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OPTICAL SENSING TECHNIQUES FOR DETECTING EDIBLE OIL ADULTERATION: AN OVERVIEW

Nur Ain Amila Rizal[a], Nurul Nadia Adnan[b*], Farah Diana Muhammad[c]

[a]Department of Physics and Chemistry, Faculty of Applied Science and Technology, Universiti Tun Hussein Onn Malaysia, Pagoh Educational Hub, 84600, Pagoh, Johor, Malaysia
[b]Photonics Devices and Sensor Research (PDSR), Department of Physics and Chemistry, Faculty of Applied Physics and Chemistry, Faculty of Applied Sciences and Technology, Universiti Tun Hussein Onn Malaysia, Pagoh, Educational Hub, 84600, Pagoh, Johor, Malaysia
[c]Department of Physics, Faculty of Science, University Putra Malaysia, 43400, UPM Serdang, Selangor, Malaysia

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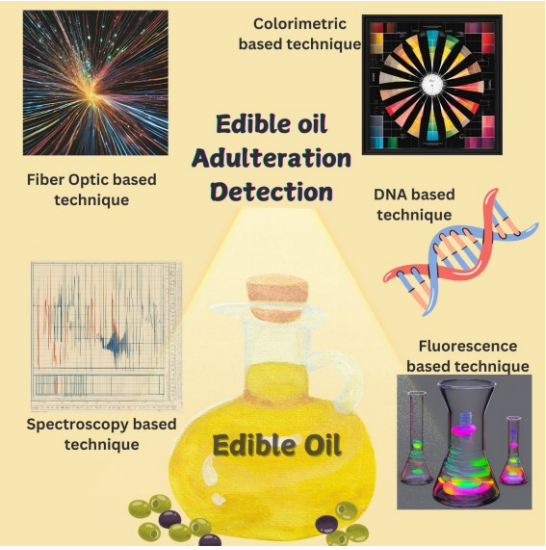
*Corresponding author
nadia@uthm.edu.my

Graphical abstract



Abstract

Edible oil adulteration significantly challenges food safety, nutritional quality, and consumer trust. This review explores the advancements in detection technologies, focusing on highly sensitive methods such as spectroscopy-based methods (UV-VIS, NIR, Raman, SERS), fluorescence-based methods, optical fiber sensors, and colorimetric approaches. These innovations leverage nanotechnology in optical sensing to improve the accuracy, sensitivity, and real-time applicability of adulteration detection. Spectroscopy methods like Raman and NIR offer molecular fingerprinting, while portable fluorescence and colorimetric systems provide cost-effective, on-site solutions. Despite these advances, challenges such as method standardization, affordability, and compatibility with diverse adulterants remain. The review underscores the critical role of integrating advanced sensing technologies to ensure food authenticity, enhance consumer protection, and uphold industry standards.

Keywords: Optical sensing, techniques, edible oils, adulteration

Abstrak

Pencemaran minyak boleh dimakan memberi cabaran besar terhadap keselamatan makanan, kualiti pemakanan, dan kepercayaan pengguna. Ulasan ini meneroka kemajuan dalam teknologi pengesanan, dengan memberi tumpuan kepada kaedah yang sangat sensitif seperti kaedah berasaskan spektroskopi (UV-VIS, NIR, Raman, SERS), kaedah berasaskan pendarfluor, sensor gentian optik, dan pendekatan kolorimetrik. Inovasi ini memanfaatkan nanoteknologi, penderiaan optik, untuk meningkatkan ketepatan, kepekaan, dan kebolehgunaan masa nyata dalam pengesanan pencemaran. Kaedah spektroskopi seperti Raman dan NIR menawarkan cap jari molekul, manakala sistem pendarfluor dan kolorimetrik mudah alih menyediakan penyelesaian kos efektif di lokasi. Walaupun terdapat kemajuan ini, cabaran seperti

penyeragaman kaedah, kemampuan kos, dan keserasian dengan pelbagai pencemar masih kekal. Ulasan ini menekankan peranan penting dalam mengintegrasikan teknologi penderiaan maju untuk memastikan keaslian makanan, meningkatkan perlindungan pengguna, dan mengekalkan piawaian industri.

Kata kunci: Penderiaan optik, teknik, minyak makan, pemalsuan

1.0 INTRODUCTION

Food adulteration involves intentionally adding substances to food products to alter composition, reduce nutritional value, mislead consumers with false label information, or fail to meet legal standards, ultimately posing health risks to consumers [1, 2, 3]. While food adulteration is a pressing issue, some argue that advancements in detection technology and increased consumer awareness can mitigate its effects. However, the ongoing evolution of adulteration techniques presents a continuous challenge to food safety. This review focuses on the adulteration of edible oils.

Edible oils are essential oils extracted from plant seeds, fruits, or animal sources, widely used for cooking, frying, and as an ingredient in processed foods [4]. Common oils include olive, sunflower, coconut, palm, and canola oils, which are critical to daily diets for their energy content, nutrient absorption support, and flavor contributions. High-quality edible oils are rich in healthy fatty acids [5], vitamins such as Vitamin E [4, 6], and antioxidants, promoting overall health and reducing cardiovascular disease risk. The global reliance on edible oils underscores the importance of ensuring their authenticity and safety [7].

Adulteration involves mixing lower-quality or cheaper oils with premium oils, such as pomace [8], soybean [9, 10, 11], sunflower [10, 12, 13], corn [10, 13, 14, 15], rapeseed [14, 16, 17], or almond oils [18]. This practice compromises the quality and authenticity of the edible oil [19]. This practice not only reduces the nutritional quality of the oil but may also introduce harmful substances, posing significant health risks to consumers. For Instance, adulterants like Sudan dyes and recycled oils have been linked to carcinogenic and toxic effects. Moreover, adulteration undermines consumer trust and violates food safety regulations. Therefore, rapid and reliable adulteration detection is critical to ensure consumer safety, maintain industry integrity, and prevent economic fraud. Advanced techniques such as spectroscopy and chemometrics have proven effective in detecting adulterants, providing non-destructive, real-time solutions for maintaining edible oil quality.

Several prior review articles have examined various analytical methods for detecting edible oil adulteration. For example, Kanwal and Musharraf provided a comprehensive overview of chromatographic, spectrometric, DNA-based, and chemometric approaches, highlighting their respective advantages and limitations across both food and non-food matrices [20]. Similarly, Hashempour-Baltork *et al*. focused on the use of chemometric-enhanced spectroscopic techniques such as FTIR, Raman, fluorescence, and UV-Vis, particularly in olive oil authentication [21]. However, these works often focused on isolated techniques or specific oil types and did not comprehensively address the potential of optical fiber-based sensors and nanomaterial-enhanced systems. In contrast, this review uniquely expands the scope by encompassing a broad spectrum of advanced optical sensing technologies, including UV-VIS, NIR, Raman, SERS, fluorescence, colorimetric assays, and particularly optical fiber-based methods such as surface plasmon resonance (SPR) and fiber Bragg grating (FBG). Notably, it emphasizes the enhancement of these techniques through nanomaterials and assesses their real-world applicability in industrial settings.

Recent advancements in optical sensing technologies have revolutionized the detection of edible oil adulteration, a critical issue affecting consumer health and the integrity of the edible oil market. These innovative techniques allow for rapid and non-destructive analysis of edible oil samples [22]. By utilizing specific wavelengths of light, these optical methods can distinguish between pure edible oil and adulterated varieties with remarkable accuracy. They analyze the unique spectral fingerprints of different oils, enabling the detection of even trace amounts of lower-quality oils or other additives that may compromise purity. As the demand for high-quality edible oil continues to rise globally [23], these optical sensing technologies play a vital role in protecting consumers and producers from the consequences of adulteration, ultimately promoting transparency and quality in the edible oil industry. While these advancements present promising solutions for detecting edible oil adulteration, challenges remain in standardizing

these methods for widespread use in the industry, particularly regarding integrating various techniques for comprehensive analysis.

This review aims to explore the scope and recent progress in advanced sensing technologies developed for the detection of adulteration in edible oils. The primary focus is on optical sensing techniques, including spectroscopy-based methods (UV-VIS, NIR, Raman, and SERS), optical fiber-based sensors (such as FBG and SPR), fluorescence-based techniques, DNA-based techniques, and colorimetric assays. The review highlights how these technologies, often enhanced by nanomaterials, improve sensitivity, specificity, and practicality in real-world applications.

2.0 OPTICAL SENSING TECHNIQUE FOR OLIVE OIL ADULTERATION DETECTION

Detecting edible oil adulteration can be effectively achieved through various optical sensor technologies, each utilizing distinct methodologies to identify and quantify adulterants. These sensors leverage different optical principles, such as interference, spectroscopy, and colorimetric analysis, to provide accurate results. This section will discuss the optical sensor used for detecting edible oil adulteration.

a) Spectroscopy-based technique

Spectroscopy is a powerful tool for detecting adulteration in olive oil because it allows for the identification of molecular fingerprints unique to pure olive oil and potential adulterants. Spectroscopy is an analytical technique that relies on the interaction between light and matter to identify substances based on their optical responses. Each compound in a sample absorbs or emits light at specific wavelengths, producing a unique spectral pattern. This behavior is described by Beer-Lambert's Law, which relates the absorbance A of light to the concentration c of the absorbing molecules, their molar absorptivity ε, and the path length l of the sample;

$$A = \varepsilon c l \qquad \text{Eqn.1}$$

where A is the absorbance, ε is the molar absorptivity, c is the concentration of the absorbing species and l is the path length of the sample. This equation provides the theoretical foundation for quantitative analysis in spectroscopy-based methods.

Various spectroscopic techniques are used to analyze olive oil's chemical composition and physical properties to detect impurities, including changes in refractive index, absorption spectra, Raman shifts, and fluorescence. Examples of techniques grounded in spectroscopy include UV-VIS, near-infrared (NIR), Raman, and surface-enhanced Raman Spectroscopy (SERS).

