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Application of optical spectroscopy techniques in fruit juice analysis: A review

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ABSTRACT

Fruit juices are widely consumed for their nutritional value and sensory appeal, but concerns regarding quality, adulteration and authenticity necessitate reliable, rapid and non-destructive analytical techniques. This review explores applications of UV-Visible spectroscopy (UV-Vis), infrared spectroscopy, fluorescence spectroscopy and Raman spectroscopy in fruit juice analysis. Literature was retrieved from Scopus, Web of Science and Google Scholar using predefined search terms. The working principles, instrumentation, and performance of these techniques are discussed, UV-Vis detection of pomegranate juice adulteration (R^2 up to 0.99), NIR prediction of Ca (RPD = 3.92), and ATR-FTIR sugar quantification ($R^2 > 0.99$). Applications include detecting and quantifying nutrients, adulterants, toxic elements and verifying quality attributes such as color, phenolic content and acidity. Integration with chemometrics and Artificial Intelligence (AI) enhances accuracy and predictive power, while miniaturization and multimodal approaches enable real-time, in-field monitoring. Despite challenges such as matrix effects and calibration complexity, optical spectroscopy shows strong potential for ensuring fruit juice safety, quality and authenticity.

KEYWORDS

UV-visible spectroscopy, infrared spectroscopy, fluorescence spectroscopy, Raman spectroscopy, fruit juice analysis

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1. INTRODUCTION

Fruit juices are widely consumed beverages globally, valued for their taste, freshness, availability, and consumers' trust in their nutritional and health benefits. These beverages are known to provide essential nutrients and bioactive compounds such as vitamins (e.g., vitamin C, folate), minerals (e.g., K, Mg), natural sugars, dietary fiber and phytochemicals such as polyphenols, monoterpenes, flavonoids and bioactive peptides like health beneficial components (Musad Saleh et al., 2025). However, fruit juices may also contain harmful contaminants, including toxic elements, pesticide residues, microplastics, pathogenic microbes such as bacteria, yeast and molds. Even health-promoting nutrients, if they exist at levels beyond recommended dietary limits, may pose health risks. Additionally, the growing number of reported adulteration and fraud cases within the fruit juice industry has eroded consumer trust and hindered its sustainable growth (Xu et al., 2022). Therefore, ensuring the quality, safety and authenticity of fruit juices is essential to protect public health, complying with regulatory standards and supporting the long-term development of industry.

Optical spectroscopy has emerged as a cornerstone of modern analytical chemistry, offering rapid, sensitive, and often non-destructive methods without reagents to evaluate complex food matrices (Magnus et al., 2021). Techniques such as ultraviolet-visible (UV-Vis) spectroscopy, infrared (IR) spectroscopy, fluorescence spectroscopy, and Raman spectroscopy have found widespread applications in fruit juice analysis. These methods are not only used to establish nutrient profiles and detect anti-nutritional factors, but also enable real-time monitoring of contaminants, assessment of physicochemical properties during processing and storage, and verification of geographical and botanical origins (Ricci et al., 2024).

Ensuring the quality and authenticity of fruit juices is a major concern for both regulatory authorities and consumers. Adulteration of fruit juices through dilution or substitution with cheap ingredients such as sugar, organic acid, artificial sweeteners or flavors and colorants compromises product integrity and introduce health risks (Xu et al., 2022). Spectroscopy techniques are instrumental in evaluating quality markers, such as stable isotope ratios, °Brix, acidity, phenolic content and color that reflect the nutritional value, freshness and authenticity of fruit juices.

Fundamentally, optical spectroscopy techniques rely on the interaction between electromagnetic radiation and matter, typically through mechanisms such as absorption, emission, or scattering of light. The specific type of interaction depends on the method: for example, UV-Vis spectroscopy is based on absorption, fluorescence spectroscopy on emission, and Raman spectroscopy on scattering. Each molecular structure produces a unique spectral fingerprint influenced by factors such as bond strength, molecular geometry, and atomic mass. These fingerprints enable accurate classification, quantification, and detection of anomalies in food products (Magnus et al., 2021).

While numerous reviews have discussed spectroscopy for general beverage analysis, few have provided an exclusive, up-to-date synthesis focused solely on fruit juice, covering major optical spectroscopy techniques – UV-Vis, IR, fluorescence, and Raman – for assessing juice quality, safety, and authenticity. Moreover, most recent studies in this field have shifted toward biosensor-based detection, leaving a gap for a comprehensive technique-oriented review on conventional optical methods. This review addresses that gap by integrating quantitative performance comparisons from recent literature and highlighting emerging trends such as AI-driven chemometrics, portable or inline instrumentation, and multimodal spectroscopy approaches.

2. METHODOLOGY: LITERATURE SEARCH AND SELECTION CRITERIA

This review was conducted to compile research articles detailing the application of optical spectroscopy techniques to fruit juice analysis, with an emphasis on their working principles, analytical performance, advantages and limitations. A comprehensive literature search was conducted across databases such as Scopus, Web of Science, and Google Scholar using the following keywords:

"fruit juice", "fruit beverage", "apple juice", "orange juice", "pomegranate juice", "UV-Vis", "ultraviolet-visible spectroscopy", "infrared spectroscopy", "near infrared", "FT-NIR", "FT-IR", "ATR-FTIR", "fluorescence spectroscopy", "Raman spectroscopy", "quality control", "authentication", "adulteration", "nutritional analysis", "chemometrics", "machine learning", and "real-time monitoring". Boolean operators (AND/OR) were used to combine terms.

Studies were included in this review if they met the following criteria:

Type of study: original research articles and peer-reviewed papers
Scope: studies focused on fruit juices or fruit-based beverages
Analytical technique: papers that discussed optical spectroscopy techniques (UV-Vis, NIR, FT-NIR, MIR, FTIR, ATR-FTIR, fluorescence spectroscopy, and Raman spectroscopy
Language: publications available in English
Exclusion criteria: Studies focusing on non-fruit matrices or non-optical techniques

3. OPTICAL SPECTROSCOPY TECHNIQUES FOR FRUIT JUICE ANALYSIS

3.1. UV-visible spectroscopy (UV-Vis)

UV-Vis spectroscopy is a widely applied analytical technique that utilizes electromagnetic radiation in the ultraviolet and visible regions of the spectrum (typically between 200 and 800 nm). It enables both qualitative and quantitative analysis of various components based on their characteristic light absorption properties. The method is capable of detecting both colored and colorless compounds due to the presence of chromophores in food matrices, which absorb radiation in the UV (200–380 nm) and visible (380–800 nm) ranges (Mandru et al., 2023; Włodarska et al., 2021).

