

## RESEARCH ARTICLE

# Edible Oil Identification Technology Based on Three-Dimensional Fluorescence Spectroscopy and MPCA-LDA

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**ABSTRACT** The issue of edible oil quality is a serious food safety hazard worldwide, posing a direct threat to public health. Based on this, research on edible oil identification technology using three-dimensional fluorescence spectroscopy combined with MPCA-LDA was conducted in this paper. Firstly, the FS920 fluorescence spectrometer was used to determine the three-dimensional fluorescence spectrum data of three types of sesame oil with different qualities. Then, the main mode features of the three-dimensional fluorescence spectrum were extracted using MPCA. Finally, an identification model for experimental samples was established using LDA. The research shows that MPCA-LDA exhibits higher accuracy and sensitivity compared to the NPLS-DA method, enabling it to identify adulterated and counterfeit sesame oil with 100% accuracy. The MPCA-LDA methods can effectively identify adulterated and inferior edible oils, thereby helping to ensure food safety and consumer health.

**INDEX TERMS** Edible oil, three-dimensional fluorescence spectroscopy, MPCA-LDA, NPLS-DA, quality identification.

## I. INTRODUCTION

Edible oil, a crucial element of daily human nutrition, is increasingly being adulterated by unscrupulous entities seeking substantial economic benefits [1], [2], [3]. This widespread issue of edible oil falsification poses a global food safety hazard, endangering consumer health [4], [5], [6]. Thus, conducting precise and reliable investigations into techniques for detecting the quality of edible oil to ensure its authenticity and adherence to standards is imperative. This endeavor not only safeguards consumer health but also fosters the sustainable growth of the edible oil industry, underscoring its significant practical importance.

Recent literature has highlighted the emergence of fluorescence spectroscopy as a potent tool for authenticating edible oils, assessing quality, and detecting adulteration due

to its high sensitivity, speed, efficiency, and minimal need for complex pretreatment [7], [8], [9]. Vegetable oils containing chlorophyll and carotenoids exhibit fluorescence upon excitation, making it theoretically viable to characterize them through fluorescence spectroscopy [10], [11]. However, conventional fluorescence spectroscopy methods often grapple with substantial spectral overlap, impeding detailed sample analysis [12]. In contrast, Excitation-Emission Matrix Fluorescence (EEMF) spectroscopy can present all fluorescent groups in a three-dimensional spectrum concurrently, offering superior selectivity compared to traditional methods [13], [14], [15]. Despite its advantages, EEMF spectroscopy encounters challenges in assigning spectral peaks accurately, complicating spectral analysis.

Spectral analysis has traditionally been hindered by collinearity among characteristic variables and a high variable count [16], [17], [18]. To address this issue, chemometric methods like Principal Component Analysis (PCA),

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Linear Discriminant Analysis (LDA), and Partial Least Squares Regression (PLSR) are commonly employed for mining and processing spectral data [19], [20]. Noteworthy studies by Pan et al. and Zhao et al. have explored adulteration detection and quality assessment in edible oils using advanced spectroscopy technologies and innovative identification approaches [21], [22]. While these studies underscore the potential of spectroscopy technology in edible oil analysis, there persist challenges and opportunities in leveraging three-dimensional fluorescence spectroscopy for oil identification, including the imperative to enhance accuracy and sensitivity, expand fluorescence fingerprint databases, and refine data processing algorithms. Furthermore, integrating this technology with other analytical methods is pivotal to devising more comprehensive and precise edible oil identification strategies.

To address these challenges, this study introduces a novel approach that combines Multivariate Principal Component Analysis (MPCA) and Linear Discriminant Analysis (LDA) for sesame oil quality identification, presenting a significant advancement over existing methods in the field. By directly extracting main mode features from three-dimensional fluorescence spectra and developing a reliable identification model, this research offers a practical solution to current challenges in edible oil analysis techniques. The proposed MPCA-LDA approach enhances the accuracy and sensitivity of detection and contributes to the broader goal of ensuring food safety and consumer health in the edible oil industry.