UV-Vis spectroscopy measures light absorption in the ultraviolet and visible ranges, correlating with the electronic transitions of specific molecules in the sample [24]. Torrecilla *et al*. introduced a novel UV-Vis spectroscopy method for detecting olive oil adulteration using chaotic parameters like the Lyapunov exponent, autocorrelation coefficients, and fractal dimensions [25]. By applying this technique to adulterated extra virgin olive oil samples, the researchers developed a model capable of accurately quantifying refined olive oil or olive pomace oil concentrations. The model achieved a correlation coefficient above 0.97 and a mean square error below 1% for low adulterant concentrations, making it an effective detection and quality control tool. Another study uses fluorescence and UV-Vis spectroscopy to compare multivariate modeling techniques for detecting extra virgin olive oil (EVOO) adulteration with soybean oil [26]. By applying partial least squares (PLS) and multiple linear regression (MLR) methods, the researchers created predictive models to quantify adulteration levels with high accuracy. Both spectroscopic techniques demonstrated similar predictive capabilities, and the models showed potential as quick, non-destructive, and cost-effective alternatives to traditional methods for identifying EVOO adulteration.

Another spectroscopy-based method is Near-infrared (NIR) spectroscopy. NIR is an analytical technique that utilizes infrared light to assess molecular structures by measuring absorption bands from overtones and combined excitations (especially C–H, O–H, N–H) [27]. This non-invasive method has gained traction across various fields, particularly in biomedical applications, food science, and environmental monitoring. Its ability to provide real-time data with minimal sample preparation makes it a valuable tool in research and industry.

Wesley 'A' *et al*. first proposed using NIR to measure adulteration levels in olive oil samples mixed with corn oil, sunflower oil, and raw olive residue oil [28]. This technique can identify adulteration by analyzing the unique spectral fingerprints of pure olive oil versus adulterants like sunflower, soybean, or palm oils, which have different fatty acid compositions and, hence, different NIR absorption patterns. This study used calibration using Partial Least Squares (PLS) regression and achieved 98% accuracy in predicting adulteration levels compared to Principal Component Analysis (PCA), which identified adulterants with a 75% success rate. The method demonstrated the potential for non-destructive, rapid, and reliable adulteration presence and type detection, suggesting NIR as a viable tool for quality control in olive oil authentication.

Another study by Melendreras *et al*. evaluates an affordable Near-Infrared (NIR) spectroscopy system

using Partial Least Squares (PLS) regression and Principal Component Analysis (PCA) to detect olive oil adulteration with seed oils like sesame, sunflower, and flax oils [29]. A total of 96 samples with binary and ternary mixtures were analyzed. The method achieved excellent calibration coefficients ($R^2 > 0.80$) for identifying and quantifying adulteration. When comparing the results of Wesley 'A' *et al*. with the Melendreras *et al*. In the NIR system study, several key distinctions emerge. The Wesley et al. study achieved 98% accuracy in quantifying adulteration using Near-Infrared (NIR) spectroscopy with Partial Least Squares (PLS) regression. Additionally, Principal Component Analysis (PCA) successfully identified adulterants with a 75% success rate, demonstrating the capabilities of laboratory-grade NIR technology. In contrast, the Melendreras et al. study utilized a portable NIR system for fraud detection, achieving calibration coefficients of $R^2 > 0.80$ and proving practical usability for on-site applications. While Wesley's study focused on achieving high precision under controlled conditions, Melendreras's study emphasizes affordability and portability, making it suitable for real-time fraud detection.

Ning Su *et al*. utilized visible and near-infrared (Vis-NIR) reflectance spectroscopy and multivariate methods to detect adulteration in sesame and rapeseed oils mixed with soybean oil [30]. As shown in Figure 1, a light source illuminates the oil sample, which is placed on a lifting platform inside a black box. The light interacts with the sample, and the resulting spectra are collected through an optical fiber and analyzed using a Vis/NIR spectroradiometer connected to a computer. Their models achieved exceptional prediction accuracy ($R^2 > 0.99$) and low error rates, highlighting the potential of Vis-NIR as a non-destructive, real-time solution for identifying oil adulterants.

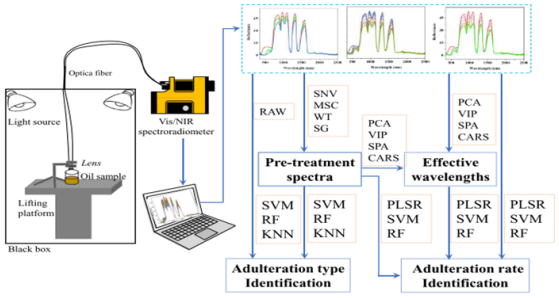


Figure 1 Schematic of measurement of Vis-NIR reflectance spectroscopy [30]

Similarly, Malavi *et al*. conducted a comparative study across multiple spectroscopic techniques, including Raman, FTIR, and UV-VIS, for detecting adulteration in extra virgin olive oil [7]. Raman spectroscopy demonstrated 96.6% classification accuracy, while hyperspectral imaging (HSI) emerged as the best method for quantification ($R^2 = 0.97$), reinforcing its value for authentication in the olive oil industry. The setup used for HSI, as shown in Figure 2 below, consists of a halogen illumination source that provides consistent lighting, a camera for capturing hyperspectral images, and a spectrograph for analyzing light spectra. The system includes a translation stage that allows controlled movement of the sample or camera for scanning. A computer is connected to process and analyze the collected spectral data.

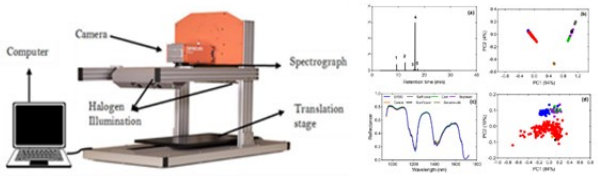


Figure 2 NIR hyperspectral imaging system [7]

Portable Raman spectroscopy has further advanced on-site oil authentication. Pulassery *et al*. developed a handheld Raman spectrometer to estimate oil iodine values, achieving high precision ($R^2 = 0.9$) and low detection limits [31]. This method eliminates the need for reagents, making it cost-effective and environmentally friendly. Additionally, de Lima *et al*. applied the technique of Raman spectroscopy with an exponential equation to detect the adulteration of olive oil mixed with rapeseed and corn oil. Raman spectroscopy is a vibrational spectroscopic technique used to study molecular structures [32]. It measures molecules' inelastic scattering of monochromatic light. When light interacts with a molecule, most of the photons are elastically scattered, a process known as Rayleigh scattering. However, a small fraction of these photons undergo energy shifts due to the vibrational modes present within the molecule. This phenomenon is referred to as the Raman effect.

This technique can provide a unique molecular fingerprint of olive oil by detecting the vibrational modes of its molecular bonds, particularly those in unsaturated fatty acids like oleic acid [33]. The Raman spectrum reveals distinct peaks corresponding to the C=C stretching vibrations in the fatty acid chains, which are prominent in olive oil due to their high unsaturation [34]. These peaks differ from those of saturated fats or adulterants, allowing for the identification of olive oil's purity and the detection of adulteration through comparative spectral analysis. The study by de Lima *et al*. analyzed Raman peak intensity ratios, and the method accurately distinguished pure olive oil (2.67) from rapeseed (3.55) and corn oils (7.10). The exponential model strongly agreed with experimental data, achieving high precision (R2>0.99) and reliably calculating adulterant fractions from 0% to 100%.

Meanwhile, the study by Zou *et al*. used Raman spectroscopy but focused on intensity ratios of specific vibrational bands plotted on a 2D distribution chart [34]. It provided a more straightforward visual

method for qualitative and semi-quantitative detection, especially distinguishing adulterated samples from genuine olive oil containing as little as 5% adulterants such as soybean, rapeseed, sunflower seed, or corn oils. Both studies used portable Raman spectroscopy, emphasizing rapid, non-destructive analysis. However, Zou *et al*. highlighted their spectrometer setup's lightweight, field-ready nature.

The use of SERS has also proven highly effective for detecting specific adulterants. Andoh *et al*. applied SERS to detect the illegal dye Sudan IV in palm oil, successfully confirming adulteration in four out of five samples [35]. This study highlighted SERS's exceptional sensitivity for identifying traces of adulterants. Similarly, Jiang *et al*. applied SERS to measure peroxide values in edible oils, allowing the detection of oxidation levels within 3 minutes [36]. This rapid, ultra-sensitive approach aligns well with industrial needs for real-time quality control.

Another study by Camerlingo *et al*. employed surface-enhanced Raman spectroscopy (SERS) to monitor EVOO bioactive components [37]. SERS is an advanced form of Raman spectroscopy that enhances the Raman scattering signals of molecules adsorbed on certain rough metal surfaces or nanostructures, such as gold, silver, or copper [38]. This enhancement can increase the Raman signal by factors of 10^6 to 10^{10}, making it possible to detect very low concentrations of analytes, even down to the single-molecule level. The method successfully amplified the Raman signal, allowing the identification and quantification of critical components like carotene, oleic acid, and phenols. For instance, phenol content varied across samples, negligible in oil from Triggiano (Italy) but reaching 12% in Bellona (Italy) and Alberobello (Italy) samples. The samples also showed clear variations in carotene and oleic acid content. This SERS-based approach proved to be a rapid, non-destructive, and reliable method, capable of differentiating oil compositions with minimal sample preparation. Its efficiency and simplicity make it highly promising for routine quality control of EVOO.

In conclusion, spectroscopy has become an essential tool for detecting adulteration in edible oils, offering unmatched precision and versatility. Techniques like UV-Vis, NIR, Raman, and SERS allow for fast, non-destructive analysis by identifying the unique molecular signatures of pure oils and their adulterants. These methods have proven highly effective in quantifying adulteration levels, identifying the types of adulterants, and ensuring the authenticity of edible oils. Research highlights the flexibility of spectroscopy, from the high precision of advanced UV-Vis and Raman systems in laboratories to the practicality of portable NIR and SERS devices for on-site use. Innovations like handheld Raman spectrometers and affordable NIR setups are making these technologies more accessible, paving the way for real-time quality control and fraud detection. Future efforts should focus on improving sensitivity to detect lower levels of adulteration, broadening the range of detectable adulterants, and integrating machine learning for better predictive accuracy. Developing affordable and portable systems for real-time applications will also help close the gap between lab-grade precision and industrial demands. By addressing these challenges, spectroscopy will continue to evolve as a reliable, efficient, and scalable solution for safeguarding the quality and authenticity of edible oils in the global market.