This technique operates by measuring electronic transitions associated with molecular chromophores. These include transitions such as π (bonding orbital at lower energy) to π^* (antibonding orbital at higher energy) and n (non-bonding orbital, typically from lone pairs at intermediate energy) to π^*, which are commonly observed in chemical groups such as carbonyl, nitro groups and conjugated double and triple bonds (Włodarska et al., 2021). In fruit juices, UV-Vis is particularly useful for the identification and quantification of naturally occurring pigments, such as chlorophylls, carotenoids and anthocyanins, due to their strong absorption in the visible region. These pigments responsible for the vibrant color of juices possess extended conjugated systems that absorb visible light. Moreover, UV-Vis is widely used to monitor changes in color intensity, which can serve as an indicator of ripeness, fermentation, oxidation or storage related spoilage. In addition, this technique enables the detection of synthetic colorants, preservatives or other additives (Dasenaki and Thomaidis, 2019). Its rapid, non-destructive nature and ease of integration into quality control systems make UV-Vis an

indispensable tool in both the industrial and research field for fruit juice authentication and quality assessment.

Włodarska et al. (2021) assessed the browning process of apple juice using UV-Vis. They observed broad absorption bands in visible regions with variable intensity due to the presence of browning products, which arise from enzymatic and non-enzymatic oxidation of phenolic compounds during processing or storage. In the UV region (200–380 nm), the spectra showed greater variability, with a prominent absorbance peak around 280 nm and shoulder of about 320 nm. These spectral features correspond to minor constituents, including aromatic amino acids (such as tyrosine and tryptophan), phenolic compounds (such as catechin and chlorogenic acids) and water-soluble vitamins (such as B_2 and B_6). The presence of these bioactive compounds not only contributed to the nutritional value and antioxidant properties of the juice but also increased the diagnostic potential of UV-Vis in the evaluation of the quality of the fruit juice. Thus, UV-Vis is an effective and non-destructive tool for both routine screening and detailed analysis of apple juice.

Bartoszek and Polak (2016) conducted a study on fruit juices using UV-Vis to determine antioxidant capacity through a $DPPH^{\bullet}$ radical recovery test. This method involves measuring reduction in the absorbance at 515 nm, as antioxidants reduce the purple-colored $DPPH^{\bullet}$ to yellow colored form. The technique proved to be accurate, rapid, simple, and cost effective. However, its accuracy may be compromised in samples with strong coloration or turbidity, such as blackcurrant and cherry juices due to interference with light absorption measurements (Table 1).

UV-Vis has also proven valuable in the authentication of fruit juices. Boggia et al. (2013) developed a rapid, cost-efficient method to detect adulteration in pomegranate juice by addition of filler juices such as grape and apple or water (Table 2). They used UV-Vis (250–660 nm) combined with multivariate analysis. Authentic pomegranate juice exhibited strong absorbance

Table 1. Comparative overview of optical spectroscopy techniques used in fruit juice analysis

Technique	Cost	Portability	Advantages	Limitations
UV-Vis	Low-moderate	High (portable devices are available)	Simple, low cost, rapid	Limited with turbid and coloured juices
NIR/FTIR	Moderate-high	Very high (handheld and inline sensors)	Fast, non-destructive, suitable for real time monitoring	Overlapping bands, poor inorganic detection
MIR/FTIR/ ATR-FTIR	Moderate-high	Limited (mostly lab based)	Strong structural information, suitable for authentication	Sensitive for water absorption, costly
Fluorescence spectroscopy	Moderate	Moderate (front face portable setups)	Good for antioxidants, quality markers, and adulteration detection	Limited to fluorescent compounds. Scattering effect in turbid juices
Raman spectroscopy	High-very high (SERS)	Increasing	Detect wide range of molecules, minimal sample preparation	High cost, fluorescence interference, less validated for multielement applications

Table 2. Overview of optical spectroscopy studies in fruit juice analysis

Technique	Analytes	Concentration range	No of samples	Accuracy/precision	Data processing method	Reference
ATR-FTIR[1]	Fructose, glucose, sucrose, total Sugar (Apple)	Fructose: 0–16 g/100 mL Glucose: 0–12 g/100 mL Sucrose: 0–8 g/100 mL Total sugar: 8–20 g/100 mL	24	Total sugar: R^2 = 0.9968, RMSECV = 0.5577; Sucrose: R^2 = 0.9983, RMSECV = 0.1366; Fructose: R^2 = 0.9952, RMSECV = 0.4778; Glucose: R^2 = 0.9961, RMSECV = 0.3209	PLS-R	Dhaulaniya et al. (2024)
ATR-FTIR	Sugars, organic acids to find adulteration	Grape and orange: 22.5–50% Peach: 18–40% Passion fruit: 4.5–10%	186	R^2 = 0.98, 0.95, 0.96, 0.96 RMSEP = 1.2%, 2.6%, 1.8%, 0.5%	PLS, IPLS-OPS	Miaw et al. (2018)
ATR-FTIR	Sugars (glucose, fructose, sucrose), organic acids, other fruit pulp presence	5.9–12 g (peach, reduced sugar) 4–7 g (peach, regular sugar) 10.3–11.8 (peach + grape) per 100 mL	69	PC1 explained 92% variance. No regression accuracy reported	PCA	Coelho et al. (2020)
FT-NIR	Sorbitol (Grape juice)	0–1467.7	40	R^2 = 0.99 (training), R^2 = 0.95 (validation)	ANN	Silveira et al. (2025)
UV-Vis[2]	Citric acid (Orange)	10		R = 0.99	NA	Hashimoto et al. (2001)
UV-Vis-NIR spectroscopy	SSC Titratable acidity pH TPC TFC (Apple)	9.6–18.1% 3.08–11.8 2.79–3.71 78.8–730.8 mg GAL/L 26.4–542.7 mg CA/L	76 (training) 29 (testing)	R^2 CV = 0.90; RPD = 3 R^2 CV = 0.94; RPD = 4 R^2 CV = 0.85; RPD = 2.6 R^2 CV = 0.86; RPD = 2.7 R^2 CV = 0.70; RPD = 1.8	PLS	Włodarska et al. (2021)

(continued)