This study presents a unique approach to sesame oil quality identification by introducing MPCA-LDA methodology, which utilizes three-dimensional fluorescence spectroscopy data from three types of sesame oil: authentic, adulterated, and inferior. The innovative application of MPCA enables the direct extraction of principal mode features from the three-dimensional fluorescence spectra, forming the basis for constructing an LDA-based model for quality identification. The results of the experiments strongly support the effectiveness of the MPCA-LDA approach in distinguishing between sesame oil samples of different qualities, providing a robust tool for enforcing food safety regulations and promoting the sustainable development of the edible oil industry. While previous research has highlighted the potential of spectroscopy technology in analyzing edible oils, the integration of MPCA and LDA in this study represents a significant advancement. By emphasizing the unique combination of MPCA and LDA with three-dimensional fluorescence spectroscopy for sesame oil quality identification, this study establishes a new standard for detecting the quality of edible oils.

Furthermore, acknowledging the promising results obtained in this study, it is essential to recognize the limitations of the proposed approach. Future research should focus on validating the scalability and applicability of the MPCA-LDA model across various edible oils, expanding fluorescence fingerprint databases, optimizing data processing algorithms, and integrating complementary analytical

methods to enhance the robustness and reliability of edible oil identification techniques. This study presents a robust tool for enforcing food safety regulations and advancing the sustainable evolution of the edible oil sector, contributing substantially to food safety and industry sustainability.

## II. THEORY

Multiprincipal component analysis combined with linear discriminant analysis (MPCA-LDA) is a common method used for dimensionality reduction and feature extraction in multivariate data. This approach combines the benefits of MPCA and LDA to enhance the performance of feature extraction and classification [23], [24].

### A. MULTIPLE PRINCIPAL COMPONENT ANALYSIS (MPCA)

Compared to traditional PCA, MPCA has the capability to handle nonlinear data structures through the utilization of nonlinear mapping functions, resulting in more accurate feature extraction. Furthermore, MPCA is capable of generating multiple principal components, each representing a distinct pattern or feature within the original data. This characteristic enables MPCA to capture correlations between multiple sets of data more effectively when analyzing such data, ultimately providing more precise and comprehensive outcomes [15].

In MPCA, the data matrix  $X$  is transformed into a feature vector  $y$  ( $m \times 1$ ) using the projection vector  $b$  ( $n \times 1$ ):

$$y = Xb \quad (1)$$

The optimal projection vector in  $b$  can be determined using the following formula:

$$J(b) = \text{tr}(S_b) \quad (2)$$

In the equation (2),  $S_b$  represents the covariance matrix of the sample projection vector,  $\text{tr}(S_b)$  denotes the trace of  $S_b$ , and  $S_b$  is calculated as follows:

$$\begin{aligned} S_b &= E(y - E_y)(y - E_y)^T = E(Xb - EXb)(Xb - EXb)^T \\ &= E[(X - EX)b][(X - EX)b]^T \end{aligned} \quad (3)$$

The expression for  $\text{tr}(S_b)$  is as follows:

$$\text{tr}(S_b) = b^T [E(X - EX)^T(X - EX)]b \quad (4)$$

The scatter matrix  $G_t$  of the data matrix is defined as follows:

$$G_t = E[(X - EX)^T(X - EX)] \quad (5)$$

Equation (2) can be rewritten as follows:

$$J(b) = b^T G_t b \quad (6)$$

Typically, a set of orthogonal constraints must be selected and the projection axis of criterion  $J(b)$  maximized,

$$\begin{aligned} \{a_1, \dots, a_d\} &= \arg \max J(a) \\ a_i^T a_j &= 0, i \neq j, i, j = 1, \dots, d \end{aligned} \quad (7)$$

Arrange the projection axes of this group as the projection matrix  $B$ , and then utilize the projection matrix  $B$  to calculate

the feature matrix  $Y$  ( $m \times d$ ) of the fluorescence spectrum data matrix  $X$ :

$$Y = XB \quad (8)$$

### B. EVALUATION METHOD

The principle of linear discriminant analysis (LDA) is applied to classify and discriminate the feature matrix  $Y$ . In this process, the similarity between samples is evaluated using the Euclidean distance  $d$ .

$$d(Y_i, Y_j) = \sum_{k=1}^d \|y_k^{(i)} - y_k^{(j)}\|_2 \quad (9)$$

where  $i$  and  $j$  represent the  $i$ -th and  $j$ -th samples, respectively, and  $d(Y_i, Y_j)$  represents the Euclidean distance between the two feature matrices  $Y_i$  and  $Y_j$ . Assuming each of the training samples is assigned to a specific class  $C_p$ , for a given test sample  $Y_i$ , if  $d(Y_i, Y_j) = \min d(Y_i, Y_j)$  and  $Y_j \in C_p$ , then the resulting decision is that  $Y_i$  belongs to class  $C_p$ .