Table 1 Summary of spectroscopy-based- sensor

Method	Type of Oils	Adulterants	Linearity/R^2	Ref.
UV-Vis and Fluorescence	EVOO	Soybean Oil	correlation coefficients > 0.97	[25]
NIR Spectroscopy	Olive Oil	Corn, Sunflower, Raw Olive Residue	PCA = 75% accuracy	[28]
Portable NIR System	Olive Oil	Sesame, Sunflower, Flaxseed Oils	R^2 > 0.80	[29]
Vis-NIR Reflectance Spectroscopy	Sesame, Rapeseed Oils	Soybean Oil	R^2 > 0.99	[30]
Hyperspectral Imaging (HSI)	EVOO	Safflower, Corn, Soybean, Canola, Sunflower, Sesame Oils	R^2 = 0.97	[7]
FTIR Spectroscopy			RPD > 2.5	
UV-Vis Spectroscopy			High accuracy (99.56%)	
Raman Spectroscopy			Effective at detecting adulterants (96.56% accuracy).	
GC-MS			Lower classification accuracy (93.72%)	
Portable Raman spectros	Coconut Oil	Sunflower Oil	R^2 = 0.9	[31]

Method	Type of Oils	Adulterants	Linearity/R^2	Ref.
copy				
Raman spectroscopy	Olive Oil	Rapeseed, Corn oil	R^2>0.99	[14]
Raman spectroscopy	Olive Oil	Soybean, Rapeseed, Sunflower Seed, Corn Oils	N/A	[34]
SERS	Palm Oil	Sudan IV dye	Detection limit: 0.1 ppm; Signal enhancement factor: ~10^5-10^6x.	[35]
SERS		Soybean, Sunflower, Corn		
Conventional Raman Spectroscopy	EVOO	N/A	N/A	[37]
Raman Spectroscopy with Wavelet-Based Analysis		N/A		

b) Fiber optic-based technique

Fiber optic sensing systems detect adulteration in edible oils by monitoring changes in light as it travels through or near the sample. In tapered or side-polished fibers, an evanescent field interacts with the surrounding oil, and any change in refractive index or absorption due to adulteration alters the light signal. These changes, analyzed using spectroscopic principles, reveal deviations from the spectral profile of pure oil, allowing for sensitive, real-time detection.

Unlike spectroscopy-based technique, fiber optic sensing integrates both light delivery and sensing within the fiber itself. This enables direct, in-situ interaction with the sample and offers higher sensitivity to local composition changes, making it more effective for continuous and on-site monitoring of oil quality. Its resistance to electromagnetic interference and capability for non-destructive analysis further enhance its effectiveness and innovation in this field.

Libish *et al*. applied a fiber optic sensing system to investigate adulteration in virgin olive oil mixed with sunflower oil [39]. They used a long-period grating (LPG) -based sensor to detect adulteration. LPG sensors are effective because even small changes in the sample's chemical composition or physical properties affect the light propagation in the grating, enabling precise identification of adulteration. It exploits the sensitivity of its resonance peaks to changes in the refractive index (RI) of the surrounding medium, such as the addition of sunflower oil to olive oil. These changes alter the attenuation bands in the transmission spectrum. Figure 3 shows the setup used in this experiment, which consists of a white light source, LPG, and an optical spectrum analyzer.

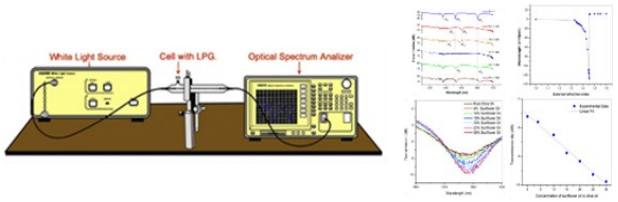


Figure 3 Experimental LPG–based sensor setup [39]

The sensor is designed to measure changes in refractive index, boasting a detection limit as low as 4% adulteration. It achieves a sensitivity of approximately 0.07 dB/vol% of adulterant within the 4% to 30% adulteration range. The results show a linear response throughout this range, with the intensity of the attenuation peaks increasing with higher levels of adulteration. However, the sensor shows low sensitivity for accurate measurements in the wavelength domain, emphasizing the need for further improvement. One possible approach to improve the sensor's sensitivity is to etch the fiber to reduce the cladding diameter. This is expected to enhance the evanescent field interaction with the surrounding medium, thereby increasing the cladding modes' sensitivity to refractive index changes and producing stronger amplitude or wavelength shifts in the LPG transmission spectrum.

Another study by Liang *et al*. employed a long-period fiber grating (LPFG) sensor to detect cottonseed oil adulteration in pure olive oil [40]. LPFG is based on the principles of LPG, as both utilize periodic modulation of the refractive index along the fiber axis to achieve specific optical properties. However, LPFGs are specifically designed to exploit the coupling of light between the core and cladding modes of the fiber. This results in unique sensing capabilities and applications across various fields. The experimental setup used by Liang *et al*. is similar to Figure 1, but it replaces the white light source with a broadband source.

The sensor operated by detecting changes in the refractive index (RI) as adulteration levels varied from 5% to 50% by weight. The results showed a linear decrease in transmission intensity as the concentration of cottonseed oil increased, while wavelength shifts were minimal and unanalyzed. This approach provided a quick, reagent-free, and sensitive method for detecting adulteration. However, the study focused on intensity changes, leaving lower adulteration levels and the potential

insights from wavelength shift analysis unexplored. These gaps highlight opportunities to enhance sensitivity and expand the method's applicability.

While both studies demonstrated the effectiveness of LPG sensors, specific gaps remain. Libish *et al*. did not test a broader range of adulterants or explore alternatives such as cottonseed oil. In contrast, Liang *et al*. investigated a broader spectrum of adulterants; however, they primarily focused on intensity changes without considering wavelength shifts, potentially overlooking subtle variations in refractive index (RI). Both studies could benefit from incorporating multi-wavelength analyses and testing a greater variety of adulterants to enhance their versatility.

The study by Castro de Barros *et al*. introduces a D-shaped optical fiber-based refractometer for detecting adulteration in extra virgin olive oil (EVOO) with five common vegetable oils: canola, corn, cotton, soybean, and sunflower oils [41]. The sensor operates by measuring changes in refractive index through interaction between the fiber's evanescent field and the external medium. The proposed sensor demonstrated a sensitivity of 0.037 dB/%, capable of detecting adulteration levels exceeding 9% by volume, with a resolution below 3% for specific oils. The mechanical robustness of the polished fiber and simplified instrumentation enhanced practicality, making it suitable for industrial applications. A notable gap in the research by Castro de Barros *et al*. is its inability to differentiate specific adulterants due to overlapping refractive index values, which limits precision in identifying adulteration sources. Additionally, while the sensor was effective for higher adulteration levels, its sensitivity could be improved for low-level adulteration detection.

The study by Puspita *et al*. explores a novel tapered plastic optical fiber (POF) coated with graphene and multi-walled carbon nanotubes (MWCNTs) for detecting lard adulteration [42]. This sensor uses the interaction between the lard and the evanescent wave in the tapered fiber to measure changes in the refractive index. The graphene-coated POF showed a selectivity coefficient of 324.19 and a sensitivity of 0.427 dBm/%. In comparison, the MWCNT-coated POF demonstrated a selectivity coefficient of 71.65 and a higher sensitivity of 1.189 dBm/%, making it more responsive to low lard concentration. While the use of graphene and MWCNTs coatings on optical fibers has proven effective, there is limited exploration of other advanced nanomaterials, such as metal oxides or hybrid composites, that could enhance sensitivity and selectivity.

Another approach employed silica optical fibers in a single-mode-multimode-single-mode (SMS) configuration Ika Puspita *et al*. [43]. This method achieved a sensitivity of 1.1107 dBm/% and a linearity of 0.99 over a 0–5% lard concentration range. This technique capitalizes on multimode interference to detect refractive index variations caused by lard adulteration, offering a simple yet effective solution. While the sensors are sensitive to lard, there is limited investigation into their ability to differentiate lard from other animal fats or plant-based adulterants. Expanding research in this area would improve the sensor's ability to identify various adulterants accurately.

Supardianningsih *et al*. utilized SPR to differentiate various vegetable oils, including coconut, corn, olive, and palm oils, based on changes in their refractive indices [44]. The study employed a gold thin-film SPR system with a He-Ne laser source, measuring shifts in SPR angles caused by water-oil emulsions. The configuration in Figure 4 monitors changes in light reflection caused by surface plasmon excitation, enabling the detection of biomolecular interactions or material properties on the gold thin film surface. This technique revealed that the saturated fatty acid content of the oils predominantly influenced the refractive index changes. The findings emphasize the feasibility of SPR-based sensors as reliable tools for ensuring food authenticity.

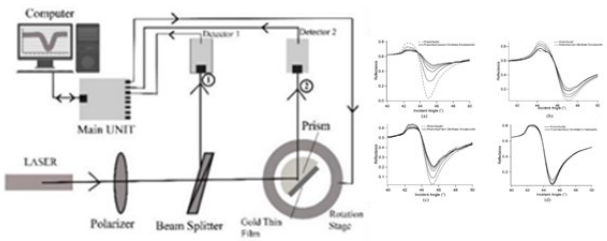


Figure 4 Example of SPR device setup [44]

Auddy *et al*. explore using LSPR technology to detect adulteration in virgin coconut oil [45]. Localized Surface Plasmon Resonance (LSPR) is an optical phenomenon that occurs when light interacts with metallic nanoparticles, such as gold or silver, causing localized oscillations of conduction electrons on the nanoparticle surface. This leads to strong absorption or scattering of light, with resonance wavelengths highly sensitive to the nanoparticles' size, shape, and surrounding refractive index. In contrast, Surface Plasmon Resonance (SPR) involves the propagation of plasmons along a planar metal-dielectric interface, requiring a continuous thin metal film and angular-dependent detection. LSPR provides nanoscale sensitivity and is ideal for detecting small-scale molecular interactions, while SPR is better suited for larger-scale bulk-sensing applications [45, 46].

