHNOLOGY

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Abstract. *For most vegetable oil adulteration detection research methods it remains difficult to popularize due to the fact that the application of experimental facilities needs professional to operate; moreover, the used experimental facilities are usually expensive. In order to solve these difficulties, a novel approach has been proposed to determination of vegetable oil adulteration by coupling standard chemical method and image texture analysis technology. Analysis of the correlation and establish the mathematical model between texture characteristic parameters and cholesterol content by least squares method. Experimental results show significant correlation between the image texture features parameters and cholesterol content, the most correlation coefficient R^2 is 0.9872, using this method can detect adulteration level which has reached 6.5%. Compare cholesterol content of mixed oil samples by this paper method and the standard chemical method, the results show that maximum relative error of cholesterol content is 3.51% by this paper method calculated value and the standard chemical method measured value. This can prove that in the range of allowable error texture analysis techniques can be used to detect vegetable oil adulteration.*

Keywords: Animal and vegetable oil, Cholesterol, Gas chromatography, Texture analysis, Model building

1. **Introduction.** Grease is an important material for mankind survival. Therefore, the edible vegetable oil quality and supervision become big problems of the national economy and the people livelihood [1-3]. However, in recent years, many unscrupulous traders to reap huge profits, add shoddy animal oil to vegetable oil; shoddy animal oil part is extracted from chicken, duck and even the bodies of dead animals, it leads to edible oil poisoning common occurrence. In addition, some communities very concern about the presence of animal fat, especially lard, which is commonly used as a raw material in consumer products. The presence of animal oil in food, cosmetics and pharmaceuticals can be viewed from two perspectives, economy and religion. From an economic perspective, some vegetable oils make good adulterate with animal oil to minimize the production cost; from a religious perspective, Islam and Judaism prohibit using or consuming food or other products containing lard or any pig-derived ingredients [4,5]; it has caused widespread concern in society as a whole. Edible blended oil (vegetable oil blended with animal oil) does not conform to <The dietary guidelines 2007 for china> and the provisions of national standard file [6]. So determination of vegetable oil blended with animal oils is very important from the standpoint of commerce and health [7,8].

At present, some analytical techniques have been proposed to detect and quantify animal fat in vegetable oils such as Fourier transform infrared spectroscopy [9], electronic

noses method and differential scanning calorimetry. B. Yaakob, C. Man et al. proposed using Fourier transform infrared (FTIR) spectroscopy to detection of lard in vegetable oils. The result showed that FTIR normal spectra and first derivative give better results in terms of high value of coefficient of determination or R^2 (>0.99) and low value of errors for analysis of lard in vegetable oils [4]. J. M. N. Marikkar, H. M. Ghazali et al. proposed distinguishing lard from other animal fats in admixtures of some vegetable oils using liquid chromatographic data coupled with multivariate data analysis. The result shown that potential of the method is evident, as oil samples that are contaminated with as little as 2% lard could easily be distinguished [10]. L. Wang, Y. Li et al. proposed using NMR to identify edible vegetable oil mixed with food and beverage industry waste grease. The results show that the method can detect more than 1% waste grease [11]. These above methods have good performance in detection results and recognition rate, but there could be long delay, complex purification measures, experimental equipment expensive and the application of equipment need professional operation, so these methods are difficult to popularize and apply. Image texture analysis technologies are used to detection and analysis vegetable oil adulteration based on the above shortages. The research results can be applied to detection of halal and kosher market, judgment whether adulteration animal oil in vegetable oil.

2. Materials and Methods.

The edible vegetable oils are commercially available soybean oil, corn germ oil and sunflower seed oil; animal oils are fresh lard, beef tallow and chicken oil.

2.1. Experimental apparatus.

Heating stirrer, magnet stirrer, stainless steel sieve, highly sensitive light source, image acquisition card, high-definition CCD camera, PC, cylindrical barrel, DSP board, the image processing analysis device is shown below.

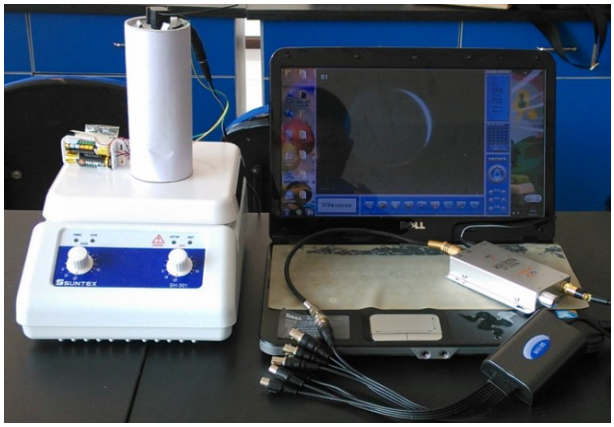


FIGURE 1. Image processing analysis device

When capture the oil sample, the captured images are great interfered due to light and other external interference factors, a set of sealing experiment device is designed based on the above shortcomings and it is a freely movable cylinder kegs. Inside the main lid install two highly sensitive light source and a high-definition CCD camera, the high-definition CCD is located vertically over the sample at a distance of 15cm. The highly sensitive light source is placed above the sample and the angle is 45° with the sample, the internal wall is painted black to avoid the external light reflections. This means forming a closed environment, it can well reduce the interference of the external environment. The oil samples are placed above the heating device, when capture sample images, highly sensitive light source and CCD camera are opened at the same time to

