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The application of portable NIR spectroscopy for food authentication and quality control

[Aplikasi spektroskopi Near-Infrared (NIR) portabel untuk autentikasi dan pengendalian mutu pangan]

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ABSTRACT

Food authentication and quality control have become major challenges in the global food industry, particularly due to issues of food adulteration that impact consumer health and product integrity in the market. Portable Near-Infrared (NIR) spectroscopy has emerged as a rapid, non-destructive, and environmentally friendly technology with great potential for detecting adulteration and ensuring product quality, directly at various points along the supply chain. This review article discusses the application of portable NIR spectroscopy in the authentication of four major categories of food products: liquids, powders, oils, and meats. The review highlights the types of samples and adulterants used, as well as the classification and prediction performance reported across studies. The results demonstrate that portable NIR can achieve high classification accuracy (>90%) and predictive performance with R^2 values exceeding 0.90 and Ratio Prediction Deviation (RPD) values above 3, depending on the product type and analytical approach. Although the performance of portable devices is generally slightly lower than benchtop instruments, their advantages in mobility and ease of use make them highly promising for field applications. Future studies are recomended to develop more universal model, broaden the range of commodities investigated, and integrate this technology with other digital approaches to strengthen food quality control systems that are faster, more precise, and sustainable.

Keywords: food authentication, food adulteration, portable NIR spectroscopy, food quality control

ABSTRAK

Autentikasi dan pengendalian mutu pangan menjadi tantangan utama dalam industri pangan global, terutama terkait dengan isu pemalsuan bahan pangan yang berdampak pada kesehatan konsumen dan integritas produk di pasaran. Spektroskopi *Near-Infrared* (NIR) portabel hadir sebagai teknologi cepat, non-destruktif, dan ramah lingkungan yang berpotensi dalam deteksi pemalsuan serta penjaminan mutu produk secara langsung di berbagai titik rantai pasok. Artikel *review* ini mengulas pemanfaatan spektroskopi NIR portabel dalam autentikasi empat kategori utama produk pangan, yaitu produk cair, bubuk, minyak, dan daging. Kajian ini menyoroti jenis sampel dan adulteran serta performa klasifikasi dan prediksi dalam berbagai studi. Hasil menunjukkan bahwa NIR portabel mampu mencapai akurasi tinggi (>90%) dalam klasifikasi, serta nilai R^2 > 0,90 dan *Ratio Predicition Deviation* (RPD) > 3 dalam prediksi tingkat pemalsuan, bergantung pada jenis produk dan pendekatan yang diterapkan. Meskipun performa instrumen portabel umumnya masih sedikit di bawah perangkat *benchtop*, keunggulan dari sisi mobilitas dan kemudahan penggunaan menjadikannya sangat potensial untuk diterapkan langsung di lapangan. Penelitian selanjutnya direkomendasikan untuk merancang model yang lebih universal, memperluas cakupan komoditas yang diteliti, serta mengintegrasikan teknologi ini dengan berbagai pendekatan digital lainnya guna menunjang sistem pengendalian mutu pangan yang lebih cepat, presisi, dan berkelanjutan.

Kata kunci: autentikasi pangan, pengendalian mutu pangan, pemalsuan bahan pangan, spektroskopi NIR portabel

Introduction

Safe, authentic, and quality-compliant food is a top priority in modern agro-industrial systems. Food product authentication is an effort to ensure a product's authenticity, both in terms of composition, variety, geographic origin, and label claims (Dimitrakopoulou & Vantarakis, 2023). Meanwhile, food quality control

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is a series of processes to ensure that products comply with applicable standards, quality, and regulations, including monitoring chemical, physical, and sensory parameters (Singh & Prashant, 2022). As the complexity of global supply chains and trade increases, issues such as food adulteration, food fraud, and claims of authenticity of varieties and geographic origin have become important concerns for industry players, regulators, and consumers (Katerinopoulou et al., 2020; Chien et al., 2023). Common authentication and quality control methods currently used include chromatography, UV-Vis, High-Performance Liquid Chromatography (HPLC), Gas Chromatography–Mass Spectrometry (GC-MS), and other laboratory methods. While accurate, these techniques are generally destructive, require sample preparation, are expensive, and are impractical for rapid field analysis (Xu et al., 2023). This situation drives the need for alternative analytical methods that are fast, non-destructive, efficient, and can be directly applied to the food supply chain.