By utilizing nanostructured gold-coated sensor chips, the system detects changes in the refractive index caused by adulterants such as coconut oil (CO) and mustard oil (MO). Auddy *et al*. developed a mobile application that processes the LSPR data into unique signatures and barcodes, allowing end-users to retrieve information about adulteration levels. The LSPR system demonstrated high sensitivity with detection limits (LOD) and quantification (LOQ) at 0.23% and 0.77% for CO and 0.21% and 0.72% for

MO, respectively. It provided a rapid detection time of under 10 minutes and outperformed conventional methods like FTIR and GC-MS in cost and speed. However, further research is required to enhance the compatibility with other edible oils and integrate artificial intelligence for large-scale industrial use.

Another innovative approach is presented by Pal *et al*., who developed a low-cost, non-destructive fiber optic device for detecting olive oil adulteration with palm oil using NIR spectroscopy [47]. Their method focuses on the 1550 nm wavelength, a region where a significant difference in reflectance, up to 23%, was observed between pure olive oil and palm oil. By utilizing off-the-shelf optical communication components, including a 1550 nm light source, a 50:50 fiber splitter, and an optical power meter, the researchers built a simple yet highly effective system. The device demonstrated a linear response with a sensitivity of 0.09 dBm/% increase in palm oil concentration, with a total measurable range from 0% to 100% adulteration. More than 100 measurements per sample were conducted to validate repeatability and accuracy, showing an average error of ±1.7 dBm. The sensor's low cost and ease of use make it particularly suitable for commercialization and field deployment. Compared to traditional NIR spectrometers and other fiber-based devices that rely heavily on refractive index changes, this system offers a reflection-based, non-contact detection approach, improving usability and reducing complexity. The study highlights not only a cost-efficient solution but also a practical advancement in real-time food authentication technology.

In conclusion, fiber optic-based sensing techniques offer advanced solutions for detecting oil adulteration, with excellent sensitivity, non-destructive analysis, and real-time monitoring capabilities. Table 2 shows the summary of fiber optic-based sensors. However, several critical research gaps must be addressed to fully realize the potential of these technologies in food authenticity testing. Specifically, improving sensitivity at lower adulteration levels, exploring a wider range of adulterants, and incorporating multi-wavelength and intensity shift analysis could significantly enhance the accuracy and versatility of these sensors. Additionally, advancements in materials, such as graphene and carbon nanotubes, as well as the integration of artificial intelligence for data analysis, could provide promising avenues for improving sensor performance. Addressing these gaps will not only improve the detection capabilities but also increase the feasibility of large-scale, cost-effective implementation in the food industry. Future research should focus on enhancing sensor specificity, expanding the range of detectable adulterants, and ensuring practical integration in commercial environments, ultimately ensuring the quality and safety of food products.

c) Fluorescence-based technique

Fluorescence is a form of luminescence where a substance absorbs light or electromagnetic radiation at a specific wavelength and then emits light at a longer wavelength [49]. This phenomenon occurs when molecules transition from an excited singlet electronic state, caused by light absorption, back to their ground state, releasing energy as photons [50]. Typically observed in aromatic compounds or molecules with conjugated double bonds, fluorescence is characterized by high sensitivity and rapid emission, often occurring within nanoseconds. Temperature, pH, solvent properties, and concentration can influence fluorescence intensity [48, 49]. In the context of edible oil analysis, fluorescence-based techniques exploit the natural fluorescence of compounds like tocopherols and chlorophylls. Each pure oil exhibits a characteristic fluorescence spectrum, and the introduction of adulterants alters this spectral profile. By exciting the oil sample with UV or visible light and analyzing the emission spectrum, even minor changes in composition can be detected, making fluorescence a sensitive and non-destructive method for identifying adulteration.

Fluorescence spectroscopy has proven highly effective in characterizing EVOO's oxidative state and adulteration. Studies employing laser-induced fluorescence (LIF) spectroscopy combined with advanced dimensionality reduction methods such as Kernel Principal Component Analysis-Linear Discriminant Analysis (KPCA-LDA) have achieved a recognition rate of 100% for adulteration detection, even at low concentrations of adulterants (2% soybean oil) [53]. Similarly, Abamba Omwange *et al*. used front-face fluorescence spectroscopy and UV fluorescence imaging to discriminate EVOO adulterated with virgin olive oil (VOO) at varying proportions [54]. Significant fluorescence peaks linked to tocopherols, phenolic compounds, and oxidation products were identified in the excitation-emission matrices (EEM), effectively separating adulterated samples from pure EVOO. A key advancement involves using LEDs and laser diodes as light sources in portable fluorescence systems, making these methods accessible for on-site quality monitoring. For instance, a study combining fluorescence emission with machine learning achieved 91–100% classification accuracies in monitoring the storage conditions and detecting adulteration in EVOO [55].

Furthermore, Wang & Wan used Confocal Raman and fluorescence spectroscopy (CRFS) and demonstrated exceptional promise by simultaneously capturing Raman and fluorescence spectra from the same EVOO sample [56]. This technique enables a deeper analysis of the molecular vibrational features (via Raman) and photosensitive substances like chlorophyll and β-carotene (via fluorescence). For example, CRFS identified unique Raman peaks (1161 and 1527 cm^{-1}) related to chlorophyll and carotenoids, alongside fluorescence quenching, significantly improving the accuracy of quantitative analysis of adulterated samples. The model achieved an impressive root mean square error (RMSE) of

0.0068 and an R^2 value of 0.9996 in predicting adulteration levels.

Ma *et al*. present a novel time-resolved laser-induced fluorescence (TRLIF) method for detecting low-level adulteration in extra virgin olive oil (EVOO) with refined olive oil, soybean oil, and sunflower oil [57]. By combining fluorescence lifetime (FLT) measurements with parallel factor analysis (PARAFAC), the TRLIF approach achieves a cross-validation coefficient of determination (R^2) above 0.90 and a prediction error below 1.40%. This demonstrates its effectiveness in classifying and quantifying adulteration, even at concentrations as low as 1%.

Hao *et al*. used laser-induced fluorescence (LIF) spectroscopy with PCA and PLS models to identify adulteration in various vegetable oils, including olive and peanut oils [58]. The method achieved prediction linearity above 0.995 and an error rate below 2%, proving its feasibility for real-time detection. Farres *et al*. also used LIF spectroscopy coupled with chemometric methods to detect adulterants in argan oil at levels as low as 0.35%. PCA classified samples effectively, and PLS regression quantified adulteration with high accuracy (R^2 = 0.99) [59].

Another study by Uncu & Ozen compares mid-infrared (FT-IR), UV-Vis, and fluorescence spectroscopy to detect adulteration of fresh olive oils with older ones [60]. Among these, when combined with orthogonal partial least squares discriminant analysis (OPLS-DA), fluorescence spectroscopy achieved over 95% correct classification accuracy for adulterated samples, with a prediction error as low as 2.82%. The combination of FT-IR and UV-Vis data further enhanced model performance, proving the strength of multi-spectral data fusion in improving detection sensitivity.

The doctoral thesis "Olive Oil Characterization Using Excitation-Emission Fluorescence Spectroscopy and Three-Way Methods of Analysis" by Francesca Guimet Vila presents a novel approach to olive oil analysis using Excitation-Emission Fluorescence Spectroscopy (EEFS) combined with chemometric techniques [61]. EEFS generates three-dimensional fluorescence data, capturing unique profiles of olive oil components such as vitamin E, chlorophylls, and oxidation products, allowing precise characterization. For example, EVOOs exhibited intense peaks near 525 nm due to higher vitamin E content, while refined oils showed broader peaks around 450 nm, linked to oxidation products. Using advanced data analysis, such as parallel factor analysis (PARAFAC) and non-negative matrix factorization (NMF), the method accurately classified oil types and detected adulterations, such as olive pomace oil mixed at low levels with extra virgin olive oil. The technique is also rapid, with EEMs recorded in as little as 2–12 minutes, depending on step size, significantly reducing analysis time compared to chromatographic methods.

Zhang *et al*. present an innovative, non-destructive method for detecting and quantifying adulteration in extra virgin olive oil (EVOO) [62]. By inducing fluorescence using LEDs across wavelengths from ultraviolet (372 nm) to blue, the study identifies the UV LED at 372 nm as the most effective for generating fluorescence spectra. Adulterated samples were prepared by mixing EVOO with peanut and soybean oils in concentrations ranging from 5% to 50% (v/v). Regression models analyzing the fluorescence spectra demonstrated substantial predictive accuracy, achieving an R^2 of 0.98 and a root mean square error (RMSE) of 0.02. This technique's high sensitivity and precision highlight its feasibility for real-time detection of adulteration. This study, however, involved the experimental setup of controlled lab conditions and prepared samples. The method's effectiveness in real-world scenarios, such as testing market-available olive oils with unknown adulteration, remains unexplored.

These studies highlight the potential of fluorescence as a reliable tool for quality control in the olive oil industry. Front-face fluorescence spectroscopy eliminates the need for sample dilution while mitigating inner filter effects. Moreover, these optical methods provide rapid results, are environmentally friendly, and require minimal sample preparation compared to traditional chromatographic techniques. For instance, a study on fluorescence imaging with UV excitation (365 nm) demonstrated effective adulteration detection even at low mixing ratios [56]. The success of these techniques in accurately quantifying adulteration levels, such as soybean oil content (ranging from 2% to 30%) or differentiating storage conditions, underscores their practical utility in preventing fraud and maintaining quality standards in the EVOO market.