capture sample images. A DSP board is fixed between the image capture apparatus and computer processing and analyzing system, the board outside enlarge image compression module, storage module and wireless transmission and receiving module, captured images are compressed and storage in memory module of DSP board, and, they are real-time transmitted to computer processing and analysis system by the wireless transmission and receiving module of DSP board. The sample images are analyzed by Matlab software for the platform, processing and analyzing data to calculate the sample cholesterol content by the least square method, the calculated cholesterol content value is sent back to wireless receiving module of the image capture devices by GPRS network. Finally, the received data is shown on the liquid crystal display screen outside of the cylinder barrel.

2.2. **Experimental design.** When preparation of lard, beef tallow and chicken oil, a 75 micron stainless steel screen is used to separate residue remained in the animal oil, ensuring the lard fat globules are not retained. Preparation of test samples are detection and recognition mixed oil samples (soybean oil, corn oil and sunflower oil adulterate respectively with lard, beef tallow and chicken oil). Soybean oil, corn oil and sunflower oil are blended with lard, beef tallow and chicken oil in varying proportions, ranging from 2 to 80%, forty mixed oil samples are prepared in each group: 98:2, 95:5, 90:10, 80:20(w/w), etc. Determination of cholesterol content of different oil samples is by standard chemical method [12]. Determination of cholesterol is 721 spectrophotometer, electric heated water bath, electric oscillator, glass stopper test tube, petroleum ether, ethanol, concentrated sulfuric acid, glacial acetic acid, excellent pure, phosphoric acid, Cholesterol standard solution, reagents were all analytical grade, water is distilled water. Preparation of sample solution: Cholesterol standard stock solution (1 mg/mL): accurately weighed and taken cholesterol 100 mg dissolved in glacial acetic acid and constant volume to 100 mL, absorb cholesterol standard stock solution 10 mL, constant volume with glacial acetic acid to 100 mL. Iron vitriol chromogenic agent, Jarosite stock solution: 4.463 g ammonium ferric sulfate [$FeNH_4(SO_4)_2 \bullet H_2O$] was dissolved in 100 mL 85% phosphoric acid, the solution was stored in desiccator and it is stable at room temperature. Iron vitriol color liquid, absorbs iron vitriol stock solution 10 mL, using concentrated sulfuric acid constant volume to 100 mL, stored in a desiccator to prevent water uptake. 50% potassium hydroxide solution: weigh 50 g potassium hydroxide, dissolved in distilled water and diluted to 100 mL. 5% sodium chloride solution: weigh 5 g sodium chloride, dissolved in distilled water and diluted to 100 mL; nitrogen: purity 99.99% [13].

Cholesterol standard solution: Absorb cholesterol standard stock solution 0.0, 0.5, 1.0, 1.5, 2.0 mL were placed in 10 mL test, glacial acetic acid was added to each test tube so that the total volume reached 4 mL, added 2 mL iron vitriol color liquid along the wall and blending. Along the wall add 2 mL iron vitriol color liquid, within 15 $\sim$ 90 min, colorimetric analysis under 560 $\sim$ 575 nm wavelength. Determination of sample: Measuring food cholesterol: 3 to 4 drops extracted grease (about containing cholesterol 300 $\sim$ 500 g) are placed in a 25 mL test tube and recorded accurately its weight. Add 4 mL anhydrous ethanol and 0.5 mL 50% potassium hydroxide solution, saponification 1 h in 65°C thermostatic water bath. Shaking the test tube for every 20 $\sim$ 30 min in order to saponify completely; after completing the saponification, remove the tubes and cooling. Add 3 mL 5% sodium chloride solution and 10 mL petroleum ether, tightly closed glass stopper, using electric oscillator shaking for 2 min, still stratification (generally takes about 1 h). Take the supernatant petroleum ether liquid 2 mL to place in 10 mL glass tube plug, using nitrogen blow dry in a 65° water bath, add 4 mL glacial acetic acid and 2 mL jarosite color liquid and blending, under 560 $\sim$ 575 nm wavelength colorimetric analysis the mixed solution after placing 15 min, measure absorbance, look up cholesterol

content in the corresponding standard curve, the formula is as follows.

$$X = \frac{m \times V \times c}{V_1 \times m_1} \times \frac{1}{1000} \tag{1}$$

In the above formula:

X – sample cholesterol content, mg/100g;

m – The cholesterol content on the cholesterol standard line based on the measured absorbance values, g;

V – The petroleum ether total volume, mL;

V_1 – The removed petroleum ether volume, mL;

m_1 – Weighed grease sample content, g;

c – The fat content of food samples, g/100g;

1/1000 – Converted into cholesterol milligrams in per 100g food samples.