One rapidly developing technology to meet these needs is NIR spectroscopy. This technology has been widely used in the food industry to efficiently measure various quality parameters such as moisture, fat, protein, and sugar content (Huck, 2020) and certain active compounds such as polyphenols (Arslan et al., 2019) and caffeine (Ayu et al., 2020). Furthermore, physical parameters such as texture can also be monitored indirectly through the NIR spectrum (Basile et al., 2022). In the context of sensory and functional quality, NIR is often applied to assess the level of sweetness (Zeb et al., 2021) or fruit ripeness (Rungpichayapichet et al., 2016). Furthermore, NIR also plays a crucial role in the safety and authentication of food products. Various studies have demonstrated its ability to detect adulteration in oil (Du et al., 2021), honey (Yang et al., 2022), and coffee (Couto et al., 2022), milk (Liang et al., 2025) as well as in identifying varieties (Shi et al., 2022) and geographic origin of products (Torres-Salinas et al., 2024).

The working principle of NIR spectroscopy is based on the interaction of near-infrared light (750–2500 nm) with chemical bonds in molecules. NIR radiation is primarily absorbed by functional groups such as O–H, C–H, S–H, and N–H, thus causing stretching or bending vibrations. The absorbed energy produces a characteristic spectrum consisting of overtones and vibration combinations, which are then used to reveal the composition and structure of molecules in a sample (Cen & He, 2007). As previously mentioned, NIR spectroscopy-based analysis has several advantages, including short measurement times, non-destructive and non-invasive nature, minimal sample preparation, and direct application in the production process (Suhandy & Yulia, 2021). Although benchtop-based NIR spectroscopy has been widely used in food quality analysis in laboratories, this technology has several limitations, such as large instrument size, relatively high cost, and limited mobility, making it limited to laboratory conditions. These factors limit its application for rapid quality control in the field or throughout the supply chain. Advances in optical and sensor technology in the last decade have led to the emergence of portable NIR devices with smaller dimensions, more affordable costs, and in-situ analysis capabilities (Arslan et al., 2019). Various portable NIR devices such as SCiO, MicroNIR, MicroPHAZIR, NeoSpectra, and nanoFTIR NIR are commercially available, enabling rapid spectrum measurements integrated with cloud-based digital systems (Beć et al., 2021; Kappacher et al., 2022). Besides being easy to use, These devices can be combined with machine learning or chemometric approaches to improve the accuracy of chemical classification and prediction. Therefore, the use of portable NIR spectroscopy in agro-industrial product quality assurance systems is becoming increasingly relevant, especially in the context of automation, efficiency, and sustainability of production.

This article aims to critically review the development of portable NIR spectroscopy applications in the authentication and quality control of agricultural food products. This review covers the main product classifications that have been extensively researched, the types of adulteration detected, the analytical tools and approaches used, and the performance trends of classification and prediction models reported in the current literature.

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Materials and method

This study was conducted to explore research trends and developments in the application of portable NIR spectroscopy in the authentication and detection of food product counterfeiting. The approach used was a combination of bibliometric analysis and thematic narrative review. Bibliometric analysis provides a quantitative overview of publication patterns and research trends, while thematic narrative review allows for a more contextual interpretation of research findings (Torres-Salinas et al., 2024). The review process was carried out in three main stages. In the first stage, a literature search was conducted using Publish or Perish (PoP) software with data sources from the Google Scholar database. The search was conducted using the keywords: "portable NIR" AND ("authentication" OR "adulteration" OR "food fraud" OR "portable near infrared spectroscopy") with publication years between 2015 and 2025. Only original research articles written in English and with full text access were considered. Review articles, editorials, and publications that did not present experimental data were excluded. This process resulted in 100 articles for further review.

The second stage involved a bibliometric analysis using VOSviewer software. Article data exported from PoP in RIS format were imported into VOSviewer to perform keyword co-occurrence mapping. This analysis aimed to identify dominant topics, relationships between terms, and thematic trends in research over the past decade. Visualization was conducted by setting a minimum threshold of five keyword occurrences, resulting in several thematic clusters. The third stage consisted of selecting and conducting a thematic analysis of the main articles. From the 100 screened articles, 32 representative studies were selected based on their content depth, relevance to counterfeit detection or authentication, and the use of portable NIR devices. The analysis focused on the tested commodities, types of adulteration, portable devices used, analytical methods, and measurement performance, including R^2 values and classification accuracy. The results are summarized in tables and discussed in the following section.