In conclusion, fluorescence spectroscopy has proven to be a highly effective and versatile tool for detecting adulteration and assessing the quality of edible oils. By identifying unique molecular fingerprints such as tocopherols, phenolic compounds, and oxidation products, it enables sensitive and rapid detection of adulterants, even at low concentrations. Techniques like laser-induced fluorescence (LIF), time-resolved fluorescence (TRLIF), and Confocal Raman and fluorescence spectroscopy (CRFS) have demonstrated precise quantitative analysis while minimizing sample preparation. Portable fluorescence systems with LEDs and laser diodes further enhance accessibility for on-site quality monitoring, and the integration of machine learning and chemometric methods has significantly improved classification accuracy and prediction reliability. Future efforts should focus on adapting fluorescence-based techniques for real-world applications and expanding their scope to detect a broader range of adulterants. Addressing these challenges will solidify fluorescence spectroscopy as a vital technology for ensuring the

authenticity and quality of edible oils in the global market.

d) DNA-based technique

DNA-based techniques detect adulteration in edible oils by identifying species-specific genetic material to verify the botanical origin of the oil. Despite processing, trace amounts of degraded DNA can often be extracted and analyzed. The core method is polymerase chain reaction (PCR), which amplifies specific DNA sequences using short primers targeting unique genetic markers.

Techniques such as quantitative PCR or DNA barcoding allow sensitive and specific detection, even at low levels of adulteration. By comparing the amplified DNA profile with known reference sequences, the presence of undeclared or cheaper plant oils can be confirmed. Unlike spectroscopic methods that analyze chemical properties, DNA-based approaches directly target the biological origin, providing robust traceability and authenticity assurance.

The study by Vietina *et al*. explores High-Resolution Melting (HRM) analysis as a powerful tool for detecting adulteration in olive oil through plant DNA identification [63]. HRM, a post-PCR technique, distinguishes DNA sequences based on their melting profiles, allowing the identification of different plant oils mixed with olive oil. In this study, DNA was extracted from various oils, including hazelnut, sunflower, maize, peanut, and soybean oils, and amplified using real-time PCR. The HRM analysis successfully differentiated these oils from olive oil by comparing their unique DNA melting profiles. Notably, the method could detect adulteration levels as low as 5%, demonstrating its high sensitivity. One of the significant advantages of HRM is its cost-effectiveness, offering a cheaper alternative to traditional chromatographic methods. Additionally, it provides rapid results without complex sample preparation and offers high specificity in identifying different plant oils in mixtures.

Building on this, Ganopoulos *et al*. developed an enhanced approach known as Barcode-HRM (Bar-HRM), which combines universal chloroplast DNA barcoding regions with HRM analysis for even more precise identification and quantification of adulterants in olive oil [64]. Using the rbcL region as the target, this method could differentiate six vegetable oil species including olive, sunflower, sesame, soya, canola, and corn oil based on their distinct melting temperature profiles. Remarkably, the Bar HRM approach demonstrated the ability to detect canola oil adulteration in olive oil at concentrations as low as 1% (w/w), outperforming previously reported HRM detection limits. The method not only preserved the advantages of conventional HRM such as cost-efficiency, speed, and closed-tube analysis but also improved its resolving power by targeting plastid DNA regions, which are more reliably recovered in oil matrices. This advancement underscores Bar-HRM's potential as a highly sensitive, accurate, and scalable tool for food authentication and forensic analysis.

Ramos-Gómez et al. present a quantitative PCR (qPCR) method for detecting hazelnut and almond adulteration in virgin olive oil, addressing concerns over food safety due to the allergenic potential of these nut oils [18]. The researchers targeted allergen-specific genes using SYBR Green fluorescence and post-PCR melting curve analysis, allowing precise identification of hazelnut (*Cor a 1*) and almond (*Pru av 1*) DNA. The assay demonstrated high specificity and sensitivity, detecting adulteration levels as low as 5% with a standard qPCR assay and down to 2.5% with a nested qPCR approach.

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Table 2 Summary of fiber optic-based sensor and fluorescence-based sensor

Method	Type of Oils	Adulterants	Sensitivity/Accuracy	Adulteration Range	Ref.
Long-period fiber grating (LPFG)	VOO	Sunflower oil	0.07 dB/vol%	4-30%	[39]
Long-period fiber grating (LPFG)	POO	Cottonseed oil	N/A	5-50%	[40]
D-shaped optical fiber refractometer	EVOO	Canola, corn, cottonseed, soybean, sunflower oils	0.037 dB/%	>9%	[41]
Tapered Plastic Optical Fiber (POF) + Graphene/MWCNT Coatings	Olive Oil	Lard	Graphene-coated POF=0.427 dBm/%, MWCNT-coated POF: 1.189 dBm/%	N/A	[42]
Silica Optical Fiber (SMS Structure)	Olive Oil	Lard	1.1107 dBm/%	0-5%	[43]
Surface plasmon resonance (SPR)	Vegetable oils (coconut, corn, olive, palm)	N/A (Analyzes variance in oils)	N/A	N/A	[44]
Localized surface plasmon resonance (LSPR)	Virgin coconut oil (VCO)	Coconut oil, mustard oil	81.67–80% accuracy in validated samples	10-90%	[45]
Fiber optic device using NIR at 1550 nm	Olive Oil	Palm Oil	0.09 dBm/%	0-100%	[47]
Fluorescence Spectroscopy (EEM)	EVOO	VOO	5% w/w of OPO	N/A	[61]
Laser-Induced Fluorescence (LIF)	EVOO	Soybean Oil (2–30%)	RMSE = 2.72%.	100%	[53]
Confocal Raman and Fluorescence (CRFS)	EVOO	Soybean Oil	RMSE = 0.0068	0-100%	[56]
Front-Face Fluorescence Imaging	EVOO	VOO	N/A	N/A	[54]
Fluorescence Spectroscopy with Machine Learning	EVOO	Expired EVOO	Classification Accuracy: 91–100%	N/A	[55]
Time-Resolved Laser-Induced Fluorescence (TRLIF)	EVOO	Refined Olive Oil (ROO), Soybean Oil (SBO), Sunflower Oil (SFO)	N/A	>1%	[57]
Fluorescence Spectroscopy + Chemometrics	Fresh Olive Oil	Old Olive Oil (from previous harvest)	Over 95% classification accuracy	N/A	[60]
LED-induced fluorescence spectroscopy	EVOO	Peanut, Soybean Oil	RMSE=0.02	5-50%	[62]

While HRM effectively detects a broad range of plant-based adulterants, it struggles with oils with similar melting profiles, such as sesame or avocado oils. On the other hand, qPCR targets specific DNA sequences, limiting its use to pre-identified adulterants like hazelnut and almond. A gap exists in developing a hybrid method that combines broad-spectrum capabilities with qPCR's specificity for comprehensive detection.

In conclusion, DNA-based analytical techniques like High-Resolution Melting (HRM) analysis and quantitative PCR (qPCR) offer significant advancements in detecting adulteration in edible oils. HRM provides a rapid, cost-effective, and sensitive method for distinguishing various plant oils through unique DNA melting profiles, enabling the detection of adulteration levels as low as 5%. Similarly, qPCR demonstrates exceptional sensitivity and specificity by targeting allergen-specific genes, detecting nut oils like hazelnut and almond at concentrations as low as 2.5%. While HRM excels in broad-spectrum analysis, its limitations with closely related oils highlight the need for hybrid methods that combine HRM's versatility with qPCR's precise targeting. Addressing these gaps can pave the way for robust, comprehensive solutions to ensure the authenticity and safety of edible oils in the global market.

e) Colorimetric-based technique

Colorimetric-based techniques offer a simple, cost-effective, and non-destructive approach for detecting edible oil adulteration by observing visually perceivable color changes caused by chemical or physical interactions. These methods rely on the formation of colored complexes through reactions between specific reagents and oil components, with adulteration inducing distinct color shifts. The intensity of the color change, often measured using a colorimeter or spectrophotometer, can be quantified using Beer-Lambert's Law (Eqn. 1), where absorbance is related to the concentration of the colored species. Colorimetric-based techniques have gained significant attention due to their portability and suitability for real-time field applications.

One innovative approach introduced by Huang *et al*. introduces a novel Colorimetric Sensor Array (CSA) for detecting adulteration in extra virgin olive oil (EVOO), offering a simple, cost-effective, and non-destructive alternative to traditional methods [65]. The CSA utilizes chemically responsive dyes on a porous PVDF membrane to detect color changes caused by interactions with volatile organic compounds (VOCs). Statistical tools such as Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) were employed to classify adulteration levels, achieving 100% accuracy in backtracking validation for soybean and corn oil adulterants. Optimized at 100°C for 20 minutes, the CSA demonstrated robust performance and practical applicability, with limitations in lower cross-validation accuracy for corn oil (81.5%), suggesting room for improvement in its discriminatory power for more challenging samples. Figure 5 shows the process of CSA, where the color of the reagent will change after being exposed to light.

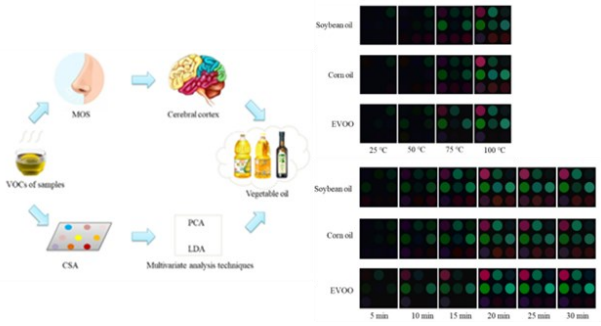

Figure 5 Process of CSA [65]

Building on this, Mehdizadeh *et al*. introduced a novel optoelectronic nose utilizing a colorimetric sensor array (CSA) to detect adulteration in quince seed oil with sunflower and sesame oils [66]. The CSA, developed using six pH indicators applied to silica gel plates, detected volatile organic compounds (VOCs) emitted by oils. Color changes from the indicators were digitally analyzed through machine learning algorithms, achieving a classification error as low as 1.29%. The study highlighted the system's cost-effectiveness, simplicity, and potential application in food quality monitoring and consumer protection.

MuthuKumar *et al*. developed a paper-based microfluidic lab-on-a-chip system for detecting palm oil adulteration in sunflower oil [67]. The device used colorimetric detection with phenolphthalein as an indicator, providing a visual signal for adulteration levels between 10% and 50% (v/v). The study demonstrated the stability of the colorimetric signal over six days and highlighted the potential for smartphone integration for field applications.

Song *et al*. demonstrated a smartphone-based approach for quantifying adulteration in extra virgin olive oil (EVOO) [68]. By illuminating samples with a sequence of colors from a phone screen and recording the changes in color spectra, the system achieved high predictive accuracy (R^2 = 0.98) for adulterant levels between 5% and 50%. This portable, low-cost device offers an accessible method for rapid adulteration detection, making it ideal for resource-limited settings.