Table 2. Continued

Technique	Analytes	Concentration range	No of samples	Accuracy/precision	Data processing method	Reference
UV-Vis	Polyphenols (ellagitannins, anthocyanins); detection of adulteration (Pomegranate)	10–40%	149	PC1 and PC2 explain 96.8%. No regression accuracy reported	PCA	Boggia et al. (2013)
UV-Vis	Polyphenols, organic acids, sugars (Pomegranate)	5–25%	105	R^2 = 0.99, sensitivity = 0.83, specificity = 1	PLS	Aykac et al. (2023)
FTIR				R^2 = 0.93, sensitivity = 1, specificity = 0.97		
MIR	Sugars (glucose, fructose, sucrose), organic acids (Apple)	NA	136	Heat-treatment classification: 77.2% correct (PLS1). Variety classification: Jonagold 100%, Bramley 100%, Golden Delicious 94.1%, Elstar 78.3% (PLS2)	PLS, PCA	Reid et al. (2005)
NIR			136	Heat-treatment classification: 77.2% correct (PLS1). Variety classification: Jonagold 100%, Bramley 100%, Golden Delicious 82.4%, Elstar 87% (PLS2)		
Fluorescence spectroscopy (excitation-emission matrix, EEM)	TPC	174–1,925 mg GAE/L	30	R^2 CV = 0.80, RMSECV = 179 mg GAE/L, RPD = 2.3	PRFAC	Włodarska et al. (2016)
	TAC (Apple)	1.1–16.7 mM		R^2 CV = 0.80, RMSECV = 1.68 mg GAE/L, RPD = 2.3		
Synchronous fluorescence spectroscopy	TPC	174–1,925 mg GAE/L	30	R^2 CV = 0.76, RPD = 2	PCA, PLS	Włodarska et al. (2017)
	TFC	42.23–298.7 mg CE/L		R^2 CV = 0.87, RPD = 2.7		
	TAC (Apple)	1.1–16.7 mM TE/L		R^2 CV = 0.79, RPD = 2.1		

(continued)

Table 2. Continued

Technique	Analytes	Concentration range	No of samples	Accuracy/precision	Data processing method	Reference
Surface-enhanced Raman spectroscopy (SERS) with gold nanoparticles	Paraquat (Apple)	WCX-SPE method: 0.02–1.0 μg mL^{-1}	28	R^2 CV = 0.98, RMSE:0.04, RPD = 7.8	PLS-R	Luo et al. (2018)
		Dilution method: 0.1–1.0 μg mL^{-1}	21	R^2 CV = 0.94, RMSE:0.4, RPD = 4.0		
Raman spectroscopy (smartphone-based)	Anthocyanins (Grape)	NA	25	R^2 CV = 0.98, RMSEP = 0.24	PCA, PLS	Gao et al. (2024)
Confocal dispersive Raman spectroscopy	Sugars (glucose, fructose, sucrose); Juice adulterants (Pomegranate)	5–95%	114	Apple juice adulteration: PLSR, R^2 = 0.94, RMSEP = 6.4%, RPD = 3.9 SVR, R^2 = 0.95, RMSEP = 5.9%, RPD = 4.3 Grape juice adulteration, PLSR, R^2 = 0.95, RMSEP = 6.3%, RPD = 4.8 SVR, R^2 = 0.95, RMSEP = 5.6%, RPD = 4.5	PLS-R, SVR	Gao et al. (2023)

Units are given as reported in the original studies.
[1]Attenuated Total Reflectance Fourier Transform Infrared Spectroscopy, [2]UV-Visible spectroscopy, [3]Near-Infrared Fourier Transform Infrared Spectroscopy, [4]Mid-Infrared Transmission Fourier Transform Infrared Spectroscopy.
IPLS-OPS: interval partial least squares-ordered predictor selection, NA: not available, PCA: principal component analysis, PLS: partial least squares, PLSR-R: partial least squares regression, PRAFAC: principal factor analysis, R^2: coefficient of determination, R^2 CV = calibration R^2, SSC: Soluble solid content, RPDP: relative predictive deviation, RMSECV: root mean square error of cross-validation, RMSEP: root mean square error of prediction, SVR: supportive vector machine regression, TAC: Total Antioxidant Capacity, TFC: Total flavonoid content, TPC: Total phenolic content.

between 250 and 300 nm and distinct band at 370–379 nm, due to ellagitannins and anthocyanins. These spectral features were used as fingerprints to distinguish authentic samples from the adulterated. Aykac et al. (2023) conducted a similar study to detect adulteration of pomegranate juice using UV-Vis, mixing sour cherry and black carrot juice between 5 and 25%. The key absorption peaks were observed at 280–300 nm and 350–400 nm, which correspond to polyphenols, particularly anthocyanin and their sugar bound forms.

Zhang et al. (2020) introduced a UV-Vis based colorimetric method for detecting paraquat herbicide (1,1′-Dimethyl-4,4′-bipyridinium dichloride) in fruit juices using gold nanoparticles functionalized with 3-mercaptopropanesulfonate. The interaction between paraquat and the modified nanoparticles induced aggregation, resulting in a visible color change and a spectral shift from 520 to 670 nm.

This method achieved a detection limit of 0.001 mg L^{-1}, demonstrated strong selectivity, and achieved high recovery rates in apple and grape juice samples. Although this approach highlights the potential of UV-Vis in combination with nanomaterials, its application in regular pesticide screening remains limited due to the need for the synthesis of nanoparticles and controlled experimental conditions.

To address the challenges posed by complex sample matrices, UV-Vis is often coupled with concentration and extraction techniques. Several studies have been conducted to assess the applicability of solvent extraction and separation, dispersive liquid-liquid microextraction, solid phase extraction, and cloud point extraction techniques for the efficient isolation of β-carotene in fruit juices (Safdarian et al., 2021).

3.2. Infrared spectroscopy (IR)

IR spectroscopy is an analytical technique that identifies and quantifies organic compounds in a sample based on their unique absorption of IR radiation by molecular bonds. When IR light interacts with matter, it induces vibrational transitions in chemical bonds, and each functional group absorbs a characteristic wavelength. It creates a unique spectral fingerprint that reveals the molecular composition of a sample. The IR region is typically classified into three regions, near-infrared (800–2,500 nm; 12,500–4,000 cm^{-1}), mid-infrared (2,500–25,000 nm; 4,000–400 cm^{-1}), and far-infrared (25,000–1,000,000 nm; 400–10 cm^{-1}) (Ozaki, 2021). Near-infrared (NIR) is particularly suitable for rapid, broad compositional assessments, while the mid-infrared (MIR) region offers more detailed structural information due to the presence of fundamental vibration bands (Chen et al., 2024). Far infrared (FIR) is used to study low-frequency phenomena such as rotational transitions, lattice vibrations and intermolecular interactions, providing valuable insight into the crystalline structure and molecular dynamics of solid materials (Ozaki, 2021). However, the application of this method to fruit juice analysis is limited due to the high water absorption rate in this region and the incompatibility of aqueous samples with FIR technology. FIR radiation typically does not have enough energy to excite fundamental intramolecular vibrational modes, so these modes are more effectively studied in the MIR region.