## III. EXPERIMENT

### A. EXPERIMENTAL SAMPLES AND DATASET ESTABLISHMENT

The quality issues of edible oil mainly involve two situations: adulteration and inferiority. Adulteration refers to the act of mixing low-quality or non-edible oil components into normal edible oil to deceive consumers or reduce production costs. Counterfeit and inferior edible oil, on the other hand, involves the addition of pigments, spices, and other ingredients to cheap or even substandard oil in order to enhance the appearance and taste of the product, aiming to achieve higher sales prices or deceive consumers. Both of these practices violate consumer rights, as they not only affect the quality and nutritional value of edible oil but also pose potential health risks.

The experimental samples utilized in this study were carefully selected to ensure a representative evaluation of the proposed methods. Adulterated oil samples (SF<sub>1</sub>-SF<sub>9</sub>) were meticulously prepared by blending sunflower seed oil (F<sub>1</sub>) with sesame oil (S<sub>1</sub>) across a range of specific proportions to simulate real-world scenarios accurately. Similarly, the counterfeit and inferior oil samples (CE<sub>1</sub>-CE<sub>9</sub>) were created by mixing corn oil (C<sub>1</sub>) and sesame essence (E<sub>1</sub>) in varying ratios to represent a broad spectrum of adulteration possibilities.

In addition to these adulterated samples, a diverse set of 14 sesame oil samples from different brands (S<sub>1</sub>-S<sub>14</sub>) were carefully selected to provide a comprehensive representation of authentic products in the market. Detailed information on each sample, including composition and source, was recorded and presented in Table 1 for transparency and reproducibility.

The establishment of this dataset was crucial in evaluating the performance of the proposed system, ensuring a comprehensive representation of different types of edible oils commonly found in the market.

### B. FLUORESCENCE SPECTROSCOPY MEASUREMENT

Fluorescence spectroscopy measurements were conducted on all experimental samples listed in Table 1 using the FS920 fluorescence spectrometer. In this process, the excitation wavelength range was set from 250nm to 550nm, with a step interval of 10nm. The emission wavelength range was set from 260nm to 750nm, with a step interval of 2nm. The slit width at both the excitation and emission ends was set to 1.1mm, resulting in a spectral resolution of 2nm.

### C. SOFTWARE USED

Data processing in this work was performed using MATLAB R2016a software (MathWorks, Inc., USA). N-PLS analyses were carried out using the *N-way Toolbox* [25].