Lastly, Wang *et al*. introduced a photometric assay for detecting copper chlorophyll adulterants in edible oils [69]. The method utilized ultraviolet photobleaching to prepare samples, followed by optical absorption measurements at specific wavelengths (600 nm, 650 nm, and 700 nm). The assay demonstrated high accuracy, with 97.9–103.6% recovery rates and a detection limit of 0.05 ppm.

In conclusion, colorimetric-based techniques present a promising, cost-effective, and non-destructive approach for detecting adulteration in edible oils, offering significant advantages in portability and real-time applicability. Innovations like Huang *et al*.'s CSA for EVOO and Mehdizadeh *et al*.'s optoelectronic nose underscore the potential of volatile organic compound detection and machine learning integration for precise classification. Similarly, MuthuKumar *et al*.'s paper-based lab-on-a-chip and Song *et al*.'s smartphone-based quantification highlight the versatility of these methods for field use and resource-limited settings. However, challenges remain, such as improving discriminatory power for complex adulterants and enhancing cross-validation accuracy. Future research could focus on refining sensor specificity, expanding the range of detectable adulterants, and incorporating advanced data analysis techniques to bridge these gaps. By addressing these limitations, colorimetric methods can become indispensable tools for safeguarding food quality and empowering consumer protection.

Table 3 Summary of DNA-based sensor and colorimetric-based sensor

Method	Type of Oils	Adulterants	Findings	Ref.
High-Resolution Melting (HRM)	Olive Oil	Maize, Sunflower, Hazelnut Oils	HRM successfully detected mixtures with different percentages, proving it cost-effective for adulteration detection.	[63]
Bar-HRM (using rbcL DNA region)	Olive Oil	Canola Oil	Detected as low as 1% (w/w) canola oil in olive oil.	[64]
qPCR with SYBR Green	VOO	Hazelnut, Almond Oils	Detected adulteration at 5% level with qPCR; nested qPCR improved detection to 2.5%.	[18]
CSA	EVOO	Soybean oil, Corn oil	CSA identified adulteration levels based on VOC-induced color changes. LDA achieved 100% accuracy in backtracking validation, and cross-validation accuracy was 90.7% for soybean oil and 81.5% for corn oil.	[65]
Optoelectronic Nose + CSA	Edible Oils	Low-quality oils, synthetic additives	Detected adulteration by analyzing colorimetric patterns with high accuracy (≥95%).	[66]
Paper-Based Microfluidic Devices	Olive oil, Palm oil	Low-grade oils, synthetic dyes	Portable, low-cost detection of adulterants with visible color changes. Detection limit: ~0.5% adulteration.	[67]
Photometric Assay	Olive Oil	Copper chlorophyll	Identified chlorophyll levels exceeding legal limits; the detection limit was 1 ppm.	[69]
Smartphone-Based Video Analysis	Sunflower Oil	Mineral oil, low-quality oils	Real-time detection using smartphone apps. Accuracy: ~90%; highly portable and affordable method.	[68]

3.0 DISCUSSION

Detecting adulteration in edible oils is an ongoing challenge, given its impact on health and market integrity. While various sensing techniques have been developed, interpreting the complex data they generate remains a significant hurdle. In this context, machine learning based systems offer a promising solution to improve detection efficiency. Machine learning algorithms can analyze large volumes of spectral or sensor data, identify patterns associated with adulteration, and make accurate predictions in real time. Moreover, machine learning enhances the robustness of sensing technologies by compensating for variations caused by temperature, sensor drift, or sample inconsistencies. Integrating machine learning into adulteration detection frameworks not only accelerates decision-making but also reduces human error, paving the way for scalable and intelligent food quality monitoring systems.

Spectroscopy methods like FTIR and Raman can provide rapid, non-destructive analysis with high sensitivity. They can detect chemical fingerprints of adulterants in oils. However, their accuracy depends

on complicated chemometric models that require large databases for different oil compositions. The main challenge is to standardize the technology and make it easy to use in daily routines.

Fiber optic sensors offer high-precision real-time monitoring, making them suitable for on-site testing. These sensors detect refractive index changes, which correlate with the purity of the oil. Despite that, they often require fine-tuned calibration and may be sensitive to environmental factors such as temperature and humidity. We need to conduct more research to make the systems more robust and easier to integrate into industrial settings. This will help improve performance and ensure that we can adopt these solutions effectively in real-world applications.

Fluorescence methods are highly selective and can detect even trace amounts of adulterants. They rely on differences in fluorescence properties between pure and adulterated oils. While effective, these techniques sometimes require expensive instrumentation and fluorescent dye labeling, which limits widespread adoption. The research gap here is improving affordability and developing label-free fluorescence approaches for easier applications.

DNA barcoding and PCR-based methods provide unparalleled specificity, particularly for detecting biological adulterants. They are incredibly powerful in identifying plant-based or animal-derived contaminants in oils. However, the main limitation is the need for specialized laboratory setups and skilled personnel. If we want to improve it, the research should focus on developing portable, user-friendly DNA-based kits for field testing to make it easier for consumers to use.

Colorimetric techniques use simple color changes to indicate adulteration, making them cost-effective and easy to use. They are widely adopted for quick screening but often result in lower sensitivity and specificity than advanced methods. The challenge is to enhance their precision while maintaining affordability, possibly by integrating them with nanomaterials for better performance.

Each detection technique has its own advantages and limitations, making it unlikely that a single method can address all challenges comprehensively. The most effective approach for edible oil adulteration detection lies in hybrid approaches that combine the high precision of fiber optic sensors, the sensitivity of fluorescence, and the practicality of colorimetric methods. By addressing the gaps in these technologies, we can move closer to developing reliable, on-the-spot detection tools that help ensure safer food for everyone. Table 4 summarizes the comparison of optical sensing techniques in terms of their principles, sensitivity, advantages, and limitations.

Table 4 Comparison of optical sensing techniques for edible oil adulteration detection

Technique	Detection principle	Sensitivity	Advantages	Limitations
Spectroscopy-based technique (e.g., FTIR / Raman	Molecular vibration (spectral fingerprinting)	Moderate to high	Rapid, non-destructive, minimal sample preparation	Requires chemometric models, limited on-site use
Fiber optic-based technique	Refractive index change detection via light transmission	High	Real-time, compact, suitable for on-site applications	Sensitive to temperature/humidity, requires calibration
Fluorescence-based technique	Emission from fluorophores upon excitation	Very high	High selectivity, trace-level detection	High cost, may need labels, complex instrumentation
DNA-based technique (e.g., PCR)	Amplification of species-specific genetic material	Very high	Excellent specificity, detects biological adulterants	Lab-based, needs trained personnel and equipment
Colorimetric-based technique	Visible colour change due to chemical reaction	Low to moderate	Simple, low-cost, easy to interpret	Lower sensitivity/specificity, prone to subjective interpretation

4.0 CONCLUSION

Edible oil adulteration remains a significant issue with implications for health, economics, and food safety. Advanced detection methods, including spectroscopy, fluorescence, and optical fiber sensors, offer innovative and effective real-time solutions for identifying and quantifying adulterants. While these techniques show exceptional sensitivity and precision, challenges like standardization, scalability for industrial use, and diverse adulterant handling must be addressed. Future research should prioritize integrating multiple techniques, enhancing portability, and incorporating artificial intelligence for improved accuracy and industrial applicability. These efforts are critical for ensuring the authenticity and quality of edible oils, fostering transparency, and protecting consumer trust.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

[1] Sharma, A., N. Batra, A. Garg, and A. Saxena. 2017. Food Adulteration: A Review. *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*. 5(11): 686–89. https://doi.org/10.22214/ijraset.2017.3129.

[2] Pal, M., and M. Mahinder. 2020. Food Adulteration: A Global Public Health Concern. *Food and Nutrition*. 1(3): 38–39. https://doi.org/10.31579/2637-8914/021.

[3] Habza-Kowalska, E., M. Grela, M. Gryzińska, and P. Listos. 2019. Molecular Techniques for Detecting Food Adulteration. *Medycyna Weterynaryjna*. 75(7): 404–406. https://doi.org/10.21521/mw.6261.

[4] Wen, C., M. Shen, G. Liu, X. Liu, L. Liang, Y. Li, *et al.* 2023. Edible Vegetable Oils from Oil Crops: Preparation, Refining, Authenticity Identification, and Application. *Process Biochemistry*. 124: 168–79. https://doi.org/10.1016/j.procbio.2022.11.017.

[5] Frančáková, H., E. Ivanišová, Š. Dráb, T. Krajčovič, M. Tokár, J. Mareček, and J. Musilová. 2015. Composition of Fatty Acids in Selected Vegetable Oils. *Potravinarstvo Slovak Journal of Food Sciences*. 9(1). https://doi.org/10.5219/556.

[6] Matthäus, B., and M. M. Özcan. 2015. Oil Content, Fatty Acid Composition, and Distributions of Vitamin-E-Active Compounds of Some Fruit Seed Oils. *Antioxidants*. 4(1): 124–33. https://doi.org/10.3390/antiox4010124.

[7] Malavi, D., A. Nikkhah, K. Raes, and S. Van Haute. 2023. Hyperspectral Imaging and Chemometrics for Authentication of Extra Virgin Olive Oil: A Comparative Approach with FTIR, UV–Vis, Raman, and GC–MS. *Foods*. 12(3): 429. https://doi.org/10.3390/foods12030429.

[8] Yang, H., and J. Irudayaraj. 2001. Comparison of Near-Infrared, Fourier Transform-Infrared, and Fourier Transform-Raman Methods for Determining Olive Pomace Oil Adulteration in Extra Virgin Olive Oil. *Journal of the American Oil Chemists' Society*. 78(9): 889–95. https://doi.org/10.1007/s11746-001-0360-6.