Results and discussion

Application of portable NIR spectroscopy for food counterfeiting detection and authentication

The use of portable NIR spectroscopy in food authentication and counterfeiting detection has increased significantly in recent years, driven by the growing need for fast, accurate, and non-destructive quality inspection systems (Amirvaresi & Parastar, 2023). Unlike benchtop IR devices, which, while accurate, fast, and non-destructive, are limited to laboratory use due to their bulky size, high instrument cost, and the need for a controlled environment, portable NIR devices are designed to be smaller, lighter, and more portable, allowing for direct field use (Beć et al., 2022). Each type of food product has different physical and chemical characteristics, thus varying analytical approaches and application challenges. In principle, NIR works by exploiting the absorption of near-infrared radiation (750–2500 nm) by specific molecular bonds such as C–H, O–H, and N–H (Aenugu et al., 2011; Czarnecki et al., 2015). This absorption produces an NIR spectrum in the form of a wave pattern that reflects the chemical composition of the sample (Munawar et al., 2022). Through spectral analysis, either directly or with the aid of chemometric methods or machine learning, information can be obtained regarding moisture, protein, fat, and sugar content, or even the differences between the original and adulterated products. In other words, NIR not only provides quantitative data on quality parameters but also produces spectral signatures specific to each type of food (Fodor et al., 2024). Therefore, the application of portable NIR spectroscopy is highly relevant in the post-harvest and distribution stages of the agro-industrial chain, as it allows on-site verification of product quality and authenticity (Ricci et al., 2024).

The following section presents an overview of the use of this technology based on the classification of food product types that has been widely studied in the literature. The discussion focuses on sample types, adulterant forms, classification and prediction performance, and the analytical approaches used in spectral data processing.

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Liquid products

Liquid products are one of the most widely studied food categories in the context of adulteration, primarily due to their homogenous nature, high economic value, and susceptibility to improper mixing of ingredients (Jha et al., 2016). In its application, the use of portable NIR spectroscopy on liquid products is relatively flexible. Several studies have reported that liquid samples can be analyzed directly without special treatment, simply by placing the instrument probe on the surface of the liquid or transparent container. In certain conditions, especially when the packaging is made of opaque or dark-colored materials, the sample must first be removed to allow the NIR radiation to penetrate and provide a representative spectrum (Ikehata, 2020).

A literature review on the application of portable NIR spectroscopy for adulteration detection indicates that dairy products are the most widely studied commodities. Milk adulteration commonly involves the addition of water, mixing with milk from other species, or the use of substances such as urea, hydrogen peroxide, sodium hypochlorite, and detergents to extend shelf life or increase apparent viscosity (Yadav et al., 2023). Such practices not only reduce nutritional quality but may also pose health risks when toxic chemicals are involved (Poonia et al., 2017). Portable NIR spectroscopy has demonstrated high effectiveness in detecting these adulterations. For instance, DD-SIMCA and PLSR models were able to differentiate pure cow's milk from samples adulterated with water, goat's milk, or urea with an R^2 of up to 0.93 (Musa & Yang, 2021). Similarly, the iSPA-PLS-DA model successfully classified goat milk adulteration levels ranging from 5–75% (dos Santos Pereira et al., 2021), while the RSE k-NN ensemble model achieved over 96% accuracy in detecting hydrogen peroxide and sodium hypochlorite in cow's milk (Ehsani et al., 2023b). A summary of studies on portable NIR applications for adulteration detection and authentication of liquid products is presented in Table 1.

Table 1. Summary of studies on the use of portable NIR spectroscopy for the detection of adulteration and authentication of liquid products

No	Products	Types of adulterants	Reference	Model	Portable NIR device	Model performance
1	Cow milk	Water (1-40%)	(Lanjewar et al., 2024)	k-NN, RF, DT, SVM, LR	DLP NIRscan Nano EVM (900-1700 nm)	k-NN R^2v = 0.99, accuracy 100%
2	Cow milk	Organic and non-organic milk	(Liu et al., 2018)	PLS-DA	Micro-NIR 1700 (908-1676 nm)	accuracy 89% (external validation)
3	Cow milk	Geographical origin	(Zhang et al., 2022)	FUDT, UDT, LDA	NIR-M-R2 (900-1700 nm)	Accuracy FUDT 98.67%, UDT 97.33%, LDA 93.33%
4	Cow milk	Bovine milk A2 and non A2	(Moraes-Neto et al., 2025)	DD SIMCA	Micro-NIR (950-1650 nm)	Accuracy 100%
5	Cow milk	Water, goat milk, starch, urea	(Musa & Yang, 2021)	DD-SIMCA, PLSR	Micro-NIR 1700 (908-1676 nm)	DD-SIMCA accurate for classification; prediction R^2p 0.87-0.93.
6	Goat milk	Cow milk (5-75 g/g)	(dos Santos Pereira et al., 2021)	OC-PLS, PLS-DA, iSPA-PLS-D	DLP NIRscan Nano EVM (900-1800 nm)	Accuracy 100% iSPA-PLS-DA