In order to verify the accuracy of the method, choose three different sample additive amount study sample recovery, results prove the sample recovery percents are more than 99.5%.

3. **Result Analysis.** The images are represented in RGB color space, due to the three components of R, G and B have a high correlation, so that the color images are difficult to digitize adjustment in detail. Therefore, RGB color space model is transformed into HIS model and the model can eliminate the intensity component influence from the color information, so that the model is called good tool based on the color description image processing method, the color description is natural and intuitive for the people's perception, it makes digital image retention wide color gamut and rich color [14]. In this paper, several techniques are used to extract image texture features, mainly includes: texture spectrum method (TSM); fractal dimension (FD); wavelet symbiotic matrix (WSM-a technology that combined with wavelet, gray level co-occurrence matrix and color features extraction technology) and improved Hu moment invariants (IHMI).

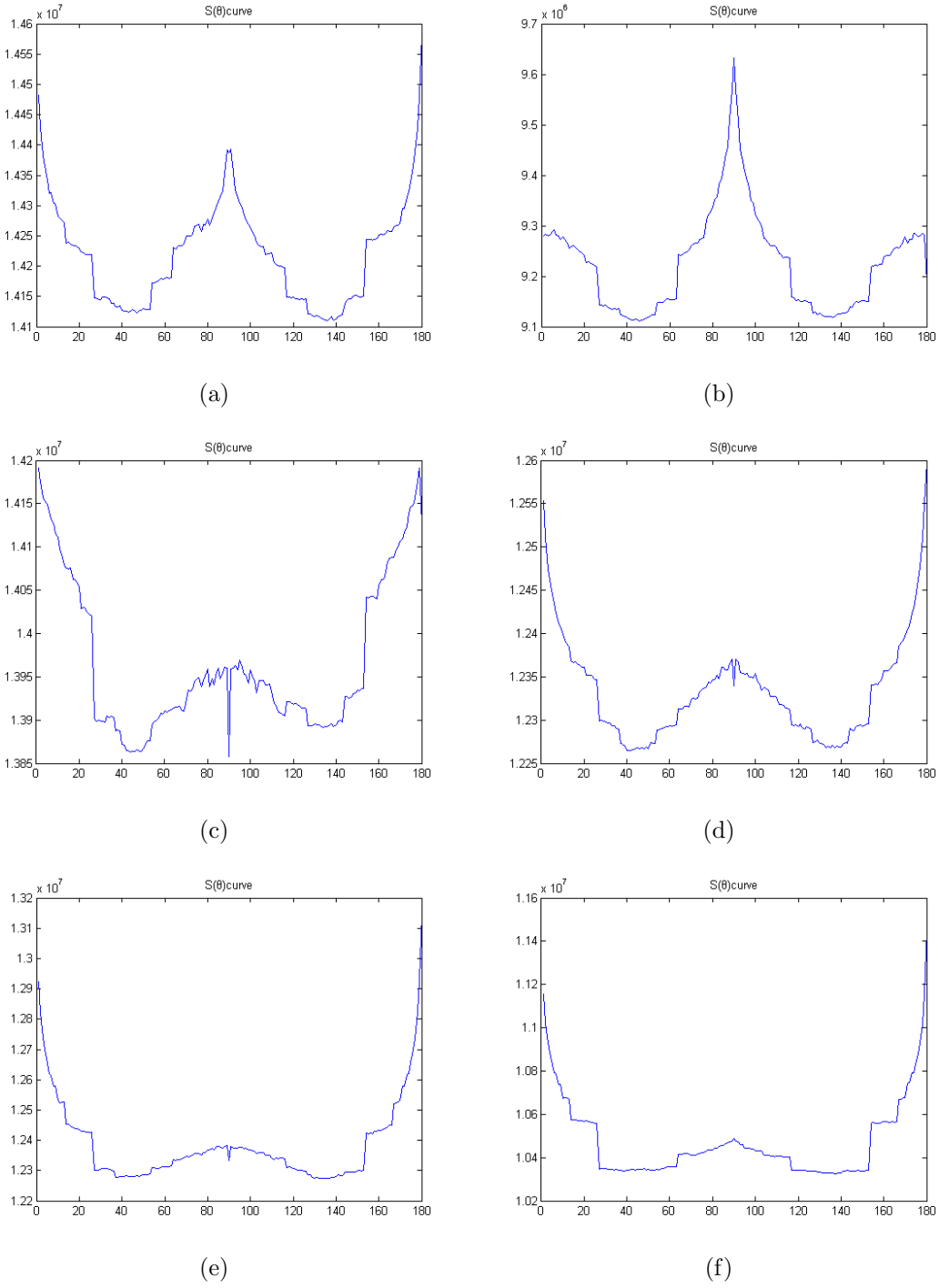
3.1. **Spectral measures of texture (TSM).** Texture spectrum measurement is a kind of global texture pattern and its frequency domain can be easy to identify, spectral measures of texture are based on the Fourier spectrum; these global texture patterns, easily distinguishable as concentrations of high-energy bursts in the spectrum, generally are quite difficult to detect with spatial methods because of the local nature of these techniques. Thus spectral texture is useful for discriminating between periodic and nonperiodic texture patterns, and, further, for quantifying differences between periodic patterns [15].