[9] Ariza-Ortega, J. A., D. G. Castillo-Torres, E. M. Molina-Trinidad, and J. Díaz-Reyes. 2023. Evaluation of Extra Virgin Olive Oil (*Olea europaea* L.) Adulterated with Soybean Oil (*Glycine max* L. Merr.). *Food Analytical Methods*. 16(6): 1145–48. https://doi.org/10.1007/s12161-023-02490-9.

[10] Jabeur, H., A. Zribi, J. Makni, A. Rebai, R. Abdelhedi, and M. Bouaziz. 2014. Detection of Chemlali Extra-Virgin Olive Oil Adulteration Mixed with Soybean Oil, Corn Oil, and Sunflower Oil by Using GC and HPLC. *Journal of Agricultural and Food Chemistry*. 62(21): 4893–4904. https://doi.org/10.1021/jf500571n.

[11] Mendes, T. O., R. A. da Rocha, B. L. S. Porto, M. A. L. de Oliveira, V. de C. dos Anjos, and M. J. V. Bell. 2015. Quantification of Extra-Virgin Olive Oil Adulteration with Soybean Oil: A Comparative Study of NIR, MIR, and Raman Spectroscopy Associated with Chemometric Approaches. *Food Analytical Methods*. 8(9): 2339–46. https://doi.org/10.1007/s12161-015-0121-y.

[12] Downey, G., P. McIntyre, and A. N. Davies. 2002. Detecting and Quantifying Sunflower Oil Adulteration in Extra Virgin Olive Oils from the Eastern Mediterranean by Visible and Near-Infrared Spectroscopy. *Journal of Agricultural and Food Chemistry*. 50(20): 5520–25. https://doi.org/10.1021/jf0257188.

[13] Özdemir, D., and B. Öztürk. 2007. Near Infrared Spectroscopic Determination of Olive Oil Adulteration with Sunflower and Corn Oil. *Journal of Food and Drug Analysis*. 15(1): 40–47. https://doi.org/10.38212/2224-6614.2447.

[14] de Lima, T. K., M. Musso, and D. B. Menezes. 2020. Using Raman Spectroscopy and an Exponential Equation Approach to Detect Adulteration of Olive Oil with Rapeseed and Corn Oil. *Food Chemistry*. 333: 127454. https://doi.org/10.1016/j.foodchem.2020.127454.

[15] Di Girolamo, F., A. Masotti, I. Lante, M. Scapaticci, C. D. Calvano, C. Zambonin, *et al.* 2015. A Simple and Effective Mass Spectrometric Approach to Identify the Adulteration of the Mediterranean Diet Component Extra-Virgin Olive Oil with Corn Oil. *International Journal of Molecular Sciences*. 16(9): 20896–912. https://doi.org/10.3390/ijms160920896.

[16] Dulf, Francisc V., Constantin Bele, M. L. Ungureşan, and Carmen Socaciu. 2007. Qualitative and Quantitative Markers to Identify the Quality and Adulteration of Olive Oil with Rapeseed Oil. *Bulletin of the University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca: Agriculture*. 63: 575–80. https://journals.usamvcluj.ro/index.php/agriculture/article/view/1469.

[17] Mildner-Szkudlarz, S., and H. H. Jeleń. 2010. Detection of Olive Oil Adulteration with Rapeseed and Sunflower Oils Using MOS Electronic Nose and SPME-MS. *Journal of Food Quality*. 33(1): 21–41. https://doi.org/10.1111/j.1745-4557.2009.00286.x.

[18] Ramos-Gómez, S., M. D. Busto, and N. Ortega. 2023. Detection of Hazelnut and Almond Adulteration in Olive Oil: An Approach by qPCR. *Molecules*. 28(10): 4248. https://doi.org/10.3390/molecules28104248.

[19] Nanou, E., N. Pliatsika, and S. Couris. 2023. Rapid Authentication and Detection of Olive Oil Adulteration Using Laser-Induced Breakdown Spectroscopy. *Molecules*. 28(24): 7960. https://doi.org/10.3390/molecules28247960.

[20] Kanwal, N., and S. G. Musharraf. 2024. Analytical Approaches for the Determination of Adulterated Animal Fats and Vegetable Oils in Food and Non-Food Samples. *Food Chemistry*. 140786. https://doi.org/10.1016/j.foodchem.2024.140786.

[21] Hashempour-Baltork, F., S. V. Zade, Y. Mazaheri, A. M. Alizadeh, H. Rastegar, Z. Abdian, *et al.* 2024. Recent Methods in Detection of Olive Oil Adulteration: State of the Art. *Journal of Agriculture and Food Research*. 16: 101123. https://doi.org/10.1016/j.jafr.2024.101123.

[22] Zarezadeh, M. R., M. Aboonajmi, and M. Ghasemi-Varnamkhasti. 2022. Applications of Ultrasound Techniques in Tandem with Non-Destructive Approaches for the Quality Evaluation of Edible Oils. *Journal of Food Science and Technology*. 59(8): 2940–50. https://doi.org/10.1007/s13197-022-05351-1.

[23] Zhou, Y., W. Zhao, Y. Lai, B. Zhang, and D. Zhang. 2020. Edible Plant Oil: Global Status, Health Issues, and Perspectives. *Frontiers in Plant Science*. 11: 1315. https://doi.org/10.3389/fpls.2020.01315.

[24] Perkampus, H.-H. 2013. *UV–VIS Spectroscopy and Its Applications*. Springer Science & Business Media.

[25] Torrecilla, J. S., E. Rojo, J. C. Domínguez, and F. Rodríguez. 2010. A Novel Method to Quantify the Adulteration of Extra Virgin Olive Oil with Low-Grade Olive Oils by UV–Vis. *Journal of Agricultural and Food Chemistry*. 58(3): 1679–84. https://doi.org/10.1021/jf903308u.

[26] Milanez, K. D. T. M., T. C. A. Nóbrega, D. S. Nascimento, M. Insausti, B. S. F. Band, and M. J. C. Pontes. 2017. Multivariate Modeling for Detecting Adulteration of Extra Virgin Olive Oil with Soybean Oil Using Fluorescence and UV–Vis Spectroscopies: A Preliminary Approach. *LWT–Food Science and Technology*. 85: 9–15. https://doi.org/10.1016/j.lwt.2017.06.060.

[27] Aenugu, H. P. R., D. S. Kumar, N. P. Srisudharson, S. Ghosh, and D. Banji. 2011. Near Infrared Spectroscopy—An Overview. *International Journal of ChemTech Research*. 3(2): 825–36.

[28] Wesley, I. J., R. J. Barnes, and A. E. J. McGill. 1995. Measurement of Adulteration of Olive Oils by Near-Infrared Spectroscopy. *Journal of the American Oil Chemists' Society*. 72(3): 289–92. https://doi.org/10.1007/BF02541084.

[29] Melendreras, C., A. Soldado, J. M. Costa-Fernández, A. López, M. Valledor, J. C. Campo, and F. Ferrero. 2023. An Affordable NIR Spectroscopic System for Fraud Detection in Olive Oil. *Sensors*. 23(3): 1728. https://doi.org/10.3390/s23031728.

[30] Su, N., S. Weng, L. Wang, and T. Xu. 2021. Reflectance Spectroscopy with Multivariate Methods for Non-Destructive Discrimination of Edible Oil Adulteration. *Biosensors*. 11(12): 492. https://doi.org/10.3390/bios11120492.

[31] Pulassery, S., B. Abraham, N. Ajikumar, A. Munnilath, and K. Yoosaf. 2022. Rapid Iodine Value Estimation Using a Handheld Raman Spectrometer for On-Site, Reagent-Free Authentication of Edible Oils. *ACS Omega*. 7(11): 9164–71. https://doi.org/10.1021/acsomega.1c05123.

[32] Shipp, D. W., F. Sinjab, and I. Notingher. 2017. Raman Spectroscopy: Techniques and Applications in the Life Sciences. *Advances in Optics and Photonics*. 9(2): 315–428. https://doi.org/10.1364/AOP.9.000315.

[33] Kakouri, E., P. K. Revelou, C. Kanakis, D. Daferera, C. S. Pappas, and P. A. Tarantilis. 2021. Authentication of the Botanical and Geographical Origin and Detection of Adulteration of Olive Oil Using Gas Chromatography, Infrared, and Raman Spectroscopy Techniques: A Review. *Foods*. 10(7): 1565. https://doi.org/10.3390/foods10071565.

[34] Zou, M. Q., X. F. Zhang, X. H. Qi, H. L. Ma, Y. Dong, C. W. Liu, *et al.* 2009. Rapid Authentication of Olive Oil Adulteration by Raman Spectrometry. *Journal of Agricultural and Food Chemistry*. 57(14): 6001–6. https://doi.org/10.1021/jf900217s.

[35] Andoh, S. S., T. Nuutinen, C. Mingle, and M. Roussey. 2019. Qualitative Analysis of Sudan IV in Edible Palm Oil. *Journal of the European Optical Society–Rapid Publications*. 15(1). https://doi.org/10.1186/s41476-019-0117-0.

[36] Jiang, Y., M. Su, T. Yu, S. Du, L. Liao, H. Wang, *et al.* 2021. Quantitative Determination of Peroxide Value of Edible Oil by Algorithm-Assisted Liquid Interfacial Surface-Enhanced Raman Spectroscopy. *Food Chemistry*. 344: 128709. https://doi.org/10.1016/j.foodchem.2020.128709.

[37] Camerlingo, C., M. Portaccio, I. Delfino, and M. Lepore. 2019. Surface-Enhanced Raman Spectroscopy for Monitoring Extra-Virgin Olive Oil Bioactive Components. *Journal of Chemistry*. 2019: 9537419. https://doi.org/10.1155/2019/9537419.

[38] Moskovits, M. 2005. Surface-Enhanced Raman Spectroscopy: A Brief Retrospective. *Journal of Raman Spectroscopy*. 36(6–7): 485–96. https://doi.org/10.1002/jrs.1362.

[39] Libish, T. M., M. C. Bobby, J. Linesh, S. Mathew, C. Pradeep, V. P. N. Nampoori, *et al.* 2013. Detection of Adulteration in Virgin Olive Oil Using a Fiber Optic Long Period Grating-Based Sensor. *Laser Physics*. 23(4): 045112. https://doi.org/10.1088/1054-660X/23/4/045112.