3.2.1. Near-infrared spectroscopy (NIR). The near-infrared spectral region is ideal for detecting compounds with O–H, C–H, and N–H bonds, which are common in fruit juices (Butz et al., 2005). The NIR measures the overtone and combination vibrations of these bonds (Fig. 1), which offer fast, chemical free and non-destructive approach for analyzing organic components (Cozzolino et al., 2011). Unlike mid-infrared spectroscopy, NIR is less affected by water

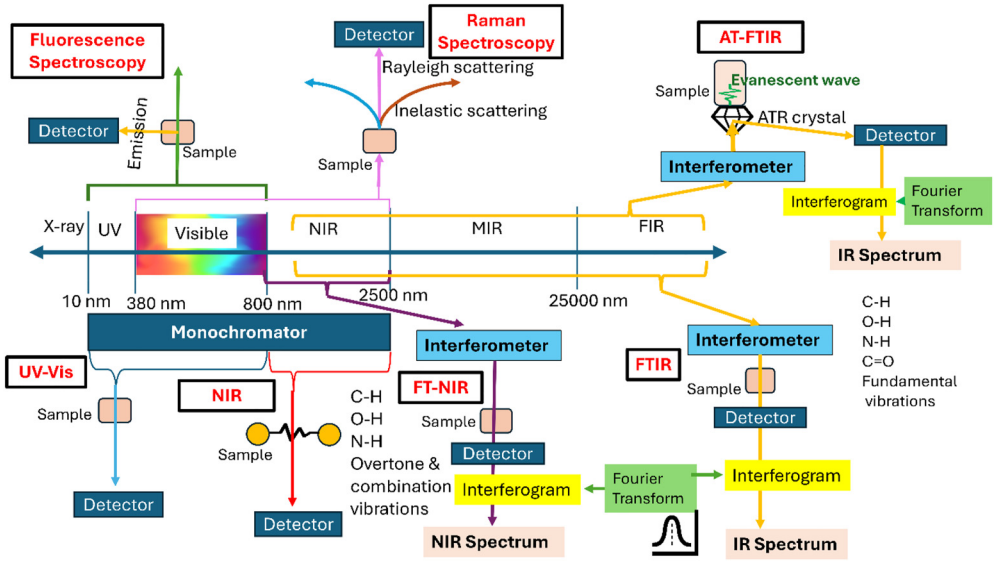

Fig. 1. Working principles of optical spectroscopy techniques - UV-Vis, NIR, FT-NIR, FTIR, AT-FTIR, fluorescence spectroscopy, and Raman spectroscopy. The figure is own source/creation

absorption due to deeper penetration depth, making it more suitable for liquid sample analysis such as fruit juices (Manley, 2014). Due to the short assessment time of sugars, acids, moisture, total soluble solids, polyphenols, and other quality-related nutrients, NIR is considered a valuable technique for quality control and authenticity testing in the fruit juice industry (Table 3) (Butz et al., 2005).

In the agricultural sector, NIR is widely used to assess food composition (e.g. sugar, moisture, protein), quality parameters (e.g. texture, color, pH) and detect adulteration (Manley, 2014). However, compared to UV-Vis, NIR spectroscopy relies heavily on a large set of accurate reference data for model calibration. NIR spectra consist of broad and overlapping peaks due to overtones and combination bands, making visual interpretation difficult (Czarnecki et al., 2015). It also has limitations in detecting inorganic compounds, such as minerals and metals, because of their weak or absent absorbance in the NIR region. Robust data analysis also relies on multivariate techniques such as principal component analysis (PCA) or partial least squares (PLS) which require expertise and computational resources for the development of complex models (Manley, 2014).

According to Butz et al. (2005), fiber optics and laser diode arrays have improved NIR performance by enhancing signal penetration and reducing noise, which is especially beneficial for turbid or pigmented juices. Its non-invasive nature also supports seamless integration into automated and inline quality control systems.

Although NIR has limitations in detecting inorganic compounds such as minerals and metals, Miró et al. (2025) conducted a study exploring the capacity of NIR to quantify mineral content. The study employed NIR in diffuse reflectance mode to predict Ca, Mg, K, and Na contents in orange juice. Reference values were obtained through chemical analysis, and the

Table 3. Importance and limitations of IR techniques in fruit juice analysis

Technique	Importance in fruit juice analysis	Limitations
NIR	• Use overtone and combination bands in the 780–2,500 nm • Rapid, non-destrictive, and suitable for real-time monitoring • Ideal for predicting °Brix, titratable acidity, and other key parameters without chemical reagents	• Lower sensitivity to minor compounds due to overtone and combination bands • Require robust calibration models • Affected by temperature, turbidity, and particle size
FT-NIR	• Use an interferometer and Fourier transformation for high resolution, high precision NIR spectra • Effective for turbid juice matrices with overlapping absorption bands – better signal-to-noise ratio • Compatible with advanced chemometric and AI based modeling • Allow multicomponent analysis from a single spectrum	• More expensive instrument • Still requires extensive calibration datasets • Sensitive to environmental conditions without proper control though generally more robust than conventional NIR
FTIR	• Targets fundamental molecular vibrations in the MIR region • High specificity for adulteration • ATR-FTIR enables direct juice analysis with minimal preparation, even for viscous samples • Works well with both qualitative and quantitative analysis	• Strong water absorption mask compounds in low concentrations • Turbid samples may require ATR or filtration • Requires baseline correction and careful spectral preprocessing as other methods, but more critical due to strong water absorption in MIR

model for Ca showed a strong correlation with laboratory data (R = 0.9418) and a residual predictive deviation (RPD) of 3.92, indicating good predictive performance. Fe showed moderate success in NIR prediction using partial least squares regression (PLSR) against chemical measurements, with an R of 0.9, a slope of 0.7, and an RPD of 1.4. This may be attributed to Fe's ability to form coordination complexes with pectin and vitamin C, which indirectly influence NIR absorption through matrix interactions. In contrast, K, Mg, and Na exhibited poor prediction results. The authors suggested that the narrow concentration range of Mg (121–143 mg kg^{-1}) may have limited model sensitivity. Additionally, Mg's lack of accessible d-orbitals may reduce its ability to participate in coordination interactions affecting NIR signals. Na (0.76–3.00 mg kg^{-1}) also showed low correlation, likely due to its fully occupied electron configuration and minimal coordination activity in aqueous media. K (1,424–2,103 mg kg^{-1}) demonstrated similarly weak correlation in PLSR modeling, which could be attributed to its low charge density and weak complexation potential. These limitations highlight the challenges of direct mineral quantification using NIR unless indirect spectral effects via matrix interactions are present.