Interpretation of spectrum features is simplified by expressing the spectrum in polar coordinates to yield a function $S(r, \theta)$, where S is the spectrum function and r and θ are the bariables in this coordinate system. Analyzing $S_\theta(r)$ for a fixed value of θ yields the behavior of the spectrum (such as the presence of peaks) along a radial direction from the origin, whereas analyzing $S_r(\theta)$ for a fixed value of r yields the behavior along a circle centered on the origin. A global description is obtained by integrating these functions:

$$S(r) = \sum_{\theta=0}^{\pi} S_\theta(r) \quad S(\theta) = \sum_{r=0}^{R_0} S_r(\theta) \tag{2}$$

R_0 is the radius of a circle and center at the origin. Different oil samples texture spectrum diagram under the same experimental environment are shown below.

Figures 2(a)-2(f) represent respectively texture spectral $S(\theta)$ of soybean oil, lard and mixed oil (Soybean oil mixed with 10%, 20%, 30% and 40% lard) sample images.



(a) (b) (c) (d) (e) (f)

FIGURE 2. The texture spectral of different oil samples

3.2. **The fractal dimension of the sample images (FD).** N. Sarkar and B. B. Chaudhuri proposed a simple, fast method and it was called differential box dimension (Differential Box Counting, DBC), it is used to calculate image fractal dimension, the main idea of extracting the image differential box dimension is shown below [16]. The $N \times N$ image is divided into $m \times m$ sub-block, $r = m/N$, imaginary image into 3 d space curved surface, the x, y represent plane position space, z represents grey value. The plane xy is divided into numerous $m \times m$ grids. In each grid has a list of $m \times m \times m$ small box, supposing the minimum and maximum gray level in the first (I, j) grid respectively located in the

first k and the first l box [16]. That is:

$$k_r(i,j) = l - k + 1 \tag{3}$$

$K_r\ (I,j)$ is the number of boxes that cover (i,j) grid, and suppose the number of boxes that cover the entire image is K_r. That is:

$$K_r = \sum_{i,j} n_r(i,j) \tag{4}$$

Fractal dimension is:

$$D = \lim \frac{\log(K_r)}{\log(1/r)} \tag{5}$$

Application of least square method for linear least squares fitting, the slope of straight line is the image difference box dimension D. In order to reduce the amount of calculation, the algorithm is improved and the improved ideas are shown below. Calculating the average grey value of a certain scale window on the basis of original DBC algorithms, judge each pixel gray level, the result is accumulated of min if the value is less than the mean gray level, on the contrary, accumulation of max. Using the max and min instead of the maximum and the minimum of the original algorithm, image fractal dimension is calculated by the least squares fitting at last and further to extract a variety of characteristics of sample images, mainly includes texture directionality, roughness and orientation degree information, combination of image fractal dimension and extracts a variety of characteristics as the texture feature set of classification and recognition sample image.

3.3. **Wavelet symbiotic matrix of sample images (WSM).** In this paper, the tree wavelet transform is used to extract image texture feature, during the process of decomposition iterations, tree wavelet transform has the advantage that it not only can decomposition the low frequency signal but also further decomposition the high frequency signal, and, it can focus on all the frequency range, the main idea of calculate wavelet energy algorithm is as follows:

$$I = \frac{1}{M \times N} \sum_{x,y=0}^{M-N-1} |s(x,y)|^2 \tag{6}$$

$M \times N$ – sub-block images size, $s\ (x,y)$ – sub-block images coefficients. The three layers tree wavelet decomposition is adopted in this paper and 10 sub-block images are obtained, calculate sub-block image energy of each decomposition level [17]. Image gray level co-occurrence matrix: Gray level co-occurrence matrix is a kind of common and effective method of extract image texture features. It reflects gray image comprehensive information about direction, adjacent interval and variation amplitude. The main idea of gray level co-occurrence matrix algorithm is shown below: supposing $f(x,y)$ is a digital image, the image size is $M \times N$, gray level is Ng, gray level co-occurrence matrix of meet certain spatial relationship is shown below.

$$p(i,j) = \#\{(x_1,y_1),(x_2,y_2) \in M \times N \,|f(x_1,y_1) = i, |f(x_2,y_2) = j\} \tag{7}$$

represents the number of elements in set x, p is $Ng \times Ng$ matrix. If the distance of (x_1,y_1) and (x_2,y_2) is d, the included angle with the horizontal axis is θ, you can get all kinds of gray level co-occurrence matrix $p\ (i,j,d,\theta)$ about separation distance and angle. Extract the correlation (COR), entropy (ENT), second moment (ASM) and inverse matrix (IDM) features of the image gray level co-occurrence matrix, several parameters expression of gray level co-occurrence matrix is shown below [18].