[40] Liang, T. C., H. S. Huang, and M. H. Chuang. 2015. Study on Fiber Grating Sensors for Concentration Measurement of Cottonseed Oil Adulteration in Pure Olive Oil. *Microelectronic Engineering*. 148: 21–24. https://doi.org/10.1016/j.mee.2015.08.003.

[41] de Barros, T. H. C., H. P. Alves, L. S. C. de Miranda, A. A. D. da Silva, E. Fontana, and J. F. Martins-Filho. 2024. D-Shaped Optical Fiber-Based Refractometer for Olive Oil Adulteration Detection. *Food Control*. 166: 110741. https://doi.org/10.1016/j.foodcont.2024.110741.

[42] Puspita, I., N. Irawati, K. A. Madurani, F. Kurniawan, S. Koentjoro, and A. M. Hatta. 2022. Graphene- and Multi-Walled Carbon Nanotubes-Coated Tapered Plastic Optical Fiber for Detection of Lard Adulteration in Olive Oil. *Photonic Sensors*. 12(4). https://doi.org/10.1007/s13320-022-0652-y.

[43] Puspita, I., D. P. Banurea, R. N. Hidayati, N. Irawati, M. Marinah, A. M. Hatta, and F. Kurniawan. 2018. Detection of Lard Adulteration in Olive Oil by Using Silica Optical Fiber. In *2018 3rd International Seminar on Sensors, Instrumentation, Measurement and Metrology (ISSIMM)*, 30–33. IEEE. https://doi.org/10.1109/ISSIMM.2018.8727640.

[44] Supardianningsih, R. D. Panggabean, I. A. Romadhon, F. D. Laksono, U. Nofianti, and K. Abraha. 2018. Detection of Vegetable Oil Variance Using Surface Plasmon Resonance (SPR) Technique. *IOP Conference Series: Materials Science and Engineering*. 367(1): 012021. https://doi.org/10.1088/1757-899X/367/1/012021.

[45] Auddy, I., B. O. Madhu, S. Saravanan, A. Rawson, and C. Anandharamakrishnan. 2024. Development of Unique Signature to Define the Extent of Adulteration in Virgin Coconut Oil (VCO) by Localized Surface Plasmon Resonance (LSPR) System. *Food Analytical Methods*. 17(8): 1149–60. https://doi.org/10.1007/s12161-024-02632-7.

[46] Bousiakou, L. G., H. Gebavi, L. Mikac, S. Karapetis, and M. Ivanda. 2019. Surface Enhanced Raman Spectroscopy for Molecular Identification—A Review on Surface Plasmon Resonance (SPR) and Localised Surface Plasmon Resonance (LSPR) in Optical Nanobiosensing. *Croatica Chemica Acta*. 92(4): 479–94. https://doi.org/10.5562/cca3558.

[47] Pal, P., J. Stephen, and J. Mathew. 2025. Fiber Optic Device for the Detection of Adulteration of Olive Oil with Palm Oil. *Microwave and Optical Technology Letters*. 67(5): e70210. https://doi.org/10.1002/mop.70210.

[48] Willets, K. A., and R. P. Van Duyne. 2007. Localized Surface Plasmon Resonance Spectroscopy and Sensing. *Annual Review of Physical Chemistry*. 58: 267–97. https://doi.org/10.1146/annurev.physchem.58.032806.104607.

[49] Jameson, D. M. 2014. *Introduction to Fluorescence*. Taylor & Francis. https://doi.org/10.1201/b16502.

[50] Kable, S. 2019. Basic Principles of Fluorescence. In *Fundamentals of Fluorescence Imaging*. 1–34. Jenny Stanford Publishing. https://doi.org/10.1201/9781351129404-1.

[51] Williams, R. T., and J. W. Bridges. 1964. Fluorescence of Solutions: A Review. *Journal of Clinical Pathology*. 17(4): 371–94. https://doi.org/10.1136/jcp.17.4.371.

[52] Sharma, A., D. Bueno, S. Bhand, J. L. Marty, and R. Muñoz. 2018. Evaluation of Various Factors Affecting Fluorescence Emission Behavior of Ochratoxin A: Effect of pH, Solvent, and Salt Composition. *Biomedical Journal of Scientific & Technical Research*. 10. https://doi.org/10.26717/BJSTR.2018.10.001979.

[53] Li, Y., S. Chen, H. Chen, P. Guo, T. Li, and Q. Xu. 2020. Effect of Thermal Oxidation on Detection of Adulteration at Low Concentrations in Extra Virgin Olive Oil: Study Based on Laser-Induced Fluorescence Spectroscopy Combined with KPCA–LDA. *Food Chemistry*. 309: 125669. https://doi.org/10.1016/j.foodchem.2019.125669.

[54] Omwange, K. A., D. F. Al Riza, Y. Saito, T. Suzuki, Y. Ogawa, K. Shiraga, et al. 2021. Potential of Front Face Fluorescence Spectroscopy and Fluorescence Imaging in

Discriminating Adulterated Extra-Virgin Olive Oil with Virgin Olive Oil. *Food Control*. 124: 107906. https://doi.org/10.1016/j.foodcont.2021.107906.

[55] Lastra-Mejías, M., M. Izquierdo, A. Torreblanca-Zanca, R. Aroca-Santos, J. C. Cancilla, J. E. Sepúlveda-Díaz, and J. S. Torrecilla. 2019. Cognitive Fluorescence Sensing to Monitor the Storage Conditions and Locate Adulterations of Extra Virgin Olive Oil. *Food Control*. 103: 48–58. https://doi.org/10.1016/j.foodcont.2019.03.033.

[56] Wang, H., and X. Wan. 2021. Effect of Chlorophyll Fluorescence Quenching on Quantitative Analysis of Adulteration in Extra Virgin Olive Oil. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*. 248: 119183. https://doi.org/10.1016/j.saa.2020.119183.

[57] Ma, T., H. Jiang, S. Tsuchikawa, and T. Inagaki. 2024. Development of a Time-Resolved Laser-Induced Fluorescence Fingerprinting Method for Detecting Low-Level Adulteration in Extra Virgin Olive Oil. *Food Chemistry*. 142125. https://doi.org/10.1016/j.foodchem.2024.142125.

[58] Hao, S., L. Zhu, R. Sui, M. Zuo, N. Luo, J. Shi, *et al.* 2019. Identification and Quantification of Vegetable Oil Adulteration with Waste Frying Oil by Laser-Induced Fluorescence Spectroscopy. *OSA Continuum*. 2(4): 1148–54. https://doi.org/10.1364/OSAC.2.001148.

[59] Farres, S., L. Srata, M. Chikri, S. Addou, and F. Fethi. 2023. Rapid Detection of Argan Oil Adulteration by Frying Oils Using Laser-Induced Fluorescence Spectroscopy Combined with Chemometrics Tools. *Grasas y Aceites*. 74(3): e520. https://doi.org/10.3989/gya.0565221.

[60] Uncu, O., and B. Ozen. 2019. A Comparative Study of Mid-Infrared, UV–Visible, and Fluorescence Spectroscopy in Combination with Chemometrics for the Detection of Adulteration of Fresh Olive Oils with Old Olive Oils. *Food Control*. 105: 209–18. https://doi.org/10.1016/j.foodcont.2019.06.013.

[61] Guimet Vila, F. 2006. Olive Oil Characterization Using Excitation-Emission Fluorescence Spectroscopy and Three-Way Methods of Analysis. PhD diss., Universitat Rovira i Virgili.

[62] Zhang, T., Y. Liu, Z. Dai, L. Cui, H. Lin, Z. Li, *et al*. 2022. Quantitative Detection of Extra Virgin Olive Oil Adulteration, as Opposed to Peanut and Soybean Oil, Employing LED-Induced Fluorescence Spectroscopy. *Sensors*. 22(3): 1227. https://doi.org/10.3390/s22031227.

[63] Vietina, M., C. Agrimonti, and N. Marmiroli. 2013. Detection of Plant Oil DNA Using High-Resolution Melting (HRM) Post-PCR Analysis: A Tool for Disclosure of Olive Oil Adulteration. *Food Chemistry*. 141(4): 3820–26. https://doi.org/10.1016/j.foodchem.2013.06.075.

[64] Ganopoulos, I., C. Bazakos, P. Madesis, P. Kalaitzis, and A. Tsaftaris. 2013. Barcode DNA High-Resolution Melting (Bar-HRM) Analysis as a Novel Close-Tubed and Accurate Tool for Olive Oil Forensic Use. *Journal of the Science of Food and Agriculture*. 93(9): 2281–86. https://doi.org/10.1002/jsfa.6040.

[65] Huang, L., M. Wang, and H. Liu. 2022. Identification of Adulterated Extra Virgin Olive Oil by Colorimetric Sensor Array. *Food Analytical Methods*. 15(3): 647–57. https://doi.org/10.1007/s12161-021-02141-x.

[66] Mehdizadeh, S. A., M. Noshad, M. Chaharlangi, and Y. Ampatzidis. 2023. Development of an Innovative Optoelectronic Nose for Detecting Adulteration in Quince Seed Oil. *Foods*. 12(23): 4350. https://doi.org/10.3390/foods12234350.

[67] Muthukumar, R., A. Kapoor, S. Balasubramanian, V. Vaishampayan, and M. Gabhane. 2021. Detection of Adulteration in Sunflower Oil Using Paper-Based Microfluidic Lab-on-a-Chip Devices. *Materials Today: Proceedings*. 34: 496–501. https://doi.org/10.1016/j.matpr.2020.03.099.

[68] Song, W., Z. Song, J. Vincent, H. Wang, and Z. Wang. 2020. Quantification of Extra Virgin Olive Oil Adulteration Using Smartphone Videos. *Talanta*. 216: 120920. https://doi.org/10.1016/j.talanta.2020.120920.

[69] Wang, H. C., Y. T. Hou, and B. C. Hsieh. 2018. Direct Photometric Assay for Copper Chlorophyll Adulterants in Edible Oil by the Aid of an Ultraviolet-Photobleaching Pretreatment. *Journal of Agricultural and Food Chemistry*. 66(33): 8859–63. https://doi.org/10.1021/acs.jafc.8b02170.