In a recent study, Cavdaroglu et al. (2025) evaluated the performance of artificial neural networks (ANN) and support vector machines (SVM) for detecting adulteration in apple juice concentrate using spectroscopic techniques, including NIR and UV-Vis. The adulterants tested

included glucose syrup, fructose syrup, date concentrate, and grape concentrate at concentrations of 3%, 7%, 10%, 20%, 30%, 40%, and 50% (w/w). Among the techniques, NIR combined with SVM achieved the highest classification accuracy (1.0 in calibration vs. 0.95 in validation), near-perfect specificity (0.84 vs. 0.83), and a high correct classification rate (97.7% vs. 93.3%) in both calibration and validation datasets. These findings highlight the potential of integrating spectroscopic techniques with machine learning models to improve food authentication. This study demonstrates a promising pathway toward non-destructive, rapid, and reliable quality control of fruit juices using AI-driven analysis.

Several studies have assessed the suitability of NIR for field, online, and real-time monitoring applications (Manley, 2014). A recent study investigated the detection of adulteration in industrial lime juice using a two-tiered analytical strategy combining portable spectroscopy and chemical validation (Hamidi et al., 2025). The first tier applied two portable spectrometers—Vis-NIR (400–1,000 nm) and NIR (900–1,700 nm)—along with chemometric models. The second tier confirmed the results via LC-MS/MS (liquid chromatography-mass spectrometry/mass spectrometry). Using soft independent modelling of class analogy (SIMCA), Vis-NIR achieved 100% sensitivity, 82% specificity, and 91% overall efficiency. The NIR sensor, after standard normal variate (SNV) or multiplicative scatter correction (MSC) preprocessing, yielded improved performance with 100% sensitivity, 90% specificity, and 95% efficiency. Although discriminant models such as partial least squares discriminant analysis (PLS-D) and SVM did not outperform SIMCA, regression models like partial least squares regression (PLS-R) and radial basis function (RBF) demonstrated high accuracy in predicting the degree of adulteration. This study highlights a robust real-world application of portable NIR combined with machine learning for rapid, cost-effective fruit juice quality control and recommends a two-step screening-confirmation strategy for industry use. Owing to excellent machine learning algorithms and technical advantages, AI can significantly enhance the resolution, classification accuracy, and predictive ability of chemometric methods when applied to complex spectral data (Qi et al., 2025).

3.2.2. Fourier transform near-infrared spectroscopy (FT-NIR). FT-NIR is an advanced form of NIR that integrates Fourier transform mathematics with interferometer-based optics to enhance performance (Fig. 1). FT-NIR captures all wavelengths simultaneously, rather than scanning them individually as in traditional dispersive NIR. It enables multiple scans to be averaged within a given time frame, resulting in improved spectral quality and signal-to-noise ratio. Further, FT-NIR is equipped with helium-neon laser as a stable wavelength reference, ensuring precise calibration, excellent measurement repeatability over time (Liu et al., 2010) and reducing the solvent interference (Rodriguez-Saona et al., 2001). According to Rodriguez-Saona et al. (2001), chemometric techniques such as PCA and PLS-R are important for multivariate spectral analysis. Among these, PLS-R performed better for accurate calibration modeling, as it extracts latent variables from the spectral matrix (X) that are most correlated with the target concentrations (Y), thereby minimizing the influence of irrelevant spectral variations.

Mabood et al. (2018) demonstrated the potential of FT-NIR combined with PLS multivariate analysis for detecting and quantifying the saccharin adulteration in six commercial fruit juices. Samples were adulterated with saccharin at levels ranging from 0 to 2.0% (w/v). The PLS-D model achieved clear discrimination between pure and adulterated samples (R^2 = 0.97, RMSE = 0.67%), while the PLS-R model yielded high prediction accuracy (R^2 = 0.97,

RMSE = 0.88%) on independent test data. A unique saccharin absorption at 6,033 cm^{-1} corresponding to overtone transitions associated with aromatic = CH stretching vibrations. and glucose-related bands at 4,728, 4,400, and 4,300 cm^{-1} were identified as key spectral features. The authors concluded that FT-NIR and PLS combination offers a robust, rapid, non-destructive, and cost-effective approach for fruit juice authenticity testing.

In recent research, FT-NIR combined with ANN was used to detect grape juice adulteration with apple juice, using sorbitol as an authenticity marker (Silveira et al., 2025). Key spectral regions (12,400–7,400 cm^{-1} and 6,400–5,500^{-1}) showed a strong correlation with sorbitol concentration, enabling accurate quantification (concentration range 0–1,467.7 mg L^{-1}, R^2 = 0.99 for training, R^2 = 0.95 for validation). This method offered high predictive capability without the need for reagents or extensive sample preparation making it suitable for routine screening. However, confirmatory chromatographic analysis remains advisable for legal enforcement.

3.2.3. Mid-infrared spectroscopy (MIR). Mid-Infrared spectroscopy is a non-invasive analytical technique that provides critical insights into intramolecular forces, intermolecular interactions, and nature of the chemical bonds by measuring the vibrational energy levels of compounds. Modern instruments often use Fourier Transform Infrared (FTIR) systems to enhance sensitivity, increase energy throughput, and accelerate data acquisition. Three main sampling methods are commonly used: transmission, transflection and attenuated total reflectance (ATR). Among these ATR is particularly effective for analyzing liquid and semi-solid matrices such as fruit juices due to minimal sample preparation (Su and Sun, 2019).

The MIR spectral region is functionally divided into four parts: the X–H stretching region (2,500–4,000 nm; 4,000–2,500 cm^{-1}), which is associated with O–H, N–H and C–H bonds; the triple bond region (2,500–5,000 nm; 4,000–2,000 cm^{-1}) for C≡C and C≡N groups; the double bond region (5,000–6,666 nm; 2,000–1,500 cm^{-1}) for detecting C=O, C=C and C=N bonds; the finger print region (6,666–25,000 nm; 1,500–400 cm^{-1}), which contains complex and molecule specific absorption patterns (Su and Sun, 2019). These divisions allow for the precise identification and quantification of various constituents in fruit juices, including sugars, organic acids, esters and other quality indicators.

In a study by Reid et al. (2005), MIR combined with chemometric analysis was used to differentiate apple juice samples based on heat treatment and varietal origin. Key spectral features in the 900–1,200 cm^{-1} range associated with sugar vibrations, achieved 77.2% accuracy for heat treatment and up to 100% for some varieties. However, visible spectral differences were minimal and required statistical techniques like principal component analysis (PCA) and partial least squares (PLS) for effective interpretation.