(1) Angular second moment (ASM)

$$ASM = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \hat{p}{}_{\sigma}^{2}(i,j) \tag{8}$$

Angular second moment is a measure means of the image gray distribution uniformity. When the distribution of GLCM elements are more concentrated in the main diagonal, the gray distribution is uniform, when the image texture is coarse, angular second moment is larger, vice versa.

(2) Entropy (ENT)

$$ENT = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \hat{p}_{\delta}(i,j) \lg \hat{p}_{\delta}(i,j) \tag{9}$$

The entropy is a measure means of image amount of information, texture information also belongs to image information. If the image does not have any texture, entropy is close to 0; if the image is full of texture, the entropy is maximum.

(3) Correlation (COR)

$$COR = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ij\, \hat{p}_{\delta}(i,j) - u_1 u_2}{\sigma_1^2 \sigma_2^2} \quad u_1 = \sum_{i=0}^{L-1} i \sum_{j=0}^{L-1} \hat{p}_{\delta}(i,j) \quad u_2 = \sum_{j=0}^{L-1} j \sum_{i=0}^{L-1} \hat{p}_{\delta}(i,j) \tag{10}$$

$$\sigma_1^2 = \sum_{i=0}^{L-1} (i-u_1)^2 \sum_{j=0}^{L-1} \hat{p}_{\delta}(i,j) \quad \sigma_2^2 = \sum_{j=0}^{L-1} (i-u_2)^2 \sum_{i=0}^{L-1} \hat{p}_{\delta}(i,j)$$

The correlation can be used to measure the GLCM elements similarity degree in row direction or column direction.

(4) Inverse matrix (IDM)

$$ENT = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \frac{\hat{p}_{\delta}(i,j)}{1+(i-j)^2} \tag{11}$$

If gray level co-occurrence matrix diagonal elements have bigger value, IDM value is larger, vice versa. Calculate GLCM parameters with the four directions, in order to make the results more accurate, we take the mean value of GLCM characteristic parameters with four directions, the calculate formulas are as follows.

$$\overline{ASM} = \frac{1}{4}\sum ASM \quad \overline{ENT} = \frac{1}{4}\sum ENT \quad \overline{COR} = \frac{1}{4}\sum COR \quad \overline{IDM} = \frac{1}{4}\sum IDM \tag{12}$$

The sample images are divided into 8×8 sub-block, Haar wavelet is used for tree wavelet decomposition and obtains 10 sub-block images. The tree wavelet, gray level co-occurrence matrix and color feature extraction technology are combined to extract optimal texture feature set, the purpose is to get more accurate classification and identification sample images. Experimental steps are shown below.

(1) Image preprocessing (image segmentation-image enhancement-smoothing filtering), the RGB color model is transformed into HIS model and extracts HIS component of samples images.

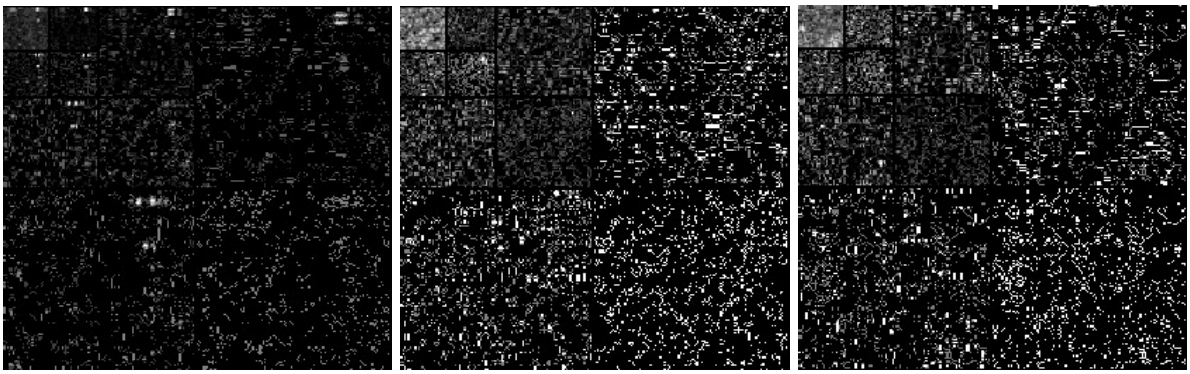
(2) The sample images are divided into 8×8 sub-block images and using three layers tree wavelet to decompose sub-block images.

(3) Gray symbiotic matrix is constructed on low frequency band (four directions: 0°, 45°, 90° and 135°), calculating four characteristic parameters average value of the co-occurrence matrix.

(4) Calculate sub-block image energy of the tree wavelet each decomposition level, gray level co-occurrence matrix statistics and color feature value are combined to extract optimal texture feature set.

(5) The optimal texture feature set is normalized processing and the result is the ultimate texture feature set of classification and recognition sample images.

(6) The improved nearest neighbor domain classifier is used for classification and recognition sample images at last. Each group of texture feature sets is average value of 160 test sample images. The three layers tree wavelet decomposition diagram of different sample images is shown below.