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No	Products	Types of adulterants	Reference	Model	Portable NIR device	Model performance
7	Cow milk	Hyrdrogen peroxide and Sodium hypochlorite	(Ehsani et al., 2023b)	Ensemble classifiers dan k-NN	Linksquare Vis-NIR; Tellspec NIR; Neospectra (400-1000nm; 900-1700 nm; 1350-2550 nm)	Accuracy 96% RSE- k-NN
8	Orange juice	Pulp wash, sucrose and citric acid	(Ehsani et al., 2023a)	PLS-DA, DD SIMCA, ensemble (Gradient Boosting Tree & AdaBoost)	Tellspec NIR; Neospectra (900-1700 nm ; 1350-2550 nm)	DD-SIMCA sensitivity and specificity 100%. GBT, AdaBoost – Tellspec Accuracy 100%
9	Lime juice	Citric acid	(Jahani et al., 2022)	PLS-DA, SIMCA	SCiO (740-1070 nm)	Accuracy 94%-94.5%
10	Lime Juice	Citric acid and water	(Jahani et al., 2020)	PLS-DA, k-NN	Tellspec NIR (900-1700 nm)	Accuracy 88%
11	Whiskey	Methanol	(Kolobaric et al., 2023)	PLS	Micro-NIR (950-1650 nm)	Methanol adulteration 0-5% R^2cv 0.95; Methanol adulteration2-5% R^2cv 0.97
12	Honey	Rice syrup; High fructose corn syrup / HFCS	(Caredda et al., 2024)	LDA, PLS	Micro-NIR (950-1650 nm)	Accuracy 90-95%

Note : k-NN = k-nearest neighbors; RF = Random Forest; SVM = Support Vector Machine; LR = Linear Regression; PLSR = Partial Least Square Regression; PLS-DA = Partial Least Squares Discriminant Analysis; DD-SIMCA = Data-Driven Soft Independent Modelling of Class Analogy; LDA = Linear Discriminant Analysis; OC-PLS = One-Class Partial Least Squares; UDT = Unsupervised Discriminant Technique; FUDT = Fuzzy Unsupervised Discriminant Technique.

Besides milk, other liquid products such as fruit juices, honey, and alcoholic beverages are also common targets for adulteration, often using methods that are less visually detectable but no less harmful to consumers (Jha et al., 2016). In lime juice, adulteration is commonly carried out by adding citric acid and water to mimic the flavor and acidity profile of the original fruit. Studies have shown that approaches using PLS-DA and SIMCA on spectral data from devices such as SCiO and Tellspec can detect adulteration of lime juice with classification accuracy reaching 94–95% (Jahani et al., 2020, 2022). This suggests that although the NIR spectra of pure and blended juice appear visually similar, chemometric algorithms are capable of detecting subtle differences that reflect changes in chemical composition. Meanwhile, in alcoholic beverages such as whiskey, the most dangerous adulteration is the addition of methanol, a toxic compound that can cause blindness or death if consumed in small amounts (4 mL) (Liberski et al., 2022). Methanol detection with portable NIR showed promising results at concentrations ≥2%, with an R^2 value of 0.95, but performance decreased at low concentrations (0.5‑1%)(Kolobaric et al., 2023). This demonstrates that while portable NIR technology holds promise for field testing, it still faces limitations in low-level detection sensitivity, particularly when adulterant concentrations are below the instrument's detection threshold. In honey products, adulteration is typically achieved by adding inexpensive carbohydrate-based syrups such as high-fructose corn syrup (HFCS) or rice syrup. Both of these adulterants have sugar compositions similar to natural honey, but their different fructose-to-glucose ratios allow for detection through NIR spectral analysis. Studies using LDA and PLS approaches have shown that pure and adulterated honey can be distinguished with a classification accuracy of >92%, and even allow for quantitative estimation of adulterant levels if adulterant concentrations are >10% in unifloral honey or

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>20% in multifloral honey (Caredda et al., 2024). Despite its relatively high quantitative detection limit, this method remains highly relevant as a rapid, non-destructive initial screening tool.