MIR is a non-destructive, rapid, and eco-friendly method; however, it functions as a secondary analytical approach that requires accurate reference values for calibration (Pavas et al., 2025). Further, interpreting MIR spectra requires skilled analysts and can be time-consuming due to its complexity and volume of wave number data involved. The MIR systems require spectra from a relatively small area, so results represent the average of localized regions within the sample. This localized scanning may affect the accuracy of internal quality assessments, particularly in samples with spatial variability (Su and Sun, 2019). Although high instrumentation costs are a common limitation in IR spectroscopy techniques, they are particularly pronounced in high resolution MIR systems, especially those using ATR or transmission modes, due to their advanced optics and specialized components (Haas and Mizaikoff, 2016).

3.2.4. Fourier transform infrared spectroscopy (FTIR). FTIR is an advanced instrumental technique that combines IR with Fourier transform mathematics and computing. Instead of using traditional dispersive optics for analysis, FTIR simultaneously collects data from all wavelengths using an interferometer. The resulting interferogram is mathematically transformed into an IR absorption spectrum with the help of the Fourier transformation, producing a detailed spectral curve across the entire IR range (Fig. 1) (Chen et al., 2024).

Compared to visible and standard IR techniques, FTIR provides a broader and comprehensive analysis, as it captures full spectrum data instead of selected peak information. It covers the spectral range from 1,000 nm to 1,000,000 nm, which includes near-, mid- and far- infrared regions (Song et al., 2020). Therefore, it facilitates the detection of various functional groups C–H, O–H and C=O which are commonly present in organic acids and sugars found in fruit juices.

Because FTIR generates highly specific molecular fingerprints, it is useful for assessing complex matrices (Table 3). However, like other IR based techniques, it requires data processing and chemometric tools for accurate interpretation, especially in aqueous samples where water absorption can interfere with signals (Chen et al., 2024).

A study by Arendse et al. (2018), compared NIR and MIR to evaluate the quality of pomegranate juice, and highlighted the strengths of MIR. Two FT-MIR instruments (ATR mode) and WineScan FT120 (transmission mode) were evaluated at approximately 2,500–10,000 nm (400–1,000 cm^{-1}) and 10,750–2,000 nm (930–5,000 cm^{-1}). The MIR spectra exhibited distinct absorption bands in the 6,900–9,520 nm (1,450–1,050 cm^{-1}) range, corresponding to the fingerprint region, associated with C–O and C–C stretches in sugars and acids. The model developed for MIR spectra using the WineScan acquisition mode provided good prediction statistics for total soluble solids (range: 8.2–17.4%; R^2 = 0.90, RMSEP = 0.31% [root mean square error of prediction]). Meanwhile, FT-MIR achieved the best predictions for pH (range: 2.64–3.93; R^2 = 0.79) and BrimA (range: 5.86–15.24; R^2 = 0.91). BrimA is a sensory-based index for sweetness, calculated as total soluble solids minus a factor of titratable acidity. Although MIR was less effective for vitamin C and anthocyanin compared to NIR, it showed superior performance for color and compositional parameters when used with appropriate spectral modes.

3.2.4.1. Attenuated total reflectance FTIR (ATR-FTIR). ATR-FTIR is a surface sensitive form of FTIR that simplifies sample analysis by avoiding the need for infrared light to transmit through the sample. In this technique, the infrared light beam is reflected within the ATR crystal, creating an evanescent wave that penetrates only a few micrometers into the sample surface. Organic compounds absorb part of evanescent wave at specific wavelengths corresponding to their molecular vibrations (Fig. 1). The system then identifies the molecular structure and surface composition of the sample based on the intensity reduction of the reflected IR signal due to the absorption of organic compounds (Blum and John, 2012).

ATR-FTIR is more versatile than conventional FTIR techniques for analyzing solids, pastes or opaque liquids as it does not require an IR beam to pass through the sample (He et al., 2021). Furthermore, it enhances the use of mid-infrared region for fruit juice analysis by eliminating common challenges and errors caused by the filling of the sample into a thin cell, cleaning of transmission cells and variations in path length due to window wear (Dhaulaniya et al., 2024). However, because it is a surface-sensitive technique, ATR-FTIR may not fully represent the internal composition of heterogeneous samples. Moreover, the accuracy of predictive models depends strongly on the quality and variability of the calibration set.

Dhaulaniya et al. (2024) used partial least squares regression (PLS-R) and principal component regression (PCR) to develop predictive models with ATR-FTIR for measuring total sugar, glucose, sucrose, and fructose content in apple juice samples. The PLS-R models outperformed PCR. For total sugar and sucrose, first derivative spectra yielded the highest prediction accuracy (Table 2), whereas raw spectra provided superior results for fructose and glucose (Table 2). All optimized models achieved very high accuracy ($R^2 > 0.99$) and low prediction errors (Table 2). These findings indicate that derivative preprocessing improves performance when spectral overlap is significant (e.g., sucrose), whereas raw spectra are optimal for analytes with distinct absorption peaks (e.g., fructose, glucose).

Miaw et al. (2018) applied ATR-FTIR with chemometric modeling to quantify the main fruit content in four nectar flavours (grape, peach, orange, passion fruit) adultered with syrup, apple juice, or cashew juice. To improve PLS model performance, variable selection methods including interval partial least squares (iPLS) method, genetic algorithm (GA) method and ordered prediction selection (OPS) method were tested individually and combined. The iPLS-OPS combination achieved the best results, reducing RMSEP from 76% to 21% while using less than 7% of the original spectral variables, with the most informative numbers located in the fingerprint region and associated with sugar and organic acid absorptions. The validated models were accurate, sensitive and unbiased, and highlighted their potential as low cost, reagent free approaches for detecting nectar adulteration.

Coelho et al. (2020) aimed to evaluate the performance of ATR-FTIR for authenticity assessment of commercial peach nectars, focusing on detecting undeclared fruit pulps and quantifying sugar content. Among the selected spectral regions, the range of 6,667–11,765 nm (corresponding to 1,500–850 cm^{-1}) was found to be the most effective for classifying sugars and acids. Principal Component Analysis (PCA), especially in the processing of secondary derivative spectra, successfully grouped nectar samples into regular, low-sugar and mixed (e.g. added grape juice) categories. This technique has proven suitable for routine quality control and detecting mislabelling or adulteration in commercial fruit juices. These studies confirm that ATR-FTIR spectroscopy, when combined with appropriate chemometric models, is a powerful and efficient tool for both quantitative and qualitative analysis in the fruit juice industry. Chemometric tools are essential for interpreting complex IR spectra, enabling feature selection, classification, and quantification of predictions of overlapping absorption bands.