(a) (b) (c)

FIGURE 3. Three layers tree wavelet decomposition diagram of sample images

Figures 3(a)-3(c) represent respectively mixed oil (soybean oil adulterate with 20% lard, beef tallow and chicken oil) sample images of three layers tree wavelet decomposition diagram.

3.4. **The improved Hu moment invariants (IHMI).** A two-dimensional $(p+q)$ order moment of digital image $f(x, y)$ is defined as:

$$m_{pq} = \sum_x \sum_y x^p y^q f(x, y) \quad p, q = 0, 1, 2, \cdots \tag{13}$$

The corresponding central moment is defined as:

$$u_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y) \quad \bar{x} = m_{10}/m_{00} \quad \bar{y} = m_{01}/m_{00} \tag{14}$$

Normalized $(p + q)$ order central moment is defined as:

$$\eta_{pq} = u_{pq}/u_{00}^r \quad p, q = 0, 1, 2, \ldots, \quad r = (p + q)/2 + 1 \tag{15}$$

Seven two-dimensional invariant moments sets and these parameters are all not sensitive about panning, zooming, mirroring and rotation, it can be derived by the following formulae [19].

$$\phi_1 = \eta_{20} + \eta_{02} \quad \phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{16}$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad \phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{17}$$

$$\begin{aligned} \phi_5 = {} & (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ & + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \tag{18}$$

$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \tag{19}$$

$$\begin{aligned}\phi_7 =& (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ &+ (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]\end{aligned} \tag{20}$$

Image matching: the color images are converted to grayscale images. Extracted texture features: image seven moment invariants, correlation, entropy, inverse matrix and angular second moment. In the following table shows 11 texture feature parameters of mixed oil sample images. Each set of data in the below table is respectively average value of 160 sample images test results, the experimental results are shown below.

TABLE 1. The texture feature parameters of different mixed oil samples

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	COR	ENT	IDM	ASM
a	6.6849	24.8714	30.3629	31.5417	62.8077	43.9942	62.1446	3.5201	0.7295	1.3480	3.0674
a1	6.8759	24.1296	29.7910	30.1920	62.1187	43.3883	61.6512	3.1796	0.6845	1.3906	2.9485
a2	6.8835	23.6854	29.5807	29.4984	61.6528	43.0785	59.3775	2.9957	0.5643	1.5357	2.7319
a3	6.8996	22.9626	28.9844	28.5612	60.8892	42.4603	59.2484	2.8582	0.5506	1.6585	2.5161
b	6.9031	26.8954	31.9067	31.8540	62.9723	47.7667	62.8319	3.9196	0.9361	1.0656	4.3247
b1	6.9267	26.3352	30.9067	31.3173	62.9407	43.7667	60.8319	3.5196	0.7861	1.3227	3.5647
b2	6.9419	25.6528	29.7593	30.9985	62.4543	43.5709	59.9976	3.2217	0.6941	1.3697	3.1849
b3	6.9568	25.0061	29.2961	29.7968	60.9915	43.0093	59.7620	3.0246	0.6312	1.3869	3.1215
c	6.9091	25.1663	31.1577	30.5185	61.5494	45.8743	62.3215	2.9985	1.4087	1.1562	5.8360
c1	6.9179	25.0654	31.0067	29.8507	60.9980	44.3350	62.2437	2.6620	1.1218	1.2325	4.7884
c2	6.9454	24.8066	30.6809	29.7264	60.1618	44.2192	60.8849	2.6123	1.1199	1.3398	4.4574
c3	6.9857	24.5704	29.8374	29.3758	60.1528	43.7357	59.7453	2.3813	1.0041	1.3722	3.8805

In the table, samples a, a1, a2 and a3; b, b1, b2 and b3; c, c1, c2 and c3 represent respectively mixed oil (soybean oil; corn oil; sunflower seed oil adulterate with 0%, 10%, 20% and 30% lard). Normalization processing extracted 11 texture parameters. The algorithm is shown below:

$$sum = \sqrt{\phi_1^2 + \phi_2^2 + \phi_3^2 + \phi_4^2 + \phi_5^2 + \phi_6^2 + \phi_7^2 + (COR)^2 + (ENT)^2 + (ASM)^2 + (IDM)^2} \tag{21}$$

$$\begin{aligned} f_1 = \phi_1/sum \quad f_2 = \phi_2/sum \quad f_3 = \phi_3/sum \\ f_4 = \phi_4/sum \quad f_5 = \phi_5/sum \quad f_6 = \phi_6/sum \end{aligned} \tag{22}$$

$$\begin{aligned} f_7 = \phi_7/sum \quad f_8 = COR/sum \quad f_9 = ENT/sum \\ f_{10} = ASM/sum \quad f_{11} = IDM/sum \end{aligned} \tag{23}$$

The normalized eigenvector is:

$$W = (f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8, f_9, f_{10}, f_{11}) \tag{24}$$

The normalized eigenvector value is as the ultimate texture feature set of classification and recognition sample images.