In general, the main advantages of using portable NIR spectroscopy in adulteration detection lie in the speed of measurement, the absence of the need for complex sample preparation, and the portability of the equipment, which allows for direct application in the field or supply chain (Teixeira Dos Santos et al., 2013). However, results from various studies also indicate that the performance of this technology is strongly influenced by factors such as the type of equipment, operational wavelength, spectral preprocessing method, and the algorithm model used. Therefore, optimization of the analytical pipeline, including model selection and validation strategy, is crucial to ensure accuracy and reliability in portable NIR-based adulteration detection of agro-industrial products.

Powder products

In addition to liquid products, such as milk, fruit juices, and vegetable oils, powdered food products are also vulnerable to counterfeiting practices driven by economic motives. This makes products like powdered milk, powdered spices, powdered protein, and fruit powders common targets for food fraud. Furthermore, powdered products offer distinct advantages in the application of NIR spectroscopy technology due to their uniform nature and the absence of complex surface reflectances as liquids (Paiva et al., 2022). Therefore, portable NIR spectroscopy-based approaches, which have proven effective on liquids, are now increasingly being adopted to detect counterfeiting in powdered products with high sensitivity and accuracy (Pu et al., 2021).

Recent studies have shown that portable NIR spectroscopy methods have very promising performance in the detection and quantification of adulteration in powdered food products. The types of food ingredients tested in various studies include cereals and legumes (such as corn, rice, wheat, almond, and melon seed flour), protein additives (whey protein concentrate), and high-value spices (such as white pepper, cumin, turmeric, and cocoa). The variety of adulterants used in these studies generally reflects economic motives, such as the use of inexpensive flour, peanut shells, starch, maltodextrin, and non-protein nitrogen compounds (such as melamine and biuret) that are potentially harmful to consumer health (Ranjan et al., 2021; Song, Wang, et al., 2025; Zhou et al., 2022).

Table 2. Summary of studies on the use of portable NIR spectroscopy for the detection of adulteration and authentication of powder products

No	Products	Types of adulterants	Reference	Model	Portable NIR device	Model performance
1	Rice flour; milk powder; corn flour; wheat flour	Cross-substitution among different types of flour	(Zhou et al., 2022)	PLS; CNN-MR; CNN-FS	DLP NIRscan Nano EVM (900-1700 nm)	PLS R^2 0.938; CNN-MR R^2 0.976; CNN-FS R^2 0.970
2	Turmeric powder	Metanil yellow powder; Sudan-dye IV; corn starch powder	(Ranjan et al., 2021)	PCA-DA; SIMCA	Neospectra SWS62221-2.5 (1300-2600 nm)	Accuracy 93-100%
3	Baobab Fruit Pulp Powder	Corn flour; wheat flour; rice flour	(Yegon et al., 2023)	PLS-DA; PLS	NIR-S-G1 (900-1700 nm)	Binary classification accuracy: 98%; multi-class classification sensitivity: 68%; prediction R^2 0.88
4	Whey protein concentrate	Maltodextrin; wheat flour; milk powder	(Song, Yun, et al., 2025)	PLS; K-ELM	Avaspec-NIR512-2.5-HSC-EVO	Prediction R^2p >0.90