3.3. Fluorescence spectroscopy

Fluorescence is the emission of light by a substance after it absorbs ultraviolet or visible light. A fluorescent molecule, called fluorophore, absorbs light at one wavelength and then emits it at a longer wavelength. This process involves excitation to a higher energy state and a quick return to the ground state while releasing energy as visible light. Emission and absorption occur over a range of wavelengths, which helps in identifying specific molecules with high sensitivity (Karoui and Blecker, 2011).

Due to its high sensitivity, selectivity and easy interpretation, recent studies have considered fluorescence instead of vibrational spectroscopy to antioxidant identification and quantification in complex matrices. However, fluorescence spectroscopy is limited to fluorescent components such as tocopherol in fruit juices, but not for ascorbic acid which is not fluorescent (Włodarska et al., 2017).

Over the years, fluorescence spectroscopy techniques have evolved and gained attention in fruit juice analysis due to their high sensitivity and ability to detect a wide range of naturally occurring compounds. However, conventional fluorescence spectroscopy, typically used in right-angle setup, is limited in food analysis because of high light absorbance and scattering in turbid or solid samples. These effects distort both excitation and emission spectra, especially when sample absorbance exceeds 0.1 (Karoui and Blecker, 2011). To minimize these problems, samples are often diluted, which alters the food matrix and reduces fluorophore concentrations below the detection limit. To address these limitations, Front Face Fluorescence Spectroscopy (FFFS) was introduced. By positioning the detector at an angle to the sample surface, FFFS minimizes scattering and enables non-destructive analysis of concentrated or opaque samples without dilution, preserving the sample's original structure (Karoui and Blecker, 2011).

To further improve analytical capabilities, Synchronous Fluorescence Spectroscopy (SFS) was introduced. SFS performs simultaneous scanning of excitation and emission wavelengths with a constant offset, providing enhanced resolution, reduced spectral overlap, and greater selectivity. For more comprehensive analysis, multidimensional fluorescence techniques such as Excitation-Emission Matrices (EEMs) and Total Synchronous Fluorescence Spectra (TSFS) have been developed (Sikorska et al., 2020). These techniques provide detailed spectral fingerprints by recording complete emission profiles across multiple excitation wavelengths or synchronous spectra over a range of wavelength offsets (Christensen et al., 2006). When combined with chemometric tools, they enable the identification and quantification of multiple fluorophores within complex juice matrices. However, TSFS has higher selectivity and sensitivity, lower spectral complexity and light scattering interferences than EEMs (Włodarska et al., 2017).

Włodarska et al. (2016) investigated the use of fluorescence spectroscopy to evaluate antioxidant properties in apple juices by using two different methods. The 2016 study used EEMs combined with parallel factor analysis (PARAFAC) and N-way PLS regression to predict total phenolic content (TPC), total antioxidant capacity, and assess natural fluorescence pattern. This study identified three fluorescent components and constructed reliable models for TPC and TAC ($R^2 > 0.8$, RPD = 2.3), which demonstrated their importance for detailed juice analysis. The 2017 study used synchronous fluorescence spectroscopy (SFS) with a single offset ($\Delta\lambda = 110$ nm) and achieved even better results for TFC ($R^2 > 0.87$, RPD = 2.7). Although SFS provides less spectral detail, it allows faster measurements and simpler modeling. Overall, EMM is better for in-depth analysis, while SFS is more practical for rapid and efficient screening.

Fluorescence-based techniques have shown great promise in assessing the quality and authenticity of mango juice. Sabir et al. (2024) used conventional fluorescence emission spectroscopy to assess mango juice composition by detecting fluorophores such as β-carotene, chlorophyll, water and tartrazine food color. A fixed excitation at 405 nm was used to evaluate the changes in fluorescence due to water and color adulteration, as well as thermal treatment effects. A decrease in fluorescence intensity observed due to both adulteration and thermal degradation, particularly at higher temperatures, indicating loss or alteration of major nutritional compounds such as β-carotene and chlorophyll. Building on this work, Sabir et al. (2025), used SFS with a wavelength offset ($\Delta\lambda = 80$ nm) for real time monitoring over a broader spectral range. It detected specific emission bands associated with tryptophan, phenolic compounds, riboflavin and chlorophyll, which serve as indicators of fruit juice quality. Similar to the previous study, water dilution and artificial coloring led to a significant decrease in fluorescence intensity. Further, deformed peaks were observed in the 410–530 nm region. Thermal treatment

up to 80 °C preserved the molecular structure of mango pulp and fluorescence intensity. Beyond that, caused phenolic degradation and an increase in overall fluorescence emission, indicating structural changes.

Fluorescent compounds in fruit juices include aromatic amino acids, vitamins, chlorophyll derivatives, food additives and phenolic compounds which act as key indicators of quality, authenticity and adulteration (Sikorska et al., 2020). Therefore, fluorescence-based techniques, especially when combined with advanced data analysis such as PCA, PLS-R, and PARAFAC, provide a powerful and non-destructive approach for comprehensive assessment of fruit juice.

3.4. Raman spectroscopy

Raman spectroscopy is based on the inelastic scattering of monochromatic light, usually from a laser source. When the sample is being irradiated by the laser beam, most of the photons are scattered elastically (Rayleigh scattering) without changing energy. However, small fractions of photons are subjected to inelastic scattering, which involves an energy exchange caused by collisions between the incident photons and the molecules of the sample. This interaction alters the vibrational and rotational energy of the molecules and leads to changes in the wavelength of the scattered light, a phenomenon known as the Raman effect. The energy difference between the scattered and incident beams is called the Raman shift. These shifts are measured and represented as spectral bands corresponding to specific chemical bonds and functional groups. The resulting Raman spectrum provides a molecular fingerprint of the sample that enables qualitative, quantitative and structural analysis (Yang and Ying, 2011).

There are four main types of Raman Spectroscopy commonly used in food analysis (Table 4).

Surface-enhanced Raman Spectroscopy (SERS), used to increase detection sensitivity by using nanoparticles. Several studies have applied SERS to detect a wide range of pesticide residues in fruit juice, including both aromatic and non-aromatic compounds. These studies have often achieved detection limits well below regulatory limits, typically ranged from 0.1 ppm to 1 ppm (Wang et al., 2021). Although SERS facilitates fast analysis and minimal sample preparation, most methods detect only one or a few pesticides at a time. Simultaneous multi-residue analysis requires preliminary separation steps such as TLC or SPE. Conventional methods such as HPLC and Thin-Layer Chromatography (TLC) are effective for detecting aromatic pesticides, but they lack the ability to identify ionic and organometallic compounds, underscoring the expanded detection capabilities and flexibility offered by SERS. Moreover, HPLC and TLC are often combined with UV or fluorescence detectors, which restrict their detection to compounds with aromatic rings (Wang et al., 2021).