Compare of feature extraction time based on different texture analysis technologies, the experimental results are shown below.

TABLE 2. Feature extraction time based on different texture analysis technologies

	TSM	FD	WSM	IHMI
Feature extraction time	290ms	410ms	215ms	258ms

Table 2 shows that wavelet symbiotic technology in terms of feature extraction time performance is most prominent under the same experimental environment, followed by the improved Hu moment invariants technology. The improved method has higher efficiency than using alone Hu moment invariants, this is due to the improved Hu invariant moment technology has strong resistance ability for image gray level change.

3.5. **The classification and recognition of test samples.** Respectively compare the classification and recognition ability of texture spectrum method, fractal dimension, wavelet symbiotic matrix and improved Hu moment invariants technologies. The improved nearest neighbor domain classifier is used to classify and identify sample images, improved method main idea is shown below.

The basic idea of neighborhood classification is: set $R_1, R_2, \ldots, R_m$ as a set of reference vector m and corresponding with $W_1, W_2, \ldots, W_m$, the vector is R_i^k in R_i, that is: $R_i^k \subset R_i$ $k = 0, 1, 2, \ldots, l$, $R_i = \{R_i^1, R_i^2, \ldots, R_i^l\}$, the distance between the input feature vectors X and R_i is represented as follows:

$$d(X, R_i) = \min |X - R_i| \quad k = 0, 1, 2, \ldots, l_i \tag{25}$$

The distance is the minimum distance of each vector between X and R_i. If the distance of sample one and sample two satisfy the formula:

$$D_i(X) = X^T R_i + R_i^T X - R_i^T R_i \quad i = 1, 2, \cdots, m \tag{26}$$

Discriminant function:

$$D_i(X) = \min \left\{ X^T R_i^k + (R_i^k)^T X - (R_i^k)^T R_i^k \right\} \quad k = 0, 1, 2, \cdots, l \quad i = 1, 2, \cdots, m \tag{27}$$

then $D_i^k(X)$ is a linear combination of the characteristic parameters, the decision boundary is piecewise linear, the corresponding class W_i is identified class.

Improving the above classification method, a large number of sample images are used as each group sample images. We set 7 feature parameters that are used to identify and classify the different types of sample images; first read the upper and lower limits values of 7 features control values, the feature vector corresponding to R_i. The obtained image feature values subtracted respectively the upper and lower limits values of N class sample images corresponding control values, the smaller difference form N number of groups and it corresponds to the formula: $d(X, R_i) = \min |X - R_i|$ $k = 0, 1, 2, \ldots, l_i$, then adds 7 feature control values of each group, 7 feature control values in N groups and the smallest number of the groups corresponding sample category is the result [20]. The experimental results show that the improved nearest neighbor classification method improves the detection speed and the recognition effect is also very well. Classification and recognition results of different mixed oil samples based on different texture analysis technologies are shown below.

TABLE 3. Classification and recognition results of different mixed oil samples based on wavelet symbiotic matrix technique

	Samples	Judging results									Accuracy rate
		a0	a1	a2	b0	b1	b2	c0	c1	c2	
a0	260	260	0	0	0	0	0	0	0	0	100.00%
a1	260	0	258	0	0	2	0	0	0	0	99.23%
a2	260	0	0	259	0	0	0	0	0	1	99.62%
b0	483	1	0	0	482	0	0	0	0	0	99.79%
b1	483	0	0	0	0	482	0	0	1	0	99.79%
b2	483	0	0	0	0	0	480	0	0	3	99.38%
c0	565	0	0	0	0	0	0	565	0	0	100.00%
c1	565	0	2	0	0	1	0	0	562	0	99.47%
c2	565	0	0	1	0	0	3	0	0	561	99.29%

In Table 3, samples a0, a1 and a2; b0, b1 and b2; c0, c1 and c2 represent respectively mixed oil (soybean oil, corn oil and sunflower seed oil adulterate with 6.5% lard; 6.5% beef tallow; 6.5% chicken oil).

TABLE 4. Classification and recognition results of different mixed oil samples based on improved Hu moment invariants technique

Samples		Judging results									Accuracy rate
		a0	a1	a2	b0	b1	b2	c0	c1	c2	
a0	260	259	0	0	0	0	0	1	0	0	99.62%
a1	260	0	257	0	0	2	0	1	0	0	98.85%
a2	260	0	0	254	0	0	4	0	0	2	97.69%
b0	483	2	0	0	481	0	0	0	0	0	99.59%
b1	483	0	3	0	0	478	0	0	2	0	98.96%
b2	483	0	0	3	0	0	473	0	0	7	97.93%
c0	565	11	0	0	5	0	0	549	0	0	97.17%
c1	565	0	5	0	0	7	0	0	553	0	97.88%
c2	565	0	0	2	0	0	5	0	0	558	98.76%

Repeat the above test, in terms of feature extraction time and classification recognition rate, wavelet symbiotic matrix technology is most prominent performance, followed by improved Hu moment invariants, fractal dimension and texture spectrum method. Using wavelet symbiotic matrix technology can detect minimum adulteration level which has reached 6.5%. When adulterating ratio more than 6.5% in vegetable oil, wavelet symbiotic matrix technology can detect and identify mixed oil samples, and, the recognition rate is 100%.