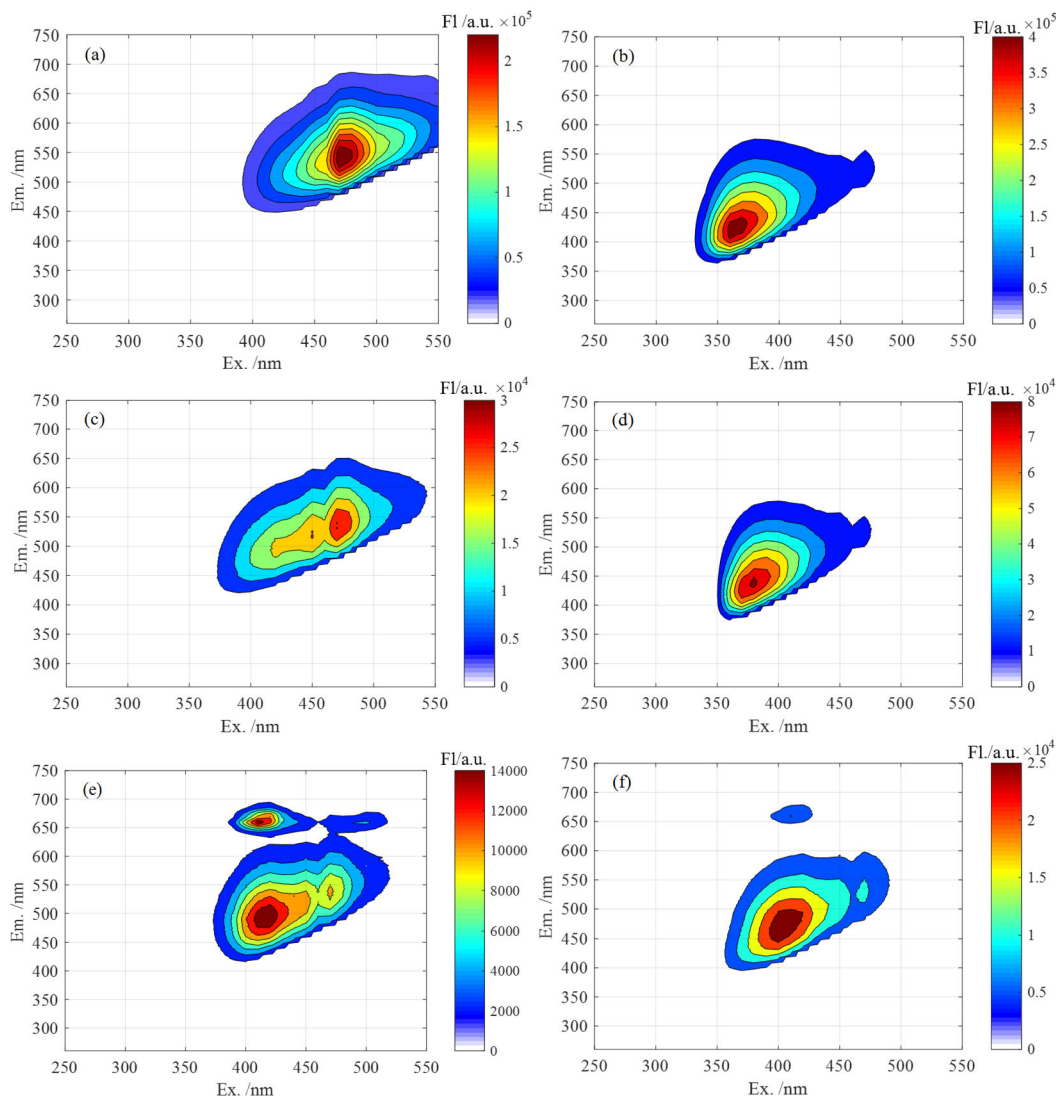
TABLE 1. Information of experimental samples.

Sample	Source	Sample	Composition
S <sub>1</sub>	Damingyongzhen	SF <sub>1</sub>	S <sub>1</sub> : F <sub>1</sub> =1: 9
S <sub>2</sub>	Fulinmen	SF <sub>2</sub>	S <sub>1</sub> : F <sub>1</sub> =2: 8
S <sub>3</sub>	Huarui	SF <sub>3</sub>	S <sub>1</sub> : F <sub>1</sub> =3: 7
S <sub>4</sub>	Lihong	SF <sub>4</sub>	S <sub>1</sub> : F <sub>1</sub> =4: 6
S <sub>5</sub>	Mingxuan	SF <sub>5</sub>	S <sub>1</sub> : F <sub>1</sub> =5: 5
S <sub>6</sub>	Fulaiwei	SF <sub>6</sub>	S <sub>1</sub> : F <sub>1</sub> =6: 4
S <sub>7</sub>	Jinlongyu	SF <sub>7</sub>	S <sub>1</sub> : F <sub>1</sub> =7: 3
S <sub>8</sub>	Damingyongzhen	SF <sub>8</sub>	S <sub>1</sub> : F <sub>1</sub> =8: 2
S <sub>9</sub>	Fulaiwei	SF <sub>9</sub>	S <sub>1</sub> : F <sub>1</sub> =9: 1
S <sub>10</sub>	Fulinmen	CE <sub>1</sub>	C <sub>1</sub> : E <sub>1</sub> =1: 9
S <sub>11</sub>	Jinlongyu	CE <sub>2</sub>	C <sub>1</sub> : E <sub>1</sub> =2: 8
S <sub>12</sub>	Luhua	CE <sub>3</sub>	C <sub>1</sub> : E <sub>1</sub> =3: 7
S <sub>13</sub>	Mingxuan	CE <sub>4</sub>	C <sub>1</sub> : E <sub>1</sub> =4: 6
S <sub>14</sub>	Damingyongzhen	CE <sub>5</sub>	C <sub>1</sub> : E <sub>1</sub> =5: 5
F <sub>1</sub>	Jinlongyu	CE <sub>6</sub>	C <sub>1</sub> : E <sub>1</sub> =6: 4
C <sub>1</sub>	Wannian	CE <sub>7</sub>	C <sub>1</sub> : E <sub>1</sub> =7: 3
E <sub>1</sub>	Shangwei	CE <sub>8</sub>	C <sub>1</sub> : E <sub>1</sub> =8: 2
-	-	CE <sub>9</sub>	C <sub>1</sub> : E <sub>1</sub> =9: 1