Luo et al. (2018) developed a SERS method using gold nanoparticles to assess Paraquat (1,1′-Dimethyl-4,4′-bipyridinium dichloride), a toxic herbicide in apple juice. Two sample preparation techniques were used, weak cation exchange solid-phase extraction (WCX-SPE) and simple dilution method. The WCX-SPE method offered high sensitivity (LOD = 0.02 μg L^{-1}) and a high linearity ($R^2 = 0.98$), although it required approximately 40 min. The simple dilution method achieved detection at 0.1 μg mL^{-1} with reduced matrix effect after 500× dilution while offering faster analysis (approximately 10 min) and decent linearity ($R^2 = 0.93$). In addition, the study revealed that significant interference hindered paraquat detection at low concentrations. Sugars caused the greatest suppression of the Raman signal, followed by organic acids, mainly by blocking paraquat absorption into gold nanoparticles.

Table 4. Four types of Raman spectroscopy, their characteristics and applications in food analysis

Dispersive Raman spectroscopy	Fourier transform Raman spectroscopy
• Utilizes a diffraction grating to separate inelastically scattered light into distinct wavelengths • High resolution spectral analysis directly from the sample • Suitable for aqueous, black color, and high-temperature samples • Suppresses fluorescence at longer wavelengths – useful for samples with high organic content	• Converts modulated Raman signals into spectra using Fourier transformation • Offer high resolution and fluorescence suppression • Easy to use and compatible with FTIR systems • Effective for high fluorescence fruit juice samples or complex mixtures
Surface-enhanced Raman spectroscopy	**Spatially offset Raman spectroscopy**
• Amplifies Raman signals by adsorbing analytes onto metallic nanostructures • Light excites surface electrons (plasmons), enhancing the local electromagnetic fields and boosting the Raman scattering • Ultra-sensitive, molecule specific, high resolution • Suitable for trace level contaminants – heavy metals, pesticide residues	• Collects Raman signals from spatially shifted points on the sample surface to access subsurface layers • Non-invasive analysis through opaque or layered materials • Minimizes interference from packaging materials – suitable for sealed juice bottles or layered samples • Rapid on-line analysis

Raman spectroscopy has emerged as a powerful, non-destructive technique for quantifying bioactive compounds such as anthocyanin in fruit juices. In a recent study, a smartphone-based Raman spectrophotometer successfully measured anthocyanin in grapes and freshly squeezed grape juice (Gao et al., 2024). Raman spectra showed distinct anthocyanin peaks (e.g. 540, 630, 730, 1,608 cm^{-1}). The study evaluated two modeling approaches, univariate linear regression (using 630 cm^{-1}) Raman peak, and multivariate linear regression (MLR) with feature selection via PCA and Recursive Feature Elimination (RFE). Although the univariate regression model showed high accuracy with grape skin, Raman peaks in juice were weaker due to interference from sugars and acids. The MLR with advanced feature selection algorithms achieved high prediction accuracy in fruit juice samples ($R^2 = 0.98$). These findings highlight the potential of integrating Raman spectroscopy with chemometric techniques for real-time, in-situ quality assessment and nutritional profiling of fruit juices.

Both IR and Raman spectroscopy offer valuable fingerprinting capabilities for identifying characteristic compounds in fruit juice through their detection of molecular vibrational modes. The abundance and sharpness of spectral peaks reflect the unique vibrational patterns of functional groups to accurately identify the components of fruit juices such as sugars, organic acids, phenolics and colorants. However, Raman spectroscopy excels in analyzing aqueous samples due to its low interference from water, whereas IR can be more sensitive to polar functional groups like hydroxyls.

In a recent study, Gao et al. (2023), used a type of dispersive Raman system, a confocal micro-Raman spectrophotometer with a 785 nm laser to quantify the adulteration of pomegranate juice with varying concentrations of apple and grape juices. The spectral data collected in the range of 432–1,623 cm^{-1} revealed distinct vibrational features associated with sugars such as glucose, fructose and sucrose. Partial Least Squares Regression (PLSR) and Support Vector Regression (SVR) were applied for chemometric modeling and achieved high prediction accuracies for adulterant levels. These results showed that Raman spectroscopy, when combined with advanced chemometric techniques, provides a rapid, non-destructive and cost-effective method for on-site authentication and quality control of fruit juices.

3.5. Future perspectives

The future of fruit juice analysis will likely be shaped by miniaturization, digitization and integration. Advances in portable and handheld spectrometers, coupled with AI-driven data processing and multimodal spectroscopy would facilitate real-time monitoring and non-destructive quality assessment, both within laboratories and directly on production lines. The combination of multimodal spectroscopy (e.g., UV-Vis + NIR + Raman) could provide complementary molecular information, enhancing detection sensitivity for both nutritional and adulteration markers.

Industrial adoption requires robust calibration libraries, standardized measurement protocols, and validation under diverse conditions. The incorporation of cloud-based data sharing would facilitate near-real-time data exchange between stakeholders.

Continued development of in-line monitoring systems and eco-friendly analytical approaches with minimal reagent usage would support sustainable food production. Integrating machine learning algorithms with these techniques would further improve nutritional profiling, adulterant detection, and authenticity verification. Moreover, standardization, method validation and regulatory acceptance will be crucial for broader adoption of spectroscopy techniques in the fruit juice industry.

4. CONCLUSIONS

This review highlights the pivotal role of optical spectroscopy in ensuring the quality, safety, and authenticity of fruit juices. Techniques such as UV-Vis, NIR, FT-NIR, MIR/FTIR, ATR-FTIR, fluorescence, and Raman spectroscopy each offer unique advantages from rapid, non-destructive or minimal sample preparation, nutrition profiling, and adulteration detection to highly specific molecular fingerprinting of sugars, organic acids, and bioactive compounds. However, challenges remain, such as spectral overlaps, interference from turbidity or water absorption, and the need for robust calibration models.

The current research trend is shifting toward the integration of AI-driven chemometrics (ANN, SVM, SVR), multimodal instrumentation, portable and handheld devices, and nanomaterial-enhanced methods (SERS). In addition, two-tier strategies combining rapid optical screening with confirmatory chemical analysis are improving operational efficiency and regulatory compliance.

Future progress will depend on method standardization, reagent-free sustainable approaches and broader adoption of AI enhanced, miniaturized, and multimodal systems. These advancements hold promise not only for protecting consumers and restoring trust but also for a more transparent, efficient, and resilient fruit juice supply chain.

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