3.6. **Model building.** In order to detect accurately animal oil doping ratio in vegetable oil, we establish multiple regression analysis equation between image texture features parameters and cholesterol content by least squares method. The multiple regression analysis results are shown below.

TABLE 5. Linear correlation between texture feature parameters and cholesterol content in the mixed oil based on wavelet symbiotic matrix technique

Samples	Multiple linear regression equation	R^2	significance level
a	$y = -200.41x_1 + 0.640x_2 - 3.016x_3 + 1.254x_4 - 7.255x_5 + 220.513$	0.9759	0.002
b	$y = -38.451x_1 - 4.395x_2 - 26.023x_3 - 11.378x_4 - 3.072x_5 + 67.695$	0.9816	0.002
c	$y = 782.551x_1 - 11.079x_2 + 13.351x_3 - 12.471x_4 - 3.996x_5 + 46.704$	0.9872	0.001

a, b and c represent respectively mixed oil (soybean oil; corn oil; sunflower seed oil adulterate with lard) sample, y represents cholesterol content, x_1, x_2, x_3, x_4 and x_5 represent respectively S component average weight, correlation, entropy, second moment and inverse matrix, model significance level value less than 0.05 in the above models, so the model is significant. Because of the cholesterol content in soybean oil, corn oil and sunflower oil is zero, so we can calculate animal oil content in vegetable oil according to cholesterol content.

3.7. **The system test.** In order to verify the validity of the proposed method, we compare cholesterol contents to different mixed oil samples with this paper method and the standard chemical method based on wavelet symbiotic matrix technology. Randomly selected from the different brand vegetable oil that sells on the local market, choose golden arowana soybean oil, west king corn germ oil corn germ oil and fook lam moon sunflower oil in this article. In the above different brand vegetable oil blended with different proportions of lard, beef tallow and chicken oil, different mixed oil samples are stirred by magnet stirrer and rotating speed is 50, 200, 500 and 1000, etc. (RPM), then the test samples are heated to 95° by heating stirrer, capture different mixed oil sample images by the homemade experimental apparatus, the captured images are transmitted to image processing and analysis system by the wireless transmission and receiving module of DSP board, and, timing, the image processing and analysis system return back the cholesterol content with the test sample to the LCD screen of homemade experimental apparatus. End of the timing, a large number of experimental results prove that longest consuming time is 46.9s, calculate and measure cholesterol content of mixed oil samples by the proposed method and standard chemical method, compare of the maximum relative error of the calculated cholesterol content value and measured cholesterol content value, the result is shown below.

TABLE 6. Measured results of cholesterol contents for different mixed oil samples with this paper method and standard chemical method based on wavelet symbiotic matrix technique

Samples	S component average weight	Cholesterol content (mg/100g)		Maximum relative error (%)
		This paper method	Standard chemical method	
a0	0.9752	7.57	7.41	2.16
a1	0.0215	7.23	7.41	2.43
a2	0.0102	7.15	7.41	3.51
b0	0.9935	10.98	10.77	1.95
b1	0.1095	10.59	10.77	1.67
b2	0.0583	10.43	10.77	3.16
c0	0.9937	8.28	8.52	2.82
c1	0.1118	8.63	8.52	1.29
c2	0.0437	8.34	8.52	2.11

In Table 6, samples a0, a1 and a2; b0, b1 and b2; c0, c1 and c2 represent respectively mixed oil (soybean oil, corn oil and sunflower seed oil adulterate with lard; beef tallow; chicken oil). As can be seen from above table, the results that maximum relative error of the calculated cholesterol content and measured cholesterol content is 3.51% with this paper method and standard chemical method, this can prove that in the range of allowable error, texture analysis techniques can be used to detect vegetable oil adulteration.

4. **Conclusion.** In order to obtain easily to popular, nondestructive and low price research methods for vegetable oil adulteration detection, this article proposed coupling standard chemical method and image texture analysis technology for detecting vegetable oil adulteration, and, the proposed method can achieve real-time determination of experimental samples by self-made testing apparatus. Wavelet symbiotic matrix has the advantages of strong adaptability, robustness and multi-scale representation image texture features, in terms of feature extraction time and classification recognition rate performance is most prominent, using this method can detect that minimum adulteration

level has reached 6.5%. In order to verify the validity of proposed method, determination of animal oil doping ratio in mixed oil samples by the proposed method and standard chemical method, the maximum relative error is 3.51% between the calculated value and measured value. Results show that in the range of allowable error using texture analysis technology to detect vegetable oil blended with animal oil is feasible. Research results can be applied in halal and kosher market due to some communities especially Muslims and Jews are very concerned about the presence of animal fats; from a religious perspective, Islam and Judaism prohibit using or consuming food or other products containing lard or any pig-derived ingredients. So the research has a great application prospect in the Muslim and Judaism market.

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