## IV. RESULTS AND DISCUSSION

### A. FLUORESCENCE SPECTRAL CHARACTERISTICS OF EXPERIMENTAL SAMPLES

The three-dimensional fluorescence spectrum obtained from the experimental samples is shown in Figure 1. Specifically, Figure 1a depicts the spectrum of sesame oil S<sub>1</sub>, Figure 1b depicts the spectrum of sunflower seed oil F<sub>1</sub>, Figure 1c shows the spectrum of adulterated oil SF<sub>5</sub>, Figure 1d illustrates the spectrum of corn oil C<sub>1</sub>, Figure 1e displays the spectrum of sesame essence E<sub>1</sub>, and Figure 1f exhibits the spectrum of counterfeit and inferior oil CE<sub>5</sub>. The main reason for the production of spectra in experimental samples is that substances such as fatty acids, vitamins, and carotenoids contained in vegetable oil have strong fluorescent properties [26], [27].

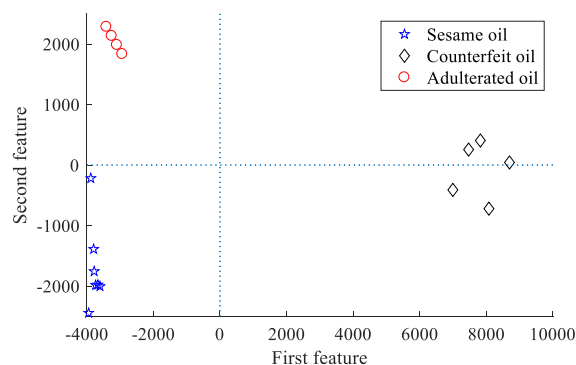


**FIGURE 1.** 3D fluorescence spectrum of experimental samples. (a) sesame oil  $S_1$ , (b) Sunflower Seed Oil  $SF_5$ , (c) Adulterated oil  $SF_5$ , (d) Corn oil  $C_1$ , (e) Sesame essence  $E_1$ , (f) Counterfeit oil  $CE_5$ .

From Figure 1, it can be seen that the fluorescence peak of sesame oil is located near the excitation/emission wavelengths of 470/550nm. Influenced by the adulterated oil, the fluorescence spectrum of the blended oil not only contains the original fluorescence peak of sesame oil but also exhibits an additional secondary fluorescence peak at 450/520nm. The fluorescence spectrum characteristics of inferior oil are determined by a combination of sesame flavoring and the adulterated oil variety. It exhibits a main fluorescence peak at 400/470nm, along with two secondary fluorescence peaks at 470/534nm and 410/662nm.