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No	Products	Types of adulterants	Reference	Model	Portable NIR device	Model performance
					(1000-2500 nm)	
5	Almond flour	Oat flour; cassava flour; peanut flour; a mixture of flours such as oat, catuaba, guarana powder, nuts, peanuts, and wheat protein	(Netto et al., 2023)	SIMCA; DD-SIMCA; OCPLS; PLS	DLP NIRscan Nano EVM (900-1700 nm); Micro-NIR (950-1650 nm); Neospectra (1350-2550 nm)	Sensitivity 100% for adulterants ≥ 5%; quantification PLS R^2 0.90
6	White pepper powder	Corn flour	(Chen et al., 2022)	LDA; SVM; PLS-DA; SIMCA; PLS	MicroNIR PAT-W (900-1700 nm)	Prediction R^2 0.973; accuracy 100%
7	Cumin powder and cumin seed	Walnut shell, peanut shell, and pecan shell	(Cruz-Tirado et al., 2023)	PCA, DD-SIMCA, PLS	DLP NIRscan Nano EVM (900-1700 nm)	DD-SIMCA sensitivity 82.4%; prediction PLS R^2p >0.90
8	Cacao powder	Cacao shell	(Oliveira et al., 2023)	PLS	DLP NIRscan Nano EVM (900-1700 nm)	Prediction PLS R^2p 0.87
9	Melon seed powder (Cucumeropsis mannii)	Soybeans powder; gari; maize grains	(Zaukuu et al., 2024)	PCA, LDA, PLS-DA	NIR-S-G1 (900-1700 nm)	Adulterant classification above 80%; PLS prediction R^2p 0.81
10	Milk powder (non fat diary milk)	Low molecule weight; nitrogen rich compound (melamine); dicyandiamide; aminotriazole; biuret; and cyanuric acid	(Karunathilaka et al., 2018)	PCA, SIMCA	Phazir handheld NIR device (1500-2400 nm)	SIMCA produced 0 false negatives at a 99% confidence level, with low specificity

Note : CNN-MR = convolutional neural network-multiple regression; CNN-FS = convolutional neural network-feature selection; PCA-DA = principal component analysis-discriminant analysis; SIMCA = soft independent modeling of class analogy; K-ELM = kernel-extreme learning machine

The success rate of adulteration classification methods using portable NIR approaches is very high, even for low adulterant concentrations (1–5%). Models such as PCA-DA, SIMCA, and LDA consistently demonstrate accuracy above 90%, while more sophisticated approaches such as DD-SIMCA, OCPLS, and CNN for single-class classification even record sensitivity and specificity approaching 100% (Cruz-Tirado et al., 2023; Netto et al., 2023). For example, in the almond flour study, this instrument was able to identify adulteration down to the 5% level with high accuracy, demonstrating its potential use for screening in retail markets. Regression algorithms such as PLSR, CNN-MR, and K-ELM can be widely used for adulterant quantification. The CNN-MR model recorded the highest performance with a coefficient of determination (R^2) of 0.976 and a Root Mean Square Error (RMSE) of 0.035 on a multi-component flour mixture (Zhou et al., 2022). Other studies on whey protein, BFPP, cocoa, and milk powder have shown that the PLSR method can generally provide excellent adulterant level prediction accuracy, with R^2 prediction (R^2p) values generally above 0.85 and residual prediction deviation (RPD) exceeding the threshold for predictive model reliability of 2.5 (Oliveira et al., 2023; Song, Yun, et al., 2025; Yegon et al., 2023). A summary of studies on

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the use of portable NIR spectroscopy for the detection and authentication of powdered products can be seen in Table 2.

The NIR spectrum used ranges from 900–2600 nm (depending on the device type). Devices such as the DLP NIRscan Nano EVM (Texas Instruments), NIR-S-G1 (Tellspec), and Avantes and MicroNIR demonstrate good performance despite their different spectral ranges. Devices with a broader spectrum (such as the Neospectra or Avantes 1000–2500 nm) tend to provide higher sensitivity in the detection of non-targeted adulterants, especially for compounds with characteristic absorbances outside the short-wavelength NIR (SW-NIR) range. However, devices with a limited spectrum can still achieve high performance when combined with appropriate preprocessing and classification algorithms, as seen in studies of turmeric, cumin, and white pepper (Ranjan et al., 2021; Chen et al., 2022). Given the complexity of food composition and spectral variations that can be influenced by factors such as geographic origin, harvest season, and processing methods, the use of portable NIR devices is a highly relevant approach, especially in the industrial and quality control sectors.

Oil products

Oil products, both vegetable and animal, are high-value commodities that are often targeted by adulteration practices. This adulteration can involve mixing high-quality oil with cheaper alternatives, or using substandard ingredients such as expired oil. Detecting these practices quickly, non-destructively, and accurately is a critical concern, especially amidst growing consumer awareness and regulatory demands (Yang et al., 2022). Several studies have demonstrated the effectiveness of portable NIR spectroscopy in detecting adulteration in various types of oils. A study by Melendreras et al. (2023) used a DLP NIRscan Nano EVM (900–1700 nm) to differentiate between virgin olive oil and those adulterated with flaxseed, sunflower, and sesame oils. Through Principal Component Analysis (PCA), this study demonstrated a clear separation between classes, while the Partial Least Squares (PLS) model was able to predict adulteration levels with a calibration R^2 of more than 0.96. These results demonstrate a very robust predictive model for field authentication applications. Moreira & Braga (2021) examined copaiba oil (Copaifera sp.), which is susceptible to adulteration by vegetable oils such as palm, sunflower, flaxseed, and soybean. Using the MicroNIR PAT-W instrument and the Data-Driven Soft Independent Modeling of Class Analogy (DD-SIMCA) approach, the classification model achieved a sensitivity and specificity of 97.3% each, with an average efficiency (EFR) of 92.3%.