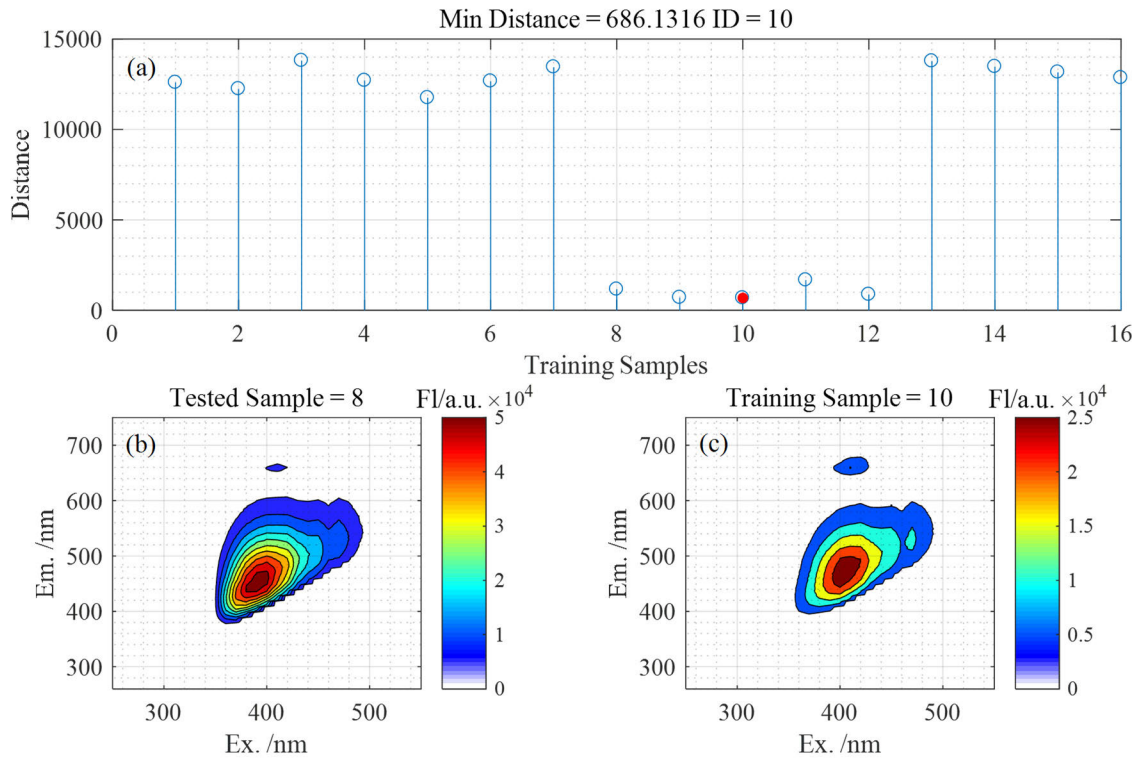
**B. CLASSIFICATION MODELS**

For robust model evaluation, a well-established dataset was utilized. The samples were randomly split into training and test sets, ensuring a balanced representation of each



**FIGURE 2.** MPCA features extracted from training samples.

sample type in both sets. The training set was employed for model training, parameter optimization, and feature extraction, while the test set served as an independent dataset for



**FIGURE 3.** Identification result of the test samples. (a) Euclidean distance between test sample and training sample, (b) 8th test sample, (c) 10th training sample.

evaluating the model’s performance under unseen data conditions.

1) FEATURE EXTRACTION RESULTS

The feature extraction process involved extracting the first two mode features from the training set samples using the MPCA method. The code implemented in MATLAB utilized the MPCA method for feature extraction as outlined in references [23] and [24]. The results of this process are visually represented in Figure 2, where the horizontal axis signifies the first mode feature, and the vertical axis represents the second mode feature. Notably, sesame oil samples are denoted by asterisks, adulterated oil samples by circles, and inferior quality oil samples by diamonds.

From the figure 2, it can be observed that all sesame oil samples are located in the third quadrant, while the adulterated oil samples are clustered in the second quadrant. Since adulterated oil is composed of sesame oil mixed with cheap oil, its fluorescence spectrum exhibits similar spectral characteristics to sesame oil. Therefore, adulterated oil and sesame oil share similar and close values in the extracted first mode feature. On the other hand, inferior quality oil samples are located in both the first and fourth quadrants. Due to significant compositional differences from sesame oil, their extracted features are distinct from those of sesame oil. The analysis results indicate that the MPCA method is effective in extracting features for classifying sesame oil, adulterated oil, and inferior quality oil.

2) IDENTIFICATION RESULTS

Subsequently, the pattern features of the test samples were extracted using the MPCA method, and the test samples were classified and identified based on the Euclidean distance between these extracted features and those of the training set samples. The implementation of this process involved utilizing the Classification toolbox for MATLAB for distance calculation and classification.

Figure 3 provides the identification result of the 8th test sample, demonstrating the practical application of the method. The minimum Euclidean distance was calculated and compared with the training samples, ultimately leading to the categorization of the test sample. This step showcased the robustness and reliability of the MPCA method in identifying the different categories of oil samples within the established dataset.

Among them, Figure 3(a) shows the Euclidean distances between the test sample and the training samples, where samples 1 to 7 are genuine sesame oil samples, samples 8 to 12 are adulterated oil samples, and samples 13 to 16 are counterfeit oil samples. The minimum Euclidean distance is indicated by a solid red circle in the figure. Figure 3(b) displays the 8th test sample, and Figure 3(c) shows the 10th training sample.

From the figure 3, it can be observed that the test sample has the minimum Euclidean distance (Min Distance = 686.1316) with the 10th training sample (ID=10), which corresponds to the category of adulterated oil. Therefore, the

**TABLE 2. Confusion matrix obtained for test set.**

Method	Category	S	SF	CE
MPCA-LDA	S	7	0	0
	SF	0	4	0
	CE	0	0	5
NPLS-DA	S	7	1	0
	SF	0	3	1
	CE	0	0	4

**TABLE 3. Evaluation results of identification method.**

Method	Evaluation index	S	SF	CE	Accuracy
MPCA-LDA	Precision	100.0	100.0	100.0	100.0
	Sensitivity	100.0	100.0	100.0	
	Specificity	100.0	100.0	100.0	
NPLS-DA	Precision	100.0	75.0	80.0	87.5
	Sensitivity	87.5	75.0	100.0	
	Specificity	100.0	91.7	91.7	

test sample is determined to be adulterated oil. Additionally, it can be noted that the test sample has smaller distances with samples of the same category in the training set, while the distances with other samples are relatively larger. This indicates that the pattern features extracted by MPCA can stably represent various types of oil samples.

### C. FURTHER ANALYSIS

In addition to the feature extraction and identification processes, a comparison between the MPCA-LDA method and the NPLS-DA (Multivariate Partial Least Squares Discriminant Analysis) method was conducted. This comparison involved a detailed analysis of confusion matrices and evaluation results obtained by both methods, as presented in Table 2 and Table 3, respectively.

From Table 2, it can be observed that the MPCA-LDA method successfully identified all test samples correctly, whereas the NPLS-DA method misclassified one adulterated oil sample as genuine sesame oil and misclassified one fake oil sample as adulterated oil. These results further demonstrate the superiority of the MPCA-LDA method in the identification of edible oil quality.

This in-depth comparison allowed for a comprehensive assessment of the performance of the proposed MPCA-LDA method, highlighting its superiority in accurately identifying and categorizing the various types of edible oil samples. The robustness and effectiveness of the MPCA-LDA approach were further underscored through this comparative analysis.

### V. CONCLUSION

In this study, a rapid and accurate method for identifying the quality of edible oil has been developed by combining three-dimensional fluorescence spectroscopy technology with the MPCA-LDA method. The effectiveness of this method was demonstrated using sesame oil as a case study. Two types of counterfeit sesame oil samples, namely adulterated oil and counterfeit oil, were prepared, and

three-dimensional fluorescence spectrum data was collected for these samples as well as genuine sesame oil.

The MPCA-LDA method successfully identified and classified the different types of oil samples, including sesame oil, adulterated oil, and counterfeit oil. The experimental results underscore the capability of the MPCA-LDA method to effectively extract classification features from the samples, enabling the identification of various types of edible oils with different qualities. This method not only offers a scientific foundation for the production and regulation of edible oil but also ensures its quality and authenticity.

Moving forward, it is recommended to further validate and optimize the MPCA-LDA model on a larger scale across multiple types of edible oils to assess its robustness and applicability in diverse scenarios. Additionally, expanding the dataset to include a wider range of adulterants and refining the data processing algorithms could enhance the precision and reliability of the classification model. Exploring the integration of complementary analytical methods, such as chromatography techniques, could provide a more comprehensive approach to edible oil quality identification. These future endeavors will contribute to advancing the field of edible oil analysis and fortifying food safety regulations.

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