This indicates that the NIR spectra of authentic samples have characteristics that can be consistently distinguished from adulterated samples, even though they originate from different geographical sources and tree species. The study by Basri et al. (2017) focused on the detection of lard in palm oil. Using MicroNIR (950–1650 nm) and the SIMCA algorithm, classification was successful with an accuracy of over 95%, while adulterant quantification using PLS yielded an $R^2 > 0.99$. This demonstrates the model's high ability to detect even low adulterant concentrations (0.5%). A study by Medeiros et al. (2023) extended the application of adulteration detection to butteroil, a dairy-based product that is also susceptible to adulteration, whether with vegetable oil, lard, or expired butter. The use of the NIRscan Nano DLP tool and a combination of PCA, PLS, DD-SIMCA, and SVM models demonstrated a classification accuracy of >90%. In the context of predicting adulteration levels, the regression models (PLS and SVM-R) recorded an RPD value of >3.0, indicating the reliability of quantitative predictions. Kaufmann et al. (2022) explored the adulteration of coriander oil with canola, soybean, and palm olein oils. The LDA and k-NN classification models, using variable selection methods such as stepwise, PCA loading, and informative region, showed accuracies between 84–99%. Meanwhile, the PLS regression model for predicting adulteration levels produced $R^2 > 0.98$ and RPD between 7.1 and 10. This indicates not only high classification accuracy but also very strong quantitative prediction capabilities, even at varying adulteration levels (1–90%).

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From these various studies, it can be concluded that portable NIR has great potential in detecting oil adulteration practically and efficiently. Devices such as MicroNIR and DLP NIRscan Nano are capable of producing spectra with sufficient resolution to distinguish the chemical characteristics between original and mixed samples. The combination with chemometric and machine learning algorithms strengthens the predictive and classificatory capabilities of this approach. In the context of agro-industry and quality control, this technology is worthy of adoption as part of an integrated quality control system, both at the production line, distribution, and consumer inspection points. A summary of studies on the use of portable NIR spectroscopy for the detection and authentication of oil products can be seen in Table 3.

Table 3. Summary of studies on the use of portable NIR spectroscopy for the detection of adulteration and authentication of oil products

No	Products	Types of adulterants	Reference	Model	Portable NIR device	Model performance
1	Olive oil (extra virgin olive oil, olive oil, virgin olive oil)	Sesame oil, sunflower oil, flax oil	(Melendreras et al., 2023)	PCA, PLS	DLP NIRscan Nano EVM (900-1700 nm)	PLS prediction R^2cv >70%
2	Copaiba oil (Copaifera sp.)	Palm oil; olive oil; sunflower oil; coconut oil; soybean oil	(Moreira & Braga, 2021)	DD-SIMCA	MicroNIR PAT-W, (900-1700 nm)	DD-SIMCA classification with 95% sensitivity, 97.3% specificity, and an average efficiency of 92.3%
3	Palm oil	Lard	(Basri et al., 2017)	SIMCA	MicroNIR (950-1650 nm)	SIMCA classification accuracy >95%; PLS quantification R^2 >0.99
4	Butteroil	Soybean oil; lard; expired butter	(Medeiros et al., 2023)	PCA, PLS, SVM-R, DD-SIMCA, PLS-DA, SVM-C	DLP NIRscan Nano EVM (900-1700 nm)	Classification with DD-SIMCA and SVM-C >90%. Prediction with PLS and SVM-R R^2v >0.93.
5	Coriander oil	Canola oil; Soybean oil; Palm olein	(Kaufmann et al., 2022)	LDA, k-NN, PLS	DLP NIRscan Nano EVM (900-1700 nm)	LDA and k-NN classification accuracy: 84–99%. PLS prediction R^2 0.98–0.99.

Note : SVM-R = support vector machine – regression; SVM-C = support vector machine classification

Meat products

Portable NIR spectroscopy has been widely used for detecting adulteration and authenticating meat products, including species identification, body part classification, and mislabeling detection. The spectral ranges commonly applied are 900–1700 nm and 1600–2439 nm, depending on the device used, such as the Thermo microPhazir RX®, MicroNIR Pro, and Innospectra's NIRS-G1. For example, Wiedemair et al. (2018) employed PLS with the microPhazir RX® device to detect the presence of foreign species in beef, chicken, goat, turkey, pork, and horse meat. Although the device was able to perform general classification, its performance remained limited for detecting low adulteration levels, with R^2 values below 0.62 and RPD values lower than 1.70, indicating low predictive ability for adulteration levels below 10%.

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Several studies have demonstrated the capability of portable NIR combined with chemometric algorithms for food classification. For example, Nolasco-Perez et al. (2019) showed that DLP-NIRS integrated with PCA, LDA, SVM, and RF could distinguish chicken body parts, with the highest accuracy (up to 73%) obtained from whole meat samples, while performance decreased in ground samples. Similarly, Grassi et al. (2018) used MicroNIR OnSite with LDA and SIMCA to differentiate cod and haddock products, achieving 100% prediction accuracy with the LDA model.

Table 4. Summary of studies on the use of portable NIR spectroscopy for the detection of adulteration and authentication of meat products

No	Products	Types of adulterants	Reference	Model	Portable NIR device	Model performance
1	Beef, chicken, mutton, turkey, pork, horse meat	Chicken; pork; mutton	(Wiedemair et al., 2018)	PLS	Thermo microPhazir RX® (1600-2439 nm))	Prediction $R^2 \leq 0.62$ and RPD ≤ 1.70, only able to detect at the 10% level.
2	Chicken meat	Differentiating chicken meat cuts: breast, thigh, and drumstick	(Nolasco-Perez et al., 2019)	PCA, LDA, SVM, RF	DLP NIRscan Nano EVM (900-1700 nm)	Classification accuracy: 97% (whole meat), 73% (minced meat)
3	Alpaca meat	Beef, pork, chicken	(Cruz-Tirado et al., 2024)	PCA, DD-SIMCA, PLS	NIR-S-G1 spectrometer (900-1700 nm)	DD-SIMCA accuracy: 99.7%. PLS prediction yielded R^2 values between 0.76 and 0.90.
4	Fillet and patty of cod and haddock fish	Differentiating fish product types from cod and haddock	(Grassi et al., 2018)	LDA, SIMCA	MicroNIR (950-1650 nm)	LDA prediction accuracy: 100%; SIMCA specificity: 74% and sensitivity: 65%.
5	Chicken breast fillet	Production system mislabeling (organic vs conventional)	(Parastar et al., 2020)	RSDE, PLS-DA, CP-ANN, Q-SVM	MicroNIR Pro NIR (908-1676 nm)	RSDE accuracy >95%, able to distinguish fresh vs frozen chicken, and classify chicken fillets (conventional, free-range, specialty, organic)

Note : CP-ANN = counter propagation artificial neural network; Q-SVM = quadratic support vector machine; RSDE = random subspace discriminant ensemble

Other studies have focused on adulteration detection and authentication. Cruz-Tirado et al. (2024) reported that portable NIRS-G1 combined with PCA, DD-SIMCA, and PLS could classify pure alpaca meat with 100% accuracy and quantify adulteration with an R^2 up to 0.91. Meanwhile, Parastar et al. (2020) applied MicroNIR Pro with several algorithms, where the RSDE model classified chicken production systems and freshness status with accuracy above 95%. Overall, these findings highlight the strong potential of portable NIR for meat authentication, although model performance is influenced by sample condition, device spectral range, and the chemometric methods used. A summary of related studies is presented in Table 4.

Conclusion

Based on the literature, portable NIR spectroscopy shows strong potential as a rapid, non-destructive tool for food authentication and quality control. It has been applied to various food matrices, including liquids, powders, oils, and meat, with high classification accuracy and the ability to detect low-level adulteration using analytical methods such as PLS, SVM, RF, and neural networks. However, practical implementation still faces challenges, including variations in raw material origin, sample types, and the limited spectral range of portable devices compared with benchtop instruments. Therefore, future research should focus on validating models under real conditions, using more diverse samples, and developing standardized protocols. Integration with machine learning is also recommended to improve faster and more reliable food quality control systems

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